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Credit concentration under macroprudential policy: An agent-based model approach

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Concentração de crédito sob política macroprudencial: Uma abordagem de modelo baseado em agentes

Gabriel Oliveira de Alarcão

Dissertação de Mestrado submetida ao Programa de Pós-Graduação em Economia da Universidade de Brasília como parte dos requisitos necessários para obtenção do grau de Mestre.

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Este trabalho é dedicado aos meus familiares e amigos.

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“And so from that,
I’ve always been fascinated with the idea that complexity can come out of such simplicity.”
(Will Wright)

Abstract

This work aims to investigate the effects of macroprudential policy on credit concentration and the behavior of financial agents in a complex setting where they interact and learn about the environment. Using the bottom-up approach of agent-based models, we simulate a situation where banks, depositors, a central bank, firms, and a clearing house compose an artificial financial system under different scenarios regarding macroprudential policy instances. Information asymmetry is introduced in the lending market. We find that the prudential policy increases concentration, measured by the Herfindahl-Hirschman Index (HHI) and Concentration Ratio (CR), in the lending market, reducing the supply of loans to small firms. At the same time, the increased concentration does not appear to exert a negative impact on financial stability.

Keywords: stability; banking; prudential policy; agent-based model; concentration.

Resumo

Este trabalho tem como objetivo investigar os efeitos da política macroprudencial sobre a concentração de crédito e o comportamento dos agentes financeiros em um ambiente complexo onde interagem e aprendem sobre o ambiente. Utilizando a abordagem bottom-up de modelos baseados em agentes, simulamos uma situação em que bancos, depositantes, um banco central, empresas e uma câmara de compensação compõem um sistema financeiro artificial sob diferentes cenários relativos a instâncias de política macroprudencial. Assimetria de informação é introduzida no mercado de crédito. Concluímos que a política prudencial aumenta a concentração, medida pelo Índice de Herfindahl-Hirschman (HHI) e pela Razão de Concentração (CR), no mercado de empréstimos, reduzindo a oferta de empréstimos às pequenas empresas. Ao mesmo tempo, o aumento da concentração não parece exercer um impacto negativo na estabilidade financeira.

Palavras-chave: estabilidade; banking; política macroprudencial; modelos baseados em agente; concentração.

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1 Introduction

The concentration of credit in financial markets has long been a key topic in economic research due to its significant implications for financial stability (Acharya; Hasan; Saunders, 2006; Shim, 2019; Tabak; Fazio; Cajueiro, 2011). High levels of credit concentration can increase systemic risk, amplifying the consequences of bank failures and credit crunches. In such scenario, a few non-performing loans can have a deep impact in the banks' financial stability and, as the financial system becomes more intertwined, this can generate cascade effects. This issue gained particular prominence after the Great Financial Crisis of 2008, which exposed vulnerabilities arising from excessive risk-taking and interconnectedness within the banking sector. As a result, policymakers and researchers have increasingly focused on the role of macroprudential policies in managing these risks (Altunbas; Binici; Gambacorta, 2018; Meuleman; Vennet, 2020; Ely; Tabak; Teixeira, 2021a).

Macroprudential policies aim to mitigate systemic risks and ensure financial stability at a macro level rather than focusing solely on individual institutions (Settlements, 2011). By regulating leverage, capital requirements, and lending practices, these policies seek to curb excessive risk accumulation that could lead to financial instability. While extensive literature examines the effectiveness of macroprudential tools in promoting overall financial stability (Claessens, 2014; Bruno; Shim; Shin, 2017), less attention has been given to their impact on credit distribution and financial agents' behavior in a concentrated credit market (Acharya; Hasan; Saunders, 2006). Understanding how these policies influence credit distribution is crucial, as it affects systemic risk (Andries; Ongena; Sprincean, 2024) and economic fluctuations (Müller; Verner, 2023).

Considering the complexity of the financial system and how interactions impact the dynamics of it, Agent-Based Models (ABMs) offer a promising approach to analyze the complex dynamics of credit concentration under macroprudential policy. ABMs simulate interactions between heterogeneous agents, such as banks, borrowers, and regulators, allowing for a more detailed representation of financial system structures (Dosi; Fagiolo; Roventini, 2010; Tesfatsion, 2006). This approach captures agents' adaptive behavior and bounded rationality, aspects often overlooked in traditional equilibrium models (Hommes, 2013).

This paper explores the impact of macroprudential policies on credit concentration using an ABM framework, focusing on how different policy settings influence credit distribution across the financial system. The study measures credit concentration using the Herfindahl-Hirschman Index (HHI) and the Concentration Ratio (CR). The model simulates banks, firms, depositors, and a central bank interacting in both the real sector and the interbank credit market, building on previous work by Barroso *et al.* (2016), Adão *et al.* (2022), and Lima, Ely, and Cajueiro (2024). Two new model features are introduced: information asymmetry in the lending market and firm heterogeneity based on size. The addition of information asymmetry happens as banks no longer know the probability of default or type of the firm that is asking for a loan from the bank. Given that, banks need to screen firms based on their size. The introduction of information asymmetry helps clarify how banks allocate credit when facing an adverse selection problem and provides a better understanding of the banks behavior, especially when it comes to leverage, in a more uncertain environment. Firm size heterogeneity is added to the model as firms have different sizes (which can be thought as their market value) and, consequently, diverse probabilities of default. The goal of this new feature is to work as a screening method to banks differentiate and classify firms and also to introduce a credit distribution channel and hence estimate the distributional effects of the macroprudential policy.

Overall, the results indicate a rise in concentration in the lending market. As capital requirements influence credit supply, forcing banks to sell excess loans, banks increase lending restrictions to smaller firms. This results points to a possible collateral effect of the macroprudential policy as increases the burden of acquiring credit for small firms, which are heavily dependent on it. Meanwhile, the effectiveness of the macroprudential policy in stabilizing the financial system holds, observed by the reduction of insolvencies in the presence of the policy. However, the role of the prudential tool looks less prominent in the presence of information asymmetry, since banks hold more capital due to the informational costs in the lending market. When we look for the impacts of credit concentration in the stability of the system, the results point in the direction that it has no negative effects, once larger firms in our model are less risky.

The analysis highlights the role of information asymmetry, bank behavior, and market structure in shaping credit dynamics. It also evaluates the impact of prudential measures, such as minimum capital requirements, in the distribution of credit in the system, as well as analyzes the relationship between credit distribution and financial stability. The findings contribute to the ongoing debate on designing effective prudential frameworks by providing a deeper understanding of the trade-offs between financial stability and credit accessibility in banking. These findings contribute to the literature on prudential policy and credit market interactions using agent-based models. While most research focuses on the relationship between prudential policy and financial instability (Cincotti; Raberto; Teglio, 2012; Hoog, 2018; Kaszowska-Mojsa; Pipień, 2020), other studies examine its impact on housing markets (Baptista *et al.*, 2016; Bardoscia *et al.*, 2025). This work adds to the literature by introducing information asymmetry into an ABM banking model and exploring prudential policy's distributional effects on the credit market.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on agent-based banking models and monetary and prudential policy research. Section 3 details the methodology, model, and its functioning. Sections 4 and 5 present the simulation outcomes and their implications, respectively. Appendix A provides a model description following the Overview, Design concepts, and Details (ODD) protocol (Grimm *et al.*, 2006; Grimm *et al.*, 2010; Müller *et al.*, 2013; Grimm *et al.*, 2020).

2 Literature Review

Our study employs an agent-based modeling (ABM) approach, adopting a bottom-up methodology. We begin by defining the relevant agents and specifying their behaviors. Subsequently, we establish the interactions between agents while considering institutional and structural constraints. The model is then simulated to analyze the resulting dynamics, capturing both aggregate and individual-level outcomes. This approach allows for the exploration of non-linear and complex interactions without relying on assumptions of strict rationality, fixed decision rules, or equilibrium conditions. For a comprehensive review of ABMs within the social sciences, see (Steinbacher *et al.*, 2021).

Agent-based models (ABMs) have emerged as a powerful tool to study the dynamics of banking systems, especially in understanding complex interactions among financial agents, institutions, and markets (Boss *et al.*, 2004; Iori *et al.*, 2007; Cajueiro; Tabak, 2008; Battiston *et al.*, 2010; Mantegna, 1999; Viegas *et al.*, 2019; Cajueiro *et al.*, 2021). ABMs are valuable for studying the structure and dynamics of interbank networks. Banks are interconnected through lending and borrowing relationships, forming complex networks that can propagate shocks throughout the system. One of the first works with interbank markets with ABMs can be circled back to Iori, Jafarey, and Padilla (2006). The authors show that in a banking system with heterogeneous banks, the interbank market plays a dual role. While higher interbank connectivity may decrease the probability of default of individual banks, the default of a bank may cause knock-on effects on its creditors. Similarly, Nier *et al.* (2007) emphasize the role of network structures in determining financial stability, highlighting that more interconnected networks can both spread and absorb shocks depending on their structure. On a macro model, Gurgone, Iori, and Jafarey (2018a) provide valuable insights into how the structure of interbank networks influences the functioning of banking systems and the broader economy. Their agent-based model demonstrates that while higher connectivity can enhance efficiency, it also poses risks to financial stability, necessitating a balanced approach in regulatory design. The mentioned articles, as well as others, investigate the implications of network topology in the credit market and system stability. One may find a review on the subject in Bardoscia *et al.* (2021).

Since the financial crisis, financial regulators have introduced new policies aimed at reducing systemic risk and financial contagions. The failure of the microprudential setup raised the necessity of a macroprudential approach (Crockett, 2000). A review of macroprudential policies can be found at Schoenmaker and Wierts (2011), Galati and Moessner (2013), Kahou and Lehar (2017). The most relevant class of prudential policies for this study is the requirement of a risk-weighted capital coverage (Bakker *et al.*, 2012). These measures are effective when it comes to reducing risk in lending and increasing financial stability

(Lorenčič; Festić, 2022; Claessens, 2014; Ely; Tabak; Teixeira, 2021b). On the other hand, there is evidence that capital requirements and other prudential policy tools reduce credit growth and increase borrowing constraints (Brockmeijer, 2012; Cerutti; Claessens; Laeven, 2017), hence having an anti-cyclical effect. Using an ABM, Catullo, Giri, and Gallegati (2021) show that a combination of micro- and macroprudential policies reduces systemic risk but at the cost of increasing banks' capital volatility. Second, it is shown that mesoprudential policy is an effective tool in reducing systemic risk through tightening the capital requirements of more connected banks only. In general, the literature finds that macroprudential measures are effective in curbing the excess of credit creation and risk-taking behavior during the expansive economic phases, dampening the procyclicality of banking activity.

Given its stated objectives, macroprudential policies would be expected to curb average firm credit growth and, potentially through the effect on credit, affect firm investment and sales growth. However, an important point is whether macroprudential policies have distributional consequences with their impact varying by type of firm. Ayyagari, Beck, and Peria (2018) indicate that macroprudential policies are negatively associated with firm financing growth, but there are heterogeneous effects depending on the type of policies and firms. MSMEs (firms with fewer than 250 employees) and young firms (those three or less years of age) are more affected by macroprudential policies than larger and older firms. Also, among MSMEs and young firms, the negative association between credit growth and macroprudential policies is stronger for the least credit worthy and riskiest firms, in line with the stability-enhancing goal of such policies. Using data from Chinese commercial banks, Ma *et al.* (2013) findings suggest that commercial banks discriminate against small businesses in lending operations, and capital requirements would intensify such discrimination, making small business loans more difficult to obtain. Kang *et al.* (2021) find a U-shaped policy effect on the debt distribution of firms in China: Bank regulation tightens credit more intensely for firms with high leverage, but only up to a threshold after which the policy effect declines.

The debate on whether banks should concentrate or diversify their portfolios is long-standing. While traditional banking theory argues that banks should diversify their portfolios in order to reduce their chances of suffering costly financial distress (Diamond, 1984; Boyd; Prescott, 1986; Rossi; Schwaiger; Winkler, 2009). In contrast, the theory of corporate finance supports the specialization of banks in order to obtain the greatest possible benefit from management expertise and to reduce agency problems (Jensen, 1986; Denis; Denis; Sarin, 1997; Acharya; Hasan; Saunders, 2006). Winton (1999) argues that the benefit from diversification should be greatest when banks' loans have medium levels of downside risk. When risks are low, banks may benefit more from specialization than from diversification, since there is a low probability of failure. Conversely, when the probabilities of insolvency are high, diversification may even worsen the situation, since the bank will expose itself to many sectors, and the downturn of one may be enough to lead this bank to bankruptcy. Empirical evidence is mixed. While Acharya, Hasan, and Saunders (2006) show that diversification increases risk in the Italian banking sector, Tabak, Fazio, and Cajueiro (2011) find that loan portfolio concentration increases returns and also reduces default risk for Brazilian banks.

This work also explores how the asymmetry of information influences the credit market. Stiglitz and Weiss (1981) conclude that credit rationing is a rational outcome for lenders in markets where they cannot perfectly observe the riskiness of borrowers.They argue that because raising interest rates further could worsen the lender's risk-adjusted returns, lenders may prefer to ration credit rather than raise rates. This means that even creditworthy borrowers might be denied loans not because they are inherently too risky, but because the information asymmetry prevents lenders from differentiating between high- and low-risk borrowers effectively.

3 Methodology

The model we present is an agent-based model built within a game-theoretical setting. Each agent has an objective function and a set of strategies and repeatedly evaluates these strategies. With bounded rationality and imperfect, incomplete information, agents do not know previously others' moves or payoffs. Instead of analyzing the game to reach a set of Nash equilibria, they rely on past experiences to assess strategy performance.

We have organized this section into four subsections. Section 3.1 explains the learning process used by all intelligent agents in our model. Section 3.2 details the behaviors and decisions of different entities, including banks, firms, depositors, the central bank, and the clearinghouse. Section 3.3 provides an overview of the simulation timeline, while Section 3.4 presents the metrics used to assess credit distribution.

3.1 Learning Process

Our paper adopts an experience-weighted attraction (EWA) mechanism, following (Barroso *et al.*, 2016) and based on the framework established by (Camerer; Ho, 1999). The EWA scheme combines two approaches to modeling agent behavior: reinforcement learning and belief-based learning. Reinforcement learning follows the law of actual effects, which states that successful strategies are more likely to be chosen again (Roth; Erev, 1995). Belief-based learning follows the law of simulated effects, which states that strategies not chosen but that would have been successful are more likely to be adopted in the future (Fudenberg; Levine, 2018). As a hybrid model, EWA blends belief-based elements (where players form beliefs about others' actions based on history) with reinforcement models (where players only consider past payoffs and not the history of play that generated those payoffs).

We describe the learning scheme using a game with n agents indexed by $(i = 1, \dots, n)$, each having a strategy set $S_i = \{s_i^1, s_i^2, \dots, s_i^j, \dots, s_i^{m_i-1}, s_i^{m_i}\}$. A general period is denoted by t, where player i selects strategy $s_i(t)$ and receives a payoff defined by $\pi_i(s_i(t), s_{-i}(t))$. The vector of strategies played by all other players (excluding i) is given by $s_{-i}(t)$.

The EWA mechanism employs an attraction function to measure strategy appeal. We use the learning setup from (Pouget, 2007; Barroso *et al.*, 2016) and (Adão *et al.*, 2022), where the attraction level of strategy j for player i at any time $t > 0$ is:

$$A_i^j(t) = \varphi A_i^j(t-1) + \pi_i(s_i^j, s_{-i}(t)), \tag{3.1}$$

where the discount factor for previous attractions is $\varphi = 0.9999$.

Agents' choices follow a mixed strategy derived from a logit model:

$$P_i^j(t+1) = \frac{e^{\lambda \cdot A_i^j(t)}}{\sum_{k=1}^{m_i} e^{\lambda \cdot A_i^k(t)}}, \tag{3.2}$$

for all players i and strategies j.

This setup incorporates both actual and simulated effects by considering both actual payoffs and past strategy attractiveness. Given the empirical validation of the EWA mechanism in multiple settings (Camerer; Ho, 1999), all intelligent agents in our model adopt this learning mechanism.

3.2 Agents

The following sections describe the relevant agents, along with their strategies sets and payoff functions. These characteristics define their behavior, which in turn shapes how the aggregate variables behave.

3.2.1 Banks

Banks play a central role in this framework as financial intermediaries, controlling several key variables. Two parameters define their balance sheet: the first is α, which represents the ratio of capital to other liabilities. This ratio determines the bank's leverage and exposure to losses. The second is β, which reflects the proportion of liquid to illiquid assets (loans) and determines the liquidity held by the banks that depositors can withdraw without issue.

The model also incorporates γ as a third strategy, which represents the ratio of high-risk loans in the bank's portfolio, capturing the bank's risk-taking behavior. The total asset value for each bank is given by the exogenous parameter T_b. These parameters are integral to the models presented by (Barroso *et al.*, 2016) and (Adão *et al.*, 2022).

Additionally, there are two variables that manage the interest rate spread setting behavior of the bank. Banks' strategy, in that sense, must account for how the interest rate depends on the associated credit risk. We consider the following maximization problem to represent the credit supply choice:

$$\max_{I} \qquad (1-p)(1+i(I))I - cI$$

This equation describes a monopolist financial institution's credit supply decision, where c is the average capital cost, p is the default probability, and $i(I)$ is the credit demand. The first-order condition, equating marginal revenue to marginal cost, results in the following pricing rule:

$$(1 + i(I)) = \frac{c}{(1-p)} i'(I)I$$

Rearranging the equation to write it in the mark-up rule form, we can rephrase it in the following way:

$$(1 + i^*) = \frac{c}{(1-p)} \frac{1}{1+\varepsilon^D}$$

where $\varepsilon^D = \frac{Ii'(I)}{1+i}$ is the elasticity of credit demand relative to the interest rate. The strategy we introduce to enable endogenous price setting is the mark-up rate $\mu = \frac{1}{1+\varepsilon^D}$. Therefore, banks choose a mark-up rate in order to define the charged interest rate in the process of trying to maximize profit. The real sector and interbank market have different mark-up rates, meaning that if a bank chooses a pair of mark-up rates μ_R and μ_{IB}, the interest rates at which it offers its credit are:

$$(1 + i_R) = \frac{c}{(1-p)} * \mu_R \qquad \text{and} \qquad (1 + i_{IB}) = \frac{c}{(1-p)} * \mu_{IB} \tag{3.3}$$

where c is the cost of the bank's funds, which is essentially an average of deposit costs and capital costs, and the value p is the client's default risk. Since the model no longer assumes perfect information, banks no longer know the true value of p. The value of p is estimated in two steps. First, the banks predict whether the firm is high or low risk, using a logit model based on the firm's size. After classifying the firm as high or low risk, the default risk of the client of type T is estimated using the following rule:

$$p_T = \overline{p_T} + \frac{\theta}{x^{(1/\mu)}} \tag{3.4}$$

where x is the firm's size, p_T is the baseline probability of default for the firm of type T and θ and μ are parameters defining the shape of the inverse power law. With that, we can capture some non-linearity in the relationship between the firm size and its default risk.

We define the entire strategy set, in general, as a vector[3] $(\alpha,\beta,\gamma,\mu_R,\mu_{IB}) \in [0,1]^5$, defining the banks' choice. Table 3.1 summarizes this setup.

Table 3.1 – Banks' strategy list

	Item	Strategy
Liability	Capital deposit ratio	$\alpha \in [0,1]$
Asset	Liquid illiquid asset ratio	$\beta \in [0,1]$
Asset	High/low risk loans ratio	$\gamma \in [0,1]$
Interest	Real sector mark-up	$\mu_R \in [0,1]$
Interest	Interbank sector mark-up	$\mu_{ib} \in [0,1]$

[3] We denote $[0,1]^n$ as the Cartesian product of the set $[0,1]$ n times.

The bank's payoff function is determined by its return on equity (ROE), measured at the end of each cycle. The profit is the difference between the final and initial capital:

$$\Pi = K^2 - K^0, \tag{3.5}$$

The banks' objective function, the one it maximizes, is then:

$$ROE = \frac{\Pi}{K^0}. \tag{3.6}$$

Another important bank variable is the Capital Adequacy Ratio (CAR), which is the ratio of capital related to Risk-Weighted Assets (RWA). The calculation of RWA in this model does not include liquid assets, as they're considered riskless assets. For a bank b, F_b is the set of firms in its lending portfolio. Then we have the following:

$$CAR_b = \frac{K_b}{w_{IL}IL_b + \sum\limits_{f \in F_b} R_{b,f} \cdot w_f}, \tag{3.7}$$

where IL_b is the amount of interbank loan, w_{IL} is its respective risk weight, $R_{b,f}$ is the loan amount to firm f, and w_f is its risk weight. Due to the imperfect information nature of the model, banks no longer know the actual risk weight. So, the weight used is the bank's estimated default probability for the borrowing firm using equation equation (3.4). The set of firms that borrow from bank b is F_b , and each of them belongs to one of the following groups: high-risk or low-risk. If necessary, a bank can adjust its CAR by selling part of its loan portfolio before its maturity. In that case, it will incur a discount of δ_L to reflect the loss due to the low liquidity of the asset. If many depositors of bank b (more than 50%) simultaneously withdraw their money, bank b faces a fire sale. Under these circumstances, the following additional discounts are granted to their illiquid assets: δ_{sHR} in the case of loans to higher risky firms; and δ_{sLR} in the case of loans to lower risky firms. These additional discounts explain the difficulty banks face in selling their illiquid assets, especially when they are facing financial difficulties.

3.2.2 Firms

Unlike the former setup of the model, firms are heterogeneous in their sizes and probability of default. The size of the firm is drawn from a power law distribution[1](Gaffeo; Gallegati; Palestrini, 2003). The probability of default of each firm is generated from the following inverse power law:

$$PD_T = \frac{\theta_T}{x^{(1/\mu_T)}} \tag{3.8}$$

[1] $P(x) \propto x^{-\theta}$

where x and T are the firm's size and type (high or low risk), respectively. Firm's type are assigned based on two-step procedure. First, based on a Logit model, is estimated the probability of the firm being low risk. In a second moment, a random variable between 0 and 1 is sorted, and if this variable's value is lower than the firm's probability of being low risk, then the firm is classified as such. Otherwise, the firm is labeled high risk. So, the firm definition timeline is: First, it's size is drawn from a Power Law distribution; then, it is classified as low or high risk, considering the procedure mentioned above; and at last, its default probability is calculated using equation Equation (3.8).

The real sector behavior is quite simple. The most relevant feature is its sensitivity to the interest rate and in order to justify this, an investment optimization model is necessary. Consider the following problem:

$$\max_{I}(1-p)F_{success}(I)+(p)F_{failure}(I)-(1+i)I$$

where I is the amount of investment, i a given interest rate and the profit of a firm follows a Bernoulli random variable with parameter $1-p$. Although the use of a Bernoulli distribution is a simplified assumption, it is noteworthy that such modeling approaches have been employed in theoretical frameworks within the literature. Similarly, (Warusawitharana, 2015) uses a Bernoulli distribution to model the probability of successful innovation of firms, while (Gómez, 2015) uses a Bernoulli distribution to model the arrival of new banks in a monopoly state.[3] Thus, the equation above simply represents the expected profit under a two-scenario setting, where production can either be a success, with probability $(1-p)$, or a failure. Without loss of information, we may consider that $F_{failure}(I)$ is 0, and the first-order condition will then yield a credit demand curve described by the equation:

$$1+i=(1-p)F'_{success}(I)$$

The firm is endowed with a credit demand equation, justified by the reasoning above, that represents the totality of the firm's behavior in this model. Specifically, in our simulation, the credit demand function is linear and takes the form[4]: $I = A * (1 - DiscountFactor) - b\frac{(1+i)}{(1-p)}$. The discount factor is introduced to differentiate firms' demand for credit according to their size. It follows:

$$DiscountFactor = \frac{\theta}{x^{(1/\mu)}} \tag{3.9}$$

[3] In a real world scenario, we may estimate a Probit or a Logit model for a sample of firms and use the attributes of a given firm in order to estimate the value of p or $1-p$.

[4] This is equivalent to having $F_{success} = \frac{AI}{b} - \frac{I^2}{2b}$

3.2.3 Depositors

Depositors act as noisy agents that exhibit unintelligent behavior. Depositors can be of two types: Patient, ie, those who will wait until $t = 2$ for their deposits to mature and withdraw the amount deposited plus the return and Impatient, ie, those who will withdraw at $t = 1$ and give up the return, receiving only the amount deposited. For simplicity, we consider that an impatient depositor withdraws the total deposit amount at $t = 1$. The decision to withdraw their deposits at an early date, which is the primary cause of liquidity shocks in this model, is purely stochastic, as in (Gabbi *et al.*, 2015). Consequently, depositors consistently create liquidity shocks and immediate liquidity needs for banks, leading them to resort to the interbank credit market.

The noisy behavior of depositors consists in withdrawing their deposits in full with probability $p = 0.15$. Since each bank has several depositors as its clients and has a total of deposits determined by the parameter α (one of its strategic decisions), the deposit size is given by the total deposit divided by the total number of depositors. The shock distribution is then given by a binomial distribution with parameter $p = 0.15$ and n equal to the number of depositors.

3.2.4 Central bank

The central bank works as the system regulator, as the monetary policy entity and as the lender of last resort. As the system regulator, it imposes minimum CAR as a regulatory measure and it enforces capital requirement policies by requiring banks to sell risky assets and comply with current regulations. If a bank's CAR is below the minimum established, the central bank will force it to rise to the minimum. If it fails to do so, the central bank liquidates the bank. As the monetary policy entity, it uses a risk-free interest rate as a monetary policy tool. Furthermore, as a lender of last resource, when a bank faces a liquidity shortfall that cannot be resolved through the interbank market, the central bank provides the necessary funds to the bank in need, albeit at a higher, punitive interest rate.

For the purpose of this work, the central bank is considered an exogenous agent and it is described by fixed parameters regarding the cited actions, which are used in a comparative way to explore policy scenarios.

3.2.5 Clearing house

The clearing house acts as an intermediary between borrowers and lenders, connecting them to each other. It collects information on all available credit suppliers and arranges them in order of the lowest to highest spread, and sorts borrowers from the riskiest to the least risky. This enables banks to compete for the best clients and offer interest rates that are low enough to facilitate lending. This process occurs in both the real sector market and the interbank market.

3.3 Simulation timeline

The simulation is structured in cycles consisting of three steps, denoted by $\tau = 0, 1, 2$, a procedure also used in (Allen; Gale, 1998) and (Allen; Gale, 2000b). At the start of each cycle ($\tau = 0$), there is no interbank activity. During this phase, agents define their strategies probabilistically, following the mixed strategies derived from the EWA learning mechanism. Banks make decisions regarding their initial balance sheets, credit supply, and interest rate markup rules. Still within $\tau = 0$, the real sector credit market operates, matching firms with banks and forming a loan network.

In the next step, $\tau = 1$, depositors withdraw funds, generating liquidity shocks. Banks must use their liquid assets or turn to the interbank credit market to cover these withdrawals. If banks cannot meet their liquidity demands through the interbank channel, the central bank steps in as the lender of last resort, providing the necessary liquidity. At this point, the central bank also reviews the banks' balance sheets and enforces any active prudential policies. Banks with $CAR > CAR_{min}$ are required to sell their risky assets to reduce their capital adequacy ratio to $CAR = CAR_{min}$.

In the final step, $\tau = 2$, banks collect loan repayments and pay interest to their creditors. If a bank becomes insolvent, with losses exceeding its capital, the central bank steps in to liquidate and penalize the bank, potentially leading to further losses. After this, banks use the EWA mechanism to update their attraction levels based on their final profits or losses, and the simulation proceeds to the next cycle. It is important to note that if a debtor defaults on interbank loans, it may cause other banks to become insolvent, leading to financial contagion.

At the end of each cycle, agents carry forward only the knowledge gained, represented by the attraction levels for each strategy, while all other variables are reset to their default values. Banks are not created or removed during this process.

The complete simulation consists of repeating the cycle 10,000 times, allowing agents to learn from experience and converge toward optimal strategies. Banks' strategies are implemented computationally using a five-dimensional grid. Each individual strategy parameter $(\alpha, \beta, \gamma, \mu_r, \mu_{IB})$ is divided into 15 increments over the interval [0,1], resulting in 15^5 strategy options per bank. To reduce the influence of random variation and enhance robustness, the Monte Carlo method is employed. Each scenario is run 20 times and the results are aggregated.

3.4 Concentration Measures

In order to assess concentration in the credit market, two different measures of concentration are implemented. The first one is the Herfindahl-Hirschman Index (HHI) (Rhoades, 1993), that has been one the most known concentration measure in Industrial Organization and in the studies about this matter, due to its relatively simplicity and is calculated as:

$$HHI = \sum_{i=1}^{N} (\frac{L_i}{L_{total}})^2$$

where L_i represents the total amount of loans of firm i and L_total is the total amount of loans granted by the banks. The second one is the Concentration Ratio (CR), that measures the concentration of credit the n firms of a industry and is estimated as:

$$CR_n = \frac{\sum_{i=1}^{N} Li}{L_{total}}$$

Due to their simplicity and direct interpretation, the HHI and the CR are good options to assess concentration in the lending market within our model.

4 Results

In this section, we present the simulation results, describing, analyzing, and comparing each relevant scenario considered. In section 4.1 we describe the parameters utilized to calibrate the model. section 4.2 analyzes the results of the model from the perspective of credit supply and distribution, and interest rates, while section 4.3 focuses on bank risk taking and financial stability.

4.1 Parameter Calibration

The parameters used to calibrate the model follow (Lima; Ely; Cajueiro, 2024). In that paper, the authors collected data from IMF databases[1]. To replicate scenarios for countries in different stages of development, the parameters values were divided between developed and emerging countries. To calibrate the demand function parameters, they paired market interest rates from the same database with the monetary policy and performed test simulations to obtain a reasonable result.

In this study, the scenario considered is closer to that of a developing country. But now an extra layer of heterogeneity is introduced in the model. First, in order to observe distributional consequences, firms have different sizes, drawn from a Power Law distribution (Gaffeo; Gallegati; Palestrini, 2003). The θ and μ parameters in equation (3.8) are chosen so that the probability of default of the firms can hover around the probability of default for each type ($\overline{p_T}$ in equation (3.4)). In the other situations, these values are tuned to keep the dynamics of the model, while introducing some non-linearity.

For the parameter CAR_{min}, which is the minimum capital adequacy ratio imposed by the monetary authority, we use the Basel III recommendations for Tier 1 Capital (BIS, 2011; BIS, 2019). Other relevant financial variables in the model are calibrated to be similar to the gathered data and values used in the literature. The number of firms and depositors is set to be sufficiently high to prevent large losses due to the concentration of loan portfolios in a single firm and to mitigate extreme liquidity shocks. For each bank, both the loan portfolio and the depositors must be diverse and sizable, so that the probability of default aligns with the parameters set in the model.

Table 4.2 presents the values of the financial parameters used in the simulations.

In the following sections, we present the simulation results for scenarios with and without the imposition of minimum capital requirements (CAR_{min}). We explore the effects

1 Financial Soundness Indicators (FSI) and International Financial Statistics (IFS)

Table 4.1 – Agents parameters values

Parameter	Description	Value
θ^{Bank}	Banks' θ in equation (3.4)	0.6
μ^{Bank}	Banks' μ in equation (3.4)	0.6
θ^{Firm}_{LR}	Firms' θ for low risk firms in equation (3.8)	0.45
θ^{Firm}_{HR}	Firms' θ for high risk firms in equation (3.8)	0.4
μ^{Firm}_{LR}	Firms' μ for low risk firms in equation (3.8)	0.9
μ^{Firm}_{HR}	Firms' μ for high risk firms in equation (3.8)	1.4
θ^{Credit}	Credit demand's θ in equation (3.9)	0.8
μ^{Credit}	Credit demand's μ in equation (3.9)	0.6

Table 4.2 – Financial parameters values

Parameter	Description	Value
N_B	Number of banks	50
N_D	Number of depositors per bank	100
i_d	Monetary policy interest rate	0.07
CAR_{min}	Minimum capital adequacy ratio	0.08
P_W	Probability of withdrawal	0.1
$P_{D_{HR}}$	Baseline High risk corporate loan default rate	0.1
$P_{D_{LR}}$	Baseline Low risk corporate loan default rate	0.05
w_i	Interbank loan risk weight	1
w_{HR}	High risk corporate loan risk weight	5
w_{LR}	Low risk corporate loan risk weight	2
T_b	Bank size parameter	1

on credit distribution among firms and how this different setup impacts the credit market and financial stability.

4.2 Credit market and interest rates

4.2.1 Credit supply

Our simulations point in the direction of a relevant influence of the presence of a prudential setup in the credit market. As shown in figure 4.1, with the introduction of a Basel III CAR requirement there is a contraction in the volume of loans issued by banks in the economy. This contraction effect of prudential policy on credit is backed by empirical evidence (Brockmeijer, 2012; Ely; Tabak; Teixeira, 2021b). Within the model, the credit reduction operates through the channel of the effect of capital requirements, which forces banks to sell excess loans, hence shrinking credit supply.

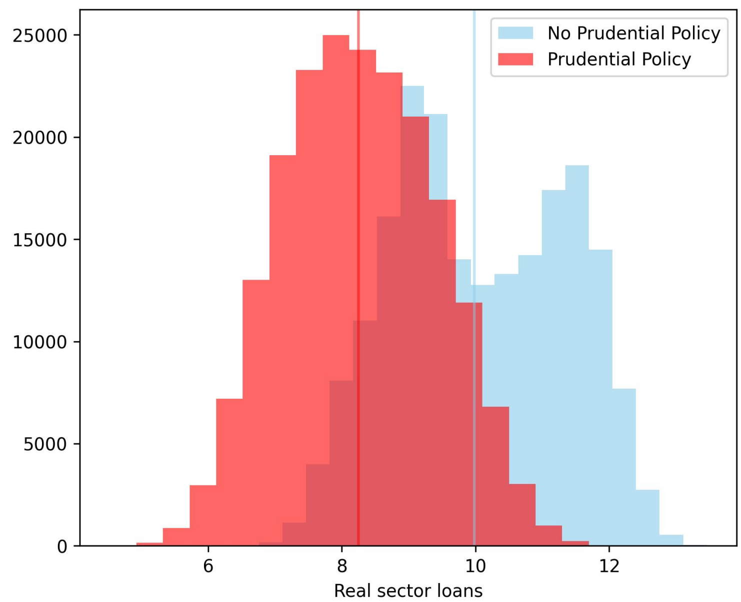
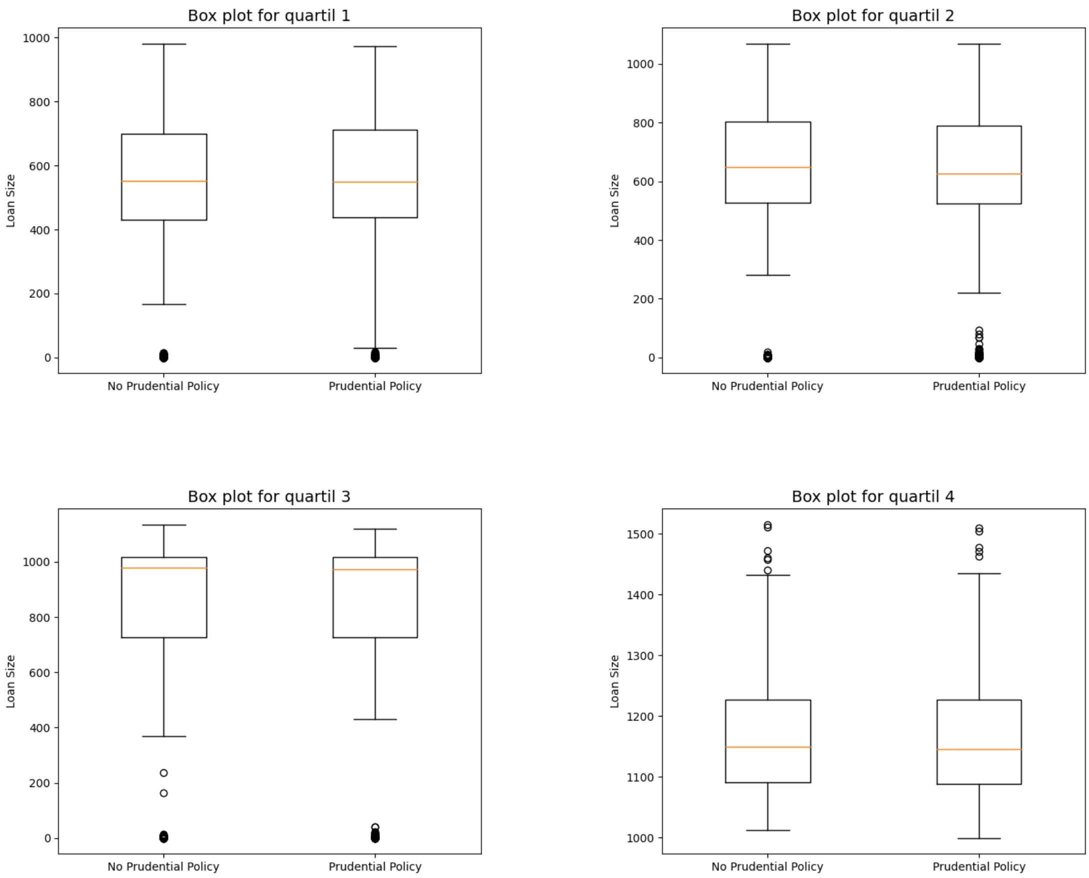


Figure 4.1 – The distribution of total credit supplied

It is also worth noticing how the implementation of the macroprudential policy changes the shape of the credit distribution. While in the baseline scenario the distribution seems more bimodal, with the prudential policy the distribution has a near normal distribution. This can indicate that, when absent of a macroprudential enforcement, banks allocate credit more unevenly, probably seeking higher profitability, either via higher yields (high-risk loans) or volume (low-risk loans).

In figure 4.2, there is the credit distribution at the firm level, grouping firms into four quartiles. As we analyze the effects of the prudential policy in the credit market, some things are worth highlighting. First, for all quartiles, there is a decrease in the median size of the loans, although very marginal. The second quartile is the most affected, with a reduction of 3,4% in the median. That results can indicate an interesting consequence of the introduction of a prudential setting, indicating that such a policy may exert a higher burden on smaller firms that had access to credit previously. The second observed fact is the increase of the variance for the upper quartiles, indicating a possible reduction in credit concentration for bigger firms. These findings indicate a heterogeneous effect on firms when faced with a prudential policy (Ayyagari; Beck; Peria, 2018).

Figure 4.2 – Quartile distribution of credit data



4.2.2 Credit Concentration

As we observe the credit supply from a distributional standpoint, there is a clear concentration in the lending market in response to the implementation of a prudential policy. In figure 4.3 and figure 4.4 we can see there is an increase in the Herfindahl-Hirschmann Index (HHI) as well as the Concentration Ratio[2] (CR5) in the aftermath of a prudential policy introduction. This result is in line with many empirical findings in the literature that show how prudential policy raises lending restrictions, especially for smaller firms with fewer financing options and considerable reliance on bank credit (Ćehajić; Košak, 2022).

2 Here was used the concentration ratio for the top 5 firms

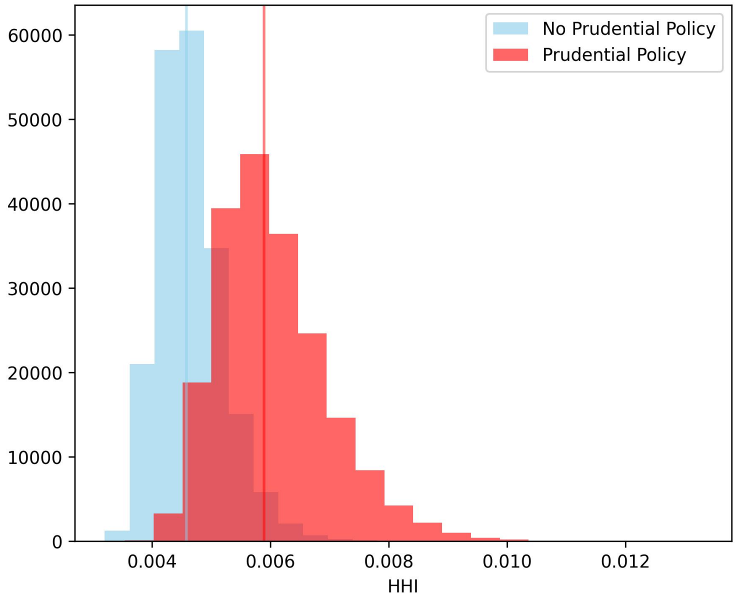


Figure 4.3 – The distribution of the Herfindahl-Hirschman Index (HHI)

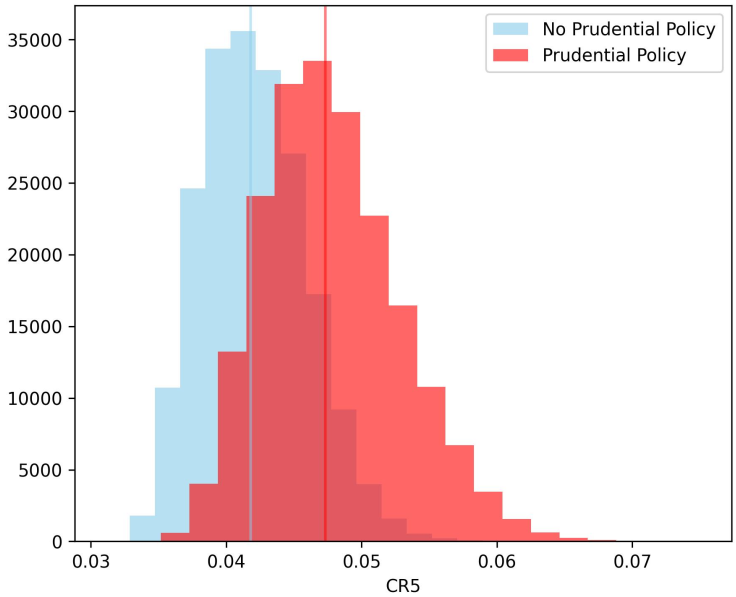


Figure 4.4 – The distribution of the Concentration Ratio (CR5)

The increase in concentration in the lending market raises a debate around the social costs of prudential policies, especially when takes into consideration the importance of bank financing to small firms (Cull *et al.*, 2006). Considering how important is credit availability for small firms (Mach; Wolken, 2012), these results increase the necessity for a better understanding of the mechanisms of transmission of the macroprudential policy as well as the coordination of such policies with credit policies.

4.2.3 Market interest rates

Concerning market interest rates, we observe a similar behavior as in the case of credit supply. In figure 4.5, we can see that prudential policy raises market interest rates as credit supply diminishes. The CAR requirement also functions as a capital tax imposed on banks, leading to higher market interest rates. Unlike the findings of the previous work (Lima; Ely; Cajueiro, 2024), the effect on interest rates is less pronounced here. The main reason behind this results is that, as lending concentration increases, the average interest rate charged by the bank also goes down, since bigger firms are usually less risky.

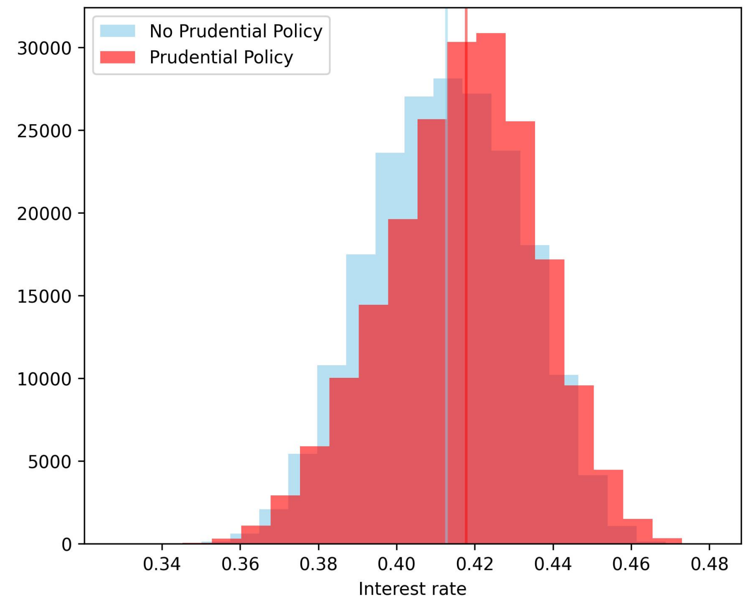


Figure 4.5 – The distribution of interest rates

4.3 Banks behavior and financial stability

Another dimension of the credit market, one related to system stability, is the behavior of banks when defining their balance sheets in terms of capital, asset portfolio, and loan risks. For instance, the ratio of liquidity assets determines how resilient a bank is to early withdrawals, while capital makes banks more resistant to losses and prevents insolvency. On the other hand, higher loan risks increase instability and the likelihood of defaults but may also bring risk premia. These variables are crucial for prudential policy, which aims to reduce systemic risk.

4.3.1 Capital

When we look at how the prudential policy affects capital, we find a counterintuitive outcome. While prudential policy seeks a higher amount of capital, to increase banks' resistance to defaults, our simulations point in the other direction, as can be seen in figure 4.6.

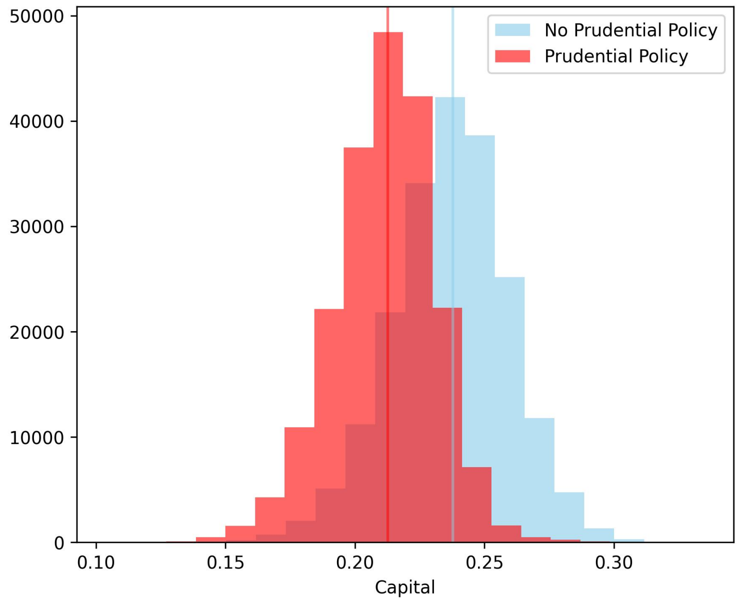


Figure 4.6 – The distribution of capital

The main channel for the reduction of banks' capital in face of a capital minimum requirement is through banks' profitability (Davis; Karim; Noel, 2022). Confronted with the policy, banks reduce risky loans and allocate more to lower-yield liquid assets, therefore reducing profits. This contraction in profits has a negative impact on banks' capital. Given this scenario, the prudential policy might produce net results contrary to those originally pursued, reinforcing the care in implementing such policies.

Despite the reduction, capital levels are higher than the previous model setup (Lima; Ely; Cajueiro, 2024). The asymmetry of information in the lending market is the main driver of this phenomena, as it increases the borrowing cost and therefore reduces the credit demand from firms.

4.3.2 Risk taking behavior and insolvency

When it comes to stability, the Capital Adequacy Ratio (CAR) requirement is effective in achieving its goal of reducing leverage and insolvencies, thereby increasing financial stability. This result is consistent with many studies in the literature that demonstrate the risk-reducing effects of macroprudential instruments (Ely; Tabak; Teixeira, 2021b; Lorenčič; Festić, 2022;

Claessens, 2014; Davis; Liadze; Piggott, 2019). In figure 4.7, we can see how insolvencies respond to capital requirements. The insolvency ratio shows a slight and consistent reduction in the presence of CAR requirements. Although banks hold less capital after the introduction of the prudential policy, they are still relatively financially sound, as we can seen from the distribution of the banks Capital Adequacy Ratio (CAR) in figure 4.8.

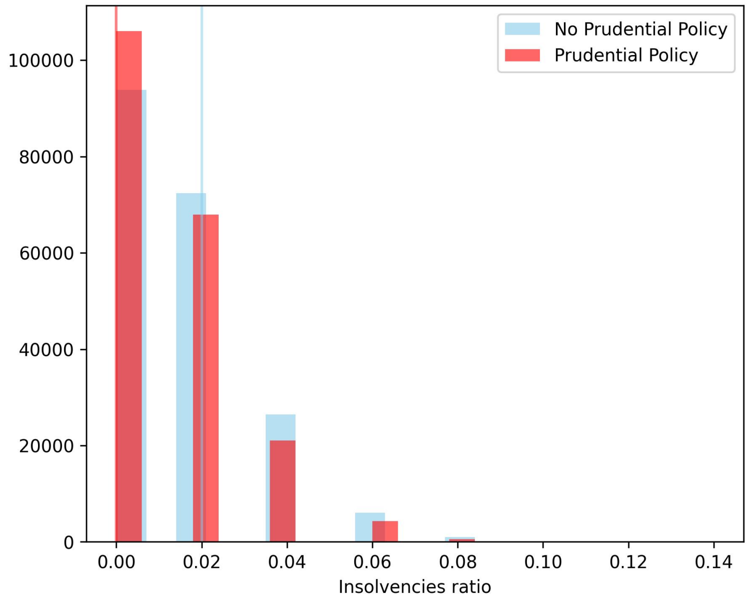


Figure 4.7 – The distribution of insolvencies

The simulations reveal that the imposition of capital requirements appears to have no effect on risk. This finding contrasts with some of the existing literature on the subject (Ely; Tabak; Teixeira, 2021b), but it can be explained by the logic and narrative of the model construction. Since banks aim to maximize profit, capital constraints make them more likely to seek higher risk premia by investing in high-risk loans while keeping the total amount of loans low. This, coupled with the capital buffer that prevents insolvency, can lead to a situation where capital requirements induce high-risk loans. But this risk-taking effect is eased by the credit concentration effect observed in the lending. In the light of a higher concentration, there is a reduction in risk, since bigger firms are less risky than smaller firms in our model, in line with the theory of corporate finance (Jensen, 1986; Denis; Denis; Sarin, 1997; Acharya; Hasan; Saunders, 2006). However, it is important to note that the model is a simplified representation of the real-world banking system, and several important features are overlooked in the analysis.

Figure 4.9 presents the results of the simulations for the ratio of high-risk loans to total loans in each scenario. It can be seen that the enforcement of capital requirements leads to an increase in the mean ratio of high-risk loans. These results suggest that policymakers

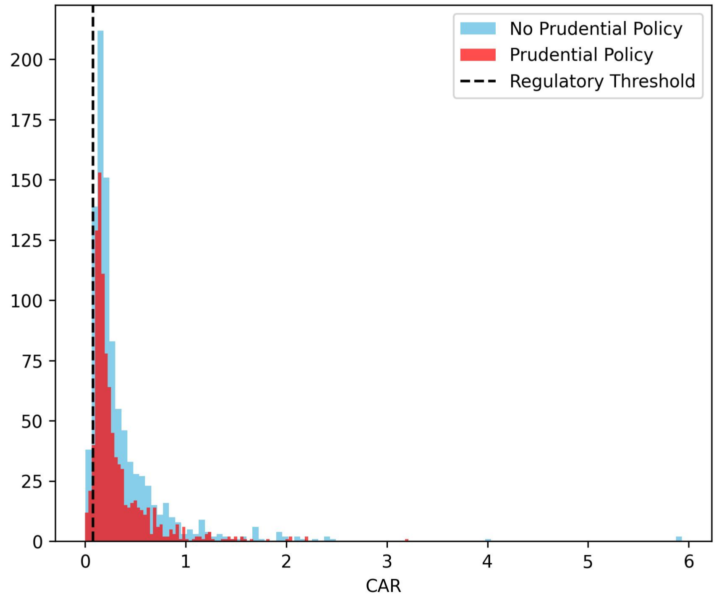


Figure 4.8 – The distribution of Capital Adequacy Ratio (CAR)

should carefully consider the potential unintended consequences of capital requirements on risk-taking behavior in the banking sector, especially in the context of low interest rates (Lima; Ely; Cajueiro, 2024). Given that, the implementation of capital requirements could be coupled with a leverage ratio limit (Acosta-Smith; Grill; Lang, 2024).

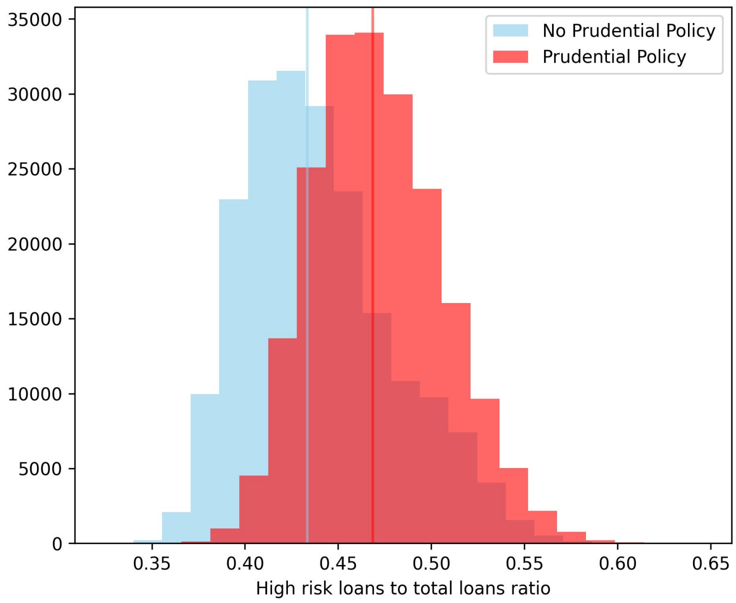


Figure 4.9 – The distribution of high risk loan to total

The fact that the usual negative relationship between restrictive prudential policies and banks' risk-taking behavior is not present in the model can be attributed to features of banking behavior and risk perception that are not accounted for in our model, such as reputation effects of lending to high-risk firms and facing defaults.

5 Conclusion

In this study, we develop an agent-based model of the banking system and simulate different policy scenarios to analyze the impact of prudential policy on credit distribution, financial stability, credit market size, and interest rates in a credit market with information asymmetry and firm heterogeneity. Our results align with other models, such as (Iori *et al.*, 2015) and (Gabbi *et al.*, 2015), and provide valuable insights for policymakers.

First, we find that increasing the minimum capital adequacy ratio (CAR) requirement contracts credit supply, consistent with both empirical and theoretical literature (Brockmeijer, 2012; Cerutti; Claessens; Laeven, 2017; Ely; Tabak; Teixeira, 2021b). This contraction arises because prudential policy directly restricts loan amounts. The retraction affects smaller firms more significantly, particularly those that were not credit-constrained before the policy's implementation. This effect appears in the increased concentration of the lending market, measured by the Herfindahl-Hirschman Index (HHI) and the Concentration Ratio (CR). These findings underscore the need for a better assessment of the distributional consequences of prudential policies. Additionally, points for possible collateral effects of the macroprudential policy.

Second, we measure financial stability through two output variables: the number of insolvencies and the ratio of high-risk loans to standard loans. Our simulations show that capital requirements reduce insolvencies, as banks decrease loan amounts and allocate more funds to larger firms with lower risk profiles. The information asymmetry in the lending market also plays a role in the stability of the system as banks hold more capital than they would under perfect information (Lima; Ely; Cajueiro, 2024), due to informational transaction costs. However, there is an increase in the high-risk loan ratio in the model, indicating banks become more risk-prone when subject to a macroprudential environment. This shows how, if not correctly assessed, the implementation of a policy may produce undesired outcomes.

Lastly, when we look at how the rise in credit concentration impacts the system, the results show a positive effect on risk, as bigger firms are less risky in our setup. This finding corroborates with the corporate finance theory, which advocates for banks' portfolio specialization. However, due to the simplified nature of the model and the relatively low levels of concentration, this result should be treated carefully.

Our study contributes to the literature on the distributional effects of prudential policies on firms. Our results align with previous studies that find significant impacts on small firms following the introduction of prudential policies (Ayyagari; Beck; Peria, 2018; Ma *et al.*, 2013; Ćehajić; Košak, 2022). Future research could explore additional economic dimensions, such as distributional effects among individuals, the inclusion of more financial assets like a mortgage market, and a more detailed real sector within the model. Further studies could also compare the effects of other prudential policies, including the capital conservation buffer, limits on bank leverage and loan-to-value ratio limits.

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Appendices

Appendix A – Overview, Design concepts and Details protocol

In this appendix, we describe our model using the ODD protocol (Grimm *et al.*, 2006; Grimm *et al.*, 2010; Müller *et al.*, 2013; Grimm *et al.*, 2020). The ODD protocol offers a template for providing a model overview, which helps to standardize ABMs to some extent. It includes the purpose and main processes that take place in the model, the Design concepts of the model, and the Details necessary for the implementation of the model.

As the protocol suggests, this appendix is divided into three subsections. section A.1 presents the overview of the model, contemplating the model's purpose and patterns. section A.2 provides a description of the model's design. The final section, section A.3, offers a detailed view of the model particularities, following the ODD protocol.

A.1 Overview

A.1.1 Purpose and Patterns

The model presented is an agent-based model built to analyze banks' individual and aggregate behavior regarding the response to different prudential policy instances. The model aims to better understand the interaction between these policy and their different impacts on the credit market, with a greater focus on credit distribution. Information asymmetry in introduced in the lending market. However, the model does not attempt to replicate the behavior of financial fluctuations or policy setting by authorities.

Patterns observed that validate the ability of the model are:

- **Contraction of the credit market when prudential policy is restrictive.**
- **Prudential policy increases credit constrainment to small firms.**

A.1.2 Entities, state variables and scales

The model includes several entities, such as banks, firms, depositors, a clearing house, and a central bank. Banks are the primary agents in the model, receiving deposits from depositors and lending to firms, with the ability to control the degree of liquidity and risk in their portfolio and set interest rates. Firms are endowed with a credit demand and invest in projects with random outcomes, and can be of two types, high or low risk. Depositors are characterized as noisy, randomly withdrawing their deposits early and creating liquidity shocks to banks, forcing them to resort to the interbank credit market or the central bank.

The clearing house ranks firms from riskiest to less risky and banks from highest to lowest interest rate, keeping records of loans in both the real and interbank sectors. Finally, the central bank acts as a lender of last resort and system supervisor, with the authority to liquidate banks if necessary.

In table A.1, we present the attributes and state variables associated with banks:

Table A.1 – The attributes and state variables associated with banks.

Variable Name	**Description**
T	Bank size parameter, total assets
α	Capital to total liabilities ratio
β	Liquid assets to total assets ratio
γ	High risk firms loans to total loans ratio
μ_R	Mark-up rule for the real sector
μ_{IB}	Mark-up rule for the interbank sector

In table A.2 and table A.3, we present the attributes and state variables associated with the firms and depositors, respectively. These attributes are more of a passive nature, as these agents are more passive in the process. Its noteworthy that depositors behave randomly and at each cycle withdraw a percentage (ρ) of their deposits with probability p_w.

Table A.2 – The attributes and state variables associated with the firms.

Variable Name	**Description**
Default Rate	Probability of default
LGD	Loss given default: percentage of loan repaid when default happens
Risk type	Firm type. Can be high or low risk
Firm Size	Firm Size. Drawn from a Power Law Distribution

Table A.3 – The attributes and state variables associated with the depositors.

Variable Name	**Description**
p_w	Probability of early withdrawal
ρ	Percentage of deposit value withdrawn

Finally, in table A.4 and table A.5, we present the attributes and state variables associated with the system regulation and mechanical authorities, central bank and clearing house, respectively. They are agents responsible for enforcing policies and organizing the credit markets in general.

Table A.4 – The attributes and state variables associated with the central bank.

Variable Name	Description
i_{mp}	Exogenous monetary policy interest rate
i_{dw}	Discount window loan interest rate
CAR_{min}	Macroprudential policy: Minimum capital adequacy ratio

Table A.5 – The attributes and state variables associated with the clearing house.

Variable Name	Description
Real sector loan matrix	Matrix of row size equal to the number of firms and columns equal to the number of banks containing loan values.
Real sector interest matrix	Matrix of row size equal to the number of firms and columns equal to the number of banks containing interest rates for each loan.
Interbank loan matrix	Square matrix with size equal to the number of banks containing values for each interbank loan.
Interbank interest matrix	Square matrix containing interest rates for each interbank loan.

A.1.3 Process overview and scheduling

The model follows three stages: setup, step, and end. Each step is composed of three sub-stages, representing different periods of time regarding the agents' relationships and actions. In the setup stage, the model creates all agents. After setup, the steps begin to take place. In the first sub-step, banks decide, based on the EWA learning mechanism, what strategy they are going to follow. This defines banks' balance sheets and how much they will lend. Still in this sub-step, the clearing house connects firms and banks, registering the outcome in a loan matrix. Then, the model moves on to the second sub-step, where liquidity shocks happen randomly through stochastic withdrawals of deposits. If a bank becomes illiquid in this step, it may resort to the interbank market to borrow from liquid banks. The clearing house registers these transactions. Finally, in the third sub-step, firms repay (or default on) their loans. When default occurs, banks may become insolvent and be liquidated by the central bank. In this scenario, they may fail to repay their interbank loans, creating financial contagion. Banks then calculate their profits and use that information to update their beliefs and learn. This concludes the step, and all relevant outcomes are recorded by the program. After the predefined number of steps, the simulation ends.

A.2 Design

A.2.1 Basic principles

The model is based on the models presented by (Barroso *et al.*, 2016) and (Adão *et al.*, 2022). It belongs to a broader group of models that employ agent-based modeling to study the

```
Setup
    Banks are initiliazed
    Depositors are initiliazed
    Central bank is initiliazed
    Clearing house is initiliazed
    Firms are initiliazed


Step
    Sub-step 0
        Banks setup balance sheets
        Clearing house makes market
    Sub-step 1
        Depositors withdraw randomly
        Banks borrow from interbank market or central bank
    Sub-step 2
        Firms pay loans
        Insolvent banks are liquidated by central bank
        Bank calculate profit and update beliefs
        Data is stored

End
    Database is recorded locally
```

Figure A.1 – The model full process.

banking system and financial crises. This literature is mostly concerned with reproducing observed patterns and studying issues that remain unclear in the banking system, specially the underlying mechanisms. Some issues that were directly treated are financial bubbles (Allen; Gale, 2000a), financial contagion (Iori; Jafarey; Padilla, 2006; Barroso *et al.*, 2016), financial stability (Gurgone; Iori; Jafarey, 2018b) and risk-taking behavior under different policy settings (Adão *et al.*, 2022). Our model focuses on the distributional effects in the lending market due to the introduction of a Capital Adequacy Ratio (CAR).

A.2.2 Emergence

Emergence occurs in the context of general market variables, which are aggregate features that result from individual decision rules. For example, market interest rates are influenced by macroprudential regulation and tend to be higher when the regulation is strict and lower when it is not. Additionally, when prudential policy tightens, banks collectively reduce the amount of credit supplied. These phenomena emerge as a result of the assumed behavior rules and the interactions that occur among the different agents.

A.2.3 Adaptation

Agents approach the environment in an objective-seeking manner. They choose strategies, observe relevant outcomes, and adjust their behavior. The incorporation of monetary policy interest rates and other exogenous variables happens indirectly since they affect banks' utility function calculation, namely their profits. Agents do not condition their behavior to exogenous variables, they learn from their experience with them instead.

A.2.4 Learning

Banks are the only agents that learn in this model. Their learning scheme is the Experience-Weighted Average Learning presented by (Camerer; Ho, 1999), which is adequate for a game theory setting. Each bank aggregates the information gathered by observing the past profits of strategies employed (or the profit that could have been generated by strategies if they were employed) in "attraction weights". These weights, denoted $A_i^j(t)$ for bank i and strategy j, are calculated recursively by the following expression:

$$A_i^j(t) = \frac{\varphi \cdot N_i(t-1) \cdot A_i^j(t-1) + [\delta + (1-\delta) \cdot I(s_i^j, s_i(t))] \cdot \pi_i(s_i^j, s_{-i}(t))}{N_i(t)} \tag{A.1}$$

where φ is the parameter that depreciates past attractions. δ is a parameter that determines how strategies that were not played are evaluated. $I(s_i^j, s_i(t))$ is an indicator function that assumes 1 if s_i^j is actually played in period t. If s_j is actually played, its profit is accounted for in full. $N(t)$ is a dampened counter updated by:

$$N_i(t) = \rho \cdot N(t-1) + 1, \tag{A.2}$$

where ρ is the fading factor. In this setting, learning is a process that embodies important cognitive effects such as forgetting, simulating scenarios that could have happened and purposefully forgetting older information due to the possibility of change in the environment.

Attraction weights are transformed into probabilities by a logit model.

A.2.5 Prediction

Agents do not use explicit predictions. When simulating the effects of non-chosen strategies, banks conduct a type of indirect prediction by calculating the profit that would have been generated.

A.2.6 Interaction

Banks interact with all other agents. They take deposits from depositors, interact with the clearing house in order to be matched to firms, lend money to the matched firms, lend money to other banks in the interbank market and are overseen by the central bank. Another very important interaction happens indirectly between banks, since they compete with each other regarding their interest rates through the clearing house matching system, that benefits lower rates.

A.2.7 Collectives

The model presents no collective behavior.

A.2.8 Heterogeneity

Heterogeneity in the model is given by individual parameters attributed in the model initialization stage. They can be summarized by table A.6:

Table A.6 – Attributes that are heterogeneous among agents

Agent type	**Parameters**
Bank	T: size parameter
Firm	Default probability Loss Given Default Size
Depositor	Withdrawal probability Percentage withdrawn

Besides that, agents' individual decisions regarding strategies also create heterogeneity.

A.2.9 Stochasticity

Stochasticity in the model is given by the different stochastic processes from different agents. Firms pay back their loans randomly, representing a risky production process. Depositors withdraw their money randomly too, imposing liquidity shocks.

A.2.10 Observation

We collect data on interest rates, total credit supply, insolvencies, capital structure and market profit at the end of the simulation step.

A.3 Details

A.3.1 Implementation Details

Our model adapts the version presented by (Barroso *et al.*, 2016) and (Adão *et al.*, 2022), adding a structure that makes the credit market interactions endogenous. The whole framework is developed using Python's Mesa library (Kazil; Masad; Crooks, 2020).

A.3.2 Initialization

table A.7 presents the initial settings of the model that do not vary among simulations. Other initial parameters vary according to the setting of the analysis done, whether it is a simulation with an active prudential policy or not.

Table A.7 – Initial settings that do not vary among different settings.

Parameter	Description	Value
N_B	Number of banks	50
N_D	Number of depositors per bank	100
P_W	Probability of withdrawal	0.1
T_b	Bank size parameter	1
i_d	Monetary policy interest rate	0.08
Number of steps	10000	

When macroprudential policy is restrictive, the central bank imposes a minimum capital requirement. The value we employed in simulations is 8%, corresponding to the one set by the Basel III CAR recommendations for Tier 1 Capital (BIS, 2011; BIS, 2019).

A.3.3 Input Data

The model is calibrated with the same parameters used in (Lima; Ely; Cajueiro, 2024). The only differences is the introduction of firm size and probability of default heterogeneity. Firm's size come from a Power Law distribution and have a minimum size of 3. Firm's probability of default is conditional on their size and risk type, according to equation (3.8).

A.3.4 Submodels

This model has a submodel that dictates the behavior of the credit market matching system and another one governing the interbank market.

A.3.5 Credit market matching

The clearing house plays an important role in the credit market matching. It ranks credit demand, namely the firms, randomly. On the demand side, it ranks banks according to their mark-up rate. Note that the mark-up rate is a strategic variable set by banks and determines the interest rate charged. The clearing house then matches firms and banks until either demand or supply is exhausted.

A.3.6 Interbank credit market

The clearing house also plays an important role in the interbank credit market. It aggregates all banks that need liquidity during substep I, after the depositors withdraw randomly, and matches them with the lowest mark-up banks that have excess liquidity. The mark-up rates in the interbank sector market is different from the real sector one, but is also a strategic decision.

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