UNIVERSIDADE DE LISBOA

ISEG Lisbon School of Economics and Management

PhD in Economics

Essays on Macroprudential Policy

Joana Luzia Monteiro Passinhas

Orientadores: Prof. Doutora Isabel Maria Dias Proença
Prof. Doutor Telmo Jorge Lucas Peixe

Tese especialmente elaborada para obtenção do grau de Doutor em Economia

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2025

Statement of Work

I confirm that a version of Chapter 1, A macroprudential look into the risk-return framework of banks' profitability, was published as a REM Working Paper No. 0265-2023 and as a Banco de Portugal Working Paper No. 202303.

Abstract

This thesis aims to add to the existing literature tools for calibrating an macroprudential instrument - the countercyclical capital buffer (CCyB) - and to assess an implemented borrower-based measure - a limit to the debt service-to-income ratio (DSTI) - in both a low and in an increasing and higher interest rate environment.

Macroprudential policy became relevant after the 2008 financial crisis, as systemic risk - the accumulation of financial imbalances that led to excessive credit and booming housing prices - was not adequately covered by existing resilience. This interaction between risk and resilience is explored in the first chapters.

In the first chapter, the focus is on how ensuring enough resilience in the financial system implies managing a trade-off between expected bank profitability and downside risk in banks' profitability. To describe this trade-off, 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) is estimated. Results indicate that an increase in cyclical systemic risk negatively affects the conditional distribution of bank profitability at the medium-term projection horizon (11 to 16 quarters ahead), confirming the findings in the literature. At the same time, the increase of capital-based resilience is found to counter the negative effects of cyclical systemic risk on banks profitability in the same projection horizon. Using these results, a novel calibration rule for the CCyB is defined, which is flexible enough to accommodate different preferences of the policymaker and that factors in the prevailing levels of cyclical systemic risk and capital-based resilience. This rule targets downside risk in banks' profitability: the CCyB rate should be enough that all existing capital-based resilience (including the calibrated CCyB rate) can absorb the effect of cyclical systemic risk on deviating a measure of downside risk (in this case on the distance between the mean and the 10th percentile of banks profitability distribution in the medium-term) from the policymaker's target.

In the second chapter, evolutionary game theory is used to identify stable strategies of cyclical systemic risk and targeted resilience through macroprudential policy, specifically the CCyB. The model considers that each decision or interaction performed in the financial system can be defined within the dichotomy risk-resilience (either high or low) which receives a payoff. The payoffs are operationalized by considering quantile regressions on banks' profitability. The payoff of high or low risk activities will be awarded based on their short-term impact on banks' median profitability and depending on the state of macroprudential policy. The payoff of macroprudential policy will be assessed based on its medium-term impact on the tail of the profitability distribution and will depend on the state of cyclical systemic risk. Both specifications also depend on the level of financial stress in the system. Results show that there are two evolutionary stable strategies that depend on the level of financial stress, i.e., two strategies that, when achieved, are robust to small disturbances in the system. When financing conditions are good (financial stress is low), cyclical systemic risk will tend to increase, as agents take advantage of good conditions to engage in riskier activities; from a risk threshold onwards, the benefits of tightening macroprudential policy (of increasing resilience) will outweigh its costs. When financial stress is heightened, cyclical systemic risk will materialize and the costs of having macroprudential policy will be higher than its benefits, indicating a need to loosen the policy.

In the third chapter, the impact of the Portuguese DSTI limit on the distribution of the loan service-to-income (LSTI) ratio for new household loans for house purchases is assessed in both low and increasing interest rate environments. The choice for assessing the impact on the LSTI ratio of new loans relies on the fact that they will be both constrained by the DSTI limit and by rising interest rates. The purpose of studying the effects over the distribution is that it is expected that interest rates increases (driven by reference rates) will have a more significant effect in increasing the number of loans given at a higher LSTI ratio, if no restriction was in place, and so it can increase the right tail at a larger magnitude than in the rest of the distribution. However, at the same time, because there is a DSTI limit, the interest rate increase might induce households to take out smaller loans or even exclude them entirely from the credit market, which can offset the previous effect. In order to estimate the two effects, instrumental variable quantile regressions are employed and the exceptions to the DSTI limit, foreseen in the Portuguese Recommendation, are used as a potential counterfactual to explore how differences between similar loans that belong to each one of the two groups (exceptions and non-exceptions) impacts the conditional distribution of the LSTI ratio. Results indicate that, in the absence of the DSTI limit, the LSTI distribution could shift rightward, both before and after interest rates started to increase, reflecting a higher financial burden on borrowers. The impact of the limit is more pronounced after March 2022, demonstrating its efficacy in mitigating the impact of rising interest rates by more stringently restricting higher LSTI ratios.

Results throughout the thesis indicate that macroprudential policy can be effective in increasing resilience and curbing systemic risk in the financial system. The multiple tools, either capital-based or borrower-based, allow for a targeted impact depending on how systemic risk is originating in the financial system.

Keywords: macroprudential policy, cyclical systemic risk, financial system, evolutionary game theory, quantile regression.

Resumo

Esta tese pretende contribuir para a literatura ao propor ferramentas para calibrar instrumentos macroprudenciais, nomeadamente a reserva contracíclica de fundos próprios (CCyB). Além disso, pretende avaliar medidas macroprudenciais dirigidas aos devedores, nomeadamente o limite ao rácio entre o montante total das prestações mensais associadas a todos os empréstimos detidos pelo mutuário e o seu rendimento mensal líquido de impostos e contribuições obrigatórias à Segurança Social (DSTI), tanto num ambiente de baixas como de crescentes e elevadas taxas de juro.

A política macroprudencial ganhou mais relevância após a crise financeira de 2008, quando se constatou que o risco sistémico, i.e. a acumulação de desequilíbrios no sistema financeiro que resultaram na concessão excessiva de crédito e no crescimento excessivo dos preços da habitação, não estava a ser completamente coberto pela resiliência existente no sistema financeiro. Esta interação entre risco e resiliência é explorada em maior detalhe no primeiro e segundo capítulos.

No primeiro capítulo, analisa-se a forma de garantir que existe resiliência suficiente no sistema financeiro para cobrir os efeitos negativos da acumulação de risco sistémico. Isso implica gerir um *trade-off* entre a rentabilidade esperada pelos bancos, principalmente no curto prazo, e o risco de cauda desses mesmos retornos, isto é, o risco de perdas bancárias associadas a um evento negativo e raro no sistema financeiro. Para descrever este *trade-off*, é estimado um modelo dinâmico de regressão de quantis, utilizando dados ao nível dos bancos em Portugal, que relaciona a rentabilidade futura dos bancos no médio prazo com o ambiente de risco sistémico cíclico atual, após ter em consideração a resiliência, definida em termos dos rácios de fundos próprios presentes no sistema bancário. Esta avaliação do risco após resiliência é também referido como o risco sistémico cíclico residual, pois é o risco que ainda permanece no sistema após se ter em conta a resiliência. Os resultados indicam que um aumento do risco sistémico cíclico afeta negativamente a distribuição condicional da rentabilidade dos bancos no horizonte de projeção a médio prazo (entre 11 e 16 trimestres), confirmando os resultados na literatura. Ao mesmo tempo, verifica-se que o aumento da resiliência (definida em termos de fundos próprios) tem um efeito contrário relativamente ao efeito negativo do risco sistémico cíclico na rentabilidade dos bancos no mesmo horizonte de projeção. Com base nestes resultados, é definida uma nova regra de calibração para o CCyB que é suficientemente flexível para acomodar diferentes preferências do decisor de política macroprudencial e que considera os níveis predominantes de risco sistémico cíclico e de resiliência. Esta regra foca-se no risco de cauda da rendibilidade dos bancos: a reserva contracíclica de fundos próprios

deve ser suficiente para que toda a resiliência, baseada nos fundos próprios existente (incluindo o valor da reserva contracíclica de fundos próprios já calibrada), possa absorver o efeito que o risco sistémico cíclico tem na distância entre a média e o percentil 10 da distribuição da rendibilidade dos bancos projetada para o médio prazo, tal que se atinja o objetivo do decisor de política macroprudencial para esta distância.

No segundo capítulo, utiliza-se teoria de jogos evolutivos para apresentar um modelo que identifica estratégias estáveis de risco sistémico cíclico e de resiliência especificamente sob a forma de política macroprudencial (neste caso considera-se o CCyB). O modelo utilizado considera inicialmente que cada decisão ou interação no sistema financeiro pode ser definido no âmbito da dicotomia risco-resiliência (alto/a ou baixo/a), a que vai ser atribuído um determinado valor designado por *payoff*. Os *payoffs* são operacionalizados considerando regressões de quantis sobre a rendibilidade dos bancos. Os *payoffs* das actividades com risco alto/risco baixo serão definidos com base no seu impacto no curto prazo sobre a rendibilidade esperada (na mediana) dos bancos, dependendo do estado da política macroprudencial. Os *payoffs* da política macroprudencial serão avaliados com base no seu impacto a médio prazo na cauda da distribuição da rendibilidade, dependendo do estado do risco sistémico cíclico. Ambas as especificações dependem também do nível de *stress* financeiro no sistema. Os resultados mostram que existem duas estratégias evolutivamente estáveis que dependem do *stress* financeiro, ou seja, duas estratégias que, quando atingidas, são resistentes a pequenas perturbações no sistema ao longo do tempo. Quando as condições de financiamento são boas (o *stress* financeiro é baixo), o risco sistémico cíclico tende a aumentar, dado que os agentes do sistema financeiro aproveitam as boas condições de financiamento para assumir maior risco. No entanto, a partir de um determinado limiar de risco, os benefícios de uma política macroprudencial mais restritiva superam os seus custos, o que sinaliza que o CCyB deve começar a ser acumulado para absorver os potenciais impactos da acumulação de risco. Quando o *stress* financeiro começa a aumentar, e as condições de financiamento dos bancos não são tão favoráveis, os bancos assumem menos riscos o que leva a uma redução do risco sistémico cíclico. Nesta situação, os custos de aumentar ou sustentar um nível positivo para o CCyB, algo que reduz a rentabilidade esperada dos bancos, são superiores aos seus benefícios, o que indica a possibilidade de diminuir o valor da reserva.

No terceiro capítulo, avalia-se o impacto que o limite ao rácio DSTI, definido na Recomendação macroprudencial portuguesa, tem na distribuição do rácio entre a prestação de um novo empréstimo para compra de habitação e o rendimento do mutuário (LSTI), tanto num ambiente de taxas de juro baixas como num ambiente de taxas de juro crescentes. A escolha em focar no rácio LSTI definido para

novos empréstimos para compra de habitação baseia-se no facto de que estes são simultaneamente condicionados pelo limite ao rácio DSTI e pelo novo ambiente de taxas de juro crescentes. O objetivo de estudar os efeitos sobre a distribuição do rácio LSTI é verificar se os aumentos das taxas de juro teriam um impacto mais acentuado no aumento do número de empréstimos com um rácio LSTI mais elevado, caso o limite ao rácio DSTI não estivesse em vigor. Sem esse limite, a cauda direita da distribuição poderia crescer de forma mais significativa do que o restante da distribuição. No entanto, ao mesmo tempo, o limite ao rácio DSTI existente, numa situação de aumento das taxas de juro, através de aumentos das taxas de referência, pode induzir as famílias a contrair empréstimos menores ou até excluí-las completamente do mercado de crédito, o que pode compensar o efeito anterior. Para estimar os dois efeitos, são utilizadas regressões de quantis com variáveis instrumentais, e as exceções ao limite ao rácio DSTI, previstas na Recomendação portuguesa, são utilizadas como um potencial contrafactual do que poderia acontecer caso o limite macroprudencial não existisse. Isto é feito através da avaliação das diferenças, ao nível da distribuição condicional do rácio LSTI, entre empréstimos semelhantes que pertencem a cada um dos dois grupos (exceções e não exceções). Os resultados indicam que, na ausência do limite ao rácio DSTI, a distribuição do rácio LSTI poderia deslocar-se para a direita, tanto no ambiente de baixas taxas de juro como no de taxas de juro crescentes e elevadas, refletindo um maior esforço financeiro para os mutuários. Os benefícios do limite ao rácio DSTI são ainda mais pronunciados após março de 2022, o que demonstra a eficácia do limite em mitigar o impacto do aumento das taxas de juro, restringindo mais rigorosamente os rácios LSTI mais elevados.

Os resultados ao longo da tese indicam que a política macroprudencial pode ser eficaz tanto para aumentar a resistência como para reduzir o risco sistémico no sistema financeiro. Os múltiplos instrumentos, baseados tanto em capital como na definição de limites baseados nas condições do empréstimo, permitem um efeito direcionado e que depende da forma como o risco sistémico impacta o sistema financeiro a cada momento.

Palavras-chave: política macroprudencial, risco sistémico cíclico, sistema financeiro, teoria de jogos evolutivos, regressão de quantis.

Presentation of Work

The work submitted in this thesis has been presented at:

- 35th MPAG Meeting
  Date: 24 January 2023
  Work Presented: A macroprudential look into the risk-return framework of banks' profitability

- 8th ISEG PhD Seminar
  ISEG, Lisbon, Portugal. Date: 27 March 2023
  Work Presented: A macroprudential look into the risk-return framework of banks' profitability

- 2023 RiskLab/BoF/ESRB Conference on Systemic Risk Analytics (Poster)
  Bank of Finland, Helsinki, Finland. Date: 8-9 June 2023
  Work Presented: A macroprudential look into the risk-return framework of banks' profitability

- 16th Annual Meeting of the Portuguese Economic Journal
  Universidade do Minho, Braga, Portugal. Date: 7 - 9 July 2023
  Work Presented: A macroprudential look into the risk-return framework of banks' profitability

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Acknowledgements

Completing my PhD thesis is a bittersweet moment. Over the past four years, this work has been a constant in my life, at times inducing anxiety and at other times bringing joy and renewing my passion for research. Throughout this journey, I have been fortunate to have the support of many remarkable individuals, whom I would like to thank.

First and foremost, I would like to express my deepest gratitude to my supervisors. Prof. Dra. Isabel Proença, who has been a guiding force since my Master's thesis and continued to mentor me through this PhD. Her insightful comments, discussions, suggestions, and words of motivation have been invaluable. Prof. Dr. Telmo Peixe, thank you for the opportunity to learn from an expert in evolutionary game theory, a field I had long wished to explore. Your feedback and discussions were instrumental, particularly in shaping the second chapter of this thesis.

Secondly, I am deeply grateful to my colleagues at Banco de Portugal. I extend my sincere thanks to Ana Cristina Leal and Inês Drumond for their insightful comments and suggestions on the first and second chapters. Your expertise in macroprudential policy, both in theory and practice, has been instrumental in shaping this thesis. I am especially thankful to you both for introducing me to the world of macroprudential policywithout your guidance, this work would not have come to fruition. I would also like to thank Fátima Silva, Ana Pereira, and Diana Lima for the many discussions and their knowledge-sharing in the area of macroprudential policy over the years. A special thanks to Ana Pereira for welcoming me into her unit, contributing significantly to my understanding of macroprudential policy, and collaborating with me on the research that forms the basis of the first chapter. Additionally, I wish to extend my thanks to the many colleagues at Banco de Portugal who provided comments and suggestions throughout my work. A special thank you to Diana Martins for her assistance with the data for chapter three.

I would like to thank Professor João Santos Silva for his valuable assistance with quantile regression models featuring fixed effects, which contributed to the work presented in the first chapter.

I am also grateful to the members of my thesis jury for their valuable comments and suggestions.

Lastly, I must thank my family and friends for their unwavering love and support, which have been a pillar of strength during these past few years. I dedicate this thesis to my nephews, Salvador and Bernardo, and niece Leonor, who are the light of my life.

Introduction

The increase of vulnerabilities in the financial system ahead of the 2008 global financial crisis had large and persistent effects of the real economy when risk materialized (Claessens, Kose, and Terrones 2010). In order to tackle risk build-up in the financial system, that can propagate to the real economy by seriously impairing the access to credit, commonly referred to as systemic risk, macroprudential policy has, more recently, been used as the primary policy. Macroprudential policy aims at promoting the necessary resilience in the financial system relatively to the level of systemic risk. To pursue this objective a diverse set of policy instruments was made available to macroprudential policymakers across Europe (Basel Committee on Banking Supervision 2011) which is primarily divided into two main types: capital-based or borrower-based instruments.

Capital-based macroprudential measures act mainly through enforcing specific capital requirements on banks to address some type of risk, while borrower-based measures act through enforcing specific solvability requirements that borrowers should meet when accessing credit.

This thesis focuses on two macroprudential measures, one is capital-based, the Countercyclical Capital Buffer (CCyB), and the other is borrower-based, a limit to the debt service-to-income (DSTI) ratio implemented in Portugal in 2018. This limit may have different effects when in a low interest rate environment (up until 2022) and in an increasing one (after the increase in policy rates within the eurozone).

The CCyB targets the cyclical dimension of systemic risk. This dimension identifies that systemic risk tends to behave pro-cyclically over time, building-up in the upward phase of the financial cycle and decreasing in the downward phase (European Systemic Risk Board 2013).

To address the procyclical behaviour of banks, the CCyB was introduced as a way to increase banks' capital buffers in periods of increased lending and excessive risk-taking (build-up phase), a buffer that can then be used to absorb unexpected losses during financial stress events (release phase), mitigating credit supply restrictions. However, this policy 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.

The structural view of systemic risk focus on the distribution of risks in the financial sector, e.g. risk related with the level of interconnectedness in the system from both direct and indirect exposures among institutions and the market. One major point of interlinkage among banks is their exposure to the residential real estate market through loans given to households. Borrower-based measures, such as a limit to the DSTI ratio, can be used to mitigate losses related with this type of risk as it ensures that borrowers are not overleveraged (European Systemic Risk Board 2014). High levels of household debt relative to income can amplify structural systemic risk by increasing the probability of defaults in the event of economic downturns, thereby threatening the stability of the broader financial system.

In the first and second chapters of this thesis, different methods for calibrating the CCyB using measures of cyclical systemic risk and resilience are explored. This risk-resilience framework is frequently explored in macroprudential policy and has been the basis of recent work on defining the stance of macroprudential policy (European Systemic Risk Board 2019, European Systemic Risk Board 2021).

In the first chapter the calibration of the CCyB is done by exploring the relationship between cyclical systemic risk and resilience on the distribution of banks' profitability, using a dynamic quantile regression model that includes banks fixed effects. Rather than focusing on the mean, quantile regressions allow to obtain estimates of the impact of changes in regressors, namely measures of cyclical systemic risk and resilience, on the whole conditional distribution of the dependent variable.

Focusing on the conditional distribution of bank profitability, measured by pre-tax return on assets, and a domestic cyclical systemic risk indicator to capture the financial cycle's dynamics, results reveal that cyclical systemic risk build-up leads to a significant decline in bank profitability uniformly across different percentiles, particularly in medium-term horizons (three to four years after risk starts building up).

To edge against the impact of risk build-up on bank profitability in the medium term, a rule to increase resilience through building the CCyB is proposed. Additionally, this chapter highlights the trade-offs faced by policymakers between enhancing financial stability in the medium-term and managing short-term profitability, emphasizing that stricter capital requirements may reduce immediate returns to banks but contribute to greater resilience against future financial stress.

In the second chapter, an evolutionary game model is proposed to study the financial system as a multicellular system composed of several cells (players) of two types: risk and resilience.

An evolutionary game model is a framework that allows for a set of strategies played in a population to be conditioned by the strategic interaction among players over time. The strategic interaction will result in the tendency for the highest fitted strategies to displace the lowest according to an adaptation process considered for the population. In this model, a pairwise combination of a risk cell and a resilience cell defines an interaction in the financial system (e.g. a new credit contract). Each cell (risk or resilience) will be either in a "low" or "high" state. This framework is further narrowed down to (cyclical systemic) risk and (macroprudential) policy cells (that when added up result in the CCyB rate), which influence the resilience of the banking system. Then, the CCyB is calibrated using the concept of evolutionary stable strategy, i.e. a strategy that cannot be disrupted by small perturbations (first defined in Smith and Price 1973), and the replicator dynamics (described e.g. in Hofbauer and Sigmund 1998) where the evolution of the frequency of each strategy, "high" or "low", will mimic natural selection. Results, using data from Portugal for 2001-2021, point to a system where the CCyB should be built-up when cyclical systemic risk and financial stress surpass certain thresholds. When financial stress is low, it will contribute to increase risk taking by banks which, at a certain point, activates the need for more resilience (activation of the CCyB); this buffer should then be released when risk materializes and there is a stress event in the financial system.

In the third chapter, the analysis examines how a borrower-based measure - a DSTI limit - restricts loans with high effort rates in both a low and in an increasing interest rate environment.

In 2022, the euro area experienced high levels of inflation, significantly surpassing its historical norms and exceeding the European Central Bank's (ECB) target of 2%. In order to tackle this issue, the ECB increased its reference rates throughout 2022 in a fast pace - increasing 450 basis points from July 2022 to September 2023. This occurred after a period of historically low interest rates and the market was quick to pass through the monetary policy action to their interbank loan rates. Ahead of the increase of interest rates, the Banco de Portugal introduced a macroprudential Recommendation in July of 2018 with several limits that can both reduce losses given default and the probability of default, including a limit of 50% to the DSTI ratio of new loans to households. This type of limit can help in reducing borrower's probability of default. In Nier et al. (2019) it is shown that, if always in place, the 40% limit to the DSTI ratio applicable in Romania would have decreased the probability of default for all mortgages by 23%. A limit to the DSTI ratio directly interacts with the evolution of interest rates as it becomes more restrictive with rate increases and less restrictive with rate decreases, everything else constant.

In this context, the impact of a rising interest rate environmentcompared to the previous low-rate periodon the distribution of the loan service-to-income (LSTI) ratio for new household loans for house purchases under a DSTI limit is assessed. Moreover, it is also evaluated whether this impact would differ significantly in the absence of a DSTI limit. The choice for the LSTI ratio of new loans relies on the fact that current DSTI ratios faced by borrowers are defined by existing debt and new acquired loans in the higher interest rate environment. Therefore, the LSTI ratio of new loans will be both constrained by the DSTI limit but also affected by the increasing interest rate environment.

To achieve this, instrumental variable quantile regressions are estimated. The role of exceptions to the DSTI limit as a potential counterfactual is explored in a cross-sectional manner by estimating differences across the conditional distribution of the LSTI ratio between similar loans from two groups: exceptions and non-exceptions. Results indicate that, in the absence of the DSTI limit, the LSTI distribution could shift rightward, both before and after interest rates started to increase, reflecting a higher financial burden on borrowers and an increased risk of default. The impact of the DSTI limit is more pronounced after March 2022, demonstrating the limit's efficacy in mitigating the impact of rising interest rates by more stringently restricting higher LSTI ratios.

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1 The CCyB and banks profitability distribution[1]

1.1 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 chapter, 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, Boyarchenko, and Giannone (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

[1]This chapter is co-authored with Ana Pereira.

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, Izzo, 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.[2] 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 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

[2]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 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.

This chapter is organized as follows. Section 1.2 summarizes the three strands of existing literature that more closely relate to our analysis. Section 1.3 presents the empirical model to be estimated along with the estimation approach. Section 1.4 provides an overview of the data used in estimation. Section 1.5 presents the results from model estimation. Section 1.6 shows how the estimation results can be used in three policy exercises that are relevant for macroprudential policy purposes and section 1.7 concludes.

1.2 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, Boyarchenko, and Giannone (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, Grinberg, et al. (2022) extended these results to a panel of advanced economies. Figueres and Jarociski (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 Babi (2018) and Babi 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; Plaíl et al. (2015) that proposes a composite indicator that better identifies the build-up phase of systemic risk in Czech Republic; and, Lang, Izzo, 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, Laakkonen, and Kalatie (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, Onorante, and Rannenberg 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 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, Javier Suarez 2022 and Cecchetti and J. 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, Javier Suarez 2022 and Cecchetti and J. 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). Javier 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 J. Suarez (2021) further explore the optimal rule of Javier 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.

1.3 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 K. Kato, A. F. Galvao, and Montes-Rojas (2012), A. F. Galvao and Wang (2015), Antonio F. Galvao and Kengo 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, $i = 1, \dots, N$ identifies the banks, $t = 1, \dots, T$ identifies the period and $h, N, T \in \mathbb{N}$. According to Koenker and Bassett Jr (1982) employing a location-scale model implies that:

$$\pi_{i,t+h} = \mu(\mathbf{X}_{i,t}) + \sigma(\mathbf{X}_{i,t})U_{i,t+h} \tag{1.1}$$

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 $l = 1, \dots, k \in \mathbb{N}$, $\mu(\mathbf{X}_{i,t})$ 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:

$$Q_{\pi_{i,t+h}}(\tau|\mathbf{X}_{i,t}) = \left[\alpha_i^h + \delta_i^h q(\tau, h)\right] + \mathbf{X}'_{i,t}\left[\boldsymbol{\beta}^h + \boldsymbol{\gamma}^h q(\tau, h)\right] = \alpha_i(\tau, h) + \mathbf{X}'_{i,t}\boldsymbol{\beta}(\tau, h) \tag{1.2}$$

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 $[U_{i,t+h} < q(\tau, h)] = \tau$.[3]

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 1.4. 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

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

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 (1.2) 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 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.

1.4 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).

1.4.1 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.[4] 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 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 1.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, 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

[4]More information on this dataset is available here.

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).

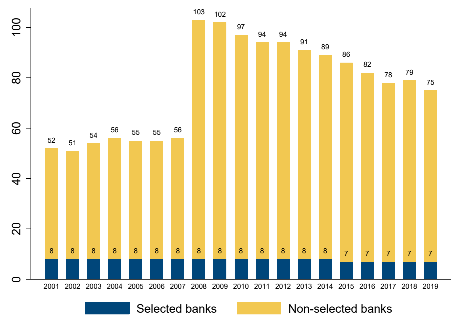
However, we argue that this set of restrictions to the composition of the bank panel is not worrisome to the extent that the selected banks are representative of the aggregate Portuguese banking sector over time, as we show below. Namely, the selected banks account for more than 80% of total assets in 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).[5] 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.[6]

In order to assess how representative the bank panel is of the Portuguese banking sector, Figure 1.1 presents the number of banks (Panel (a)) and asset coverage (Panel (b)) of the selected banks and non-selected banks over time considering

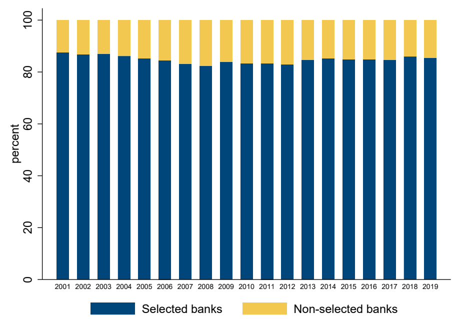
[5]LSF Nani results from considering information from Espírito Santo Financial Group between 2001Q1 and 2014Q2, from Novo Banco, SA between 2014Q3-2018Q3 and from LSF Nani Investments S.a.r.l between 2018Q4 and 2019Q4. SICAM results from considering information from Caixa Central de Crédito Agrícola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

[6]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.

the information available in the SLB database. Panel (a) of Figure 1.1 shows that the chosen panel of banks represents a small share of the number of banks that comprise the Portuguese banking sector over time.[7] 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 1.1). 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.[8] We compare this counterpart country aggregate to an aggregate that results from our sample of selected banks.



(a) Number of banks



(b) Assets

Figure 1.1: 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 1.2 presents the results for the distribution of coverage levels over time.[9]

[7]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.

[8]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.

[9]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.

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.

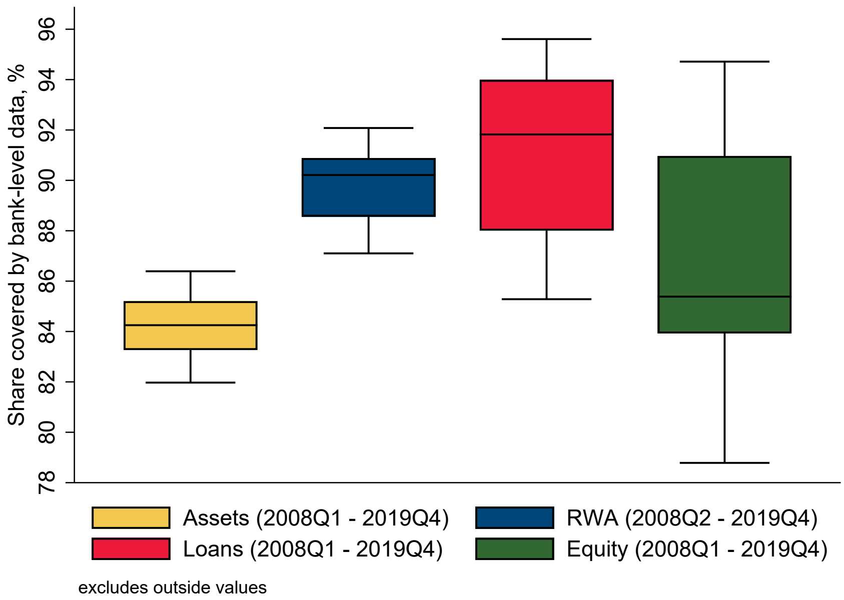


Figure 1.2: Coverage levels of the selected bank panel for different variables

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.

1.4.2 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 set of regressors allows for a parsimonious model while still controlling for the most relevant aggregate effects.[10] 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, Izzo, 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) and Lang, Izzo, 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 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 1.3 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.

[10]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 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.

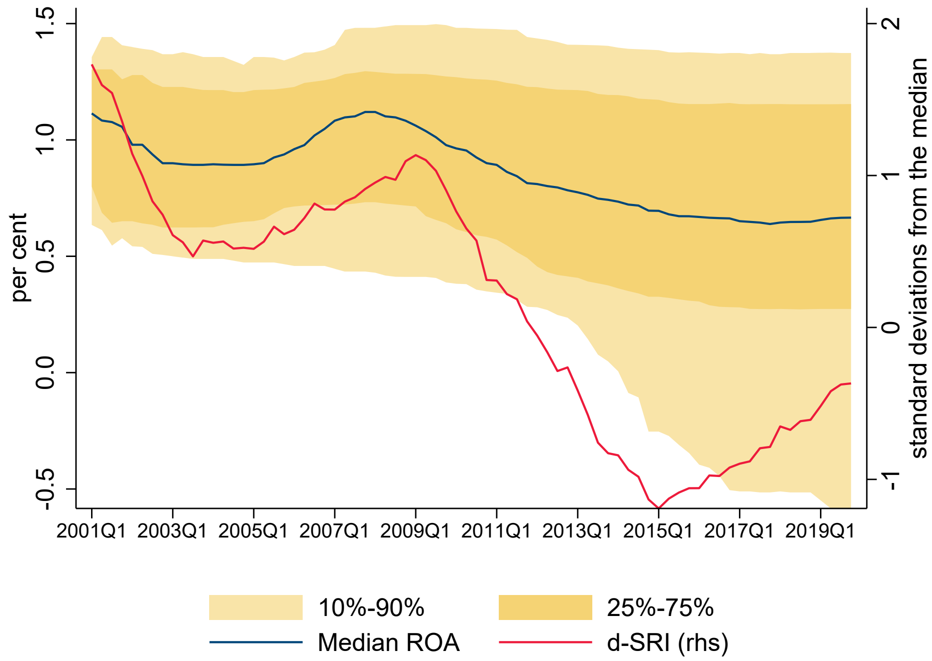


Figure 1.3: Cyclical systemic risk and the cross-sectional distribution of ROA

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

1.4.3 Descriptive statistics

Table 1.1 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%.[11] 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%.

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 1.1: 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.

[11] 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%.

1.5 Estimation results

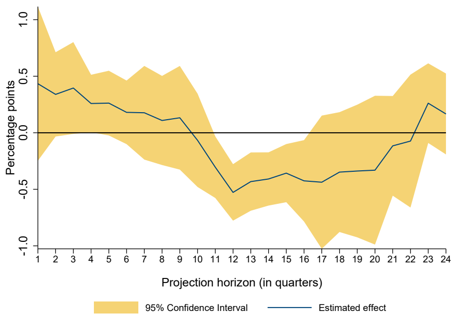
This section discusses the estimation results of the quantile regression model presented in Section 1.3. Figure 1.4 plots the estimated marginal impact on selected percentiles ($\tau = 0.1, 0.2, 0.5, 0.9$) of the conditional distribution of bank profitability following a one unit increase in the cyclical 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.[12] 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 (1.2), the estimated marginal impact of the cyclical systemic risk indicator is given by:

$$\hat{\theta}_{\text{d-SRI}}(h, \tau, \text{T1R}_{i,t}) = \hat{\beta}^h_{\text{d-SRI}} + \hat{\gamma}^h_{\text{d-SRI}} q(\tau, h) + \left[\hat{\beta}^h_{\text{d-SRI}\times\text{T1R}} + \hat{\gamma}^h_{\text{d-SRI}\times\text{T1R}} \hat{q}(\tau, h)\right] \times \text{T1R}_{i,t} \quad (1.3)$$

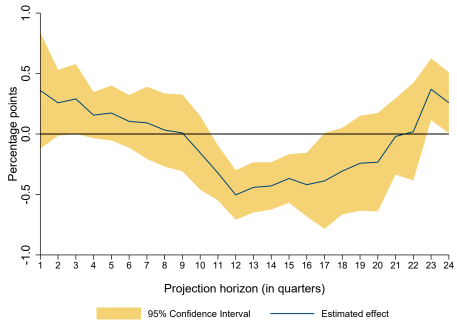
We choose to set Tier 1 capital ratio equal to its pooled average $(\text{T1R}_{i,t} = \overline{\text{T1R}})$ and use $\hat{\theta}_{\text{d-SRI}}(h, \tau, \overline{\text{T1R}})$ following the standard practice. Three findings emerge from Figure 1.4. First, the impact on bank profitability is mostly 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 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

[12] 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 (1.3).

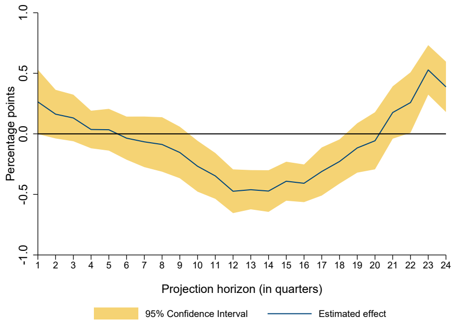
impact of cyclical systemic risk on the left tail, in their case the 5th percentile, of bank profitability distribution is of an order of magnitude larger than the impact on the median.



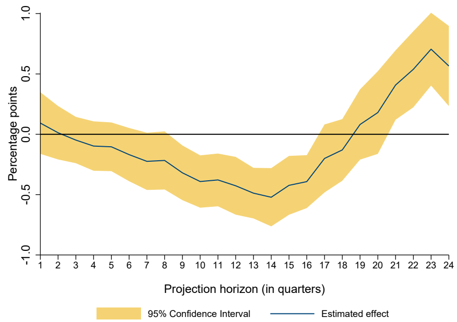
(a) 10th percentile



(b) 20th percentile



(c) 50th percentile

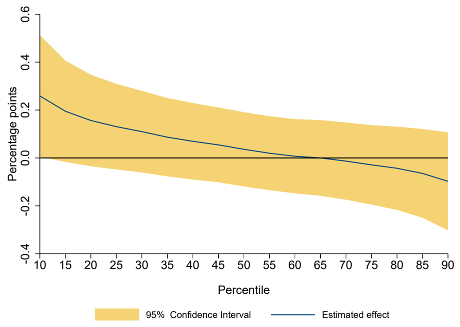


(d) 90th percentile

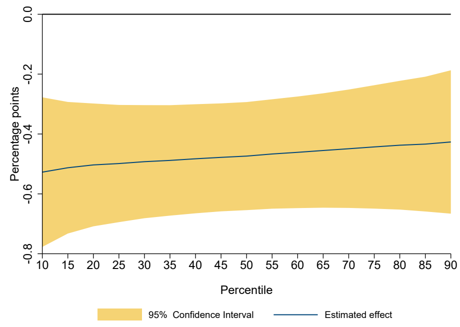
Figure 1.4: Estimated marginal effect of an increase in the cyclical systemic risk indicator on selected percentiles of the conditional distribution of bank profitability across projection horizons

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.

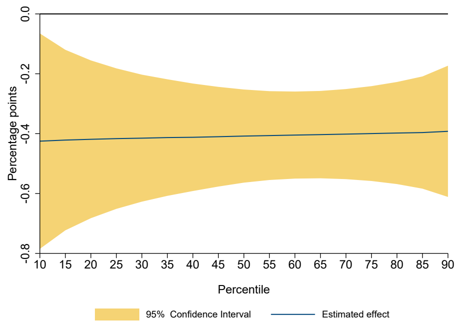
The panels in Figure 1.5 display the estimated marginal impact of a one unit increase in the cyclical systemic risk indicator when Tier 1 capital ratio is at its pooled average (9.59%) on different percentiles of the conditional distribution of bank profitability for selected projection horizons ($h = 4, 12, 16, 24$). Focusing on the medium-term horizons, Panels (b) and (c) of Figure 1.5 show that the estimated negative effect, shown in Figure 1.4 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 1.5). 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 1.4). 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.



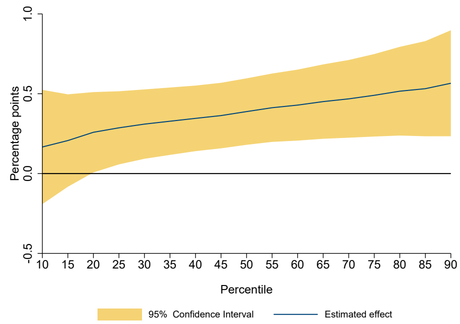
(a) 4-quarters ahead



(b) 12-quarters ahead



(c) 16-quarters ahead



(d) 24-quarters ahead

Figure 1.5: 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 1.2 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 1.2 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 1.2). The last four columns of Table 1.2 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	-	-	-	-
$\hat{q}(\tau, 16)$	-	-	-1.757	-1.126	-0.026	1.600

Table 1.2: 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 1.3. 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 with 200 iterations.

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.

1.6 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.

1.6.1 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 1.2, 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 1.2, in particular, it holds for the medium-term horizons linked to the macroprudential decision horizon. The indicative calibration rule is expressed as follows:

$$\text{CCyB}_t = max\left\{0, \frac{\sum_{h=12}^{16} -\hat{\theta}_{\text{d-SRI}}(h, 0.5, \text{T1R}_t)}{arw_t} \times \text{d-SRI}_t\right\} \tag{1.4}$$

where $\hat{\theta}_{\text{d-SRI}}(h, 0.5, \text{T1R}_t)$ is presented in equation (1.3) 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.[13] The inverse of arw_t is used in equation (1.4) 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 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 (1.4), 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

[13] In equation (1.4), the risk weight is defined in terms of average total assets and not in terms of total assets.

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.

Results

Figure 1.6 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.

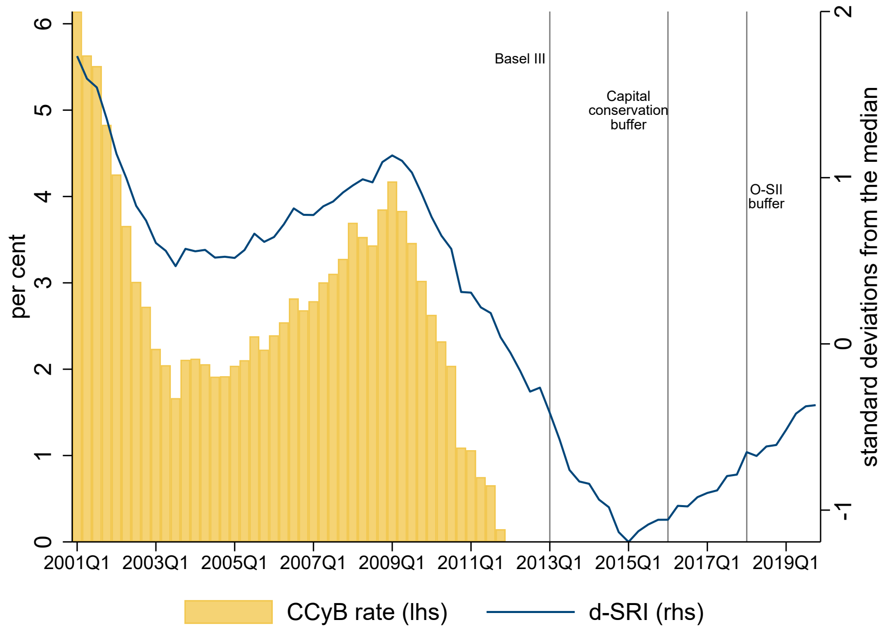


Figure 1.6: Indicative rate for the CCyB

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.

1.6.2 Return-at-risk

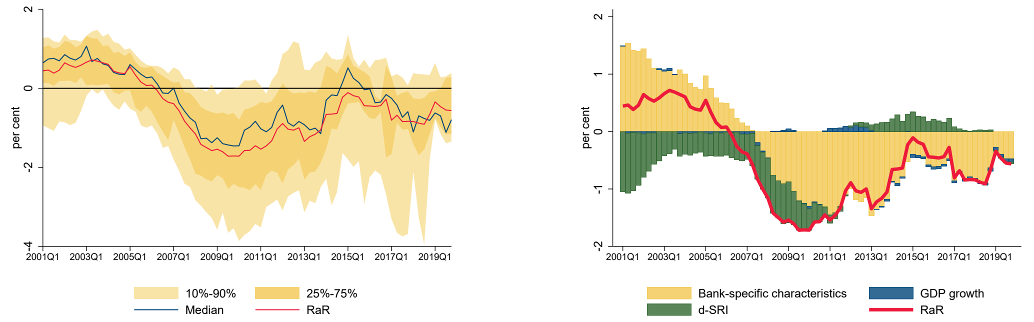
The empirical results, presented in Section 1.5, are also used to produce a tail risk metric that indicates how weak profitability in the banking sector can be in a specific projection horizon, given the current cyclical systemic risk environment and the prevailing level of capital-based resilience. 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:

$$\text{RaR}_{t+h}^{10\%} = \sum_{i=1}^{N_t} \hat{Q}_{\pi_{i,t+h}}(0.1|\mathbf{X}_{i,t}) \times \frac{a_{i,t}}{\sum_{k=1}^{N_t} a_{k,t}} \tag{1.5}$$

where N_t represents the number of banks in the panel at time t, $\hat{Q}_{\pi_{i,t+h}}(0.1|\mathbf{X}_{i,t})$ 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.

Results

In what follows, we focus the analysis on the 16-quarters ahead projection horizon matching the choice made in Section 1.5. Panel (a) of Figure 1.7 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 1.7 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 1.7: 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 1.4, 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.

1.6.3 The macroprudential stance space

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) and Javier 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.

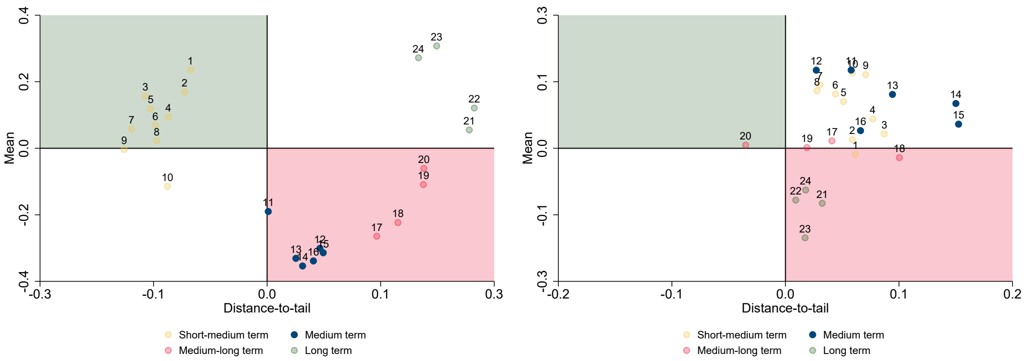
Against this background, the discussion on macroprudential policy stance space, anchored in the risk-return analysis and considering the specified empirical model, will take place through a graphical representation of a coordinate plane that is centred at $(0, 0)$ on the xy-axis. The x-axis represents 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.[14]

Results

Figure 1.8 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 scenario, in which residual

[14]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 $-\left[\hat{\gamma}^h_{\text{d-SRI}}\hat{q}(0.1, h) + \hat{\gamma}^h_{\text{d-SRI}\times\text{T1R}}\hat{q}(0.1, h) \times \text{T1R}_t\right] \times \text{d-SRI}_t$.

cyclical systemic risk contributes to decrease expected future bank profitability and to increase downside risk.



(a) 2006Q1

(b) 2019Q4

Figure 1.8: 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.

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.[15] 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

[15] 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.

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 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:

$$target(\text{risk}) = \begin{cases} g\,(\text{risk}) < 0 & \text{, risk build-up} \\ 0 & \text{, muted risk} \\ f\,(\text{risk}) > 0, & \text{, risk materialisation} \end{cases} \tag{1.6}$$

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 1.3 and estimated in 1.5 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:

$$\phi^h_{\text{d-SRI}} \times \text{d-SRI}_t + \phi^h_{\text{d-SRI}\times\text{T1R}} \times (\text{d-SRI}_t \times \text{T1R}_t) \tag{1.7}$$

where $\phi^h_{\text{d-SRI}} = -\gamma^h_{\text{d-SRI}} q(0.1, h)$ 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 $\phi^h_{\text{d-SRI}\times\text{T1R}} = -\gamma^h_{\text{d-SRI}\times\text{T1R}} q(0.1, h)$ represents the effect of the existing cyclical systemic risk-targeted resilience. The last term of equation (1.7) 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:

$$\phi^h_{\text{d-SRI}} \times \text{d-SRI}_t + \phi^h_{\text{d-SRI}\times\text{T1R}} \times [\text{d-SRI}_t \times (\text{T1R}_t + \text{CCyB}_t)] = target(\text{d-SRI}) \tag{1.8}$$

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 (1.8) to obtain the following general calibration rule for the CCyB:

$$\text{CCyB}_t(h) = max\left\{0, \frac{target(\text{d-SRI})}{\phi^h_{\text{d-SRI}\times\text{T1R}} \times \text{d-SRI}_t} - \frac{\phi^h_{\text{d-SRI}} + \phi^h_{\text{d-SRI}\times\text{T1R}} \times \text{T1R}_t}{\phi^h_{\text{d-SRI}\times\text{T1R}}}\right\} \tag{1.9}$$

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 (1.8) follows:

$$\phi^h_{\text{d-SRI}} + \phi^h_{\text{d-SRI}\times\text{T1R}} \times (\text{T1R}_t + \text{CCyB}_t) = 0 \tag{1.10}$$

which allows gauging the Tier 1 capital ratio implied by the target chosen by the policymaker:[16]

$$\text{T1R}^*_t(h) = (\text{T1R}_t + \text{CCyB}_t(h))^* = -\frac{\phi^h_{\text{d-SRI}}}{\phi^h_{\text{d-SRI}\times\text{T1R}}} \tag{1.11}$$

and obtain the following CCyB calibration rule

$$\text{CCyB}_t(h) = max\left\{0, -\frac{\phi^h_{\text{d-SRI}}+\phi^h_{\text{d-SRI}\times\text{T1R}}\times\text{T1R}_t}{\phi^h_{\text{d-SRI}\times\text{T1R}}}\right\} = max\left\{0, -\frac{\phi^h_{\text{d-SRI}}}{\phi^h_{\text{d-SRI}\times\text{T1R}}} - \text{T1R}_t\right\} \tag{1.12}$$

[16] 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 $\text{T1R}^*_t(h) = \frac{\frac{target}{\text{d-SRI}_t} - \phi^h_{\text{d-SRI}}}{\phi^h_{\text{d-SRI}\times\text{T1R}}}$.

Considering the estimation results presented in table 1.2, we can assign values to the unknown parameters of equation 1.12 and obtain the following estimated calibration rule for the 16-quarters ahead projection horizon:

$$\textbf{Calibration rule 1:} \quad \widehat{\text{CCyB}}_t(16) = max\,\{0, 9.9 - \text{T1R}_t\} \tag{1.13}$$

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 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,

$$target(\text{d-SRI}) = \eta\left[\beta^h_{\text{d-SRI}} \times \text{d-SRI}_t + \beta^h_{\text{d-SRI}\times\text{T1R}} \times [\text{d-SRI}_t \times (\text{T1R}_t + \text{CCyB}_t)]\right] \tag{1.14}$$

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 (1.6), 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 (1.14) the parameters with their estimates, we obtain:

$$\widehat{target}(\text{d-SRI}) = \eta\left[-0.938 \times \text{d-SRI}_t + 0.055 \times [\text{d-SRI}_t \times (\text{T1R}_t + \text{CCyB}_t)]\right] \tag{1.15}$$

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

$$\widehat{target}(\text{d-SRI}) = \begin{cases} < 0 & \text{, d-SRI} > 0 \text{and T1R} < 17.1 \\ 0 & \text{, d-SRI} = 0 \text{and T1R} < 17.1 \\ > 0, & \text{, d-SRI} < 0 \text{and T1R} < 17.1 \end{cases} \tag{1.16}$$

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 (1.8), we obtain the following general CCyB calibration rule:

$$\text{CCyB}_t(h) = max\left\{0, \frac{-\phi^h_{\text{d-SRI}} + \eta\beta^h_{\text{d-SRI}} - (\phi^h_{\text{d-SRI}\times\text{T1R}} - \eta\beta^h_{\text{d-SRI}\times\text{T1R}}) \times \text{T1R}_t}{\phi^h_{\text{d-SRI}\times\text{T1R}} - \eta\beta^h_{\text{d-SRI}\times\text{T1R}}}\right\} \tag{1.17}$$

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

$$\textbf{Calibration rule 2:} \quad \widehat{\text{CCyB}}_t(16) = max\left\{0, 14.2 - \text{T1R}_t\right\} \tag{1.18}$$

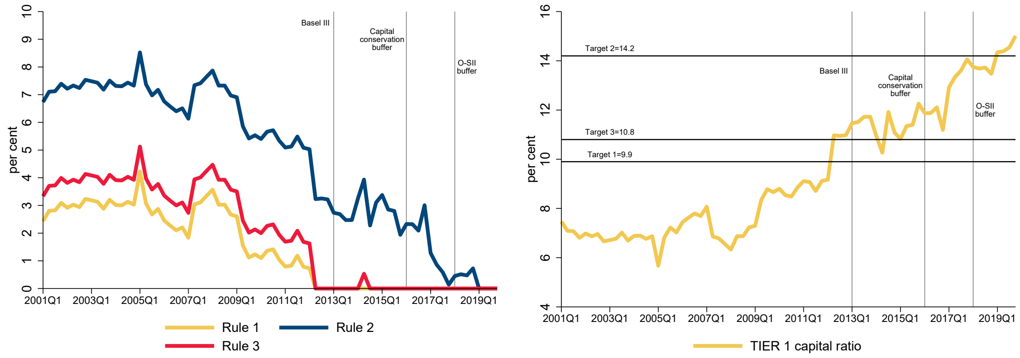
and calibration rule number 3 when setting $\eta = 0.1$

$$\textbf{Calibration rule 3:} \quad \widehat{\text{CCyB}}_t(16) = max\left\{0, 10.8 - \text{T1R}_t\right\} \tag{1.19}$$

Results

Panel (a) of Figure 1.9 presents the simulation results for Portugal. Panel (b) of Figure 1.9 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.

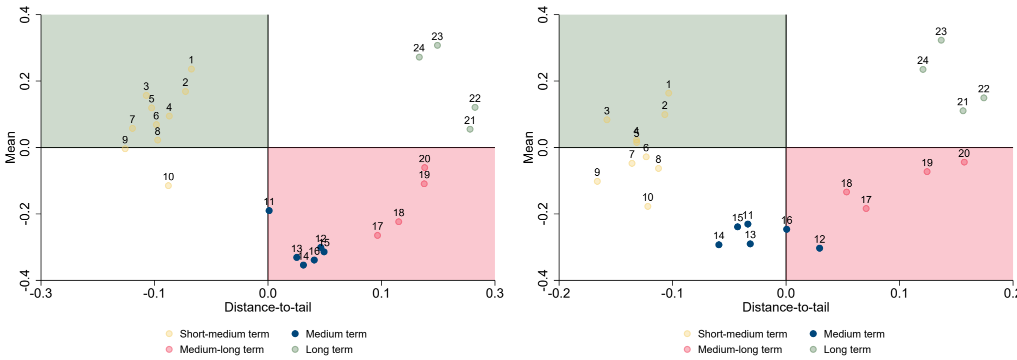


(a) CCyB calibration (b) Aggregate Tier 1 capital ratio

Figure 1.9: 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 (1.13), (1.18) and (1.19) 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 (1.13). Panel (a) of Figure 1.10 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 1.8). Panel (b) of Figure 1.10 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 1.10: 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 (1.13).

1.7 Conclusion

This chapter 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.

A Data

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, Izzo, 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 1.A.1: Variables definition and data sources

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.

Alternative sample period

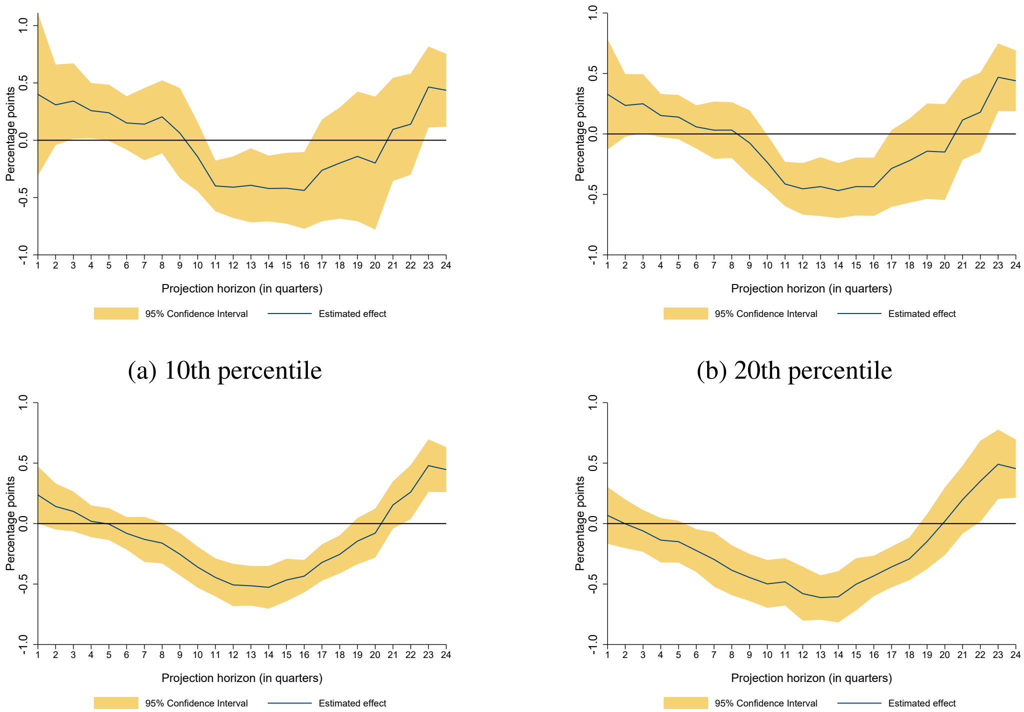
The estimation results presented in section 1.5 rely on information that spans from 2001Q1 to 2019Q4. In this subsection of the Appendix, we show that the estimation results still hold if the sample period is expanded back to 1990. The information available between 1990 and 2001 for the majority of the 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 1.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.[17] These results compare directly to those in Figure 1.4 and the expression used to obtain the estimated marginal effect of the cyclical systemic

[17]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%.

risk indicator is presented in equation (1.3). 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 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

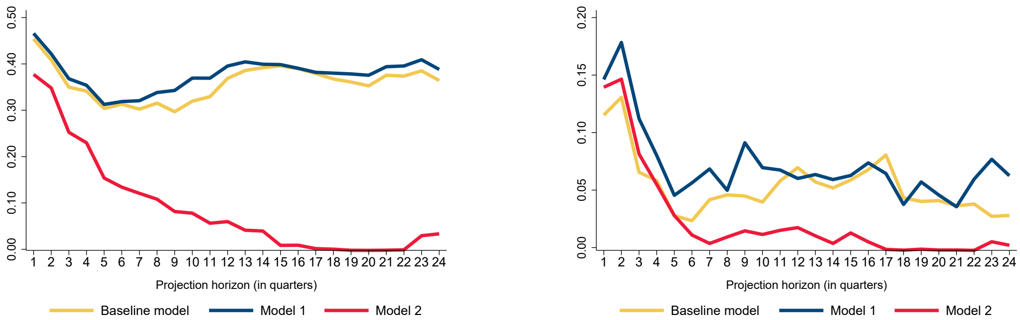
(d) 90th percentile

Figure 1.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.

Alternative sets of regressors

For the reasons discussed in section 1.4, 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 1.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

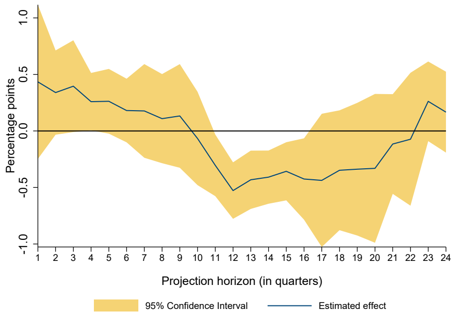
Figure 1.B.2: Adjusted R-squared for different model specifications

Notes: Baseline model is presented in sections 1.3 and 1.4, Model 1 includes the full set of variables considered by Lang and Forletta (2020) and Model 2 is an order one autoregressive model.

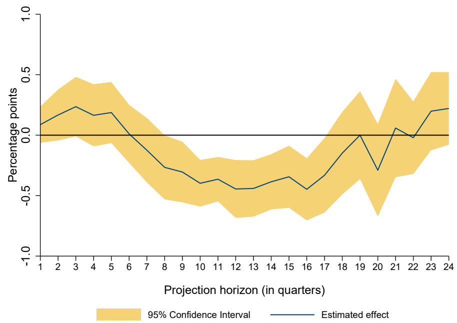
Alternative estimation method

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 acknowledge 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.

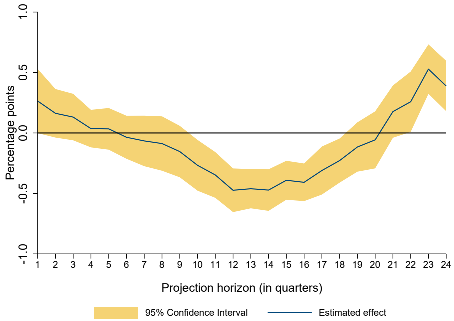
Figure 1.B.3 presents the estimated marginal impact of a one unit increase in d-SRI on the 10th and 50th percentiles of the conditional distribution of bank profitability at various projection horizons considering two different estimators. The results are overall very similar in terms of economic effects. When focusing on the 10th percentile (Panels (a) and (b) of Figure 1.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 chapter. Results for the 50th percentile (Panels (c) and (d) of Figure 1.B.3) provide the same conclusions: the negative and statistically significant estimated effect of d-SRI is similar in magnitude across estimation methods.



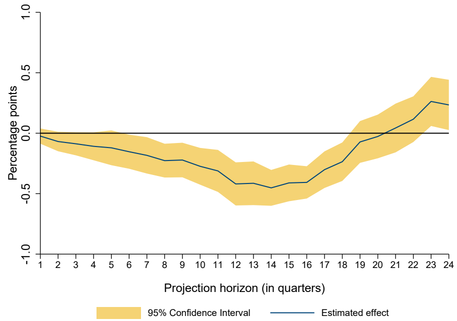
(a) 10th percentile - Machado and Santos Silva (2019)



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



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



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

Figure 1.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.

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2 The macroprudential game

2.1 Introduction

Following the 2008 global financial crisis it became evident that aggressive risk-taking by different financial institutions, during good financing conditions, could result in booms in the credit and asset markets. The increase of vulnerabilities in the financial system ahead of the crisis had large and persistent effects of the real economy when risk materialized. In order to tackle risk build-up in the financial system that can propagate to the real economy by seriously impairing the access to credit, commonly referred to as systemic risk, macroprudential policy was introduced as the primary policy. Macroprudential policy aims at promoting the necessary resilience in the financial system relatively to the level of systemic risk.

In this context, cyclical systemic risk and the CCyB have taken a prominent role. As mentioned in the previous chapter, cyclical systemic risk focus on how systemic risk tends to behave pro-cyclically over time, building-up in the upward phase of the financial cycle and decreasing in the downward phase, while the structural view of systemic risk focus on the distribution of risks in the financial sector (European Systemic Risk Board 2013). The CCyB is an instrument designed to make banks retain an additional capital buffer during times where they could engage in a pro-cyclical build-up of risk. This buffer is meant to be used in periods of financial stress to absorb unexpected losses. Its properties of dampening the financial cycle are a second order effect, through the impact that higher requirements might have on institutions risk-taking and activity.

This chapter uses an evolutionary game model based on the replicator dynamics to assess the relationship of macroprudential policy (focusing on the CCyB) and cyclical systemic risk in the banking system. An evolutionary game model is a framework that allows for a set of strategies played in a population to be conditioned by the strategic interaction among players over time. The strategic interaction will result in the tendency for the highest fitted strategies to displace the lowest according to an adaptation process considered for the population. In Smith and Price (1973) the concept of evolutionary stable strategy is defined as a strategy that cannot be invaded by any mutant strategy once most members of the population adopt it. This means that, in addition to being the highest fitted strategy, the evolutionary stable strategy has to be robust to the invasion of a small number of individuals using an alternative strategy. Picking up on this work, Friedman (1991) proposed a framework to use evolutionary games for economic applications, by considering each game as repeated anonymous interactions. The work also classifies the asymptotic behaviour for evolutionary game models, essential to determine dynamically stable equilibrium points.

In the context of regulating the financial system at least two other papers have explored the subject using evolutionary game models. An et al. (2021) simulated the dynamic game process between financial regulation and financial innovation to analyse the stable equilibrium strategies of both regulation institutions and financial institutions. Using data from the U.S. they found that financial regulation and financial innovation promote the development of each other. In Xu and Bao (2023) several evolutionary game models are developed to assess the dynamic relationship between financial technology regulators and financial institutions.

The novelty of this chapter is twofold: it does not pose as players the dichotomy financial institution-regulator and it proposes a framework to study the financial system as a multicellular system with several cells of two types: risk and resilience. A pairwise combination of a risk cell and a resilience cell define either a financial institution, a borrower or even each decision made in the financial system (e.g. a new credit contract). Each cell (risk or resilience) will be either in a "low" or "high" state. This representation of the financial system in terms of risk-resilience is relevant for assessing the stance of macroprudential policy (European Systemic Risk Board 2019). In this case, it is assumed that it is not the financial system that is assessed in terms of aggregate risk and resilience but each individual interaction. When aggregated, the joint risk and resilience of each interaction in the financial system will represent the aggregate risk and resilience of the system. This framework is further narrowed down to (cyclical systemic) risk and (macroprudential) policy cells, which influences the resilience of the banking system. This is made in order to focus on the dynamic relationship between cyclical systemic risk and macroprudential policy induced resilience.

Using the replicator dynamics described e.g. in Hofbauer and Sigmund (1998), the evolution of the frequency of each strategy "high" or "low", for each cell type, risk and policy, will mimic the effect of natural selection. In this type of dynamics, the rate of change of the frequency of a strategy depends on its evolutionary success in the population which is defined in terms of the difference between expected fitness of said strategy and average fitness of the population. The concept of evolutionary stable strategy, where an equilibrium is stable if it is robust to small perturbations, is also explored.

To operationalize the framework, data from Portugal from 2001-2021 is used. Results show that there are two evolutionary stable strategies for cyclical systemic risk and targeted macroprudential policy: either risk build-up leads macroprudential policy to tighten or the materialization of cyclical systemic risk allows for the release of targeted-macroprudential policy. However, both the dynamics and the stable equilibrium depend on the level of financial stress. When financing conditions are good risk will tend to increase but, at some risk threshold, the benefits of tightening macroprudential policy will outweigh its costs in this low financial stress environment. When financial stress is heightened, cyclical systemic risk will materialize and the costs of having macroprudential policy will be higher than its benefits, indicating a need to loosen the policy.

The remainder of this chapter is structured as follows: Section 2 sets the game by introducing the players and the evolutionary game model. Section 3 defines and operationalizes the payoffs while section 4 explores the dynamics and stability of the game. Section 5 concludes.

2.2 Setting the game

Macroprudential policy arised from the need to conciliate individual-based actions with collective results. Its objective of promoting financial stability is not sustained by means of supervising each financial institution or relationship within the system, but the whole system. This implies that, while each financial institution or borrower only takes into consideration their own utility, the macroprudential authority has to assess the joint risk that emerges from individual interactions, usually referred to as systemic risk. This type of risk can be assessed in two dimensions: cyclical and structural. While the foremost focus on how systemic risk tends to behave pro-cyclically through time, e.g. each institution has an incentive to increase lending in good times and borrowers increase demand for credit during the same times, the latter focus on the distribution of risk in the financial system at each point in time that can exist due to the interconnectedness of institutions (European Systemic Risk Board 2013). The macroprudential authority then comes to tackle these market failures and acts as a stabilizer agent that, at the same time, does not want to disturb the supply of financial services. To do this, the macroprudential authority has a set of instruments to increase resilience in the whole system.

In European Systemic Risk Board (2019) the conceptualization of macroprudential policy stance leverages on a risk-resilience framework. This framework portrays the financial system defined in terms of aggregate risk and resilience. Macroprudential policy then arises as the instrument that conciliates the result of individual decisions taken without internalizing potential externalities, which lead to some aggregate level of risk and resilience, with the desired outcome for the financial system as a whole. In this aggregate context, the financial system can be thought of as a live multicellular organism where cells of systemic risk and resilience exist and have one of two strategies: high or low (Figure 2.2.1).

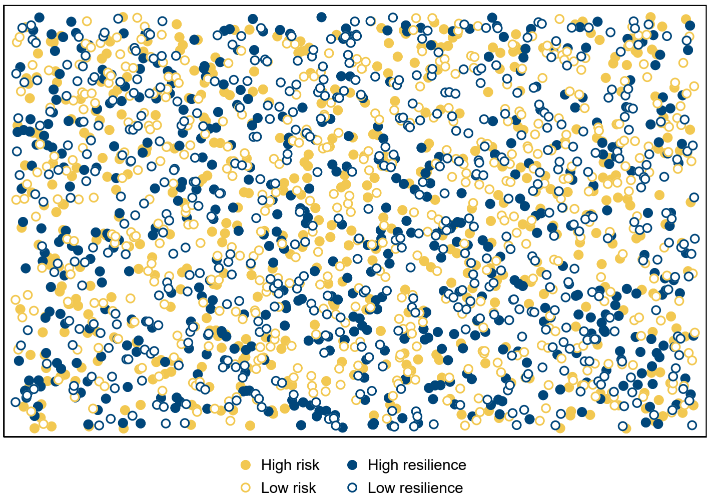
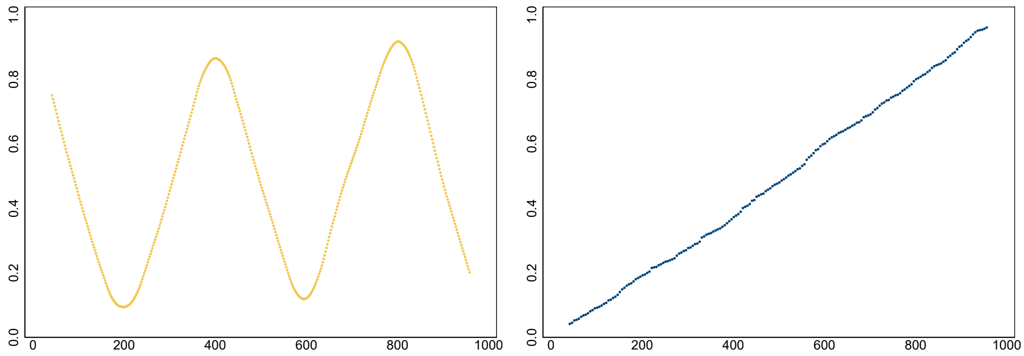


Figure 2.2.1: The financial system

Notes: Stylized concept of the financial system as a live multicellular organism where cells of systemic risk and resilience exist and have one of two strategies: high or low.

Each cell type, risk or resilience, is a player in a paired game where they can become one of two different states: either high or low. The strategy employed by each cell changes according to a rule that emerges from multiple paired interactions. Each paired interaction (one risk cell - one resilience cell) can be thought as representing either a financial institution, a borrower or a financial interaction (e.g. a new credit contract). This means e.g. that a credit institution that engages in low risk activities and has high resilience is the result of a game where their risk cell chose the "low" strategy and their resilience cell chose the "high" strategy.

At each time period, the joint risk from all paired games, defined as the proportion of risk cells that choose "high" as their strategy, leads to a measure of risk in the system (stylized example portrayed in Panel (a) of Figure 2.2.2). The interpretation is that when the proportion of high risk cells increases, e.g. when more institutions or borrowers engage in risky activities, risk in the financial system as a whole also increases. When this proportion decreases, and so the proportion of low risk cells increase, risk in the financial system decreases. A similar definition of resilience in the financial system, which is conditioned by macroprudential policy, can be thought of (a stylized example in Panel (b) of Figure 2.2.2).



(a) Risk (b) Resilience

Figure 2.2.2: Example of a path for the proportion of high risk (panel (a)) and resilience (panel (b)) cells over 1000 periods

Notes: Stylized example of a risk metric portrayed as a financial cycle with similar upward and downward phases (as one of financial cycles obtained in Schüler, Hiebert, and Peltonen 2020) and of a strictly increasing resilience metric.

Then players (cells) will have, in each game played, the following payoffs:

		Player *Resilience*	
		High	*Low*
Player *Risk*	*High*	(a_1, b_1)	(a_2, b_2)
	Low	(a_3, b_3)	(a_4, b_4)

Payoffs will represent net benefits, i.e. benefits after taking into account possible costs, which can be positive or negative, to each cell in a game that depends on the chosen risk and resilience strategies. When both risk and resilience cells chose the "high" strategy a_1 will be the payoff for the risk cell and b_1 will be the payoff of the resilience cell. In the context of the financial system these payoffs can be viewed as the ones of a financial institution that engages in risky activities but also has high resilience. The other payoffs read in a similar manner.

2.3 The game evolving

By using an evolutionary game model it is possible to identify dynamic paths regarding strategy selection for the two types of cells.[1] Most importantly, the response that resilience should make in respect to the strategy employed by risk is relevant for macroprudential policy. Instead of employing the traditional game theory method, whereas it is assumed perfect rationality by both players, the evolutionary model assumes a dynamic adjustment of the strategies played by each player. In this model, it is assumed that it is difficult to obtain the equilibrium result by playing only one game - players have to learn and adjust their strategies according to several games played by risk and resilience cells paired at random (e.g. several interactions or decisions done in the financial system), from a population of cells - the financial system as an organism. This framework is applicable in this context as systemic risk and resilience change through a dynamic process: high risk in the financial system can prompt a higher resilience in order to absorb potential losses that may happen when risk materializes, but the higher resilience has a cost and so risk can decrease which then leads resilience to adjust to the lower risk level. This new adjustment might lead again to a risk increase since the costs of resilience are now lower. This means that the system may self-regulate depending on the composition of the financial system, i.e. the proportion of high/low risk and resilience cells.

In order to explore dynamics of strategies similar to those of traits in a species, work in the context of evolutionary game models has employed the replicator equation and the bimatrix replicator. The replicator equation was introduced in Taylor and Jonker (1978) where strategy selection, both in the present and regarding its likeliness to be chosen in the future, depends on how fit the strategy is, at any moment. The rationale behind this hypothesis is that individuals will tend to switch to strategies that are doing better, its offspring will tend to replicate those same fitter strategies and these better-off individuals will tend to have more offspring - similar to natural selection.

Considering a population with only one pure strategy, S, Taylor and Jonker (1978) shows how the change in the proportion of individuals that choose strategy S will depend on the difference between its growth rate and the average growth rate of the population. In the game framework the growth rates will be replaced by the fitness of each strategy represented as their payoffs. Therefore, the dynamic replicator equation of strategy S becomes:

[1] Applications of evolutionary game theory in cell biology have been explored in Hummert et al. (2014) where cells traits are viewed as strategies that are subject to selection.

$$\dot{s} = s(U_s - \bar{U}) \tag{2.1}$$

where $\dot{s} = \frac{ds}{dt}$, s is the proportion of the population that chooses strategy S, U_s is the payoff of strategy S and $\bar{U}$ is the average payoff of the population.

When the goal is to model the interaction of two different populations where each group has a set of strategies, the bimatrix replicator (introduced in Schuster, Sigmund, et al. 1981 and Schuster and Sigmund 1981 with the dynamics explored in Hofbauer 1996) is used in a similar way to the replicator equation.

The game as presented in Section 2.2 can be represented in bimatrix form:

$$A = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \quad B = \begin{bmatrix} b_1 & b_3 \\ b_2 & b_4 \end{bmatrix}$$

where matrix A has the payoffs a risk cell can obtain in a game and matrix B has the payoffs that a resilience cell can obtain in a game (corresponds to the transpose of the table in Section 2.2 for resilience cells).

In this case, using the bimatrix replicator means that the dynamics will be defined by the system of equations:

$$\begin{cases} \dot{p} = p(U_{HRi} - \bar{U}_{Ri}) \\ \dot{q} = q(U_{HRe} - \bar{U}_{Re}) \end{cases} \tag{2.2}$$

where p is the proportion of cells that choose a high risk action, that can be seen as the level of risk in the financial system, and so $1 - p$ will represent the remaining component that is left before achieving the peak, q is the proportion of resilience cells that choose "high", relative to total amount of cells, and so $1 - q$ will be the proportion that chooses "low", U_{HRi} is the expected payoff of strategy "high" for risk cells, $\bar{U}_{HRi}$ is the average expected payoff of all risk cells, U_{HRe} is the expected payoff of strategy "high" for resilience cells and $\bar{U}_{Re}$ is the average expected payoff of all resilience cells.

The risk cells will have an expected payoff when choosing "high" equal to:

$$U_{HRi} = qa_1 + (1 - q)a_2 \tag{2.3}$$

and when choosing "low"

$$U_{LRi} = qa_3 + (1-q)a_4 \tag{2.4}$$

With an average expected payoff of risk equal to

$$\bar{U}_{Ri} = pU_{HRi} + (1-p)U_{LRe} \tag{2.5}$$

Then the replicator equation of risk in the system of equations (2.2) is:

$$\dot{p} = p(U_{HRi} - \bar{U}_{Ri}) = p(1-p)[q(a_1 - a_3) + (1-q)(a_2 - a_4)] \tag{2.6}$$

The expected payoff of high resilience is:

$$U_{HRe} = pb_1 + (1-p)b_3 \tag{2.7}$$

and of low resilience is

$$U_{LRe} = pb_3 + (1-p)b_4 \tag{2.8}$$

With an average expected payoff of resilience equal to

$$\bar{U}_{Re} = qU_{HRe} + (1-q)U_{LRe} \tag{2.9}$$

Then the replicator equation of resilience in the system of equations (2.2) is:

$$\dot{q} = q(U_{HRe} - \bar{U}_{Re}) = q(1-q)[p(b_1 - b_2) + (1-p)(b_3 - b_4)] \tag{2.10}$$

2.4 Defining the payoffs

2.4.1 Conceptualization

In order to obtain the payoffs it is first necessary to define what they mean in this context. As previously defined, systemic risk can have both cyclical and structural dimensions. In this chapter, the focus will be on cyclical systemic risk and on the role of macroprudential policy in defining its targeted resilience. Therefore, the payoffs of the risk cells will be limited to cyclical risk and of the resilience cells will be narrowed to the ones shaped by macroprudential policy. The payoff matrix of interest is then restricted to the influence of (macroprudential) policy on the (cyclical) risk cells, with the other macroprudential instruments being left out.

The payoff matrices A and B are now re-defined as the ones for (cyclical systemic) risk cells (A) and for (macroprudential) policy cells (B):

$$A = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \quad B = \begin{bmatrix} b_1 & b_3 \\ b_2 & b_4 \end{bmatrix}$$

Column 1 of matrix A represents payoffs for risk cells when policy is high, while its second column displays their payoffs when policy is low. For the same matrix, the first row are the payoffs when risk is high and the second row when risk is low. Matrix B has the payoffs for policy cells when risk is high (first column) and low (second column) and when policy is high (first row) and low (second column).

The focus is also narrowed down to the banking system. In this context, the risk cells will relate to the risk appetite of banks. Net benefits to banks when engaging in risky activities can be assessed on a measure of bank profitability, e.g. expected return-on-assets (ROA). Banks, through their risk cells, will then choose a strategy based on its net benefits that will depend on the strategy employed by the policy cell (policy requirements in place) but also on the financial stress at the moment. It is also considered that payoffs will be the ones expected in four quarters. This is meant to reflect the short sighted perspective that financial institutions have when deciding their risk strategy - focusing on their "short-term" expected return of risky decisions (Dallas 2011). Risk payoffs will change with each period of time t and can be defined as:

$$a_{i,t}(ROA_{central,t+4}) = Q_{ROA,central,t+4}(R_t, P_t, FS_t) \quad i = 1, 2, 3, 4 \qquad (2.11)$$

where $a_{i,t}$ refers to payoff a_i, $i = 1, 2, 3, 4$, of previously defined A matrix, now varying across time as it will depend on the value of each point in time of its determinants, $ROA_{central,t+4}$ is a central projection of ROA 4 quarters ahead, reflecting the more short-term sight of banks behaviour, $Q_{ROA,central,t+4}(.)$ is some function that will be defined later, R_t is the risk decision, either high or low, P_t is the policy decision, either high or low, and FS_t is a financial stress indicator.

The policy cells will reflect the internalization, through decisions made by the macroprudential authority, of the effect of individual risky decisions that have a systemic impact. Policy in this context will mostly reflect the benefits of having more capital to counterbalance the negative effect of engaging in risky activities. This effect will be assessed on a tail metric of banks' ROA projected to happen in 8 quarters. This is to reflect (i) the objective of macroprudential policy of minimizing both the frequency and severity of losses from episodes of systemic risk materialization, (ii) policy lags or phasing-in periods and (iii) the medium-term horizon view of policymakers.[2] The focus on a tail metric for macroprudential policy purposes has been explored in recent years (European Systemic Risk Board 2021 and Javier Suarez 2022) using the tail of GDP growth distribution as the target variable (Growth-at-risk) of macroprudential policy as a whole.

Policy payoffs will change with each period of time t and can be defined as:

$$b_{i,t}(ROA_{tail,t+8}) = Q_{ROA,tail,t+8}(R_t, P_t, FS_t) \quad i = 1, 2, 3, 4 \tag{2.12}$$

where where $b_{i,t}$ refers to payoff b_i, $i = 1, 2, 3, 4$, of previously defined B matrix, now varying across time as it will depend on the value of each point in time of its determinants, $ROA_{tail,t+8}$ is a tail projection of ROA 8 quarters ahead, $Q_{ROA,tail,t+8}(R_t, P_t, FS_t)$ is some function that will be defined later.

2.4.2 Operationalization

Payoffs of risk (Equation (2.11)) and policy (Equation (2.12)) cells are obtained by estimating two quantile regressions using the method introduced by R. Koenker and Bassett (1978). Projections will be obtained using the local projections method of Jordà (2005). Quantile regressions are useful to identify different effects on the distribution of a variable. Recently, this technique has been used to identify the costs and benefits of macroprudential policy by assessing the effects of financial and policy variables on a central metric and on the tail of the distribution of relevant variables such as GDP (Adrian, Boyarchenko, and Giannone 2019; Aikman et al. 2019; Galán 2020; Cecchetti and J. Suarez 2021; European Systemic Risk Board 2021; Javier Suarez 2022) and ROA (Lang and Forletta 2020 and Passinhas and A. Pereira 2023). For Portugal, there has been at least three works related to at-risk measures that employed quantile regressions for different target variables: GDP (Buratta, Feliciano, Maia, et al. 2022a), credit (Buratta, Feliciano, Maia, et al. 2022b), and ROA (Passinhas and A. Pereira 2023). In this chapter, rather than trying to predict a quantile or identify the effect of some regressor on the distribution of the dependent variable, the goal is to estimate different effects, of risk and policy, on the payoff functions that are obtained

[2]The choice for 8 quarters instead of other medium-term horizon e.g. 12 quarters is also justified by the sharp decrease of fit that the estimation presents starting from 8 quarter projections see Figure 2.B.1. This may be due to the fact that quantile regressions need a large sample in order to identify estimates in a reliable manner.

at different percentiles of the ROA distribution, similar to what was done in the previous chapter.

In order to obtain the impact of risk strategies on the payoffs a measure of the financial cycle is used as a proxy for risk. The impact of policy strategies is focused on capital-based instruments. To estimate its impact on the payoffs a capital ratio metric is used to identify the effect of capital-based macroprudential policy. This means that results are under the hypothesis that the impact of one percentage point capital ratio is the same whether it was required by the macroprudential authority or built for other reasons. Quantile models estimated are as follows:

Risk payoff function:

$$\hat{Q}_{ROA,0.5,t+4} = \hat{\alpha}_r + \hat{\beta}_{1,r} FC_t + \hat{\beta}_{2,r} T1_t + \hat{\beta}_{3,r} FS_t FC_t \tag{2.13}$$

where $\hat{Q}_{ROA,0.5,t+4}$ is the estimate of median ROA four quarters ahead, FC_t is a financial cycle indicator, $T1_t$ is the Tier 1 capital ratio, FS_t is a financial stress indicator, $\hat{\beta}_{1,r}$ is the benefit risk cells obtain in behaving in a pro-cyclical manner, $\hat{\beta}_{2,r}$ represents the cost that each percentage point of Tier 1 capital (in terms of average weighted assets) has, $\hat{\beta}_{3,r}$ is a cost of incurring in risky activities during financial stress events, which is expected to add-on to the usual cost of capital as stress events usually coincide with worse financing conditions, and $\hat{\alpha}_{1,r}$ is a constant that captures other determinants of median ROA.

Policy payoff function:

$$\hat{Q}_{ROA,0.1,t+8} = \hat{\alpha}_p + \hat{\beta}_{1,p} FC_t + \hat{\beta}_{2,p} T1_t + \hat{\beta}_{3,p} FS_t T1_t + \hat{\beta}_{4,p} FC_t T1_t \tag{2.14}$$

where $\hat{Q}_{ROA,0.1,t+8}$ is the estimate of the 10^{th} percentile of ROA eight quarters ahead, $\hat{\beta}_{1,p}$ represents the cost of risk on the tail of profitability, $\hat{\beta}_{2,p}$ the cost of capital, $\hat{\beta}_{3,p}$ the added cost of capital in tight financing conditions, $\hat{\beta}_{4,p}$ is the potential benefit of capital in decreasing the negative effects of risk and $\hat{\alpha}_{1,p}$ is a constant that captures other determinants of the 10^{th} percentile of ROA.

Data and results

Data employed is for Portugal, between 2001 and 2021, and is obtained from several sources. The ROA and Tier 1 capital ratio are from the *Historical Series of the Portuguese Banking Sector Database (SLB database)* published by the Banco de Portugal, the financial cycle indicator is from Schüler, Hiebert, and Peltonen

(2020) and the financial stress indicator is the *Indicador Compósito de Stress Financeiro* (ICSF) from Banco de Portugal constructed as in Braga, I. Pereira, and Reis (2014). The advantage of using this dataset is that it is long enough to cover both periods of high and low risk (Panel (a) of Figure 2.A.1) and periods of high and low resilience (Panel (c) of Figure 2.A.1) which will be used to estimate the effect of policy in the two states.

The financial cycle as described in Schüler, Hiebert, and Peltonen (2020) is measured as the co-movement of credit to the private non-financial sector and asset prices across all main asset markets (house prices, equity prices, and corporate bond prices). They do so under the assumption that changes in asset prices will have an effect on the economic agents net worth, which will then influence lending developments. By focusing on the co-movement of credit and asset prices, their common expansions and contractions provide a way to measure how strong the balance sheet of an agent is which leads to an assessment on how excessive credit growth is at each point in time. For Portugal, from 2001 to 2021, the financial cycle increased sharply from the beginning of the financial crisis (2008) to the beginning of the European Sovereign Debt Crisis (end of 2009), indicating the increase in risk of the time due to excessive credit lending (Panel (a) of Figure 2.A.1). The period after and until 2012 reflects the materialization of risk that followed, which consisted in a decrease of both credit and asset prices. Since 2014, the financial cycle shows a higher level of risk, in comparison to this period of materialization, that represents the post-crisis period where both credit and asset prices began to recover.

ROA and Tier 1 capital ratio are from the balance sheets of the financial institutions in Portugal. They exhibit two striking situations: the first is related to the period between 2011-2015 where banking losses from the financial crisis increased and mirrored a turbulent period in Portuguese banking system (Panel (b) of Figure 2.A.1), and the second is the supervision authorities response since 2013 in building more capital-based resilience that led to a sharp increase of capital ratios (Panel (c) of Figure 2.A.1).

The financial stress indicator for Portugal described in Braga, I. Pereira, and Reis (2014) is an aggregation of several indicators related to the money market, bond market, equity market, financial intermediaries and foreign exchange market. The composite indicator identifies and measures the most relevant stress events of the Portuguese financial markets since 1999. Using this indicator, the authors identify a threshold equal to 0.20 that defines the point that signals a high stress regime. For Portugal, in the period between 2001 and 2021, stress levels were above that threshold in the 2008 financial crisis and the European Sovereign Debt Crisis and then again in 2020 in the wake of the Covid-19 crisis.

Results for equations (2.13) and (2.14) are presented in Table 2.4.1.[3] Results are aligned with their expected signs on the target variables: risk payoffs are positively influenced by current risk environment and negatively influenced by Tier 1 capital ratio (cost of having capital) and by periods of financial stress; policy payoffs are positively influenced by the effect of more capital when risk is higher ($FC \times T1$) and negatively influenced by risk, capital (cost of capital) and increasing capital in times of financial stress ($FS \times T1$).

	Risk		**Policy**	
Variable	Coefficient	Value	Coefficient	Value
FC	$\hat{\beta}_{1,r}$	1.38* (0.80)	$\hat{\beta}_{1,p}$	-6.11*** (2.33)
$T1R$	$\hat{\beta}_{2,r}$	-0.12* (0.06)	$\hat{\beta}_{2,p}$	-0.56*** (0.18)
$FS \times FC$	$\hat{\beta}_{3,r}$	-4.43*** (1.15)	-	-
$FS \times T1R$	-	-	$\hat{\beta}_{3,p}$	-0.22*** (0.07)
$FC \times T1R$	-	-	$\hat{\beta}_{4,p}$	0.75*** (0.27)
Constant	$\hat{\alpha}_r$	1.46*** (0.38)	$\hat{\alpha}_p$	4.94*** (1.37)
Pseudo-R^2		0.22		0.63
T		80		76

Table 2.4.1: Risk and policy payoff functions

Notes: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (in parenthesis) are obtained by block bootstrap considering overlapping blocks of length equal to four observations. The Pseudo-R^2 is the one proposed by Roger Koenker and Machado (1999) to assess the goodness of fit of quantile regressions. It compares the sum of weighted deviations for the model with the ones from a model in which only the intercept appears. Higher values indicate a better fit.

The payoffs operationalized

Besides these estimates, it is also necessary to define what high and low means in this context, both for risk and policy. High risk is defined as the peak of the financial cycle, so when the financial cycle indicator is at 1 ($FC = 1$), while low is the situation where the cycle is at its trough, when the financial cycle indicator is at 0 ($FC = 0$). Although these two values are not in the sample, the coverage is

[3]For simplicity the time subscript "$_t$" is omitted hereinafter.

comprehensive enough to use these two points as the estimates (Figure 2.A.1 and Table 2.A.1). The macroprudential policy "low" state will be defined as the state where the countercyclical capital ratio is at zero, while the "high" strategy will correspond to the soft-limit of the countercyclical capital buffer (2.5%) which has been implemented in some countries (e.g. Czech Republic, Denmark and Norway). Then the payoffs for risk cells are:

- $a_1 = 1.46 + 1.38 - 0.12 \times 2.5 - 4.43 \times FS = 2.54 - 4.43 \times FS$
- $a_2 = 1.46 + 1.38 - 4.43 \times FS = 2.84 - 4.43 \times FS$
- $a_3 = 1.46 - 0.12 \times 2.5 = 1.16$
- $a_4 = 1.46$

and the payoffs for policy cells are:

- $b_1 = 4.94 - 6.11 - 0.56 \times 2.5 - 0.22 \times FS \times 2.5 + 0.75 \times 2.5 = -0.695 - 0.55 \times FS$
- $b_2 = 4.94 - 6.11 = -1.17$
- $b_3 = 4.94 - 0.56 \times 2.5 - 0.22 \times FS \times 2.5 = 3.54 - 0.55 \times FS$
- $b_4 = 4.94$

For example, in the fourth quarter of 2021 (2021Q4), the most recent data point (where $FS = 0.146$ [4]), the payoff bimatrix would look like:

$$A = \begin{bmatrix} 1.89 & 2.19 \\ 1.16 & 1.46 \end{bmatrix} \quad B = \begin{bmatrix} -0.78 & 3.46 \\ -1.17 & 4.94 \end{bmatrix}$$

Matrix A translates the higher payoff of risk cells when they choose "high" against a policy cell in a "low" state relatively to a policy cell in a "high" state (2.19>1.89) when the financial stress is low. On the policy side, matrix B shows a preference for a low risk environment (column 2>column 1) and the cost of having a low policy (versus a high policy) in a high risk environment (-1.17<-0.78).

2.5 Game dynamics

2.5.1 Replicator equations and evolutionary stability analysis

Using results from Section 2.4.2 on Equations (2.6) and (2.10) it is possible to obtain the replicator equations for risk and policy cells:

[4] For other possible values of FS see Appendix A.

Risk replicator equation:

$$\dot{p} = p(1-p)(1.38 - 4.43FS) \tag{2.15}$$

Policy replicator equation:

$$\dot{q} = q(1-q)(-1.4 + 1.875p - 0.55FS) \tag{2.16}$$

As in An et al. (2021) and Xu and Bao (2023) it is important to study the possible equilibria of the evolutionary game and their stability. The equilibrium of the evolutionary game is obtained as the strategy profile in the equilibrium point (p, q) of the bimatrix replicator. The evolutionary game has multiple equilibrium points.

Proposition 1. *The evolutionary game defined by equations* (2.15) *and* (2.16) *admits the following characterisation of its equilibria, considering that FS is only defined between* 0 *and* 1*:*

1. *The points $e_1(0,0)$, $e_2(1,0)$, $e_3(0,1)$, and $e_4(1,1)$, which correspond to pure strategy equilibria;*

2. *If $FS = \frac{138}{443} \approx 0.31$, then there is a continuum of equilibria of the form:*
   - $(p, 0)$, *for any* $0 < p < 1$*;*
   - $(p, 1)$, *for any* $0 < p < 1$*;*
   - $\left(\frac{27844}{33225}, q\right)$, *for any* $0 \leq q \leq 1$*;*

3. *If $FS = \frac{19}{22} \approx 0.86$, then there is a continuum of equilibria of the form $(1, q)$, for any $0 < q < 1$.*

Proof. Equilibrium points arise when $\dot{p} = 0$ and $\dot{q} = 0$. Replacing each of the equilibria in Equations (2.15) and (2.16) the condition is verified for all. QED

By equation (2.15), we have that $\dot{p} = 0$ if $FS = \frac{1.38}{4.43} \approx 0.31$. From this point onwards, we focus on the four equilibrium points that do not require FS_t to be a specific value, as that is not as relevant for policy making and risk assessment, where financial stress levels can change at any time.

Proposition 2. *Dynamics of policy strategies will depend on the proportion of "high" risk cells and the level of financial stress, while the dynamics of risk strategies will only depend on the financial stress.*

Proof. Using results of Equation (2.15), the proportion of risk cells that employ "high" as their strategy increases ($\dot{p} > 0$) when $0 < p < 1$ and $1.38 - 4.43FS > 0$, that is, when financial stress is below a certain threshold $FS < FS^{\star}$. When financial stress is above that threshold, then risk cells will start to choose the "low" strategy until all risk cells employ that strategy. At the point $FS = FS^{\star}$ the strategy profile of risk cells will not change regardless of the value for q. When $0 < q < 1$, the proportion of policy cells that play the "high" strategy will increase ($\dot{q} > 0$), based on results presented in Equation (2.16), if $-1.4 + 1.875p - 0.55FS > 0$, that is, when the proportion of "high" risk cells is higher than $\frac{1.4+0.55FS}{1.875}$. In this case, the population of "high" policy cells will increase until all of policy cells are employing the "high" strategy. In the case that $p < \frac{1.4+0.55FS}{1.875}$, the population of "high" policy cells decreases and $\dot{q} = 0$ is obtained when $q = 0$, i.e. all policy cells employ the "low" strategy. When $p = \frac{1.4+0.55FS}{1.875}$ then there will be no change in the proportion of policy cells that use either strategy. QED.

Corollary 1. *An equilibrium point will be evolutionary stable if it is robust to small perturbations. This means that small deviations in each proportion, either p or q, when they are at their equilibrium points, should be temporary and revert to the equilibrium strategy profile. Only equilibrium points (0,0) and (1,1) are evolutionary stable equilibria, but their stability depends on the level of financial stress.*

Proof. As shown in Friedman (1991) and Friedman (1998), this notion of evolutionary stable equilibrium can be identified, for the four equilibrium points in pure strategies, through the stability analysis of the Jacobian matrix of the system. The Jacobian matrix of the bimatrix replicator is:

$$J_{(p,q)} = \begin{bmatrix} (1-2p)(1.38-4.43FS) & 0 \\ q(1-q)1.875 & (1-2q)(-1.4+1.875p-0.55FS) \end{bmatrix}$$

The equilibrium point will be an evolutionary stable strategy if:

1. The value of the determinant of the Jacobian matrix is positive with:

   $det\ J_{(p,q)} = (1-2q)(-1.4+1.875p-0.55FS)(1-2p)(1.38-4.43FS)$

2. The trace of the Jacobian matrix is negative with:

   $tr\ J_{(p,q)} = (1-2q)(-1.4+1.875p-0.55FS) + (1-2p)(1.38-4.43FS)$

Only equilibrium points (0,0) and (1,1) satisfy these conditions for certain levels of financial stress. QED

Table 2.5.1 shows in more detail whether the four points with pure strategies are evolutionary stable strategies, by considering the determinant and trace of the Jacobian matrix at every equilibrium point as obtained in Appendix C. For simplicity values are rounded to hundredths. If the conditions regarding the determinant and the trace of the Jacobian matrix are satisfied than the local equilibrium is the evolutionary stable strategy. If the determinant is negative then the local point will be a saddle point; if both the determinant and the trace are positive then the equilibrium point is unstable.

Equilibrium (p,q)	(0,0)	(0,1)	(1,0)	(1,1)
Positive $det\ J$	FS>0.31	0.31<FS<0.86	FS<0.31	FS<0.31 or FS>0.86
Negative $tr\ J$	any FS values	FS<0.23	FS>0.72	FS<0.37
Stability	Stable if FS>0.31	Not stable	Not stable	Stable if FS<0.31

Table 2.5.1: Stability analysis of the equilibrium points in the macroprudential game

Results show that, under some conditions, there are two evolutionary equilibria: (0,0) and (1,1). This means that, depending on stress levels, any trajectory starting from any combination of (p,q) will converge either to points (0,0) or (1,1). Remaining equilibrium points are never stable and so, are not evolutionary stable equilibria.

The stable equilibrium (0,0), which is a low-risk, low-policy environment, is stable when financial stress is relatively high (above the stress threshold identified in Braga, I. Pereira, and Reis 2014 of 0.2) where the cost of engaging in risky activities is high. This leads to the stability of a low risk environment which does not need an activation of policy. If financial stress decreases below the identified threshold, then risk will tend to increase which makes the equilibrium point a saddle point.

The stable equilibrium (1,1) occurs when financial stress is low, and so risk is stable at its maximum value. At these values of financial stress, the benefits of policy are higher than the costs and so, there is no need to loosen up macroprudential policy.

2.5.2 Dynamics across stress scenarios

To reach the stable equilibria, it is important to study the dynamics that lead to them. In order to explore these two extreme situations are considered: scenario 1 when stress in the financial system is very low ($FS = 0$) and scenario 2 when stress is at its highest ($FS = 1$). These give the range of payoffs for both risk and policy that can be obtained using results from Section 2.4.2.

The payoff bimatrix for scenario 1 will be:

$$\text{Scenario 1} \quad A = \begin{bmatrix} 2.54 & 2.84 \\ 1.16 & 1.46 \end{bmatrix} \quad B = \begin{bmatrix} -0.70 & 3.54 \\ -1.17 & 4.94 \end{bmatrix}$$

Matrix A shows how engaging in risk might be appealing to banks in times of good financing conditions/ low financial stress, as "high" is a dominant strategy. In matrix B, the policy cells, meant to represent the internalization of the effect of risk indicate that in these conditions the "high" strategy is preferred to the "low" strategy when risk is "high". The reverse happens when risk is "low" as there is no need to internalize effects of risky activities.

The payoff bimatrix of for scenario 2 will be:

$$\text{Scenario 2} \quad A = \begin{bmatrix} -1.89 & -1.59 \\ 1.16 & 1.46 \end{bmatrix} \quad B = \begin{bmatrix} -1.25 & 2.99 \\ -1.17 & 4.94 \end{bmatrix}$$

In scenario 2 where financial stress is high, payoffs paint a very different picture. In this case, "low" is the dominant strategy for risk cells, meaning it is the best strategy against any strategy performed by the paired policy cell. For policy cells, the dominant strategy is "low" even when risk cells choose a "high" strategy. This happens as the costs of increasing capital in stress periods is higher than its benefits.

The dynamics in these two scenarios are straightforward: given initial conditions for the proportion of "high" risk and policy cells, it is possible to obtain the equilibrium point by using Equations (2.15) and (2.16). Consider initial conditions of $p = 0.5$, a point of risk reflecting the middle of the financial cycle, and of $q = 0.4$, which is the same as a CCyB= 1%. Then, for each scenario 1 and 2 dynamics will be shaped by the equations:

Scenario 1 - Low financial stress

Risk replicator equation:

$$\dot{p} = p(1-p)1.38 \tag{2.17}$$

Policy replicator equation:

$$\dot{q} = q(1-q)(-1.4 + 1.875p) \tag{2.18}$$

which means that risk will increase until all risk cells employ the "high" strategy while policy cells decrease at first and start to increase when $p > \frac{1.4}{1.875}$ which is approximately 0.75. This would eventually lead to the evolutionary stable equilibrium in pure strategies with $p = 1$ and $q = 1$ (Panel (a) of Figure 2.5.1).

Scenario 2 - High financial stress

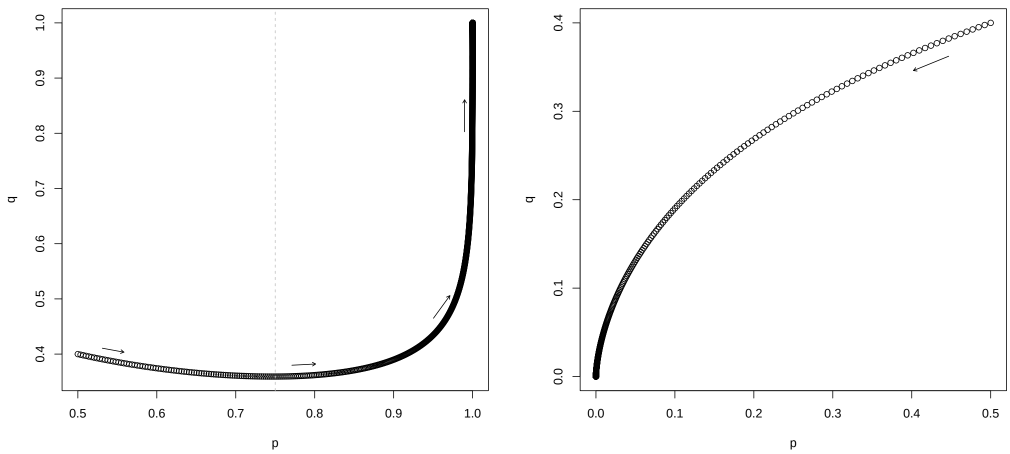
Risk replicator equation:

$$\dot{p} = p(1-p)(-3.05) \tag{2.19}$$

Policy replicator equation:

$$\dot{q} = q(1-q)(-1.95 + 1.875p) \tag{2.20}$$

which means that both risk and policy will decrease until all cells employ the "low" strategy. This would eventually lead to the evolutionary stable equilibrium in pure strategies with $p = 0$ and $q = 0$ (Panel (b) of Figure 2.5.1).



(a) Scenario 1 - Low financial stress

(b) Scenario 2 - High financial stress

Figure 2.5.1: The macroprudential game dynamics for different financial stress scenarios

Notes: Figure obtained using R and the initial conditions of $p = 0.5$ and $q = 0.4$.

2.6 Conclusions

Using evolutionary game theory, this chapter presents a novel framework to study the stable strategies of cyclical systemic risk and targeted macroprudential policy. The general framework initially considers that each decision or interaction performed in the financial system can be defined within the dichotomy risk and resilience.

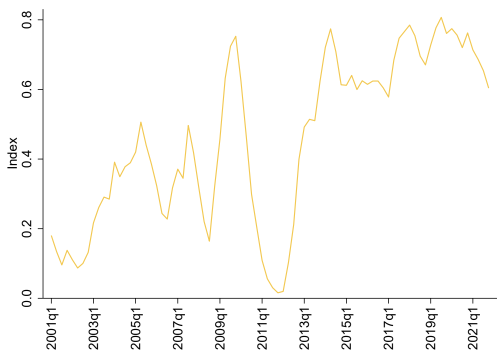
To operationalize the framework, data from the Portuguese banking system from 2001-2021 is used. By focusing on cyclical systemic risk and resilience-induced macroprudential policy, results show that there are two evolutionary stable strategies for cyclical systemic risk and targeted macroprudential policy: either risk build-up leads macroprudential policy to tighten or the materialization of cyclical systemic risk allows for the release of targeted-macroprudential policy. However, both the dynamics and the stable equilibrium depend on the financial stress in each period of time. When financing conditions are good risk will tend to increase but, at some risk threshold, the benefits of tightening macroprudential policy will outweigh its costs. When financial stress is heightened, cyclical systemic risk will materialize and the costs of having macroprudential policy will be higher than its benefits, indicating a need to loosen the policy. The framework then provides thresholds for both financial risk and financial stress that may help decision making for macroprudential policy purposes.

Results obtained in this chapter relate to the ones obtained in the previous one as it indicates that there are benefits in increasing resilience (via increasing the CCyB rate) when cyclical systemic risk builds up. However, this chapter adds to the previous chapter as it identifies both risk and financial stress thresholds that signal when to increase the CCyB. It also adds a novel framework to do the calibration, as it employs an evolutionary game theory model.

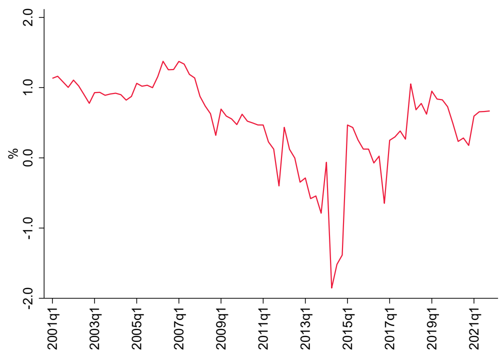
In future work, the operationalization of the framework could be extended to different macroprudential instruments other than the CCyB and to either structural systemic risk, rather then just cyclical, or even both dimensions of systemic risk. Within the scope of this chapter, payoffs could also be operationalized in different manners to further assess the robustness of the obtained results.

A Data

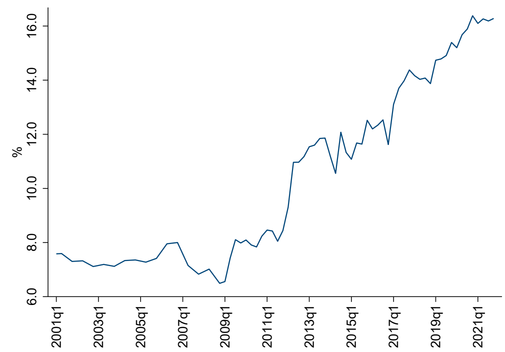
Cronograms



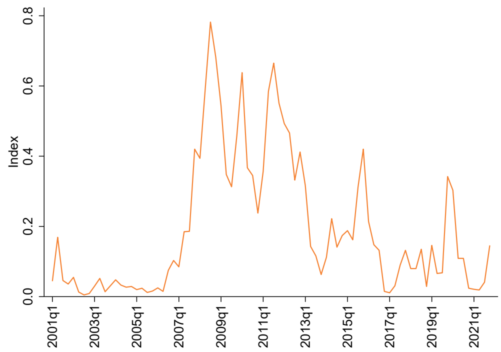
(a) Financial cycle



(b) ROA



(c) Tier 1 capital ratio



(d) FS

Figure 2.A.1: Cronograms of the relevant variables 2001-2021

Sources: Financial cycle from Schüler, Hiebert, and Peltonen (2020). ROA and Tier 1 capital ratio from *Historical Series of the Portuguese Banking Sector Database* published by the Banco de Portugal. FS represents the stress indicator *Indicador Compósito de Stress Financeiro* (ICSF) from Banco de Portugal.

Descriptive statistics of variables

	Mean	Sd	P5	P25	P50	P75	P90	P95	T
Financial cycle	0.46	0.24	0.09	0.25	0.48	0.68	0.76	0.77	84
ROA	0.50	0.63	-0.65	0.24	0.63	0.93	1.14	1.25	84
Tier 1 capital ratio	10.22	3.21	6.92	7.34	8.43	12.52	15.20	16.10	84
FS	0.19	0.20	0.01	0.03	0.12	0.32	0.49	0.59	84

Table 2.A.1: Data summary

Notes: Last observation 2021Q4. Data is in quarters, Tier 1 capital ratio linearly interpolated from bi-yearly frequency to quarterly from 2001 to 2008.

B Details on estimations

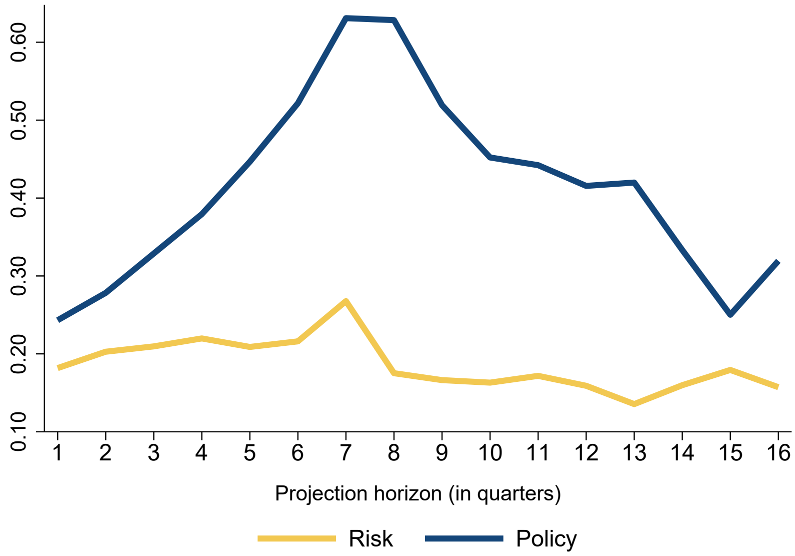


Figure 2.B.1: Pseudo-R^2 of the quantile regressions, used to identify risk and policy pay-off functions, across different projection horizons

The Pseudo-R^2 is the one proposed by Roger Koenker and Machado (1999) to assess the goodness of fit of quantile regressions. It compares the sum of weighted deviations for the model with the ones from a model in which only the intercept appears. Higher values indicate a better fit.

C Jacobian matrices

In order to study the evolutionary stable equilibria we perform a stability analysis of the Jacobian matrix of the system. The Jacobian matrix of the bimatrix replicator is:

$$J_{(p,q)} = \begin{bmatrix} (1-2p)(1.38-4.43FS) & 0 \\ q(1-q)1.875 & (1-2q)(-1.4+1.875p-0.55FS) \end{bmatrix}$$

The analysis of the Jacobian matrix at each equilibrium follows. For simplicity values are rounded to hundredths.

Equilibrium point (0,0)

$$J_{(0,0)} = \begin{bmatrix} (1.38-4.43FS) & 0 \\ 0 & (-1.4-0.55FS) \end{bmatrix}$$

det $J_{(0,0)} = (1.38-4.43FS)(-1.4-0.55FS)$

det $J_{(0,0)}$ is positive when $FS > 0.31$ or $FS < -2.55$ however $0 \leq FS \leq 1$, zero when $FS = 0.31$ and negative in the remaining case

if $FS = 0.31$ then *det* $J_{(0,0)} = 0$

tr $J_{(0,0)} = (1.38-4.43FS) + (-1.4-0.55FS) = 0.02 - 4.98FS < 0$

Equilibrium point (0,1)

$$J_{(0,1)} = \begin{bmatrix} (-1.38+4.43FS) & 0 \\ 0 & (-1.4+1.875-0.55FS) \end{bmatrix}$$

det $J_{(0,1)} = (-1.38+4.43FS)(-1.4+1.875-0.55FS)$

det $J_{(0,1)}$ is positive when $0.31 < FS < 0.86$, zero when $FS = 0.31$ or $FS = 0.86$ and negative in the remaining case

tr $J_{(0,1)} = (-1.38+4.43FS) + (-1.4+1.875-0.55FS)$

tr $J_{(0,1)}$ is negative when $FS < 0.23$, zero when $FS = 0.23$ and positive in the remaining case

Equilibrium point (1,0)

$$J_{(1,0)} = \begin{bmatrix} (1.38 - 4.43FS) & 0 \\ 0 & (1.4 + 0.55FS) \end{bmatrix}$$

det $J_{(1,0)} = (1.38 - 4.43FS)(1.4 + 0.55FS)$

det $J_{(1,0)}$ is positive when $FS < 0.31$, zero when $FS = 0.31$ and negative in the remaining case

tr $J_{(1,0)} = (1.38 - 4.43FS) + (1.4 + 0.55FS)$

tr $J_{(1,0)}$ is negative when $FS > 0.72$, zero when $FS = 0.72$ and positive in the remaining case

Equilibrium point (1,1)

$$J_{(1,1)} = \begin{bmatrix} (-1.38 + 4.43FS) & 0 \\ 0 & (1.4 - 1.875 + 0.55FS) \end{bmatrix}$$

det $J_{(1,1)} = (-1.38 + 4.43FS)(1.4 - 1.875 + 0.55FS)$

det $J_{(1,1)}$ is positive when $FS < 0.31$ or $FS > 0.86$, zero when $FS = 0.31$ or $FS = 0.86$, negative in the remaining case

tr $J_{(1,1)} = (-1.38 + 4.43FS) + (1.4 - 1.875 + 0.55FS)$

tr $J_{(1,1)}$ is negative when $FS < 0.37$, zero when $FS = 0.37$ and positive in the remaining case

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3 A DSTI limit in an increasing interest rate environment: benefits across the LSTI distribution

3.1 Introduction

In 2022, the euro area started to experience very high levels of inflation relatively to its history and way above the 2% target of the European Central Bank (ECB). To tackle this issue, the ECB increased its reference rates throughout 2022 in a fast pace - increasing 450 basis points from July 2022 to September 2023. This occurred after a period of historically low interest rates and the market was quick to pass through the monetary policy action to their interbank loan rates. In fact, banks anticipated this action with the Euro Interbank Offered Rate (Euribor) starting to increase in March of 2022 for all fixation periods, ahead of the first monetary policy contraction in July. The Euribor is commonly used as a reference rate in Portugal to set interest rates for new loans for house purchase. As higher interest rates lead to higher loan service ratios, which can increase of the probability of borrower's defaulting (see e.g. Slaymaker et al. 2019 and Byrne, Kelly, and O'Toole 2022), this reaction to monetary policy is relevant for macroprudential policy, which focuses on the stability of the financial system.

Before this period of increasing interest rates, the Banco de Portugal introduced a macroprudential Recommendation, in July of 2018, with several limits that can both reduce the loss given default and the probability of default of loans for house purchase. Besides limits to the loan-to-value (LTV) ratio and to maturity, it was introduced a limit to the debt service-to-income (DSTI) ratio of new loans to households, meaning the ratio between all debt (new and old) repayments relatively to the borrower's income. For floating rate loans, the measure also requires consideration of a stress scenario that assesses the borrower's ability to repay the loan after an interest rate increase of up to 300 basis points. The DSTI of new loans to households in this scenario, where interest rates would increase significantly, had to be equal or lower than 50%, with some exceptions.

The DSTI limit directly interacts with the evolution of interest rates as it becomes more restrictive with rate increases and less with rate decreases, everything else constant. However, there are exceptions provided in the Recommendation that allow for financial institutions to grant loans to borrowers with a DSTI ratio above 50%. The percentage of total amount of new loans granted by each financial institution with a DSTI between 50% and 60% was of 20% from 2018 to 2020 when it was reduced to 10%, while for DSTIs above 60% the percentage was 10% which was also reduced in 2020 to 5%. In order to use these exceptions, institutions have to justify them using proven financial capacity of the borrowers by the existence of a protection of a real nature.

A DSTI limit can help in reducing borrower's probability of default. In Nier et al. (2019) it is shown that, if always in place, the 40% limit to the DSTI ratio applicable in Romania would have decreased the probability of default for all mortgages by 23%. In Gross and Población (2017) it is found that LTV caps have a stronger potential to reduce loss given default while DSTI limits have a higher impact on the probability of default. In particular, for Portugal, they estimate that the initial probability of default (around 2%) significantly decreases after the introduction of a DSTI limit around 60%, reaching 1.5% when considering DSTI limit of 40% and a minimum of 0.5% in the extreme case of a DSTI limit of 10%.

In this context, a key issue for macroprudential authorities is to assess the impact that a higher or increasing interest rate environment (relatively to the previous low interest rate environment) has on the distribution of the loan service-to-income (LSTI) ratio of new loans to households for house purchase when being constrained by a DSTI limit and if this impact would be significantly different in the case that there was no DSTI limit. The choice for the LSTI ratio of new loans relies on the fact that current DSTI ratios faced by borrowers are defined by existing debt (e.g. consumer loans which are usually set at a fixed interest rate) and new acquired loans in the new higher interest rate environment. Therefore, the LSTI ratio of new loans will be both constrained by the DSTI limit but also affected by the increasing interest rate environment. The purpose of studying the effects over the distribution is that it is expected that interest rates increases will have a more significant effect in increasing the number of loans given at a higher LSTI ratio, if no restriction was in place, and so it can increase the right tail at a larger magnitude than the rest of the distribution. However, at the same time, because there is a DSTI limit, the interest rate increase might induce households to take out smaller loans or even exclude them entirely from the credit market, which can offset the previous effect. So, there are two different effects: the effect that would have happen if no DSTI limit was in place, and so is entirely due to the increase of interest rates, and the effect that can be attributed to the DSTI limit. The choice for using borrower's and loan characteristics at origination is because banks, in their solvability assessment, cannot be fully forward looking and control future affordability. Therefore, the macroprudential perspective, in this case the assessment of the impact of the DSTI limit, should focus on loan-related risks that can be prevented by prudent loan origination criteria.

In order to obtain the benefits of the DSTI limit and how they change across interest rate environments, micro-data from the Portuguese Central Credit Register (hereinafter CCR) is used, restricting the sample to monthly information of all new loans of credit institutions operating in Portugal vis-à-vis Portuguese households from July 2018 to June 2023. In order to explore the effects across the LSTI distribution, instrumental variable quantile regressions are estimated and the role of the exceptions as a potential counterfactual is explored in a cross-sectional manner, exploring how differences between the similar loans that belong to one of the two groups (exceptions and non-exceptions) impacts the conditional distribution of the LSTI ratio.

Results indicate that if the DSTI limit did not exist, LSTI ratios could be 5 percentage points higher, before March 2022. This value increases to 7 percentage points in the increasing interest rates environment. This indicates that, in the absence of the DSTI limit, the LSTI distribution could shift rightward, reflecting a higher financial burden on borrowers and an increased risk of default. The impact of the DSTI limit, even more pronounced after March 2022, demonstrate the DSTI limit's efficacy in mitigating the impact of rising interest rates by more stringently restricting higher LSTI ratios. Since the impact of rising reference rates are identified as more striking on the LSTI ratios of borrowers in the lowest income quintiles, the increase restrictiveness of the DSTI limit ensures that less resilient borrowers maintain effort rates that mitigate increased default probability.

The rest of this chapter is structured as follows: Section 2 discusses the related literature. Section 3 presents the data and some descriptive statistics. Section 4 describes the empirical model and discusses the results. Section 5 concludes.

3.2 Related literature

This chapter relates to two strands of literature: effectiveness of borrower-based measures, namely limits on the DSTI ratio, and its interaction with monetary policy, differentiating between periods of low and periods of increasing interest rates.

The assessment of borrower-based measures has mostly been done in terms of its effectiveness in curbing credit growth and housing prices growth (see e.g. Alam et al. 2019 or a meta-analysis of the empirical literature on macroprudential policy conducted in Araujo et al. 2024). The results most relevant for DSTI limits are: a tightening of a DSTI limit has a negative effect on household credit growth but no statistically significant effect on house prices growth (Alam et al. 2019); DSTI limits are found to have a statistically significant effect on household credit in 45% of the estimates obtained in the literature considered in Araujo et al. (2024), while for housing prices this value decreases to 20%; the meta-analysis in Araujo et al. (2024) finds that tighter limits to the DSTI ratio reduces both total credit and household credit by about 0.06 and 0.05 standard deviations, respectively, but its average effect on house prices is statistically insignificant.

However, one can make the case that other target variables could be relevant for both macroprudential policy calibration and assessment. As macroprudential policy aims at maintaining stability in the financial system, which can be done by minimizing generalized expected losses, the relationship between household risk parameters (household's probability of default and loss given default) and borrower's capacity in servicing their debt are important to investigate. In particular, the effect of higher DSTI ratios, through new loans with a high LSTI ratio driven by increasing interest rates, is relevant for macroprudential policy as it can increase borrower's probability of default.

The relationship between higher debt service ratios and higher probability of default has been explored at least: i) in Ireland in OToole and Slaymaker (2021) where they find that a positive shock to the DSTI increases the probability of default and ii) in the Romanian credit market, with two papers (Mihai, Popa, and Banu 2018, tested with both current DSTI ratio and at origination, and Nier et al. (2019), only with current DSTI ratio), showing that higher DSTI ratios are an important factor in increasing borrower's probability of default.[1] These three papers also identify non-linear effects: in OToole and Slaymaker (2021) larger positive shocks to the DSTI ratio have a greater effect on the probability of default and a positive shock also contributes to a higher likelihood of defaulting if the level of the DSTI ratio in the previous period was above 25%; in both Mihai, Popa, and Banu (2018) and Nier et al. (2019) the non-linear effect is identified with stronger effects on the probability of default for borrowers with a DSTI level above a certain level (50% in Nier et al. 2019). The non-linearity in the relationship between DSTI and the probability of default points to the importance of caps on debt service ratios to significantly reducing the probability of default.

There is evidence that the implemented caps on DSTI ratios have been effective in limiting default rates. In Nier et al. (2019) it is shown that, if always in place, the 40% limit to the DSTI ratio applicable in Romania would have decreased the probability of default for all mortgages by 23%. Additionally, they estimate that when considering the impact on mortgages with high DSTI (above 50%) the probability

[1] The relationship between higher debt service ratios and higher probability of arrears or household credit risk has also been explored for Estonia (Kukk et al. 2016) and for Hungary (Holló and Papp 2007), respectively.

of default drops by more than 40%. In Gross and Población (2017) they develop an integrated micro-macro model framework to assess the efficacy of borrower-based measures, which include debt service-to-income ratio caps. They find that LTV caps have a stronger potential to reduce LGDs while DSTI caps have a higher impact on the probability of default. In particular, for Portugal, they estimate that the initial probability of default (around 2%) significantly decreases after a DSTI cap around 60%, reaching 1.5% for a DSTI cap of 40% and a minimum of 0.5% in the extreme case of a DSTI cap of 10%.

Looking at probabilities of default is even more important in the context of increasing interest rates. In Slaymaker et al. (2019) they find that, for Irish households, a 100 basis point increase in policy rates would lead to a 0.5 percentage point increase in new default flows. In Byrne, Kelly, and O'Toole (2022), again for Ireland, they find that a 1% increase in instalment is associated with a 5.8% increase in the likelihood of default over the following year.

Since the DSTI ratio includes debt servicing with new loans and existing debt, one can also conclude that higher LSTI ratios at origination will also translate into higher probabilities of default. This is specially relevant when interest rates increase, after a low interest rate period, as it translates into a positive shock in debt servicing costs relatively to the previously contracted new loans. Then the two environments, low and high interest rates, can translate into different system-wide probabilities of default if the LSTI ratio distribution significantly changes, specially if the changes are at the tail, since non-linearities are important in determining higher probabilities of default.

Although there has been some research on the complementarity relationship between monetary and macroprudential policies, with tighter monetary policy enhancing the impact of macroprudential tightening on credit growth (e.g. Revelo, Lucotte, and Pradines-Jobet 2020 and Kim and Mehrotra 2018), literature on the effect of borrower-based measures in a high interest rate environment is scarce. This relates to the fact that macroprudential policy has mostly coincided with a period of very low interest rates and loose monetary policy, at least in the euro area. In Budnik (2020), the interaction terms between borrower-based instruments, in the form of loan-to-value and debt-to-income/ debt-service-to-income ratios limits, and the real interest rate have a negative effect on total credit (both instruments) and on household credit (only limits to debt-to-income and debt-service-to-income ratios). This means that when there are debt-to-income and debt-service-to-income ratios limits in place and the real interest rate increases, both total and household credit will decrease, reinforcing the pass-through of monetary policy.

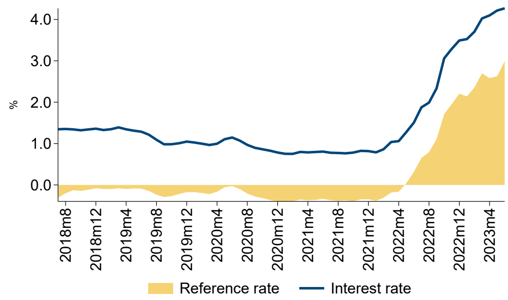
3.3 Data

On July 2018, Banco de Portugal introduced a macroprudential Recommendation with several limits: to the LTV ratio, to maturity, and to the DSTI ratio of new loans to households.[2] The limit on the DSTI ratio is applied to a stress scenario (i.e. considering an interest rate increase and a reduction in income, regarding origination conditions) and is equal to 50%. This limit directly interacts with the evolution of interest rates as it becomes more restrictive with rate increases and less restrictive with rate decreases, everything else constant. Using micro-data from the Portuguese Central Credit Register (hereinafter CCR), this chapter employs information from July 2018 to June 2023 which contains monthly information on all approved new loans of credit institutions operating in Portugal vis-à-vis households. This dataset has information on all new contracts for each point in time but does not follow the credit throughout its lifetime and so it is cross-sectional. [3] Although the limit to the DSTI ratio affects all new loans to households, the interest rate increase had a large immediate impact on new loans to households for house purchase which are usually set at a variable interest rate. For that reason, and since it is the largest type of loan a household usually takes in Portugal, this chapter focuses on new loans to households for house purchase. Variables considered for the analysis are both at the loan and borrower level: loan service-to-income, its interest rate, which corresponds to a reference rate plus a spread, its maturity, loan amount and value of the protection that the borrower gave to obtain the loan, borrower's income, education level and relation to unemployment (definitions are in Table 3.A.1 of the Appendix). The monthly loan instalment considered in the LSTI ratio is computed considering constant monthly instalments, taking into account a loan's maturity and the interest rate. We limit the range of LSTI values between 3% and 100%, corresponding to the 1st and 99th percentiles, respectively, of the original unconditional distribution, by eliminating extreme values as they can arise from measurement errors.

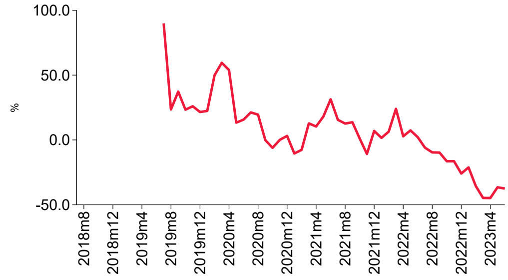
Reference rates started to increase in March 2022 (Figure 3.3.1 (a)), in anticipation of the monetary policy normalization (policy rates then increased in July of 2022) to tame the high inflation in the euro area. This contributed to a significant drop of the annual percentage change in new loans for house purchase from the second semester of 2022 onwards (Figure 3.3.1 (b)).

[2] It also introduced a requirement of regular payments of capital and interest and a convergence, until the end of 2022, of average maturity of new loans to 30 years. More information can be obtained in: `https://www.bportugal.pt/en/page/ltv-dsti-and-maturity-limits`.

[3] The cut-off date coincides with the month prior to an announcement that the Banco de Portugal could change the DSTI limit introduced in the Recommendation.



(a) Average interest and reference rates

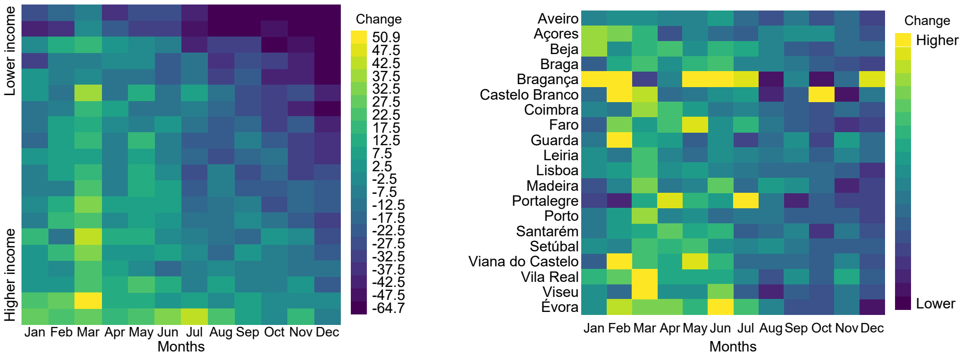


(b) Annual percentage change in new loans for house purchase

Figure 3.3.1: Average interest and reference rates and new loans for house purchase

Source: Banco de Portugal (Central Credit Register).
Notes: Last observation: June 2023. Average values are weighted by loan amount.

In 2022, new loans for house purchase increased in amount in the first semester, relatively to the same period in 2021, for mostly all income groups and districts (Figure 3.3.2). This increase was most relevant in March, the same month that reference rates started to increase, pointing to some anticipation by borrowers of further rate increases. Following the increase of reference rates, new loans for house purchase decreased, with values in December representing less than 25% of the values for the same period in 2021 in aggregate terms. This was especially relevant for lower income groups which experienced a larger and more immediate decrease. Across 2022, the annual percentage change in new loans for house purchase does not have a clear pattern depending on district that it was granted in (Panel (b) of Figure 3.3.2).



(a) By income

(b) By district

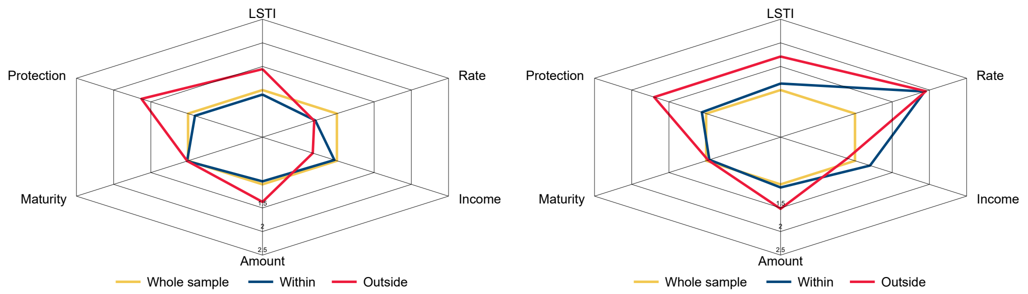
Figure 3.3.2: Annual percentage change in new loans for house purchase between 2022 and 2021

Source: Banco de Portugal (Central Credit Register).

The exceptions provided for in the Recommendation allow for some loans to be granted with a DSTI ratio above 50%. From 2018 to 2020 each financial institution could grant 20% of total amount of new loans with a DSTI between 50% and 60% and 10% with DSTIs above 60%. These percentages were reduced in 2020 to 10% and 5%, respectively. In order to use these exceptions, institutions have to justify them using proven financial capacity of the borrowers by the existence of a guarantee or protection given by the borrower's parents and/or the existence of other protections of a real nature (Banco de Portugal 2023b). These exceptions can then be a good counterfactual, once estimations are controlled for the value of the protection given, to estimate the solvability conditions that banks would have used to give loans to all borrowers in the case where the Recommendation had not been introduced. The role of other limits defined in the Recommendation, namely to the LTV ratio and to maturity, are not explored in this chapter as there are no comparable exceptions and so it is not possible to estimate their counterfactual. In any case, it is expected that the stringency of both limits to maturity and to the LTV to be similar for both loans granted within and outside the DSTI limit as statistics regarding maturity and the LTV ratio for the whole sample (see Table 3.A.2 of the Appendix) are similar to the ones for the exceptions (see Table 3.A.3 of the Appendix).

Relative to the whole sample, loans within the Recommendation's DSTI limit are similar to the average loan when considering the whole sample (considering all periods and all loans), except on the reference rate which is below the periods before March 2022 (Figure 3.3.3 Panel (a)) and two times larger than average after

March 2022 (Figure 3.3.3 Panel (b)). This also happens for loans that are outside the limit (DSTI>50%), showing how substantial (and similar) the increase of reference rates was for both groups of borrowers. Despite similar values for the average reference rate, loans outside of the DSTI limit have a higher LSTI (almost 1.5 times higher), are larger in initial amount, but also in value of protection (around 1.5 times higher), and the income is lower on average. After March 2022 (Figure 3.3.3 Panel (b)), besides the reference rate increase, loans within stayed with similar average values as before in all other characteristics except income which increased. Loans outside the DSTI limit saw a more considerable average LSTI increase, although also of the protection value and income. Average maturity is similar for all cases and all samples.



(a) Before March 2022

(b) After March 2022

Figure 3.3.3: Average characteristics of loans within and outside the Recommendation before and after March 2022 relatively to the whole sample

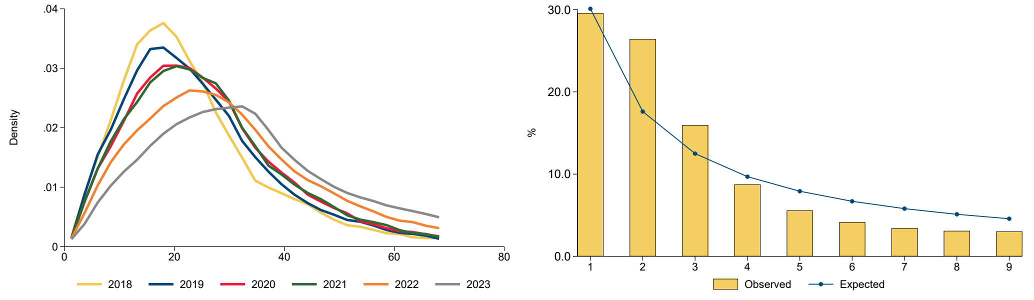
Source: Banco de Portugal (Central Credit Register).
Notes: LSTI is the loan service-to-income ratio, rate the interest rate, income is the net income of borrowers, protection is the protection value given as collateral for a loan. Whole sample represents reference values for each characteristic as it corresponds to the average values of the whole sample (including before and after March 2022 and loans characterised as within and outside). They appear in the Figure with a value of one as the remaining labels "Within" and "Outside" are compared with the average values of the whole sample. "Within" and "Outside" refer to loans within and outside the DSTI limit, respectively.

Rather than focusing on one point of the LSTI distribution, it is interesting to see how the unconditional distribution has changed in the context of interest rate increases and an active macroprudential policy measure. Relatively to 2018 and 2019, in the first years of the Covid-19 pandemic (2020 and 2021) there seems to have been a slight shift of the unconditional distribution of LSTI to the right from a small increase of the density of higher LSTI values (Panel (a) Figure 3.3.4). In 2022 and 2023, the increase of density in the upper tails was even more significant. This may indicate that, even with some affordability constraints, new loans for house purchase imply now a higher effort rate on borrowers than before the reference rates increase.

An interesting observation is that values of the LSTI ratio display a similar distribution, regarding its first-digit, to the one observed in several real-life data sets that follow Benford's law (Panel (b) Figure 3.3.4). The law proved that in several databases with real-life sets of numerical data the first-digit of the set of numbers is more likely to be small with the digit 1 representing 30% of the cases while the digit 9 only being less than 5% of the cases (Benford 1938; Berger and Hill 2021). The larger differences regarding the observed distribution of the first-digit in our LSTI ratio sample in comparison to the expected one from Benford's law is related to excess values in the 20% to 30% range and by the lack of values for LSTI ratios between 50% and 90%. As Benford's law is mostly used to identify data anomalities from real-life data, it could be seen as the counterfactual scenario where data is unrestricted (as the law usually works better in data that spans several orders of magnitude). In this case, the LSTI ratio is not an usual candidate to follow this law as, although, theoretically, it can span multiple orders of magnitude, realistically, due to borrower's and/or bank's aversion to risk, it is usually limited. However, it is exactly this aversion to risk that introduces the similarity with the law, i.e. where low LSTI ratios are much more representative in the sample. If the expected percentages are then looked as a counterfactual scenario, where banks and borrowers are more risk neutral, one could use the deviations regarding observed values from Benford's law to measure risk aversion in the housing credit market. In addition, the higher percentage, relatively to Benford's law, of loans with LSTI ratios in the 20% to 30% range might also derive from the DSTI limit, which can limit the LSTI ratio. In the terms of this chapter, it indicates that the benefits of a DSTI limit might not only be reflected in decreasing the percentage of loans with high LSTI ratios (by leaving some of the riskier loans outside of the market) but also, and more significantly, in increasing the percentage of loans granted with low LSTI ratios. Then, the law can be seen as the expected first-digit distribution that would be obtained if banks, borrowers and authorities relaxed their risk aversion actions.

The effects of a DSTI limit similar to the Portuguese one have been assessed using the exceptions (loans granted outside the DSTI limit), which acted as a counterfactual, in Levenko, Kukk, and Reigl (2023).[4] They first identify that the DSTI approximately follows a normal distribution but truncated at the DSTI limit, something that is also observed with DSTI ratios in our sample both for before and after the references rates increase that started in March 2022 (Figure 3.3.5). In Levenko,

[4] As in Portugal, Estonia implemented a %50 limit on a stressed DSTI ratio. Exceptions to these measures are permitted up to 15% of the amount of housing loans issued by a credit institution in a quarter.



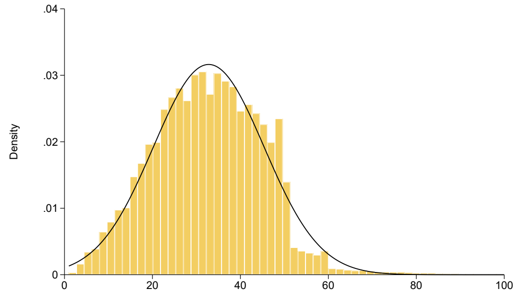
(a) Unconditional LSTI distribution

(b) First-digit frequency of LSTI

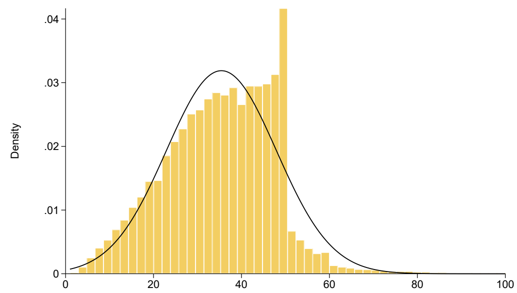
Figure 3.3.4: LSTI distribution characteristics through time and regarding frequency of first-digit

Source: Banco de Portugal (Central Credit Register).
Notes: The first-digit frequency tells the percentage of LSTI ratios with each number as the first digit in the sample. E.g. the values for "1" tells the percentage of LSTI ratios in the sample that start with the number 1, this will be ratios in the 10s as the sample only has LSTI values between 3% and 100% as mentioned. The "Expected" line represents the expected percentage for each number according to Benford's Law.

Kukk, and Reigl (2023) this is used to estimate the loss of tail-borrowers, that happened from enforcing a DSTI limit, by considering the difference between several hypothetical normal distributions and the observed one. Using the same method, distributions of Figure 3.3.5 seem to indicate that the benefits of the Portuguese DSTI limit are also in reducing the right-tail of the DSTI distribution, as the observed values (in yellow) have lower density than the counterfactual distribution (normal distribution displayed as the black line). This effect is observed both before (Panel (a)) and after (Panel (b)) the reference rates increase. Excess values are observed near the 50% limit, a situation usually referred as bunching, which is more prevalent after March 2022. This may indicate that the period of increasing reference rates led to a reduction of density in the middle of the distribution which was replaced by a bunching around the DSTI limit. In the case that no DSTI limit was in place, this increasing interest rate environment would have led to a slightly higher density above 50% than in the previous environment of low interest rates.



(a) Before March 2022



(b) After March 2022

Figure 3.3.5: DSTI distribution before and after March 2022

Source: Banco de Portugal (Central Credit Register).
Notes: Bars in yellow represent the histogram of the DSTI ratio. Black line represents the normal density curve of a normal distribution with the same mean and standard deviation as the DSTI data.

3.4 Empirical methodology and results

The increase of interest rates, through the increase of reference rates, can have different effects on the LSTI conditional distribution for new loans granted within and outside the DSTI limit. Within the limit, loans are granted with an active constraint where the amount granted has to comply with the DSTI limit. In this case, borrowers may take on smaller loans than before which translates into a higher impact of the increasing interest rate environment due to the DSTI limit. [5] For loans granted outside the DSTI limit this constraint is more relaxed or does not exist meaning the loan amount might be larger than of loans within the DSTI limit with similar loan conditions, although lower than they would in a low interest rate environment. Therefore, these loans, which are technically unrestricted, will be used to estimate a counterfactual scenario where the DSTI limit was not in place. By comparing estimates of the conditional LSTI distribution of loans within the DSTI limit with the counterfactual this section assesses, using instrumental-variable quantile regressions (IVQR), the benefits of having a DSTI limit in both the previous low and the new increasing interest rate environment.

To estimate the LSTI conditional distribution a set of borrower and loan specific criteria will be used: i) loan: if it is within or outside the DSTI limit, if it was

[5] The increasing interest rate environment might also lead to a higher number of rejected loans which we cannot estimate from our sample. However, results from Bank Lending Surveys of July 2022-2023 for Portugal indicate that the share of household loan applications for house purchase that were completely rejected remained basically unchanged (Banco de Portugal 2022; Banco de Portugal 2023a).

granted before or after March 2022, the protection value given, the loan's maturity and interest rate spread; ii) borrower: their income and relation to employment (if a salaried employee, a student, retired or employed by himself). In particular, it is necessary to consider that the LSTI and spread on origination may be simultaneously determined, as borrowers and institutions may negotiate the spread taking into account the resulting LSTI. By considering the spread, we are then able to compare quantile estimates of the LSTI distribution for loans with similar risk (spread), which is also more relevant for policy making. Additionally, if the possible endogeneity was not accounted for, estimation would be inconsistent.

3.4.1 Methodology

In order to tackle the endogeneity, a linear instrumental-variables quantile regression as defined in Chernozhukov and C. Hansen (2005) is considered. The literature has provided some estimation methods for this purpose (see Chernozhukov and C. Hansen 2006 and Chernozhukov and C. Hansen 2008, Kaplan and Sun 2017 and Machado and Santos Silva 2019 or Chernozhukov and C. Hansen 2013 for a review). In this chapter, we employ the STATA command 'ivqregress smooth' which fits a linear IVQR model as described in Chernozhukov and C. Hansen (2006) and Chernozhukov and C. Hansen (2008), estimated by smoothing the indicator function as proposed by Kaplan and Sun (2017).

A good summary of the linear IVQR model and how it is estimated in STATA can be found in its command syntax (StataCorp 2023). In the same way, we start our linear IVQR model written as a "random coefficients" model: [6]

$$Q_y(d, \boldsymbol{x'}, u_y) = d\alpha(u_y) + \boldsymbol{x'\beta(u_y)} \tag{3.1}$$

where $y = LSTI$, $\boldsymbol{x}$ contain the exogenous variables, $d = \{spread\}$ is the endogenous variable that depends on both the exogenous and instrumental variables $\boldsymbol{z}$, u_y is a variable that characterizes the heterogeneity of the outcome for LSTI for loans with the same observed characteristics, and $\alpha(.)$ and $\boldsymbol{x'\beta(.)}$ are random coefficients that depend on u_y.

The exogenous variables contains information at both borrower and loan level: borrower's income, protection value given for that loan contract acting as the guarantee, maturity of the loan and a dummy variable equal to 1 if the borrower is a salaried employee (and not unemployed, a student, retired or employed by himself). In addition, we also consider dummies that aim at identifying the effects

[6] For notational simplicity, the observational subscript i that would represent a new loan for house purchase was dropped.

of the DSTI limit (variable equal to 1 for loans outside the DSTI limit) and the effects of the increasing interest rates environment that started after March 2022 (variable equal to 1 for loans granted after that date.)

The chosen instrumental variables have to be exogenous, meaning uncorrelated with the structural error term, and correlated with the spread of each contract. In this case we chose two borrower level variables: their highest level of education and age. These variables were chosen based on the assumption that the spread, which is related with the risk of a borrower defaulting, will be, after taking into consideration their income and employment status and the protection value and maturity of the loan, influenced by their education level and age, which may indicate stability in maintaining debt payments in the future.[7] Since we are choosing two instruments for one endogenous variable, we test the validity of the additional instruments by looking at the *J* statistic (L. P. Hansen 1982) using the Generalized Method of Moments estimator. Results concluded that we cannot reject the null hypothesis that our instruments are valid at the 5% significance level, although it is rejected at the 10%. In addition we looked at the F-statistic (with a value of 386.454) of the first stage regression of the same estimation and rejected the hypothesis of weak instruments.

Conditional on $\mathbf{z}$ and $\boldsymbol{x}$, u_y is uniformly distributed between 0 and 1. Then u_y is considered a ranking variable for $LSTI$ which, when set to a fixed level τ, turns equation (3.1) in the IVQR model at the specific quantile τ. Under some regularity conditions (Chernozhukov and C. Hansen 2005), and considering that $\tau \rightarrow d\alpha(\tau) + \boldsymbol{x'\beta(\tau)}$ is strictly increasing in τ, the IVQR model satisfies the conditional probability

$$Pr(y \leq d\alpha(\tau) + \boldsymbol{x'\beta(\tau)}|\mathrm{x}, \mathbf{z}) = \tau \tag{3.2}$$

Equation (3.2) implies the unconditional moment condition:

$$E([\tau - I(y \leq d\alpha(\tau) + \boldsymbol{x'\beta(\tau)})\Psi]) = 0 \tag{3.3}$$

where $I(\cdot)$ is the indicator function, $\Psi = (\hat{d}', \boldsymbol{x'})'$ and $\hat{d}$ is the linear prediction of d using $\boldsymbol{x}$ and $\boldsymbol{z}$.

The smoothed estimating equations estimator used throughout this chapter replaces the indicator function in (3.3) with a smooth function using a kernel method to approximate the indicator function (Kaplan and Sun 2017).

[7] Other instruments were considered but not choosen as they did not pass the usual statistical tests.

For the purpose of estimating the impact of a DSTI limit on the conditional LSTI ratio distribution, we estimated the following instrumental variable quantile regression:

$$\begin{aligned}\hat{Q}_{LSTI_i}(\tau) = \hat{\beta}_{0,\tau} + \hat{\beta}_{1,\tau} Ex_i + \hat{\beta}_{2,\tau} Post_i + \hat{\beta}_{3,\tau} Ex_i \times Post_i \\ + \sum_{j=2}^{5} \hat{\beta}_{4,j,\tau} incq_{i,j} + \sum_{j=2}^{5} \hat{\beta}_{5,j,\tau} incq_{i,j} \times Post_i \\ + \hat{\beta}_{6,\tau} prot_i + \hat{\beta}_{7,\tau} mat_i + \hat{\beta}_{8,\tau} emp_i + \hat{\beta}_{9,\tau} spread_i\end{aligned} \tag{3.4}$$

where i represents a new loan for house purchase, Ex_i is a dummy variable that identifies for each loan if it is above the 50% DSTI limit, $Post_i$ is a dummy variable that is 1 if the loan was granted after March 2022 and zero otherwise, $incq_{i,j}$ is equal to one if the borrower of the loan i belongs to the j-th income quintile group, $j = 2, 3, 4, 5$, and zero otherwise, $prot_i$ is the protection value (which includes collateral and other real protection) in hundred thousands of euros given in the loan i, mat_i is the loan maturity on origination in months, emp_i is a dummy variable that identifies if the borrower is a salaried employee (and not unemployed, a student, retired or employed by himself) and $spread_i$ is the interest rate spread of the contract. [8]

In this case, the quantile treatment effect that we are trying to estimate is the role of being considered an exception on the quantile estimate of the LSTI ratio. There are two quantile treatment effects (i) before March 2022: $\hat{\beta}_{1,\tau}$ and (ii) after March 2022: $\hat{\beta}_{1,\tau} + \hat{\beta}_{3,\tau}$.

Since we are conditioning by the spread, income and protection value (which contains the value of the collateral given, usually the house that was bought), each quantile treatment effect will estimate the average amount (measured in LSTI units at a specific τ percentile) that could have been obtained if the DSTI limit did not exist. Banks have to minimize expected losses meaning, the probability of a borrower defaulting and/or the loss given default. As we are controlling for the spread, a measure of borrower risk, and for the protection given for the loan, a measure of how much a bank can recover given default, it is assumed that banks would be wiling to give the same loan amount to borrowers with similar risk and protection value. Then, when comparing two loans with similar credit

[8] The choice for considering income quintiles is based on the work of Acharya et al. (2022) that find that high-income borrowers are more distant from the regulatory limits, such as limits to the loan-to-income ratio, than low-income borrowers.

characteristics (including spread and protection value but also the other exogenous variables) differences regarding the conditional LSTI distribution between loans granted within and outside the DSTI limit are theorized to be due to the limit. Therefore, the underlying hypothesis of the quantile treatment effects is that, after controlling by the relevant variables, loans in the exceptions can be a counterfactual for what could happen if the DSTI limit did not exist. As we have seen in the previous section, the largest differences between these two groups are related with borrower's income, the loan amount and value of protection given.

Estimating equation (3.4) will also allow to obtain the quantile effects of the increasing interest rate environment on the LSTI ratio distribution. This is done by considering all coefficients associated with variable $Post_i$: (i) $\hat{\beta}_{2,\tau}$ is the quantile effect of the increasing interest rate environment on new loans that are given within the DSTI limit and for borrowers in the first income quintile, (ii) by adding to (i) the estimated coefficient $\hat{\beta}_{3,\tau}$ it gives the same quantile effect but on loans outside the DSTI limit and (iii) by adding $\hat{\beta}_{5,j,\tau}$ to (i) or (ii) the same effects are obtained both for a borrower from the j-income quintile. The quantile effect obtained in (ii) aims at estimating how the increasing interest rate environment would impact the LSTI conditional distribution if there was no DSTI limit. If $\hat{\beta}_{3,\tau}$ is positive then the τ percentile of the LSTI distribution would be larger in the increasing interest rate environment if there was no DSTI limit.

3.4.2 Results

Over selected percentiles

Results for selected percentiles are presented in Table 3.4.1. The chosen percentiles (25th, 50th, 75th and 90th) aim at covering the LSTI ratio distribution in a parsimonious manner.

Overall, the spread has a negative impact on the LSTI distribution as expected since a higher spread, everything else constant, implies a higher cost of credit for the borrower and higher risk for the bank. From the borrower side, to maintain adequate effort rates, a higher spread might require a smaller loan while the bank, trying to minimize risk, might also lend less to risky borrowers. Although the magnitude of the estimated coefficients seem large, the spread does not vary so much in the sample (see Table 3.A.2 of the Appendix).

The benefits of the DSTI limit on the LSTI distribution before March 2022 are identified in the second row of Table 3.4.1. It is estimated that loans that were granted outside of the DSTI limit have a higher LSTI than similar loans that were within the DSTI limit. The estimates are increasing with the percentile and are over 5 percentage points, meaning LSTI ratios given outside the DSTI limit, i.e. with less restrictions, are around 5 percentage points higher than those that lied within the restriction. This reflects the benefits of the DSTI limit across the LSTI distribution - since we are considering loans given outside the DSTI limit as the counterfactual then, if there was no DSTI limit, the LSTI distribution would shift at least 5 points to the right.

The period after March 2022 increases the expected value of the LSTI for the selected percentiles, in comparison with similar loans given before this new increasing rates environment. This is given by the estimated coefficient associated with Post which is positive and increasing with the percentiles of the LSTI distribution, and by the fact that negative coefficients of interaction terms of Post with the income quintile dummies are always lower. For contracts that lie outside the DSTI limit this positive impact is heightened, as can be observed in the estimates associated with the interaction term Exceptions x Post, and is around 2 percentages points. These estimates indicate that the benefits, in terms of containing risk measured in terms of LSTI distribution, of having a DSTI limit are higher in a increasing interest rates environment.

The impact of income on the LSTI ratio appears to be non-linear, as the coefficients associated with each income quintile dummy are significant and become more negative as the estimated percentile increases. When interacted with the dummy variable that identifies the period after March 2022, the estimated coefficients are also mostly statistically significant and negative throughout. This implies that increasing interest rate environment has different effects depending on where the borrower lies on the income distribution.

Results for the coefficients show that the higher your income, the lower will be your LSTI ratio. For example, the 90th percentile of the LSTI distribution, meaning the top 10% riskier loans, for borrowers in the highest income quintile is, before March 2022, around 20% while for borrowers in the lowest income quintile it is around 60%. When looking at the effect of the increasing interest rate environment (given by the interaction terms of the income quintiles with the variable Post) the differences between the highest income quintiles (fifth and fourth) and the lowest are accentuated throughout the LSTI distribution (significantly from the $50\%$the percentile to the 90%th). As increasing reference rates increase the cost of credit, high income borrowers might prefer getting a smaller loan and use their own capital while low income borrowers may not have that option, explaining why their difference in LSTI ratios is heightened in a higher interest rate environment.

Results for protection value, maturity and the dummy variable that identifies if the borrower is a salaried employee are as expected: giving a higher protection value, all else constant, will allow access to a higher loan, which increases LSTI ratio, a higher maturity spreads out the cost and repayments of the loan for a longer period and having a stable employment contract (rather than being a student, unemployed or working for themselves) might be related with higher savings, reducing the need for a higher loan amount.

	P25	P50	P75	P90
Spread	-9.09***	-16.80***	-15.84***	-16.30***
	(0.7)	(0.67)	(0.56)	(0.62)
Exceptions	5.26***	5.38***	5.61***	7.97***
	(0.12)	(0.12)	(0.16)	(0.229)
Post	1.60***	3.49***	8.61***	10.43***
	(0.2)	(0.23)	(0.32)	(0.43)
Exceptions x Post	2.02***	1.31***	1.49***	1.96***
	(0.29)	(0.24)	(0.32)	(0.52)
incq_2	-5.72***	-8.29***	-12.76***	-17.73***
	(0.08)	(0.1)	(0.12)	(0.18)
incq_3	-9.44***	-13.31***	-19.12***	-25.50***
	(0.09)	(0.1)	(0.11)	(0.18)
incq_4	-13.00***	-18.20***	-25.06***	-32.38***
	(0.1)	(0.11)	(0.11)	(0.19)
incq_5	-18.87***	-25.70***	-33.34***	-41.10***
	(0.15)	(0.14)	(0.12)	(0.18)
incq_2 x Post	0.98***	0.76***	-1.06***	1.03**
	(0.23)	(0.24)	(0.35)	(0.46)
incq_3 x Post	0.68***	-0.34	-3.76***	-3.19***
	(0.21)	(0.23)	(0.32)	(0.44)
incq_4 x Post	-0.04	-1.47***	-5.58***	-6.97***
	(0.2)	(0.23)	(0.31)	(0.43)
incq_5 x Post	-1.22***	-3.53***	-8.14***	-10.25***
	(0.19)	(0.22)	(0.3)	(0.42)
Protection	2.11***	3.16***	4.36***	4.73***
	(0.02)	(0.04)	(0.08)	(0.12)
Maturity	-0.0045***	-0.021***	-0.0401***	-0.0659***
	(0.0004)	(0.0004)	(0.0008)	(0.0016)
Employment	-0.82***	-1.57***	-3.04***	-5.39***
	(0.06)	(0.07)	(0.11)	(0.22)
Constant	34.77***	59.46***	77.50***	103.85***
	(1.07)	(1.11)	(1.25)	(1.88)

Table 3.4.1: Coefficient estimates for selected percentiles

Notes: Columns display the target percentile (τ) of the estimated IV quantile regression. Post is a dummy variable that identifies if the loan was granted after March 2022. incq_j is a dummy variable that identifies the income quintile of the borrower with $j = 2, 3, 4, 5$. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parenthesis. Number of observations: 522 448 contracts.

In order to make sense of the impact of the increasing interest rate environment across the LSTI distribution and income quintiles Figure 3.4.1 shows the average predicted percentiles (25th, 50th, 75th and 90th) for all five quintile groups before and after March 2022. The largest differences between interest rate environments (before, in yellow, and after March 2022, in blue) is observed on the 75th and 90th percentiles for the lower income quintiles (first, second and third), where more than a 10 percentage point increase is observed after March 2022. In the lower percentiles, it is estimated that, after March 2022, the 25th percentile of the LSTI ratio distribution increased around 3 to 5 percentage points across income quintiles, while the 50th increased around 5 and 9. However, both percentiles are still estimated to be below 50% for all income quintiles.

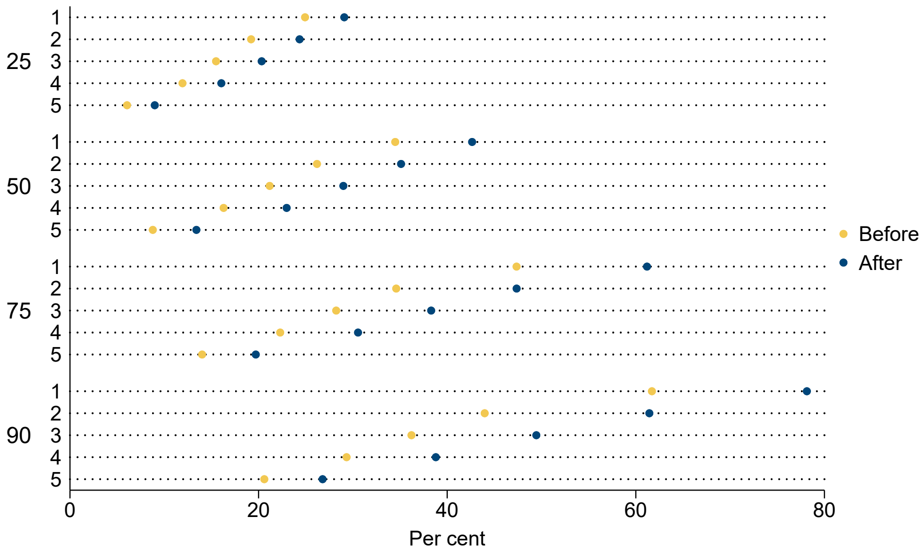


Figure 3.4.1: Average predicted percentiles of the LSTI distribution across income quintiles

Notes: Values on the y-axis represent: (i) the 25th, 50th, 75th and the 90th percentiles and (ii) the five income quintiles. "Before" and "After" refer to before and after March 2022, respectively. Yellow dot is the average predicted percentile of the LSTI distribution for each income quintile before March 2022 while the blue dot is for after March 2022. Estimations done using 522 448 contracts.

Benefits of the DSTI limit

The quantile treatment effect on the LSTI distribution of being included in the exceptions to the DSTI limit identify the benefits of the limit. As discussed, the loans that are granted outside of the DSTI limit are used to identify the counterfactual scenario where no limit was in place. This means that if there was no DSTI in place, the LSTI distribution would change, across all percentiles, according to the estimated quantile treatment effects.

We compute the quantile treatment effect for before and after interest rates started to increase in March 2022. Estimates, obtained for percentiles 5 to 90 in steps of 5 percentage points, and 95% confidence intervals are displayed in Figure 3.4.2. Results confirm that, if the DSTI limit was not in place, all of the LSTI ratio distribution would shift to the right, in about 5 percentage points, and the right tail would increase. This follows from the fact that quantile treatment effects are always statistically significant and positive, specially at the right tail (90th percentile). This would happen both before and after the increase of interest rates, and would be heightened in the latter case. The benefits of the DSTI limit before the interest rates increase seem to be broadly around 5 percentage points across the distribution (except at the tails). At lower percentiles, in the 5th and 10th percentile, the benefit is smaller, between 2 and 3 percentages points which indicates that the DSTI limit is not very restrictive for loans that do not represent a large effort on borrower's income. The rationale behind this may be that these are more risk-averse borrowers which may already have significant savings reducing their preference for capital. In the higher percentiles, higher than the 70th percentile, the benefits are larger, ranging from 6 to 8 percentage points reflecting the main benefits of the limit of restricting high risk loans. After March 2022, the benefits of the DSTI limit were amplified, specially on the low to mid part of the LSTI conditional distribution (i.e. percentiles between 15 and 45) and on the higher percentiles (higher than 70), increasing in 2 percentage points. This suggests that, in an increasing interest rates environment, a DSTI limit both restricts the tails of the LSTI distribution, limiting high risk loans, and limits the effort rate of less-risky loans.

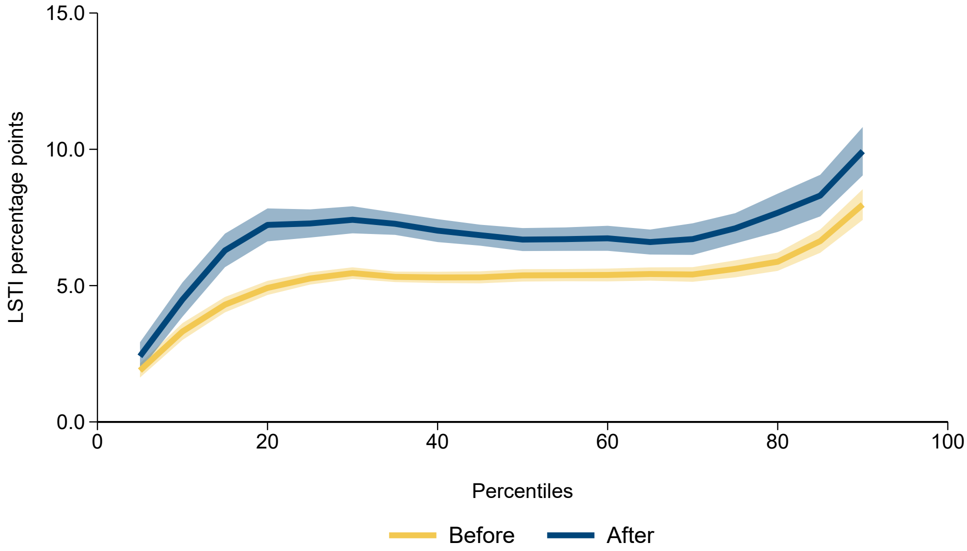
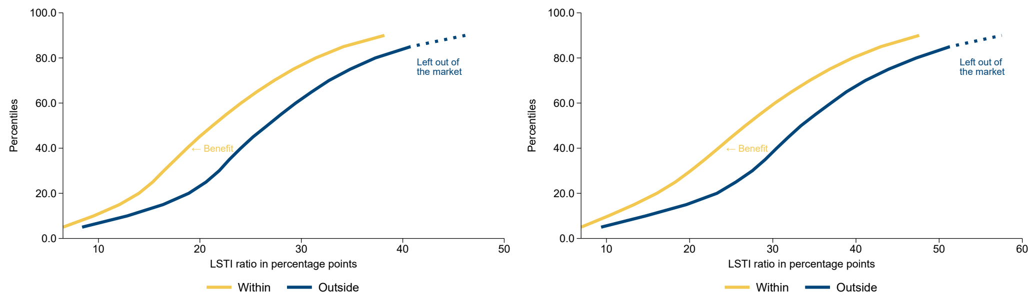


Figure 3.4.2: Quantile treatment effect of being outside the DSTI limit before and after March 2022

Notes: "Before" and "After" refer to before and after March 2022, respectively. Shaded areas represent 95% confidence intervals. Estimations done using 522 448 contracts.

Using results obtained by estimating equation (3.4), we plot the average predicted values for the situations where all loans would have been (i) within or (ii) outside the DSTI limit (keeping all other variables as in the original loan). This average prediction value is assessed for percentiles 5 to 90 in steps of 5 percentage points in Figure 3.4.3 with Panel (a) focusing on the period before March 2022 and Panel (b) on the period after. The yellow line shows the predicted percentiles of the LSTI ratio if all contracts were given within the DSTI limit while the blue line is the distribution in case all contracts lied outside the DSTI limit, giving the counterfactual scenario where the limit would have not existed. The difference between the two lines correspond to the quantile treatment effects identified in Figure 3.4.2.

The benefits of the DSTI limit are twofold. First, riskier loans were left out of the market. In both panels of Figure 3.4.3 the LSTI ratios of the higher percentiles (85th and 90th) of the LSTI distribution would be, if all loans were outside the DSTI limit, above 40% and 50% before (Panel (a)) and after (Panel (b)) references rates started to increase. This is in contrast to the highest predicted LSTI ratios for the case where loans have to respect the DSTI limit, which are below those values. As identified in Nier et al. (2019), a borrower's probability of default increases when the DSTI ratio is higher than 50%. As the DSTI ratio on origination is just the LSTI ratio plus other debt payments over income, one could use this same threshold to infer that LSTI higher 50% should be limited. Second, as estimated in the previous analysis with the quantile treatment effects, the DSTI limit also had a benefit on the whole distribution as the distribution of the LSTI ratio where loans are all within the DSTI limit is estimated as having lower LSTI values for all percentiles. This benefit is overall larger for the period after March 2022. More specifically, before March 2022, it is predicted that the median LSTI ratio would be 27% if the DSTI limit was not in place, while the median value for the case with the limit in place is predicted as 21%. In the increasing interest rate environment, even with the DSTI limit in place, the median LSTI is estimated to have increased to 26%, a value that in the scenario with no DSTI limit would increase to 33%, i.e. the monthly loan servicing would be, for 50% of loans, higher than one third of borrower's income.



(a) Before

(b) After

Figure 3.4.3: Predicted percentiles before and after March 2022

Notes: "Within" and "Outside" refer to predicted percentiles if all loans were given within and outside the DSTI limit, respectively. Estimations done using 522 448 contracts.

3.5 Conclusion and policy implications

Macroprudential policy has been a crucial element in the euro area's modern financial regulation since the 2008 financial crisis. As countries began to actively employ borrower-based measures, where loans are subjected to restrictions, the literature has studied its effects on variables such as loans and house price growth, as well as on the probability of default and loss given default. However, the study of macroprudential policy has been confined to a historically low interest rate environment in the euro area.

Following the ECB's reference rate increase in 2022, we aim at adding to the literature in two ways. First, by estimating the benefits of a borrower-based measure on less studied metrics such as the LSTI distribution. As it is measured relative to a borrower's income, the LSTI provides a measure of how, on the time of loan origination, borrowers and banks balance the dichotomy risk-resilience. A higher LSTI on origination leaves less room for a borrower to save for bad times, making them less resilient to shocks (e.g. on their income), and may even lead to default if the shock is large enough. If the LSTI distribution that considers all loans is concentrated in very large values, for example above the 50% threshold identified in Nier et al. (2019) as the value for which higher DSTI ratios increase a borrower's probability of default, then the banking system might be less resilient. Second, by differentiating between the period before and after March 2022, we are able to estimate the benefits of the borrower-based measure in two different interest rate environments: low rates and increasing/high rates, respectively.

The borrower-based measure assessed is the Portuguese DSTI limit of 50%, implemented in 2018. This measure was chosen as it directly interacts with the interest rate environment becoming, all else constant, more stringent when rates increase. The fact that in Portugal the limit was defined with some exceptions, i.e. some loans may be given with a DSTI above 50% if protections of real nature are given and which accounted for up to 15% of overall loans, is used to obtain a counterfactual scenario, as these loans were granted under the same temporal conditions as loans under the DSTI limit.

To account for endogeneity in the spread, which may be simultaneously defined with the LSTI ratio, instrumental-variable quantile regressions were employed to obtain the conditional LSTI distributions of new loans for house purchases granted both within and outside (exceptions) the DSTI limit, controlling for borrower's income, maturity of the loan, interest rate spread, employment status of the borrower and the real protections given for the loan. Differences across estimated percentiles of the two conditional distributions represent the benefits of the DSTI limit and were obtained for the periods of low and increasing interest rates.

Results indicate that if the DSTI limit did not exist, LSTI ratios could be higher, in general, 5 percentage points, before March 2022. This value increases to 7 percentage points in the increasing interest rates environment. This indicates that, in the absence of the DSTI limit, the LSTI distribution would shift rightward, reflecting a higher financial burden on borrowers and an increased risk of default. The positive impact of the DSTI limit, even more pronounced after March 2022, demonstrates the DSTI limit's efficacy in mitigating the impact of rising interest rates by more stringently restricting higher LSTI ratios. Since the impact of rising reference rates are identified as more striking on the LSTI ratios of borrowers in the lowest income quintiles, the increase restrictiveness of the DSTI limit ensures that less resilient borrowers maintain effort rates that mitigate increased default probability.

In addition, the DSTI limit is also estimated to prevent riskier loans from even entering the market. In both time periods, it is estimated that if all loans were outside the DSTI limit, the LSTI ratios of the higher percentiles (85th and 90th) of the LSTI distribution would lie above 40% and 50%. This is in contrast to the highest predicted LSTI ratios for the case where loans have to respect the DSTI limit, which are below those values.

The role of other limits defined in the Recommendation, namely to maturity and to the LTV ratio, are not explored in this chapter as there are no comparable exceptions and so it is not possible to estimate their counterfactual. However, it can be expected that in the case that there was no limit on maturity, an increasing interest rate environment could introduce an incentive to increase loan maturity in a way to decrease borrowers' effort rate (LSTI) or increase the loan amount for the same LSTI. In this case, the effectiveness of the DSTI limit would be lower, as banks and borrowers could dilute the impact of higher interest rates over the maturity of the loan. The impact of the limit to the LTV ratio is not directly influenced by interest rates. Indirectly, if higher interest rates were to be reflected in lower house prices and no limit to the LTV ratio was in place, loan amounts could be higher depending on the interaction with other limits in place such as a DSTI limit. In this case, it could be expected that an increasing interest rate environment could have a negative impact across the LSTI distribution.

A Variables and descriptive statistics

Variable	Definition
LSTI	Loan-service-to-income of the borrower at contract origination considering constant monthly instalments.
Age	Oldest borrowert's age at contract origination.
Loan amount	Loan amount at contract origination (in hundred thousands of euros).
Protection	Value of protection given at contract origination (in hundred thousands of euros).
Type of interest rate	Loan interest rate type (fixed or floating).
Interest rate	Annual nominal interest rate (%).
Reference rate	Annual nominal interest rate minus the spread (%).
Income	Borrower's monthly net income at contract origination.
Maturity	Loan maturity (in months).
Education	Variable that identifies whether the borrower's highest level of education is primary education, upper secondary education, or higher or equal than Bachelor's.
Employment	Binary variable equal to 1 if the borrower is a salaried employee, 0 if unemployed, a student, retired or employed by himself.
Exceptions dummy	Binary variable equal to 1 if the loan is within the exceptions and 0 otherwise. A loan is considered to be in the exceptions if the new DSTI of the borrower (defined as in the Portuguese macroprudential Recommendation, with income and interest rates shocks, and which considers all loans in force at the time of the new loan) becomes over 50%.
Post dummy	Binary variable equal to 1 if the loan was given out after March 2022.

Table 3.A.1: Variable definitions

Notes: Loans with more than one borrower consider the information of the oldest borrower - the exception is income, which is the sum of the income of both borrowers. All variables refer to the date the loan was granted.

	Mean	P25	P50	P75	P90	P95	N
LSTI	28.3	16.3	24.9	36.1	50.8	6210	774131
Age	39.5	33.1	38.9	45.1	51.0	55.0	774131
Loan amount	1.93	0.99	1.42	2.10	3.22	4.67	774131
Protection	3.04	1.45	2.16	3.31	5.30	7.54	690056
Floating rate (%)	79.5						760683
Reference rate (%)	0.2	-0.5	-0.3	0.2	2.0	2.9	714041
Spread (%)	1.2	1.0	1.0	1.3	1.6	2.0	714041
Income	3402.2	1118.0	1733.1	2987.0	5612.7	9186.9	774131
Maturity	395.2	353.0	420.0	480.0	481.0	481.0	774131
Exceptions (%)	7.3						774131
LTV (%)	75.9	67.5	80.0	89.8	90.0	90.0	773912

Table 3.A.2: Descriptive statistics - whole sample new loans for house purchase

Source: Banco de Portugal (Central Credit Register).
Note: Statistics weighted by loan amount.

	Mean	P25	P50	P75	P90	P95	N
LSTI	41.1	29.2	38.1	51.7	71.0	81.8	43154
Age	40.2	33.2	39.7	46.0	52.4	56.1	43154
Loan amount	2.70	1.25	1.85	2.90	5.00	7.30	43154
Protection	5.01	2.15	3.31	5.43	9.06	13.40	40649
Floating rate (%)	86.1						43154
Reference rate	0.2	-0.4	-0.2	0.2	2.3	3.1	40076
Spread (%)	1.2	1.0	1.0	1.3	1.5	1.8	40076
Income	2596.3	1004.8	1504.0	2547.8	4709.9	7176.2	43154
Maturity	395.5	349.0	420.0	480.0	481.0	481.0	43154
LTV (%)	74.6	64.7	80.0	88.2	90.0	90.0	43131

Table 3.A.3: Descriptive statistics - new loans for house purchase with DSTI $\geq 50\%$ (exceptions)

Source: Banco de Portugal (Central Credit Register).
Note: Statistics weighted by loan amount.

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Final remarks

The global financial crisis of 2008 highlighted the role of system-wide risk in the build-up of financial imbalances, in particular how increased risk taking by several institutions, simultaneously, against a sound macroeconomic environment, resulted in excessive credit and booming housing prices (Galati and Moessner 2013). This type of risk was not accounted for by previous regulation and policy which focused on a purely micro-based approach. In the aftermath of the crisis, policymakers looked to macroprudential policy as a means to tackle this systemic risk.

The main objective of macroprudential policy is to safeguard the stability of the financial system as a whole, by limiting the risks and costs of systemic crises (Galati and Moessner 2013). In order to do so, macroprudential instruments may either reduce risk build-up or increase resilience in the system so that when a shock happens, the system is not significantly impaired. In this case, losses are either absorbed or reduced which helps maintain the flow of credit in the economy, preventing the financial system to deepen or create a crisis.

The literature has highlighted the role of two dimensions of systemic risk: the time dimension (usually referred as cyclical systemic risk) and the cross-section dimension (usually referred as structural systemic risk). Macroprudential instruments, typically capital-based and borrower-based, can both limit the build-up of risk (focusing on one of two dimensions) and enhance resilience within the system. While cyclical systemic risk examines how procyclicality in the financial system leads to system-wide risk-taking during good times, structural systemic risk highlights the role of risk distribution within the system. In particular, common exposures in an interconnected financial system may amplify losses during a shock (Galati and Moessner 2013).

The primary objective of this thesis is to contribute to the existing literature by providing new ways of calibrating and assessing macroprudential instruments, based on data from Portugal. The chosen instruments were the CCyB, a capital-based tool that aims at creating resilience against the materialization of cyclical systemic risk, and the Portuguese DSTI limit which creates resilience for both borrowers and banks by limiting overindebtedness. While the focus of this thesis on the CCyB was in ways to calibrate the buffer, the Portuguese DSTI limit was assessed in its effectiveness in building resilience, by limiting overindebtedness, when banks and borrowers agree on a housing lending contract, which limits banks exposure, in a system-wide manner, to the residential real estate market.

To calibrate the CCyB, the Basel Committee on Banking Supervision (2010) introduced a linear rule based on a measure of credit cycle, the Basel gap, as a reference for Basel countries to calibrate the CCyB rate. However, experience shows that the use of this rule for setting a positive CCyB rate in European countries has been limited (Babi 2018 and Babi and Fahr 2019). 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 (Lozej, Onorante, and Rannenberg 2018 and Aguilar et al. 2019). In addition, calibration exercises based on stress test approaches, where the CCyB should cover losses from a countercyclical stress scenario, i.e. where the degree of severity increases as the economy moves up the financial cycle, have been explored (e.g. Bank of England 2016, Anderson et al. 2018 and Oordt 2018).

This thesis contributes to the literature on calibrating the CCyB in the first and second chapter. On the first chapter, the concept of stance, recently employed in macroprudential policy (European Systemic Risk Board 2019, European Systemic Risk Board 2021, Javier Suarez 2022 and Cecchetti and J. Suarez 2021), is used to propose a novel rule for the calibration of the CCyB rate. The macroprudential policy stance balances systemic risk against built-in resilience (which includes the effect of macroprudential policy) to assess if policy is tight or loose (European Systemic Risk Board 2019). A tight stance would indicate a need to make macroprudential policy less restrictive while a loose assessment would indicate otherwise. By assessing the impact of cyclical systemic risk and resilience on banks profitability distribution, the proposed rule to calibrate CCyB rate is illustrated for three scenarios. In scenario one, the policymaker targets a zero contribution of cyclical systemic risk to medium-term downside risk in bank profitability (a measure of risk). 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 (a measure of return). 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. 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.

In the second chapter the calibration of the CCyB is explored using evolutionary game theory. It does so by studying the stable strategies of cyclical systemic risk and targeted macroprudential policy (CCyB). The model initially considers that each decision or agent in the financial system can be defined within the dichotomy risk and resilience, a dichotomy also employed in the first chapter. To operationalize the model, data from the Portuguese banking system from 2001-2021 is used. By focusing on cyclical systemic risk and resilience-induced macroprudential policy, results show that there are two evolutionary stable strategies for cyclical systemic risk and targeted macroprudential policy: either risk build-up leads macroprudential policy to tighten or the materialization of cyclical systemic risk allows for the release of targeted-macroprudential policy. However, both the dynamics and the stable equilibrium depend on the financial stress in each period of time. When financing conditions are good risk will tend to increase but, at some risk threshold, the benefits of tightening macroprudential policy will outweigh its costs. When financial stress is heightened, cyclical systemic risk will materialize and the costs of having macroprudential policy will be higher than its benefits, indicating a need to loosen the policy. The model then provides thresholds for both financial risk and financial stress that may help decision making for macroprudential policy purposes.

The third chapter focuses on assessing the impact of the Portuguese DSTI limit on risk taking in new loans for house purchase both in a low and in an increasing interest rate environment. The assessment of borrower-based measures has mostly been done in terms of its effectiveness in curbing credit growth and housing prices growth (Araujo et al. 2024). One of the contributions of this chapter is that it explores the benefits of a borrower-based measure on less studied metrics such as the LSTI distribution. If the distribution is very concentrated around high LSTI ratios this may indicate a less resilient financial system, where a shock may result in wide-spread defaults. Following the ECB's reference rate increase in 2022, the second contribution of this chapter is that it estimates the benefits of the DSTI limit in two different periods: the period before (of low) and after March 2022 (of increasing interest rates). It also accounts for endogeneity in the spread, which may be simultaneously defined with the LSTI ratio, by employing instrumental-variable quantile regressions that also control for borrower's income, maturity of the loan, employment status of the borrower and the real protections given for the loan. Results indicate that if the DSTI limit did not exist, LSTI ratios could be 5 percentage points higher, before March 2022. This value increases to 7 percentage points in the increasing interest rates environment. This indicates that, in the absence of the DSTI limit, the LSTI distribution would shift rightward, reflecting a higher financial burden on borrowers and an increased risk of default. The positive impact of the DSTI limit, even more pronounced after March 2022, demonstrates the DSTI limit's efficacy in mitigating the impact of rising interest rates by more stringently restricting higher LSTI ratios. In addition, the DSTI limit is also estimated to prevent riskier loans from even entering the market. In both time periods it is estimated that if all loans were outside the DSTI limit, the LSTI ratios of the higher percentiles (85th and 90th) of the LSTI distribution would lie above 40% and 50%. This is in contrast to the highest predicted LSTI ratios for the case where loans have to respect the DSTI limit, which are below those values.

Results throughout the thesis indicate that macroprudential policy can be effective in both increasing resilience and curb systemic risk. The multiple tools allow for a more target impact depending on how systemic risk is building up in the financial system. It is able to target both cyclical and structural dimensions of systemic risk and build resilience through banks and borrowers.

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