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The Natural Interest Rate in a Credit Economy

Dissertação de Mestrado

Masters dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Prof. Carlos Viana de Carvalho

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Abstract

Abreu, Marco Antonio Vargas Monteiro Novaes de; Carvalho, Carlos (Advisor). **The Natural Interest Rate in a Credit Economy**. Rio de Janeiro, 2026. 81p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

This paper studies the natural rate of interest in a credit economy through two complementary approaches. First, we estimate a medium-scale New Keynesian DSGE model for Brazil that incorporates default risk, imperfect banking competition, and credit market frictions. Our findings show that banking market power and credit constraints affect the economy's natural interest rate. We also document how macroeconomic shocks propagate through credit and financial channels, shifting the flexible-price benchmark rate. Second, we conduct a Monte Carlo experiment to assess whether including credit variables improves the recovery of the natural rate in empirical estimation. The results indicate substantial gains in accuracy when credit information is incorporated. Our framework captures key features of emerging markets and suggests that credit variables contain crucial information for properly measuring the natural rate and the stance of monetary policy.

Keywords

Natural Interest Rate; Monetary Policy; Financial Frictions; Bayesian Estimation.

Resumo

Abreu, Marco Antonio Vargas Monteiro Novaes de; Carvalho, Carlos. **A Taxa Natural de Juros em uma Economia com Crédito**. Rio de Janeiro, 2026. 81p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Este artigo investiga a taxa natural de juros em uma economia com crédito por meio de duas abordagens complementares. Primeiro, estimamos um modelo DSGE Novo-Keynesiano de médio porte para o Brasil que incorpora risco de inadimplência, competição bancária imperfeita e fricções no mercado de crédito. Os resultados indicam que o poder de mercado dos bancos e as restrições de crédito afetam a taxa natural da economia. Mostramos também como choques macroeconômicos se propagam por canais financeiros e de crédito, alterando a taxa de equilíbrio sob preços flexíveis. Em seguida, conduzimos um experimento de Monte Carlo para avaliar se a inclusão de variáveis de crédito melhora a estimação da taxa natural. Os resultados confirmam ganhos de precisão. O arcabouço destaca características típicas de economias emergentes e evidencia que variáveis de crédito são fundamentais para medir a taxa natural e a postura da política monetária.

Palavras-chave

Taxa Natural de Juros; Política Monetária; Fricções Financeiras; Estimação Bayesiana.

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List of Abreviations

AR – Autoregressive

Adm cost – Administrative cost

b.p. – basis points

BCB – Brazilian Central Bank

BGG – Bernanke, Gertler Gilchrist (1999)

CDB – Certificate of Bank Deposit (Certificado de Depósito Bancário)

CES – Constant Elasticity of Substitution

CSLL – Constribuição Social sobre Lucro Líquido

DSGE – Dynamic Stochastic General Equilibrium

FOC – First-Order Condition

GDP – Gross Domestic Product

HH – Household

IOF – Imposto sobre Operações Financeiras

IR – Imposto de Renda

IRF – Impulse Response Function

IRPJ – Imposto sobre Renda das Pessoas Jurídicas

PIS/COFINS – Program de Incentivo Social/Contribuição para o Financiamento de Seguridade Social

p.p. – percentage points

TFP – Total Factor Productivity

UK – United Kingdom

US – United States

All models are wrong, but some are useful.

George Box.

1
Introduction

The concept of the natural interest rate (denoted $R_t^\star$ in the model) has deep roots in the history of economic thought, tracing back at least to the seminal contributions of Knut Wicksell. As Wicksell (1898) (p. 102) notes,

> "There is a certain rate of interest on loans which is neutral in respect to commodity prices, and tends neither to raise nor to lower them. This is necessarily the same as the rate of interest which would be determined by supply and demand if no use were made of money and all lending were effected in the form of real capital goods."

In modern macroeconomics, this idea is formalized within the New Keynesian framework. Woodford (2003) defines the natural rate of interest as the equilibrium real rate that would prevail under fully flexible prices, abstracting from nominal rigidities. Beyond its role in textbook models, the natural rate summarizes the forces governing intertemporal allocation, including preferences, technology, and the balance between saving and investment.

The natural rate also provides a central benchmark for the assessment of monetary policy. As Wicksell himself stresses, in Wicksell (1898) (p. 25),

> "It is not a high or low rate of interest in the absolute sense which must be regarded as influencing the demand for raw materials, labour, and land or other productive resources, and so indirectly as determining the movement of prices. The causative factor is the current rate of interest on loans as compared to what I shall be calling the natural rate of interest on capital."

What matters, therefore, is not the level of the policy rate per se, but its position relative to the natural rate. When the policy rate lies below the natural rate, monetary conditions are expansionary and stimulate aggregate demand. When it lies above the natural rate, private expenditure contracts and the policy stance becomes contractionary. For this reason, the comparison between the policy rate and the natural rate lies at the core of modern monetary policy analysis.

As argued in Del Negro et al. (2015), the natural rate of interest can vary substantially over time as a result of multiple structural forces, including long-run potential growth, demographic trends, households' saving behavior, the perceived profitability of investment opportunities, and fiscal factors such as government spending and taxation. These forces shape the equilibrium balance between saving and investment and, therefore, the level of the real interest rate.

At the same time, recent macroeconomic developments and a growing empirical literature have highlighted the importance of financial frictions and credit intermediation for macroeconomic dynamics. In particular, Bernanke, Gertler and Gilchrist (1999) show how asymmetric information and borrowers' net worth generate a financial accelerator mechanism that amplifies and propagates shocks. Subsequent contributions extend this framework to incorporate imperfect competition in banking as in Gerali et al. (2010), as well as risk shocks in Christiano, Motto and Rostagno (2014). Taken together, these insights suggest that an accurate estimation of the natural rate may require a framework that accounts not only for traditional macroeconomic determinants, but also for financial frictions and institutional features shaping credit allocation and intermediation.

Beyond the literature discussed above, Brazil provides a compelling case study given its historically high real interest rates. According to Segura-Ubiergo (2012), Brazil recorded the highest real interest rate among emerging economies between 2002 and 2009. More recently, MoneYou and Lev Intelligence (2026) show that Brazil ended 2025 with the second-highest real interest rate worldwide. These findings suggest that elevated real rates are not merely episodic, but rather a persistent feature of the Brazilian economy.

Brazil also stands out along several dimensions of its credit market. According to the World Bank, average lending spreads reached 32.21 percentage points in 2019, well above the global median of 5.78 percentage points and substantially higher than the median for Latin America and the Caribbean, at 6.55 percentage points. In addition, as documented by Luz (2024), default rates and banking-sector concentration are salient features of the Brazilian economy. The coexistence of high real interest rates, elevated credit spreads, and concentrated banking markets points to potentially important interactions between financial frictions and the natural rate of interest. This motivates the use of a framework that explicitly incorporates credit-market frictions to understand the mechanisms shaping the natural rate in Brazil.[1]

In line with these observations, this paper incorporates financial frictions into a quantitative framework to analyze the natural rate of interest. In this respect, it is related to studies that also examine the natural rate in

[1]While the analysis emphasizes financial and credit frictions, traditional determinants of the natural rate, such as productivity, are not abstracted from the analysis. Instead, the framework allows us to assess whether and how the credit structure amplifies or modifies the effects on the natural rate.

environments with financial frictions. In particular, Del Negro et al. (2017) use a BGG-type framework to study the natural rate in the United States, focusing on the convenience yield on Treasury securities, which they interpret as a low-frequency component of the spread between corporate and Treasury bonds with the same maturity but different safety and liquidity characteristics. Likewise, Cúrdia and Woodford (2010) develop a DSGE model with two types of agents—borrowers and savers—and credit frictions to evaluate whether monetary policy rules should respond to credit spreads or aggregate credit. Their results show that financial conditions matter for the assessment of monetary policy and for the behavior of the interest rates. However, their framework is intentionally stylized and does not explicitly model the underlying sources of spreads. It also abstracts from several features that are central to our analysis, such as capital accumulation, collateralized borrowing by both households and firms, endogenous default, imperfect competition in the banking sector, and monitoring and administrative costs of intermediation.

Our paper builds on the insight that credit spreads and financial intermediation are relevant for macroeconomic stabilization, but shifts the focus toward the natural rate in an emerging economy with richer banking structure. To that end, we estimate a medium-scale DSGE model for Brazil with household and firm borrowing, collateral constraints, endogenous default, bank market power, and regulatory capital frictions. This framework allows us to study how they shape the level, dynamics, and empirical recovery of the natural rate of interest. We pursue this objective through two complementary steps.

First, we estimate a medium-scale DSGE model following Luz (2024). It is estimated using Brazilian data from 2000 to 2024. To recover the natural rate, we consider a counterfactual environment without nominal rigidities, while retaining distortions arising from financial frictions.

Second, we conduct a Monte Carlo experiment in which the model serves as the data-generating process. This exercise evaluates how accurately the model-based procedure recovers the latent natural rate under alternative sets of observables. More specifically, it examines whether credit-market variables provide additional information that improves the recovery of $R_t^\star$ relative to standard macroeconomic observables.

The analysis yields a set of results regarding both the level and the dynamics of the natural rate of interest in Brazil. The estimated real natural rate averages 8.00% over the full sample. Impulse response functions further show that financial and credit frictions play a meaningful role in shaping the response of the natural rate to macroeconomic shocks, particularly through collateral values and shifts in credit supply and demand. Forecast error variance decompositions indicate that, while productivity shocks dominate long-run fluctuations, credit-related shocks—especially durable-goods preferences and bank capital—contribute significantly to short- and medium-run dynamics. Finally, counterfactual exercises show that banking market power raises the equilibrium level of $R^{\star}$, whereas capital requirements and operational costs also have quantitative effects.

Our estimation remains systematically above the values reported in studies that abstract from financial frictions. This pattern also holds when comparisons are restricted to the sample periods covered by each study. For instance, Alves (2021), using a DSGE model for the period 1999–2019, report an average of 5.35%, whereas we obtain 9.12% for the same interval. Similarly, Palma and Portugal (2017) find an average of 6.9% for the period 2001–2015, while our estimate reaches 10.03%. For more recent years, measures reported by the Brazilian Central Bank (BCB) (Brazilian Central Bank (2024)) place the natural rate at around 5%; in contrast, we estimate an average of 9.10% for the period 2022–2024, although with a declining trend at the margin. Our estimates also indicate that, on average, the observed real policy rate lies below the estimated natural rate, implying a more expansionary monetary policy stance according to the model-based policy gap. This pattern is consistent with inflation dynamics in Brazil, where inflation frequently remains above target or, when within the target range, closer to its upper bound. Taken together, these results suggest that structural features of the credit market play an important role in shaping the equilibrium real interest rate.

Consistent with these results, the Monte Carlo experiment shows that augmenting standard macroeconomic observables with credit variables improves the recovery of the latent natural rate by about 4% when parameters are fixed and by 15–20% when parameters are jointly estimated. Overall, these findings underscore the relevance of financial frictions for understanding the level, dynamics, and policy interpretation of the natural rate in the Brazilian economy.

Literature. A large literature seeks to estimate the natural interest rate, using a wide range of methodologies and modeling assumptions. Following Giammarioli and Valla (2004), this literature can be broadly grouped into three approaches. The first relies on reduced-form and multivariate time-series methods, such as Hamilton et al. (2016) and Christensen and Rudebusch (2017). The second employs semi-structural models in which the natural rate is treated as a latent variable linked to potential output growth and additional low-frequency components, as in Laubach and Williams (2003) and Holston, Laubach and Williams (2017) for the United States, and Mésonnier and Renne (2007) and Fries et al. (2016) for the euro area. A third strand adopts fully structural frameworks, either through overlapping-generations models Gagnon, Johannsen and Lopez-Salido (2016), Kara and Thadden (2016), Eggertsson, Mehrotra and Robbins (2017), Carvalho, Ferrero and Nechio (2016) or New Keynesian DSGE models Edge, Kiley and Laforte (2008), Justiniano and Primiceri (2010), Barsky, Justiniano and Melosi (2014), Cúrdia et al. (2015), Del Negro et al. (2015), Del Negro et al. (2017), Hristov (2016).

An important distinction relative to semi-structural approaches concerns the definition of the natural rate itself. In models such as Laubach and Williams (2003) and Holston, Laubach and Williams (2017), the natural rate evolves over time through unit-root processes linked to long-run determinants, making it primarily a trend concept. In contrast, in our framework the natural rate is defined as as the equilibrium real rate that would prevail under fully flexible prices, conditional on each realization of shocks. As a result, shocks lead to immediate movements in the natural rate followed by gradual reversion, rather than permanent shifts in its steady state. Consistent with this view, Brand, Bielecki and Penalver (2018) show that natural-rate estimates derived from DSGE models tend to be more volatile than those obtained from semi-structural approaches, reflecting the fact that natural output in DSGE models reacts immediately to economic disturbances.

As highlighted by Del Negro et al. (2017), DSGE models offer two key advantages in this context. First, they allow the natural rate to respond endogenously to business-cycle shocks, capturing short-run fluctuations. Second, they provide a coherent framework for evaluating the monetary policy stance when the natural rate varies over time. At the same time, as emphasized by the same authors, this approach has an important limitation: inference is conditional on the assumed model structure and is therefore potentially sensitive to model misspecification. In this sense, the results should be interpreted as model-based estimates that provide a disciplined and internally consistent benchmark for analyzing the natural rate, rather than as a definitive measure.

For Brazil, existing estimates illustrate the relevance of modeling and periodo amostral choices. Time-series approaches, such as Borges and Silva (2006), obtain average natural rates close to 10% per year, while semi-structural models following Laubach and Williams (2003) typically deliver lower values, around 8% Ribeiro and Teles (2013). More recent studies using multiple methodologies, including adaptations of Holston, Laubach and Williams (2017), report estimates between 6.4% and 8% Moreira and Portugal (2019). DSGE-based estimates are less common, but Palma and Portugal (2017) find an average natural rate of approximately 6.9% per year, while Alves (2021) report a mean of 5.35% per year for the period between 1999 and 2019. These differences reinforce the importance of using structural models that discipline the dynamics of the natural rate through explicit economic mechanisms.

The model used in this paper is developed in Luz (2024) and builds on the financial accelerator mechanism of Bernanke, Gertler and Gilchrist (1999). It incorporates risk shocks (Christiano, Motto and Rostagno (2014)), imperfect competition in the banking sector (Gerali et al. (2010)), and credit to both households and firms (Becard and Gauthier (2022)). In addition, it distinguishes between credit demand and credit supply shocks, following Justiniano, Primiceri and Tambalotti (2015) and Justiniano, Primiceri and Tambalotti (2019). By integrating these features, the model provides a unified structural framework to analyze how financial frictions affect the natural rate of interest and its response to macroeconomic shocks. It therefore complements existing studies that abstract from a more complete credit environment and from the mechanisms underlying those frictions (Del Negro et al. (2017) and Cúrdia and Woodford (2010)).

The remainder of the paper is organized as follows. Section 2 presents the structure of the model. Section 3 describes the Bayesian estimation using Brazilian macro-financial data. Section 4 reports the main results and examines how credit market frictions affect the natural rate. Section 5 presents the Monte Carlo results. Section 6 concludes.

2
Model

In this paper, we use a medium-scale New Keynesian DSGE model incorporating enhanced financial frictions inspired by Bernanke, Gertler and Gilchrist (1999) extended to include a banking sector modeled along the lines of Gerali et al. (2010). The model features two distinct types of borrowers—impatient households and entrepreneurs—both subject to limited contract enforcement and default risk. Banks operate in monopolistically competitive deposit and loan markets. They set interest rates endogenously and generating spreads that reflect both default risk and market power. The model follows Luz (2024).

The economy is populated by four types of agents. Patient households supply labor, consume both durable and nondurable goods, and hold deposits at banks; their relatively high discount factor makes them net lenders. Impatient households also supply labor and consume both goods. Due to their lower discount factor, they borrow from banks to finance durable consumption, using these durable goods as collateral. Entrepreneurs acquire raw capital, convert it into effective capital and employ it in production. They finance investments either through internal net worth or external borrowing, similarly facing potential default risk. Finally, a monopolistically competitive banking sector intermediates funds by collecting deposits from patient households and extending loans to both impatient households and entrepreneurs.

On the production side, the economy features capital producers, durable-goods producers, wholesale firms, retail firms and a competitive final-goods firm. Capital producers transform final goods and undepreciated capital into new capital, facing investment adjustment costs. Durable-goods producers accumulate durable stocks subject to adjustment frictions. Wholesale firms hire labor and rent capital to produce intermediate goods. Retail firms differentiate goods and set prices above marginal cost. They face nominal rigidities in price adjustment, capturing key New Keynesian dynamics. Finally, a competitive aggregator combines these differentiated retail varieties into a single final good.[1]

[1] Since production side is standard in the literature, we leave the detailed description for the appendix.

2.1 Patient Households

Patient households are characterized by a relatively high discount factor, β^P, which exceeds that of impatient households ($\beta^P > \beta^I$). As a result, they behave as net savers and accumulate deposits at banks. They choose nondurable consumption (C_t^P), durable goods (S_t^P), labor supply (L_t^P), and bank deposits (D_t). We assume a preference with exogenous habit formation on non-durable consumption:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^P)^t \left[\epsilon_t^p \ln\Big(C_t^P - hC_{t-1}^P\Big) + \psi_t \ln\Big(S_t^P\Big) - \zeta_t \frac{(L_t^P)^{1+\varphi}}{1+\varphi} \right]. \tag{2-1}$$

Parameter $h \in [0, 1)$ governs the degree of exogenous habit formation in nondurable consumption. The stochastic processes ϵ_t^p, ψ_t, and ζ_t represent preference shocks affecting nondurable consumption, durable goods, and labor disutility, respectively. The inverse Frisch elasticity of labor supply is given by $\varphi > 0$.

Patient households act as net lenders by depositing funds at banks, thereby funding credit to impatient households and entrepreneurs. In return, they earn the nominal deposit rate r_t^d, which is subject to a tax τ^{rd}.[2] Their period-by-period budget constraint is given by:

$$C_t^P + D_t + Q_t^s \left(S_t^P - S_{t-1}^P\right) \leq W_t^P L_t^P + \frac{1 + r_{t-1}^d (1 - \tau^{rd})}{\pi_t} D_{t-1} + T_t^P, \tag{2-2}$$

where W_t^P denotes the real wage, Q_t^s the relative price of durable goods in terms of num-durable goods prices, $\pi_t \equiv \frac{P_t}{P_{t-1}}$ is the gross inflation rate, where P_t denotes the aggregate price level. T_t^P lump-sum transfers or dividends distributed by banks, entrepreneurs, and retail firms.

2.2 Impatient Households

Impatient households are characterized by a relatively low discount factor, β^I, which makes them natural borrowers in equilibrium. To model borrowing and durable goods demand in a tractable way, each impatient household is composed of three types of members: workers, brokers, and financiers.

Workers supply labor and consume final goods, while financiers make intertemporal decisions, including how much to borrow from banks in order to

[2] We adopt the convention of writing nominal interest rates in lower-case and real interest rates in upper-case.

finance purchases of durable goods. Funds can be freely transferred between workers and financiers, implying perfect consumption insurance within the household. The broker intermediates the acquisition of durable goods by the financier.[3]

2.2.1 Workers

Impatient workers supply labor (L_t^I), consume nondurable goods (C_t^I), and rent the stock of durable goods (S_t^I) from financiers at the rental rate RR_t^s. Their preferences are identical to those of patient households, except for a lower discount factor β^I.

Workers do not own durable goods, so their consumption of durables takes the form of rental services provided by financiers. They choose labor supply and consumption to maximize utility subject to the following budget constraint:

$$C_t^I + RR_t^s S_t^I \leq W_t^I L_t^I + \Xi_t, \tag{2-3}$$

where W_t^I denotes the real wage earned by impatient workers and Ξ_t is a transfer from financiers. This transfer ensures adequate consumption smoothing within the impatient household and is not required to be positive.

2.2.2 Broker

The broker intermediates the acquisition of durable goods between producers and financiers, introducing adjustment costs in durable purchases. This agent buys durable goods from producers and resells them to financiers, taking prices as given.

The broker chooses the stock of durable goods S_t^I to maximize the expected present value of profits:

$$\max_{S_t^I} \; \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^I \left[Q_t^s S_t^I - Q_t^s S_t^I \left(1 + Z^s \left(\frac{S_t^I}{S_{t-1}^I} \right) \right) \right], \tag{2-4}$$

where $\Lambda_{0,t}^I$ is the stochastic discount factor of the impatient household and

$$Z^s \left(\frac{S_t^I}{S_{t-1}^I} \right) = \frac{\kappa_s}{2} \left(\frac{S_t^I}{S_{t-1}^I} - 1 \right)^2. \tag{2-5}$$

[3]As highlighted in Luz (2024), this is a modeling device that allows for adjustment costs in the price of durable goods, which helps smooth the dynamics of durable consumption without affecting the household's risk-sharing properties.

This formulation smooths the dynamics of durable accumulation by financiers.

2.3 Borrowers: Entrepreneurs and Financiers

We consider two types of borrowers: financiers (impatient households) and entrepreneurs. Although they acquire different assets, both face a similar borrowing problem. For this reason, we describe their optimization jointly and highlight differences only when necessary.

2.3.1 General Setup

For each borrower type $o \in \{I, E\}$, there is a continuum of agents indexed by $j \in [0, 1]$. In period t, borrower j combines internal net worth $N^o_{j,t}$ with bank borrowing $B^o_{j,t}$ to acquire an asset $X^o_{j,t}$ at price Q^o_t:

$$Q^o_t X^o_{j,t} = N^o_{j,t} + B^o_{j,t}. \tag{2-6}$$

The nature of the asset depends on the borrower type. For financiers ($o = I$), $X^I_{j,t}$ corresponds to durable goods. For entrepreneurs ($o = E$), $X^E_{j,t}$ represents raw capital, which is subsequently transformed into effective capital for production. Heterogeneity within each borrower type arises from differences in net worth $N^o_{j,t}$ and idiosyncratic returns on assets.

At the beginning of period $t+1$, borrowers are subject to an idiosyncratic shock $\omega^o_{t+1}(j)$ that affects the realized value of their asset holdings:

$$Q^o_t X^o_{j,t} \longrightarrow \omega^o_{t+1}(j) Q^o_t X^o_{j,t}. \tag{2-7}$$

Following BGG, the shock $\omega^o_{t+1}(j)$ is independently and identically distributed across borrowers and over time, with a lognormal distribution and unit mean. $F^o(.)$ denotes the distribution of these random variables. For entrepreneurs, it captures uncertainty in transforming raw capital into effective capital. For financiers, it reflects random movements in the value of durable goods.

After acquiring the asset, borrowers rent it out in the subsequent period at a rental rate RR^x_{t+1}. For entrepreneurs, capital is rented to wholesale firms and, after production, the remaining depreciated capital $(1-\delta^k)K_{j,t}$ is sold back to capital producers at price Q^k_{t+1}. The gross return on capital for entrepreneur j is therefore given by

$$\omega^E_{t+1}(j)\left(1+R^k_{t+1}\right)=\omega^E_{t+1}(j)\frac{RR^k_{t+1}+(1-\delta^k)Q^k_{t+1}}{Q^k_t}. \tag{2-8}$$

This formulation implies that entrepreneurs, independently of their net worth, have access to a stochastic constant-returns-to-scale technology. For financiers, the return on durable goods is defined excluding rental income and is given by[4]

$$1+R^s_t=\frac{Q^s_t}{Q^s_{t-1}}. \tag{2-9}$$

At this stage, borrowers are required to repay their debt. However, due to limited enforcement of debt contracts, repayment depends on the realization of the idiosyncratic shock, giving rise to endogenous default.

2.3.2 Financial Friction and Default Decision

Debt contracts are subject to limited enforcement. Borrowers privately observe the realization of the idiosyncratic shock $\omega^o_{t+1}(j)$, while banks can verify it only by incurring a costly state verification expense. As in Bernanke, Gertler and Gilchrist (1999), lending takes the form of standard debt contracts, under which the borrower pledges the entire asset as collateral.[5]

Given this contract structure, borrower j defaults whenever the realized value of the pledged asset falls short of promised debt repayments:

$$\omega^o_{t+1}(j)\left(1+R^x_{t+1}\right)Q^o_tX^o_{j,t}<\left(1+R^{b,o}_t\right)B^o_{j,t}, \tag{2-10}$$

where $1+R^x_{t+1}$ denotes the gross return on asset $X^o_{j,t}$ and $1+R^{b,o}_t$ is the gross interest rate charged on loans.

This condition defines an endogenous default threshold $\bar{\omega}^o_{t+1}$, implicitly given by:

$$\bar{\omega}^o_{t+1}\left(1+R^x_{t+1}\right)Q^o_tX^o_{j,t}=\left(1+R^{b,o}_t\right)B^o_{j,t}. \tag{2-11}$$

[4]Following Luz (2024), rental income is excluded from the return on durable goods because banks cannot seize rental payments and idiosyncratic shocks affect only asset prices. This assumption simplifies the solution by making durable returns independent of rental rates.

[5]Standard debt contracts might not be optimal in this environment. We nonetheless adopt an exogenously incomplete market structure in which this is the only available lending instrument. Carlström, Fuerst and Paustian (2016) show that, within a BGG framework, the optimal contract may feature richer forms of indexation. Standard debt contracts are, however, widely used in the literature on financial frictions and provide a realistic and tractable benchmark.

Borrowers repay their debt whenever $\omega^o_{t+1}(j) \geq \bar{\omega}^o_{t+1}$ and default otherwise. In the event of default, banks seize the pledged collateral and incur monitoring costs. Next, we provide the description of the borrowers' objectives.

2.3.3 Entrepreneurs

Entrepreneurs finance capital acquisitions using internal net worth and bank borrowing. Given limited enforcement, lending takes the form of standard debt contracts. Following Christiano, Motto and Rostagno (2014), entrepreneurs choose from a menu of contracts offered by banks, where each contract is summarized by the ordered pair $(\bar{\omega}^E_{t+1}, \Theta^E_t)$. The default threshold $\bar{\omega}^E_{t+1}$ determines repayment, while leverage is defined as $\Theta^E_t \equiv \frac{Q^k_t K_{t+1}}{N^E_t}$.[6]

Taking prices and the available contract menu as given, entrepreneurs choose next-period capital, bank borrowing, and the default threshold to maximize the pre-dividend expected net worth in t+1. The set of feasible contracts is restricted by banks' optimality conditions (given by equation (2-14)), which are described in Section 2.4.4.

Formally,

$$\max_{K_{t+1}, B^E_t, \bar{\omega}^E_{t+1}} \mathbb{E}_t \left[\int_{\bar{\omega}^E_{t+1}}^{\infty} \left[\omega \left(1 + R^k_{t+1}\right) Q^k_t K_{t+1} - \left(1 + R^{b,E}_t\right) B_t \right] dF(\omega) \right] \tag{2-12}$$

$$\text{s.t. } \bar{\omega}^E_{t+1} \left(1 + R^k_{t+1}\right) Q^k_t K_{t+1} = \left(1 + R^{b,E}_t\right) B^E_t \tag{2-13}$$

$$\left(1 - F\left(\bar{\omega}^E_{t+1}\right)\right) \left[\left(\frac{\eta^E_b - 1}{\eta^E_b} \right) \left(1 + r^{b,E}_t\right) \left(1 - \tau^{rb}\right) + \tau^{rb} \right] + \frac{(1-\mu) E_t \Phi^E_{t+1}}{B^E_t} = \\ = \left(1 + r^{wb}_t\right) + \tau^b \tag{2-14}$$

2.3.4 Financiers

Financiers solve a dynamic optimization problem in which they choose the stock of durable goods and bank borrowing in order to maximize the expected discounted value of dividend transfers to impatient workers, taking prices and the contract menu as given.

[6] We introduce an exogenous leverage shock ε^x_t that scales the effective amount of capital entrepreneurs can acquire relative to their net worth. Formally, the effective leverage is given by $\Theta^E_t \equiv \frac{Q^k_t K_{t+1}}{N^E_t \varepsilon^x_t}$. A positive realization of ε^x_t allows entrepreneurs to finance a larger capital position for a given level of net worth, capturing time variation in credit conditions faced by firms. We also allow for exogenous fluctuations in entrepreneurs' aggregate net worth through an equity shock γ^e_t following Becard and Gauthier (2022).

Each period, financiers receive (or pay) transfers $\Xi_{j,t}$, acquire durable goods at price Q_t^s, and repay outstanding debt. Resources are generated by the resale value of previously acquired durables, which is subject to idiosyncratic price shocks, by rental income from durables, and by new borrowing. This flow of funds is summarized by the period budget constraint. As in Iacoviello (2005) and Gerali et al. (2010), we assume that the borrowing constraint binds and therefore holds with equality in equilibrium. Appendix D shows that, in the steady state, a sufficient condition for this is $\beta^I(1+r^{b,I})<1$. The intuition is straightforward: if the impatient household's rate of time preference is sufficiently high relative to the effective borrowing rate it faces, then it is optimal to borrow up to the limit implied by the contract. This condition is satisfied under our calibration. We then follow the literature in assuming that the constraint continues to bind in a neighborhood of the steady state, which is the relevant environment for first-order approximations.

The set of feasible contracts is restricted by the bank's incentive compatibility condition, which ensures that expected lending returns are consistent with banks' optimal behavior and is formally stated below in equation (2-18) and explained later in Section 2.4.4.

$$V_{j,t} = \max_{S^I_{j,t},B^I_{j,t}} \left\{ \Xi_{j,t} + \mathbb{E}_t \left[\Lambda^I_{t,t+1} \max\left\{0, V_{j,t+1}\right\} \right] \right\} \tag{2-15}$$

$$\text{s.t.} \quad \Xi_{j,t} + Q^s_t S^I_{j,t} + \left(1 + R^{b,I}_{t-1}\right) B^I_{j,t-1} \leq \omega^I_{j,t} \left(1 + R^s_t\right) Q^s_{t-1} S^I_{j,t-1} + RR^s_t S^I_{j,t} + B^I_{j,t} \tag{2-16}$$

$$\bar{\omega}^I_{t+1} \left(1 + R^s_{t+1}\right) Q^s_t S^I_{t+1} = \left(1 + R^{b,I}_t\right) B^I_t \tag{2-17}$$

$$\left(1 - F^I\left(\bar{\omega}^I_{t+1}\right)\right) \left[\left(\frac{\eta^I_b - 1}{\eta^I_b} \right) \left(1 + r^{b,I}_t\right)\left(1 - \tau^{rb}\right) + \tau^{rb} \right] + \frac{(1-\mu)\mathbb{E}_t \Phi^I_{t+1}}{B^I_t} = \left(1 + r^{wb}_t\right) + \tau^b \tag{2-18}$$

2.4
Banking Sector

Banks intermediate funds between patient households, who supply deposits, and the two types of borrowers. The banking sector is modeled following a structure inspired by Gerali et al. (2010), featuring monopolistic competition in both deposit and loan markets and explicitly accounting for borrower default risk through BGG-style debt contracts.

There is a continuum of banks indexed by $l \in [0,1]$. Each bank operates through three distinct units. A deposit branch collects deposits from patient households and sets deposit rates under monopolistic competition. A loan branch supplies credit to entrepreneurs and impatient households, setting loan rates while internalizing expected default risk. A wholesale unit (or holding company) connects the two retail branches, manages the balance sheet of the bank, and may be subject to capital requirements, which are introduced below.

Monopolistic competition in financial markets serves as a tractable way to introduce bank market power. In equilibrium, all banks lend to all borrowers and accept deposits from all savers, which allows for aggregation and diversification of idiosyncratic borrower risk across the banking system.

2.4.1 Monopolistic Competition and Demand for Financial Products

Households and borrowers do not contract with a single bank when saving or borrowing. Instead, they demand bundles of differentiated financial products supplied by a continuum of banks.

We model this aggregation using constant-elasticity-of-substitution (CES) bundles. The elasticity of substitution across deposit services is denoted by η_d, while the elasticity across loan products of type $o \in \{I, E\}$ is given by η_b^o. This structure implies downward-sloping demand schedules for individual banks and provides a tractable representation of bank market power.

Specifically, the demand for deposits supplied by bank l is given by

$$D_t(l) = \left(\frac{1 + r_t^d(l)}{1 + r_t^d} \right)^{\eta_d} D_t, \tag{2-19}$$

while the demand for loans of type $o \in \{I, E\}$ granted by bank l is

$$B_t^o(l) = \left(\frac{1 + r_t^{b,o}(l)}{1 + r_t^{b,o}} \right)^{-\eta_b^o} B_t^o. \tag{2-20}$$

Here, $1 + r_t^d$ and $1 + r_t^{b,o}$ denote aggregate deposit and loan rates, D_t and B_t^o are aggregate deposits and loans, and η_d and η_b^o govern the degree of substitutability across banks. Because individual banks face downward-sloping demand curves, they have market power when setting deposit and loan rates relative to wholesale benchmarks.

2.4.2 Deposit Branch

The deposit branch operates under monopolistic competition and collects funds from patient households by setting a bank-specific deposit rate $r_t^d(l)$.

Deposit demand is given by the CES schedule in equation (2-19). Collected deposits are transferred to the holding company, which remunerates them at the wholesale deposit rate r_t^{wd}.

Taking the wholesale rate as given, the deposit branch chooses $r_t^d(l)$ to maximize the expected present value of cash flows, internalizing the effect of the deposit rate on its market share:

$$\max_{r_t^d(l)} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \frac{P_0}{P_t} \left[\left(1 + r_t^{wd}\right) D_t(l) - \left(1 + r_t^d(l)\right) D_t(l) \right]. \tag{2-21}$$

The objective reflects the spread between the return paid by the holding company and the remuneration offered to depositors, adjusted for the endogenous response of deposit demand to changes in the bank-specific rate.[7]

2.4.3
Bank Holding Company (Wholesale Branch)

The bank holding company manages the balance sheet of each bank and operates as a wholesale unit interacting with the retail deposit and loan branches under perfect competition. On the liability side, it combines deposits $D_t(l)$ raised by the deposit branch with internal bank capital $K_t^b(l)$. On the asset side, it supplies total loans

$$B_t(l) = B_t^I(l) + B_t^E(l), \tag{2-22}$$

which satisfy the balance sheet identity

$$B_t(l) = D_t(l) + K_t^b(l). \tag{2-23}$$

Providing loans entails a proportional operational cost $\xi B_t(l)$. In addition, following Gerali et al. (2010), the holding company is subject to regulatory or macroprudential constraints captured by a target capital-to-assets ratio ν^b. Deviations from this target are penalized through a quadratic cost,

$$\frac{\kappa_{Kb}}{2} \left(\frac{K_t^b(l)}{B_t(l)} - \nu^b \right)^2 K_t^b(l), \tag{2-24}$$

which introduces an endogenous link between bank leverage and lending spreads.

Let r_t^{wb} and r_t^{wd} denote the internal wholesale rates on loans and deposits respectively and using the stochastic discount factor of patient households, $\Lambda_{0,t}^P$, the holding company chooses deposits and loans to maximize expected

[7] P_t denotes the aggregate price level of final goods.

discounted cash flows:

$$\max_{\{B_t(l),D_t(l)\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \Big[\Big(1+r_t^{wb}\Big) B_t(l) - B_{t+1}(l)\pi_{t+1} + D_{t+1}(l)\pi_{t+1} - \Big(1+r_t^{wd}\Big) D_t(l)$$
$$+ K_{t+1}^b(l)\pi_{t+1} - K_t^b(l) - \frac{\kappa_{Kb}}{2}\left(\frac{K_t^b(l)}{B_t(l)} - \nu^b\right)^2 K_t^b(l) - \xi B_t(l)\Big], \quad (2\text{-}25)$$

subject to the balance sheet constraint above. Bank capital $K_t^b(l)$ evolves through retained profits, as described in Section 2.4.5.[8]

2.4.4 Loan Branch

The loan branch operates under monopolistic competition and intermediates wholesale funds obtained from the holding company to two classes of borrowers: entrepreneurs and financiers. In contrast to Gerali et al. (2010), loans in our framework are subject to default risk, as in a standard BGG environment.

Borrowers may default whenever the realization of their idiosyncratic shock falls below the contractual threshold. Upon default, banks seize the pledged collateral, but only a fraction $(1-\mu)$ can be effectively recovered due to monitoring and enforcement frictions. Let $1+r_t^{b,o}(l)$ denote the bank-specific nominal loan rate charged to borrower type $o \in \{I, E\}$, and let $F^o(\bar{\omega}_{t+1}^o)$ be the corresponding default probability. The expected value of seized collateral is denoted by $\mathbb{E}_t[\Phi_{t+1}^o]$.

The loan branch chooses loan rates to maximize the expected present value of cash flows, taking into account loan demand, default risk, and the cost of wholesale funding:

$$\max_{r_t^{b,E}(l),\, r_t^{b,I}(l)} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \frac{P_0}{P_t}\Big\{\Big[1 - F^E(\bar{\omega}_{t+1}^E)\Big]\Big(1 + r_t^{b,E}(l)\Big) B_t^E(l) + (1-\mu)\frac{B_t^E(l)}{B_t^E}\mathbb{E}_t[\Phi_{t+1}^E]$$
$$+ \Big[1 - F^I(\bar{\omega}_{t+1}^I)\Big]\Big(1 + r_t^{b,I}(l)\Big) B_t^I(l) + (1-\mu)\frac{B_t^I(l)}{B_t^I}\mathbb{E}_t[\Phi_{t+1}^I]$$
$$- \Big(1 + r_t^{wb}\Big) B_t(l)\Big\}, \quad (2\text{-}26)$$

subject to the loan demand schedules in equation (2-20) and to borrowers' default thresholds.

The optimality condition for loan pricing implies that loan rates incorporate both compensation for expected default losses and a monopolistic markup.

[8] Following Gerali et al. (2010), we assume that the holding company can borrow or lend funds externally at the policy rate r_t, so by no-arbitrage $r_t^{wd} = r_t$.

In equilibrium, this yields the following spread condition:

$$\left[1 - F^o(\bar{\omega}^o_{t+1})\right] \left(\frac{\eta^o_b - 1}{\eta^o_b}\right) \left(1 + r^{b,o}_t\right) + (1-\mu)\frac{\mathbb{E}_t[\Phi^o_{t+1}]}{B^o_t} = 1 + r^{wb}_t, \tag{2-27}$$

for $o \in \{I, E\}$.

Equation (2-27) ensures that the expected revenue from lending equals the wholesale funding cost, adjusted for expected default losses and the monopolistic markup arising from imperfect competition.[9]

The expected value of seized collateral is given by[10]

$$\mathbb{E}_t[\Phi^o_{t+1}] = \pi_{t+1} \int_0^{\bar{\omega}^o_{t+1}} \omega\left(1+R^x_{t+1}\right) Q^x_t X_{t+1} \varepsilon^{\eta^o_t}\, dF^o(\omega), \qquad (o,x) \in \{(I,s),(E,k)\}. \tag{2-28}$$

2.4.5
Bank Profits and Capital Accumulation

Let J_t denote total bank profits realized at the end of period t, after idiosyncratic shocks are realized and loan repayments or defaults occur. Profits aggregate net cash flows from the loan and deposit branches, as well as regulatory and operational costs borne by the holding company.

Bank profits are given by:

$$\begin{aligned} J_t \;=\; & \underbrace{\left(1 - F^I(\bar{\omega}^I_{t+1})\right)\left(1 + r^{b,I}_t(1-\tau^{rb})\right)B^I_t + (1-\mu)\,\mathbb{E}_t[\Phi^I_{t+1}]}_{\text{net revenue from impatient-household loans}} \\ & + \underbrace{\left(1 - F^E(\bar{\omega}^E_{t+1})\right)\left(1 + r^{b,E}_t(1-\tau^{rb})\right)B^E_t + (1-\mu)\,\mathbb{E}_t[\Phi^E_{t+1}]}_{\text{net revenue from entrepreneur loans}} \\ & - \underbrace{(1+r^d_t)D_t}_{\text{deposit remuneration}} - \underbrace{K^b_t}_{\text{bank capital outlay}} - \underbrace{\xi B_t}_{\text{operational lending cost}} - \underbrace{\kappa_t}_{\text{capital regulation cost}}, \end{aligned} \tag{2-29}$$

where the capital regulation cost is defined as

$$\kappa_t = \frac{\kappa_{Kb}}{2}\left(\frac{K^b_t}{B_t} - \nu^b\right)^2 K^b_t. \tag{2-30}$$

[9]Linearity of borrowers' objective functions implies that, in equilibrium, all borrowers of a given type choose the same default threshold and leverage. This result is established for entrepreneurs by Christiano, Motto and Rostagno (2014) and extended to impatient households by Becard and Gauthier (2022).

[10]We introduce sector-specific redeployment shocks η^i_t and η^e_t, which act as wedges on the value of collateral recovered upon default for financiers and entrepreneurs, respectively, and are isomorphic, up to first order, to shocks to idiosyncratic risk. Specifically, η^e_t is similar to the risk shock studied in Christiano, Motto and Rostagno (2014). So, we will refer to them as risk shocks.

Bank capital evolves through retained earnings according to:

$$K_t^b = (1 - \delta^b)\, K_{t-1}^b\, \varepsilon_t^{kb}, +(1 - \Delta^b)(1 - \tau)\, J_{t-1} \tag{2-31}$$

where δ^b denotes the depreciation rate of bank capital, Δ^b is the dividend payout ratio, and ε_t^{kb} is a bank capital shock, introduced following Gerali et al. (2010). Higher dividend payouts reduce retained profits, limiting future bank capital accumulation and, through regulatory constraints, the supply of bank credit.

2.5 Government and Monetary Policy

The government consists of a fiscal and a monetary authority. The fiscal authority finances public expenditures G_t through distortionary taxes and is assumed to balance its budget in every period. Since our focus is on the interaction between taxation, banking spreads, and financial intermediation, we explicitly introduce four taxes related to the banking sector.

Specifically, the government levies: (i) a tax on loan interest revenues at rate τ^{rb}; (ii) a tax on loan principal amounts at rate τ^b; (iii) a tax on interest income earned by depositors at rate τ^{rd}; and (iv) a tax on bank profits at rate τ. These taxes are motivated by the structure of financial taxation in Brazil and allow us to study their effects on credit spreads and aggregate outcomes.

The fiscal budget constraint is given by:

$$\begin{aligned} G_t = \tau^{rb} &\left[\Big(1 - F^E(\bar{\omega}_t^E)\Big)\frac{r_{t-1}^{b,E} B_{t-1}^E}{\pi_t} + \Big(1 - F^I(\bar{\omega}_t^I)\Big)\frac{r_{t-1}^{b,I} B_{t-1}^I}{\pi_t}\right] + \tau^b \frac{B_{t-1}}{\pi_t} \\ &+ \tau^{rd}\frac{r_{t-1}^d}{\pi_t} D_{t-1} + \tau J_{t-1}, \end{aligned} \tag{2-32}$$

where tax revenues are collected on realized financial flows from the previous period.

The monetary authority sets the nominal policy interest rate according to a Taylor-type rule, following Gerali et al. (2010):

$$1 + r_t = (1 + \bar{r})^{1-\rho_r}(1 + r_{t-1})^{\rho_r} \left(\frac{\pi_t}{\bar{\pi}}\right)^{\phi_\pi(1-\rho_r)} \left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_y(1-\rho_r)} \varepsilon_t^m, \tag{2-33}$$

where $\bar{r}$ and $\bar{\pi}$ denote the steady-state nominal interest rate and inflation, respectively. The parameters ϕ_π and ϕ_y govern the policy response to inflation and output growth, ρ_r captures interest-rate smoothing, and ϵ_t^m represents a monetary policy shock.

2.6 Equilibrium and Market Clearing

In equilibrium, all markets clear, including labor, deposits, loans, wholesale goods, durable goods, and final goods markets. The aggregate resource constraint for final goods is given by:

$$Y_t = C_t + I_t + G_t + \frac{\xi B_{t-1}}{\pi_t} + \frac{\mu \Phi_t^E}{\pi_t} + \frac{\mu \Phi_t^I}{\pi_t} + Adj_t. \tag{2-34}$$

The term $\xi B_{t-1}/\pi_t$ captures real operational costs of financial intermediation. Monitoring costs associated with default arise from entrepreneurs and impatient households and are given by $\mu \Phi_t^E/\pi_t$ and $\mu \Phi_t^I/\pi_t$, respectively. The term Adj_t collects the adjustment costs in the economy:

$$Adj_t = \underbrace{\frac{\kappa_{Kb}}{2}\left(\frac{K_t^b}{B_t} - \nu^b\right)^2 K_t^b}_{\text{bank capital adjustment}} + \underbrace{\frac{\kappa_P}{2}\left(\pi_t - \pi_{t-1}^{\iota}\bar{\pi}^{1-\iota}\right)^2 Y_t}_{\text{price adjustment cost}}. \tag{2-35}$$

In this environment, the natural interest rate corresponds to the real interest rate that would prevail under flexible prices, consistent with Woodford (2003).

3
Estimation

This section presents the data and outlines the estimation procedure. The model is estimated using Bayesian methods. We estimate the parameters governing the dynamic behavior of the economy, while parameters determining the steady state are calibrated to match key empirical moments in the data. This approach is standard in the DSGE literature and allows combining prior information from previous studies with the information contained in the data through the likelihood function implied by the model.

3.1
Data

The estimation is conducted using quarterly data covering the period from 2000Q4 to 2024Q4. All series are expressed at a quarterly frequency to match the timing of the model.

We use a total of ten observable variables: real GDP, real consumption, real investment, hours worked, IPCA inflation, the short-term nominal interest rate (SELIC), credit to firms, credit to households, credit spreads for firms and households relative to the policy rate.

Special care is taken in the construction of the credit-related observables. On the firm side, credit and credit spreads are measured using non-earmarked corporate credit, which closely corresponds to the type of bank lending faced by entrepreneurs in the model. On the household side, we focus on non-earmarked credit for vehicle acquisition. This choice reflects the substantial heterogeneity across household credit instruments in Brazil—such as payroll loans, unsecured personal credit, and collateralized credit—which differ markedly in terms of interest rates and delinquency behavior. Vehicle financing is a collateralized form of household borrowing directly associated with durable goods purchases and represents the dominant category of goods-related household credit, accounting for around 90% of durable goods financing by households. As such, it provides a closer empirical counterpart to the borrowing behavior of impatient households in the model.[1] Credit spreads are constructed as the difference between the nominal interest rate charged on the respective credit

[1]Although mortgages represent a larger share of total household credit, they fall under earmarked credit in Brazil and are subject to regulatory constraints on interest rates. As a result, mortgage rates are not well suited to discipline the market-based borrowing conditions faced by households in the model.

category and the policy interest rate, capturing time variation in borrowing conditions faced by firms and households.

To ensure consistency with the stationary representation of the model, GDP, consumption, investment, household credit and firm credit are expressed in real per capita terms and enter the estimation in log first differences. Hours worked enter as the HP-filtered cycle of log per capita hours. Inflation is measured as the log first difference of the IPCA price index. The nominal short-term interest rate and both credit spreads are included as gross rates. All observable series are demeaned prior to estimation in order to abstract from low-frequency movements and focus on business-cycle fluctuations. [2]

Table 3.1: Observable variables, definitions, and transformations

Observable	**Definition**	**Transformation**	**Source**
GDP (s.a.)	GDP per capita	Log first diff., demean	IBGE
Consumption (s.a.)	Consumption per capita	Log first diff., demean	IBGE
Investment (s.a.)	Investment per capita	Log first diff., demean	IBGE
Hours worked (s.a.)	Hours worked per capita	HP-filtered cycle	IBGE
Inflation (IPCA, s.a.)	Log difference of IPCA price index	Demean	IBGE
Policy rate	SELIC	Demean	BCB
Firm credit (s.a.)	Corporate credit per capita	Log first diff., demean	BCB
Household credit (s.a.)	Vehicle acquisition credit per capita	Log first diff., demean	BCB
Firm spread	Corporate loan rate spread	Demean	BCB
Household spread	Vehicle credit rate spread	Demean	BCB

3.2 Calibrated Parameters

A subset of parameters is calibrated rather than estimated. These parameters are chosen either because they have clear empirical counterparts in the Brazilian economy, because they are commonly used in the literature, or because they discipline steady-state relationships that the model is designed to replicate. Table 3.2 reports the calibrated parameters. In general, the cali-

[2] The mapping between model variables and the observed data is formalized through a set of observation equations, which are consistent with the data transformations described above and with the stationary representation of the model. These equations are reported in Appendix B.1.

bration can be divided into three groups: (i) parameters with direct empirical counterparts in Brazilian data, (ii) parameters commonly adopted in the literature, and (iii) parameters obtained through internal calibration by matching selected moments of the data.

Parameters with direct empirical counterparts Some parameters are calibrated using observable counterparts in Brazilian data or institutional features of the financial system.

Administrative costs in the banking sector, $\xi = 0.0099$, are set following Brazilian data as reported in Luz (2024). This parameter captures the ratio of administrative costs to bank assets and reflects the operating costs associated with financial intermediation. The monitoring cost parameter, $\mu = 0.8153$, reflects the proportion of loan value that cannot be recovered through enforcement procedures in the event of borrower default, based on World Bank indicators. The steady-state growth rate of labor-augmenting technology, $\mu_z = 1.003$, is calibrated using quarterly Brazilian data from IBGE. The target bank capital-to-asset ratio, $\nu^b = 0.18$, follows Brazilian regulatory data reported in Ferreira and Nakane (2018).

Tax parameters are mapped directly to the Brazilian tax system. The tax on bank profits, $\tau = 45\%$, reflects the combined incidence of IRPJ and CSLL. The tax on loan revenues, $\tau^{rb} = 4.65\%$, captures the PIS/Cofins taxation on financial revenues. The tax on loan amounts, $\tau^b = 0.47\%$, corresponds to the IOF tax on credit operations. Finally, the tax on deposit returns, $\tau^{rd} = 17.5\%$, reflects the taxation applied to fixed-income investments with maturities between one and two years.

Parameters adopted from the literature A second group of parameters follows values commonly used in the DSGE literature or in models calibrated for the Brazilian economy.

The capital share in production is set to $\alpha = 0.448$, following Castro et al. (2015). The inverse Frisch elasticity of labor supply, $\varphi = 1$, and the preference parameter for durable goods, $\psi_t = 1$, follow the calibration in Carvalho et al. (2023). The discount factor of impatient households is set to $\beta^I = 0.938$, following Iacoviello (2005), ensuring that borrowing constraints bind in equilibrium.

Durable good depreciation is set equal to capital depreciation, $\delta^s = \delta^k$, following the strategy adopted in Carvalho et al. (2023). The elasticity of substitution across wholesale goods is set to 6 as in Carvalho et al. (2023), implying a steady-state markup of approximately 20 percent.

Table 3.2: Calibrated parameters

Parameter	**Value**	**Source / Target**
Parameters with direct empirical counterparts		
Administrative cost of lending (ξ)	0.0099	BCB
Bank capital-to-asset ratio (ν^b)	0.180	Ferreira and Nakane (2018)
Monitoring cost (μ)	0.8153	World Bank
Trend growth rate (quarterly) (μ_z)	1.0030	IBGE
Tax on bank profits (τ)	0.450	Brazilian tax system (IRPJ + CSLL)
Tax on loan revenues (τ^{rb})	0.0465	PIS/Cofins
Tax on loan principal (τ^b)	0.0047	IOF
Tax on deposit returns (τ^{rd})	0.1750	Brazilian fixed-income taxation
Parameters adopted from the literature		
Capital share in production (α)	0.448	Castro et al. (2015)
Discount factor (impatient households) (β^I)	0.938	Iacoviello (2005)
Deposit demand elasticity (η_d)	537.73	Luz (2024)
Inverse Frisch elasticity (φ)	1.000	Carvalho et al. (2023)
Preference for durable goods (ψ)	1.000	Carvalho et al. (2023)
Elasticity of substitution (η)	6.000	Carvalho et al. (2023)
Durable good depreciation (δ^s)	0.0703	-
Parameters internally calibrated		
Discount factor (patient households) (β^P)	0.9785	Internal calibration
Loan demand elasticity (firms) (η_b^E)	971.36	Internal calibration
Loan demand elasticity (households) (η_b^I)	296.70	Internal calibration
Capital depreciation (δ^k)	0.0703	Internal calibration
Bank capital depreciation (δ^b)	0.0110	Internal calibration
Variance of idiosyncratic shock (firms) (σ^E)	0.4822	Internal calibration
Variance of idiosyncratic shock (households) (σ^I)	1.0799	Internal calibration
Entrepreneur dividend payout (Δ^e)	0.0937	Internal calibration
Labor disutility scale (ζ)	3.7322	Internal calibration

Internally calibrated parameters Finally, a group of parameters is determined through internal calibration. These parameters are chosen to match key steady-state moments of the Brazilian economy. Table 3.3 reports the targeted moments and the corresponding model-implied values.

The discount factor of patient households, β^P, is chosen to match the average real return on bank deposits observed in Brazilian CDB rates. The elasticities of loan demand for entrepreneurs (η_b^E) and households (η_b^I) are calibrated to match the interest rate calculated by the Central Bank of Brazil for the credit operations.

Several parameters discipline the relative size of financial aggregates in the steady state. Capital depreciation δ^k is set to reproduce the investment-to-GDP ratio in the data. The depreciation rate of bank capital δ^b is chosen to match the observed bank capital-to-asset ratio.

The variances of idiosyncratic shocks affecting entrepreneurs and impa-

Table 3.3: Internal calibration targets

Parameter	Value	Target	Moment	Data	Model
β^P	0.9785	CDB rate	r^d	11.07%	12.55%
η_b^E	971.36	ICC (non-earmarked firms)	r^{bE}	25.20%	25.20%
η_b^I	296.70	ICC (non-earmarked households)	r^{bI}	28.16%	27.68%
δ^k	0.0703	Investment-to-GDP ratio	I/Y	17.90%	17.90%
δ^b	0.0110	Bank capital ratio	K^b/B	0.18	0.18
σ^E	0.4822	Firm delinquency rate	$F(\bar{\omega}^E)$	3.26%	3.26%
σ^I	1.0799	Household delinquency rate	$F(\bar{\omega}^I)$	4.32%	4.32%
Δ^e	0.0937	Entrepreneur leverage	X	1.4	1.4
ζ	3.7322	Steady-state hours worked	L	1	1

tient households, σ^E and σ^I, are calibrated to match observed delinquency rates for firms and households, respectively. Since household delinquency rates are higher in the data, the corresponding shock variance is larger.

Finally, the entrepreneur dividend payout rate Δ^e is calibrated to reproduce steady-state entrepreneurial leverage, while the scale parameter of labor disutility ζ_t is chosen to normalize steady-state hours worked to unity.

3.3 Prior Distributions

Tables 3.4 and 3.5 summarize the prior and posterior distributions of the estimated parameters. Overall, the choice of priors closely follows the DSGE literature for models with nominal rigidities and financial frictions, in particular Gerali et al. (2010), Becard and Gauthier (2022), and Castro et al. (2015).

The inflation response coefficient ϕ_π is assigned a Normal prior, ensuring a stabilizing policy response while remaining consistent with estimated Taylor rules for Brazil Castro et al. (2015). The output response ϕ_y follows a Gamma prior centered at a small positive value, reflecting standard empirical estimates in line with Castro et al. (2015). Interest-rate smoothing ρ_r follows a Beta prior with a high mean, capturing gradual policy adjustment, as commonly assumed in the literature as in Castro et al. (2015). The price adjustment cost parameter κ_p follows a Gamma prior centered at a relatively high mean, consistent with the magnitude typically used to generate realistic inflation dynamics in DSGE models with financial frictions Gerali et al. (2010). Inflation indexation ι follows a Beta prior with a low-to-moderate mean, allowing for inertial inflation dynamics without imposing strong indexation a priori, in line with Gerali et al. (2010).

Habit formation h follows a Beta prior centered at standard values used

Table 3.4: Estimated structural parameters: priors and posteriors

Description	**Param.**	**Prior**			**Posterior**	
		Distrib.	**Mean**	**SD**	**Mode**	**SD**
Taylor-rule inflation response	ϕ_π	Normal	2.0	0.35	2.3880	0.2022
Taylor-rule output response	ϕ_y	Gamma	0.25	1	0.1401	0.0463
Interest-rate smoothing	ρ_r	Beta	0.6	0.15	0.7292	0.0457
Price adjustment cost	κ_p	Gamma	50.0	20.0	5.1082	1.3771
Indexation to past inflation	ι	Beta	0.50	0.15	0.1896	0.0894
Dividend payout (banks)	Δ_b	Beta	0.50	0.20	0.5721	0.1281
Capital-ratio adjustment cost	κ_{Kb}	Gamma	20	5	34.0889	5.6460
Habit formation	h	Beta	0.75	0.10	0.1974	0.0260
Patient labor share	Ω	Beta	0.85	0.05	0.3164	0.0698
Investment adjustment cost	κ_i	Gamma	2.5	1	0.5566	0.1267
Durable investment adjustment cost	κ_s	Gamma	2.5	1	1.9695	0.8953

in medium-scale DSGE models for Brazil as Castro et al. (2015). Capital investment adjustment costs κ_i and durable good investment adjustment cost κ_s follow a Gamma prior consistent with Gerali et al. (2010), while the patient labor share Ω follows a Beta prior reflecting conventional labor-income shares in line with Becard and Gauthier (2022). The dividend payout ratio Δ_b also follows a Beta prior with a loose dispersion, avoiding strong assumptions on banks' retained earnings. The capital adjustment cost κ_{Kb} follows a Gamma prior aligned with the calibration strategy in Ferreira and Nakane (2018).

All AR(1) persistence parameters follow Beta priors centered at 0.5 as in Becard and Gauthier (2022). Shock standard deviations follow Inverse-Gamma priors with loose dispersion, in line with standard practice in DSGE estimation with financial frictions as Gerali et al. (2010).

3.4 Posterior Results

Tables 3.4 and 3.5 summarize the posterior distributions of the estimated parameters.[3] Regarding monetary policy, the posterior estimates point to a standard response to inflation, output, and interest-rate smoothing. The posterior mean for the inflation coefficient is 2.39, close to the value reported by Castro et al. (2015), 2.43. The response to output is estimated at 0.14,

[3]Posterior distributions are obtained using the Metropolis–Hastings algorithm implemented in `Dynare`. The estimation relies on Markov Chain Monte Carlo (MCMC) methods to approximate the posterior distribution of the parameter vector. We run two blocks with 900,000 draws each. Convergence diagnostics indicate satisfactory convergence of the chains, and the posterior moments reported in Tables 3.4 and 3.5 are computed after discarding 30% of the draws as burn-in.

Table 3.5: Estimated shock processes: persistences and shock standard deviations

Description	**Param.**	**Prior**			**Posterior**	
		Distrib.	**Mean**	**SD**	**Mode**	**SD**
AR(1) persistence parameters						
TFP persistence	ρ_a	Beta	0.50	0.20	0.9625	0.0109
Leverage persistence	ρ_{e_x}	Beta	0.50	0.20	0.7030	0.1491
Entrepreneur net worth persistence	ρ_{γ^E}	Beta	0.50	0.20	0.6703	0.1226
Bank capital shock persistence	ρ_{kb}	Beta	0.50	0.20	0.6098	0.0991
Monetary policy shock persistence	ρ_m	Beta	0.50	0.20	0.4659	0.0698
Markup shock persistence	ρ_{markup}	Beta	0.50	0.20	0.4993	0.1763
Preference (consumption) persistence	ρ_p	Beta	0.50	0.20	0.8312	0.0493
Preference (durables) persistence	ρ_{ψ^i}	Beta	0.50	0.20	0.5228	0.0536
Risk shock (entrepreneurs) persistence	ρ_{risk^e}	Beta	0.50	0.20	0.9315	0.0259
Risk shock (households) persistence	ρ_{risk^i}	Beta	0.50	0.20	0.9242	0.0272
Trend technology persistence	ρ_{μ^z}	Beta	0.50	0.20	0.9615	0.0112
Labor disutility shock persistence	ρ_ζ	Beta	0.50	0.20	0.5378	0.1968
Investment adj. cost shock persistence	ρ_{ζ^i}	Beta	0.50	0.20	0.5089	0.1988
Shock standard deviations						
TFP shock std. dev.	$\sigma_{\varepsilon a}$	Inv-Gamma	0.01	0.05	0.0190	0.0015
Monetary policy shock std. dev.	$\sigma_{\varepsilon m}$	Inv-Gamma	0.01	0.05	0.0040	0.0013
Inv. adj. cost shock std. dev.	$\sigma_{\varepsilon\zeta^i}$	Inv-Gamma	0.01	0.05	0.0088	0.0006
Entrep. levarage shock std. dev.	σ_{ε_x}	Inv-Gamma	0.01	0.05	0.0037	0.0007
Preference shock std. dev. (cons.)	$\sigma_{\varepsilon p}$	Inv-Gamma	0.01	0.05	0.0140	0.0017
Durables preference shock std. dev.	$\sigma_{\varepsilon\psi^i}$	Inv-Gamma	0.01	0.05	0.2371	0.0202
Labor disutility shock std. dev.	$\sigma_{\varepsilon\zeta}$	Inv-Gamma	0.01	0.05	0.0048	0.0015
Risk shock std. dev. (HH)	$\sigma_{\varepsilon\text{risk}^I}$	Inv-Gamma	0.01	0.05	0.1888	0.0152
Risk shock std. dev. (Ent.)	$\sigma_{\varepsilon\text{risk}^E}$	Inv-Gamma	0.01	0.05	0.0098	0.0014
Bank capital shock std. dev.	$\sigma_{\varepsilon kb}$	Inv-Gamma	0.01	0.05	0.0177	0.0031
Markup shock std. dev.	$\sigma_{\varepsilon\text{markup}}$	Inv-Gamma	0.01	0.05	0.0060	0.0022
Trend technology shock std. dev.	$\sigma_{\varepsilon\mu^z}$	Inv-Gamma	0.01	0.05	0.0040	0.0005
Entrepreneur net worth shock std. dev.	$\sigma_{\varepsilon\gamma^E}$	Inv-Gamma	0.01	0.05	0.0048	0.0009

compared to 0.16 in Castro et al. (2015), while the interest-rate smoothing parameter is estimated at 0.73, relative to 0.79 in the same study. Overall, these estimates are broadly in line with previous empirical Taylor-rule estimates for Brazil and other economies, such as Gerali et al. (2010) and Castro et al. (2015).[4] For nominal rigidities, the posterior estimates suggest a relatively low degree of price stickiness, 5.10. Gerali et al. (2010) reports a value of 30.57

[4]Appendix B provides additional details on the estimation, including the measurement equations, convergence diagnostics, observed data series, and prior and posterior distributions for all estimated parameters.

for the United States and Ferreira and Nakane (2018) estimates 14.16 for Brazil. This suggests that the data provide some discipline for the identification of nominal rigidities in the model. The inflation indexation parameter is estimated at 0.18, below its prior mean and consistent with Ferreira and Nakane (2018) and Castro et al. (2015), as well as Gerali et al. (2010), who find a similar value of 0.17 for the United States.

In the banking sector, the estimated capital adjustment cost is $\kappa_{Kb} = 34.08$, which is higher than the value reported by Ferreira and Nakane (2018) (22.96). This implies a stronger penalty for deviations from the target capital ratio, leading to a more tightly regulated banking sector in the model. On the production side, the investment adjustment cost for physical capital is estimated at 0.56, which is substantially lower than the values around 3.40 reported by Castro et al. (2015) and Ferreira and Nakane (2018). In contrast, the adjustment cost for durable goods is estimated at 1.97, indicating a relatively higher degree of rigidity in durable investment.

Regarding preferences, the habit formation parameter is slightly below the value typically found in the literature, such as 0.74 in Castro et al. (2015). The share of patient agents in production is estimated at 0.32. These differences are consistent with the notion that posterior estimates reflect not only prior information but also the specific features of the data and model used in the estimation. In particular, differences in the sample period, the set of observed variables, and the presence of financial frictions can all affect parameter identification, leading to values that differ from those reported in previous studies.

The estimated shock processes display a high degree of persistence for several key disturbances. In particular, productivity and trend technology shocks are highly persistent, indicating that supply-side innovations have long-lasting effects in the data. Risk shocks affecting both entrepreneurs and households also exhibit strong persistence, pointing to sustained fluctuations in financial conditions, while preference shocks related to consumption are moderately persistent. Financial variables such as leverage and net worth show intermediate persistence, whereas monetary policy, markup, and investment-related shocks are comparatively less persistent, reflecting more transitory dynamics.

4
The Natural Interest Rate

Figure 4.1 displays the posterior smoothed estimate of the natural interest rate for Brazil, expressed at an annual frequency. For comparison, the figure also reports the ex-ante real interest rate, constructed as the difference between the nominal policy rate (SELIC) and expected inflation.[1] This comparison provides a useful benchmark for monetary policy analysis, as expectations-based real rates are the relevant margin for intertemporal decisions.

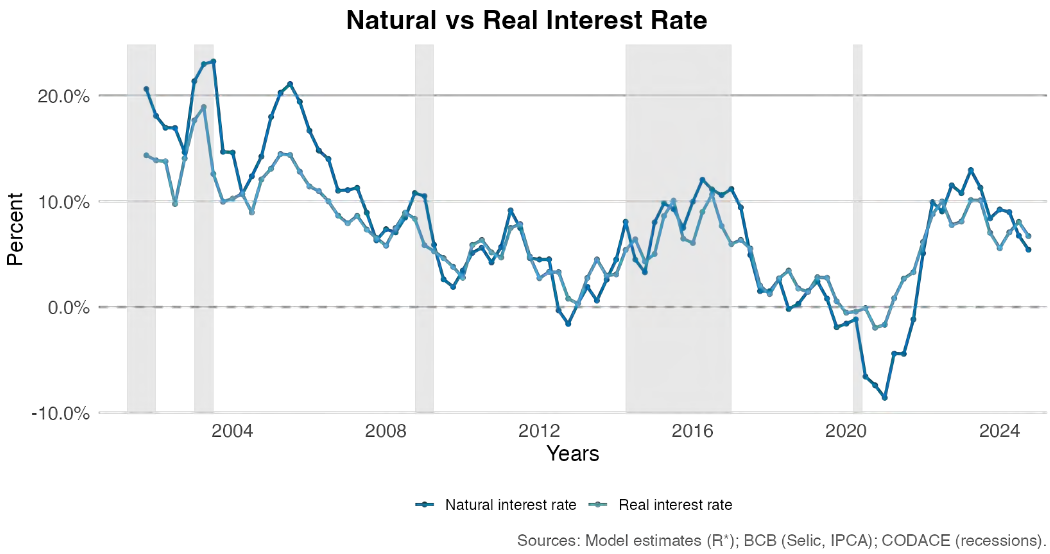

Figure 4.1: Posterior smoothed natural real interest rate and ex-ante real interest rate

Two main features of the estimated natural rate emerge. First, it exhibits substantial time variation, in line with DSGE-based estimates such as Justiniano and Primiceri (2010) and Del Negro et al. (2017). Second, the series displays a downward trend over most of the sample, a pattern widely documented for both advanced and emerging economies, including Brazil (Barsky, Justiniano and Melosi (2014), Hristov (2016), Neri and Gerali (2019), Alves (2021)). This trend experiences occasional interruptions, but appears to have resumed in recent years.

Beyond these broad patterns, the estimated natural rate displays economically meaningful movements around major macroeconomic episodes. The relatively high level of $R_t^\star$ in the early 2000s, peaking around the third quarter

[1]Inflation expectations correspond to the median forecast from the Central Bank of Brazil's survey of professional forecasters (FOCUS).

of 2003 at 23.23%, coincides with a period of heightened uncertainty surrounding the presidential election. As uncertainty declined and the policy framework gained credibility, the natural rate fell toward levels more consistent with underlying fundamentals.

From 2005 to the onset of the global financial crisis, $R_t^\star$ follows a sustained downward trajectory, consistent with improved macroeconomic conditions and expanding credit. The global crisis is associated with a temporary increase in the natural rate, reflecting a tightening of financial conditions. A similar pattern is observed during the domestic recession of 2014–2016, when deteriorating economic activity and a contraction in credit contributed to an increase in the natural rate. As macroeconomic conditions gradually stabilize thereafter, the natural rate declines to low, and at times negative, levels in the period leading up to the COVID-19 shock.

The pandemic is associated with a sharp decline in $R_t^\star$, which reaches its lowest level in the sample at -8.60%. In the subsequent recovery, the natural rate increases for several quarters, reflecting a normalization of economic activity and financial conditions. From 2023 onward, $R_t^\star$ resumes a downward trajectory, consistent with a gradual easing of macro-financial conditions.

The behavior of $R_t^\star$ across these episodes highlights the role of financial frictions in the model. Periods of stress are associated with increases in the natural rate, reflecting higher spreads, elevated default risk, and tighter balance-sheet constraints. Conversely, improvements in credit conditions allow the economy to sustain a given level of activity at lower equilibrium real rates. By explicitly incorporating financial intermediation, the model attributes part of the variation in $R_t^\star$ to endogenous financial conditions, rather than solely to shifts in productivity or preferences.

4.1 Stance of monetary policy

Estimating the natural real interest rate allows us to assess the stance of monetary policy over time. We define the policy stance as the difference between the ex-ante real policy rate and the estimated natural rate. A positive gap indicates a contractionary stance, while a negative gap corresponds to expansionary monetary conditions. In the economy, these deviations matter because persistent differences between the policy rate and $R_t^\star$ affect aggregate demand and inflation dynamics.

Figure 4.2 reports the evolution of the policy gap over the sample period. The gap is predominantly negative during the sample, indicating that monetary conditions were often accommodative relative to the model-implied equilibrium rate.

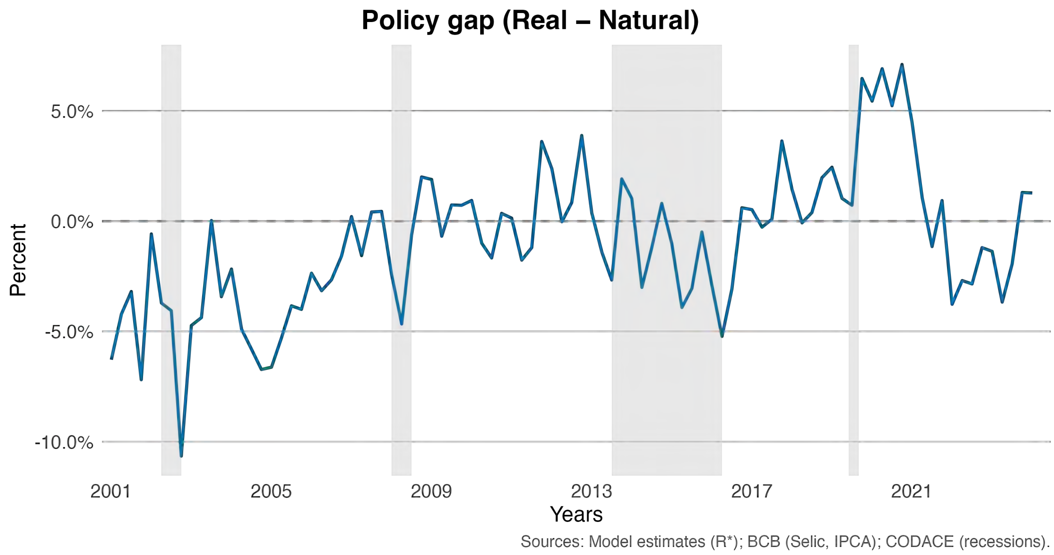

Figure 4.2: Policy gap

The evolution of the policy gap is closely related to inflation outcomes, as illustrated by Figure 4.3. Periods characterized by a persistently negative gap are often associated with inflation running near the upper bound or above the target range, whereas episodes in which the gap turns positive tend to coincide with a gradual re-anchoring of inflation. In the early 2000s, for instance, accommodative real monetary conditions are followed by repeated breaches of the inflation target, particularly between 2001 and 2004. By contrast, the tightening episode that begins in mid-2005 coincides with a return of inflation toward the target, in line with the standard transmission mechanism emphasized in the inflation-targeting literature.

Figure 4.3: Inflation dynamics

Following the domestic recession, the period from 2016 to 2019 is characterized by a mostly positive policy gap, with inflation converging toward the center—and at times the lower bound—of the target range. In contrast, the post-pandemic period displays a negative gap, accompanied by inflation remaining above target since 2021. Toward the end of the sample, the policy gap turns positive again, indicating a shift toward a more contractionary monetary stance. These patterns suggest that deviations of the real policy rate from the estimated natural rate provide a useful benchmark for understanding inflation dynamics in Brazil, particularly in an environment where financial conditions and credit frictions play a central role in monetary transmission. Relative to previous estimates for Brazil—which typically find a predominantly positive policy gap—our results point to a more expansionary stance over much of the sample. This pattern reflects, in part, the relatively high level of the estimated natural rate generated by the model when compared to other works for Brazil such as Alves (2021), Palma and Portugal (2017), Neto and Candido (2018). Importantly, this alternative benchmark aligns more closely with observed inflation dynamics, reinforcing the view that financial conditions and credit spreads contain relevant information for assessing the effective stance of monetary policy.

4.2 Forward Rates

Following Justiniano and Primiceri (2010) and Del Negro et al. (2017), we forecast the filtered natural real interest rate at 2- and 5-year horizons. We refer to these forecasts as forward rates. Figure 4.4 shows that, while forward rates are smoother than the contemporaneous natural rate, they still display non-negligible time variation. This pattern indicates that part of the movements in the natural rate reflects persistent components, which are not fully absorbed even at medium-term horizons. This finding aligns with the argument of Del Negro et al. (2017), who emphasize that DSGE models can provide a comprehensive view of fluctuations in the natural rate across frequencies, encompassing both short-run dynamics and longer-run expectations within a unified structural framework.

Looking more closely at the time-series behavior of the natural rate across horizons, Figure 4.4 reveals systematic differences between short- and medium-term expectations. In the early 2000s, the contemporaneous natural rate lies above its forward counterparts, indicating tighter short-term conditions relative to medium-term expectations.

Between 2008 and 2017, the series move closely together, suggesting that

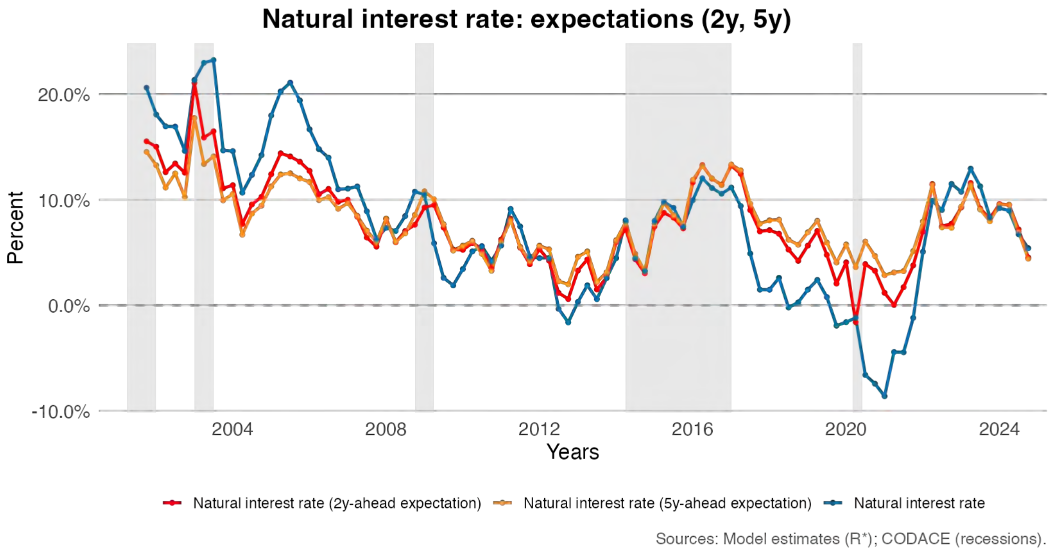

Figure 4.4: Forward natural real interest rate, $\mathbb{E}_t\left(R^{\star}_{t+h}\right)$, and the short-run natural rate

both the decline in the natural rate in the early part of the period and its temporary increase during the crisis are consistently captured across horizons. After this period, the series begin to diverge again until around 2022, when they gradually reconverge.

Overall, all measures display similar trends over time, although forward rates are smoother and less responsive to short-run fluctuations. This is particularly evident during the COVID-19 episode, when the contemporaneous natural rate declines sharply, while forward rates remain comparatively stable and do not fall below zero. This episode generates the largest divergence in the sample. In the post-pandemic period, all series initially increase and, after 2022, converge toward more stable levels, reflecting a normalization of both short- and medium-term expectations regarding the equilibrium real interest rate.

4.3 Historical Decomposition

Figure 4.5 presents the historical decomposition of the natural real interest rate, indicating that fluctuations are driven by a relatively small set of quantitatively dominant shocks. In the early part of the sample, large movements are primarily associated with technology shock. At the same time, preference shocks, related to durable and nondurable consumption, banking capital shocks and financier risk shocks play a relevant role in shaping dynamics, contributing to the persistence of fluctuations in the natural rate.

From the middle of the sample onward, persistent negative contributions

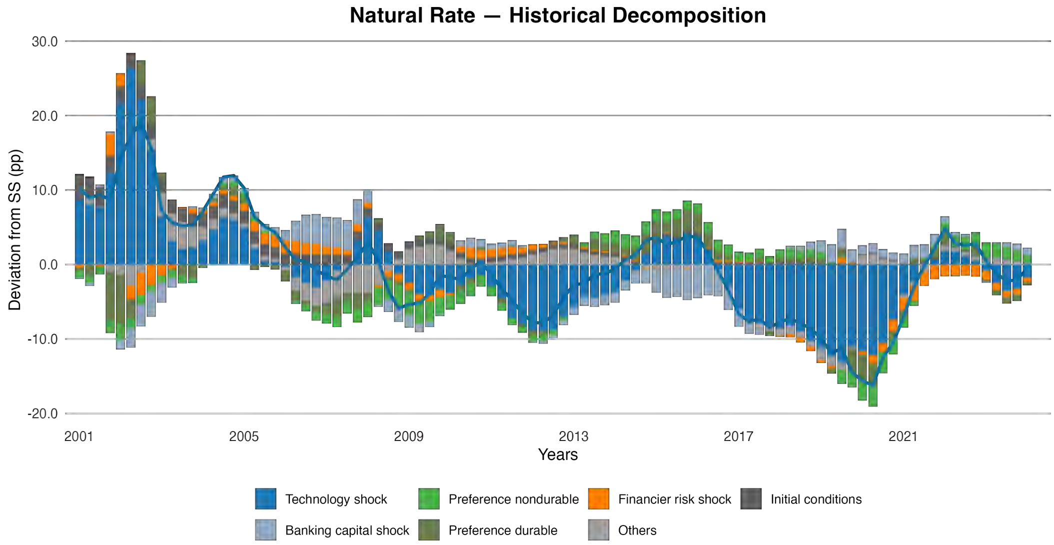

Figure 4.5: Shock Decomposition

from the technology shock are central to explaining the decline in the natural rate. These movements are again reinforced by preference shocks and by financial disturbances. In the final periods, the recovery of the natural rate reflects a partial reversal of these forces, with positive contributions from preference and banking-related shocks. Overall, the evidence suggests that fluctuations in the natural rate are largely driven by the interaction between preference, financial, and productivity shocks.

4.4 Forecast Error Variance Decomposition

Table 4.1 presents the forecast error variance decomposition of the natural real interest rate across horizons, highlighting the key structural drivers of its fluctuations. At short horizons, durable preference shocks play a dominant role, accounting for approximately 64% of the one-quarter-ahead variance, while technology shocks contribute modestly. Although not strictly financial in nature, durable preference shocks operate through the credit channel in the model, as durable goods serve as collateral for borrowing. As a result, shifts in preferences affect collateral values, borrowing capacity, and credit conditions, amplifying their impact on the natural rate. In addition banking capital shock also contribute to short- and medium-term dynamics, reinforcing the role of credit market frictions.

At longer horizons, the decomposition becomes increasingly dominated by technology shocks, which explain about 64% of the variance at 8 quarters and nearly 80% at horizons of 20 quarters and beyond. In contrast, the contribution of durable preference shocks declines. Financial shocks continue to

Table 4.1: Top 3 shocks by average contribution to the conditional variance decomposition

Shock	1 qtr	4 qtr	8 qtr	20 qtr
Technology	25.70	47.24	64.91	80.81
Durable Preference	63.47	33.79	19.66	10.34
Bank Capital	2.91	6.27	5.68	3.11

account for a non-negligible share of medium-term fluctuations. Overall, the evidence suggests that, although long-run movements in the natural rate are primarily driven by persistent technology forces, credit market mechanisms—both directly, through financial shocks, and indirectly, through preference-driven collateral effects—are central to understanding its short- and medium-run dynamics.

4.5 Impulse Response Functions

We compute impulse response functions for the full set of structural shocks in the model. For expositional clarity, the discussion focuses on the shocks that are quantitatively most relevant for the dynamics of the natural rate of interest.[2]

To illustrate how banking structure and regulatory features shape the magnitude and propagation of shocks, we report impulse responses under two alternative configurations. Specifically, we compare the baseline model with one counterfactual scenario that replicate more traditional frameworks in the literature. In the figures, the blue line corresponds to the standard financial accelerator model with perfect competition and no capital requiremnts in the banking sector (BGG) and the black line denotes the baseline specification, which combines imperfect competition with binding capital requirements.

4.5.1 Credit Demand Shock – Preferences for Durable Goods

As in Luz (2024), we model a credit demand shock through a positive preference shock that affects the demand for the durable good used as collateral in the economy. Figure 4.6 summarizes the dynamic responses.

A positive durable preference shock increases the demand for collateralizable assets, leading impatient households to expand borrowing. At the same time, the reallocation of consumption toward durables is associated with a de-

[2]Relevance is assessed based on their contribution to the forecast error variance decomposition reported in Section 4.4.

cline in non-durable consumption, affecting households' saving behavior and the intertemporal allocation of resources. On impact, higher durable prices strengthen collateral values and relax borrowing constraints, reducing default probabilities despite the increase in credit volumes. Over time, as credit expands, lending rates and default risk increase, gradually tightening financial conditions.

The natural rate of interest declines following the shock, reflecting the adjustment required to sustain the equilibrium allocation in the presence of stronger demand for durables and shifts in saving and borrowing decisions. Lower non-durable consumption contributes to this adjustment by altering the saving–investment balance. At the same time, banks reduce lending rates to entrepreneurs, which, together with the expansion in household credit and aggregate demand, creates incentives for increased investment. The resulting rise in capital accumulation further strengthens collateral values in the entrepreneurial sector and relaxes borrowing constraints, thereby contributing to improved credit conditions over time.

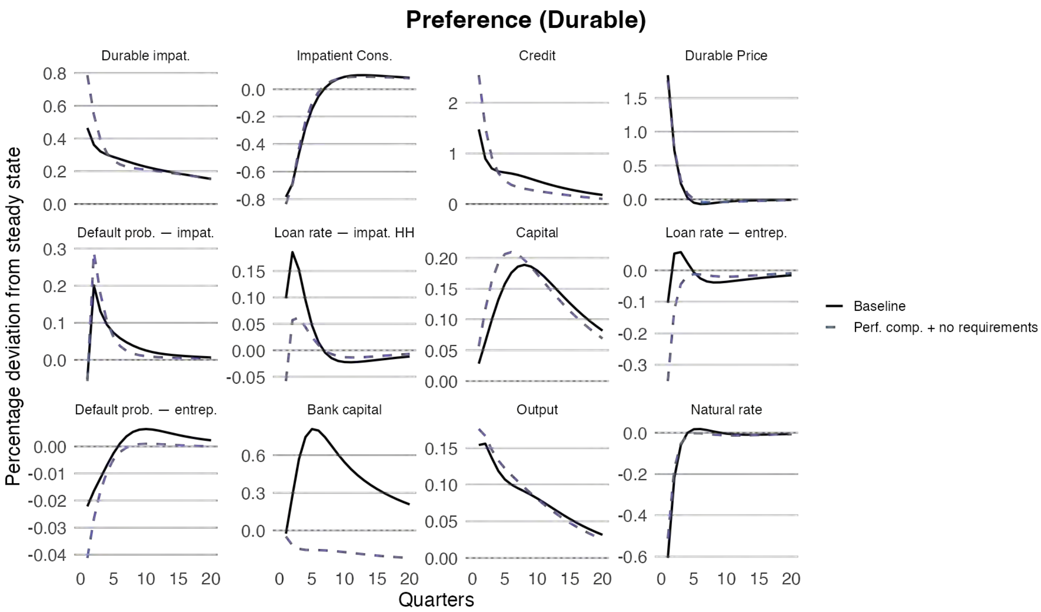

Figure 4.6: Impulse Responses to Durable Good Preference Shock

From a financial perspective, the propagation of the shock depends critically on the structure of the banking sector, as emphasized by Luz (2024). In the baseline model, the increase in credit demand forces banks to adjust their balance sheets in order to comply with capital requirements. Banks respond by raising lending rates initially for impatient households and subsequently for entrepreneurs, dampening credit expansion while preserving the capital-to-asset ratio. This adjustment implies a smaller short-run expansion of credit. In contrast, in the BGG model without capital requirements, bank capital remains largely unchanged, so credit expands more than in the baseline model.

4.5.2 Credit Supply Shock - Bank Capital

We next consider a negative shock to bank capital, which tightens the supply of credit by increasing banks' leverage. As shown in Figure 4.7, the decline in bank capital generates a sharp increase in wholesale funding spreads[3] and lending rates, reflecting higher intermediation costs and balance-sheet pressures in the banking sector. As a result, total credit contracts sharply on impact, signaling an abrupt tightening of financial conditions.

The contraction in credit supply propagates quickly to the real economy. Higher borrowing costs and tighter lending conditions lead to a pronounced decline in investment, which gradually reduces the capital stock and depresses the price of capital. The associated deterioration in entrepreneurs' net worth raises default risk and further restrains credit. Impatient households are affected through similar channels: although there is a brief initial easing, lending rates soon rise as credit conditions tighten and demand for durable goods weakens.

Non-durable consumption of both patient and impatient households increases slightly on impact, reflecting short-run substitution effects and temporary labor income adjustments. However, as investment, capital, and output decline, wages fall and consumption moves persistently below its steady state.[4] Output fall immediately confirming the strongly contractionary nature of a negative bank capital shock.

In the alternative specification, banks are not required to rebuild capital following the shock, as deviations from the target capital ratio are not penalized. Consequently, the wholesale spread remains largely unchanged, allowing banks to reallocate resources toward lending. As a result, credit to both entrepreneurs and impatient households increases on impact, supporting a modest expansion in investment, capital accumulation, and consumption.

The natural rate of interest initially increases on impact, reflecting the tightening of financial conditions and the higher equilibrium return required to clear goods and credit markets in the presence of an contraction in credit supply. As investment falls and aggregate demand weakens, the natural rate falls below its steady state. Overall, the responses illustrate how disruptions in

[3]Defined as the difference between the wholesale lending rate for the loan branch (r^{wb}) and the wholesale funding rate (r^{wd}).

[4]The decline in the capital stock reduces the marginal productivity of labor, exerting downward pressure on wages.

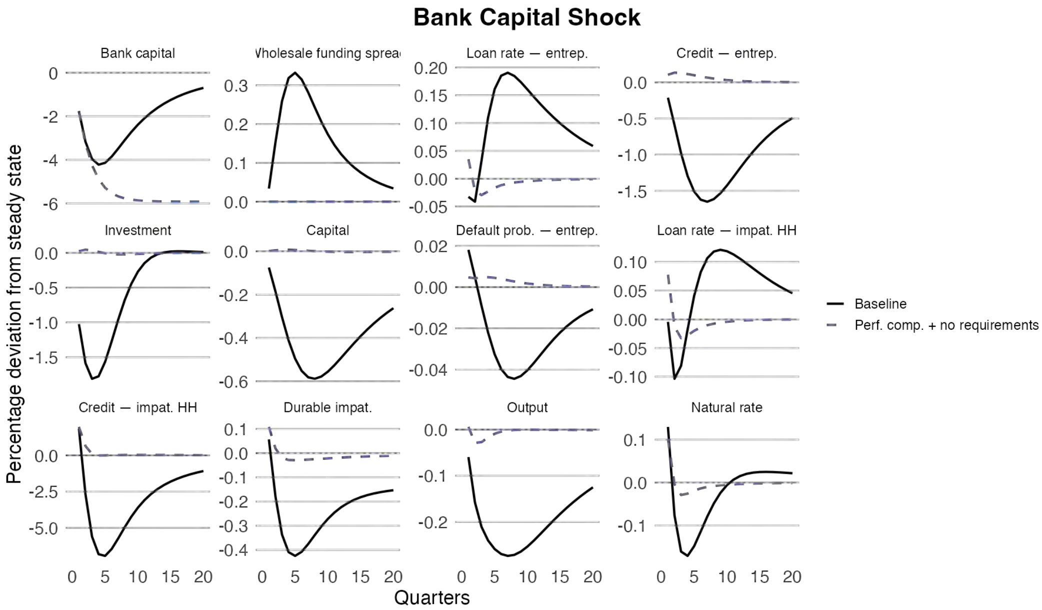

Figure 4.7: Impulse Responses to Credit Supply Shock

bank balance sheets affect the natural rate through their dynamic interaction with credit conditions, investment, and aggregate demand.

4.5.3 TFP shock

A positive productivity shock raises output and improves factor productivity, leading to higher wages and an increase in the marginal product of capital. These improvements stimulate both investment demand and household consumption, generating expansionary effects on real activity. In this environment, the natural rate of interest declines, reflecting the equilibrium adjustment associated with changes in consumption-savings decisions, a result consistent with DSGE-based estimates in the literature.

The expansion in investment leads to an increase in the capital stock. As demand for capital rises, its price increases, boosting entrepreneurs' net worth and relaxing borrowing constraints. At the same time, higher income raises demand for durable goods, increasing their prices and further strengthening collateral values. This joint improvement in balance sheets reduces default risk and lowers borrowing costs for both households and entrepreneurs. As a result, credit expands and financial conditions ease endogenously, reinforcing the real effects of the productivity shock through the credit channel.

The propagation of this shock depends on the structure of the banking sector. In the baseline model, banks must accumulate capital to comply with regulatory constraints, which raises the cost of funds and dampens the decline in lending rates over time relative to models without capital requirements.

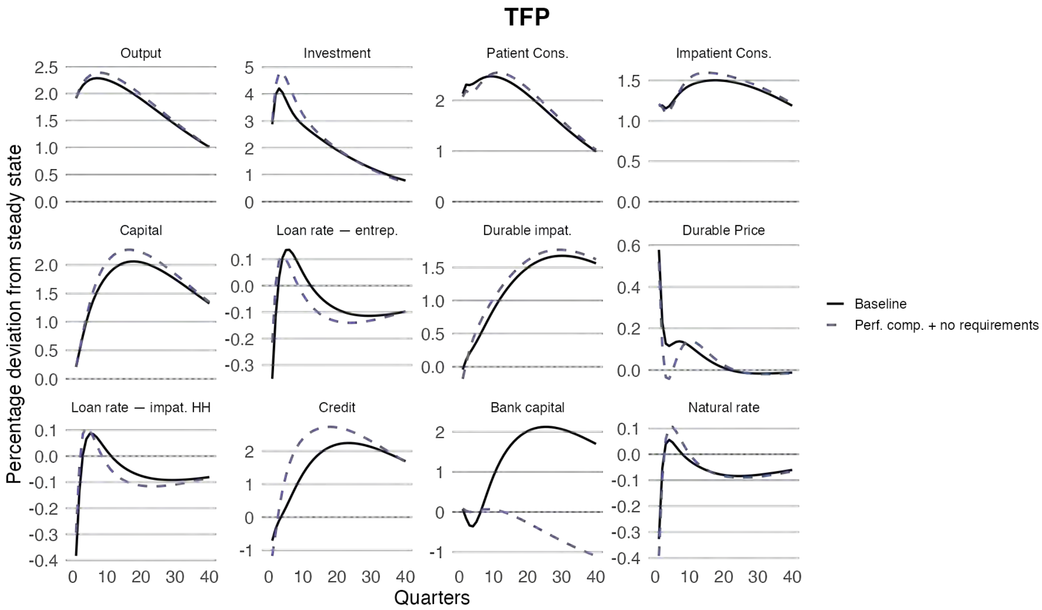

Figure 4.8: Impulse Responses to a TFP Shock

Consequently, capital, investment, consumption, and output grow less in the baseline model compared to the BGG model.

4.6 Counterfactual Analysis

In this section, we explore a set of counterfactual scenarios within the model to assess how alternative structural features affect the natural rate of interest. We analyze how changes in selected parameters modify the estimated path of the natural rate over the sample period.

To conduct the sensitivity analysis, we proceed as follows. We start from the sequence of structural shocks recovered in the estimation stage. These shocks provide a parsimonious summary of the exogenous forces that affected the economy over the sample period, conditional on the estimated model and observed data.

Using the calibrated parameters and the posterior mode of the estimated parameters, we reconstruct the path of the natural rate of interest through a direct simulation of the model, holding the sequence of shocks fixed. Counterfactual exercises are then implemented by selectively changing specific structural parameters while keeping the same historical shocks. For each alternative parameter configuration, the model is re-solved and simulated, generating a new trajectory for the natural rate.

This approach isolates the role of structural features in shaping the dynamics of the natural rate, as all counterfactual paths are driven by the same underlying shocks. Differences across scenarios therefore reflect changes in the propagation mechanisms embedded in the model, rather than differences in exogenous disturbances.

The first counterfactual exercise compares the natural rate of interest implied by the baseline model with that obtained from a version of the model that replicates the BGG framework. To this end, we impose perfect competition in the banking sector and eliminate the cost associated with deviations from the optimal bank capital-to-asset ratio.

Figure 4.9 shows that the natural rate implied by the BGG-type model is lower than that of the baseline specification for most of the sample. This difference highlights the role of imperfect competition and regulatory capital frictions in raising the equilibrium real rate in the baseline economy. Under imperfect competition, banks charge markups over marginal cost, increasing borrowing rates and limiting credit expansion. At the same time, capital requirements force banks to internalize balance-sheet constraints, as loan growth must be backed by additional capital, which raises the cost of funds. Together, these frictions generate higher lending spreads and reduce the efficiency of financial intermediation. As a result, a higher natural rate is required to sustain equilibrium levels of credit and investment. By contrast, in the BGG-type model—characterized by perfect competition and the absence of regulatory capital constraints—spreads are lower, intermediation is more efficient, and the equilibrium real rate is correspondingly reduced for most of the sample.

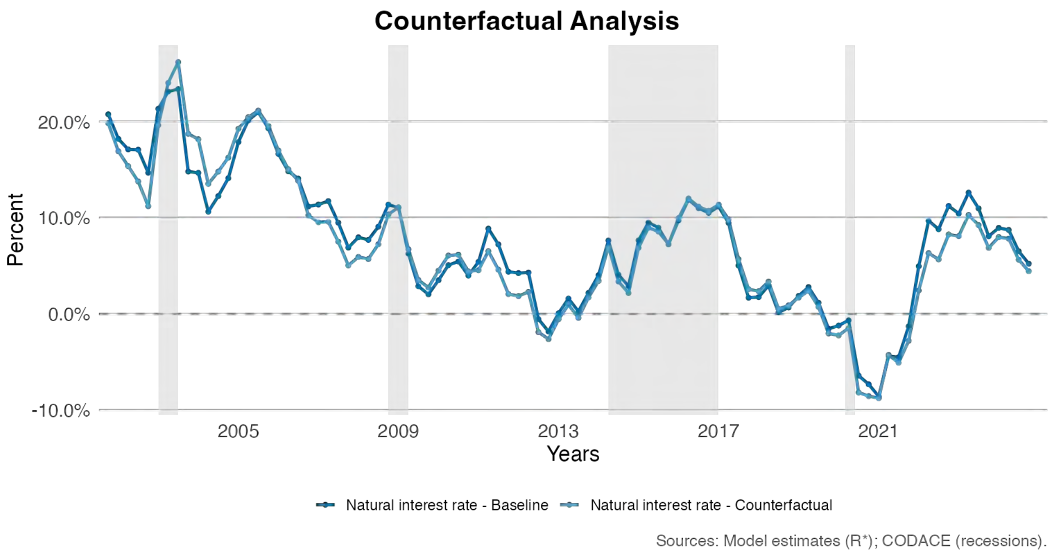

Figure 4.9: Counterfactual - BGG Model

An interesting feature of the comparison is that the gap between the two natural rates largely vanishes from around 2015 onward and remains negligible until approximately 2022. One possible interpretation is that this period coincides with structural changes in the Brazilian banking sector aimed at fostering competition, including regulatory initiatives promoted by the Central Bank—such as the BC+ and BC# agendas—as well as the entry of new market participants, notably digital banks and payment institutions. These developments may have reduced effective market power and compressed intermediation spreads, bringing the economy closer to the frictionless benchmark captured by the BGG framework.

Figures 4.10 and 4.11 report counterfactual exercises that alter the monitoring cost faced by banks—by increasing collateral recovery[5]—and eliminate administrative intermediation costs, respectively. In contrast to previous experiments, these modifications do not generate a clear directional effect on the natural rate.

This ambiguity reflects the fact that these frictions primarily affect the banking sector through marginal cost channels rather than through persistent changes in market structure. As discussed in Luz (2024), a reduction in monitoring costs lowers lending rates, allowing for higher leverage and raising the default threshold. In this environment, banks optimally take on more risk given the higher expected recovery in the event of default. A similar mechanism operates under a reduction in administrative costs, which also lowers the marginal cost of intermediation and encourages greater credit expansion. As a result, the impact on the natural rate is state-dependent and less systematic than in counterfactuals that alter competition and capital regulation.

More specifically, two distinct patterns emerge over the sample. In the early period, up to around 2013, the counterfactual natural rate is generally higher than in the baseline. This reflects the macroeconomic environment of strong growth in output, consumption, investment, and credit. In such a context, improvements in collateral recovery or reductions in intermediation costs amplify credit expansion and aggregate demand, requiring a higher natural rate to sustain equilibrium. In contrast, from 2014 onward—marked by recession, weak economic activity, and stagnant credit conditions—the pattern reverses, with the baseline natural rate exceeding its counterfactual counterparts. In this environment, the same counterfactual changes in financial conditions generate weaker amplification effects, and the equilibrium real rate declines, highlighting the state-dependent nature of financial frictions in shaping the natural rate of interest.

[5]Specifically, we increase the recovery rate by 20 percentage points, setting $\mu = 0.6$

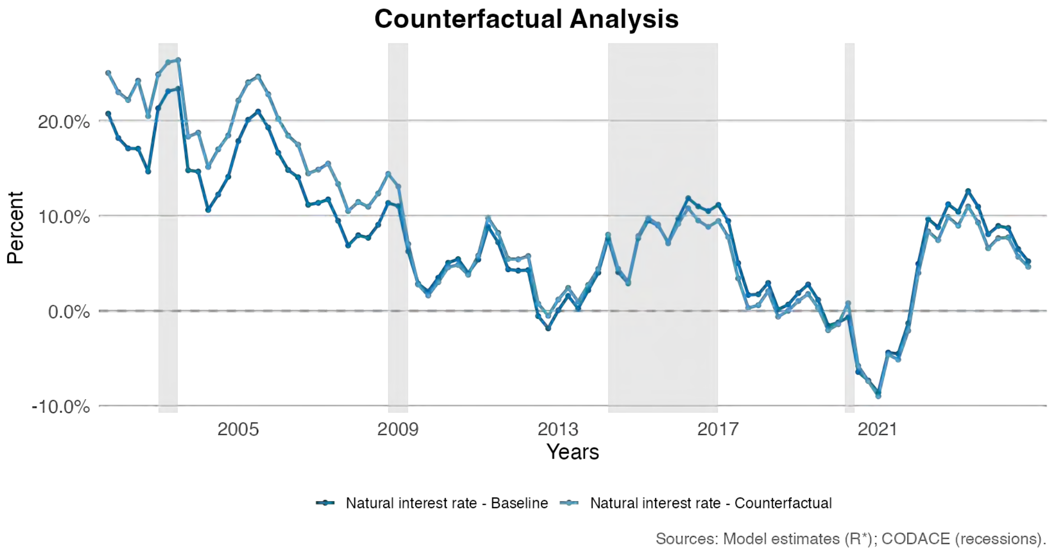

Figure 4.10: Counterfactual - Lower Monitoring Cost

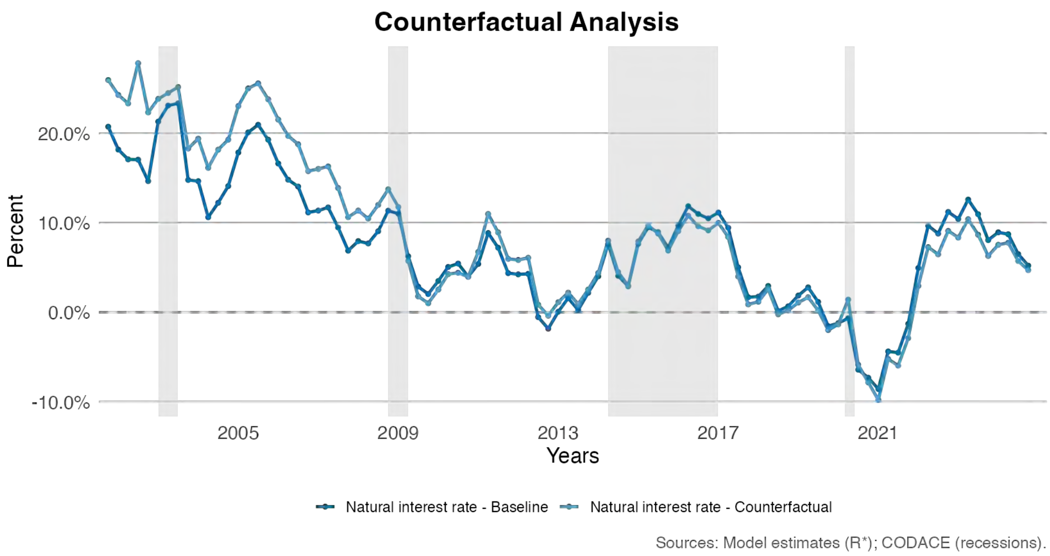

Figure 4.11: Counterfactual - No Administrative Cost

Taken together, these counterfactuals indicate that banking frictions are relevant for the determination of the natural rate of interest and, consequently, for the assessment of the monetary policy stance. While changes in monitoring and administrative costs generate state-dependent and non-monotonic effects, alterations in banking competition lead to systematic reductions in the level of the natural rate. So, properly accounting for these frictions is therefore essential for aligning model-implied policy assessments with observed macroeconomic outcomes.

5
Monte-Carlo Experiment

In this section, we evaluate the recovery of the natural real interest rate within the model. To do so, we conduct a Monte Carlo experiment in which the DSGE model is treated as a data-generating process. The objective is to assess how accurately the model-based procedure recovers the natural rate under alternative sets of observables. More specifically, the experiment is designed to measure whether credit-market variables provide additional information that improves the recovery of $R_t^\star$, relative to standard macroeconomic observables.

The model is first calibrated so that its steady state matches key statistics of the Brazilian economy. The calibration used in the Monte Carlo exercise closely follows the strategy adopted in Section 3.2. For brevity, the detailed description of the calibration procedure is reported in Appendix C.1.

With the calibrated model in hand, we simulate the economy repeatedly, generating 4,000 artificial samples. Each simulation produces a corresponding "true" natural real interest rate, $R_t^\star$, together with time series for all endogenous variables. For each of the 5,000 artificial datasets, we conduct four recovery exercises.

In the first exercise, we apply a Kalman filter using a set of observables that are standard in the Bayesian estimation of DSGE models Del Negro et al. (2017), Becard and Gauthier (2022), Gerali et al. (2010), Castro et al. (2015), Alves (2021), Neri and Gerali (2019). This set includes GDP, consumption, investment, hours worked, inflation, and the policy interest rate. From this point onward, these variables are referred to as *Macro* variables.

For each simulation, we evaluate how well the filtering procedure recovers the simulated "true" natural rate. Recovery accuracy is assessed using distance-based metrics—RMSE and MAE—as well as the correlation between the recovered and true natural rates[1].

In the second exercise, we extend the Kalman filter by augmenting the *Macro* information set with one additional endogenous variable at a time, while keeping the same 4,000 simulated samples. For instance, we recover the natural rate using the *Macro* variables together with household credit, then

[1]Let $R_t^\star$ denote the simulated "true" natural rate and $\widehat{R}_t^\star$ its recovered counterpart. The root mean squared error (RMSE) is defined as RMSE $= \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widehat{R}_t^\star - R_t^\star)^2}$, while the mean absolute error (MAE) is given by MAE $= \frac{1}{T}\sum_{t=1}^{T}|\widehat{R}_t^\star - R_t^\star|$. In addition, recovery accuracy is also evaluated through the sample correlation between $\widehat{R}_t^\star$ and $R_t^\star$, which captures the ability of the procedure to track the cyclical co-movement of the natural rate.

with entrepreneurial credit, and so on, repeating this procedure for all model variables.

This design allows us to identify which variables provide the largest informational gains in recovering $R_t^\star$ relative to the *Macro*-only benchmark. As reported in Table 5.1, the variables that deliver the largest gains are those directly related to credit markets. In particular, household spreads and household credit provide the strongest improvements, reducing RMSE and MAE by around 2% relative to the *Macro*-only specification. This constitutes a first result of the exercise and indicates that incorporating credit variables can improve the recovery of the natural rate relative to the baseline specification based solely on standard macroeconomic observables.

Table 5.1: Individual information gains from credit-related observables

Additional observable	**RMSE gain (%)**	**MAE gain (%)**	**CORR gain (%)**
Household spread	-2.47	-2.64	0.43
Household credit	-2.02	-1.98	0.41
Entrepreneur spread	-1.94	-1.63	0.36
Entrepreneur credit	-1.81	-1.67	0.35
Credit (aggregate)	-1.58	-1.49	0.31
Deposits	-1.46	-1.38	0.30
Bank capital	-1.09	-1.33	0.23
Durable-goods price	-0.40	-0.65	0.08

Notes: Reported gains are measured relative to the *Macro-only* specification. Negative values for RMSE, MAE, and MSE indicate error reduction, while positive values for CORR indicate higher correlation with the true natural rate.

The third exercise builds on these results. We recover the natural rate using the Kalman filter with the *Macro* information set augmented by the five variables that delivered the largest informational gains in the second exercise.[2] The results, reported in Table 5.2, show that the joint inclusion of these credit-related variables further improves the recovery of the natural rate. In particular, augmenting the *Macro* specification with credit variables reduces RMSE and MAE by approximately 4% and increases the correlation with the true natural rate from 0.916 to 0.922. These findings suggest that credit-market information contains additional signals that help identify $R_t^\star$ beyond standard macroeconomic observables.

Finally, the fourth exercise replaces the Kalman filter with full Bayesian estimation. This step mirrors the standard approach in the natural-rate literature and is also consistent with the estimation strategy used in this paper. Bayesian estimation introduces an additional layer of uncertainty, not only

[2]Total credit is not included, as it is mechanically the sum of household and entrepreneurial credit.

Table 5.2: Monte Carlo estimation with Bayesian inference

Observables	**RMSE**	**MAE**	**CORR**
Macro-only	0.0097	0.0078	0.916
Macro + Credit	0.0093	0.0075	0.922
Improvement (%)	-4.2	-3.9	0.6

Notes: Improvement reports the percentage gain of the *Macro + Credit* specification relative to the *Macro-only* case. Negative values for RMSE and MAE indicate error reduction, while positive values for CORR indicate higher correlation with the true natural rate.

through the data but also through the parameters. The estimation procedure follows that described in Section 3 and is implemented for all 4,000 artificial samples under two information sets: *Macro* variables only, and *Macro* variables plus the credit variables identified as most informative in the previous exercises.

Table 5.3: Monte Carlo estimation: macro vs. macro + credit

Observables	**RMSE**	**MAE**	**CORR**
Macro-only	0.049	0.015	0.571
Macro + Credit	0.040	0.013	0.632
Improvement (%)	-22.06	-15.51	10.67

Notes: Improvement reports the percentage gain of the *Macro + Credit* specification relative to the *Macro-only* case. Negative values for RMSE and MAE indicate error reduction, while positive values for CORR indicate higher correlation with the true natural rate.

The results, reported in Table 5.3, show that once parameter uncertainty is taken into account, the inclusion of credit variables becomes even more important. In particular, augmenting the *Macro* specification with credit variables reduces RMSE from 0.049 to 0.040 and MAE from 0.015 to 0.013, while increasing the correlation with the true natural rate from 0.571 to 0.632. In percentage terms, this corresponds to improvements of roughly 22% in RMSE, 15% in MAE, and 10% in correlation relative to the *Macro*-only benchmark.

Taken together, the results from the four exercises point to a consistent conclusion. Credit-related observables contain valuable information for the recovery of the natural rate of interest. While the standard *Macro*-only specification is already able to track the simulated natural rate with reasonable accuracy, augmenting the information set with credit variables systematically improves performance across all exercises. These gains are present both when the natural rate is recovered through filtering and when the model is estimated using full Bayesian methods, and become particularly pronounced once parameter uncertainty is taken into account. Overall, the Monte Carlo evidence suggests that incorporating credit-market information can meaningfully enhance the empirical identification of $R_t^\star$ relative to approaches that rely solely on standard macroeconomic observables.

6
Conclusion

This dissertation uses a medium-scale DSGE model that incorporates key financial and credit frictions relevant to the Brazilian economy in order to study the natural rate of interest. The analysis proceeds along two dimensions: first, the estimation of the natural rate of interest within the structural model, allowing for an assessment of how financial frictions affect its level and dynamics; second, a Monte Carlo exercise designed to evaluate whether the inclusion of credit-market variables improves the recovery of the latent natural rate.

The results show that the real natural rate in Brazil exhibits a declining trend over the sample, with temporary reversals and signs of renewed decline in recent years. At the same time, its estimated level remains higher than in related studies, suggesting that the presence of financial frictions increases the real equilibrium rate. For example, imperfect competition and intermediation costs shift the equilibrium real rate. In addition, the Monte Carlo results show that credit variables contain significant informational content for identifying $R_t^\star$, improving the accuracy of the estimates by approximately 4 percent under a Kalman filter approach and by 15 to 20 percent when states and parameters are jointly estimated.

Taken together, these findings highlight the central role of financial intermediation in shaping the natural rate of interest. By affecting both credit conditions and the transmission of shocks, banking frictions alter the assessment of monetary policy stance and can generate systematic deviations between observed policy rates and the underlying equilibrium rate. Incorporating credit-market variables is therefore essential for a more accurate measurement of $R_t^\star$, particularly in emerging economies such as Brazil. Future research could extend this framework by introducing fiscal policy, open-economy channels, and demographic factors, further enhancing the analysis of monetary policy and macroeconomic stability.

7
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A
Production Sector

The production side of the economy follows a standard multi-stage New Keynesian structure. Production starts with wholesale firms operating under flexible prices, whose output is then purchased by retail firms. Retail firms differentiate goods and set prices subject to nominal rigidities, thereby introducing the key New Keynesian friction in the model. Final goods are assembled by a competitive aggregator. In addition, capital and durable goods producers are included, featuring investment adjustment costs that help smooth the dynamics of capital and durable accumulation.

A.1
Wholesale Firms

Wholesale firms produce a homogeneous intermediate good using capital and labor. Production features labor-augmenting technology as in Becard and Gauthier (2022) to be able to capture long-term productivity trends in the model. They maximize period-by-period profits by choosing capital and labor inputs:

$$\max_{K_t, L_t^P, L_t^I} \frac{P_t^W}{P_t} \varepsilon_t^a K_t^\alpha \Big(z_t L_t\Big)^{1-\alpha} - RR_t^k K_t - W_t^P L_t^P - W_t^I L_t^I, \tag{A-1}$$

taking factor prices as given. ε_t^a denotes total factor productivity and z_t is a labor-augmenting technology shifter[1]. The resulting first-order conditions equate the marginal products of capital and each type of labor to their respective real rental rates and wages.

Aggregate labor input L_t is a Cobb–Douglas composite of labor supplied by patient and impatient households:

$$L_t = \Big(L_t^P\Big)^\Omega \Big(L_t^I\Big)^{1-\Omega}, \tag{A-2}$$

with $\Omega \in (0, 1)$ governing the relative importance of patient-household labor.

A.2
Retail Firms with Nominal Stickiness

Retail firms purchase the wholesale good at price P_t^W, differentiate it costlessly, and sell differentiated varieties under monopolistic competition. Retail prices

[1] To solve and estimate the model, all real variables are expressed in efficiency units by normalizing with respect to labor-augmenting technology z_t. This transformation removes deterministic trends and allows the model to be solved around a stationary steady state. As an example, output is defined as $y_t = Y_t/z_t$.

are subject to nominal rigidities, modeled through a quadratic price adjustment cost.

Each retailer $m \in [0,1]$ chooses its nominal price $P_t(m)$ to maximize expected discounted real profits:

$$\max_{\{P_t(m)\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \left[\left(P_t(m) - P_t^W \varepsilon_t^{\mu^p} \right) Y_t(m) - \frac{\kappa_P}{2} \left(\frac{P_t(m)}{P_{t-1}(m)} - \pi_{t-1}^{\iota} \bar{\pi}^{1-\iota} \right)^2 P_t Y_t \right], \tag{A-3}$$

subject to the demand schedule for retail varieties. The parameter κ_P governs the degree of price stickiness, $\iota \in [0,1]$ captures indexation to past inflation, and $\bar{\pi}$ denotes the steady-state inflation target. We also introduce an exogenous markup (cost-push) shock $\varepsilon_t^{\mu^p}$, which shifts the effective marginal cost faced by retailers.

A.3
Final Goods Producer

A perfectly competitive final goods firm aggregates differentiated retail varieties $Y_t(m)$ into a homogeneous final good Y_t using a CES technology:

$$Y_t = \left[\int_0^1 Y_t(m)^{\frac{\eta-1}{\eta}} dm \right]^{\frac{\eta}{\eta-1}}, \tag{A-4}$$

where $\eta > 1$ is the elasticity of substitution. Cost minimization by this aggregator yields the demand for each retail variety:

$$Y_t(m) = \left(\frac{P_t(m)}{P_t} \right)^{-\eta} Y_t, \tag{A-5}$$

with the aggregate price index defined as:

$$P_t = \left[\int_0^1 P_t(m)^{1-\eta} dm \right]^{\frac{1}{1-\eta}}. \tag{A-6}$$

A.4
Capital Producers

Capital producers purchase investment goods I_t and undepreciated capital $(1-\delta^k)K_t$ from entrepreneurs to produce new capital stock K_{t+1}. They face quadratic investment adjustment costs $Z^i(I_t/I_{t-1})$. Their optimization problem is:

$$\begin{aligned} \max_{I_t} \quad & \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \left[Q_t^k (K_{t+1} - (1-\delta^k)K_t) - I_t \right], \\ \text{s.t.} \quad & K_{t+1} = (1-\delta^k)K_t + \varepsilon_t^{\zeta^i} \left[1 - Z^i \left(\frac{I_t}{I_{t-1}} \right) \right] I_t, \end{aligned} \tag{A-7}$$

with adjustment costs satisfying steady-state conditions $Z^i(\cdot) = 0$ and $Z^{i\prime}(\cdot) = 0$. Specifically, we use:

$$Z^i\left(\frac{I_t}{I_{t-1}}\right) = \frac{\kappa_I}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2.$$

The shock $\varepsilon_t^{\zeta^i}$ is interpreted as a marginal efficiency of investment shock, capturing time variation in the effectiveness with which investment expenditures are transformed into new capital.

A.5 Durable Goods Producers

Durable goods producers operate similarly to capital producers, converting investment goods I_t^s and undepreciated durable stock $(1-\delta^s)S_t$ into next-period durable stock S_{t+1}. Their problem is:

$$\begin{aligned} \max_{I_t^s} \quad & \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^P \left[Q_t^s(S_{t+1} - (1-\delta^s)S_t) - I_t^s\right], \\ \text{s.t.} \quad & S_{t+1} = (1-\delta^s)S_t + \left[1 - Z^i\left(\frac{I_t^s}{I_{t-1}^s}\right)\right] I_t^s, \end{aligned} \tag{A-8}$$

where again the adjustment cost function is:

$$Z^i\left(\frac{I_t^s}{I_{t-1}^s}\right) = \frac{\kappa_s}{2}\left(\frac{I_t^s}{I_{t-1}^s} - 1\right)^2.$$

B
Estimation Complement

The model is estimated using Bayesian methods. Formally, Bayesian estimation combines prior distributions over the vector of structural parameters, denoted by $p(\theta)$, with the likelihood of the data implied by the model, $L(y^T \mid \theta)$, where $y^T = \{y_1, \ldots, y_T\}$ denotes the set of observable variables. This yields the posterior distribution $p(\theta \mid y^T)$. Since the posterior distribution is not available in closed form, it is explored numerically using a Markov Chain Monte Carlo (MCMC) sampling scheme. In particular, we rely on the random-walk Metropolis–Hastings algorithm to generate draws from the posterior distribution and compute posterior moments and credibility intervals. The estimation is implemented using `Dynare`, which solves the model, evaluates the likelihood, and performs the numerical implementation of the Metropolis–Hastings algorithm.

Following common practice in the Bayesian estimation of DSGE models (e.g., Adolfson et al. (2008); Christiano, Trabandt and Walentin (2011)), we allow for measurement errors in the observation equations. Measurement errors capture discrepancies between model-implied variables and observed data arising from data construction, aggregation, or model misspecification. Consistent with JÄÄSKELÄ and NIMARK (2011), the variance of the measurement error associated with each observable series is calibrated to correspond to 10% of the variance of the respective data series, with the exception of the nominal policy interest rate and credit spreads, for which no measurement errors are included.[1]

The model features a total of thirteen exogenous stochastic shocks, capturing disturbances to preferences, technology, investment adjustment, price-setting behavior, financial conditions, and banking-sector dynamics. These shocks are assumed to follow independent AR(1) processes.[2]

[1] Allowing for measurement errors serves two main purposes. First, measurement errors help resolve potential stochastic singularity issues. Second, macroeconomic time series are subject to noise stemming from data construction, aggregation, and measurement, which measurement errors help absorb without distorting inference on the model's structural parameters.

[2] Let x_t denote a generic shock with steady-state value $\bar{x}$. Its dynamics are given by

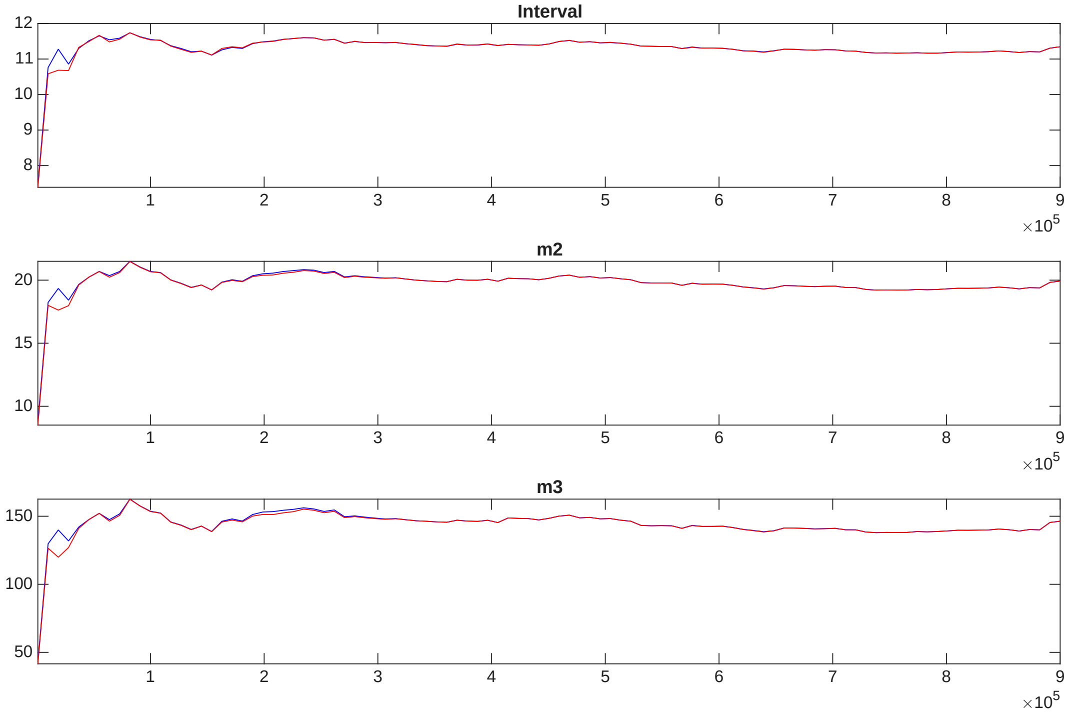
$$\ln\left(\frac{x_t}{\bar{x}}\right) = \rho_x \ln\left(\frac{x_{t-1}}{\bar{x}}\right) + \varepsilon_t^x, \qquad \varepsilon_t^x \sim \mathcal{N}(0, \sigma_x^2).$$

B.1 Observation Equations

We specify the observation equations that map model variables into their empirical counterparts. The superscript obs denotes observable variables. Variables that grow along the balanced growth path are expressed in gross growth rates and normalized by the steady-state growth rate of labor-augmenting technology, μ_z. We define the gross growth rate of labor-augmenting technology as $\mu_{z,t} \equiv \frac{z_t}{z_{t-1}}$, where z_t denotes labor-augmenting productivity. Real variables are expressed in efficiency units, so that growth-rate observables correspond to log differences of efficiency-unit quantities. Steady-state values are denoted by bars.

Gross domestic product:	$y_t^{\text{obs}} = 1 + \ln\Big(\frac{y_t \mu_{z,t}}{y_{t-1}}\Big) - \ln(\mu_z) = \frac{y_t}{y_{t-1}} \cdot \frac{\mu_{z,t}}{\mu_z}.$
Consumption:	$c_t^{\text{obs}} = \frac{c_t}{c_{t-1}} \cdot \frac{\mu_{z,t}}{\mu_z}.$
Investment:	$i_t^{\text{obs}} = \frac{i_t}{i_{t-1}} \cdot \frac{\mu_{z,t}}{\mu_z}.$
Hours:	$l_t^{\text{obs}} = 1 + \ln l_t - \ln \bar{l} = \frac{l_t}{\bar{l}}.$
Inflation:	$\pi_t^{\text{obs}} = \frac{\pi_t}{\bar{\pi}}.$
Nominal interest rate:	$R_t^{\text{obs}} = (1 + r_t) - (1 + \bar{r}).$
Household credit:	$b_{i,t}^{\text{obs}} = \frac{b_{i,t}}{b_{i,t-1}} \cdot \frac{\mu_{z,t}}{\mu_z}.$
Household spread:	$S_{i,t}^{\text{obs}} = (1 + r_{bi,t}) - (1 + r_t) - \Big[(1 + \bar{r}_{bi}) - (1 + \bar{r})\Big].$
Business credit:	$b_{e,t}^{\text{obs}} = \frac{b_{e,t}}{b_{e,t-1}} \cdot \frac{\mu_{z,t}}{\mu_z}.$
Business spread:	$S_{e,t}^{\text{obs}} = (1 + r_{be,t}) - (1 + r_t) - \Big[(1 + \bar{r}_{be}) - (1 + \bar{r})\Big].$
Bank deposits:	$d_t^{\text{obs}} = \frac{d_t}{d_{t-1}} \cdot \frac{\mu_{z,t}}{\mu_z}.$

B.2
Figures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m2
m3
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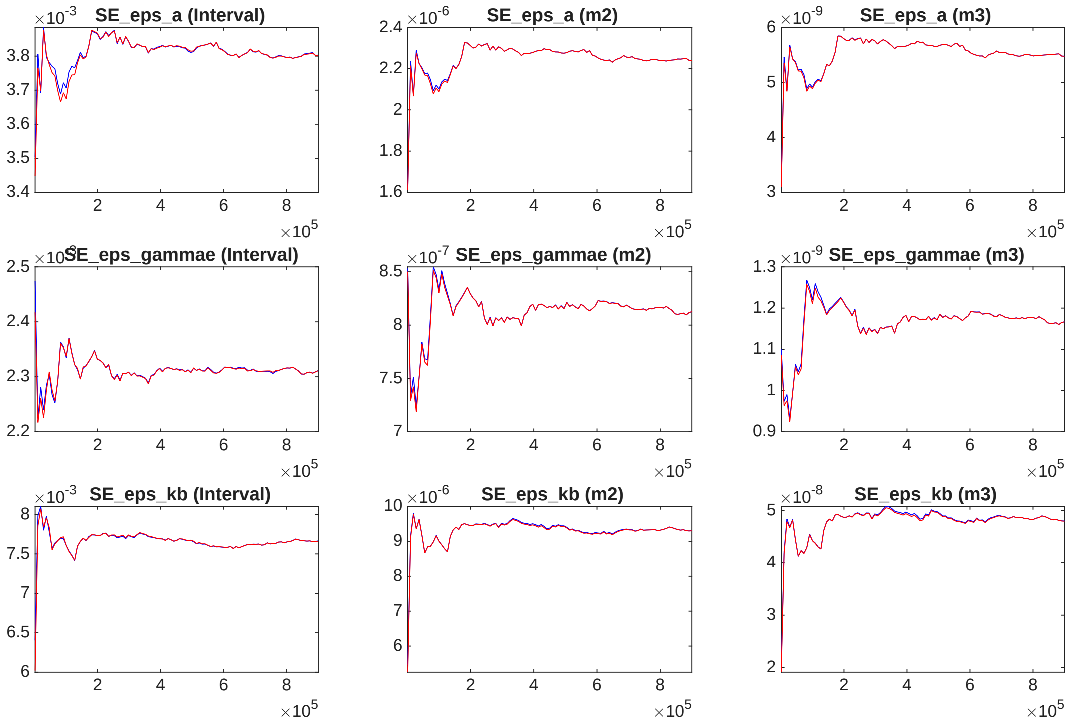
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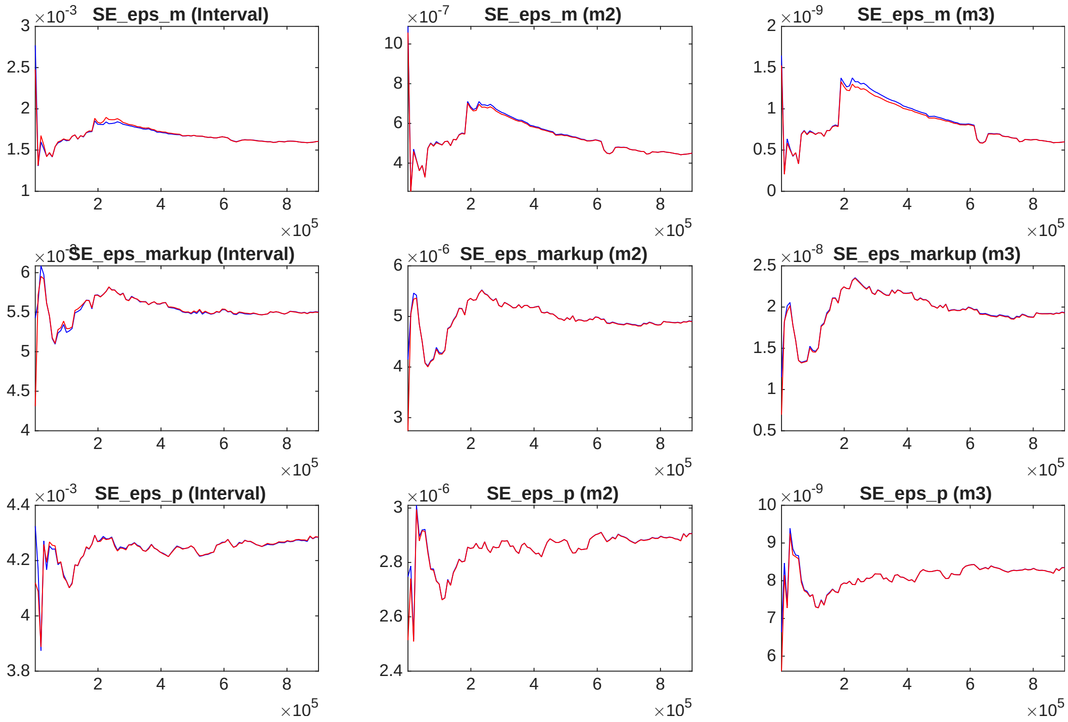
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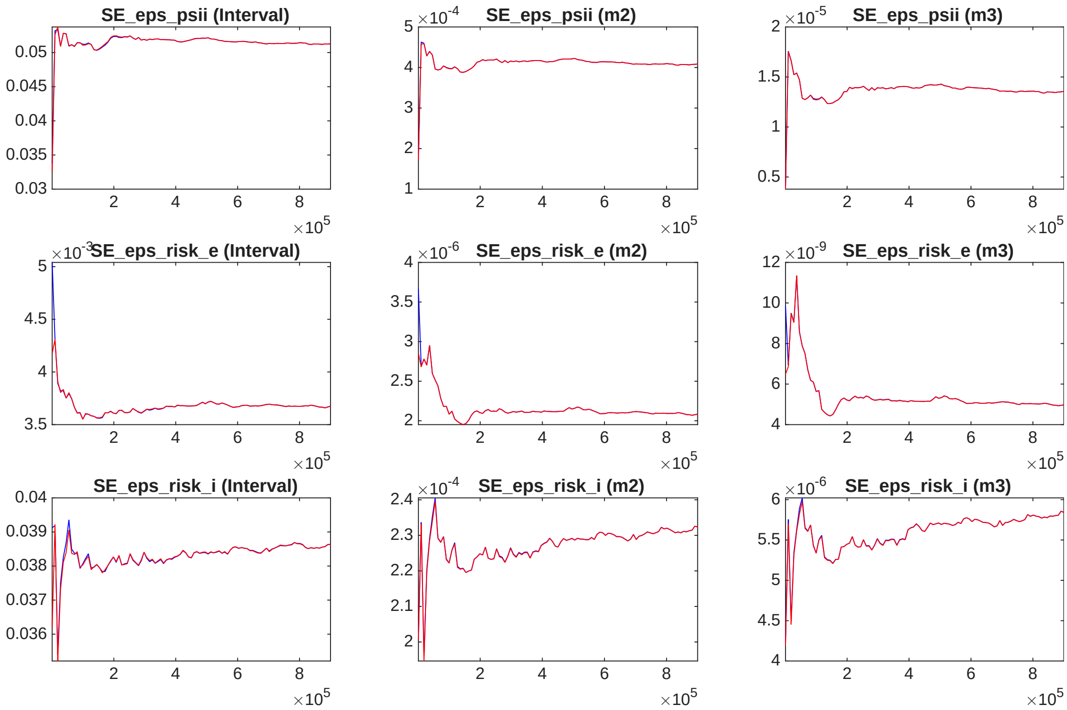
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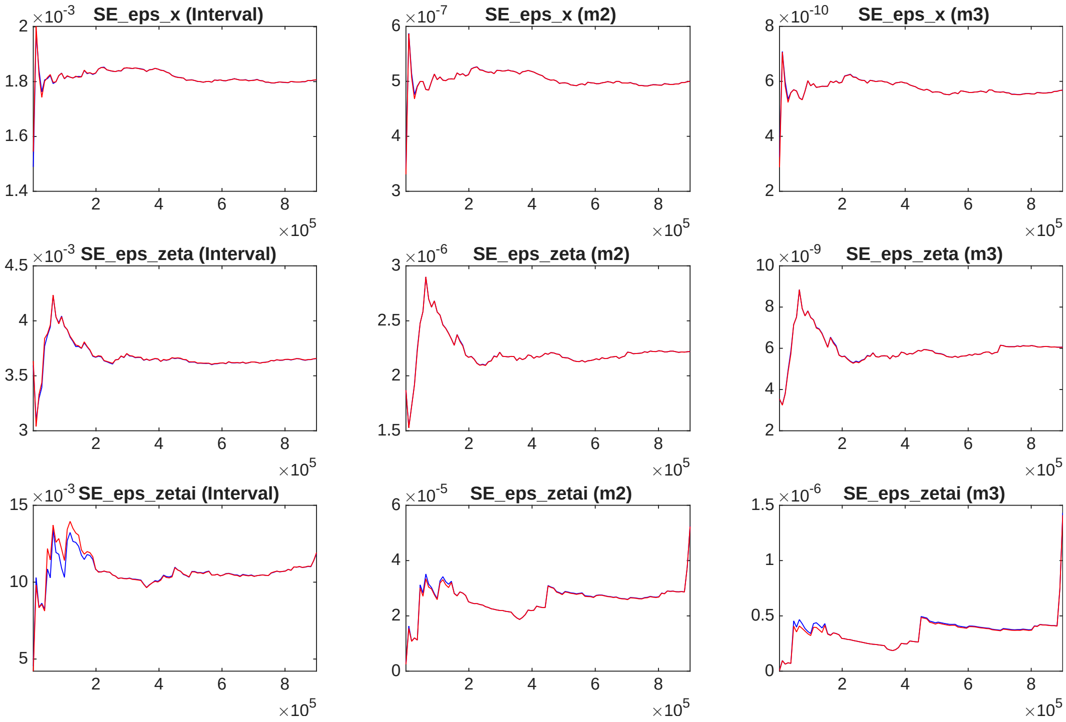
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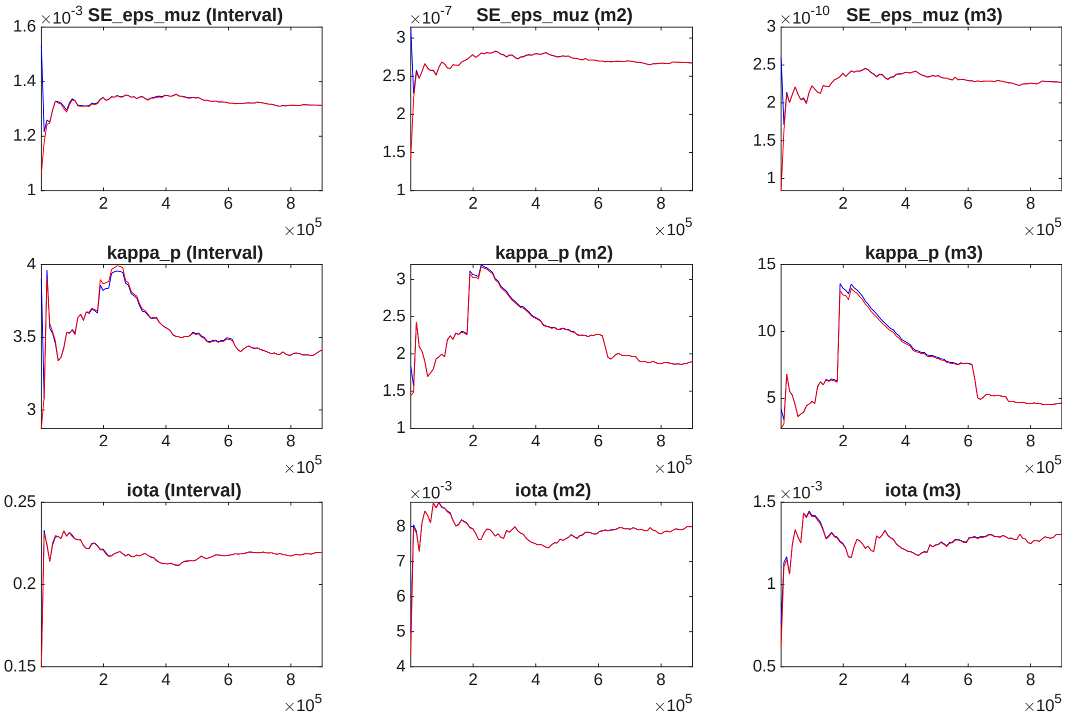
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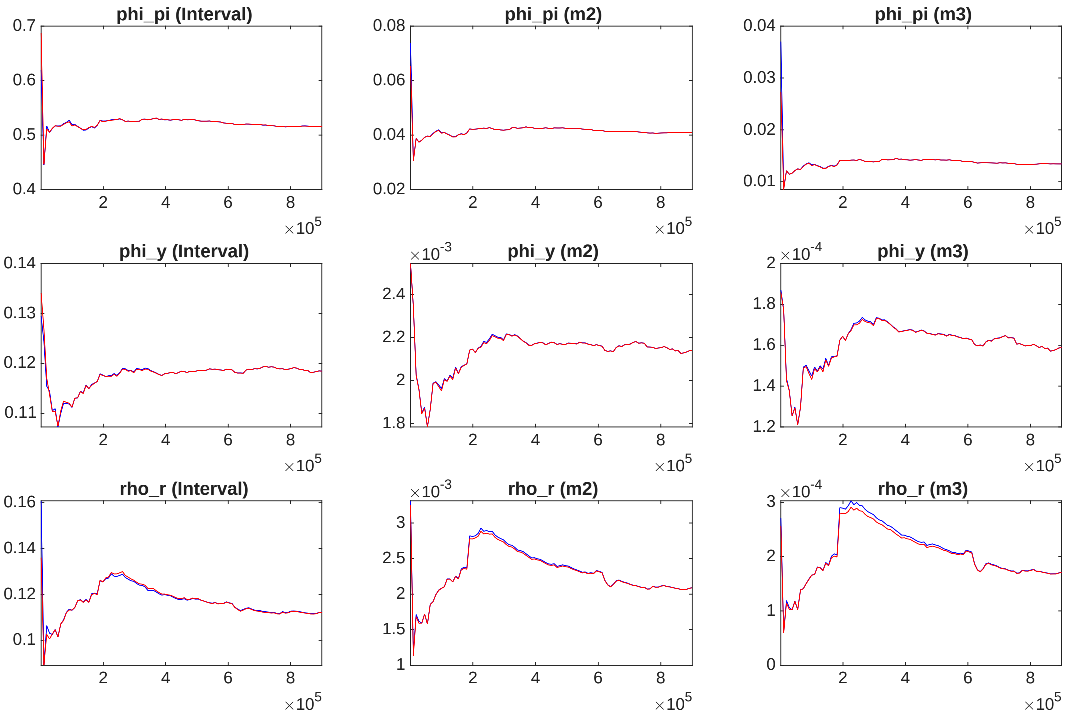
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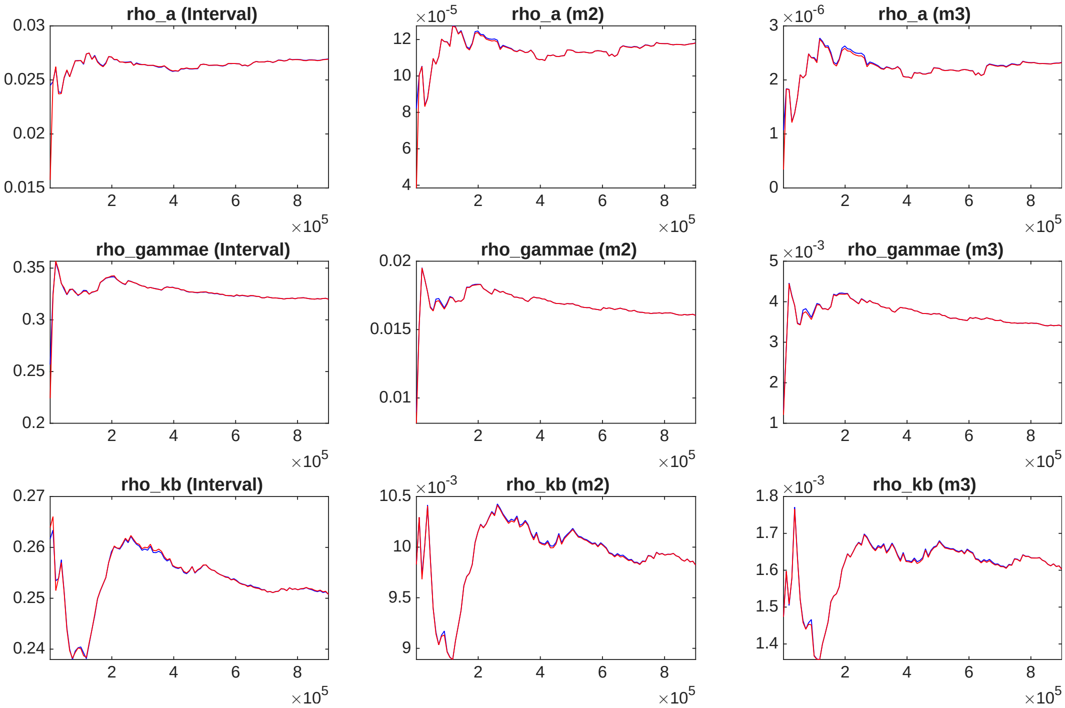
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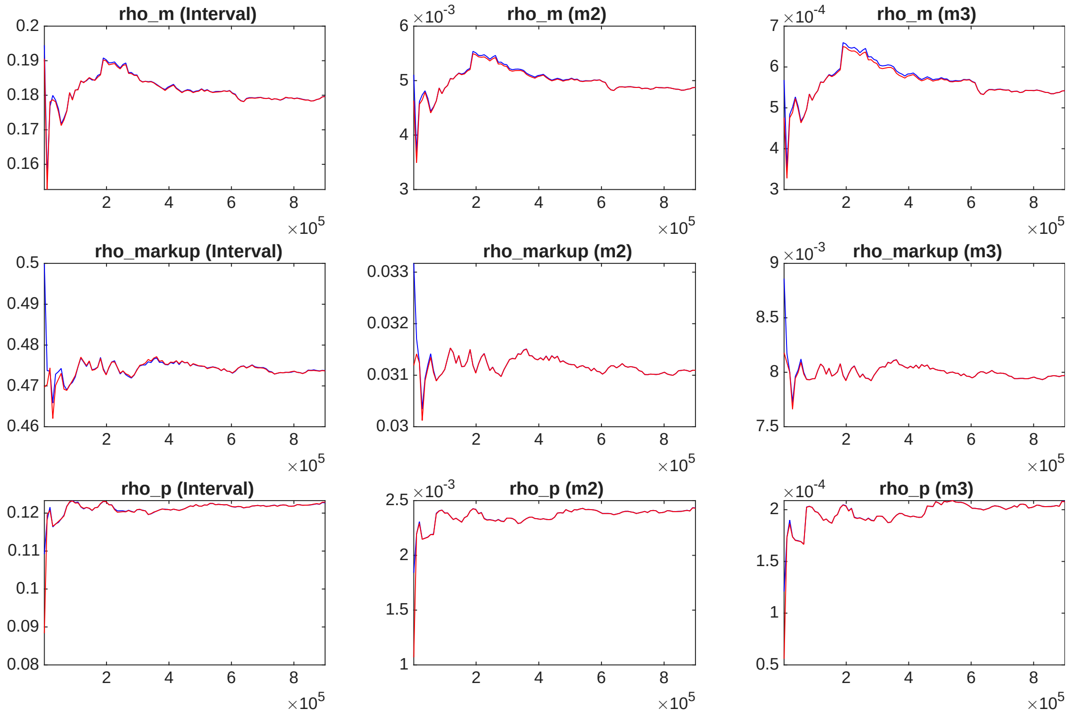
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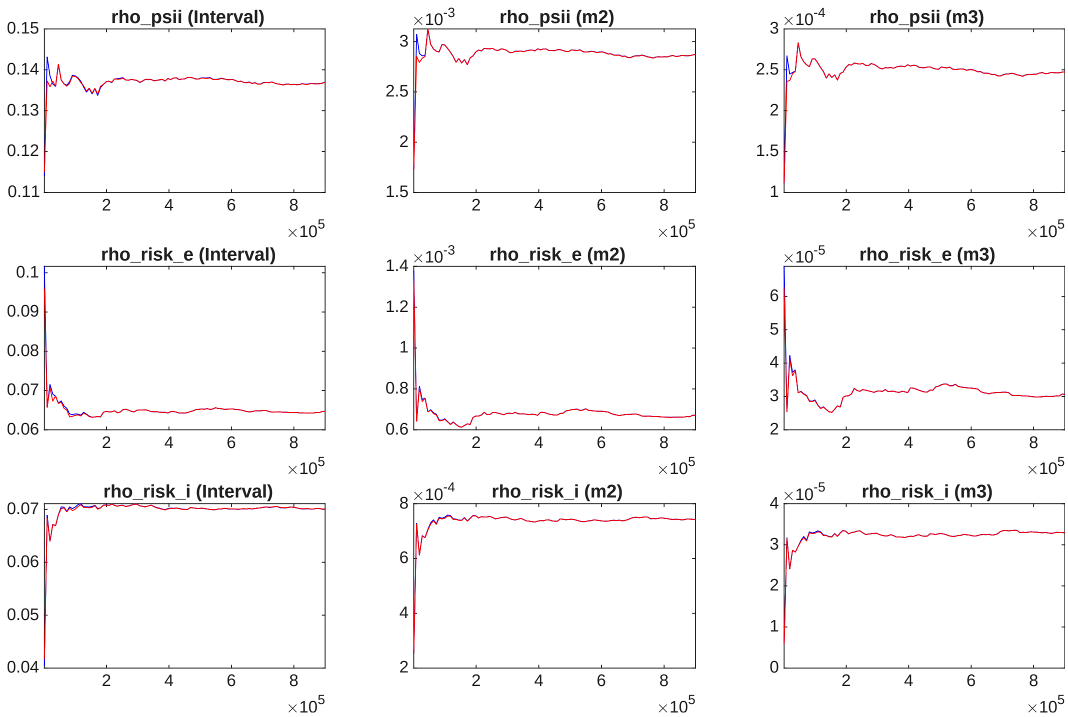
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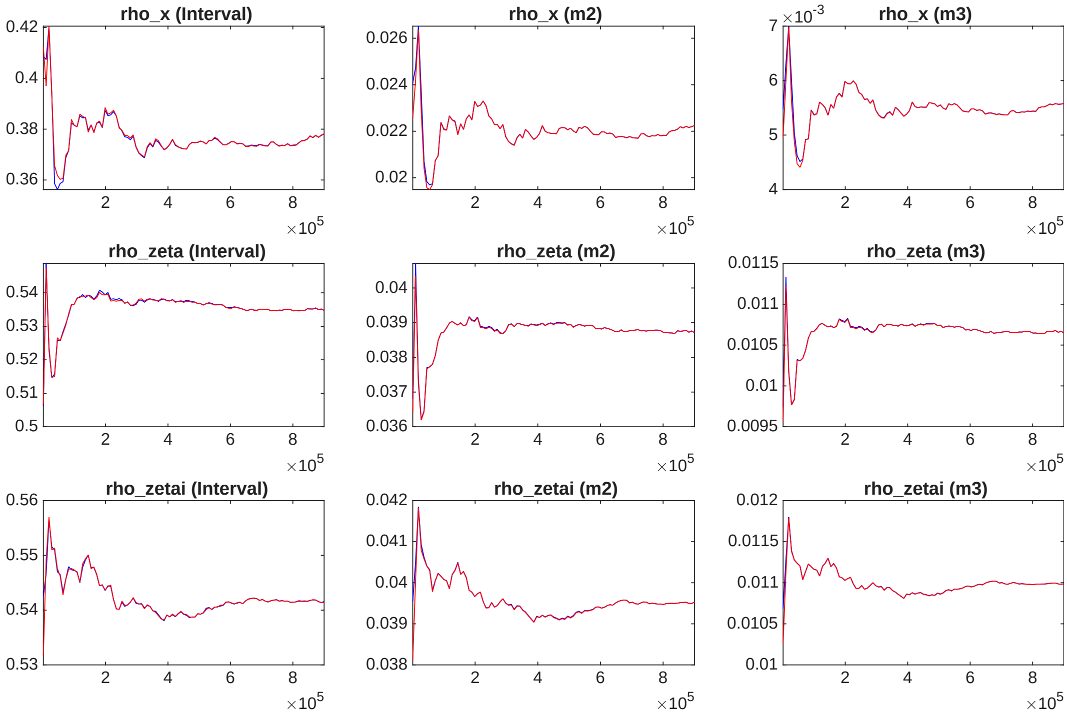
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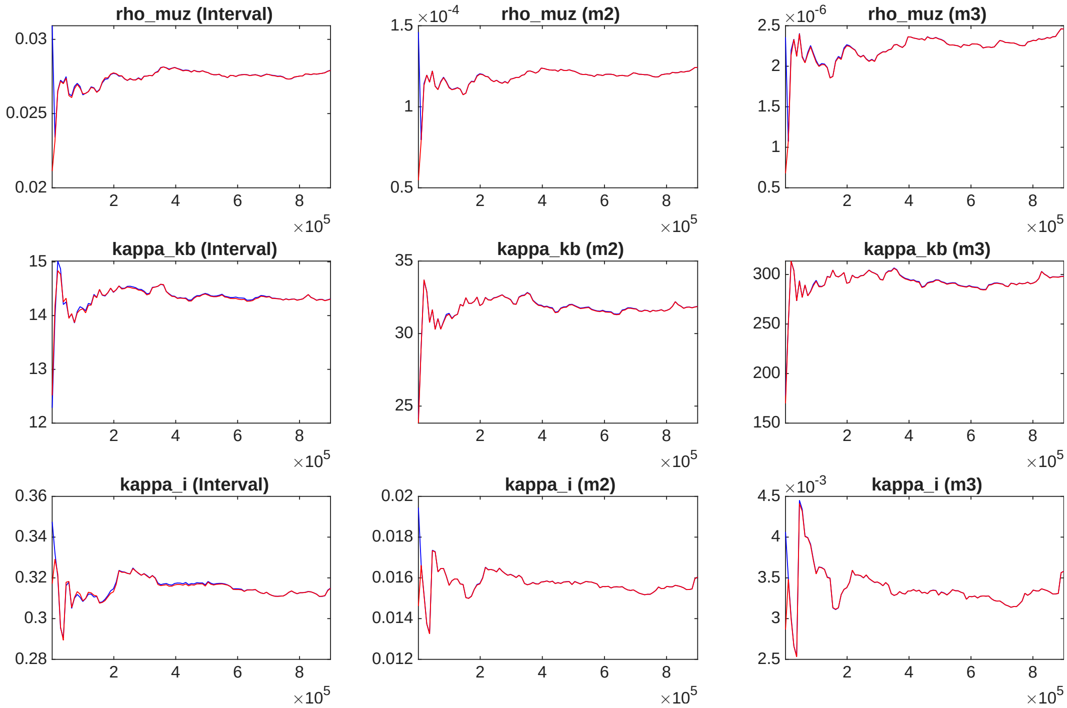
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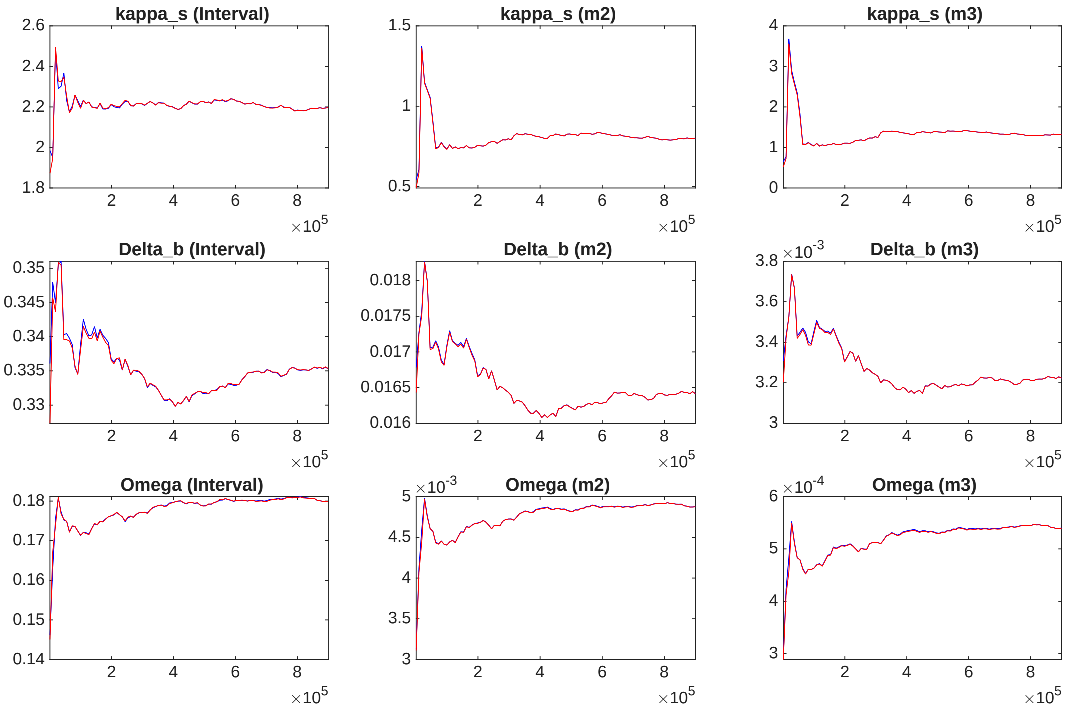
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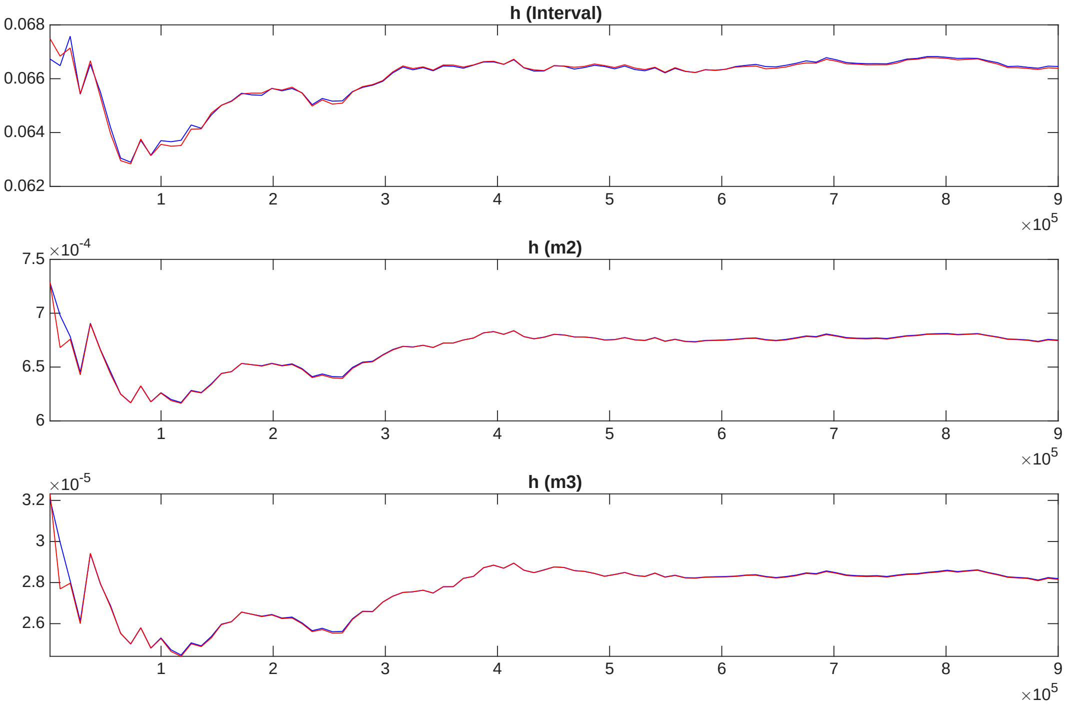
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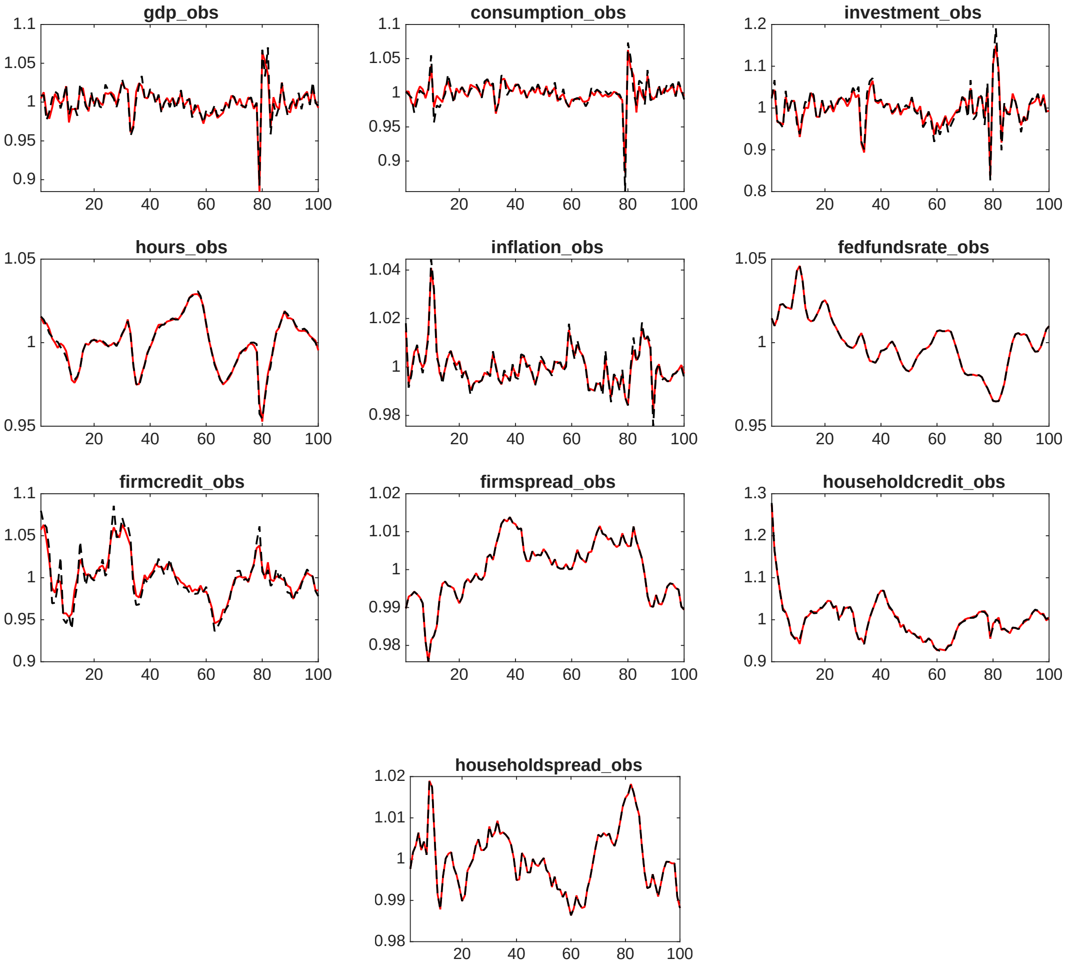
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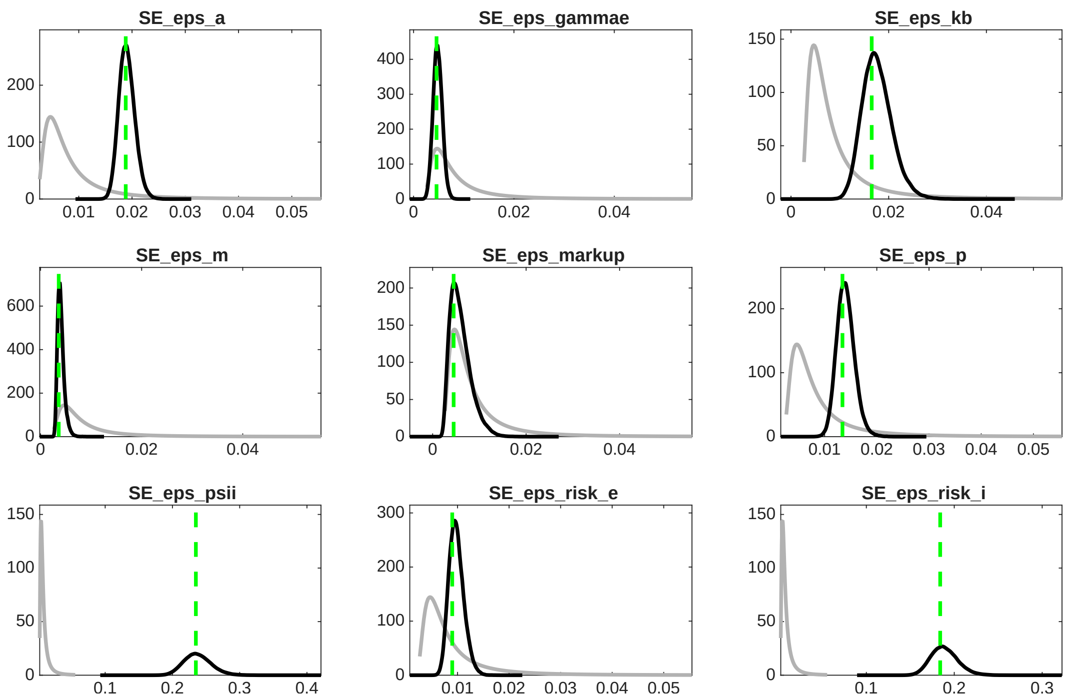
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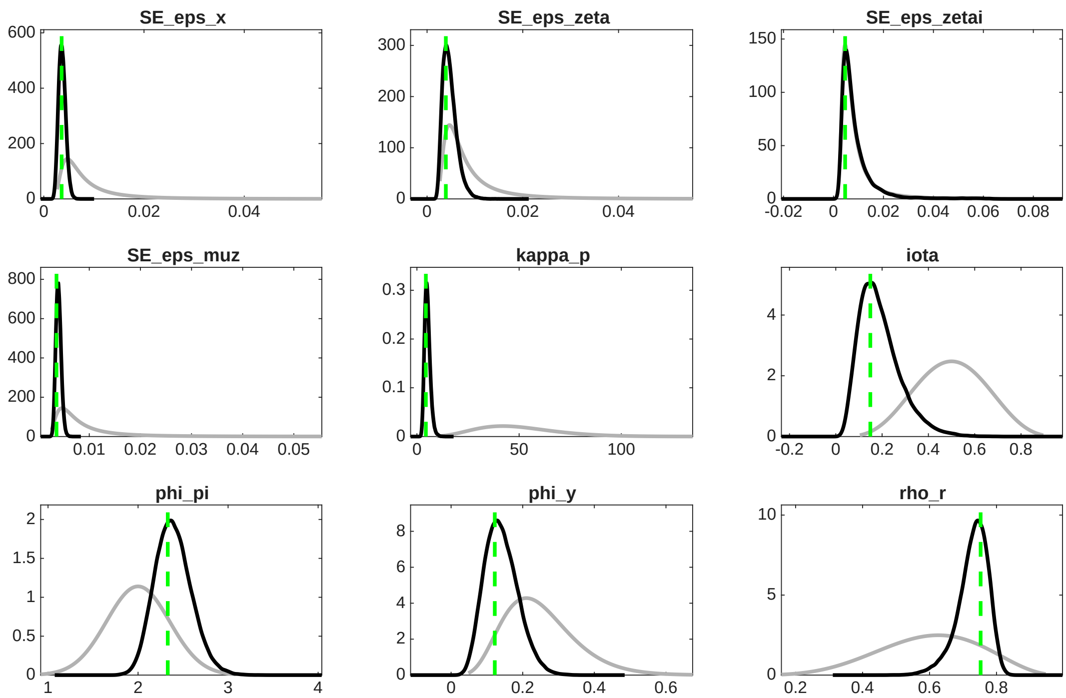
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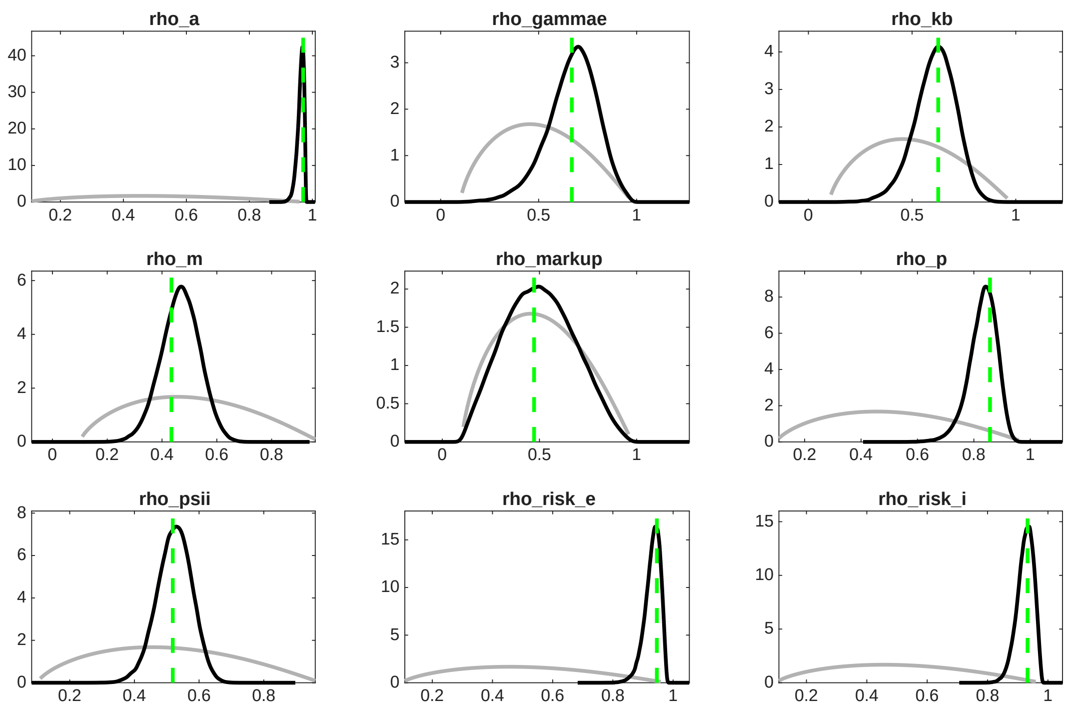
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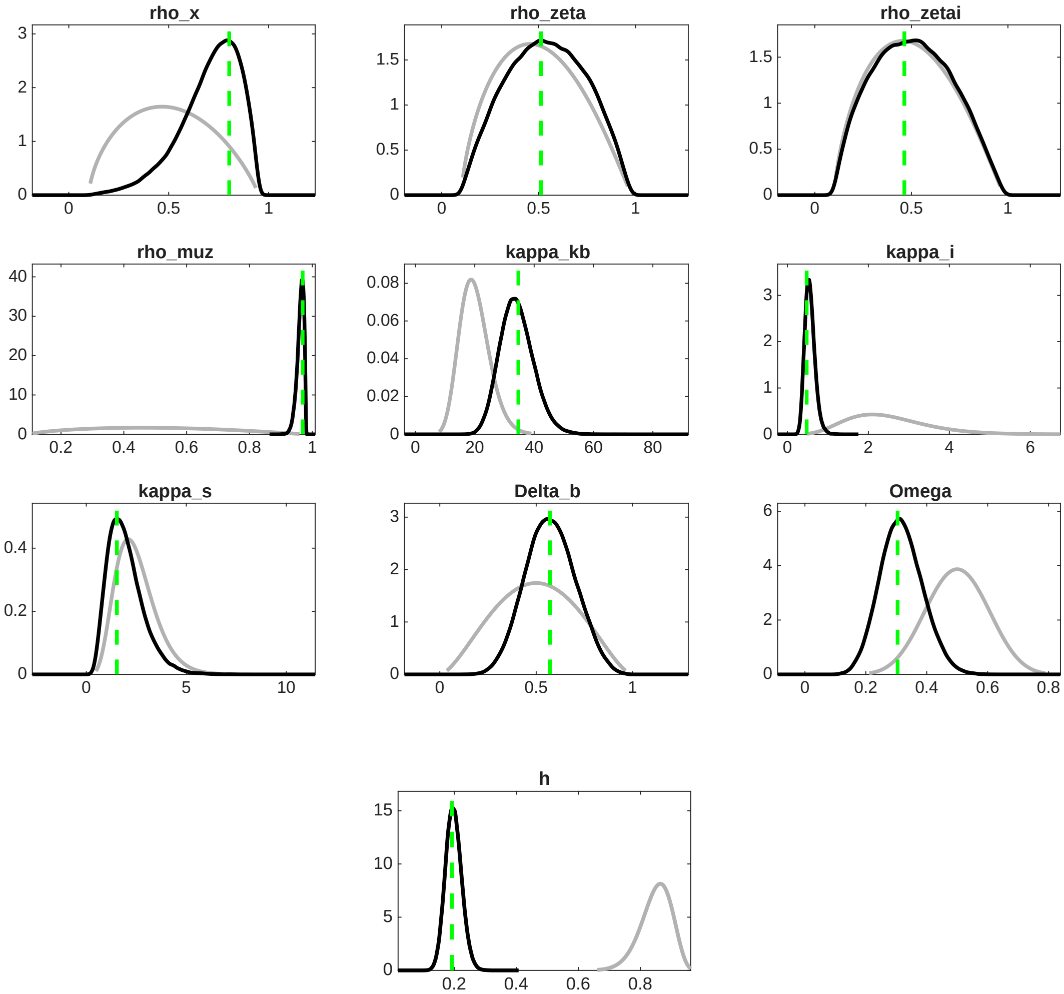
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Delta_b
Omega
h

C
Monte Carlo Experiment

C.1
Calibration

Table C.1 reports the full set of calibrated parameters used in the Monte Carlo simulations. As discussed in the text, the calibration closely follows the strategy adopted in the estimation section.

In the Monte Carlo exercise, however, the parameters that are estimated in the baseline specification are instead fixed at calibrated values in order to define the data-generating process. These parameters govern key aspects of the model dynamics, including nominal rigidities, monetary policy, financial frictions, and household preferences. Due to time constraints, the calibration used relies on parameter values drawn from the literature, rather than on the posterior modes obtained from our Bayesian estimation. At the time this exercise was implemented, the estimation stage had not yet been completed, and the posterior estimates were therefore not available. In addition, the calibration is based on data for the period 2013–2023. As a result, some parameters used to replicate the steady state may differ slightly from those reported in Section 3, where the model is estimated using an expanded sample. These differences simply reflect the need to maintain consistency between the steady-state calibration and the specific sample used in the Monte Carlo exercise.

Specifically, the price adjustment cost is set to $\kappa_P = 50$ and the indexation parameter to $\iota = 0.158$, following Carvalho et al. (2023). The monetary policy rule parameters are calibrated to $\phi_\pi = 2.43$, $\phi_y = 0.16$, and $\rho_r = 0.79$, consistent with values commonly used in the Brazilian DSGE literature. On the financial side, the bank dividend payout is set to $\Delta^b = 0.4648$, based on the average value observed in the sample, while the bank capital adjustment cost is fixed at $\kappa_{Kb} = 22.96$ following Ferreira and Nakane (2018). Finally, the habit formation parameter is set to $h = 0.74$ following Castro et al. (2015), the patient labor share is calibrated to $\Omega = 0.7025$ through internal calibration to match steady-state moments, and the investment adjustment cost is set to $\kappa_i = 2.53$ following Carvalho et al. (2023). These calibrated values ensure that the simulated economy remains consistent with the parameterization used in the baseline model.

Table C.1: Model Calibration Parameters

Description	Parameter	Value	Source
Literature-based Parameters			
Habit formation parameter	h	0.74	Castro et al. (2015)
Capital share	α	0.448	Castro et al. (2015)
Elasticity of substitution - final good	η	6	Carvalho et al. (2023)
Inverse of Frisch elasticity	φ	1	Carvalho et al. (2023)
Optimal capital-to-asset ratio (bank)	ν^b	0.1799	BCB
Discount factor - impatient	β^I	0.938	Iacoviello (2005)
Durable goods preference	ψ	1	Carvalho et al. (2023)
Deposit Elasticity	η_d	537.7368	Luz (2024)
Direct Data Analogues			
Dividend payout - bank	Δ^b	0.4648	Reuters
Monitoring cost	μ	0.8153	World Bank
Tax rate on bank profit	τ	45.00%	BCB
Tax rate on loan revenue	τ^{rb}	4.65%	BCB
Tax rate on entrepreneur loan	τ^b	0.47%	BCB
Tax rate on return of deposit	τ^{rd}	17.50%	BCB
Scale of administrative cost function	ξ	0.0099	BCB - Cosif
Internally Calibrated Parameters			
Discount factor - patient	β^P	0.9943	-
Elasticity of substitution - entrepreneur loan	η_b^E	817.60	-
Elasticity of substitution - impatient loan	η_b^I	247.96	-
Patient labor share	Ω	0.7025	-
Capital depreciation rate	δ^k	0.0497	-
Banks' capital depreciation rate	δ^b	0.0091	-
Variance of idiosyncratic shock - entrepreneur	σ^E	0.4822	-
Variance of idiosyncratic shock - impatient	σ^I	0.5534	-
Dividend payout - entrepreneur	Δ^e	0.0694	-
Labor disutility	ζ	2.3344	-
Parameters Affecting Dynamics			
Investment adjustment cost	κ_i	2.53	Carvalho et al. (2023)
Capital-to-asset adjustment cost	κ_{Kb}	22.96	Ferreira and Nakane (2018)
Interest smoothing parameter	ρ_r	0.79	Carvalho et al. (2023)
Responsiveness to inflation in Taylor rule	ϕ_π	2.43	Carvalho et al. (2023)
Responsiveness to output in Taylor rule	ϕ_y	0.16	Carvalho et al. (2023)
Price adjustment cost - final good	κ_P	50	Carvalho et al. (2023)
Steady-state inflation weight - indexation	ι	0.158	Carvalho et al. (2023)

Table C.2: Steady-state model fit

Moment	Symbol	Data	Model
Deposit interest rate (CDB)	r^d	8.83%	8.83%
Loan rate — firms (non-earmarked)	r^{bE}	20.06%	21.19%
Loan rate — households (non-earmarked)	r^{bI}	23.02%	23.20%
Household debt to GDP	B^I/Y	14.11%	14.11%
Investment to GDP	I/Y	17.90%	17.90%
Bank capital to assets	K^b/B	0.18	0.18
Delinquency rate — firms	$F(\bar{\omega}^E)$	3.26%	3.26%
Delinquency rate — households	$F(\bar{\omega}^I)$	4.32%	4.32%
Entrepreneur leverage	X	1.40	1.40
Steady-state hours worked	L	1.00	1.00

D
The Borrowing Constraint is Binding in Steady State

We show that, in steady state, impatient household financiers always operate at the limit of their borrowing constraint. Throughout, we impose $\pi = 1$, $\epsilon^c = 1$, all variables constant over time, $Z^s = Z^{s\prime} = 0$, $K^b/B = \nu^b$, $\Lambda^I_{t,t+1} = \beta^I$, $\Lambda^P_{t,t+1} = \beta^P$, and $1 + R^s = Q^s_t/Q^s_{t-1} = 1$.

Lemma 1 (Equilibrium rate chain)**.** *In steady state:*

$$r^{wb} > r > r^d, \qquad 1 + r^{wb} > 1 + r > \frac{1}{\beta^P}. \tag{D-1}$$

Proof. (i) Deposit rate. The patient household Euler equation for deposits yields $1 = \beta^P(1 + r^d(1 - \tau^{rd}))$, so

$$1 + r^d = \frac{1}{\beta^P(1 - \tau^{rd})} + \frac{\tau^{rd}}{1 - \tau^{rd}} > \frac{1}{\beta^P},$$

since $\beta^P < 1$ and $\tau^{rd} \geq 0$.

(ii) Interbank rate. The deposit branch first-order condition gives

$$1 + r = \frac{\eta^d + 1}{\eta^d}(1 + r^d) > 1 + r^d > \frac{1}{\beta^P}.$$

(iii) Wholesale rate. With $K^b/B = \nu^b$, the quadratic capital adjustment cost vanishes in the holding company first-order condition, leaving

$$r^{wb} = r + \xi\gamma + \tau^b > r,$$

where $\xi = 0.0099 > 0$ and $\tau^b = 0.0047 > 0$, so $1 + r^{wb} > 1/\beta^P$.

Lemma 2 (Linearity and net gradient in $B^I_{j,t}$)**.** *The normalized dividend $\xi_{j,t} \equiv \Xi_{j,t}/S^I_{j,t-1}$ is linear in $(S^I_{j,t}, B^I_{j,t})$ for given $S^I_{j,t-1}$:*

$$\xi_{j,t} = \omega^I_{j,t}(1 + R^s_t)Q^s_{t-1} - (1 + R^{b,I}_{t-1})\frac{B^I_{j,t-1}}{S^I_{j,t-1}} + \frac{RR^s_t - Q^s_t}{S^I_{j,t-1}}\, S^I_{j,t} + \frac{1}{S^I_{j,t-1}}\, B^I_{j,t}. \tag{D-2}$$

The net effect — current plus discounted future — of increasing $B^I_{j,t}$ on the normalized value $v_{j,t} \equiv V_{j,t}/S^I_{j,t-1}$ is:

$$\frac{\partial v_{j,t}}{\partial B^I_{j,t}} = \frac{1 - \beta^I(1 + r^{b,I})}{S^I_{j,t-1}}. \tag{D-3}$$

Proof. Linearity. Solving the budget constraint for $\Xi_{j,t}$ and dividing by $S^I_{j,t-1} > 0$ yields (D-2) directly. The coefficients of $S^I_{j,t}$ and $B^I_{j,t}$ depend only on variables predetermined at t, establishing linearity.

Net gradient. The current effect of increasing $B^I_{j,t}$ on $\xi_{j,t}$ is $\partial \xi_{j,t}/\partial B^I_{j,t} = 1/S^I_{j,t-1}$. The future effect arises because $B^I_{j,t}$ enters $\xi_{j,t+1}$ as $B^I_{j,t-1}$ with coefficient $-(1+R^{b,I}_t)/(g^I_{j,t}S^I_{j,t-1})$. Converting to units of $v_{j,t}$ by multiplying by $g^I_{j,t}$, the discounted future effect on $v_{j,t}$ is:

$$-\beta^I \frac{(1+R^{b,I}_t)}{g^I_{j,t}S^I_{j,t-1}} \cdot g^I_{j,t} = -\frac{\beta^I(1+r^{b,I})}{S^I_{j,t-1}}.$$

Summing both effects gives (D-3).

Proposition D.1 (Binding constraint in steady state)**.** *Under the condition $\beta^I(1+r^{b,I}) < 1$, satisfied at the calibrated parameter values, the financier always maximizes $B^I_{j,t}$ for given $S^I_{j,t}$. Consequently, the default cutoff binds with equality:*

$$\bar{\omega}^I(1+R^s)Q^sS^I = (1+R^{b,I})B^I, \qquad \bar{\omega}^I > 0. \tag{D-4}$$

Proof. Step 1: The financier maximizes $B^I_{j,t}$. From Lemma 2, under $\beta^I(1+r^{b,I}) < 1$:

$$\frac{\partial v_{j,t}}{\partial B^I_{j,t}} = \frac{1-\beta^I(1+r^{b,I})}{S^I_{j,t-1}} > 0.$$

The financier's value is strictly increasing in $B^I_{j,t}$, so for given $S^I_{j,t}$ the financier always raises $B^I_{j,t}$ to the maximum permitted by the bank's incentive compatibility condition (ICC).

Step 2: The ICC maximum is exactly the default cutoff. For given $S^I_{j,t}$ and threshold $\bar{\omega}^I$, the maximum $B^I_{j,t}$ consistent with the ICC is pinned down by the default cutoff:

$$B^I_{j,t} = \frac{\bar{\omega}^I(1+R^s_{t+1})Q^s_tS^I_{j,t}}{1+R^{b,I}_t}.$$

Since the financier always reaches this maximum (Step 1), the default cutoff (D-4) holds with equality.

Step 3: $\bar{\omega}^I > 0$. Suppose $\bar{\omega}^I = 0$. The default cutoff then implies $B^I_{j,t} = 0$. But with $B^I_{j,t} = 0$ and $S^I_{j,t-1} > 0$, Step 1 gives $\partial v_{j,t}/\partial B^I_{j,t} > 0$, so the financier has a strict incentive to increase $B^I_{j,t}$ — a contradiction. Hence $\bar{\omega}^I > 0$, which implies $F^I(\bar{\omega}^I) > 0$ and a positive probability of default.

Parametric condition. The condition $\beta^I(1+r^{b,I}) < 1$ is necessary and sufficient for the financier's value to be strictly increasing in $B^I_{j,t}$: it ensures that the present cost of repaying one unit of debt tomorrow, discounted at rate β^I, is less than the current benefit of receiving it today. It is also necessary for consistency of the optimality conditions: from the first-order condition for $S^I_{j,t}$ evaluated in steady state,

$$Q^s(1-\beta^I) = RR^s + \frac{B^I}{S^I}\left[1-\beta^I(1+r^{b,I})\right],$$

a solution with $B^I > 0$ requires the right-hand side to exceed RR^s, which holds if and only if $\beta^I(1+r^{b,I}) < 1$. The condition is verified numerically at the calibrated steady state of the model.