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Joana Passinhas, Ana Pereira

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Portugal

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Rua Miguel Lupi, 20
1249-078 LISBOA
Portugal

Telephone: +351 - 213 925 912
E-mail: rem@iseg.ulisboa.pt

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A macroprudential look into the risk-return framework of banks' profitability

Joana Passinhas
Banco de Portugal
Lisbon School of Economics & Management (UL)

Ana Pereira
Banco de Portugal
Lisbon School of Economics & Management (UL)

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Abstract
Ensuring the resilience of the financial system implies managing a trade-off between expected bank profitability and tail risk in bank returns. To describe this trade-off, we estimate a dynamic quantile regression model using bank-level data for Portugal that links future bank profitability to the current cyclical systemic risk environment net of the prevailing level of capital-based resilience (residual cyclical systemic risk). We find that an increase in residual cyclical systemic risk negatively affects the conditional distribution of bank profitability at the medium-term projection horizons, confirming the findings in the literature. We propose a novel calibration rule for the countercyclical capital buffer (CCyB), which is flexible enough to accommodate different preferences of the policymaker and factors in the prevailing levels of cyclical systemic risk and capital-based resilience. We illustrate the operationalisation of this rule under different assumptions for the policymaker preferences and show how tightening capital requirements alters the risk-return relationship of future profitability in the banking sector. We find evidence that increasing the CCyB rate improves the outlook for medium-term downside risk in bank profitability and worsens the outlook for short-term expected profitability, stressing the trade-off faced by the policymaker when deploying policy instruments and the misalignment in the horizons at which costs and benefits take place.

JEL: C21, C54, G17, G21, G28

Keywords: Macroprudential policy, systemic risk, bank profitability, quantile regression.

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E-mail: jpassinhas@bportugal.pt; arnpereira@bportugal.pt/anapereira@phd.iseg.ulisboa.pt

1. Introduction

The role of macroprudential policy is to ensure the resilience of the financial system against the materialisation of systemic risk, i.e. developments that may threaten financial stability as a whole and consequently spillover to the economy. To pursue this objective a diverse set of policy instruments was made available to macroprudential policymakers across Europe (Basel Committee on Banking Supervision 2011), building on the experience from the 2008 Global Financial Crisis (GFC). One of these instruments is the countercyclical capital buffer (henceforth CCyB) designed to deal with the time-varying dimension of systemic risk, known as cyclical systemic risk. Past evidence shows that banks tend to engage into herding behaviours of excess risk taking during the upswing of the financial cycle and of excessive deleveraging in the downswing of the financial cycle. Deleveraging behaviours cause disruptions in the provision of credit that jeopardise consumption and investment in the economy. To address this procyclical behaviour, policymakers may increase bank capital buffers in periods of increased lending and excessive risk taking that can be drawn down to absorb unexpected losses during financial stress events, mitigating credit supply restrictions. However, taking action comes with trade-offs given that *ex-ante* restrictions imposed on economic agents are costly and the benefits of avoiding a financial crisis are invisible. In this paper, we provide insights on how cyclical systemic risk net of the prevailing capital-based resilience impacts bank profitability at different horizons and discuss the trade-off between expected profitability and tail risk in bank returns faced by policymakers when deciding on a policy stance for macroprudential capital-based instruments.

Following the growing literature on at-risk models, first applied to financial stability surveillance by Adrian *et al.* (2019) and, more specifically, the work of Lang and Forletta (2020), we characterise the link between bank profitability and cyclical systemic risk in Portugal for a small panel of banks representative of the domestic banking sector over time. Specifically, we use a dynamic quantile regression model to quantify the impact of cyclical systemic risk on the conditional distribution of bank profitability. As macroprudential interventions are preventive in nature and there are lags in policy implementation and transmission, we resort to local projections over several projection horizons to gauge this link between future bank profitability and cyclical systemic risk. Bank profitability is measured by the pre-tax return expressed as a percentage of assets. As a measure of cyclical systemic risk, we employ the domestic cyclical systemic risk indicator (d-SRI) proposed by Lang *et al.* (2019). This indicator approximates the dynamics of the financial cycle combining information about the risk level in the domestic credit market, real estate market and external imbalances. Besides this indicator, the model is also populated with bank-specific controls and macrofinancial indicators as well as bank individual fixed effects. An interaction term between cyclical systemic risk and a bank capital ratio measure is also included in the model to capture how existing resilience affects the impact of risk on future bank profitability. The estimation of the unknown parameters relies on recent methods proposed in the literature for panel estimation of quantile regression models with individual fixed effects. Specifically, we employ the Method of Moments-Quantile Regression (MM-QR) approach developed by Machado and Santos Silva (2019), which allows for location and scale shifts of the conditional distribution of future bank profitability to be driven not only by the regressors but also by bank individual fixed effects.

Our findings indicate that the estimated impact of an increase in residual cyclical systemic risk, i.e. the level of cyclical systemic risk after taking into account the prevailing level of capital-based resilience, on the conditional distribution of bank profitability is mostly negative and statistically significant at the medium-term horizons (between 11 and 16-quarters ahead), confirming the findings in the literature. As a result, an increase in residual cyclical systemic risk increases the likelihood of experiencing bank losses in the future. However, in contrast with the literature (Lang and Forletta (2020)), we find no evidence of asymmetric impacts of residual cyclical systemic risk on the quantiles of the conditional distribution of bank profitability at the medium-term projection horizons. Thereby, the estimated negative impact on profitability of an unit increase in residual cyclical systemic risk is of the same magnitude across percentiles and hovers around 0.5 percentage points of return-on-assets.

Provided with these insights, we discuss the policy implications of the results. The results are employed in three policy exercises that are relevant for macroprudential policymakers as they involve the risk assessment or the calibration of instruments. First, we use the empirical results to specify a calibration rule that provides an indicative rate for the CCyB as in Lang and Forletta (2020). The indicative rule provides the capital ratio add-on that would cover the impact of current residual cyclical systemic risk on median profitability at medium term horizons. This indicative calibration rule may be added to the already existing calibration approaches underlying the guided discretion framework that informs the decisions on the CCyB rate at the European Union.[1] More policy calibration rules are often better than a single one, to diminish the uncertainty surrounding the policy instrument calibration exercise. The simulation for Portugal shows that the indicative CCyB rates closely follows the dynamics of the cyclical systemic risk over the sample period. The rate increases when cyclical systemic risk is rising, as in the period ahead of the GFC, and decreases when cyclical systemic risk is either receding or materialising. The indicative CCyB rates seem high, especially at the beginning of the sample period, considering that they surpass the 2.5% soft limit enshrined in the European banking regulation. However, we argue that these calibrations reflect the more limited bank capitalisation in Portugal prior to the implementation of the Basel III reforms, and consequently the existing capital-based resilience might have been lower than the desirable to cover the future median losses estimated by the model. If bank capital requirements were more stringent in

1. The principle of guided discretion alludes to the use of a rule-based approach combined with discretion on the part of the policymaker when deciding on the appropriate buffer rate. This principle is laid out in Directive 2013/36/EU and Recommendation ESRB/2014/1.

the past, then the indicative CCyB rate would be lower, even for the same level of cyclical systemic risk.

Second, the predicted left tail quantile of the conditional distribution of future bank profitability is used to assess how much return is at risk in a specific projection horizon given the current cyclical systemic risk environment and the prevailing level of capital-based resilience. Results for Portugal show that tail risk in banking sector profitability started to increase in the beginning of 2006, shortly ahead of the GFC, and attained its worse value in 2010Q1, shortly after the onset of the European Sovereign Debt Crisis (ESDC). Moreover, the dispersion in tail risk across banks widened after 2009, reflecting most likely the differentiated impact of the crises on banks.

Third, the estimation results are used to explore how residual cyclical systemic risk shapes the risk-return relationship in bank profitability in Portugal. For that, the risk contribution to a distance-to-tail metric (downside risk) is compared with the risk contribution to expected return. We show that the risk-return relationship in bank profitability for a given level of residual cyclical systemic risk varies across projection horizons, but it tends to be similar within clusters of projection horizons. Leveraging on this risk-return relationship in bank profitability and on the concept of macroprudential policy stance, we propose a novel rule to guide the calibration of the CCyB rate, which is flexible enough to incorporate different preferences of the policymaker and factors in the prevailing levels of cyclical systemic risk and capital-based resilience. More specifically, we assume that the policymaker defines the CCyB rate with the objective of guaranteeing that the contribution of residual cyclical systemic risk to downside risk in bank profitability in a medium-term horizon is non-positive, in line with its mandate of guaranteeing the resilience of the banking sector against adverse events. We illustrate the operationalisation of our novel calibration rule under different assumptions for the policymaker preferences (three scenarios). The results for Portugal ensue calibration rules that suggest setting a positive CCyB rate whenever banking sector Tier 1 capital ratio is below 9.9% in scenario one, 14.2% in scenario two and 10.8% in scenario three. Overall, the rule derived under scenario two is the most demanding in respect to how much more resilience was needed in the banking sector to tackle risk over the sample period. This result follows, on the one hand, from the more demanding target set by the policymaker, which is consistent with a more risk averse policymaker, and, on the other hand, from the limited level of bank capitalisation prior to the introduction of Basel III reforms in the aftermath of the GFC. Finally, we illustrate the trade-offs faced by macroprudential policymakers in terms of bank profitability while managing cyclical systemic risk through the imposition of more stringent capital requirements. We present a counterfactual for the trade-offs of increasing the CCyB rate in Portugal from 0% to 2.60% in 2006Q1, ahead of the financial crisis. Increasing the CCyB rate translates into a better outlook for the medium-term downside risk in bank profitability, but a worse outlook for short-term expected bank profitability. These results find support on the existing literature that highlights that the costs associated with capital requirements increases tend to be more pronounced in the short term, while the benefits arise in the medium to long term.

The remaining of our paper is organized as follows. Section 2 summarizes the three strands of existing literature that more closely relate to our analysis. Section 3 presents the empirical model to be estimated along with the estimation approach. Section 4 provides an overview of the data used in estimation. Section 5 presents the results from model estimation. Section 6 shows how the estimation results can be used in three policy exercises that are relevant for macroprudential policy purposes and section 7 concludes.

2. Literature review

Our analysis is related to three strands of recent but growing literature. The first strand focus on assessing the asymmetric impacts of financial conditions and/or financial vulnerabilities on the conditional distribution of a variable of interest to assess the drivers of tail risk. The second focus on methods to inform the calibration of time-varying capital-based macroprudential instruments, in particular, the CCyB. The third relates to the application of the concept of stance to macroprudential policy.

The pioneering contribution of Adrian *et al.* (2019) documents for the US, using a quantile regression model, the existence of an asymmetric relationship between financial conditions and the conditional distribution of future GDP growth. Thereafter, Adrian *et al.* (2022) extended these results to a panel of advanced economies. Figueres and Jarociński (2020) explore which measures of financial conditions in the euro area perform better in signalling tail risks to GDP growth. The use of these findings for macroprudential policy purposes was established by Aikman *et al.* (2019). They find evidence that some indicators typically included in macroprudential risk monitoring frameworks are useful for explaining changes in tail risk of GDP growth at the medium-term horizons. Galán (2020) expands this analysis by including the effect of implemented macroprudential measures. Our analysis employs the same methodological framework explored in these papers to bank profitability.

As for calibration methods, the literature has been expanding as countries' experience in macroprudential policymaking grows. Finding the appropriate size for a capital buffer is a challenging task for policymakers and should be guided by a cost-benefit analysis anchored in multiple approaches, so that calibration uncertainty is somewhat reduced. In this vein, the Basel Committee on Banking Supervision (2010) introduced the concept of guided discretion for CCyB decisions and a linear rule for the calibration of the CCyB rate based on a measure of credit cycle. However, experience shows that the use of this rule for setting a positive CCyB rate in European countries has been limited, as discussed by Babić (2018) and Babić and Fahr (2019). Instead, complementary approaches to calibrate the buffer have been used. These range from simply considering other measures of credit cycle to more complex approaches such as the use of structural models. Also, approaches based on unexpected credit losses gain much attention as they are linked straightforward to the objective of the CCyB.

The assessment and timely identification of the position of the economy in the credit cycle can rely on a broad set of indicators. Examples include Rychtárik (2014) and Rychtárik (2018) that proposes using the cyclogram, a composite indicator that combines core and supplementary information in a single indicator, in addition to credit gaps to guide the discussion on the size of the buffer rate in Slovakia; Plašil *et al.* (2015) that proposes a composite indicator that better identifies the build-up phase of systemic risk in Czech Republic; and, Lang *et al.* (2019) that proposes the domestic systemic risk indicator for the euro area by merging information from several segments of the economy. Related to this latter approach is also the use of multivariate early warning frameworks based on logit and probit models as, among others, those proposed by Detken *et al.* (2013), Dekten *et al.* (2014), Anundsen *et al.* (2016), Coudert and Idier (2018) and Tölö *et al.* (2018).

On a structural perspective, DSGE models can be used to obtain optimal CCyB calibration rules. These rules are obtained by the optimization of an objective, that may be the maximization of a social welfare function or the minimization of the volatility of a variable of interest (e.g. Lozej *et al.* 2018 and Aguilar *et al.* 2019). Calibration exercises based on stress test approaches, in particular macroprudential stress tests, have also gained attention in recent years. These models allow to assess how much capital buffer is desirable in order to withstand losses from a stress scenario. This scenario can be designed to be countercyclical in such a way that the degree of severity increases as the economy moves up the financial cycle (e.g. Bank of England 2016, Anderson *et al.* 2018 and van Oordt 2018). Our proposed framework for CCyB calibration deviates from these two latter approaches as we do not directly measure the impact on the economy of tightening capital buffers.

Finally, in the spirit of the applicable regulation that envisages the combination of calibration approaches, Bennani *et al.* (2017) and Couaillier and Scalone (2021), among others, propose an hybrid calibration strategy for macroprudential policy instruments. These authors suggest considering early warning models, stress testing tools and DSGE models combined with an active role for expert judgment. Despite the differences in the modelling approaches, all these frameworks relate to our analysis in the sense that they link cyclical systemic risk to banks' losses and aim to improve on the guidance to calibrate the CCyB rate.

Our analysis, also, picks up on the scarce literature related to the assessment of macroprudential policy stance (European Systemic Risk Board 2019, European Systemic Risk Board 2021, Suarez 2022 and Cecchetti and Suarez 2021) for proposing a novel rule for the calibration of the CCyB rate. Policy stance has mostly been assessed in the context of monetary policy to indicate periods where it was either loose, that is, when it sought to stimulate economic growth, or tight when it sought to slow economic growth to head off inflation. Similarly, the concept of macroprudential policy stance has been developed to assess how the current macroprudential policy fares in targeting its objective of promoting financial stability. The macroprudential policy stance, according to European Systemic Risk Board (2019), is obtained after assessing how the implemented macroprudential measures are influencing systemic risk net of the prevailing level of resilience. Then, the level of residual systemic risk is compared with a neutral level, which is the level that does not put financial stability at stake. If residual systemic risk is above the neutral level and the macroprudential policy already in place is not able to diminish this distance, via either countering risks or raising resilience, then macroprudential policy stance is loose, contributing to stimulate the financial cycle. If the implemented macroprudential policy pushes residual systemic risk to be below the neutral level, then macroprudential policy stance is tight, contributing to excessively dampen the financial cycle.

In order to operationalize the concept of macroprudential policy stance the recent literature has pointed to an assessment of the impact of systemic risk and macroprudential policy indicators on a central measure (either the mean or the median) and on a central-to-tail measure of the GDP growth distribution (European Systemic Risk Board 2021, Suarez 2022 and Cecchetti and Suarez 2021). GDP growth has been chosen as a target variable given that stress in the financial system contributes to increase the likelihood and severity of economic crises, which translate into changes in the GDP growth distribution. In addition, the European Systemic Risk Board (2021) also presents a framework for stance space in which the median-to-tail distance of the GDP growth distribution is linked to median growth. This framework illustrates the trade-offs faced by macroprudential policymakers when deciding on policy implementation as it maps its effects on risk (benefits) at the expense of median/mean growth (costs). Suarez (2022) shows that by targeting a mean-to-tail distance it is possible to obtain an optimal macroprudential policy that does not depend on the level of systemic risk. The optimal policy is based instead on the cost-effectiveness of macroprudential policy and depends on a risk preference parameter set by the policymaker. Cecchetti and Suarez (2021) further explore the optimal rule of Suarez (2022) by setting the macroprudential policy stance as the result of the comparison between the optimal policy rule and current conditions of risk and policy. In this report, the authors also argue that macroprudential policymakers should target a future horizon (h-periods ahead) since policy takes time to have an effect on the financial system and it is subject to operationalisation lags. This is something that we also embedded in our empirical model.

3. Quantile regression model

We consider a dynamic quantile regression model for panel data to characterise the response of the conditional distribution of future bank profitability to increases in residual cyclical systemic risk. The empirical model combines linear local projections, as proposed by Jordà (2005), with quantile regression under the form of a linear location-scale panel data model, as proposed by Machado and Santos

Silva (2019). The model allows for the inclusion of fixed effects that control for time-invariant unobserved heterogeneity of banks, which is a common assumption when modelling bank profitability.

Quantile regressions are particularly useful in understanding outcomes that are non-normally distributed, as it is most likely the case of bank profitability, and allow to explore the relationship between regressors and the outcome variable across the whole conditional distribution and not only at the mean. As such, we implicitly assume *ex-ante* that the regressors may have a different impact on each percentile of the conditional distribution of future bank profitability. The specification of the model in terms of local projections allows to incorporate in the analysis the pre-emptive nature of macroprudential policy, and recognising that undertaking such policy measures requires advanced warning, due to implementation lags as pointed out by Aikman *et al.* (2019).

Estimators for quantile regression models applied to panel data are relatively recent when compared with the estimators available for standard panel data models for the conditional mean. Quantile regression models were introduced by Koenker and Bassett (1978) and allow to identify the presence of different effects on the distribution of interest from changes in the regressors. Advances in the estimation of quantile regression models considering individual fixed effects are even more recent. The challenge in this task is that the standard method of differentiating out the individual fixed effects, used in the context of linear panel data regression models for the conditional mean, is not valid and this leads to the incidental parameters problem. Koenker (2004) and Canay (2011) assume a model in which individual fixed effects would only cause parallel (location) shifts in the conditional distribution of interest, i.e. would not vary across quantiles. However, imposing *ex-ante* that individual fixed effects do not vary across quantiles might be too restrictive. One approach to let fixed effects affect other characteristics of the distribution, and not just location, would be to estimate quantile-by-quantile regressions based on the standard approach, allowing for different fixed effect estimates at each quantile (Koenker 2005). However, the large sample properties of the estimator only remain comparable to those of the estimator used in standard quantile regressions when the time dimension is large, in absolute terms and relative to the cross-sectional dimension, which is not always the case. Alternative approaches, as those proposed by Kato *et al.* (2012), Galvao and Wang (2015), Galvao and Kato (2016) and Machado and Santos Silva (2019), specify location-scale models in which individual fixed effects can produce location and scale shifts in the conditional distribution of interest. Some of these estimators have good large sample properties that hold under less demanding conditions in terms of panel data dimensions.

Departing from Lang and Forletta (2020), we employ a location-scale quantile model with individual fixed effects that vary across quantiles to characterize future bank profitability. In our empirical model, we assume that future bank profitability, $\pi_{i,t+h}$, follows a distribution conditional on a set of regressors, where h stands for a certain number of periods ahead in the future, $i = 1, \ldots, N$ identifies the banks, $t = 1, \ldots, T$ identifies the period and $h, N, T \in \mathbb{N}$. According to Koenker and Bassett Jr (1982) employing a location-scale model implies that:

$$\pi_{i,t+h} = \mu(\mathbf{X}_{i,t}) + \sigma(\mathbf{X}_{i,t})U_{i,t+h} \tag{1}$$

where $\mathbf{X}_{i,t} \in \mathbb{R}^k$ denotes a vector of k regressors with l^{th} element denoted by $X_{l,i,t}$ for $l = 1, \ldots, k \in \mathbb{N}$, $\mu(\mathbf{X}_{i,t})$ represents the conditional mean of the regression model, known as the location function; $\sigma(\mathbf{X}_{i,t})$ stands for the conditional scale, a measure of variability known as the scale function; and $U_{i,t+h}$ is the error term, assumed to be independent of $\mathbf{X}_{i,t}$ and originated by a distribution with quantile function $q(\tau, h)$ where $\tau \in (0, 1)$ is the quantile. We also assume that $\mu(\cdot)$ and $\sigma(\cdot)$ are linear functions of $\mathbf{X}_{i,t}$. The corresponding conditional quantile regressions for future bank profitability are given by:

$$Q_{\pi_{i,t+h}}(\tau|\mathbf{X}_{i,t}) = \left[\alpha_i^h + \delta_i^h q(\tau, h)\right] + \mathbf{X}'_{i,t}\left[\boldsymbol{\beta}^h + \boldsymbol{\gamma}^h q(\tau, h)\right] = \alpha_i(\tau, h) + \mathbf{X}'_{i,t}\boldsymbol{\beta}(\tau, h) \tag{2}$$

where $(\alpha_i^h, \boldsymbol{\beta}^h)$ are unknown location parameters, $(\delta_i^h, \boldsymbol{\gamma}^h)$ are unknown scale parameters and $q(\tau, h)$ verifies $\Pr\left[U_{i,t+h} < q(\tau, h)\right] = \tau$.[2]

Bank fixed effects are captured by the term $\left[\alpha_i^h + \delta_i^h q(\tau, h)\right]$ or $\alpha_i(\tau, h)$, where α_i^h denotes a location shift that can be interpreted as the average effect of fixed effects on bank i's future profitability and δ_i^h a scale parameter that allows fixed effects to have different impacts across the conditional distribution of future bank profitability. These effects, also referred to in the literature as quantile-τ fixed effect for bank i, control for unobservable factors that differ across banks but are constant over time.

The set of regressors comprises two groups of explanatory variables, for which details are provided in Section 4. The first group includes variables specific to the bank, among others, the contemporaneous value of the profitability measure, while the second group covers macrofinancial variables that are invariant at the bank level, such as a measure of cyclical systemic risk. The marginal effect of a specific l regressor $(X_{l,i,t})$ on the $\tau-$quantile of the conditional distribution of $\pi_{i,t+h}$ is given by $\left[\beta_l^h + \gamma_l^h q(\tau, h)\right]$, which also consists of a location parameter β_l^h and a scale parameter γ_l^h. In the same way, β_l^h will denote the average effect of regressor l on future bank profitability while $\gamma_l^h q(\tau, h)$ represents the scale of the shift from average effect to the $\tau-$quantile of the conditional distribution of future bank profitability. The estimates for the scale parameters allow assessing which regressors are more relevant to shape the dispersion of future bank profitability.

We estimate equation (2) for prediction horizons between 1 and 24 quarters $(h = 1, \ldots, 24)$ and for various percentiles. For estimation, we employ the Method of Moments-Quantile Regression (MM-QR) approach developed by Machado and

2. For more details about the characteristics and conditions that must be verified by $U_{i,t+h}$ see Machado and Santos Silva (2019).

Santos Silva (2019). In comparison with other estimators proposed in the literature for our particular setting, which is a small panel data with not very large time series dimension, the chosen estimator has some advantages. First, it produces non-crossing estimates of the quantiles of the conditional distribution. Second, the estimator is computationally much easier to implement than the competing ones that also allow fixed effects to vary across quantiles. Lastly, the asymptotic properties of the estimator are valid under panel datasets with a smaller T relative to N than it is usually necessary to obtain reliable estimates within quantile regressions. Machado and Santos Silva (2019) find, based on simulation exercises, that for N/T up to 10 the confidence intervals of the MM-QR estimates are reasonable. Inference on parameter estimates is based on bootstrapped standard errors. We do not consider clustered standard errors at bank-level as they are only consistent in micro panel set-ups, in which the number of clusters goes to infinity. Additionally, economic endogeneity in the form of reverse causality is not an issue given that the model is specified in terms of local projections.

4. Data and variables

In this section, we first present the data sources and the regressors used in the empirical model to describe the distribution of future bank profitability. Second we document the main characteristics of our dataset through descriptive statistics. The set of regressors builds on the work of Lang and Forletta (2020), which considers a comprehensive set of bank-specific and macrofinancial variables to assess downside tail risk to profitability. As such, our panel dataset for Portugal comprises two groups of information. The first consists of information at the bank-level (micro-level data) and the second includes macroeconomic and financial data at the country-level (macro-level data).

4.1. Bank-specific data and variables

Bank-specific data is collected from *Historical Series of the Portuguese Banking Sector Database (SLB database)* published by the Banco de Portugal.[3] This dataset includes consolidated data for banking groups and stand-alone institutions resident in Portugal for the period between 1990 and 2019. It covers a diverse set of variables but our focus is on financial indicators from the balance sheet, income statement and solvency reports that cover features as size, portfolio composition, cost efficiency, asset quality, risk-taking and bank capitalisation. In particular, the set of bank-specific regressors includes: the logarithm of total assets, the ratio of net loans to total assets, the cost-to-core-income ratio, the net interest income as a percentage of total assets, the ratio of loan loss provisions and impairments to total

3. More information on this dataset is available here.

assets, the average risk weight, the ratio of tangible equity to tangible assets and the Tier 1 capital ratio. The bank profitability variable is pre-tax return expressed as a percentage of assets (hereinafter referred to as ROA). Return is the annualized value of net income before taxes and minority interests. The denominator is defined in terms of a weighted average of total assets (henceforth referred to as average total assets). Average total assets are considered instead of total assets to attenuate the impact of temporary and abrupt fluctuations in banks' assets and provide a more accurate representation of the assets underlying the generated return. Variables definition are detailed in Table A.1 in the Appendix.

Data is available at an annual frequency between 1990 and 2000 and at a quarterly frequency between 2001 and 2019, although some variables in some instances are only available at a bi-annual frequency. In order to have a more balanced panel setting and to centre our estimates on a time span characterised by a relatively stable financial system in terms of structural features, we used data only from 2001 to 2019. In Appendix B.1, we analyse the robustness of the estimation results considering a sample period that spans from 1990 to 2019.

Instead of considering all banks for which information is available in the SLB database, we restrict the sample to a relatively homogeneous set of large banks given that the factors that underlie profitability in small banks might differ from those that impact the largest banks. Also, for estimation purposes it is important to have as much as possible a balanced panel in terms of cross-sectional units, which can only be achieved by considering a subset of all the banks in the database. In addition, the asymptotic properties of the employed estimator only hold when the time dimension of the dataset is moderately larger than the number of cross-sectional units, in this case banks. Given that the available time span is not very wide, this also constrained our selection of banks. It is also important to recall that our focus is on macroprudential surveillance, and more specifically on estimating the impact of cyclical systemic risk on banking sector future profitability, so it is important that the selected banks are those that mainly drive the dynamics in cyclical systemic risk. In terms of time coverage, our concern was to ensure a sufficient coverage of the period prior to the onset of the GFC, which can only be achieved by considering a subset of all the banks in the database, and also to focus the analysis on a time period in which the financial system was somehow similar throughout time (from 2001 onwards).

However, we argue that this set of restrictions to the composition of the bank panel is not worrisome to the extent that the selected banks are representative of the aggregate Portuguese banking sector over time, as we show below. Namely, the selected banks account for more than 80% of total assets in the banking sector. This is indicative that the sample of banks might be seen as appropriate to discuss the use of the estimation results to postulate some considerations about capital-based instruments that vary along the financial cycle. Finally, some of the macroprudential policies already in place, which affect banks' decisions regarding the level of the capital ratio and indirectly their profitability, only apply to a subset of banks selected according to their systemic importance. As a result, the sample considers the banks that have been the most relevant for the Portuguese banking sector throughout 2001-2019 at their highest level of consolidation at the country level: LSF Nani Investments S.a.r.l (LSF Nani); Santander Totta, SGPS, SA (BST); Banco Comercial Português, SA (BCP); Caixa Geral de Depósitos, SA (CGD); Banco Português de Investimento, S.A. (BPI); Caixa Económica Montepio Geral, Caixa Económica Bancária, SA (CEMG); Banif - Banco Internacional do Funchal, SA (BANIF) and Sistema Integrado do Crédito Agrícola Mútuo (SICAM).[4] The bank-panel is mostly balanced over the sample period comprising a maximum of eight banks. Only near the end of the sample, there is a bank exiting from the sample due to a resolution process.[5]

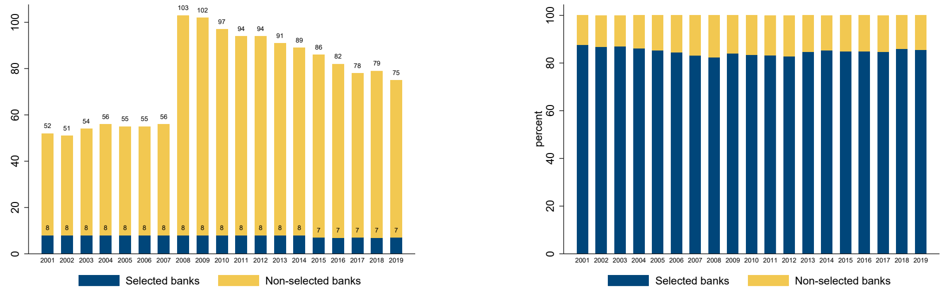
In order to assess how representative the bank panel is of the Portuguese banking sector, Figure 1 presents the number of banks (Panel (a)) and asset coverage (Panel (b)) of the selected banks and non-selected banks over time considering the information available in the SLB database. Panel (a) of Figure 1 shows that the chosen panel of banks represents a small share of the number of banks that comprise the Portuguese banking sector over time.[6] Notwithstanding, this set of banks covers more than 80% of the total assets of the banking sector between 2001 and 2019 (panel (b) of Figure 1). To further assess the coverage level of our sample of selected banks, we also consider aggregate counterparts of other bank-level variables, in particular loans, risk-weighted assets and equity. The aggregate variable, constructed based on the information available in the SLB database, corresponds to the variable computed for the whole Portuguese banking sector and is available for the period 2008Q1-2019Q4.[7] We compare this counterpart country aggregate to an aggregate that results from our sample of selected banks.

4. LSF Nani results from considering information from Espírito Santo Financial Group between 2001Q1 and 2014Q2, from Novo Banco, SA between 2014Q3-2018Q3 and from LSF Nani Investments S.a.r.l between 2018Q4 and 2019Q4. SICAM results from considering information from Caixa Central de Crédito Agrícola Mútuo between 2001Q1 and 2013Q4 and from Sistema Integrado do Crédito Agrícola Mútuo between 2014Q1 and 2019Q4.

5. On December 19, 2015, Banco de Portugal, as the Portuguese resolution authority, applied a resolution measure to Banco Internacional do Funchal, S.A.. In the same year, a share of its assets and liabilities were sold to Banco Santander Totta, therefore after the resolution measure a share of BANIF's consolidated balance sheet is kept on the information covered by the selected bank panel.

6. The sharp increase in the number of banks within the banking sector in 2008 is explained by a change in the type of institutions included in the banking sector aggregate. Up to 2007, the banking sector is composed of only other monetary financial institutions (OMFI) and from 2008 onwards it includes, in addition to OMFI, credit financial institutions and investment firms.

7. An alternative would be to use information from the Consolidated Banking Dataset available by country at the ECB statistical data warehouse. Coverage levels assessed using this dataset are very similar to those presented in this analysis. Results are available upon request to the authors.



(a) Number of banks

(b) Assets

Figure 1: Coverage levels of the selected bank panel in terms of number of banks and assets

Source: Banco de Portugal (SLB database). Notes: The SLB database considers two types of institutions over time to assemble the banking sector perimeter: between 1990 and 2007 the banking sector perimeter covers the set of Other Monetary Financial Institutions (OMFIs) and between 2008 and 2019 the banking sector perimeter covers the set of OMFIs, credit financial institutions and investment firms. The values presented are of the end-of-year from quarterly data.

Figure 2 presents the results for the distribution of coverage levels over time.[8] Overall, the set of selected banks can be regarded as representative of the banking sector also with respect to variables other than assets. The median coverage across variables is always above 80%. This result strengths the outcome from our bank selection process, but most importantly tells us that if cyclical systemic risk materializes the bulk of losses will likely be mostly concentrated in our sample of banks. In the aftermath of the GFC and of the ESDC, the largest banks in Portugal recognised significant amounts of losses that had an impact on equity levels. This temporary situation explains the wide dispersion found in the coverage levels associated with equity.

4.2. Macrofinancial data and variables

The macrofinancial regressors included in the quantile regression model aim at capturing factors at the country level that impact bank profitability. To account for the relatively short time series dimension of the bank panel, we include only a limited set of macrofinancial variables. As such, the model includes a measure of the financial cycle, proxied by the domestic cyclical systemic risk indicator (d-SRI), a measure of the business cycle, proxied by real GDP growth, and an interaction term between the cyclical systemic risk indicator and the bank-level Tier 1 capital ratio to account for the level of existing resilience against risk materialisation. This

8. The figure covers only the period between 2008 and 2019 in which the banking sector consists of OMFI, credit financial institutions and investment firms. For the period between 2001 and 2007 in which the banking sector consists of only OMFI the results are quite similar and are available upon request to the authors.

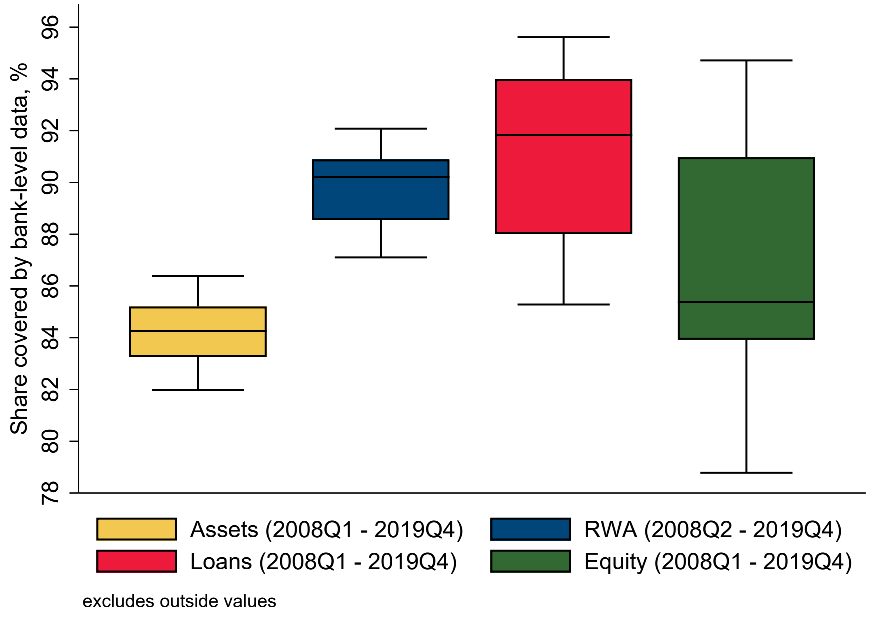


Figure 2: Coverage levels of the selected bank panel for different variables

Notes: The figure excludes outlier values. The time spans presented within brackets stand for the overlapping period between the two aggregates being compared. RWA stands for risk-weighted assets.

set of regressors allows for a parsimonious model while still controlling for the most relevant aggregate effects.[9] The data underlying the cyclical systemic risk indicator is collected from various datasets available at European Central Bank's Statistical Data Warehouse while the data on GDP are collected from Statistics Portugal.

The d-SRI proposed by Lang *et al.* (2019) is a composite indicator relevant to inform on the risk level prevailing in the domestic credit market, real estate markets, asset prices markets, and external imbalances. All these factors have been identified in the literature as potential culprits for triggering systemic financial crises (Borio and Lowe 2002; Lang *et al.* 2019), exactly the type of crisis that macroprudential policymakers try to avoid or mitigate their impact. The d-SRI fits in the set of indicators exhibiting good early-warning properties regarding

9. Other macrofinancial regressors, such as inflation rate, house prices index, credit-to-GDP ratio, concentration index or 3-month EURIBOR, were also included in a preliminary version of the model, but they were not statistically significant. Even though, we acknowledge that the absence of statistical significance should not be read as evidence of no effect, we chose to drop these regressors from the model to ensure that the model is parsimonious and the estimation methods are valid. Nonetheless, in Appendix B.2 we show that the results of the model with our chosen set of macrofinancial regressors are to a large extent similar to the results of the model with a larger set of macrofinancial regressors.

financial crises and ranks above the well-known credit-to-GDP gap proposed by Borio and Lowe (2002), justifying its choice for this analysis. The standard indicator is obtained as a weighted average of six indicators, however we use a modified version to account for national specificities of the financial system, i.e. the absence of a deep and liquid capital market, by excluding the subindicator related to equity prices. In what follows, any reference to the cyclical systemic risk indicator refers to this modified version.

Figure 3 presents the d-SRI against specific quantiles of the cross-sectional distribution of ROA over time. The cyclical systemic risk indicator peaks years ahead of the sharp decrease of the 10th percentile of the profitability distribution, which justifies the use of local projections to gauge the impact of risk on future profitability. At the same time, the median and 90th percentile of the profitability distribution remained broadly stable, providing some evidence that these percentiles may not be so influenced by the developments in cyclical systemic risk. This points to a potential asymmetric impact of the dynamics of cyclical systemic risk on the profitability distribution, hence the use of a quantile regression approach. Additionally, the figure also points to a more asymmetric cross-sectional distribution of ROA from 2014 onwards.

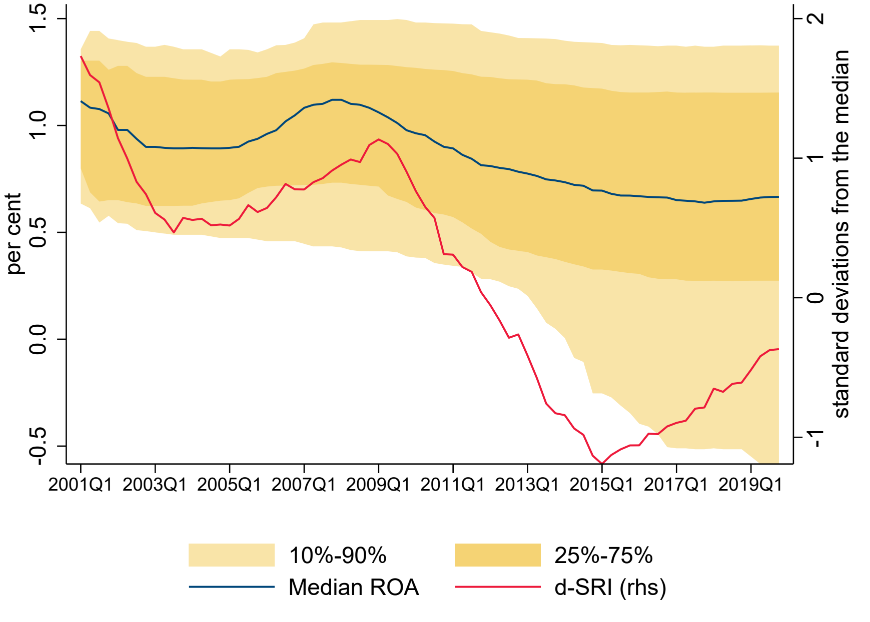


Figure 3: Cyclical systemic risk and the cross-sectional distribution of ROA

Notes: d-SRI stands for a modified version of the d-SRI as proposed by Lang *et al.* (2019) that excludes equity prices.

4.3. Descriptive statistics

Table 1 presents standard descriptive statistics for the variables used in the quantile regression model. The pooled average ROA is 0.53% with a standard deviation of 1.04 percentage points. The median ROA (0.67%) slightly deviates from the mean due to an outlier observed in the aftermath of the GFC and the ESDC. If this outlier is excluded from the sample then the average and median ROA would be very similar and slightly above 0.60%. On average, risk weighted assets were around 66% of bank's total assets and 99% of our observations showed a risk weight lower or equal to 87.23%. However, an analysis at the bank-level shows that this ratio started to decline for the majority of the banks in the sample from 2011 onwards. In contrast, there is evidence of a steady increase in the level of the Tier 1 capital ratio over the sample period across banks, meaning that the Portuguese banking sector has improved its resilience against the materialisation of cyclical systemic risk. This evolution is partially explained by the adoption of the Basel III Accord (in 2013) in the European context that introduced more stringent capital requirements. In addition, since 2016 some macroprudential capital buffers have been activated in Portugal, such as the capital conservation buffer (2016) and the buffer for other systemically important institutions (2018). The pooled average Tier 1 capital ratio was 9.59%, a value above the current minimum requirement of 6%.[10] The variable with the highest volatility in the sample is the cost-to-core-income.

Turning to the macrofinancial variables, the key variable is the d-SRI. The mean of this variable was 0.15 over the sample period, a value that significantly deviates from the median value of 0.5. As a result, the distribution over time is skewed to the left, meaning that it is more likely to observe positive values of the d-SRI, i.e. periods when the underlying risk indicators were above their median values are more represented in this time period. Taking into account the time period under analysis, this is not surprising as the run up to the GFC is characterised by the accumulation of risks and vulnerabilities, which are captured by the positive values taken by this variable. Average real GDP growth over the sample period is slightly below 1% and half of the quarters in the sample are associated with a real GDP growth above 1.83%.

10. The minimum Tier 1 capital requirement of 6% is comprised of a minimum common equity Tier 1 capital requirements of 4.5% and a minimum additional Tier 1 capital requirements of 1.5%.

Bank-specific variables	Mean	Std Dev.	p1	p5	p25	p50	p75	p95	p99	N×T
Return on assets (%)	0.53	1.04	-2.62	-1.26	0.27	0.67	1.15	1.53	2.41	591
Net interest income (%)	1.80	0.67	0.67	0.96	1.37	1.75	1.98	3.46	3.81	591
Cost-to-core-income (%)	70.24	14.60	46.10	48.92	60.49	69.33	76.75	98.78	120.93	591
Loan impairments / Assets (%)	0.76	0.73	-0.13	0.07	0.39	0.62	0.91	2.05	3.03	591
Net Loans/ Assets (%)	67.14	8.25	51.41	54.28	61.84	65.73	72.36	83.78	90.49	591
Average risk weight (%)	66.10	10.2	39.11	47.5	59.41	66.35	72.28	81.97	87.23	590
Equity / Assets (%)	7.50	8.33	0.83	1.93	3.61	5.85	8.74	18.19	58.07	591
Tier 1 capital ratio (%) (T1R)	9.59	3.15	4.51	5.46	7.23	8.85	11.86	15.25	18.85	590
Log of assets	10.39	0.82	8.64	9.01	9.67	10.56	11.18	11.51	11.65	591
Macrofinancial variables	**Mean**	**Std Dev.**	**p1**	**p5**	**p25**	**p50**	**p75**	**p95**	**p99**	**T**
Cyclical systemic risk (d-SRI)	0.15	0.83	-1.18	-1.08	-0.67	0.50	0.81	1.37	1.74	76
Real GDP growth (%)	0.91	3.10	-8.85	-6.35	-0.42	1.83	3.12	4.21	4.58	76

Table 1. Variables overview

Notes: For the bank-specific variables, statistics are computed for the pooled sample. Equity over assets stands for tangible equity over tangible assets. Net loans stand for loans net of imparments. Net interest income as a percentage of total assets.

5. Estimation results

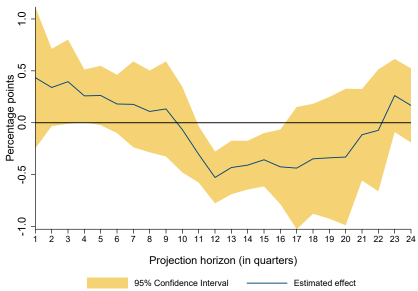
This section discusses the estimation results of the quantile regression model presented in Section 3. Figure 4 plots the estimated marginal impact on selected percentiles ($\tau = 0.1, 0.2, 0.5, 0.9$) of the conditional distribution of bank profitability following a one unit increase in the cyclical systemic risk indicator, holding constant all other regressors and considering that Tier 1 capital ratio is at its pooled average (9.59%), across various projection horizons.[11] The analysis of the effects on the left tail percentiles provides insights about how tail risk in bank profitability responds to changes in the risk environment, while the analysis of the effects on the higher percentiles provides information on how the risk environment may affect positive returns. Considering equation (2), the estimated marginal impact of the cyclical systemic risk indicator is given by:

$$\hat{\theta}_{\text{d-SRI}}(h, \tau, \text{T1R}_{i,t}) = \hat{\beta}^h_{\text{d-SRI}} + \hat{\gamma}^h_{\text{d-SRI}} q(\tau, h) + \left[\hat{\beta}^h_{\text{d-SRI}\times\text{T1R}} + \hat{\gamma}^h_{\text{d-SRI}\times\text{T1R}} \hat{q}(\tau, h)\right] \times \text{T1R}_{i,t} \quad (3)$$

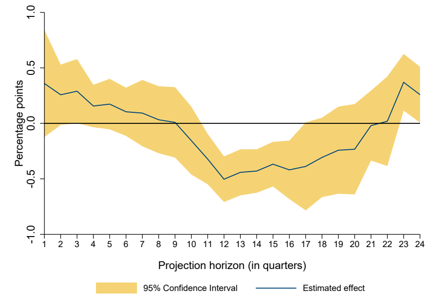
We choose to set Tier 1 capital ratio equal to its pooled average ($\text{T1R}_{i,t} = \overline{\text{T1R}}$ or $\hat{\theta}_{\text{d-SRI}}(h, \tau, \overline{\text{T1R}})$) following the standard practice. Three findings emerge from Figure 4. First, the impact on bank profitability is mostly statistically significant over the medium-term projection horizons, i.e. in the window 11 to 16-quarters ahead. These projection horizons can be understood as the ones relevant for macroprudential policymakers, due to the existence of operationalisation and

11. The need to set a value for the Tier 1 capital ratio when analysing the impact of an increase in cyclical systemic risk on the conditional distribution of bank profitability follows from the inclusion of an interaction term between risk and resilience as a regressor in the quantile regression model. This implies that the impact of the cyclical systemic risk can be obtained for different levels of bank capitalisation as shown by Equation (3).

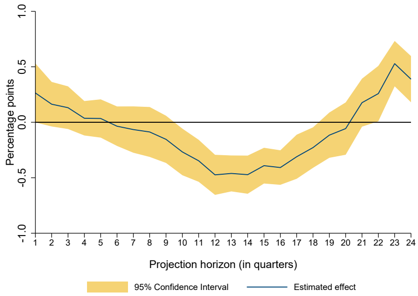
transmission lags when implementing policy measures. Second, results suggest that the effects of an increase in cyclical systemic risk at the medium-term horizons are negative. Negative effects over an horizon of 12 to 20 quarters (referred as the medium term) are also found in Lang and Forletta (2020) for bank profitability using a panel of EU banks and in Aikman *et al.* (2019) regarding downside risk to GDP growth for a panel of advanced economies. Third, these negative effects are of similar magnitude across the selected percentiles. This implies that an increase in cyclical systemic risk shifts the entire conditional distribution of future bank profitability to the left increasing downside risk to bank profitability and reducing the median bank profitability in the future. Also, it implies that the data do not support the presence of an asymmetric effect of cyclical systemic risk on bank profitability for the projection horizons relevant for macroprudential policymakers. These results are in contrast with Lang and Forletta (2020) that find that the impact of cyclical systemic risk on the left tail, in their case the 5th percentile, of bank profitability distribution is of an order of magnitude larger than the impact on the median.



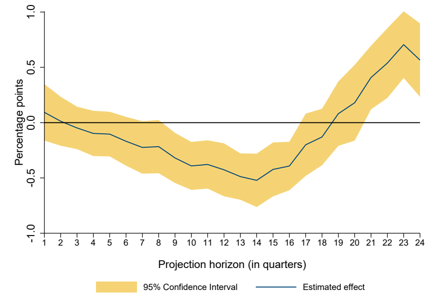
(a) 10th percentile



(b) 20th percentile



(c) 50th percentile

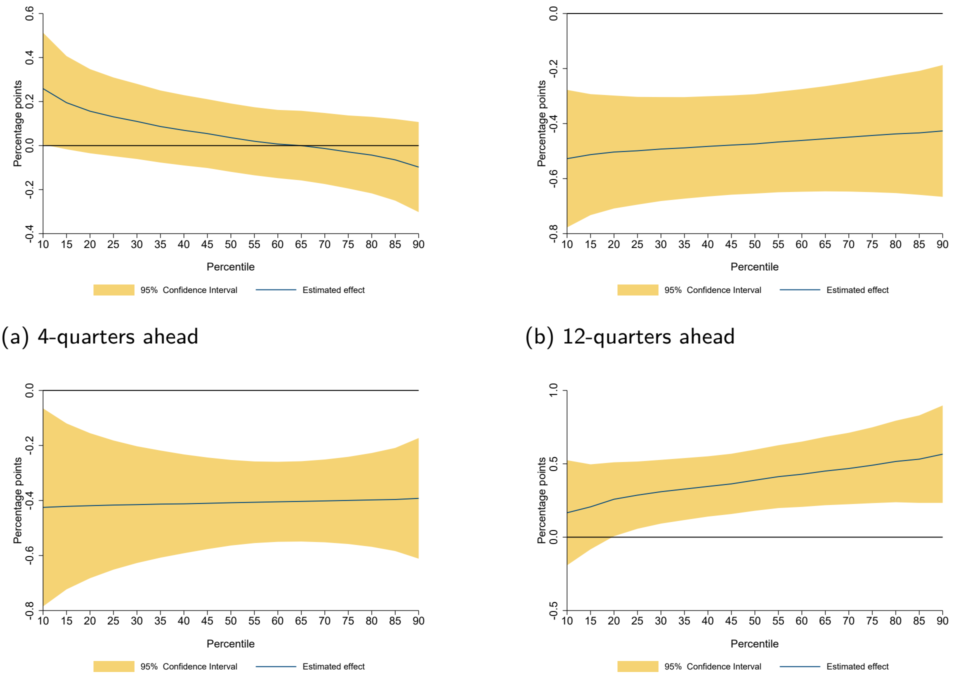


(d) 90th percentile

Figure 4: Estimated marginal effect of an increase in the cyclical systemic risk indicator on selected percentiles of the conditional distribution of bank profitability across projection horizons

Notes: Estimated effect stands for the estimated marginal effect of a one unit increase in d-SRI, holding constant all other regressors and considering that Tier 1 capital ratio is at its pooled average (9.59%), on the conditional distribution of future bank profitability. The 95% confidence interval is based on bootstrapped standard errors.

The panels in Figure 5 display the estimated marginal impact of a one unit increase in the cyclical systemic risk indicator when Tier 1 capital ratio is at its pooled average (9.59%) on different percentiles of the conditional distribution of bank profitability for selected projection horizons ($h = 4, 12, 16, 24$). Focusing on the medium-term horizons, Panels (b) and (c) of Figure 5 show that the estimated negative effect, shown in Figure 4 for only four percentiles, is almost flat across the whole conditional distribution of bank profitability. Hence, a one unit increase in d-SRI is expected to shift the conditional distribution of ROA in the medium-term horizons between 0.4 and 0.6 percentage points to the left. This suggests that, when cyclical systemic risk is increasing, the outlook for bank profitability for the medium-term horizons is expected to deteriorate, both for the central (median or mean) and more adverse (left tail quantiles) scenarios. In contrast, the short-term effect, proxied by the results at the 4-quarters projection horizon, of an increase in cyclical systemic risk on future bank profitability percentiles is mostly not statistically significant (Panel (a) of Figure 5). In the long-term (i.e. at the 24-quarters projection horizon), the impact of increasing cyclical systemic risk is statistically significant and positive from the 25th percentile upwards and it is increasing with the percentile (Panel (d) of Figure 4). This result suggests that following an increase in cyclical systemic risk, the conditional distribution of bank profitability at the long-term horizon exhibits a higher expected outcome and larger outcomes in extremely good times (high percentiles), possibly meaning that the risk inherent when granting credit today eventually can benefit bank profitabilitiy in the future.



(a) 4-quarters ahead

(b) 12-quarters ahead

(c) 16-quarters ahead

(d) 24-quarters ahead

Figure 5: Estimated marginal effect of an increase in the cyclical systemic risk indicator on the conditional distribution of bank profitability over selected projection horizons

Notes: Estimated effect stands for the estimated marginal effect of a one unit increase in d-SRI, holding constant all other regressors and considering that Tier 1 capital ratio is at its pooled average (9.59%), on the conditional distribution of future bank profitability. The 95% confidence interval is based on bootstrapped standard errors.

Table 2 presents the estimation results for the linear projection of bank profitability 16-quarters ahead (4-years ahead) across different percentiles. This analysis adds to the previous one by providing insights on which regressors are driving the results. We present results for the 16-quarters horizon as this horizon is the most important in Lang and Forletta (2020) analysis and in which the relevant regressors are all statistically significant. Also, this projection horizon can be taken as representative of the link between bank profitability and cyclical systemic risk net of prevailing resilience over the medium-term horizons, given that the estimated impact of the d-SRI is almost flat in the window 11 to 16-quarters ahead. This means that estimation results for another medium-term horizon would imply similar conclusions. Finally, we argue that this projection horizon is, among others, relevant for macroprudential policymakers given that it provides sufficient time to implement preventive measures, if warranted, and for these measures to pass through to the bank profitability distribution. Columns (1) and (2) of Table 2 report the estimates of the parameters in the location and scale functions of regressor l, respectively (i.e. $\hat{\beta}_l^h$ and $\hat{\gamma}_l^h$ as presented in equation 2). The last four columns of Table 2 display the quantile regression estimates for the coefficient of each regressor on selected percentiles ($\tau = 0.1, 0.2, 0.5, 0.9$) of the conditional distribution of future bank profitability. Standard errors for the parameters in the location and scale functions are reported in parenthesis and obtained as in Driscoll and Kraay (1998); for the quantile estimates standard errors are obtained by bootstrap.

	(1)	(2)	(3)	(4)	(5)	(6)
Bank-level regressors	**Location** $(\hat{\beta}_l^{16})$	**Scale** $(\hat{\gamma}_l^{16})$	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.9$
Return on assets (%)	0.158	-0.227***	0.556***	0.413***	0.164*	-0.204*
	(0.102)	(0.050)	(0.192)	(0.141)	(0.090)	(0.117)
Net interest income (%)	0.160	0.220*	-0.226	-0.087	0.154	0.511**
	(0.263)	(0.127)	(0.254)	(0.205)	(0.179)	(0.255)
Cost-to-core-income (%)	0.003	0.005	-0.007	-0.003	0.003	0.011
	(0.008)	(0.004)	(0.014)	(0.011)	(0.007)	(0.007)
Loan impairments / Assets (%)	0.024	-0.259***	0.479	0.316	0.031	-0.389**
	(0.121)	(0.078)	(0.318)	(0.227)	(0.131)	(0.163)
Net Loans/ Assets (%)	-0.050***	0.003	-0.055***	-0.054***	-0.050***	-0.046***
	(0.010)	(0.008)	(0.015)	(0.011)	(0.009)	(0.015)
Average risk weight (%)	-0.029***	0.010	-0.046**	-0.040***	-0.029***	-0.013
	(0.008)	(0.006)	(0.019)	(0.015)	(0.011)	(0.014)
Equity / Assets (%)	-0.005	0.035**	-0.067*	-0.044	-0.006	0.051
	(0.037)	(0.015)	(0.038)	(0.031)	(0.025)	(0.036)
Tier 1 capital ratio (%)	-0.106***	0.028	-0.154**	-0.137***	-0.107***	-0.062*
	(0.028)	(0.026)	(0.064)	(0.050)	(0.033)	(0.034)
Log of assets	-2.772***	0.560**	-3.756***	-3.403***	-2.787***	-1.879***
	(0.360)	(0.220)	(0.780)	(0.559)	(0.347)	(0.423)
Macrofinancial regressors						
Real GDP growth	-0.012	0.0004	-0.012	-0.012	-0.012	-0.011
	(0.020)	(0.010)	(0.033)	(0.025)	(0.014)	(0.016)
d-SRI	-0.938***	0.208	-1.303***	-1.172***	-0.943***	-0.607
	(0.262)	(0.154)	(0.413)	(0.340)	(0.293)	(0.372)
d-SRI $\times$ Tier 1 capital ratio	0.055**	-0.021	0.092**	0.079**	0.056*	0.022
	(0.229)	(0.016)	(0.040)	(0.034)	(0.030)	(0.035)
Observations $(N \times T)$	462	462	462	462	462	462
Number of banks (N)	8	8	8	8	8	8
R-squared	0.406	0.092	-	-	-	-
$\hat{q}(\boldsymbol{\tau}, \mathbf{16})$	-	-	-1.757	-1.126	-0.026	1.600

Table 2. Estimation results for the conditional distribution of ROA 16-quarters ahead

Notes: The location and scale columns display the impact of each regressor on the mean and dispersion, respectively, of the conditional distribution of bank profitability 16-quarters ahead. τ represents the target percentile of the respective quantile estimation. The estimated marginal effect of each regressor l, presented in columns (3) to (6), is given by $\hat{\theta}_l^{16}(\tau) = \hat{\beta}_l^{16} + \hat{q}(\tau)\hat{\gamma}_l^{16}$, where $\hat{\beta}_l^{16}$ is the estimate of the location parameter of regressor l, $\hat{q}(\tau)$ is the τ-quantile estimate of the standardized residuals and $\hat{\gamma}_l^{16}$ is the estimate of the scale parameter of regressor l. The quantile regression model includes bank-fixed effects that vary across quantiles as presented in Section 3. Equity over assets stands for tangible equity over tangible assets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (in parenthesis) for the parameters in the location and scale functions are as in Driscoll and Kraay (1998); for the quantile estimates standard errors are obtained by bootstrap.

Focusing on the estimates for the location parameters, six regressors are statistically significant to explain the 16-quarters ahead projection of expected bank profitability: the ratio of net loans to assets, average risk weight, Tier 1 capital ratio, total assets, cyclical systemic risk indicator and its interaction with Tier 1 capital ratio. All of these regressors, excluding the interaction term, have a negative effect, meaning that an increase in one of these regressors is estimated to reduce expected bank profitability at the 16-quarters projection horizon. The cost associated with increasing the bank capital ratio on future bank profitability is given by the negative estimated impact of the Tier 1 capital ratio and average risk weight on expected bank profitability. An increase in total assets mainly contributes to reduce expected profitability via the denominator of ROA, since it is assumed nothing else changes. The negative and statistically significant estimated coefficient for net loans-to-assets implies that, over this period, loans did not provide higher returns than other assets. This is not surprising given that over more than half of the sample period is associated with crises periods. The negative estimate for the location parameter associated with the d-SRI (disregarding the interaction term) allows to obtain the estimated effect of an increase in cyclical systemic risk, when there is no capital-based resilience in the banking sector (Tier 1 capital ratio set to zero), on expected bank profitability. The estimated location parameter of the interaction term is positive, suggesting that an increase in the level of bank resilience diminishes the estimated negative effect of increases in cyclical systemic risk on expected profitability. This result partially reflects one of the goals embedded in macroprudential mandates.

The estimation results for the scale parameters provide information on which regressors are relevant for explaining the differences between the estimated quantiles of the conditional distribution of future bank profitability. For the 16-quarters projection, the statistically significant scale parameters are associated to the following regressors: ROA, ratio of loan impairments to total assets, accounting leverage ratio, total assets and net interest income. According to the estimation results, higher profitability or poorer asset quality is expected to reduce the dispersion of the conditional distribution of bank profitability 16-quarters ahead, while increasing bank size or leverage ratio is positively correlated with the dispersion of the conditional distribution of future bank profitability. However, loan impairments-to-assets is only statistically significant in the 90th percentile (of the selected percentiles) with a negative effect, meaning that the contribution of poor asset quality to reduce dispersion on the distribution is only relevant in approximating higher percentiles to the median.

The magnitude of the estimated marginal impact of d-SRI, when Tier 1 capital ratio is zero (implausible situation given the existence of minimum capital requirements), varies between -1.303 and -0.943 percentage points, considering only the statistically significant effects. However, these effects are toned down as bank resilience increases: each percentage point increase in Tier 1 capital ratio seems to reduce the negative impact of d-SRI between 0.056 and 0.092 percentage points. Nevertheless, the estimated marginal impact of residual cyclical systemic risk does not differ much across percentiles, in line with the results presented above. In contrast, the current level of profitability seems to have an asymmetric effect across the conditional distribution of medium-term bank profitability. All else equal, an increase in profitability today is estimated to have a larger effect on shifting to the right the lower percentiles of the conditional distribution of ROA 16-quarters ahead (0.556 and 0.413 percentage points for the 10th and 20th percentiles, respectively) than in shifting to the left the highest percentile considered of the same distribution (-0.204 percentage points for the 90th percentile). The net interest income and the ratio of loan impairments to total assets are only statistically significant at the 90th percentile and display estimated effects on future bank profitability with the expected signs, positive and negative, respectively. The estimated marginal effects of the average risk weight and Tier 1 capital ratio when cyclical systemic risk is at its median (d-SRI set to 0) are negative and statistically significant at the 10th, 20th and 50th percentiles showcasing the cost of capital increases on medium-term bank profitability. Increasing bank size worsens medium-term bank profitability across the four selected percentile, but the response is more pronounced in the lower left quantiles.

6. Establishing a link with macroprudential policy

The estimation results presented in the previous section establish a relationship between cyclical systemic risk and future bank profitability. This section presents three policy exercises that explore that relationship and are relevant for macroprudential policymakers.

In the first exercise, we discuss the results of applying the indicative rule proposed by Lang and Forletta (2020) to guide the calibration of time-varying capital buffers, such as the CCyB. This exercise delivers the buffer rate level that would be sufficient to absorb the total amount of estimated median losses projected over medium-term horizons, taking into account the current level of cyclical systemic risk net of prevailing capital-based resilience (also known as residual cyclical systemic risk).

In the second exercise, we construct an indicator for monitoring tail risk in banking sector profitability with a forward-looking perspective. This indicator builds on the *at-risk* literature and provides the value of banking sector profitability in a specific projection horizon that is associated with the left tail of the estimated conditional distribution.

In the last policy exercise, we first show how monitoring the contribution of residual cyclical systemic risk to the risk-return relationship of future bank profitability can be used by macroprudential policymakers to pin down the trade-offs embedded in specific policy actions. Second, we leverage on the newly introduced concept of macroprudential stance space (European Systemic Risk Board 2019) to propose a novel rule to guide the calibration of the CCyB, which is flexible enough to accommodate different preferences of the policymaker. We illustrate the operationalisation of the calibration rule for three hypothetical scenarios of policymaker's preferences and simulate the impact of tightening capital buffers targeting cyclical systemic risk.

6.1. Calibration rule for an indicative CCyB rate based on median losses

The main time-varying macroprudential capital buffer enshrined in the European regulation for the banking sector is the CCyB. This buffer aims to increase the resilience of the banking sector against the materialisation of cyclical systemic risk while preventing bank deleveraging. It is build-up in the upturn of the financial cycle, when the accumulation of cyclical systemic risk takes place, and it is drawn down in the downturn ensuring that the banking sector maintains the flow of credit to the economy, while absorbing losses. We use the results of our empirical analysis linking cyclical systemic risk to bank profitability to derive an indicative rule to guide de calibration of the CCyB rate in Portugal. This calibration rule adds to, and does not replace, the existing approaches considered in the guided discretion framework that informs the decisions on the CCyB rate in European Union countries. Following Lang and Forletta (2020), the calibration rule is defined as a linear function of the marginal impact of the cyclical systemic risk indicator, on future bank profitability. We consider the estimated marginal effect on median future bank profitability and not on expected (average) future bank profitability as in the original formulation of the calibration rule. However, as shown in Table 2, using the estimated effect of the d-SRI on the median or on the average would yield similar results, as the estimates of the location parameters ($\hat{\beta}^h_{\text{d-SRI}}$ and $\hat{\beta}^h_{\text{d-SRI}\times\text{T1R}}$), which provide the impact on expected future bank profitability, are almost identical to the estimates of the parameters in the median quantile regression model. This result also holds for projection horizons other than the 16-quarters ahead shown in Table 2, in particular, it holds for the medium-term horizons linked to the macroprudential decision horizon. The indicative calibration rule is expressed as follows:

$$\text{CCyB}_t = max\left\{0, \frac{\sum_{h=12}^{16} -\hat{\theta}_{\text{d-SRI}}(h, 0.5, \text{T1R}_t)}{arw_t} \times \text{d-SRI}_t\right\} \tag{4}$$

where $\hat{\theta}_{\text{d-SRI}}(h, 0.5, \text{T1R}_t)$ is presented in equation (3) and represents the estimated marginal impact of the d-SRI on median future bank profitability at the projection horizon h and evaluated at the aggregate Tier 1 capital ratio at time t, arw_t is the average risk weight for the panel of banks at time t, and d-SRI$_t$ is the observed value of the cyclical systemic risk indicator at time t.[12] The inverse of arw_t is used in equation (4) to express the result in terms of average risk weight and match the definition of prudential capital ratio requirements. The rule provides the capital ratio add-on that should be held by banks during the build-up phase of cyclical systemic risk to ensure a constant level for median bank profitability through the financial cycle. Two assumptions are implicit in this rule: (i) banks will not deliberately retain profits obtained in good times to absorb losses in a downturn period, and (ii) banks would still want to payout dividends in downturn

12. In equation (4), the risk weight is defined in terms of average total assets and not in terms of total assets.

periods as they do in upturn periods. In the latter case, credit supply restrictions are prone to occur if the adequate loss absorbing capacity has not been built ahead. The indicative rate for the CCyB that follows from the calibration rule sets the capital ratio add-on that covers all risk-related median banking losses estimated to occur over the medium-term horizons, i.e. $h = 12, ..., 16$. Over these projection horizons, the estimated marginal impact of cyclical systemic risk on median profitability is negative for levels of the aggregate Tier 1 capital ratio around the pooled average, which explains the need to include a minus sign in the sum. The projection horizons considered in the calibration rule should be intended as purely indicative and are closely linked to the empirical results for Portugal. A different number or other projection horizons can be used in the rule to accommodate other policymaker preferences concerning the suitable horizons for conducting macroprudential policy. According to equation (4), the indicative CCyB rate at time t depends on the levels of cyclical systemic risk and banking sector capitalisation. Increases in cyclical systemic risk are estimated to generate losses over the medium-term horizons, but those are expected to decrease as the level of capital-based resilience increases. Thus, the indicative rate for the CCyB is positive if the existing capital-based resilience is not sufficient to cover the losses expected to arise from cyclical systemic risk and/or moderate the accumulation of cyclical systemic risk. This latter case directly relates to a secondary objective assigned to the CCyB, which is that of dampening the financial cycle, being the primary one that of building resilience during the upswing of the financial cycle. Finally, by accounting for the current level of cyclical systemic risk net of prevailing capital-based resilience, the calibration rule averts, to some extent, the double counting of risk.

6.1.1. Results

Figure 6 presents the indicative level for the CCyB rate in Portugal between 2001 and 2019 if the above mentioned calibration rule had been used. The grey bars highlight periods associated with the implementation of some of the prudential rules enacted after the GFC. As expected, the path of the implied rate follows the dynamics of the cyclical systemic risk over the sample period, the rate increases ahead of the GFC in 2008Q4, when risk was building-up, and decreases when risk was receding or materialising. In 2006Q4, two years before the onset of the GFC, the indicative CCyB rate was 2.68%, slightly above the current upper limit for buffer reciprocation. This buffer rate would be sufficient to cover the median bank losses, strictly induced by developments in cyclical systemic risk and not covered by existing resilience, expected to occur between 2009Q4 and 2011Q4. Expected median bank losses originating from sources other than cyclical systemic risk are not considered for setting the indicative CCyB rate. As the cyclical systemic risk indicator becomes negative in 2012, signalling either a period of risk materialisation or of recovery after a downturn, the indicative CCyB rate is 0%.

The indicative CCyB rates seem high, especially at the beginning of the sample period, given that they largely surpass the 2.5% cap enshrined in the European banking regulation. However, they reflect the fact that bank capitalisation levels were more limited prior to the implementation of the Basel III reforms in Europe, and consequently the level of capital-based resilience in place might have been lower than the desirable to cover the future median losses arising from cyclical systemic risk and projected by the model. If bank capital requirements were more stringent in the past, as they are now following Basel III implementation, then the indicative CCyB rates would be lower. On the one hand, there would be more capital available to absorb the expected risk-related losses decreasing the need for further increases in capital requirements. On the other hand, higher capital requirements would contribute to slowdown the accumulation of cyclical systemic risk, reducing loss absorption capital needs.

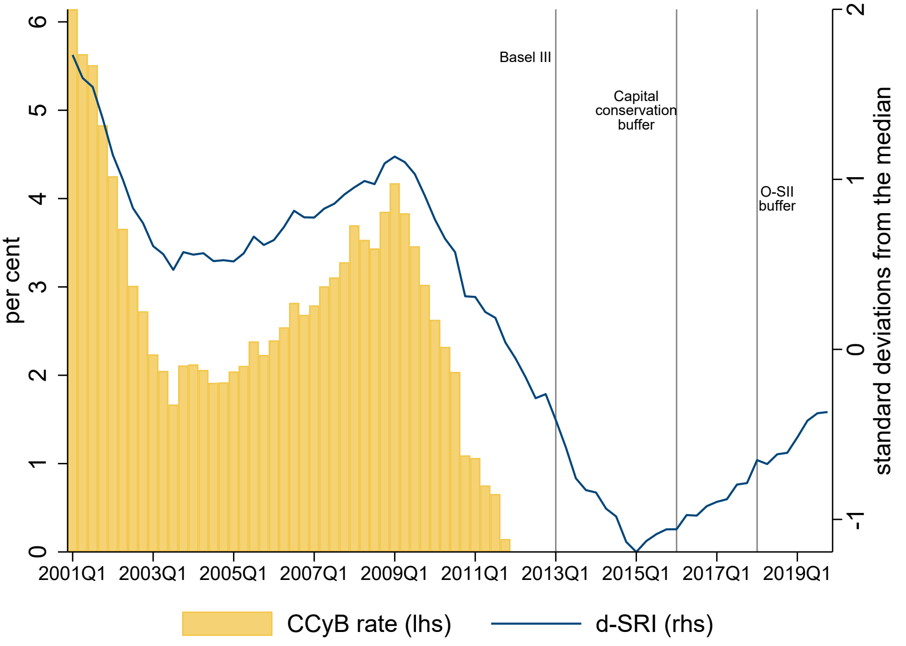


Figure 6: Indicative rate for the CCyB

Notes: The grey bars highlight periods associated with the implementation of some of the prudential rules enacted in Portugal after the GFC. Basel III regulations started to be implemented in 2013. The phasing-in periods for the gradual implementation of the capital conservation buffer and of the capital buffer for other systemically important institutions (O-SII) started in the first quarter of 2016 and in the first quarter of 2018, respectively.

6.2. Return-at-risk

The empirical results, presented in Section 5, are also used to produce a tail risk metric that indicates how weak profitability in the banking sector can be in a specific projection horizon, given the current cyclical systemic risk environment and the prevailing level of capital-based resilience. In the same vein as the "Bank Capital-at-Risk" metric suggested by Lang and Forletta (2020), the "Return-at-Risk" metric (RaR) for the sample of selected banks at time t and projection horizon h is given by:

$$\text{RaR}_{t+h}^{10\%} = \sum_{i=1}^{N_t} \hat{Q}_{\pi_{i,t+h}} \left(0.1|\mathbf{X}_{i,t}\right) \times \frac{a_{i,t}}{\sum_{k=1}^{N_t} a_{k,t}} \tag{5}$$

where N_t represents the number of banks in the panel at time t, $\hat{Q}_{\pi_{i,t+h}} \left(0.1|\mathbf{X}_{i,t}\right)$ is the predicted 10th percentile of the conditional distribution of profitability for bank i and projection horizon h, and $\frac{a_{i,t}}{\sum_{k=1}^{N_t} a_{k,t}}$ represents the share of bank i assets in the amount of total assets of the bank panel at time t. To obtain a system-wide tail risk metric, we take the asset-weighted sum over bank-quarter specific lower tail of the conditional distribution of future profitability as a proxy for the level of profitability that is at risk for the whole banking sector h quarters ahead. We argue that this assumption is reasonable because the selected banks cover a significant share of the credit granted in Portugal over the sample period. Consequently, if losses occur, then it is plausible to expect that these losses will be concentrated within these banks. Also, if significant losses occur in smaller banks, these would contribute little to the tail risk given the low share that would be assigned to such banks for the overall value of RaR. An increase in tail risk in banking sector profitability is linked to an increase in losses that may have the potential to impair financial intermediation to the real economy and for that reason may flag the need for a policy action. The RaR metric can also be easily obtained on a bank by bank level, which is the sort of metric that may be more relevant for microprudential surveillance and, as such, it is outside the scope of this analysis.

6.2.1. Results

In what follows, we focus the analysis on the 16-quarters ahead projection horizon matching the choice made in Section 5. Panel (a) of Figure 7 presents the cross-sectional distribution of the RaR metric (predicted 10th percentile) over time for Portugal. A positive value for the RaR indicates low risk of large losses in the future in the banking sector considering the current environment (low level of tail risk), whereas a negative value indicates a high level of tail risk to banking sector future profitability. Panel (b) of Figure 7 displays the breakdown of the tail risk metric into underlying drivers allowing to assess which factors are most important in driving the results. The contribution of bank-specific characteristics includes the impact of the set of bank-specific regressors and bank fixed effects.

The contribution of the d-SRI is the sum of the contribution of the d-SRI and the contribution of the interaction term with Tier 1 capital ratio. As such, it will be negative when the prevailing level of resilience is not enough to offset the negative effect of the current level of cyclical systemic risk on the left tail of the conditional distribution of future bank profitability in the medium-term. The opposite happens when the contribution is positive.

(a) Cross-sectional distribution of RaR over time

(b) Breakdown of RaR into drivers

Figure 7: Return-at-risk for the 16-quarters ahead projection horizon and 10th percentile

Notes: The contribution of bank-specific characteristics includes the impact of the set of bank-specific regressors, as presented in section 4, and bank fixed effects. The contribution of the d-SRI is the sum of the contribution of the d-SRI with the contribution of the interaction term with Tier 1 capital.

Over the sample period, tail risk to banking sector profitability was assessed as high for the first time in 2006Q2 (negative value for RaR). Considering the risk environment and the level of capitalisation in 2006Q2, the empirical results show that there was a 10% probability of observing a level of ROA of -0.06% in the banking sector in 2010Q2. From 2006Q2 and until the end of the sample period, the RaR was always negative. However, it is worth stressing that these outcomes are linked to a low (10%) probability of occurrence. The lowest value for the RaR, of approximately -1.72%, was attained in 2010Q1, shortly after the onset of the GFC. The results also show that the dispersion of the cross-sectional distribution of tail risk widened after 2009, meaning that the heterogeneity across banks in terms of extreme negative outcomes for profitability in the medium term increased, reflecting most likely the differentiated impact of the crisis on the banks. Tail risk seemed to be mainly driven by bank-specific characteristics, given the low contribution of economic activity for the dynamics of the RaR and, in particular, of the cyclical systemic risk indicator after 2011. More specifically, the contribution of the d-SRI for tail risk dynamics is only positive between 2012Q1 and 2018Q4, indicating that, only during that period, did the existing resilience seemed appropriate to attenuate the negative effects of the prevailing cyclical systemic risk environment. Considering the economic and financial environment in 2019Q4, the results show that banking sector losses could amount to 0.5% of assets 16-quarters ahead with a 10% probability. Even though the tail risk to banking sector profitability in the future is not worrisome, from the viewpoint of macroprudential policy there is not much room for manoeuvre as the predicted tail risk seems to be largely motivated by bank-specific characteristics and not by the prevailing level of cyclical systemic risk.

6.3. The macroprudential stance space

6.3.1. Methodological approach

In this last exercise, we first explore the contribution of cyclical systemic risk net of the prevailing level of capital-based resilience (residual cyclical systemic risk) to the risk-return relationship of future bank profitability with the objective of pinning down the trade-offs associated with macroprudential policy actions. This exercise resorts to the newly introduced concept of macroprudential stance space (European Systemic Risk Board 2019). It connects the upside of increasing cyclical systemic risk, i.e., the fact that, historically, in such periods bank profitability is also rising; to its downside which is the increased risk of experiencing large bank losses in a downturn. To illustrate this trade-off, we analyse the estimated contribution of cyclical systemic risk to expected future bank profitability (average return) jointly with its estimated contribution to downside risk to future bank profitability (risk), hence the designation of risk-return framework. We adopt the distance-to-tail metric as the downside risk metric. This metric is defined as the distance between the central point of the predicted conditional distribution of future bank profitability, the mean, and a tail quantile of the same distribution, in this case the 10th percentile. This metric allows the policymaker to target the shape of the conditional distribution of future bank profitability and disregard shifts of the entire distribution. This metric has been suggested in recent papers as relevant for macroprudential analysis (European Systemic Risk Board 2021; Suarez 2022) but in a context in which policymakers are targeting the conditional distribution of future GDP growth. We target instead the conditional distribution of future bank profitability arguing that macroprudential policymakers are foremost interested in limiting the likelihood and severity of financial crises, which can be achieved by managing the risk-return relationship of bank profitability in aggregate terms.

In what follows, we assume that the macroprudential policymaker, in line with his mandate, aims to ensure that the contribution of cyclical systemic risk to downside risk to future bank profitability is non-positive (either no impact or contributes to decrease downside risk). In terms of expected future bank profitability, we assume that the macroprudential policymaker exerts no targeting. However, a positive contribution of cyclical systemic risk to expected bank profitability may be preferable to a negative contribution from an economic point of view.

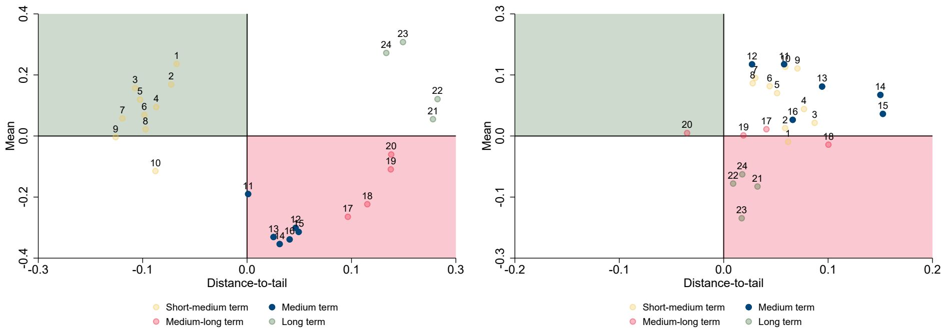
Against this background, the discussion on macroprudential policy stance space, anchored in the risk-return analysis and considering the specified empirical model, will take place through a graphical representation of a coordinate plane that is centred at $(0, 0)$ on the xy-axis. The x-axis represents the estimated contribution of the cyclical systemic risk indicator net of the current level of aggregate Tier 1 capital ratio to downside risk to future bank profitability, i.e. to the distance-to-tail, while the y-axis represents the contribution of residual cyclical systemic risk to expected future bank profitability.[13]

6.3.2. Results

Figure 8 presents the policy stance space for Portugal across different horizons and considering the figures for the cyclical systemic risk indicator and aggregate Tier 1 capital ratio in 2006Q1 (Panel a) and in 2019Q4 (Panel b). Each dot represents the estimated contribution to the two metrics and the colors breakdown the estimated contributions into four sets of projection horizons: short-medium term $(h = 1, \ldots, 10)$, medium term $(h = 11, \ldots, 16)$, medium-long term $(h = 17, \ldots, 20)$ and long term $(h = 21, \ldots, 24)$. Movements along the x-axis to the right from any position indicate that the current level of cyclical systemic risk net of the prevailing level of resilience is contributing to widening the distance-to-tail, i.e. to increasing downside risk at an unchanged level of expected future profitability. An upward movement along the y-axis indicates that the current risk environment net of the prevailing level of resilience portraits higher expected future bank profitability at an unchanged level of downside risk. Across time periods, if the movement from the earlier period to the later one is upwards and to the left then the change in residual cyclical systemic risk contributed to an improvement of both metrics, increasing the expected future bank profitability while reducing downside risk. A shift in the opposite direction, downwards and to the right, entails deteriorations for both the mean and the distance-to-tail of future bank profitability. The bottom-left and top-right quadrants imply a trade-off between the estimated contribution of residual cyclical systemic risk to expected future bank profitability and the contribution to downside risk to future bank profitability. The top-right quadrant mirrors the situation where the contribution of residual cyclical systemic risk has a positive effect on the expected future bank profitability at the cost of increasing downside risk for the banking sector. The reverse is true for the bottom-left quadrant. The quadrant shaded in green displays the best scenario, in which residual cyclical systemic risk is contributing positively to expected future bank profitability and to narrow the distance-to-tail metric. The quadrant shaded in red displays the worse

13. The estimated contribution of cyclical systemic risk to expected future profitability is given by $\hat{\beta}^h_{\text{d-SRI}} \times \text{d-SRI}_t + \hat{\beta}^h_{\text{d-SRI}\times\text{T1R}} \times (\text{d-SRI}_t \times \text{T1R}_t)$ and to the distance-to-tail metric is given by $-\left[\hat{\gamma}^h_{\text{d-SRI}}\hat{q}(0.1, h) + \hat{\gamma}^h_{\text{d-SRI}\times\text{T1R}}\hat{q}(0.1, h) \times \text{T1R}_t\right] \times \text{d-SRI}_t$.

scenario, in which residual cyclical systemic risk contributes to decrease expected future bank profitability and to increase downside risk.



(a) 2006Q1

(b) 2019Q4

Figure 8: Macroprudential policy stance space

Notes: The mean axis represents the contribution of cyclical systemic risk net of resilience for the mean of the future bank profitability distribution while the distance-to-tail axis represents the contribution for the distance between the mean and the 10th percentile of the same distribution. Balls in full represent points where both estimates (related to x and y-axis) are statistically significant at least at 10%. Numbers identify the projection horizon of each point.

In 2006Q1, fairly ahead of the GFC, the positive value of cyclical systemic risk (0.643 standard deviations above the median value) and the relatively low aggregate Tier 1 capital ratio (7.4%) contributed to short-medium term improvements in the conditional distribution of future bank profitability, both to the mean and through decreasing downside risk. For the other horizons, results show that the levels of cyclical systemic risk and resilience prevailing at the time induced an increase in downside risk to future bank profitability. However, at long-term horizons the contribution of residual cyclical systemic risk is placed on the top right quadrant. This situation illustrates the trade-off between the level of prevailing resilience and the risk taken by the banking sector. From the point of view of the banking sector, the risk environment was beneficial given the prospects of positive returns in the long term, but the costs for the system were not internalised, as shown by the positive contribution to the distance-to-tail metric.

In 2019Q4, the results are overall very different due to the negative value of the cyclical systemic risk indicator (-0.368 standard deviations below the median value) and to the substantially higher value of the aggregate Tier 1 capital ratio (15%). In the medium term, on the one hand, the negative value of d-SRI contributes positively to expected bank profitability while the prevailing level of Tier 1 capital ratio contributes to reduce this positive effect, given that funding through capital is typically more costly than through other types of instrument. On the other hand, the distance-to-tail metric is negatively affected by the level of the d-SRI but the positive effect of the Tier 1 capital ratio outweighs that effect. This situation illustrates how the cost, approximated by a deterioration in downside risk associated with holding capital, can outweigh its benefits when cyclical systemic risk is subdued.

6.3.3. Calibration rules based on macroprudential policy stance

This framework can also be employed to assess how tightening time-varying capital-based macroprudential instruments, such as the CCyB, can affect the risk-return tradeoffs of the banking sector profitability across various projection horizons, akin to an ex-ante impact assessment.[14] For this exercise, we rely on the risk-resilience framework put forward by the European Systemic Risk Board (2019) to develop the concept of macroprudential space, in which gross systemic risk is compared to the prevailing level of resilience and to the effect of macroprudential measures already implemented (residual systemic risk). Macroprudential policy stance consists in comparing the level of residual systemic risk with a target level set by the policymaker. This target level is defined as the neutral level of residual systemic risk that the policymaker is willing to accept. If the existing resilience and/or macroprudential measures in place are not enough to achieve the neutral level of systemic risk, then the stance is assessed as loose and tightening macroprudential policy may be a warranted course of action. The reverse means that the policy stance is assessed as tight. Leveraging on this conceptual framework, we propose a calibration rule for time-varying capital buffers under the hypothesis that the macroprudential policymaker can achieve the exogenously set target by affecting, through its policy actions, the contribution of residual cyclical systemic risk to the distance-to-tail of the conditional distribution of future bank profitability in the medium term horizon. The main difference between our approach and the one proposed by the ESRB is that we narrow the target of the policymaker to cyclical systemic risk, setting aside the structural component of systemic risk which is related to the interconnectedness of institutions in the financial system.

Macroprudential policymakers build resilience in banking sector against cyclical systemic risk mainly using the CCyB, thus the neutral level for the contribution of the residual cyclical systemic risk to downside risk to future bank profitability should be set in a countercyclical manner. In good times, the policymaker should target a negative contribution of residual cyclical systemic risk on the distance-to-tail metric, narrowing the distance between the two statistics, by increasing the resilience of the banking sector. During a risk materialisation period, the policymaker allows the contribution of residual cyclical systemic risk to be temporarily positive to ensure that the banking sector actively contributes to the recovery. This implies that the

14. Even though capital buffers with a macroprudential nature are met with Common Equity Tier 1 (CET1) capital, in this exercise we assume that increasing Tier 1 capital ratio delivers to a large extent the same effect as increasing CET1 capital ratio. As the model is linear, an alternative would be to rescale the Tier 1 capital ratio to the CET 1 capital ratio using the historical scale factor observed between the two ratios which is, on average, 97% for the Portuguese banking sector.

policymaker's target is state contingent, i.e. negative during risk build-up periods, allowing the contribution of resilience to be larger than the effect of gross cyclical systemic risk, and positive in risk materialisation periods, allowing banks to absorb losses while maintaining credit supply. This can be represented as follows:

$$target(\text{risk}) = \begin{cases} g\left(\text{risk}\right) < 0 & \text{, risk build-up} \\ 0 & \text{, muted risk} \\ f\left(\text{risk}\right) > 0, & \text{, risk materialisation} \end{cases} \tag{6}$$

where $g(.)$ and $f(.)$ are functions that may differ.

Provided with the policymaker's target for the contribution of residual cyclical systemic risk, we use the empirical model presented in section 3 and estimated in 5 to devise a calibration rule that allows the policymaker assessing how best to deploy the available policy instruments to attain his target. The contribution of residual cyclical systemic risk, evaluated at the aggregate Tier 1 capital ratio, to the distance-to-tail metric of the conditional distribution of bank profitability at projection horizon h is given by:

$$\varphi^h_{\text{d-SRI}} \times \text{d-SRI}_t + \varphi^h_{\text{d-SRI}\times\text{T1R}} \times (\text{d-SRI}_t \times \text{T1R}_t) \tag{7}$$

where $\varphi^h_{\text{d-SRI}} = -\gamma^h_{\text{d-SRI}} q(0.1, h)$ represents the effect of cyclical systemic risk, before taking into account the effect of the prevailing level of capital-based resilience, on the distance-to-tail metric, while $\varphi^h_{\text{d-SRI}\times\text{T1R}} = -\gamma^h_{\text{d-SRI}\times\text{T1R}} q(0.1, h)$ represents the effect of the existing cyclical systemic risk-targeted resilience. The last term of equation (7) accounts for all types of capital-based resilience expressed in terms of Tier 1 capital ratio: microprudential, macroprudential, and bank management buffers.

Lets assume now, that macroprudential policy buffers are set to a value equal to CCyB_t, to reach the policymaker's target. Then:

$$\varphi^h_{\text{d-SRI}} \times \text{d-SRI}_t + \varphi^h_{\text{d-SRI}\times\text{T1R}} \times [\text{d-SRI}_t \times (\text{T1R}_t + \text{CCyB}_t)] = target(\text{d-SRI}) \tag{8}$$

The last term on the right hand side of the previous equation measures the effect of setting a positive CCyB rate at time t on the contribution of the residual cyclical systemic risk to downside risk at time $t + h$. Considering that the d-SRI is an early-warning indicator for risk materialisation and for that reason suited to guide the calibration of the CCyB, we use equation (8) to obtain the following general calibration rule for the CCyB:

$$\text{CCyB}_t(h) = max\left\{0, \frac{target(\text{d-SRI})}{\varphi^h_{\text{d-SRI}\times\text{T1R}} \times \text{d-SRI}_t} - \frac{\varphi^h_{\text{d-SRI}} + \varphi^h_{\text{d-SRI}\times\text{T1R}} \times \text{T1R}_t}{\varphi^h_{\text{d-SRI}\times\text{T1R}}}\right\} \tag{9}$$

Different policymaker's target values and/or projection horizons will lead to different indicative values for the CCyB rate.

To illustrate the application of this calibration rule and discuss its implications, we consider three different assumptions for policymaker preferences that reflect distinct target choices. In the first case, the policymaker targets a zero contribution of residual cyclical systemic risk to the distance-to-tail metric of the conditional distribution of future bank profitability in the medium-term horizon. Targeting a zero contribution can be interpreted in two ways. It can be the policymaker's choice when it is difficult to identify which of the risk periods is prevailing in the financial system, i.e risk build-up or risk materialisation. Or it can be the policymaker's choice linked to setting a positive neutral rate for the CCyB, i.e. the one that should be in place in periods when cyclical systemic risk is neither accumulating nor materialising. Then, using equation (8) follows:

$$\varphi^h_{\text{d-SRI}} + \varphi^h_{\text{d-SRI}\times\text{T1R}} \times (\text{T1R}_t + \text{CCyB}_t) = 0 \tag{10}$$

which allows gauging the Tier 1 capital ratio implied by the target chosen by the policymaker:[15]

$$\text{T1R}^*_t(h) = (\text{T1R}_t + \text{CCyB}_t(h))^* = -\frac{\varphi^h_{\text{d-SRI}}}{\varphi^h_{\text{d-SRI}\times\text{T1R}}} \tag{11}$$

and obtain the following CCyB calibration rule

$$\text{CCyB}_t(h) = max\left\{0, -\frac{\varphi^h_{\text{d-SRI}} + \varphi^h_{\text{d-SRI}\times\text{T1R}} \times \text{T1R}_t}{\varphi^h_{\text{d-SRI}\times\text{T1R}}}\right\} = max\left\{0, -\frac{\varphi^h_{\text{d-SRI}}}{\varphi^h_{\text{d-SRI}\times\text{T1R}}} - \text{T1R}_t\right\} \tag{12}$$

Considering the estimation results presented in table 2, we can assign values to the unknown parameters of equation 12 and obtain the following estimated calibration rule for the 16-quarters ahead projection horizon:

$$\textbf{Calibration rule 1:} \quad \widehat{\text{CCyB}}_t(16) = max\{0, 9.9 - \text{T1R}_t\} \tag{13}$$

where 9.9% is the Tier 1 capital ratio that implies a zero contribution of residual cyclical systemic risk to the distance-to-tail metric of the conditional distribution of future bank profitability. It is also the minimum value of Tier 1 capital ratio that the banking sector should hold if the policymaker is uncertain regarding the phase of the financial cycle.

In the second and third cases, we explore the risk-return trade-offs faced by the policymaker when tightening capital requirements to define the target. The benefits of increasing resilience are seen in this approach through the effect of the residual cyclical systemic risk both on the contribution to downside risk and to expected returns. As such, the policymaker, aiming to managing the benefits of

15. If the policymaker's choice is to target a non-zero contribution of residual cyclical systemic risk to the distance-to-tail metric, then the implied Tier 1 capital ratio is given by $\text{T1R}^*_t(h) = \frac{\text{d-SRI}^{target}_t - \varphi^h_{\text{d-SRI}}}{\varphi^h_{\text{d-SRI}\times\text{T1R}}}$.

its policy actions, can target a certain trade-off between these two contributions. This can be achieved by assuming that the policymaker's target depends on the contribution of residual cyclical systemic risk to expected future bank profitability. Specifically,

$$target(\text{d-SRI}) = \eta \left[\beta^h_{\text{d-SRI}} \times \text{d-SRI}_t + \beta^h_{\text{d-SRI}\times\text{T1R}} \times [\text{d-SRI}_t \times (\text{T1R}_t + \text{CCyB}_t)]\right] \quad (14)$$

where η sets the proportion of the contribution of residual cyclical systemic risk to expected future profitability that will be targeted by the policymaker. For calibration rule number 2, we assume that the policymaker is risk averse and sets $\eta = 1$, which means that the contribution to risk-return is on a 1:1 basis. For calibration rule number 3, we consider $\eta = 0.1$, which means that the contribution to risk-return is a 1:10 trade-off between downside risk and expected returns, meaning that the policymaker is less risk-averse than in rule 2. The latter value of $\eta = 0.1$ is set on a uninformed way and is not linked to the historical relationship between the contribution to downside risks and the contribution to expected future bank profitability of residual cyclical systemic risk.

In order for this target to be countercyclical, as defined in equation (6), we have to determine the conditions under which this contribution is the opposite of the phase of the financial cycle. The contribution of residual cyclical systemic risk to expected future profitability will need to be negative when risk is building-up, so that the policymaker targets a lower downside risk environment by narrowing the distance between the left tail and the average of the conditional distribution of future profitability, and positive when risk materialises, meaning that the policymaker tolerates a higher downside risk environment to provide banks room for absorbing losses in the event of a negative shock. This also highlights the trade-off between targeting a negative contribution to downside risk at the same time that the contribution to expected future profitability is negative. In order to do this, we also need to define what is a risk build-up/materialisation phase. For convenience, we use the d-SRI and consider that periods in which the d-SRI is positive are signalling risk build-up periods, while periods in which the d-SRI is negative are signalling risk materialisation periods. By replacing in equation (14) the parameters with their estimates, we obtain:

$$\widehat{target}(\text{d-SRI}) = \eta \left[-0.938 \times \text{d-SRI}_t + 0.055 \times [\text{d-SRI}_t \times (\text{T1R}_t + \text{CCyB}_t)]\right] \quad (15)$$

Then, the target will be countercyclical when $0.055 \times (\text{d-SRI}_t \times \text{T1R}_t) < 0.938 \times \text{d-SRI}_t$, which happens when $\text{T1R}_t < 17.1$

$$\widehat{target}(\text{d-SRI}) = \begin{cases} < 0 & , \text{d-SRI} > 0 \text{and T1R} < 17.1 \\ 0 & , \text{d-SRI} = 0 \text{and T1R} < 17.1 \\ > 0, & , \text{d-SRI} < 0 \text{and T1R} < 17.1 \end{cases} \quad (16)$$

In risk build-up periods, the contribution of risk to both the expected profitability and to the distance-to-tail metric is negative allowing for a lower risk at the cost of a lower expected return. In risk materialisation periods the reverse happens: the contribution of risk is positive to expected future profitability, improving the loss-absorbing capacity of the banking sector, at the cost of a higher downside risk environment.

Replacing this target in equation (8), we obtain the following general CCyB calibration rule:

$$\text{CCyB}_t(h) = max\left\{0, \frac{-\varphi^h_{\text{d-SRI}}+\eta\beta^h_{\text{d-SRI}}-(\varphi^h_{\text{d-SRI}\times\text{T1R}}-\eta\beta^h_{\text{d-SRI}\times\text{T1R}})\times\text{T1R}_t}{\varphi^h_{\text{d-SRI}\times\text{T1R}}-\eta\beta^h_{\text{d-SRI}\times\text{T1R}}}\right\} \quad (17)$$

which provides calibration rule number 2 when setting $\eta = 1$

$$\textbf{Calibration rule 2:} \quad \widehat{\text{CCyB}}_t(16) = max\left\{0, 14.2 - \text{T1R}_t\right\} \quad (18)$$

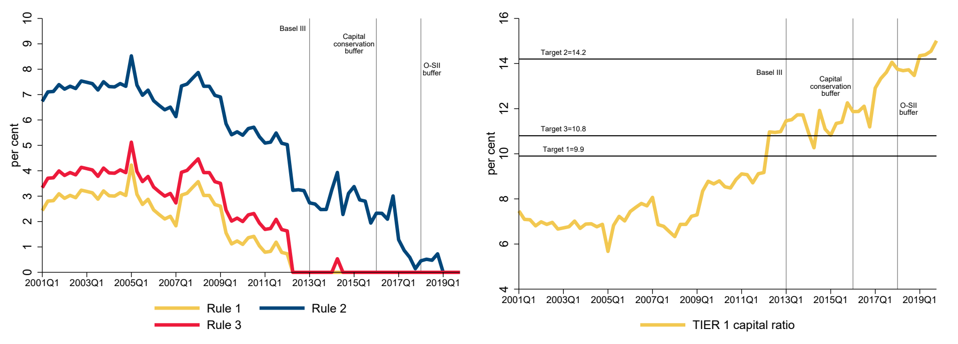
and calibration rule number 3 when setting $\eta = 0.1$

$$\textbf{Calibration rule 3:} \quad \widehat{\text{CCyB}}_t(16) = max\left\{0, 10.8 - \text{T1R}_t\right\} \quad (19)$$

6.3.4. Results

Panel (a) of Figure 9 presents the simulation results for Portugal. Panel (b) of Figure 9 displays the level of aggregate Tier 1 capital ratio for the set of banks included in the panel over the sample period, and the three Tier 1 capital ratios implied by the targets associated with the indicative rules (horizontal lines). The indicative calibration rule number one always delivers the lowest rate for the CCyB as the targeted Tier 1 ratio implied by the choice of the policymaker is the lowest among the three calibration rules. The second and third calibration rules imply a trade-off between risk and return through higher capitalisation that is countercyclical. When risk is building-up the implied CCyB rate will reduce the contribution of risk to the distance-to-tail to a value that matches either 100% or 10% of the lowest contribution of risk to expected future profitability that is induced by the implied CCyB rate. The second calibration rule is the most demanding in respect to how much additional resilience is needed to tackle risk, which is consistent with a higher aversion to risk by the policymaker.

The indicative CCyB rates fluctuate according to the level of aggregate Tier 1 capital ratio. Prior to the onset of the GFC in 2008Q4, all indicative buffer rates were positive. They presented a mild increasing trajectory until 2005 and then a decreasing path in the period 2006-2007, which coincides with a period in which aggregate Tier 1 capital ratio exhibits an increase. During the GFC and ESDC crises periods, the calibrations rules suggested a gradual release of the CCyB, in line with the observed materialisation of cyclical systemic risk and increased losses. The additional capital that would be available to the banking sector, if the buffer was in place at the time, would have contributed positively to mitigate the economic effects of those crises by alleviating credit supply constraints. The introduction of the Basel III reforms in the European banking sector in 2009 led to a strong and steady increase in aggregate Tier 1 capital ratio in Portugal, as shown in panel (b). Shortly after this reform, calibration rules one and three have mostly indicated a CCyB rate of 0%, as the level of prevailing resilience seemed appropriate to the risk environment. This result also benefited from the implementation of two macroprudential buffers that were not available to policymakers prior to 2016. In the first quarter of 2016, the Banco de Portugal initiated the phasing-in period for the gradual introduction of the capital conservation buffer, which was fully phased-in to a value of 2.5% in 2019. In the first quarter of 2018, the O-SII capital buffer was also introduced for a set of banks included in our sample according to a phase-in period. Calibration rule number two also indicated a CCyB rate of 0% as of 2019.



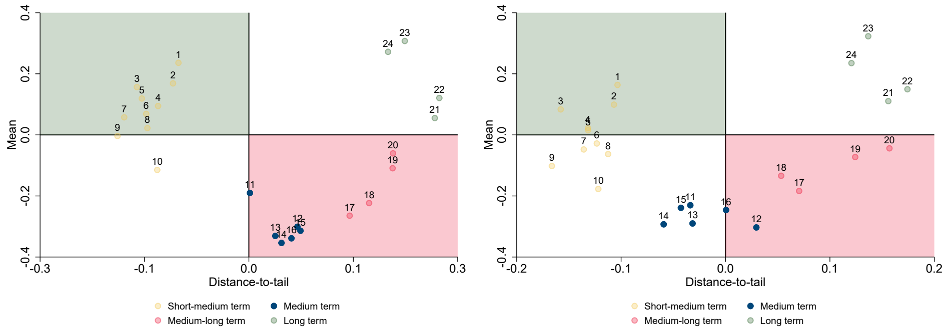
(a) CCyB calibration

(b) Aggregate Tier 1 capital ratio

Figure 9: Indicative levels for the CCyB rate in Portugal

Notes: The calibration rules used to obtain the indicative levels for the CCyB rates result from assuming that the policymaker targets a specific contribution of residual cyclical systemic risk to the distance-to-tail metric of the 16-quarters ahead conditional distribution of bank profitability. See equations (13), (18) and (19) for calibration rules number 1, 2 and 3, respectively.

Finally, we assess the impact on the conditional distribution of bank profitability of tightening the CCyB rate using the risk-return framework previously discussed. We focus on the effects of implementing the indicative value for the CCyB rate in 2006Q1 suggested by the calibration rule number 1 presented in equation (13). Panel (a) of Figure 10 shows the starting position in which no CCyB is required to be maintained by banks, i.e. the contribution of residual cyclical systemic risk to expected profitability (y-axis) and downside risk (x-axis) to bank profitability over various projection horizons considering a CCyB rate of 0% (same as panel (a) of Figure 8). Panel (b) of Figure 10 shows the ending position if a CCyB rate was implemented, i.e. the contribution of residual cyclical systemic risk to expected profitability and downside risk to profitability over various projection horizons considering a CCyB rate of 2.60% (indicative buffer rate for $h = 16$ and $t = 2006\text{Q1}$). Overall, increasing the CCyB rate translates into a better outlook for the contribution of residual cyclical systemic risk to medium-term downside risk (blue dots move to the left almost in a parallel way, contributing to decrease the distance-to-tail), but a worse outlook for short-term expected bank profitability (yellow dots move down). These results find support on the existing literature that highlights that the costs associated with capital requirements increases tend to be more pronounced in the short term, while the benefits arise in the medium to long term. This exercise illustrates the trade-offs that macroprudential policymakers face in terms of bank profitability when tightening capital-based instruments. Increasing the resilience of the banking sector has the benefit of reducing the potential negative effects of risk materialisation (the left tail of the distribution of bank profitability becomes closer to the average profitability), but at the same time it comes with the cost of potentially introducing constraints to bank's returns level (expected profitability decreases), which can spillover in a negative way to the real economy.



(a) 2006Q1 imposing a CCyB rate of 0%

(b) 2006Q1 imposing a CCyB rate of 2.60%

Figure 10: Effects on the risk and expected return of increasing the CCyB rate from 0% to 2.60%.

Notes: The y-axis represents the contribution of cyclical systemic risk net of resilience to the mean of the future bank profitability distribution, while the x-axis represents the contribution to the distance between the mean and the 10th percentile of the same distribution. Balls in full represent points where both estimates (related to x and y-axis) are statistically significant at least at 10%. The value for the CCyB rate results from applying the calibration rule number 1 presented in Equation (13).

7. Conclusion

This paper empirically investigates the impact of cyclical systemic risk net of the prevailing level of capital-based resilience, designated as residual cyclical systemic risk, on the entire distribution of bank profitability projected at different horizons. The identification of the impact is done using a dynamic quantile regression model for panel data coupled with local projections, while the estimation is based on data available between 2001 and 2019 for a small panel of banks representative of the banking sector in Portugal. Regardless of the percentile of the conditional distribution, estimation results suggest that the impact of residual cyclical systemic risk on bank profitability is mostly statistically significant over the medium-term horizons, i.e. between 11 and 16-quarters ahead into the future. This time window lies within the horizons that are generally considered by policymakers as relevant for macroprudential oversight, stressing the potential of this analysis to support policy decisions. Results, also, show that these estimated impacts associated with an increase in cyclical systemic risk are negative across the medium-term horizons, confirming the findings in the literature. The impacts are fairly of the same magnitude across the percentiles of the conditional distribution of bank profitability over the medium-term horizons, meaning that an increase in cyclical systemic risk shifts the entire distribution to the left. A result that diverges from existing empirical evidence for a large panel of EU banks.

Provided with these insights, the results are then employed in three policy exercises that are relevant for macroprudential policymakers as they may guide and support policy actions triggered by the prevailing residual cyclical systemic risk environment. First, we use the empirical results to specify a calibration rule that provides an indicative rate for the countercyclical capital buffer (CCyB). This indicative rate delivers the capital ratio add-on that would cover the median losses estimated to occur in the banking sector over the medium-term horizons. This rule takes into account the current level of cyclical systemic risk net of the prevailing capital-based resilience, avoiding to some extent the double counting of risk. The simulation for Portugal shows that the indicative CCyB rate closely follows the dynamics of the cyclical systemic risk over the sample period. The rate increases when cyclical systemic risk is rising, as in the period ahead of GFC, and decreases when cyclical systemic risk is either receding or materialising. The indicative CCyB rates seem high, especially at the beginning of the sample period, considering that they surpass the 2.5% soft limit enshrined in the European banking regulation. We argue that these higher calibrations reflect the more limited bank capitalisation in Portugal prior to the implementation of the Basel III reforms, and consequently the existing capital-based resilience was lower than the desirable capital ratio implied by the model. If bank capital requirements as a whole were more stringent in the past, then the indicative CCyB rate would be lower, even for the same level of systemic risk buffer.

Second, we use the estimation results for a specific left tail percentile to construct an indicator for monitoring tail risk in banking sector profitability with a forward-looking perspective. This tail risk metric indicates how weak profitability in the banking sector can be in a specific projection horizon, given the current cyclical systemic risk environment and the prevailing capital-based resilience. An increase in the tail risk of banking sector profitability is linked to an increase in losses that may have the potential to impair financial intermediation to the real economy and for that reason may flag the need for a policy action. In the case of Portugal, results show that the tail risk for banking sector profitability 16-quarters ahead started to increase in the beginning of 2006, well ahead of the GFC, and attained its worst value in 2010Q1, shortly after the onset of the GFC. Moreover, the dispersion of the cross-sectional distribution of the tail risk widened after 2009. This situation means that the heterogeneity across banks in terms of extreme negative outcomes for profitability in the medium-term increased, reflecting most likely the differentiated impact of the crises on the banks. The estimated tail risk for banking sector profitability is mainly driven by bank-specific characteristics over the sample period and more prominently in the last years, underscoring that macroprudential policy should not take the lead in increasing the resilience of the banking sector.

Third, we explore how residual cyclical systemic risk shapes the risk-return relationship in bank profitability in Portugal. For that, the risk contribution to a distance-to-tail metric (downside risk) is compared with the risk contribution to expected return. We show that the risk-return relationship in bank profitability for a given level of residual cyclical systemic risk varies across projection horizons, but it tends to be similar within clusters of projection horizons. In addition, the risk-return relationship in bank profitability in 2006Q1 is different from the one existing in 2019Q4, notably for the short and medium-term horizons. Underlying this result is the very different situation in terms of cyclical systemic risk environment and capital-based resilience in the two periods.

Leveraging on this risk-return relationship in bank profitability and on the concept of macroprudential policy stance, we propose a novel rule to guide the calibration of the CCyB rate, which is flexible enough to incorporate different preferences of the policymaker. More specifically, we assume that the policymaker defines the CCyB rate with the objective of guaranteeing that the contribution of cyclical systemic risk to downside risk in bank profitability in a medium-term horizon is non-positive, in line with its mandate of guaranteeing the resilience of the banking sector against adverse events. In terms of expected future bank profitability, we assume that the macroprudential policymaker exerts no targeting on the contribution of cyclical systemic risk. We illustrate the operationalisation of our novel calibration rule under different assumptions for the policymaker preferences. In scenario one, the policymaker targets a zero contribution of residual systemic risk to medium-term downside risk in bank profitability, whereas in scenarios two and three the target for the contribution of residual systemic risk to downside risk is made dependent on the contribution of residual systemic risk to medium-term expected profitability. These two latter scenarios aim at showing that the policymaker may choose to tackle downside risk without harming too much expected profitability, exploring the trade-offs that occur when deploying policy instruments. The results for Portugal ensue calibration rules that suggest setting a positive CCyB rate whenever banking sector Tier 1 capital ratio is below 9.9% in scenario one, 14.2% in scenario two and 10.8% in scenario three. Overall, the rule derived under scenario two is the most demanding in respect to how much more resilience was needed in the banking sector to tackle risk over the sample period. This result follows, on the one hand, from the more demanding target set by the policymaker, which is consistent with a more risk averse policymaker, and, on the other hand, from the limited level of bank capitalisation prior to the introduction of Basel III reforms in the aftermath of the GFC. Finally, we illustrate the trade-offs faced by macroprudential policymakers in terms of bank profitability while managing cyclical systemic risk through the imposition of more stringent capital requirements. We present a counterfactual for the trade-offs of increasing the CCyB rate in Portugal from 0% to 2.60% in 2006Q1. Increasing the CCyB rate translates into a better outlook for the medium-term downside risk in bank profitability, but a worse outlook for short-term expected bank profitability. These results find support on the existing literature that highlights that the costs associated with capital requirements increases tend to be more pronounced in the short term, while the benefits arise in the medium to long term. Increasing the resilience of the banking sector has the benefit of reducing the potential negative effects of risk materialisation as projected losses are lower, but it comes with the cost of potentially introducing constraints to bank's expected returns, which can spillover in a negative way to the economy.

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Appendix A: Variables and data sources

Variables	Definition and data sources
Return on assets (%)	Ratio of return to assets. Return is the annualized value of net income loss before taxes and minority interests (QA2_14). Assets is the weighted average of total assets (QA1_11). SLB database
Net interest income (%)	Net interest income (QA2_3) is expressed in annual flows as a percentage of total assets (QA1_11). Net interest income is the difference between the interest income generated by banks and the amount of interest paid out to their lenders. SLB database
Cost-to-core-income (%)	Ratio of operational costs to core income. Operational costs cover staff expenses, other administrative expensives and depreciation (QA2_9+QA2_10+QA2_11). Core income is net interest income (QA2_3) plus net income from fees and commissions (QA2_5). Net interest income is the difference between the interest income generated by banks and the amount of interest paid out to their lenders. All variables are expressed in terms of annual flows. SLB database
Loan loss provisions and impairments over assets (%)	Loan loss provisions and impairments (QA2_12) are expressed in annual flows. Total assets (QA1_11). SLB database.
Net loans over assets (%)	Loans are net of impairments and consist of loans to customers, which include loans to public administration, other financial institutions, non-financial corporations and households (QA1_4). Total assets (QA1_11). SLB database.
Average risk weight (%)	Ratio of risk-weighted assets (QA3_3) to total assets (QA1_11). Synthetic ratio of the amount of risk taken by a bank compared to its assets. SLB database.
Tangible equity over tangible assets (%)	Accounting leverage ratio. Tangible equity is obtained as the difference between equity (QA1_17) and intangible assets (QA1_9). Tangible assets (QA1_8). SLB database.
Tier 1 capital ratio (%)	Ratio of Tier 1 capital (QA3_1) to risk-weighted assets (QA3_3). SLB database
Logarithm of total assets (%)	Total assets (QA1_11). SLB database.
Cyclical systemic risk (standard deviations from the median)	Modified version of the d-SRI proposed by Lang *et al.* (2019) that excludes equity prices. Various datasets available at European Central Bank's Statistical Data Warehouse.
Real GDP growth (%)	Year-on-year rate of change of real GDP. GDP is deflated by the Consumer Price Index. Statistics Portugal.

Table A.1. Variables definition and data sources

Appendix B: Robustness of the results

In this section we show that the results discussed in the main sections of the analysis still hold under different assumptions for the sample period, set of regressors and estimation method.

B.1. Alternative sample period

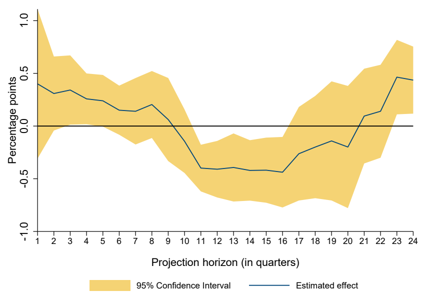
The estimation results presented in section 5 rely on information that spans from 2001Q1 to 2019Q4. In this subsection of the Appendix, we show that the estimation results still hold if the sample period is expanded back to 1990. The information available between 1990 and 2001 for the majority of the variables has a annual frequency, meaning that we will be adding at least 11 observations per institution to the main sample considered.

In the period prior to 2001, the Portuguese banking sector went through a financial liberalisation process. This process started in the mid-80's and culminated in the participation of the Portuguese economy in the euro area in 1999. Important reforms took place during this process, such as the privatisation of state-owned financial institutions and the elimination of administrative controls on interest rates and credit. These reforms increased the competition between banks and fostered the financial innovation in the Portuguese banking sector. Finally, the participation in the euro area guaranteed permanently lower financing costs and more stable financing conditions, which may be factors that condition banks profitability. As such, between 1990 and 2000 the Portuguese banking sector was very different in comparison with the period between 2001 and 2019. In particular, there was less stability in the sector induced by the reforms that were taking place and less banking regulation at the European Union level resulting in more heterogeneous practices across banks in terms of risk assessment and capital levels. Given this background, we believe that the shortest sample period is more appropriate to discuss the use of quantile regression models for macroprudential surveillance.

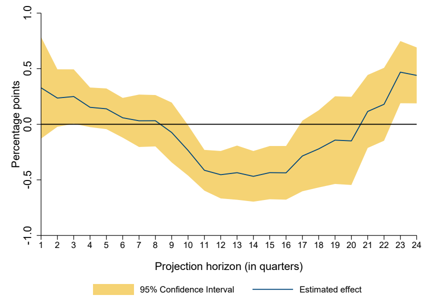
Figure B.1 plots the estimated marginal impact on selected percentiles of the conditional distribution of bank profitability following a one unit increase in the cyclical systemic risk indicator, holding constant all other regressors and considering that Tier 1 capital ratio is at its pooled average (9.60%), across various projection horizons.[16] These results compare directly to those in Figure 4 and the expression used to obtain the estimated marginal effect of the cyclical systemic risk indicator is presented in equation (3). Overall, results are qualitatively and quantitively very similar. The estimated impact of an increase in cyclical systemic risk on future bank profitability is u-shaped over the projection horizons for the four percentiles

16. The pooled average of the Tier 1 capital ratio between sample periods is not very different. Between 2001Q1 and 2019Q4 the average is 9.59% while between 1990Q1 and 2019Q4 the average is 9.60%.

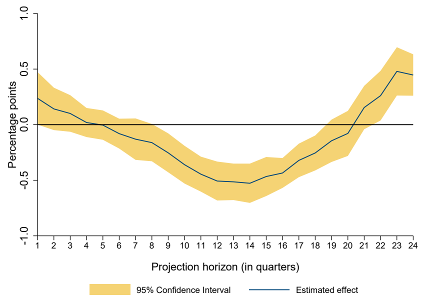
analysed. Also, the effect is negative and statistically significant over the medium-term (11 to 16-quarters ahead)



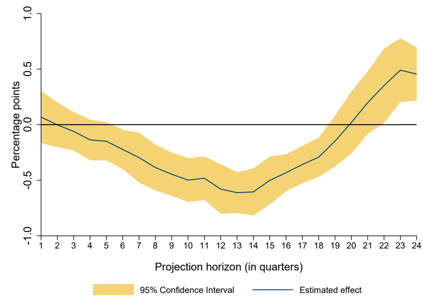
(a) 10th percentile



(b) 20th percentile



(c) 50th percentile



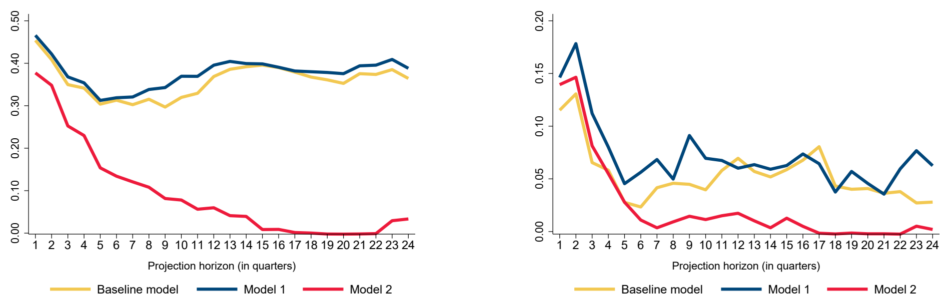
(d) 90th percentile

Figure B.1: Estimated marginal effect of an increase in the cyclical systemic risk indicator on selected percentiles of the conditional distribution of bank profitability across projection horizons

Notes: Estimated effect stands for the estimated marginal effect of a one unit increase in d-SRI, holding constant all other regressors and considering that Tier 1 capital ratio is at its pooled average (9.60%), on the conditional distribution of future bank profitability. The 95% confidence interval is based on bootstrapped standard errors.

B.2. Alternative sets of regressors

For the reasons discussed in section 4, the specified baseline model uses a subset of the regressors used by Lang and Forletta (2020). This could potentially lead to a significant lower adjustment of the model to the data. To investigate this issue, we compare the adjusted R-squared of the location and scale functions for the baseline specification to that of two models that differ from the previous one in terms of the set of regressors considered. The adjusted R-squared is a standard goodness-of-fit measure that controls for the number of regressors in the model. For the comparison exercise, we consider a model that includes the full set of variables considered by Lang and Forletta (2020) to model future bank profitability (labelled as model 1) and another model that consists of an order one autoregressive model (labelled as model 2). Panels (a) and (b) of Figure B.2 present the adjusted R-squared for the location and scale functions, respectively, for different projection horizons and considering different sets of variables. The results show that our baseline set of regressors explains a similar amount of the variability of bank profitability to that of model 1 across the different projection horizons. In addition, the naïve model 2 fits very poorly the data in comparison with the baseline specification, especially at long projection horizons. These conclusions are true for both the location and scale functions, although the explanatory power of the regressors is higher for the mean than for the percentiles. Overall, this exercise provides evidence that moderately shrinking the set of regressors does not imply a substantial loss in terms of goodness-of-fit.



(a) Location function

(b) Scale function

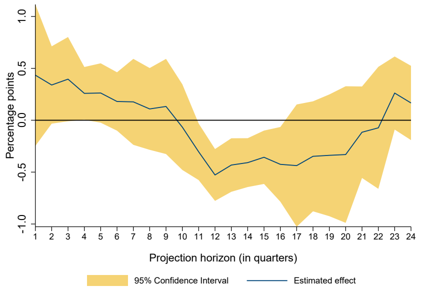
Figure B.2: Adjusted R-squared for different model specifications

Notes: Baseline model is presented in sections 3 and 4. Model 1 includes the full set of variables considered by Lang and Forletta (2020) and Model 2 is an order one autoregressive model.

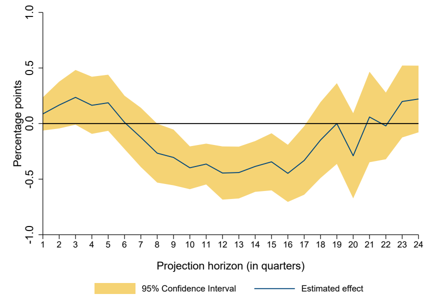
B.3. Alternative estimation method

In this section of the Appendix, we investigate if model results are dependent of the chosen estimation approach. Even though we have strong reasons to prefer the estimation approach proposed by Machado and Santos Silva (2019), we aknowledge that there are other alternatives in the literature that could be discussed. As such, we compare our main estimation results to those obtained using an alternative method proposed by Koenker and Bassett (1978), which has been widely used in the context of quantile regression models combined with panel data. Under this approach, each quantile model has a different fixed effect and the large sample properties are ensured if T (time series dimension) is large with respect to N (cross-sectional dimension). The advantages of using Machado and Santos Silva (2019) relative to Koenker and Bassett (1978) are several. First, when bank fixed effects vary across quantiles, estimates based on the standard quantile regressions only keep their desirable large sample properties when the time dimension is large, in absolute terms and relative to the cross-sectional dimension, which may not the case of our dataset. Furthermore, when employing Machado and Santos Silva (2019) to obtain an estimate for a specific percentile we obtain an implicit estimate of the mean, which is consistent throughout all percentile estimates. Lastly, the quantile estimates produced by Machado and Santos Silva (2019) do not cross, which is a nice to have feature.

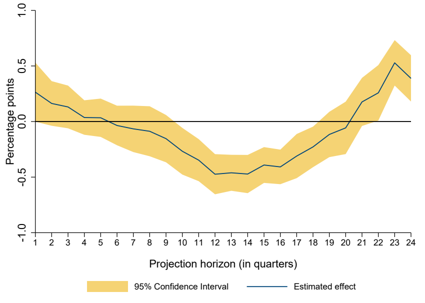
Figure B.3 presents the estimated marginal impact of a one unit increase in d-SRI on the 10th and 50th percentiles of the conditional distribution of bank profitability at various projection horizons considering two different estimators. The results are overall very similar in terms of economic effects. When focusing on the 10th percentile (Panels (a) and (b) of Figure B.3), the negative and statistically significant estimated effect of d-SRI found in the medium term using the estimator proposed by Machado and Santos Silva (2019), our employed method, is also identified when employing the estimator proposed by Koenker and Bassett (1978). This estimated effect evaluated at the pooled average Tier 1 capital ratio is also similar in magnitude, showing the robustness of the results used throughout the paper. Results for the 50th percentile (Panels (c) and (d) of Figure B.3) provide the same conclusions: the negative and statistically significant estimated effect of d-SRI is similar in magnitude across estimation methods.



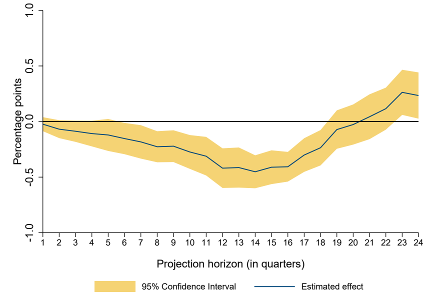
(a) 10th percentile - Machado and Santos Silva (2019)



(b) 10th percentile - Koenker and Bassett (1978)



(c) 50th percentile - Machado and Santos Silva (2019)



(d) 50th percentile - Koenker and Bassett (1978)

Figure B.3: Estimated marginal effect of an increase in the cyclical systemic risk indicator on selected percentiles of the conditional distribution of bank profitability across projection horizons

Notes: Estimated effect stands for the estimated marginal effect of a one unit increase in d-SRI, holding constant all other regressors and considering that Tier 1 capital ratio is at its pooled average (9.59%), on the conditional distribution of future bank profitability. Estimates based on Machado and Santos Silva (2019) estimator were obtained using the XTQREG command on STATA, while the estimates based on Koenker and Bassett (1978) were obtained using the QREG command. The 95% confidence interval is based on bootstrapped standard errors in both estimation approaches.