ANEXO I

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THE IMPACTS OF MONETARY POLICY ON BANKS' RISK-TAKING IN REAL SECTOR LOANS: AN AGENT-BASED MODEL APPROACH

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25 DE MAIO DE 2021

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Dissertação apresentada ao Departamento de Economia da Universidade de Brasília como parte dos requisitos necessários à obtenção do título de Mestre em Economia.

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Resumo

O estudo investiga a relação entre política monetária e risco assumido pelos bancos a partir de um modelo baseado em agentes (ABM). O modelo, que conta com cinquenta bancos de diferentes tamanhos, mostrou que a política monetária expansionista estimula as instituições financeiras a aumentar o montante de empréstimos ao setor real e a assumir mais riscos. Como *proxy* para "risco", usamos o total de empréstimos aos clientes mais arriscados do setor real. Como medida de "tamanho" do banco, usamos o valor total dos seus ativos. A política monetária restritiva, por outro lado, torna o mercado interbancário mais dinâmico, sendo ela mais efetiva sobre bancos menos líquidos. Para ambos os cenários de política monetária, bancos evitam empréstimos do Banco Central. Resultados secundários do modelo sugerem que quando o ambiente econômico é marcado por um baixo nível de taxas de juros, os bancos tendem a ser maiores que no cenário de maior nível de taxa de juros. Além do mais, o mercado interbancário é marcado por *money centers*.

Palavras-chave: Banking, Agent-Based Model, Risk-taking, BankSim

Abstract

The study investigates the relationship between monetary policy and bank risk-taking using an agent-based model (ABM) approach. The model, which counts with fifty different sized banks, shows that the expansive monetary policy stimulates banks to increase the value of the loans to the real sector firms, and take on more risks. We use the total loan amount to the risky real sector clients as a proxy for banks' risk and the sum of bank's assets as the measurement for its size. The restrictive monetary policy, on the other hand, makes the interbank market more dynamic and such a stance is more effective on less liquid banks to reduce their loans. For both monetary policy stances, financial institutions shun window discount loans. Model's minor results suggest that when a low level of interest rate marks the economic environment, banks tend to be larger than when the interest rate level is high. Furthermore, money center characterizes interbank market's structure.

Key-words: Banking, Agent-Based Model, Risk-taking, BankSim

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List of abbreviations and acronyms

ABNT	Associação Brasileira de Normas Técnicas
ABM	*Agent-Based Model* (Modelo baseado em agentes)
CAR	*Capital Adequacy Ratio* (Taxa de Adequação de Capital)
CB	*Central Bank* (Banco Central)
EWA	*Experience-Weighted Attraction*
ROE	*Return on Equity* (Retorno sobre o Patrimônio)
MP	*Monetary Policy* (Política Monetária)

Contents

Introduction

This study evaluates how monetary policy stance affects banks' risk-taking in terms of the profile of their lending to the real sector firms. We investigate the two stances of monetary policy and their implications: expansive (low-interest rates and low firms' probability of default) and restrictive (high-interest rates and high firms' probability of default). Banks can lend to two types of companies: low-risk and high-risk. We use the total amount of loans to the latter as the banks' measure of risk. The intuition is as follows: the more a financial institution lends to such a type, the riskier it is. To carry on such analysis, we make use of the BankSim Model[1], a banking agent-based simulation framework that Barroso (2011) originally created[2], and Silva (2018) coded in Python 3+[3]. Because its original design only evaluates regulation policies, we altered the coding to conduct our proposed task. Thereby, we contribute to the original work by adding features that account for monetary policy. BankSim's framework consists of an iteration of discrete-time simulation cycles in which agents have bounded rationality and can learn and adapt their strategies according to Camerer and Ho (1999) learning structure. This structure captures situations in which subjects use the history of plays by opponents and full information about their own prospective payoffs when adjusting their choice behavior.

Regarding our model's results, part of them converges with what the literature claims about monetary policy impacts on banks' behavior. Rajan (2005), Chen et al. (2017) and Agur and Demertzis (2012) state that when the monetary policy eases, there is an augmentation of real sector loans in general and for the risky clients, which means that banks take on more risks (according to our measure of risk). Furthermore, Lucchetta (2007) concludes that the higher the interbank rate is (a characteristic of the restrictive monetary policy), the higher the amount of money that banks with an excess of liquidity decide to lend in the interbank market. At the same time, she also finds that banks tend to increase their liquidity when such a rate is high. Kashyap and Stein (2000) shows that the restrictive monetary policy has more effect on less liquid banks to diminish their amount of loans. Regarding the window discount loans, Armantier et al. (2010) evidence that banks tend not to borrow resources from the Central Bank not only because of the punitive interest rate but also due to a stigma. Depositors and other banks may perceive the borrower institutions as being in a weakened financial condition. Our model ratifies all the aforementioned results; nonetheless, we go beyond the final results. Because we

1 The seminal papers of Diamond and Dybvig (1983), Franklin and Gale (1998), and Franklin and Gale (2000) are the base of this model.

2 Lima (2014) and Barroso (2014) enhanced the model. Barroso et al. (2016) summarized the contributions.

3 It is available on the Github website<https://github.com/banking-project/banksim>

use an agent-based approach, our study contributes to the literature by presenting banks' and depositors' evolving strategies or the learning path they use up to their final optimal behavior. One more aspect that calls attention in our model result is the interbank market structure. Its characteristic is the formation of "money centers," banks that have exposures to many banks and are the most important source of large lending. For example, Cajueiro and Tabak (2008) found this topology for the Brazilian interbank market.

Our model opens an avenue for the discussion of a result that authors still little explore in the literature. Then, we need further investigation to validate it: banks tend to be larger when monetary policy stance eases. In other words, a low-interest-rate environment tends to allow banks to grow larger than when interest rates are high. In our study, we use banks' total assets as the measure for size[4]. According to what we find in the financial literature, this hypothesis is not far-fetched. As already discussed, Rajan (2005), Chen et al. (2017) and Agur and Demertzis (2012) conclude that low-interest rates foster banks to take on more risks because risk perception is diminished. The financial institutions engage in activities that once they deemed as risky, but they do not consider to be anymore, such as loans to real sector clients that have no credit history. One explanation for this fact is that their guarantee's present value increases as interest rates plunge. Knowing that "loans" are part of banks' asset and in empirical studies, such as Levine (2012) and Bolton, Freixas and Shapiro (2007), the natural logarithm of banks' asset is the measure for banks' size, if banks choose to lend more because the interest rates are low, they grow larger (banks' total asset enlarges). However, further validation is important because it is true that the financial institutions may engage in other ventures to the detriment of lending, such as bank intermediation activities (Brei; Borio; Gambacorta, 2020). In this case, lending may decrease, and no change in banks' size may happen.

Our study uses an agent-based model (ABM), which, according to Adami, Schossau and Hintze (2016), is a valuable tool of analysis when we deal with finite populations, stochastic decisions, communication between agents, and spatial interactions. In ABM, we model each agent as an individual who carries his/her own rules of behavior that determine his/her decisions. We can only ascertain the evolutionary outcome by evolving the population of agents forward in time. Furthermore, by running the model, we can get to the final solution (equilibrium) and access the entire simulation history, which allows the analysis of the transient state.

The use of agent-based models does not mean that we discard mathematical methods. As Adami, Schossau and Hintze (2016) state, although ABM can predict evolutionary outcomes where purely mathematical treatments cannot tread, mathematics is still crucial to validate the computational methods. In the economic literature, we can find several

[4] We do not use the natural logarithm, as many empirical studies do, because banks' total asset sum distribution is normalized in our sample.

studies that use an approach that integrates ABM with mathematical models, such as evolving game theory, allowing heterogeneous agents. Silveira et al. (2020), for instance, combine the mathematical framework of evolving games and differential equations with an agent-based model to analyze the impact of Brexit on the displacement of firms in the UK and the European Union. The authors use two kinds of firms to carry on the study. When it comes to our proposed task, we use the ABM integrated with the mathematics from the EWA game theory model.

Besides this introduction, we organize the rest of our work as follows: chapter 1 presents a brief review of the literature of agent-based models and the impacts of monetary policy on banks' behavior. Chapter 2 introduces the model we use to make the analysis, chapter 3 shows the simulation results, and the conclusion finalizes the paper.

1 Review of the literature

In the finance literature, we can find some papers in which the authors make use of computational methods and benefit from the analysis that such models allow to make, in comparison to purely mathematical models. For example, combining the knowledge of the detailed structure of a real world banking network with an economic model, Boss, Summer and Thurner (2004) use a computational model to reconstruct Austria's banking network and study the flow of funds through the banking network following exogenous shocks to the system. Their goal is to estimate the functional stability and robustness of the financial network and they find that the Austrian interbank system is relatively stable because individual banks' defaults are unlikely to spread over the entire network.

Defying the Efficient Market Hypothesis, that preaches that security markets are efficient and immediately incorporate new information into prices, Alfarano and Lux (2005) construct a herding model through the ABM approach to analyze an artificial financial market of two types of traders. The authors' goal is to find a closed solution for the distribution of returns and they conclude that the tail shape that characterizes the fatness of the unconditional distribution of returns comes directly from the herding propensity; i.e., an autonomous switching tendency. In other words, the authors replicate a herd behavior in their model and show that the interactions between agents, who are heterogeneous, affect price and returns.

Cajueiro and Tabak (2008) conduct an empirical analysis of the Brazilian interbank network structure using a complex network-based approach. The authors find evidence that the Brazilian interbank market is constituted of money centers; i.e., banks which have exposure to many banks and are the most important source of large amounts of lending. Furthermore, they conclude that different types of bank have different roles in the network: retail banks play a major role in the interbank market, public banks are net lenders, and foreign banks are net borrowers.

Using an ABM approach, Barroso et al. (2016) study the impacts of some regulation policies over banks' behavior and the stability of the system. They find that an interbank clearing house acting as the central counterparty that requires collateral and information disclosure from participants is successful regarding the reduction of the risk of contagion between banks. Furthermore, such a reduction has a low cost in terms of credit supply to the real side of the economy. When it comes to deposit insurance, it successfully reduces the risk of bank runs; nevertheless, such an insurance also triggers moral hazard because it removes depositor's incentives to monitor banks' risk-taking strategies. The second scenario can outweigh the first one and lead to bank failure.

Bookstaber (2017) uses the ABM approach to model financial crisis, embodying the contagion and cascades that occur due to financial leverage and market concentration of agents. Moreover, the author also compares ABM with standard economic approach to financial crises and shows the ways in which the former overcomes the limitations of the latter. He concludes that because ABM allow non-ergodic dynamics, which are present during financial crises, such models are more prone for analysis of financial crises.

Alfarano and Lux (2018) recognize that the adoption of ABM is hindered due to the absence of general reliable operational calibration methods. So, they start with a different calibration angle. They allow agent-based models to construct novel types of advanced warning systems of market crises, based on the emergent collective intelligence of several ABMs built on optimal decision trees that can be reversed engineered from real financial data.

The literature about how monetary policy stance affects banks' risk-taking is also copious, and we do not intend to show it exhaustively in this paper. For example, Rajan (2005) states that monetary policy stance influences the risk-appetite of banks. When it is expansive, banks lend more to borrowers with bad or no credit history, turning the new loans more hazardous than they would typically be. Because the short-term interest rate is low, collateral's values increase, which makes the borrowers seem less risky. Furthermore, because the returns from riskless assets decrease, financial institutions go to a "search-for-yield" and start to hold riskier assets. On the other hand, when the monetary policy stance is restrictive, banks perceive augmented risks and, because of it, give fewer loans and mostly shun risky borrowers and risky assets (Jiménez et al., 2014).

By modeling banks that choose both asset volatility and leverage, and the existence of a regulator, whose tool is a risk-based capital requirement, Nicolo et al. (2010) identify how monetary policy transmits to bank risk. The regulator trades off bank risk and credit supply. The authors concluded that regulation cannot neutralize the policy rate's impact and monetary policy matters for financial stability.

Agur and Demertzis (2012) agree that monetary policy easing can induce greater risk-taking through a search for yield or its effects on leverage and asset prices. Notwithstanding, they advocate that the relationship between the monetary policy stance and bank risk-taking is more complex than this usual thought. Using some evidence from the USA, the authors concluded that if the interest rate is low, well-capitalized banks increase risk-taking, whereas poorly capitalized banks do the opposite.

Using bank-level panel data from more than 1000 banks in 29 emerging economies during 2000–2012, Chen et al. (2017) find that banks' riskiness increases when monetary policy eases. According to the authors, this result is robust when adopting alternative measures of monetary policy and bank risk and using different econometric methodologies.

2 The Model

2.1 General Organization

Five types of agents populate our stochastic game model: banks, depositors, the Central Bank, firms, and the clearing house. The first two ones have adaptive strategies to play in each cycle and have bounded-rationality. Although the remaining players do not possess any strategy, their actions impact the decisions of the first two agents, as we demonstrate ahead.

As a consequence of being a stochastic model, we execute the simulation several times to smooth the "randomness bias." We name each iteration as "cycle" and divide it into three time horizons: t_0, t_1, and t_2. We can construe t_0 as "today". At this time, banks and depositors set their strategy for the entire cycle (the three horizons). They define the amounts reserved for real sector loans (discriminating between high and low-risk borrowers), liquid assets, deposits, capital, and, consequently, the capital adequacy ratio (CAR)[1]. Depositors choose the minimum CAR they accept that the banks have. Banks' and depositors' process of choice follow a rule of behavior that we explain more deeply in the subsections to come.

We attribute the "short term" to t_1. Now, banks face a liquidity shock, expressed by the proportion of depositors who withdraw their resources prematurely to anticipate their consumption[2]. Moreover, the Central Bank (CB) observes whether banks respect the minimum capital adequacy ratio requirement. If they are not, the CB obligates the financial institutions to sell part of their real sector loans to achieve the requirement. Eventually, financial institutions with liquidity shortages can borrow either from other banks or from the Central Bank.

Finally, t_2 is the "long term". At this moment, real sector loans mature, the remaining depositors withdraw their resources to consume, and the banks calculate their return on equity (ROE) to update their strategies through the learning scheme. The ROE value determines whether the bank chose the best strategy or it can ameliorate for the future. Banks can become insolvent due to losses in their real sector loans or due to financial contagion through the interbank market when a bank fails to pay back its interbank loan.

Our model is a sequential non-collaborative game of imperfect and incomplete

[1] CAR is a measurement of a bank's available capital expressed as a percentage of a bank's risk-weighted credit exposures. Its usage is to protect depositors and promote the stability and efficiency of financial systems.

[2] For simplicity, we consider that depositors withdraw the total deposit amount, and never a fraction of it.

information. Players do not know either each one's moves or payoffs. They only have information about themselves and, thus, cannot cooperate. Depositors are the first ones to play and select their strategy. Then, banks set their strategy without knowing what depositors played. After the only two agents with adaptive strategies play, the clearing house acts as the central counterparty and organizes the interbank market. The Central Bank follows suit, acting as the system supervisor and lender of last resort. After it, and only in the last period of the cycles, the two types of firms pay back the loan or default.

Banks, our agents of central interest, are not isolated; instead, they connect to each other via interbank loans, available in the interbank market. When a financial institution needs liquidity, and another one has excess, the former borrows from the latter, creating a connection. If the borrower takes on too much risk and goes insolvent, it does not pay back the loan. It may lead the lender bank into hardship because the guarantees paid by the clearing house may not be enough, and it destabilizes the financial system (i.e., augmentation of the number of insolvent banks). On the other hand, if the borrower gets to pay back, besides avoiding its insolvency, it enlarges the lender's profit, making the financial system more robust. This connection is a consequence of the adaptive strategies and the presence of stochastic shocks in the economy.

One note to remember is that our primary goal is to analyze the impacts of monetary policy changes on banks' risk-taking. Our measurement of risk is the total loan amount they address to the risky real sector firms.

2.2 Agents

We now describe the agents' behavior, namely banks, the Central Bank, depositors, real sector firms, and the clearing house.

2.2.1 Banks

The agents of central interest in this framework are the banks. They are the financial intermediaries of the system, channeling funds from the depositors to firms. They also connect to other banks via the interbank market and to the Central Bank when necessary. In each simulation, which means each cycle, there are B banks in the economy, represented by their balance sheets. The design of such balance sheets allows banks to fund long-term illiquid assets with short-term liquid liabilities, i.e., cash deposits (banks' primary source of funding) fund loans (banks' principal source of revenue). Due to this situation, banks face a tradeoff between the risks associated with lending too much (which yields higher profits) and the forfeited revenue resulted from keeping high reserves (which can avoid future problems of liquidity shortage). The capital (updated throughout the cycles and used to calculate the ROE), the cash deposits (which are liquid liabilities), and the two types of loans taken by the bank in case of liquidity shortage are the components of the liability side of the bank b's balance sheet. Table 1 summarizes the items.

Table 1 – Banks' liabilities

Symbol	Liability	Maturity	Cost
K_b	Capital	-	-
D_b	Cash deposits	$t+2$	i_d
IL_b	Interbank loans	$t+1$	i_i
C_b	Central Bank loans	$t+1$	i_{cb}

Bank b's assets consist of liquid assets (cash or cash equivalent used as a reserve to face depositors' withdrawal requests; i.e., the liquidity shocks), interbank loans (if the bank under analysis is the lender), and real sector loans (loans to the high-risk and low-risk real sector firms). It is important to mention that banks know exactly whether a firm is high-risk or not. In reality, choosing the number of high-risk clients to receive a loan is part of banks' strategy choice. Table 2 summarizes the items.

Table 2 – Banks' assets

Symbol	Asset	Maturity	Return
L_b	Liquid assets	t	-
IL_b	Interbank loans	$t+1$	$r_i = i_i$
$R_{b_{HR}}$	High-risk real sector loans	$t+2$	$r_{b_{HR}}$
$R_{b_{LR}}$	Low-risk real sector loans	$t+2$	$r_{b_{LR}}$

Banks' bounded rationality is on the fact that they know precisely neither the payoff that their strategies yield nor what the other banks and depositors play. For example, they may choose a large number of high-risk firms to lend money, a small total amount of liquid assets to hold (so that more resources remain for lending), and a low level of CAR. This strategy has the potential to give banks a hefty profit. Nevertheless, suppose some firms default and many clients anticipate their withdrawals, imposing liquidity shocks to the financial institutions, which have few liquid assets to respond to. In that case, the once-profitable choice becomes a tough loss. Thus, the uncertainty surrounding their choices' outcomes is what limits their rationality. On the other hand, banks are rational agents because, in each cycle after the first one, they choose their strategy to maximize their profit based on the information they have.

Given that agents aim at the highest possible payoffs in the game, we can infer that banks will only use deposits to fund loans to the real sector, facing the associated risks of this activity if they expect to gain from it. Besides, because there are two kinds of firms in the model[3], the high-risk and low-risk firms, in order for banks to lend money to the former to the detriment of the latter, it seems logical that compensation, in terms of the expectation of higher profit, must exist as an incentive. In other words, the following constraint must be valid: $E(r_{b_{HR}}) > E(r_{b_{LR}}) > i_d$. The relationship between banks and firms when there is a variation in monetary policy stance changes a little. If the monetary policy tightens, banks become more suspicious regarding firm's credit quality. Because the financial institutions cannot anticipate whether a firm will default (bounded-rationality), they shun the risky companies, as we see in Chapter 3. On the other hand, when the monetary policy eases, banks' risk perception decreases, and they end up lending more to the risky firms.

It is important to forestall banks from funding real sector loans with Central Bank loans. Thereby, we set $i_{cb} > E(r_{b_{HR}}) > E(r_{b_{LR}})$ and make i_{cb} a punitive rate. Because funding through deposits is cheaper for financial institutions, the interbank rate must be such that $i_i = r_i > i_d$. It is important to mention that the interest rates are exogenous in this model, and we can summarize their values in the following rule:

$$i_{cb} > E(r_{b_{HR}}) > E(r_{b_{LR}}) > i_i = r_i > i_d. \tag{2.1}$$

In the simulations of the model, banks, which have the exogenously determined size T_b (the sum of all assets or, likewise, the sum of all liabilities), play an iterated simultaneous game, in which they try to maximize their ROE. We can represent bank b's strategy with the vector $s_b^j = (\alpha^j, \beta^j, \gamma^j)$, where α is the total amount of capital and β represents the total amount of liquid assets. Our contribution to the BankSim Model is the addition of the parameter γ, which captures the number of risky firms that bank b has as clients and determines the fraction of real sector loans held by bank b that it destines to risky firms. In other words, it measures the appetite for risk of the financial institutions.

At the beginning of each cycle ($t = 0$), there is no interbank activity; it only happens $t = 1$ hence. Bank b determines the entire balance sheet through the choice of strategy s_b^j and the exogenous size parameter T_b. Table 3 summarizes.

As already discussed, bank b chooses the parameter γ. According to the value of such a parameter, b chooses the fraction destined for its high-risk clients and low-risk clients from the amount reserved for real sector loans. Moreover, from a universe of one hundred firms (fifty of each kind of risk), banks select fifty in total. The parameter γ gives the percentage of the fifty risky clients. Finally, we can split real sector loans according to what Table 4 presents.

[3] The probability of default is what differs between "high-risk" and "low-risk" real sector firms. Such a probability is exogenous to the model.

Table 3 – Determining bank b balance sheet

Side	Item	Strategy
Liability	Capital	$K_b = \alpha^j * T_b$
Liability	Cash deposits	$D_b = (1 - \alpha^j) * T_b$
Asset	Liquid assets	$L_b = \beta^j * T_b$
Asset	Real sector loans	$R_b = (1 - \beta^j) * T_b$

Table 4 – Bank b's real sector clients

Classification	Symbol	Strategy
High Risk	$R_{b_{HR}}$	$\gamma^j * (1 - \beta^j) * T_b$
Low Risk	$R_{b_{LR}}$	$(1 - \gamma^j) * (1 - \beta^j) * T_b$

By the end of a cycle, bank b calculates its profit (or loss) as:

$$\Pi_b = K_b^2 - K_b^0, \tag{2.2}$$

where K_b^0 is the capital in $t = 0$ and K_b^2 is the capital in $t = 2$. The variable ROE_b is the one that the learning scheme takes into account, and its calculation follows:

$$ROE_b = \frac{\Pi_b}{K_b^0}. \tag{2.3}$$

As we consider regulation policy implications in our analysis, it is crucial to define the capital adequacy ratio (CAR), which is the ratio to risk-weighted assets (RWA). In this model, the calculation of RWA does not include liquid assets because we consider them as riskless assets. Given that there is no inflation in our environment, liquid assets yield 0%, and there is no risk of depreciating this value. For bank b, we have:

$$CAR_b = \frac{K_b}{IL_b + \sum\limits_{f \in F_b} R_{b,f} \cdot w_f}. \tag{2.4}$$

In equation 2.4, $R_{b,f}$ is the loan amount to firm f and w_f is its risk weight. The set of firms borrowing from bank b is F_b, and each one 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 asset's low liquidity.

2.2.2 Central Bank

In this model, the Central Bank (CB) plays two roles: system supervisor and lender of the last resource. As the system supervisor, the Central Bank supervises whether banks respect the minimum capital adequacy ratio (CAR_{min}) that we endogenously determine. If bank b's CAR falls below the required threshold ($CAR_b < CAR_{min}$), the Central Bank obligates it to raise to the minimum. In case it fails to do so, the CB liquidates such a bank. These measures aim to guarantee the stability of the financial system. On the other hand, as the lender of the last resource, CB lends money to the banks that do not solve their liquidity shortage problem via the interbank market.

As already stated, differently from the original model, we consider monetary policy in our analysis in this paper. The determination of the "risk-free interest rate," Central Bank's monetary policy tool, is exogenous to the model. Our CB acts as the monetary authority of a country that is in a monetary union. It is a reality, for example, of the countries that belong to the European Union. In the last decades, for instance, the monetary policy in Spain was mainly exogenous, i.e., decided at the European Central Bank, located in Germany (Jiménez et al., 2014). Moreover, in this model, the minimum capital requirement is exogenous too. We test for different levels of it in Appendix A and Appendix B.

2.2.3 Depositors

We establish that depositor's anticipated withdrawal decisions engender liquidity shocks on banks. It is possible to set two kinds of depositors: patient (only withdraws when the deposit matures in $t = 2$ and, because of it, receives the amount deposited plus the return) and impatient (withdraws the total deposit amount prematurely in $t = 1$, giving up the returns).

In the model, depositors make their decision strategically, according to the EWA learning scheme. Given that they wish to maximize their utility, they act to minimize their risks of loss. For a given depositor d, the risk tolerance parameter κ_d is the only parameter used to define his/her strategy, s_d. Observed in $t = 1$, it represents the minimum capital adequacy ratio he/she is willing to withstand in a bank. The depositor compares κ_d with the bank's capital adequacy ratio CAR_b and decides whether he/she accepts the risk incurred by bank b and waits until $t = 2$ to withdraw ($\kappa_d < CAR_b$) or not ($\kappa_d > CAR_b$).

Depositors are always risk-averse and have the following utility function:

$$U_d(c_d^1, c_d^2) = \ln\left(\frac{c_d^1 + c_d^2}{D_d}\right). \tag{2.5}$$

where c_d^1 and c_d^2 are, respectively, the short-term and the long-term consumption. Parameter D_d represents the total amount deposited. Once there is no preference of time for consumption, the only explanation for its eventual anticipation is the depositor's increasing risk perception, i.e. when κ_d becomes higher than CAR_b. There are no inherently impatient depositors.

2.2.4 Firms

There are two types of firms in the model: high-risk and low-risk. Neither one of them acts strategically in this framework, and their probability of default is contingent on their risk type, being higher for the high-risk. Consequently, low-risk firms pay a lower interest rate on their loans. This situation presents a tradeoff between risk and profit for banks. Furthermore, companies cannot conceal their nature from their lender financial institutions.

Because we want to evaluate the lending channel of the monetary policy (and not the "borrowing channel"), we follow Barroso et al. (2016) and set that firms' demand for credit is inelastic. It means that they borrow the entire credit supply, no matter its price (interest rate). This fact is interesting for our analysis because when banks' strategies lead to fewer real sector loans, part of the demand is not served. So, we can purely measure the banking lending channel impact over the real side of the economy when monetary policy changes.

2.2.5 Clearing house

The clearing house is a designated intermediary between a buyer and seller in a financial market. It is responsible for ensuring that both the buyer and the seller honor their contractual obligations. In our model, the clearing house does not have a set of strategies to choose from. However, it is responsible for organizing the interbank loan market, collecting the collateral, and organizing a line for borrower banks to receive: from the least risky to the riskiest in terms of the values of α and β.

2.3 Learning Scheme

It is possible to analyze the financial system within the framework of game theory. We can interpret each participant as a player whose actions aim at the highest possible payoffs and influence the other players' outcomes. As we already stated, our model is a non-collaborative sequential game in which each class of agents plays at a time, and they do not cooperate. In non-collaborative games, the interactions between players may result in one or more Nash equilibria (if there are any) that are not Pareto optimal. If we allow players to learn as interactions go by, however, the outcome may differ. From a particular interaction onward, the Nash equilibrium gets close to the Pareto optimality and eventually equals it. Having it in mind, we can observe that the manner that players choose their strategy is vital to assure potential optimality to the final equilibrium. In our model, players set their strategies on each cycle according to the experience-weighted attraction (EWA) mechanics, as Camerer and Ho (1999) propose.

The EWA framework encompasses principles of actual, simulation, and declining effects. Actual effects assert that if a chosen strategy shows success, i.e., yields to a positive payoff, the player's likelihood of choosing such a strategy again increases. By its turn, simulated effects state that unchosen strategies that would have returned high payoffs are more likely to be selected in the future. On the other hand, declining effects state that the effect of payoffs on choices diminishes over time (Camerer; Ho, 1999). Besides containing the principles as mentioned above, EWA is a kind of hybrid model which blends elements of belief-based models (players form some belief about what another player will play based on history) and reinforcement models (players only consider the payoffs yielded in the past and do not care about the history of play that created such payoffs).

Before dealing with the mathematical aspects of EWA and how it works, it is important to establish some notations. In this paper, we follow the same that Camerer and Ho (1999) uses. Let's consider the financial system as a game populated with n agents indexed by i ($i = 1, \ldots, n$). Player i has S_i as his/her strategy space, which consists of m_i possible choices; i.e., $S_i = \{s_i^1, s_i^2, \ldots, s_i^j, \ldots, s_i^{m_i-1}, s_i^{m_i}\}$. Player i plays the strategy $s_i(t)$ and his/her payoff is $\pi_i(s_i(t), s_{-i}(t))$, both in time t (the simulation cycle), where $s_{-i}(t)$ is a vector that counts with the strategies that all players play, except player i.

Banks and depositors adapt their choices through functions called "strategies attractions." They reflect the initial predisposition towards strategies and are updated based on both experience and simulated payoffs after the realized outcomes. The attraction update of strategy j for agent i in t is:

$$A_i^j(t) = \frac{\phi \cdot N_i(t-1) \cdot A_i^j(t-1) + [\delta + (1-\delta) \cdot I(s_i^j, s_i(t))] \cdot \pi_i(s_i^j, s_{-i}(t))}{N_i(t)}, \tag{2.6}$$

where ϕ is the parameter that depreciates past attractions, δ weights the foregone payoffs[4] and $I(s_i^j, s_i(t))$ is an indicator function that equals 1 when $s_i^j = s_i(t)$ and 0 otherwise. Finally, $N(t)$ is the measure of experience, which is updated by:

$$N_i(t) = \rho \cdot N(t-1) + 1, \tag{2.7}$$

4 Camerer and Ho (1999) points out that this is the most important parameter in EWA because it captures the effects of the two fundamental principles of learning: the law of actual effects and the law of simulated effects.

where ρ is the depreciation of experience. Together, ρ and ϕ capture cognitive phenomena like forgetting and consciously discounting old experiences when the environment is changing (Camerer; Ho, 1999).

We calculate the probability of player i choosing strategy j by the logit model, which Pouget (2007) also uses:

$$P_i^j(t+1) = \frac{e^{\lambda \cdot A_i^j(t)}}{\sum_{k=1}^{m_i} e^{\lambda \cdot A_i^k(t)}}, \tag{2.8}$$

with λ measuring players' sensitivity to attractions, which captures aspects of perception and motivation.

Observe that if we set $\rho = 0$ and $\delta = 0$, we reach the reinforcement model. On the other hand, setting $\delta = 1$ and $\rho = \phi$ leads us to the belief-based model. Because we do not want to evaluate such special cases of EWA, the parameters assume other values, which we discuss when we get to the simulations section.

2.4 Cycles

As already mentioned, a cycle is divided into three periods: $t = 0$ (today), $t = 1$ (short-term), and $t = 2$ (long-term). Within a cycle, there is a sequence of events that are worthy of discussion. In each time horizon, agents have different decisions and actions.

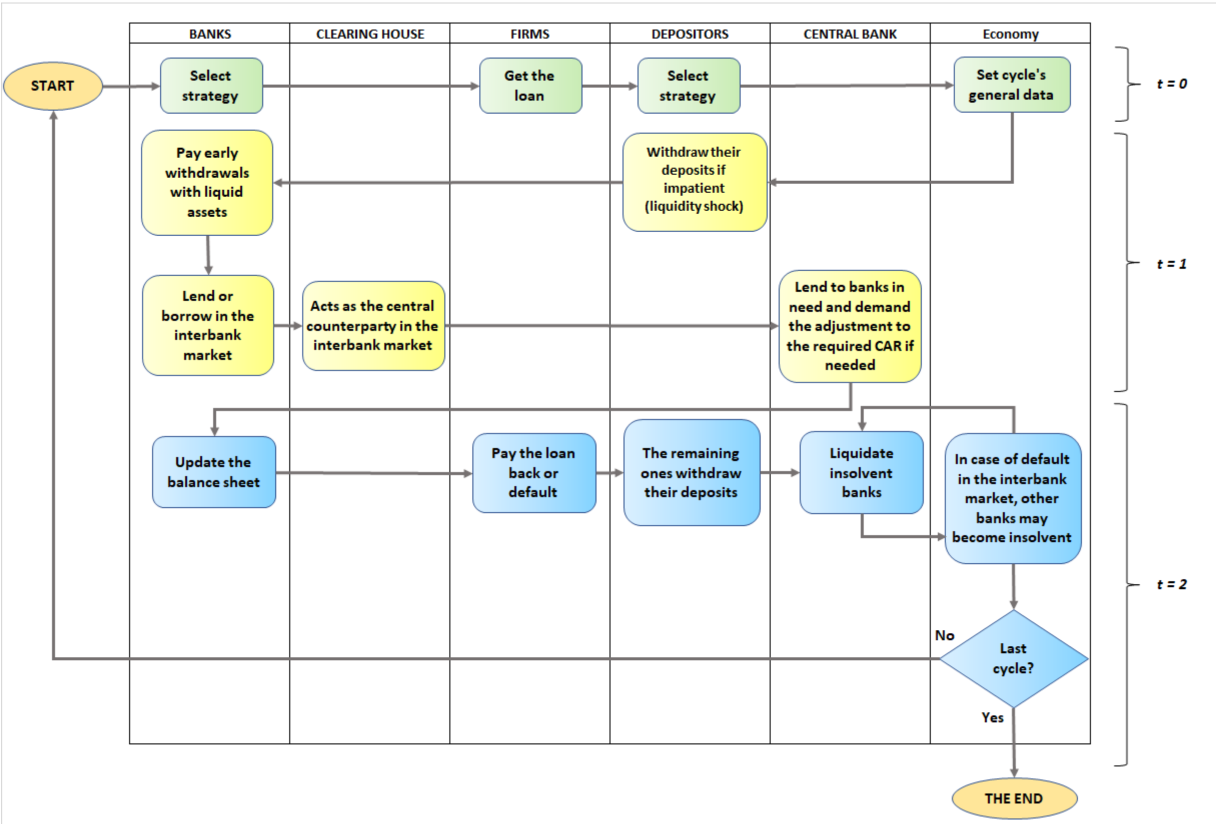
In $t = 0$, or today, all the agents make their decisions for one whole cycle (three periods of time). Banks set their values for $s_b^j = (\alpha, \beta, \gamma)$ (i.e., amounts of capital, deposits, liquid assets, and real sector loans for high-risk and low-risk firms) and depositors set their values for $s_d^j = (\kappa)$. Each agent makes the individual choice considering the experience they acquired through the EWA learning scheme in previous cycles. Regarding the first cycle, when there is no experience accumulated, agents choose their strategies randomly because the attraction for all strategies is equal.

In $t = 1$, or the short-term, impatient depositors trigger liquidity shocks on banks. If any bank face a liquidity shortage as a response, the first interbank transactions can happen. Notwithstanding, acting as the lender of the last resort, the Central Bank may have to lend money to those banks that do not get enough liquidity from the interbank market. As the system supervisor, the CB forces banks to meet the CAR_{min} if they are below this threshold. These banks have to sell part of their real sector loan portfolio (at discounted prices) to accomplish such a rule.

In $t = 2$, or the long-term, deposits, interbank, and real sector loans mature, banks realize their profits, and banks and depositors update their attraction function in the EWA learning model. Banks whose losses exceed their capital become insolvent, and the Central Bank liquidates them. Additionally, this financial authority will apply a penalty over their asset's values. This fact will increase banks' loss and, consequently, give incentives for these institutions to avoid this situation in future cycles. There is a use of the assets of insolvent banks to repay their liabilities. It is worth mentioning that the financial institutions that do not pay back interbank loans cause local losses that may turn other banks insolvent (contagion).

When a cycle gets to the end, agents only carry the experience acquired to the next cycle. All other variables restore to their default values. Figure 1 summarizes what happens within a cycle.

Figure 1 – Cycle in details



3 Simulation

The monetary policy instrument is a financial market price, which central banks set or closely control. For Central Banks with floating exchange rates, such an instrument is a short-term interest rate, which happens to be the yield-to-return of the national sovereign bonds, considered the risk-free assets of the market. Because these government bonds are collateral in many of the interbank loan operations, they affect the price of such loans to the point that the interbank rate follows sovereign bonds' interest rate. Thereby, Central Banks have the potential to affect the interbank market and financial stability through monetary policy (Smets, 2014; Altunbas; Gambacorta; Marques-Ibanez, 2014). Due to the aforementioned relationship, we use the interbank rate as the monetary policy instrument in our model. It is also important to note that we produce our results considering a regulated financial environment, where there is a minimum capital requirement that banks must respect.

Table 5 presents the values of some financial parameters for the two monetary policy (MP) stances and the Central Bank's capital requirement. We arbitrarily choose such values but respecting the narrative that literature states. In the scenario of low interest rates, banks perceive their real sector clients as less risky and set lower levels of interest rates for the borrowers. On the other hand, the high-interest rate environment makes banks more suspicious about their clients' credit quality. As a consequence, they demand a higher level of interest rate to accept to lend funds. Moreover, the more expensive the loan is, the higher the firm's probability of default is and vice-versa (Gambacorta, 2009; Neuenkirch; Nöckel, 2018)[1].

Following Silva (2018), we simulate one thousand cycles because the agents of our model achieve their optimal strategies after about one thousand interactions. Table 6 presents the EWA parameters' values.

Figure 2, Figure 3 and Figure 4 present the main results of our work. While Figure 2 presents the dynamic behavior of some financial variables, Figure 3 exhibits the dynamic behavior of depositors, and Figure 4 shows the behavior of discount window loans for the two stances of the monetary policy. An inherent characteristic of the figures is that agents' behavior in the initial cycles differs from ending cycles. As the cycle goes by, agents learn the advantages and drawbacks of their strategies and consider other players' behavior to choose other strategies.

Figure 2a shows that the expansive monetary policy stance produces a higher level

[1] Appendix A and Appendix B simulate the model using different values for the Central Bank's minimum CAR.

Table 5 – Financial parameter's values (lenient Central Bank)

Parameter	Meaning	Expansive	Restrictive
B	Number of banks	50	50
i_i	Interbank rate	0.5%	2%
$r_{b_{HR}}$	High-risk loan interest rate	10%	12%
$r_{b_{LR}}$	Low-risk loan interest rate	4.5%	8%
D_{HR}	Default Rate (High-risk client)	3%	10%
D_{LR}	Default Rate (Low-risk client)	2%	6%
CAR_{min}	Minimum Capital Requirement	10%	10%

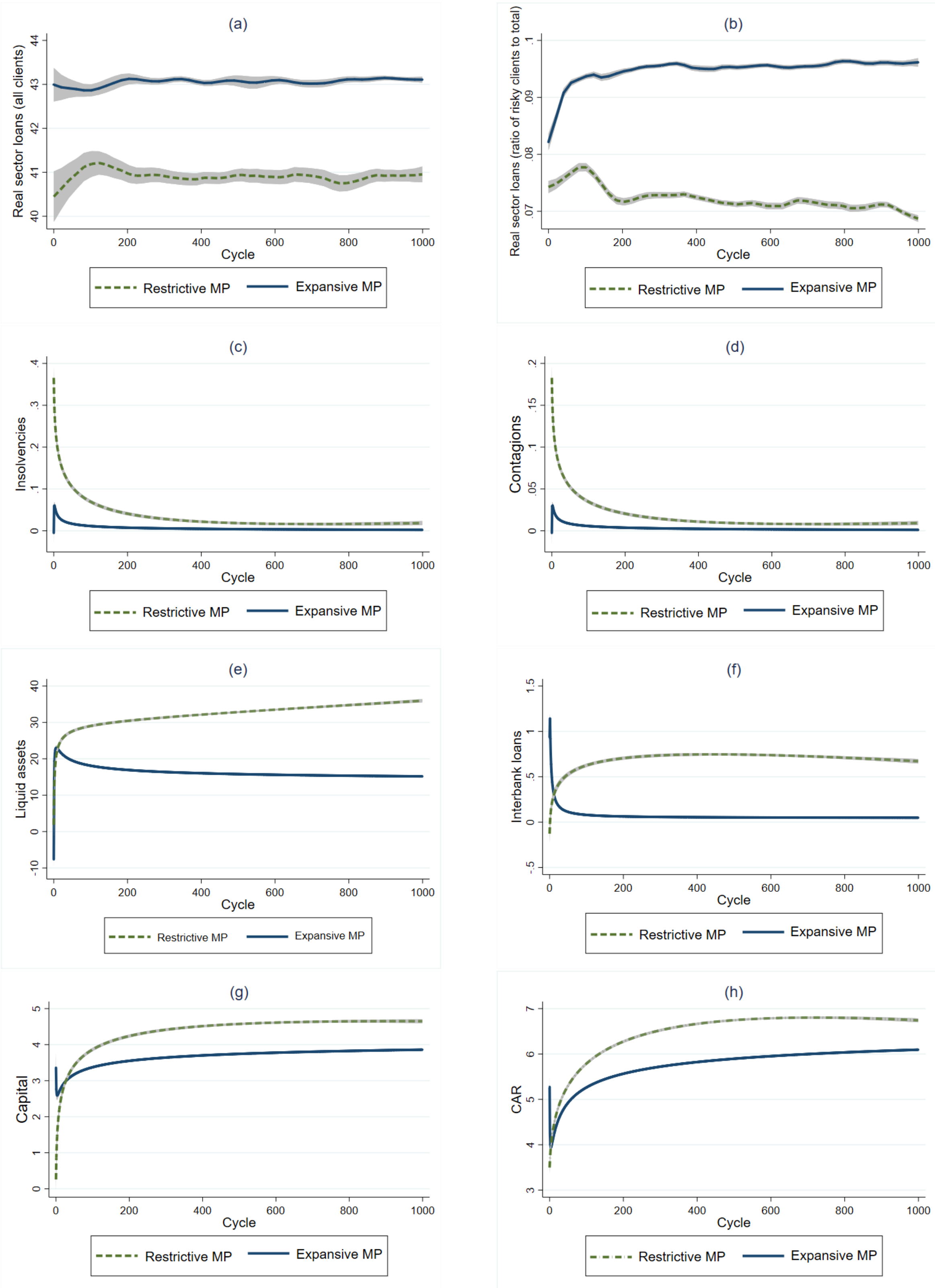
Table 6 – EWA parameters

Parameter	Meaning	Value
ρ	Retrospective discount factor	0
ϕ	Discount factor of previous attractions	1
$N(0)$	Initial experience	1
δ	Weight given to past payoffs	1
$A(0)$	Initial attraction	0
λ	Sensibility to attractions	1
C	Number of cycles	1,000

of loans to the real sector firms than the restrictive stance. Banks perceive a diminished risk from their potential clients, even from the ones once deemed as risky. Consequently, they accept to incur more credit transactions to increase their profitability because firms' default probability reduces. On the other hand, when the monetary policy tightens, banks become less active in the lending activity in order to protect themselves against the increased risks (augmented probability of default for both types of firms) that the high interest rate level brings about.

Figure 2b shows us our variable of interest: banks' risk-taking. It measures the ratio of the total amount of loans for risky real sector firms to the total amount of loans for the real sector as a whole (risky and low-risk firms). When the monetary policy stance is expansive, banks lend a higher percentage of their total loans to risky clients than when it is restrictive. According to our metric of risk, banks take on more risks. The rationale to lend to risky companies is, as Table 5 shows, to receive a larger amount of interest when the firm pays the loan back. Notice that the same table exposes the trade-off between risk and return: the companies that can yield larger returns for banks are the ones that are more likely to default. When interest rates are low, and consequently risks are low too, banks are more biased to search for yield and accept more risks. One explanation that we find in literature is that firms' guarantees' present value increases, making loans cheaper (harder to default). It happens for the two types of firms (Rajan, 2005). On the other hand, when interest rates are high, banks are more prone to shun risks at the expanses of

Figure 2 – Expansive and Restrictive monetary policy (MP) stances on some variables



returns. They avoid liquidity shortages and resort to outside liquidity sources, which are expensive when the monetary policy is restrictive (interbank loan and window discount loan).

In the earlier cycles, Figure 2b shows us that when the monetary policy stance is expansive, banks learn that it is more profitable to increase the percentage of risky clients in their real sector loans portfolio. It then stabilizes at a higher level around the cycle 200 onward. On the other hand, financial institutions have an opposite behavior when the monetary policy stance is restrictive. They learn in early cycles that it is more advantageous to diminish the percent of loans to risky clients in their loan portfolio. The learning process becomes more evident as we check the other variables in the figure. Some "teaching lessons" that banks take to learn how to calibrate their risk-taking in Figure 2b is from Figure 2c and Figure 2d. We can notice that when the monetary policy stance is restrictive, insolvencies and contagions are at a high level. Nevertheless, they decrease as the cycle goes by up to the point that they converge to the same levels that the expansive monetary policy stance registers. Banks learn that they need to take on less risk in the high-interest rate environment to avoid insolvency. As they do it, they diminish the level of such a variable. Because fewer banks are insolvent, it is expectable that fewer banks become insolvent due to other banks; then, contagion decreases too. On the other hand, the always-low level of insolvency and contagion when interest rates are low allows banks to search for yield, increasing the percentage of loans destined to risky clients. The convergence when comparing the two monetary policy stances calls attention. It shows that "insolvency" and "contagion" are equally undesired in both scenarios because they represent loss, whereas banks look for profits.

Figure 2e shows a very significant learning process. When the monetary policy stance is restrictive, banks diminish their loan amount to the real sector (Figure 2a) and, as a consequence of what Table 2 shows, they increase their liquidity as the cycle goes by. In economic terms, throughout the simulation, financial institutions learn that they must have liquid assets to pay depositors who withdraw earlier; otherwise, they have to resort to interbank loans or the window discount loan, which impose higher costs than simply accruing liquid assets. Thanks to such learning, banks shun insolvency and contagions. Regarding the expansive monetary policy environment, liquid assets accruing diminishes as the cycle goes by. Banks learn that lending it to the real sector is a better strategy once they face few liquidity shocks (anticipated depositors’ withdrawals), as Figure 3c shows.

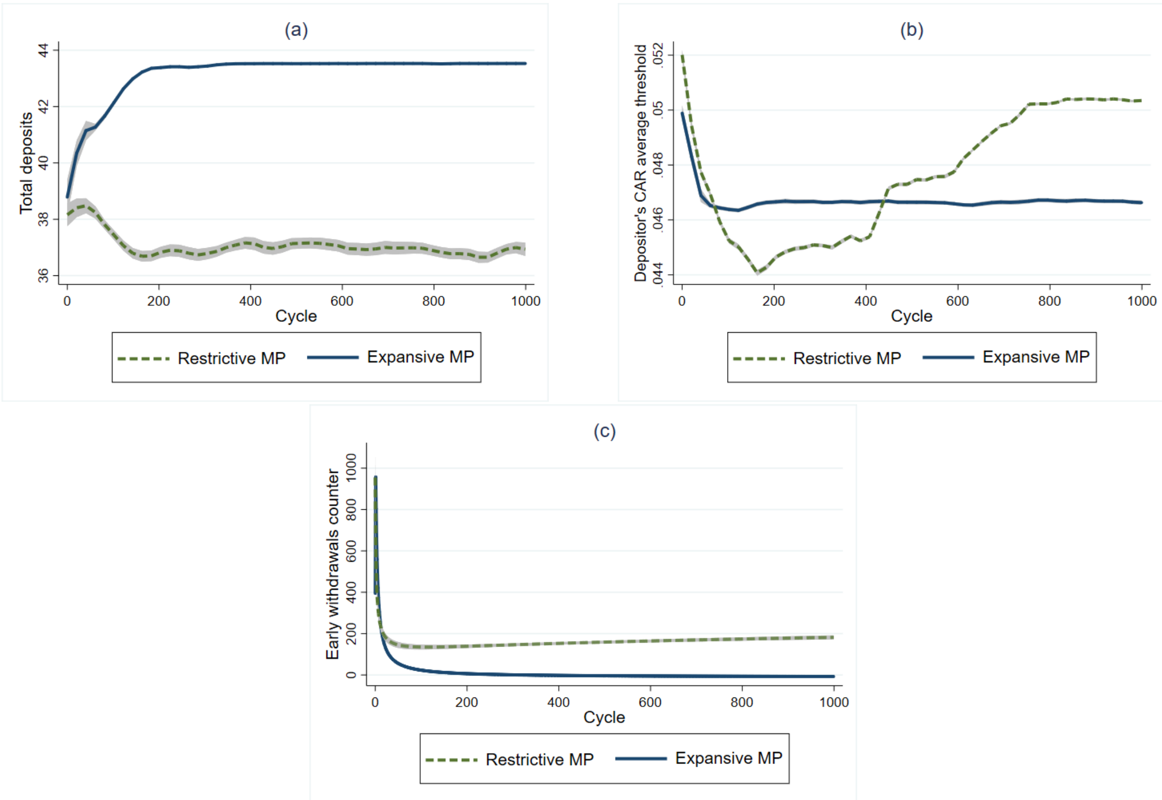
When banks faced liquidity shortages in the first cycles, the availability of interbank loans was low, as Figure 2f shows. This fact associated with the low liquidity (Figure 2e) produced high levels of insolvencies and contagions during the restrictive monetary policy stance (Figure 2c and Figure 2d). Banks neither had liquidity to pay the anticipated withdrawals nor could borrow some liquidity from other banks. However, as the cycle goes by, liquidity increases and also the number of interbank loans for banks in need. Given that banks already learned to accrue liquidity (as the last paragraph presents), they now learn that they can gain some interest using part of such liquid assets once they do not use the total amount to face liquidity shortages. Thus, they can diversify the excess liquidity into two "investments": lending to other banks (receiving interest on it) and accruing as a reserve to face possible liquidity shortages (yielding no interest). Notwithstanding, the increase of interbank loans reaches a ceiling because banks also learn how to become more liquid and depend less on interbank loans, as we discussed previously. In any case, because of the more frequent liquidity shocks that banks suffer when the monetary policy stance is restrictive (Figure 3c), more banks need outside liquidity to pay back withdrawals. Thus, the augmentation of the number of banks offering and demanding liquidity heats the interbank market.

Analyzing when the monetary policy eases in Figure 2f, because banks learn how to avoid liquidity shortages still in the earlier cycles and there are less frequent liquidity shocks, financial institutions need less outside liquidity to pay the anticipated withdrawals. Then, the interbank market does not produce many loans in later cycles due to, essentially, the small demand. The difference between the two scenarios of the monetary policy stance ratifies what we can see in reality. In the real world, the positive relationship between the interbank rate and banks' decision to lend to other banks and to accrue liquid assets is one of the findings of Lucchetta (2007).

Regarding capital levels (Figure 2g and Figure 2h), when the monetary policy is restrictive, banks keep a higher level of capital and CAR (Capital Adequacy Ratio) when compared to the expansive monetary policy stance. In the environment of higher interest rates, banks start their capital and CAR at low levels, matching with the same period of their high level of insolvencies, contagions, and frequent liquidity shocks (Figure 3c). When it comes to the expansive monetary policy, we can observe that the valley in the early cycles jibes with the peaks of the Figure 2c and 2d. In both scenarios, as the cycle goes by, banks learn that they have to keep their capital and CAR at higher levels to signalize to depositors that they are not taking excessive risks. Consequently, they dissuade depositors from anticipating their withdrawals and avoid liquidity shocks, which led them to insolvency in the earlier cycles. The gap between the two monetary policy stances is not a surprise even though Central Bank's requirement is equal for both (10% of bank's assets). The risks become augmented when the monetary policy gets strict; thus, banks' signals to depositors must be more substantial. We can conclude that depositors regulate banks, imposing a limit for risk-taking.

Regarding Figure 3, some aspects call attention. Figure 3a shows that banks' total deposits are lower when the monetary policy stance is restrictive. This fact diminishes banks' capability to lend because of fewer available resources. In the world out of our model, depositors could be more attracted to invest in financial instruments that yield higher interest. Regarding depositors' CAR threshold tolerance, it is higher when the monetary policy tightens. Nevertheless, this behavior is not true during the entire simulation. In the first cycles, depositors drop their threshold to a level that is even lower than

Figure 3 – Depositors' behaviour

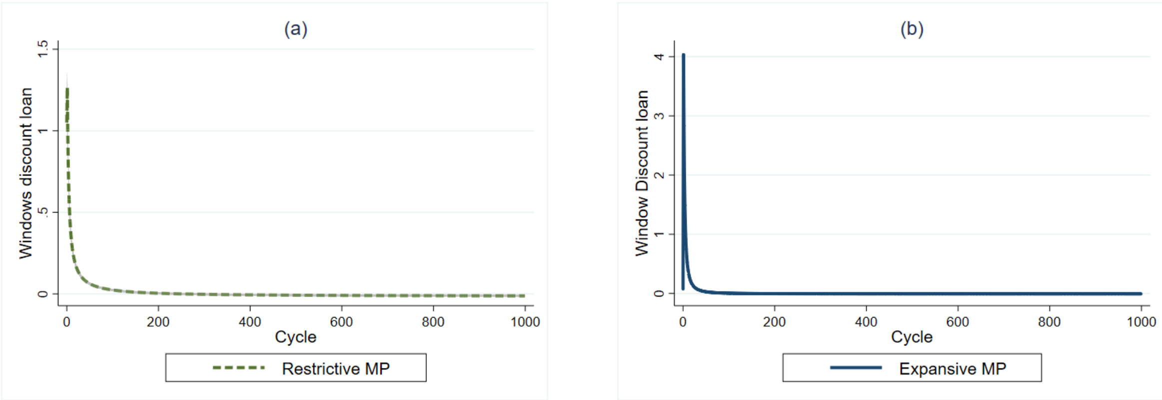


when risks are low (the monetary policy stance is expansive). This period coincides with the period in which contagions and insolvencies are very high (Figure 2b and Figure 2c) and the anticipated withdrawals plunge (Figure 3c). After understanding the analytical process, we can get further into economic intuition. Because banks are insolvent, many depositors lose their deposits, do not maximize their utility function (equation 2.5), and have to change their strategy for the following cycle. Thus, depositors increase their CAR threshold average little by little. Because banks' CAR also augments (as a response to depositors) and their insolvencies and contagions stabilize at lower levels, depositors end up anticipating fewer withdrawals. At the end of the simulation, depositors' CAR threshold is higher than when the monetary policy eases.

As we already discussed, and Figure 3c attests, banks suffer more liquidity shocks from their depositors when interest rates are high. When the monetary policy eases, hardly does a depositor anticipate his/her withdrawing. He/She drops his/her CAR threshold tolerance and withdrawal anticipations in the first cycles up to a level that practically does not change during the rest of the simulation. We can notice that the same happens with the levels of insolvencies and contagions (Figure 2c and Figure 2d). The cause of these facts is the low-risk perception.

Regarding the window discount loan (the Central Bank's loan), Figure 4 shows that it converges to zero still in the early cycles for both monetary policy stances. This

Figure 4 – Window discount loan



dropping behavior coincides with the diminishing of banks' insolvencies and contagions. Banks learn how not to go insolvent and, consequently, solve all their liquidity needs in the interbank market. In our model, the banks' preference for interbank loans is due to the punitive rate of the CB's loan. Because of it, banks shun the lender of last resort. In the real world, however, we can add another reason to it: "stigma." According to Armantier et al. (2010), depositors and other banks may perceive the financial institution that borrows from the CB as being in a weakened financial condition and anticipate its insolvency. The authors also show that even during the crisis of 2008, such loans were rare. Banks preferred to pay the high-interest rate of the interbank market (that became "punitive" due to the augmented risk) than the window discount rate, which was the cheapest outside liquidity option for banks at that time. It is all thanks to the "stigma." Consequently, our model reveals a behavior that is present in the real world: banks shun as much as they can window discount loans.

We can notice that our model ratifies what the neoclassical monetary policy transmission channel states: monetary policy stance affects banks' risk-taking. However, one advantage of this framework is that we can see banks' learning process. Understanding the final results and the evolving path allows us to analyze the economy in the transient state and not only in the stationary state. For example, as Havraneka and Rusnak (2013) shows through sixty-seven published studies, there exists a lag between the Central Bank's action-taking about the monetary policy and the full effect of such a policy on the aggregate output. Thus, there is a period of time between agents' "receiving" the news about the policy and their final optimizing behavior, which they use to adapt their strategies. The analysis of this transient path gives essential insights to understand intensely how financial players and the economy react to changes in the monetary policy stance up to the equilibrium. Figure 2b, for instance, shows that when interest rates increase, banks augment the volume of loans to risky clients in order to take advantage of the higher interest rate and make more profit (they are out of equilibrium). Kumar, Acharya and Ho (2020) shows this same result for New Zealand: banks increase their profits in the short term. However, as our model also presents, banks diminish the total amount lent as the cycle goes by (they are in equilibrium). Thanks to the learning path, we can comprehend this changing of points. It is a response to the calibration of other variables. Thus, we can complete analysis and explain facts that happen when the economy is not at equilibrium.

After running the simulation model several times, we analyzed the behavior of the fifty banks at the end of the second period of the one-thousandth cycle. According to Table 7, we can split the fifty simulated banks into four clusters based on their size: "small," "medium," "medium-big," and "big." This table also presents the frequency within each cluster. We use the value of total assets as a proxy for size. Finally, it is crucial to notice that, for example, a bank is big concerning the other banks. We have not established any threshold of the size of assets or other variables.

Table 7 – Distribution of banks according to their size and monetary policy stance

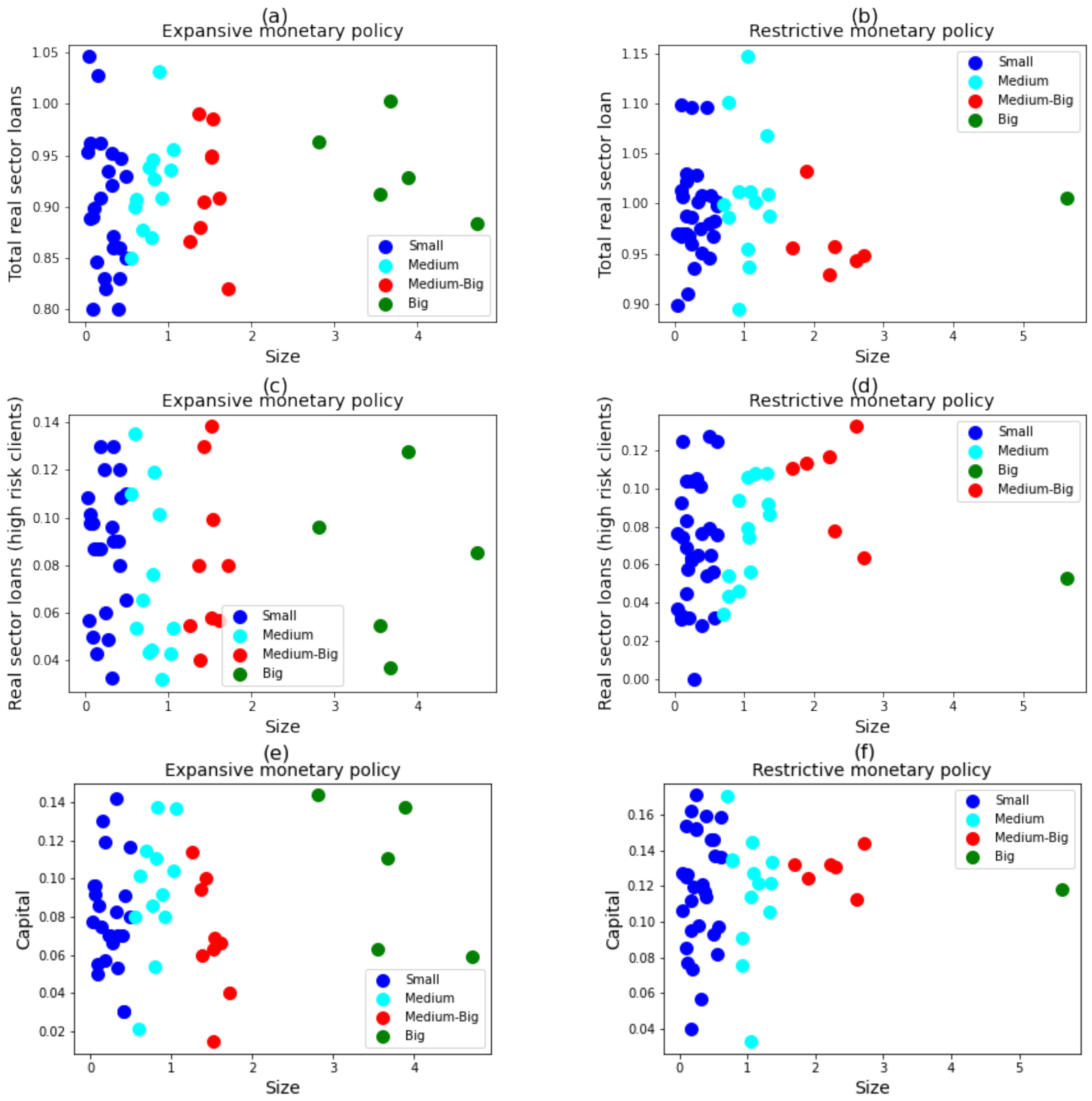
	Expansive MP	Restrictive MP
Size	Frequency	
Small	24	30
Medium	12	13
Medium-Big	9	6
Big	5	1

Banks' size distribution calls attention when we analyze Table 7. Because banks are larger when the monetary policy stance is expansive, our result suggests that an environment marked by a low-interest rate level is more propitious for banks to grow than when interest rates are high. This fact has to do with the bank's learning process to avoid depositors' anticipated withdrawals (liquidity shocks). Because the institutions have to keep a level of capital as high as the risk taken, the general augmented risk resulting from high-interest rates stops banks from taking part in more credit operations. Consequently, their size hits the maximum at a lower level when compared to the environment of lower risks, a reality when interest rates are at a low level. Many institutions do not take as many risks as they wish and end up not growing too much (paid back loans increase banks' assets and, consequently, our measure of their size). A way to circumvent this situation is through off-balance operations, a strategy that many banks adopt in the world out of our model.

The literature presents the relation between interest rates and banks' assets. Borio and Gambacorta (2017) analyze the effectiveness of the monetary policy on bank lending in a low-interest-rate environment. Using a sample of 108 large international banks, they conclude that reductions in short-term interest rates are less effective in stimulating bank lending growth if such rates are already at a very low level. Brei, Borio and Gambacorta (2020) explains the aforementioned fact by stating that the environment of persistently low-interest rates induce banks to shift their activities from interest-generating (i.e., loans) to fee-related and trading activities. Banks also moderately adjust their funding structure and start to depend more on deposits. Moreover, a significant period of low interest rates diminishes banks' profitability due to the lower net interest margins. It may make them more vulnerable to risks and less able to provide loans in the longer term (Borio; Gambacorta, 2017). We can conclude that if banks in low rates environment are larger than in the high rates environment, as our model suggests, it is not because they sustain an increase in lending as time goes by. It may have to do with changes in their activities, which may lead to future vulnerabilities.

Regarding banks' size evaluation, Tabak, Fazio and Cajueiro (2013) find that a highly unequal banking market in terms of assets is detrimental not only for the performance of smaller banks but also for the stability of the whole system.

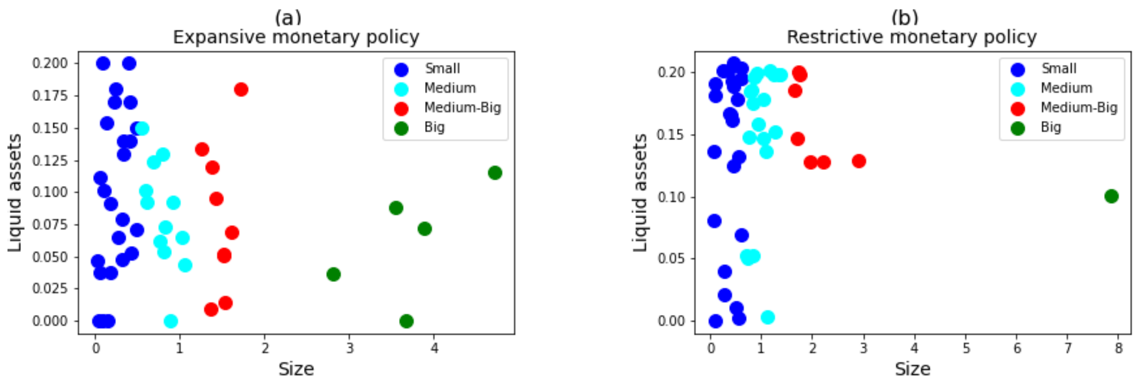
Figure 5 – Banks' loans and capital for different monetary policy stances



In Figure 5, we plot the values of some financial variables as a percentage of banks' total assets, which is our measure of banks' size. According to the graphs, our first result is that there is no relation between the financial institutions' size and total real sector loans (as a percentage of total assets), loans to risky clients (as a percentage of total loan), or capital (as a percentage of total assets).

What makes Bank A decide to lend more resources to the real sector as a percentage of its total assets than Bank B? Given that size does not play any role, we can evaluate the influence of capital, as Figure 5e and Figure 5f show. More capitalized banks tend to lend more, including to risky clients, considering both monetary policy stances. It happens because this fact allows banks to be robust against liquidity shocks that their impatient depositors impose. Once they signalize that they are not taking on excessive risks, they dissuade early withdrawals and avoid liquidity shortages. Thus, they can engage in the lending activity to the real sector because they need neither the interbank market nor the window discount. There is no liquidity shortage to face. On the other hand, less capitalized banks are more exposed to liquidity shocks from their depositors and tend to engage in fewer lending activities. Strictly these banks observe a reduction in their liquidity and resort to outside sources of liquidity, which impose augmented costs, especially when the monetary policy stance is restrictive.

Figure 6 – Banks' liquid assets for different monetary policy stances



Regarding the level of money destined for loans, it plunges in the restrictive monetary policy scenario as Figure 2a and 2b exhibit. As Table 7 shows, many banks diminish their size and become small or medium when monetary policy tightens. Notwithstanding, it calls attention in Figure 5 that some financial institutions seem to enlarge their lent resources when the monetary policy tightens. Once again, liquidity explains this behavior (Figure 6a and Figure 6b). Enough liquidity pays depositors' withdrawal requests and allows banks to continue lending as much as they wish without resorting to the more expansive interbank loan or window discount loan. This way, the monetary policy has a stronger effect on banks with less liquidity. This result ratifies the "Kashyap and Stein liquidity puzzle" (Kashyap; Stein, 2000).

The interbank money market plays a crucial role in the execution of the monetary policy, and analyzing its structure to understand its functioning is vital (Jürgen; Ulrike, 2003). As Figure 2f shows, our model suggests that the interbank market has fewer loans when the monetary policy stance is expansive than when it is restrictive. Notwithstanding, the topology of such a market (or the design of the financial network) is similar in both scenarios.

Figure 7 – Interbank network (expansive monetary policy stance)

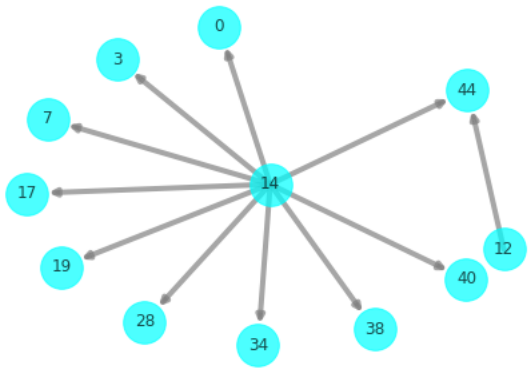


Figure 8 – Interbank network (restrictive monetary policy stance)

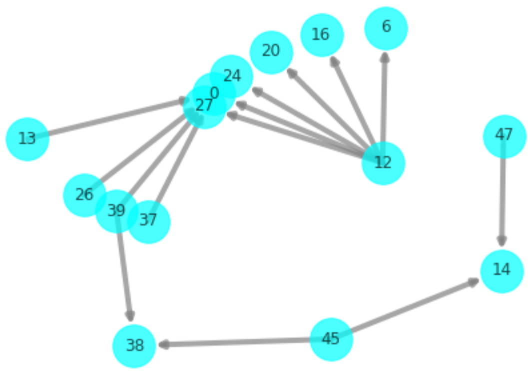


Figure 7 and Figure 8 show that the interbank market's topology in our model is compatible with the free-scale networks. In other words, the market characteristic is the formation of "money centers," banks that have exposures to many banks and are the most important source of large lending. The financial literature also reports this type of structure in the real world. Cajueiro and Tabak (2008) find that money centers mark the Brazilian interbank market, a fact that is also true, for instance, for the German and the Iranian interbank markets (Craig; Peter, 2014; Zanganeh et al., 2020). A relevant aspect of this type of structure is that because the money centers link to otherwise disconnected banks, the risk of contagion decreases (Degryse; Nguyen, 2007). We can observe a low level of contagion in our financial system in the one-thousandth cycle, as Figure 2d shows.

Conclusion

The study investigates the relationship between monetary policy and bank risk-taking using an agent-based model (ABM) approach. Our model counts with fifty different sized banks. We use the amount of banks' loan to risky real sector clients as a proxy for risk. To carry on such analysis, we make use of the BankSim Model, a banking agent-based simulation framework that Silva (2018) coded in Python 3+. Because the model's original design is to evaluate regulation policies, we altered the coding in order to conduct our proposed task.

After running the simulations several times, our model showed that the expansive monetary policy produces a higher level of loans to the real sector firms than the restrictive monetary policy. Moreover, risky clients get to borrow more significant amounts when the monetary policy stance is expansive. That is, banks take on more risks. Regarding insolvencies and contagions, the two stances produce convergent values. It is due to banks' learning process. Our model shows that banks get more connected through interbank loans when the monetary policy tightens. It happens due to an increase in the demand (banks face more liquidity shortages because of more frequent anticipated depositors' withdrawals) and in the supply (the higher interbank rate impels banks with an excess of liquidity to lend to the institutions in need). Besides, not mattering the monetary policy stance, banks shun the punitive interest rate of the window discount loans and prefer to get interbank loans when they need liquidity.

In the world out of our model, during liquidity crises, although many banks demand interbank resources, the financial institutions with an excess of liquidity tend not to lend because they either fear the borrower's default (contagion) or to suffer a potential future liquidity shock themselves. Our model may probably show that this situation could be smoothed if the information could flow more freely, i.e., less asymmetric information. Thus, the more information asymmetry problem is tackled, the more interconnections banks create. As a result, during liquidity crises, the financial system becomes more stable. Because banks in need can easily borrow from other banks, they would go insolvent less frequently. We need to empirically test this hypothesis, however.

We split the fifty simulated banks into four clusters based on their size to understand banks' behavior deeply. Considering the expansive and restrictive monetary policy stances, we notice that most banks are small or medium (including medium-big). Nevertheless, regarding the monetary policy stance, when it is restrictive, banks tend to be smaller than when it is expansive. Thereby, our model suggests that an environment of higher interest rates tends to make banks smaller. This result, however, needs further validation. Furthermore, banks take on more risks if they well-capitalized. Finally, we conclude that money centers characterizes the interbank market's structure.

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APPENDIX A – Robustness Test (Tough Central Bank)

To show the robustness of the results that we present in Chapter 3, we change the Central Bank's capital requirement to a more strict level and simulate the model again. That is, in Table 5, we change the last row (CAR_{min}) to 13% of bank's assets. We keep the same value for all the other parameters, including all the ones in Table 6.

Figure A.0.1, Figure A.0.2, and Figure A.0.3 show our main results. We can attest that our model produces the same outcomes of Chapter 3 even if we increase Central Bank's minimum capital requirement. The learning process is not exactly the same, but the path is very similar.

Regarding interest rate level and bank size, Table A.0.1 shows that banks tend to be smaller when interest rates are high. This model's outcome, already introduced in Chapter 3, is true even if the Central Bank enlarges its minimum capital requirement. Nevertheless, this fact seems to become stronger when the CB is tough.

Table A.0.1 – Bank size distribution - tough CB

	Expansive MP	Restrictive MP
Size	Frequency	
Small	18	23
Medium	20	19
Medium-Big	7	7
Big	5	1

Figure A.0.1 – Expansive and Restrictive monetary policy (MP) stances on some variables - tough CB

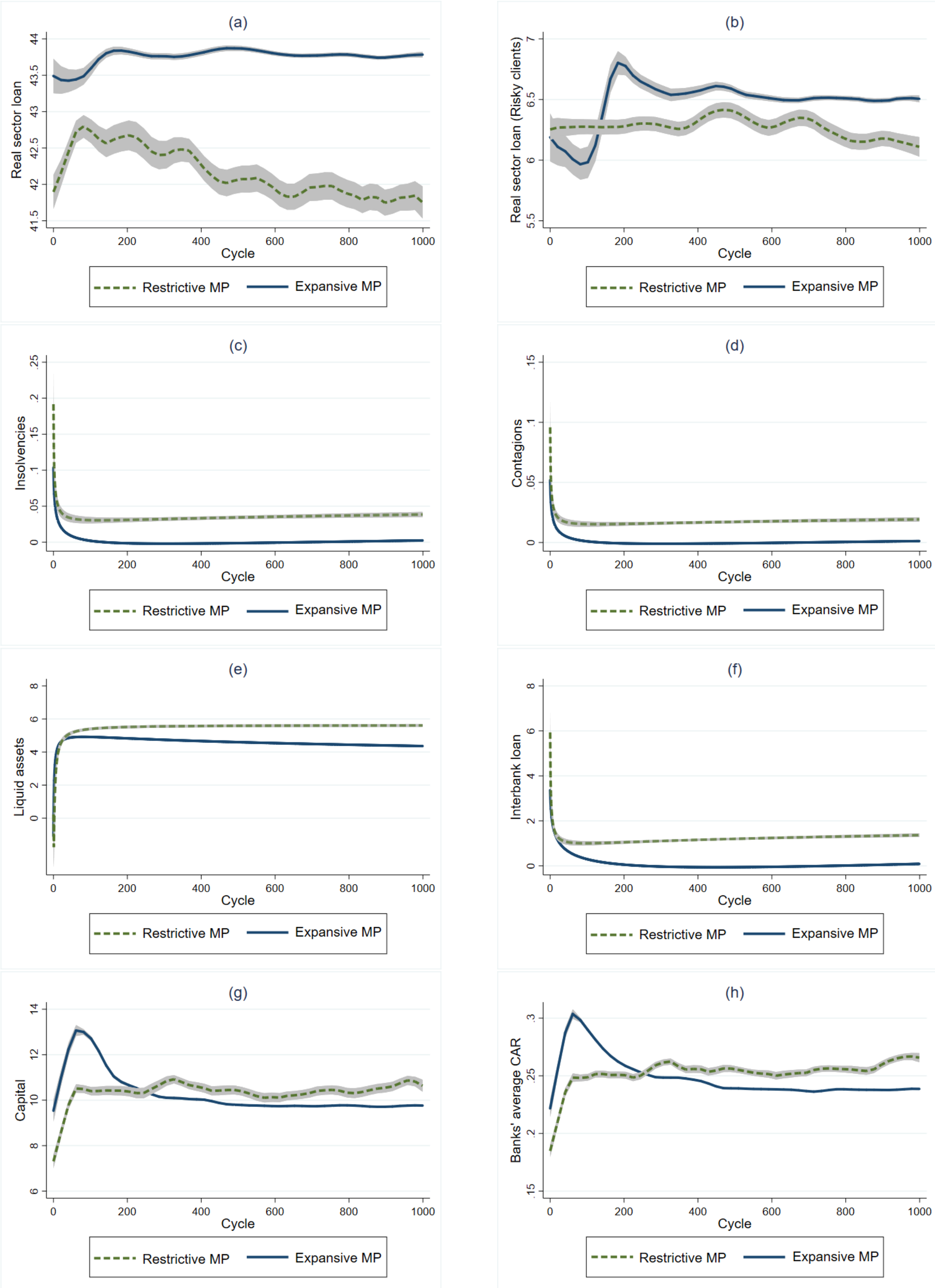


Figure A.0.2 – Depositors' behaviour - tough CB

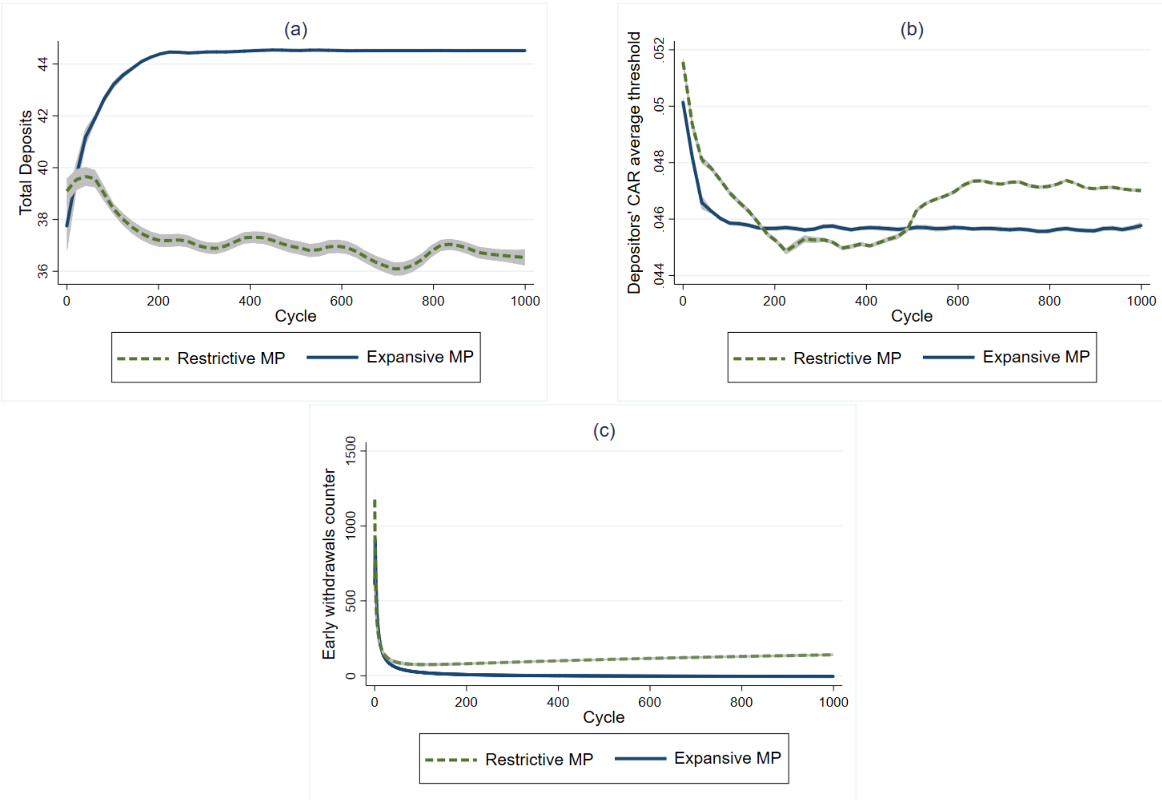


Figure A.0.3 – Window discount loans - tough CB

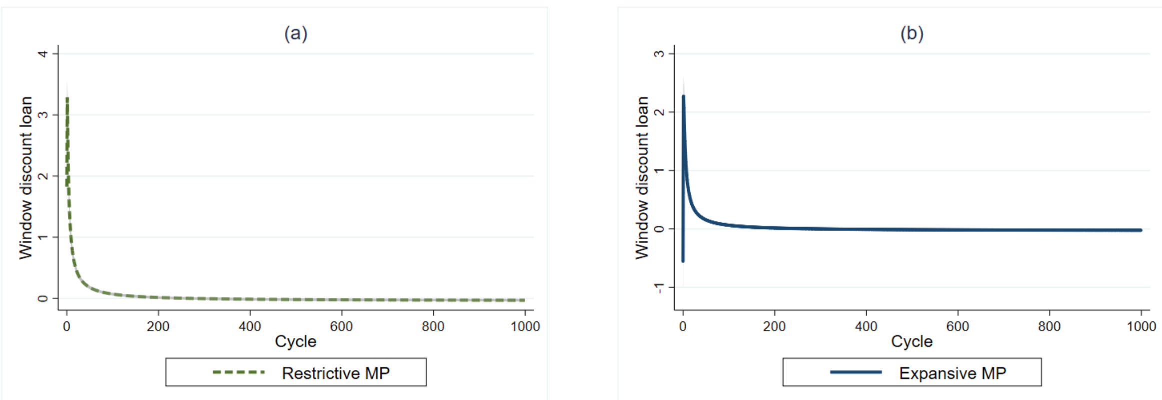
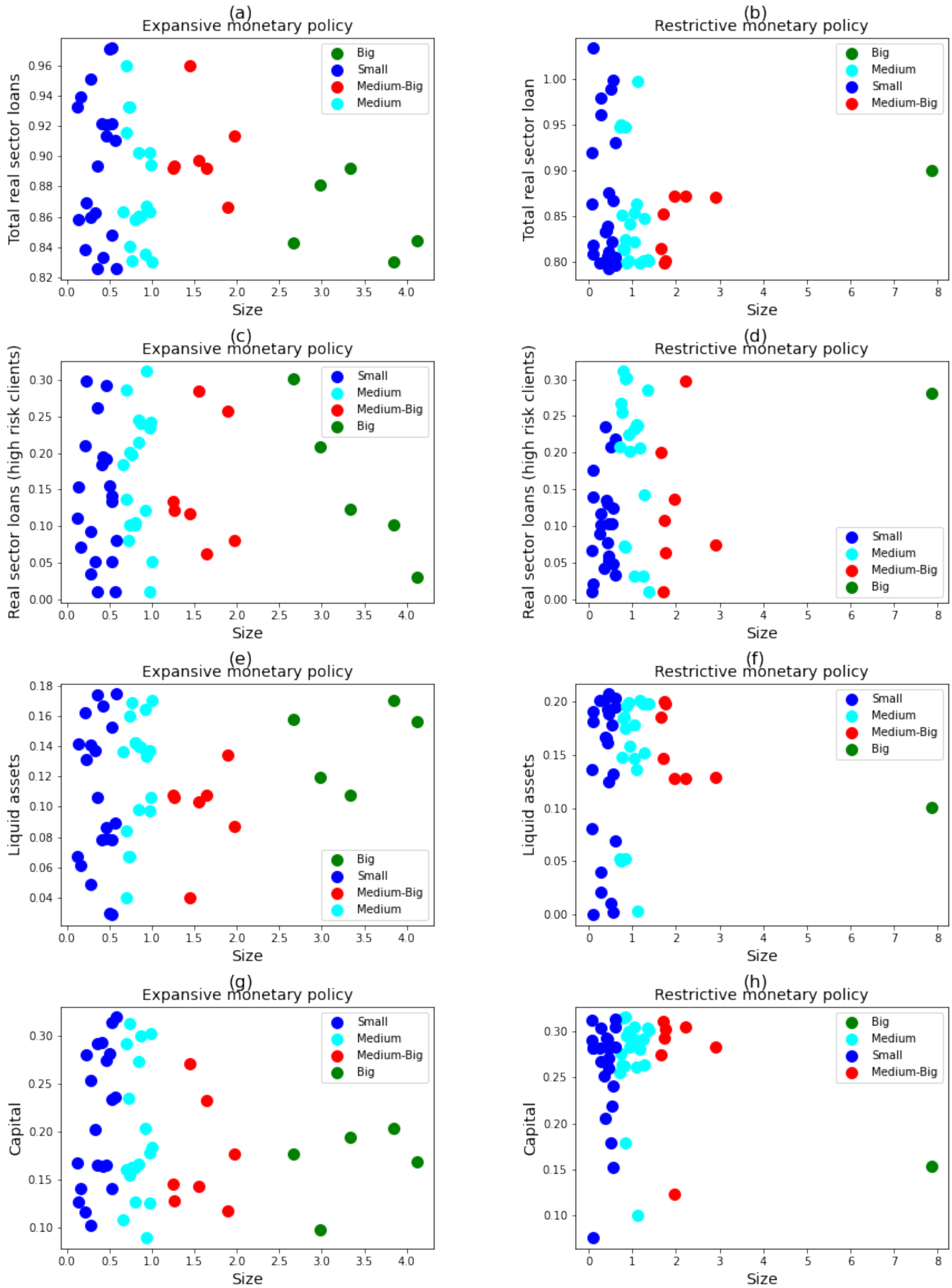


Figure A.0.4 – Financial variables by bank size - tough CB



APPENDIX B – Robustness Test (Lenient Central Bank)

In this appendix, we consider the Central Bank to be lenient. We change its capital minimum requirement to a lower level and simulate the model again. In the last row of Table 5, we change (CAR_{min}) to 7% of bank's assets. We keep the same value for all the other parameters, including all the ones in Table 6.

Figure B.0.1, Figure B.0.2, and Figure B.0.3 show the our main results. We can notice that our model produces the same outcomes of Chapter 3 even if we diminish Central Bank's minimum capital requirement. Although not exactly equal, the learning process is very similar.

Regarding interest rate level and bank size, Table B.0.1 shows that banks tend to be smaller when interest rates are high. This model's outcome, already introduced in Chapter 3, is true even if the Central Bank diminishes its minimum capital requirement. Nevertheless, this fact seems to become less evident when the CB is lenient.

Table B.0.1 – Bank size distribution - lenient CB

	Expansive MP	Restrictive MP
Size	Frequency	
Small	25	32
Medium	17	12
Medium-Big	5	4
Big	3	2

Figure B.0.4 reinforces some results that we found in Chapter 3. As Figure B.0.4a, Figure B.0.4b, Figure B.0.4c, and Figure B.0.4d show that there is no relation between banks' size and their decision to lend to the real sector loan, including risky clients. One more time, capital and liquidity play relevant roles in the decision.

Figure B.0.1 – Expansive and Restrictive monetary policy (MP) stances on some variables - lenient CB

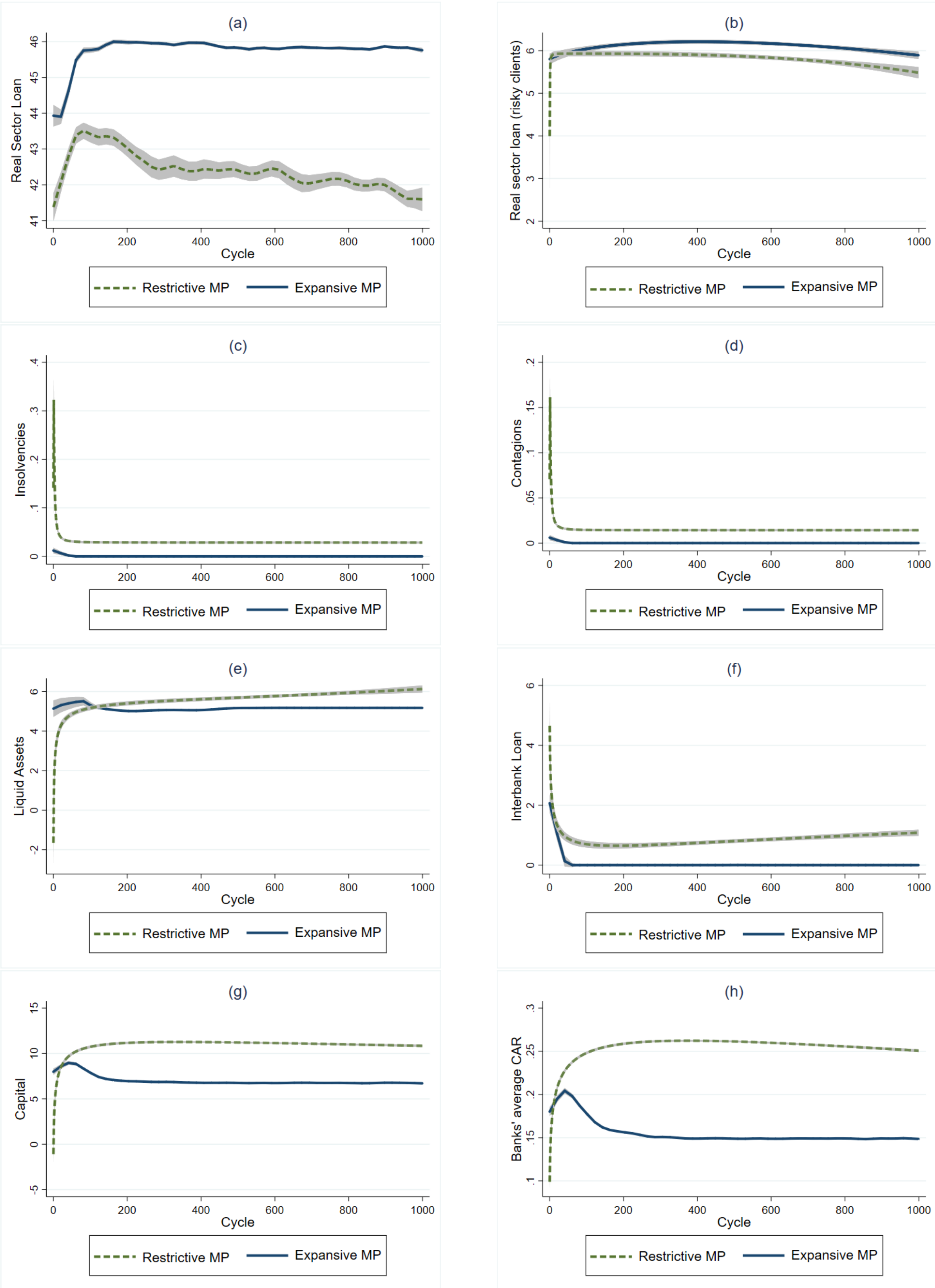


Figure B.0.2 – Depositors' behaviour - lenient CB

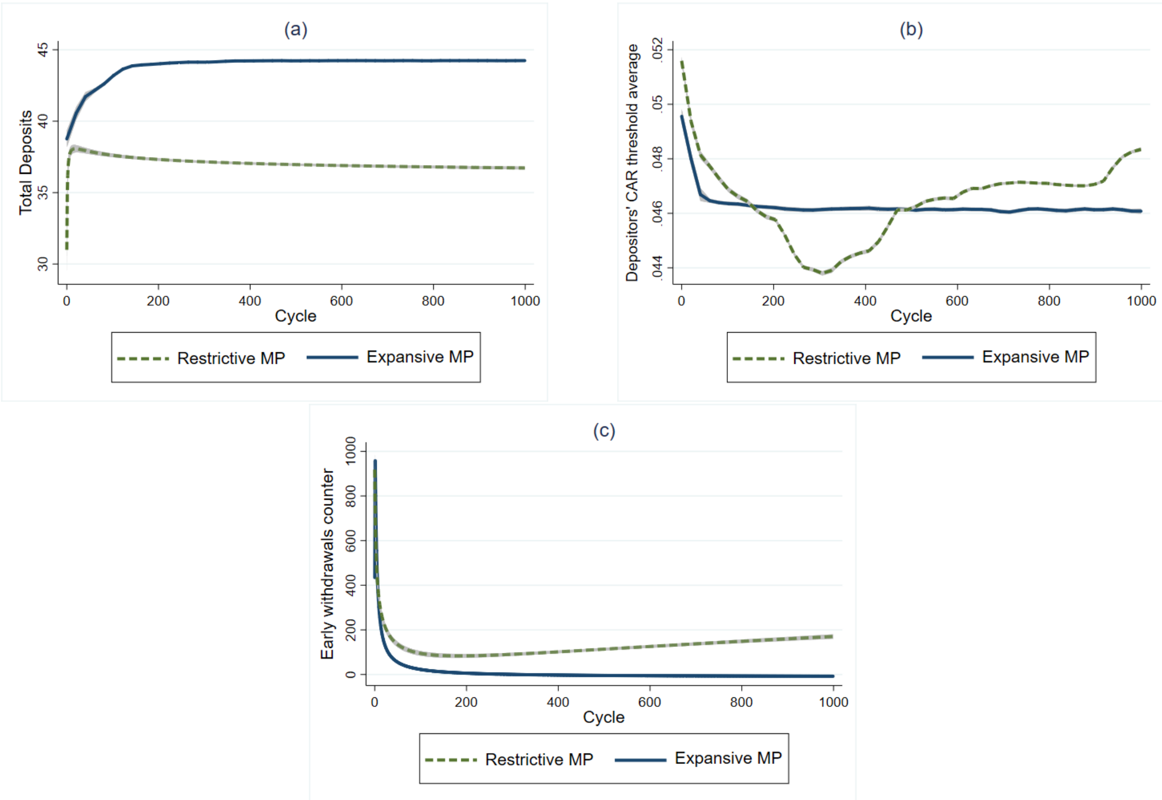


Figure B.0.3 – Window discount loans - lenient CB

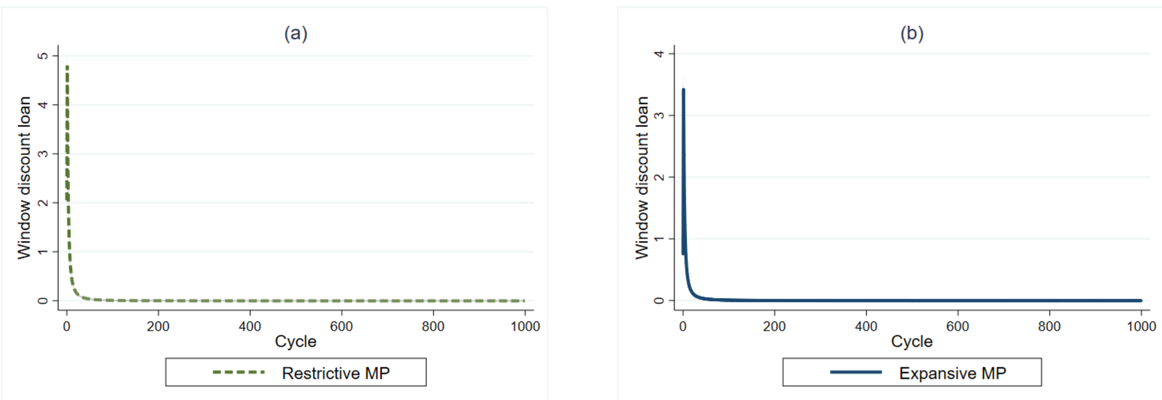


Figure B.0.4 – Financial variables by bank size - lenient CB