The Heterogeneous Bank Lending Channel of Monetary Policy*

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Abstract

This paper develops a quantitative model to analyze the role of bank heterogeneity in the transmission of monetary policy through the bank lending channel. We calibrate the model to the euro area to capture two distinct forms of heterogeneity: ex-ante differences in loan pricing practices and ex-post variation in capital positions driven by idiosyncratic default risks. Consistent with empirical impulse responses, banks in fixed-rate economies experience severe net interest margin compression during monetary tightening as funding costs rise while income from legacy loans remains unchanged, leading to capital erosion and deeper lending contractions. The elasticity of new lending to monetary policy is approximately one-third larger in fixed-rate economies. Highly leveraged banks drive these differences: without default risk, banks would remain far from their regulatory limits. We discuss additional tradeoffs between monetary policy and financial stability, study the implications for gradual policy rate increases, and demonstrate fundamental limitations of representative-agent banking models.

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1. Introduction

This paper develops a model to analyze the role of heterogeneity in bank interest-rate risk exposure in the transmission of monetary policy. It is widely accepted that monetary policy transmits to the real economy, in part, by inducing changes in the bank-credit supply schedule. This mechanism, known as the bank-lending channel (Bernanke and Gertler, 1995), is conceptually understood to operate by altering the risk-return tradeoff faced by banks when deciding on their leverage, thereby changing the supply of credit. This tradeoff is influenced by monetary policy, which alters the relative returns of assets.

While the bank-lending channel is a well-understood concept, banks may respond differently depending on their exposure to interest-rate risk, resulting in heterogeneous effects across banks. For instance, when monetary policy induces increases in banks' short-term funding costs, banks having to roll over fixed-rate loans will experience a decline in their net interest income. Potentially, this leads to a different risk-return trade-off than for banks whose loan rates adjust in tandem with funding costs. Central banks may want to know theoretically when they should expect differential responses across banks, and, quantitatively, by how much? The answers to these questions are crucial for understanding whether we should expect regional or sectoral differences in the supply of credit, for understanding the implications for financial stability, for adequately pacing monetary policy adjustments, and for assessing the interaction between monetary policy and bank regulation appropriately.

The goal of this paper is to answer these questions and illustrate the implications of these answers. Theoretically, we demonstrate an irrelevance result: heterogeneity in interest-rate risk exposure, even in the presence of loan-portfolio adjustment costs, matters only when banks reach their regulatory capital limits. Thus, the impact of heterogeneity is intimately linked with financial regulation. Quantitatively, we find that heterogeneity becomes significant only when a substantial number of banks approach binding regulatory constraints—a situation that arises in our calibrated model due to high portfolio adjustment costs and substantial ex-post heterogeneity from loan-default risks. Under these conditions, a 100 basis point monetary tightening induces a [X%] decline in lending in fixed-rate systems compared to [Y%] in variable-rate systems. The divergence also extends to bank failure rates: tightening increases failures in fixed-rate economies while reducing them in variable-rate systems.

An early empirical literature has established that rebalancing following changes in monetary policy varies systematically across banks with different risk exposures and risk-bearing capacities. Early work by Kashyap and Stein (2000) documented how the strength of the bank lending channel depends on banks' characteristics. More recent work with improved identification has established that banks with low risk-bearing capacity—those with high leverage or low capital ratios—transmit changes in policy rates more strongly than well-capitalized banks (see, for instance, Jiménez et al., 2012; Dell'Ariccia et al., 2017; Altavilla et al., 2020).[1] Likewise, banks with greater interest-rate risk exposure—those with a higher share of fixed-rate loans—exhibit stronger monetary policy transmission (Altunok et al., 2023).

While this empirical literature identifies important differences in bank responses to monetary policy shocks, structural models are essential for two complementary reasons. First, quantitative models are needed to understand aggregate responses: cross-sectional estimates explain differences in lending responses across banks, but these heterogeneous effects do not translate directly to aggregate responses. Second, empirical estimates do not allow for meaningful counterfactual analysis. For instance, models are required to quantify how monetary policy transmission would change if banks were homogeneous (identical replicas of each other), to measure the effect of heterogeneity on bank failure rates during tightening cycles, and to assess how the role of heterogeneity varies with the stringency of regulatory constraints and the magnitude of adjustment costs. The contribution of this paper is to build such a model.

We calibrate our model to the euro area—a region where interest-rate risk exposure heterogeneity is particularly pronounced: Banks in France, Germany, Belgium, and the Netherlands predominantly price loans at fixed rates, while those in Spain, Italy, Finland, and Portugal use variable rates. This institutional variation creates systematic differences in interest-rate risk exposures across countries. Thus, a particularly pressing question for the European Central Bank is whether this ex-ante heterogeneity translates into different responses across countries to changes in their monetary policy stance. Our model allows us to quantify precisely how much this ex-ante heterogeneity matters for aggregate outcomes and under what monetary policy and regulatory conditions it becomes most consequential.

[1] Other references include Gambacorta and Mistrulli, 2004, Kishan and Opiela, 2000, and Holton and Rodriguez d'Acri, 2018.

The model. Our quantitative framework models two banking systems—one with fixed-rate loans and another with variable-rate loans—each containing a distribution of banks that differ in their leverage due to idiosyncratic default shocks. Banks face convex loan origination costs, liquidity requirements, and capital requirements. The model is calibrated to euro area data for 2013-2023, targeting both aggregate moments and the dispersion in capital buffers across banks. This calibration discipline enables us to assess whether the observed heterogeneity in loan-pricing practices yields quantitatively significant differences in monetary transmission.

Within each banking system, there is a unit mass of atomistic banks. Each bank invests in central-bank reserves and loans. Banks are financed through a combination of short-term liabilities (insured deposits and wholesale debt), and retained earnings (internal equity). Banks face a risky maturity transformation problem since their deposit liabilities mature in one period, whereas loans are long-term and subject to default risk. The demand for loans and supply of deposits is determined in general equilibrium, but all the action is focused on banks.[2]

The loan portfolio comprises vintages of long-term loans. The issuance of new loans is subject to convex loan-origination costs. Once in the balance sheet, loan defaults are correlated according to the single risk factor model of Vasicek (2002). Upon a loan default, the bank loses the interest payments, recovers a fraction of the principal, and writes off the principal loss. Idiosyncratic credit risk induces ex-post heterogeneity. Reserves at the central bank are short-term (mature in one period) and pay an interest rate controlled by the central bank.

Banks face regulatory constraints designed to capture real-world prudential policy: In terms of liquidity regulation, banks must hold reserves above a fraction of their total short-term liabilities at any point in time. In terms of capital regulation, banks must comply with the capital regulatory requirement to operate; failing to do so leads to a bank failure.[3]

Despite the richness in the sources of risks, portfolio variables, and regulatory environment, banks' policies are size-independent: the only relevant individual state variables are the leverage and the average interest rate of their loan portfolio. This

[2]The model also features entrepreneurs, households, and the government. Entrepreneurs have access to long-term investment projects requiring bank funding. Households consume, own the banks, and save in deposits. The government includes the central bank operations, the management of the deposit insurance scheme, and tax receipts.

[3]A bank is declared *bankrupt* whenever its capital fails to satisfy the minimum capital requirement.

parsimonious state space is sufficient to capture various relevant forms of heterogeneity observed in the empirical analysis. This tractability makes the model-data contrast particularly transparent.

Quantitative results. The calibrated model demonstrates that the interaction between ex-ante heterogeneity in interest-rate risk exposure and ex-post heterogeneity in leverage generates meaningful differences in monetary policy transmission. Fixed-rate banks experience capital erosion when rates rise, as their existing loan portfolios yield below-market returns. When combined with substantial dispersion in bank leverage—driven by idiosyncratic default shocks—this capital erosion pushes a meaningful fraction of highly leveraged institutions into binding regulatory constraints that amplify lending contractions. Variable-rate banks face the opposite dynamic: rising rates improve interest margins, bolstering capital positions and relaxing constraints.

This mechanism produces differential failure rates across systems. Monetary tightening increases failure probabilities in fixed-rate economies while reducing them in variable-rate systems, reflecting how interest rate changes affect bank capital through their existing loan portfolios. The role of ex-post heterogeneity is critical: when we counterfactually eliminate idiosyncratic default risk, making all banks ex-ante identical replicas, the differences between fixed and variable rate systems shrink dramatically. Aggregate lending responses converge and failure rate differentials nearly disappear. This confirms that ex-ante heterogeneity in interest-rate risk exposure matters for monetary policy precisely because ex-post heterogeneity in leverage pushes banks to their borrowing limits, where the type of interest rate exposure becomes decisive.

Implications. These findings carry important implications for monetary policy in currency unions and for macroeconomic modeling. For the ECB, our results demonstrate that a single monetary policy generates meaningfully heterogeneous effects across member states—not just in the cross-section of banks, but in aggregate credit supply and financial stability outcomes at the country level. The magnitude of these differences depends on how close national banking systems operate to regulatory constraints.

For macroeconomic modeling, our analysis reveals limitations of representative-bank frameworks: such models fundamentally mischaracterize transmission by abstracting from the distribution of banks near regulatory limits, where the interaction between leverage constraints and interest rate risk becomes quantitatively important.

However, this conclusion is contingent on calibration—specifically, on matching the observed dispersion in bank capital buffers and the magnitude of adjustment costs in loan origination. The substantial differences that emerge when we eliminate ex-post heterogeneity underscore that realistic modeling of the banking sector requires accounting for both sources of heterogeneity to generate quantitatively accurate predictions about monetary policy transmission.

Related Literature. Our work contributes to the literature on heterogeneous banks and monetary policy transmission by providing a quantitative assessment of when and why heterogeneity matters. Within macro-banking, we develop a model that combines ex-ante heterogeneity in loan rate fixation and ex-post heterogeneity in leverage. Our framework is well-suited to study the strength of monetary policy transmission along these two key dimensions of heterogeneity. Banks' heterogeneity along other dimensions has been the focus of related works. For example, Coimbra and Rey (2023) study the risk-taking channel of monetary policy. Corbae and D'Erasmo (2021) analyze the impact of regulatory policies on bank risk-taking. Rios-Rull et al. (2020) study the aggregate effects of capital requirements. Bianchi and Bigio (2022) examine the credit channel of monetary policy in a framework where interbank market frictions interact with deposit withdrawal shocks. Jamilov and Monacelli (2025) introduce ex-ante heterogeneity in banks' rates of return—alongside idiosyncratic return risk—within an intermediation framework à la Gertler and Kiyotaki (2010) to show how these features amplify real and financial fluctuations relative to a representative bank model, and Bellifemine et al. (2022) study monetary policy transmission based on a similar setup but with nominal frictions. Varraso (2025) study monetary transmission when intermediaries invest in both short and long-term assets. Relative to these papers, ours adds an extra degree of heterogeneity—namely, in loan rate fixation patterns—whose interaction with heterogeneity in leverage we identify as fundamentally shaping the transmission of monetary policy.

Our approach departs from the classical representative-bank macro literature through several key modeling assumptions. First, rather than assuming that banks directly hold productive assets—as in Gertler and Karadi (2011), Gertler and Kiyotaki (2010), He and Krishnamurthy (2013), or Brunnermeier and Sannikov (2014), among others—we explicitly model loan contracts between borrowers and banks. Second, our framework accounts for default risk in banks' loan portfolios, with defaults correlated within each bank according to Vasicek (2002) single risk factor model. This captures the asymmetric risk profile of defaultable loans, characterized by limited upside but unlimited downside risk (Nagel and Purnanandam (2020); Mendicino et al. (2024)). Third, we treat capital requirements as occasionally binding constraints, in contrast to previous models that assume always-binding capital constraints (see, e.g., Boyarchenko and Adrian (2015); Clerc et al. (2015); Mendicino et al. (2018, 2020)).

We contribute to the literature on the transmission of monetary policy to the real economy in heterogeneous-agent economies (Kaplan et al., 2018; Auclert, 2019; Garriga and Hedlund, 2020). These works develop models in which households face uninsurable income risk, transaction costs, and borrowing constraints, while taking a simplified approach to the supply side of the credit market, abstracting from the heterogeneity of lenders. Related works also investigate the transmission of monetary policy through the mortgage market with heterogeneous households. For instance, Berger et al. (2021) and Eichenbaum et al. (2022) emphasize the path-dependency of policy rates in the transmission to household consumption. Greenwald (2018) highlights the role of loan-to-valuation constraints and payment-to-income on monetary policy transmission, while Beraja et al. (2018) underscores the relevance of home equity in determining households' ability to respond to interest rate changes.

Finally, our paper also relates to recent research on how exposure to interest rate risk affects monetary policy transmission. Guren et al. (2021) and Elenev and Liu (2025) examine how mortgage contract design—fixed versus adjustable rates—shapes macroeconomic volatility, household default risk, and housing demand. Elenev and Liu (2025) is closer to our credit supply analysis, as they explore how the type of mortgage contract influences financial intermediaries' equity positions in a representative bank framework, and provide insights into how financial stability interacts with monetary policy.

2. The model

We consider an infinite-horizon, discrete-time economy, where time is indexed by $t \in \{0, 1, 2, \dots\}$ and there is a single good. The economy is populated by four types of agents: a representative household, a mass of entrepreneurs, a continuum of competitive banks, and a consolidated government, which includes a macroprudential authority, a deposit insurance agency, a fiscal authority, and a monetary authority.

The core of the model features a banking sector that intermediates funds from households to entrepreneurs, who undertake risky long-term productive investment projects but require external financing. Banks engage in maturity transformation by funding risky long-term loans with short-term retail deposits, wholesale debt, and their own equity. This activity exposes them to credit risk and interest rate risk. The regulatory framework, which includes capital and liquidity requirements, as well as a deposit insurance scheme, shapes banks' decisions and their response to aggregate shocks. The interaction between banks' lending capacity and entrepreneurs' investment demand determines aggregate activity.

We analyze two distinct institutional arrangements regarding loan-rate fixation: one where loan contracts stipulate a fixed interest rate for the life of the loan, and another where the interest rate is variable, resetting each period. This allows us to study how the exposure to interest-rate risk affects the banking sector and, in turn, macroeconomic outcomes. The following subsections detail the objectives, constraints, and technology available to each agent.

2.1 Banks

The banking sector consists of a continuum of ex-ante identical, perfectly competitive banks, indexed by $j \in [0,1]$. Banks operate under limited liability and are managed by risk-neutral bankers with a subjective discount factor $\beta \in (0,1)$ who maximize the discounted value of dividends for their owners, the households. They finance their asset portfolio, comprised of risky long-term loans and safe short-term assets, through a combination of short-term, insured deposits and wholesale debt, and with equity accumulated via retained earnings. Their operations are subject to capital and liquidity regulation. We first describe the composition and dynamics of a bank's asset portfolio, then its liability structure and equity dynamics, the regulatory framework it faces, and finally, its dynamic optimization problem.

Assets. A bank's assets consist of a portfolio of risky long-term loans and safe short-term assets, or central bank reserves.[4] At the beginning of period t, bank j holds a portfolio of legacy loans, L_{jt} originated in previous periods. It then chooses its origination of new loans, N_{jt}, and its holdings of central bank reserves, M_{jt}.

[4] In the remaining, we will refer to these safe short-term assets as central bank reserves, but they could also be thought of as safe short-term government bonds.

Central bank reserves, M_{jt}, are a risk-free, one-period asset that pays a net interest rate r_t^M, which is the policy rate set by the monetary authority.

The loan portfolio comprises a continuum of long-term loans, each with a principal normalized to one. Following Leland and Toft (1996), each loan matures with an i.i.d. probability $\delta \in (0,1)$, implying an average loan maturity of $1/\delta$. These loans are subject to credit risk, which we model using the single-risk-factor framework of Vasicek (2002), described in Appendix A.6. This implies that the fraction of a bank's loan portfolio that defaults, ω_{jt+1}, is a random variable drawn from a time-invariant distribution $F(\omega)$ with mean $\mathbb{E}[\omega] = p \in [0,1]$. Upon default, the bank recovers a fraction $1-\lambda$ of the loan's principal, where $\lambda \in [0,1]$ is the loss given default.

The law of motion for the bank's legacy loan portfolio is given by

$$L_{jt+1} = (1-\omega_{jt+1})(1-\delta)(L_{jt} + N_{jt}), \tag{1}$$

reflecting that the loan portfolio in period $t+1$ consists of the previous period's total loans, $L_{jt} + N_{jt}$, net of maturing and defaulted loans.

Originating new loans incurs a cost, specified as $f(N_{jt}/L_{jt})L_{jt}$, where $f(\cdot)$ is an increasing and convex function. This cost captures screening expenses or decreasing returns to finding profitable investment opportunities.

The contractual net interest rate of a bank's loans depends on the contracting environment. The interest rate on new loans originated at time t is denoted r_t^N.[5] In the *fixed-rate regime*, the net interest rate r_t^N is stipulated at origination and remains constant for the life of the loan. In the *variable-rate regime*, what is stipulated at origination is the spread s_t^N, which is added to the policy rate r_t^M set by the monetary authority (i.e., in this case, $r_t^N = r_t^M + s_t^N$). Hence, in this case, the contractual spread remains constant for the life of the loan, but the interest rate fluctuates over time with the policy rate.

Given these assumptions about interest-rate fixation, the law of motion of the average interest rate on a bank's legacy loan portfolio, r_{jt}^L, can be obtained as

$$r_{jt}^L = \frac{r_{jt-1}^L L_{jt-1} + r_{t-1}^N N_{jt-1}}{L_{jt-1} + N_{jt-1}} \tag{2}$$

[5] Note that, given our perfect-competition assumption, banks are price-takers in the loan market, making this rate the same for all banks in a given period and thus not indexed by j.

for banks operating in the fixed-rate environment (henceforth, fixed-rate banks), and $r^L_{jt} = r^M_t + s^L_{jt}$ for banks operating in the variable-rate environment (henceforth, variable-rate banks), where

$$s^L_{jt} = \frac{s^L_{jt-1} L_{jt-1} + s^N_{t-1} N_{jt-1}}{L_{jt-1} + N_{jt-1}} \tag{3}$$

denotes the average contractual spread in a bank's legacy loan portfolio.

Liabilities. The bank's assets are funded with a mix of wholesale debt, (retail) deposits, and equity. Wholesale debt, denoted B_{jt}, is a one-period liability that pays a net interest rate r^B_t. Retail deposits, denoted D_{jt}, are also one-period debt liabilities and pay a net interest rate r^D_t and provide liquidity services to depositors (which implies that, in equilibrium, $r^D_t \leq r^B_t$). A bank's ability to issue deposits is constrained by the size of its legacy loan portfolio:

$$D_{jt} \leq \alpha L_{jt}, \tag{4}$$

with $\alpha \geq 0$.[6] We assume that retail deposits are fully insured by the government and that, while wholesale debt is not, its returns are also risk-free in equilibrium.[7]

Banks accumulate equity exclusively through retained earnings (i.e., we assume there is no external equity issuance). Its law of motion is:

$$E_{jt+1} = E_{jt} + (1-\tau)\Pi_{jt+1}, \tag{5}$$

where $\tau \in (0,1)$ is the corporate tax rate and Π_{jt+1} denotes the bank's pre-tax profits realized between period t and $t+1$. These are given by

$$\begin{aligned} \Pi_{jt+1} = (1-\omega_{jt+1})\left(r^L_{jt} L_{jt} + r^N_t N_{jt}\right) + r^M_t M_{jt} - r^D_t D_{jt} - r^B_t B_{jt} \\ - \lambda \omega_{jt+1}(L_{jt} + N_{jt}) - f\left(\frac{N_{jt}}{L_{jt}}\right) L_{jt} - \bar{\pi} L_{jt}. \end{aligned} \tag{6}$$

[6]We think of this constraint as capturing, in reduced form, the complementarity between a bank's loan origination and deposit issuance businesses. In particular, one can think of this complementarity as stemming from the fact that, in order to expand its loan business, a bank may invest in offices across different geographies that are also required to provide deposit-related services (such as those related to access to cash provided by ATMs, etc.).

[7]To obtain this result, we need to assume that wholesale debt is either senior to deposits, or that it is collateralized with the bank's assets. This imposes some parametric restrictions in terms of the relative size of each of these sources of funding and/or the recovery value of a bank's assets in case of default, such that wholesale debt returns are effectively risk free (see Appendix A.3 for a derivation of those restrictions).

Profits are determined by interest income on loans and reserves, net of interest expenses on deposits and wholesale debt, realized credit losses, loan origination costs, and operational costs, which are a constant factor $\bar{\pi} > 0$ over the legacy loan portfolio.

The balance sheet of the bank is:

$$L_{jt} + N_{jt} + M_{jt} = D_{jt} + B_{jt} + E_{jt}. \tag{7}$$

Regulation. The banking system is subject to both liquidity and capital regulation, akin to the Basel III framework. Liquidity regulation imposes a minimum amount of reserve holdings proportional to the bank's short-term liabilities:

$$M_{jt} \geq \theta(D_{jt} + B_{jt}). \tag{8}$$

Capital regulation imposes that a bank's equity must cover at least a fraction $\gamma \in (0,1)$ of its total loan portfolio:

$$E_{jt} \geq \gamma(L_{jt} + N_{jt}). \tag{9}$$

Bank failure, entry and exit. If the bank cannot satisfy the minimum capital requirement, it fails and is resolved by the regulator. This is, a bank fails if, after the realization of portfolio defaults ω_{jt+1}, its equity falls below the minimum requirement relative to its legacy loan portfolio: $E_{jt+1} < \gamma L_{jt+1}$. Upon failure, the bank's equity is wiped out, and a deposit insurance agency seizes its assets, which are partly sold to new, entering banks, and partly liquidated (in proportions to be specified below). The agency allocates is proceedings to the bank's liability holders, in order of seniority, and repays all retail depositors in full.

Additionally, banks face an exogenous exit shock with probability $\chi \in (0,1)$ each period. An exiting bank repays all liabilities, and the remaining equity is distributed to its owners in the form of dividends.

To maintain a constant mass of banks, each exiting bank is replaced by a new entrant. New entrants start with an exogenous amount of equity $\bar{E}_t$. Each individual new bank starts with a random amount of legacy loans that ensures that the leverage distribution of new banks is the same as that of surviving banks. These exit and entry dynamics ensure a stationary distribution of bank sizes. The fraction of loans in the legacy loan portfolio of exiting banks at $t+1$ that is not distributed among new banks, which we denote $\tilde{\chi}$, is liquidated.[8]

Recursive formulation. The state of an individual bank j at time t is summarized by its legacy loans L_{jt}; equity E_{jt}; and the average interest rate on its legacy portfolio r^L_{jt}, for fixed rate banks, or the average spread s^L_{jt}. The bank's dynamic programming problem is represented by the following Bellman equation:

$$V_t\left(L_{jt}, E_{jt}, x^L_{jt}\right) = \mathbf{1}_{\{E_{jt} \geq \gamma L_{jt}\}} \left[\max_{\{N_{jt}, M_{jt}, D_{jt}, B_{jt}\}} \beta \mathbb{E}_t \left[(1-\chi) V_{t+1}\left(L_{jt+1}, E_{jt+1}, x^L_{jt+1}\right) + \chi E_{jt+1} \right] \right], \tag{10}$$

with $x_{jt} = \{r^L_{jt}, s^L_{jt}\}$ in the case of fixed- or variable-rate banks, respectively, and subject to the law of motion for loans (1); the law of motion for average interest rate (2) of the legacy loan portfolio in the case of fixed-rate banks, or the average spread (3) in the case of variable-rate banks; the constraint on retail deposits (4); the law of motion for equity (5); the balance-sheet constraint (7); and the regulatory constraints (8) and (9). The indicator function captures the failure condition. Appendix A.2 shows that the problem can be written more parsimoniously in terms of two state variables: the bank's leverage (L_j/E_j) and either the average loan rate (r^L_j) of the legacy loan portfolio for fixed-rate banks, or the average spread for variable-rate banks (s^L_j).

2.2 Entrepreneurs: microfoundation for the loan demand

A mass of risk-neutral entrepreneurs, indexed by $i \in [0,1]$, has access to an investment technology that requires an upfront investment of one unit of the final good. Entrepreneurs are endowed with no internal funds and must obtain a bank loan to finance their projects.

Once initiated, a project yields A units of the final good each period it remains active. At the end of each period t, an active project may terminate for one of three reasons: (i) it reaches successful completion, which occurs with probability δ; (ii) it fails, which occurs with probability p; or (iii) its loan is liquidated as a result of the exit of its

[8] We fix the amount of equity of entering banks $\bar{E}$ in the steady state to normalize the aggregate size of the banking sector. Given this parameter value, we can calculate the implied steady-state value of $\tilde{\chi}$. In response to shocks $\bar{E}_t$ adjusts such that the implied $\tilde{\chi}$ remains constant and equal to its steady state value.

financing bank, which occurs with probability $\tilde{\chi}$. If the project is completed or the bank exits, the loan principal is repaid in full. If the project fails, the bank recovers only $1-\lambda$ of the principal.

To initiate a project, an entrepreneur must exert an effort that entails a utility cost of $a(N_t)$, where $a(\cdot)$ is an increasing and convex function of N_t, the aggregate volume of new projects. This cost generates an upward-sloping supply curve for new projects. Free entry for entrepreneurs means that, in equilibrium, the expected lifetime value of a new project must equal this startup cost. This condition implies a uniform interest rate r_t^N for all new loans originated at time t.

The value of a project depends on the loan contract type. For a variable-rate loan, the value at time t of a project with spread s_i^N is:

$$V_{it}^E(s_i^N) = \sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1} \left[A - \left(r_{t+k-1}^M + s_i^N\right)\right], \tag{11}$$

Imposing the free-entry condition, $V_{it}^E(s_t^N) = a(N_t)$, yields the aggregate demand for variable-rate loans:

$$N_t = a^{-1}\left(\sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1} \left[A - \left(r_{t+k-1}^M + s_t^N\right)\right]\right). \tag{12}$$

Loan demand is forward-looking, as entrepreneurs form expectations about future interest rates.

For a fixed-rate loan, the interest rate is constant for the life of the project. The value at time t of a project with interest rate r_i^N is:

$$V_{it}^E(r_i^N) = \sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1} \left(A - r_i^N\right), \tag{13}$$

The corresponding aggregate loan demand is:

$$N_t = a^{-1}\left(\sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1} \left(A - r_t^N\right)\right). \tag{14}$$

In this case, loan demand is not forward-looking with respect to future interest rates, as the bank bears all interest-rate risk. This distinction is central in the transmission mechanism in our analysis.

2.3 Households: microfoundation for the deposit supply

The household problem is presented in detail in Appendix A.1. Households solve a consumption-savings problem in which they decide their holdings of bank retail deposits D_t, wholesale debt B_t and safe short-term assets (in this case, government bonds) M_t^H. The equilibrium return on government bonds is equalized to that of reserves, r_t^M. The demand schedule for retail deposits, wholesale debt and government bonds results from a joint asset-in-advance constraint and establishes the following relationship:

$$D_t + B_t + M_t^H = h(r_t^D, r_t^B, r_t^M), \tag{15}$$

where $h(\cdot)$ is a convex and increasing function in each of its arguments.[9]

We assume an elastic supply of government bonds, which implies that the demand for deposits and wholesale debt by households are also fully elastic. Furthermore, on the one hand, since government bonds and wholesale debt are perfect substitutes from the household's perspective, their respective returns must be equal in equilibrium. On the other, we assume that households obtain liquidity services from their deposit holdings, so in equilibrium their required return is lower than that of the other short-term assets available (i.e., $r_t^D \leq r_t^M = r_t^B$).

2.4 Consolidated government

The consolidated government includes a central bank that sets the policy rate r_t^M (i.e., the rate of remuneration of reserves deposited by banks at the central bank) as well as a fiscal authority that raises taxes from banks and from households, and manages the deposit insurance scheme. All these operations are consolidated in the following government budget constraint:

$$T_t + \tau \Pi_t + M_t = \left(1 + r_{t-1}^M\right) M_{t-1} + \Upsilon_t, \tag{16}$$

where T_t are lump-sum taxes on households, Π_t are aggregate profits from banks, M_t is the aggregate supply of safe short-term assets, and Υ_t represents the net operating deficit of the deposit insurance scheme. Appendix A.2 presents the consolidated

[9] Similar to Bianchi and Bigio (2022), this formulation simplifies the computation of general equilibrium dynamics, while delivering allocations consistent with market clearing in the deposits and goods markets. The same assumptions are standard in new-monetarist models (Lagos and Wright, 2005; Lagos et al., 2017), which assume different goods can be purchased with different assets.

government in more detail.

2.5 Equilibrium

An equilibrium is a set of functions such that:

1. Banks optimal choices $\{N_{jt}, M_{jt}, B_{jt}, D_{jt}\}$ solve the problem of an individual bank (10), taking prices $\{r_t^L, r_t^M, r_t^B, r_t^D\}$ as given.

2. Entrepreneurs aggregate demand of credit $\{N_t\}$ is consistent with the free entry condition, taking prices $\{r_t^N\}$ or $\{s_t^N\}$ as given.

3. Household optimal choices $\{C_t^D, C_t^B, C_t^M, D_t, B_t, M_t^H\}$ solve the household's problem in Appendix A.1, taking prices $\{r_t^D, r_t^B, r_t^M\}$ as given.

4. The credit market for new loans clears:
$$N_t = \int N_{jt} \mathrm{d}j.$$

5. The deposit market clears:
$$D_t = \int D_{jt} \mathrm{d}j.$$

6. The wholesale debt market clears:
$$B_t = \int B_{jt} \mathrm{d}j.$$

7. The safe short-term asset market clears:
$$M_t = M_t^H + \int M_{jt} \mathrm{d}j.$$

8. The consolidated government budget constraint in (16) is satisfied.

9. The consumption goods market clears (i.e., the aggregate resource constraint satisfies):
$$Y_t = C_t^D + C_t^B + C_t^M + (L_t + N_t - L_{t-1} - N_{t-1}) + RC_t, \tag{17}$$
where Y_t denotes total output, C_t^D, C_t^B and C_t^M denote the different components of households' consumption, and RC_t denotes resource cost due to bank resolution and loan issuance.

Appendix A.2 provides more details on all equilibrium objects.

2.6 Characterization

A key feature of our model is that banks' optimal policies exhibit size independence, which substantially simplifies the analysis while preserving the essential heterogeneity. As shown in Appendix A.2, banks' decision rules can be expressed independently of their current equity level. Specifically, we can factor out current equity from all policy functions, leaving leverage—the ratio of loans to equity—as the sole relevant state variable for individual bank decisions.

This size independence property means that two banks with the same leverage ratio will make identical portfolio choices regardless of their absolute size, and consequently, bank growth becomes independent of size, but depends on leveraged returns and idiosyncratic shocks. This allows us to characterize the entire cross-sectional distribution of bank behavior through the distribution of leverage alone. While this simplification reduces the dimensionality of the problem considerably, it preserves the crucial interactions between leverage, regulatory constraints, and loan pricing that drive the heterogeneous transmission of monetary policy. The model thus captures the essential economic forces while remaining tractable enough for quantitative analysis across different monetary and regulatory policy scenarios.

On the non-financial sector, we assume static loan demand and deposit supply functions that do not exhibit internal dynamics. To generate a realistic deposit rate pass-through following monetary policy shocks—which empirically differs substantially from complete pass-through—we introduce preference shocks to the deposit supply function. This allows the model to match the observed gradual adjustment of deposit rates while maintaining the focus on the bank-lending channel.

Rate-Exposure Irrelevance. In our model, the only source of cross-sectional heterogeneity comes from the existence of idiosyncratic loan default rate shocks at the bank level. By switching off the cross-sectional dispersion of these shocks, our model collapses to a representative bank model.[10]

[10] Even without idiosyncratic loan default rates, our model still features dispersion in bank sizes due to entry and exit. However, as discussed above, policy functions in our model are scale invariant.

Proposition 1. For parameter configurations in which the capital requirement is not binding in the deterministic steady state, the representative bank version of our model features identical aggregate prices and allocations in the fixed and variable rate economies.

Proof. See Appendix A.7.

2.7 Solution method

To solve the model, we use a value function iteration algorithm for the bank problem defined in Appendix A.2 and keep track of the bank distribution over log-equity $\log(E_{jt})$, leverage $l_{jt} = \frac{L_{jt}}{E_{jt}}$, and the loan rate/spread x_{jt} using the method of Young (2010). The steady state can then be found in an iterative procedure where, for a given guess of the loan rate r^N, we first solve for the policy functions using value function iteration and then compute the bank distribution using those policy functions. During this procedure, the guess for the loan rate is adjusted until an equilibrium in the loan market is found. The transitional dynamics after an MIT shock are computed similarly to Boppart et al. (2018). For a guess of a transition path for the loan rate $\{r_t^N\}_{t=0}^T$, we make a backward pass along the transition to compute the policy functions, followed by a forward pass to compute the distribution along the transition. Similar to our steady state algorithm, we adjust the transition path for the loan rate $\{r_t^N\}_{t=0}^T$ until the loan market clears in each period. Appendix C provides more details on the solution algorithm.

3. Calibration and model fit

We base the quantitative analysis on a calibration tailored to the euro area. Subsection 3.1 specifies functional forms adopted in the calibration, subsection 3.2 presents parameter values, and subsections 3.3 and 3.4 evaluate the model fit along the cross-sectional and time-series dimensions, respectively.

3.1 Functional forms

Loan-origination cost. The new-loan origination cost is quadratic:

$$f(N_{jt}/L_{jt}) = \eta\left(\frac{N_{jt}}{L_{jt}}\right)^2, \tag{18}$$

with $\eta > 0$.

Default-rate distribution. The cumulative distribution function (cdf) of the default rates ω_{jt+1} follows the Vasicek (2002) single risk-factor model (see Appendix A.6):

$$F_j(\omega) = \Phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(\omega) - \Phi^{-1}(p)}{\sqrt{\rho}}\right). \tag{19}$$

The cdf formula for defaults is given by the cdf of a standard normal $\Phi(\cdot)$, with inverse $\Phi^{-1}(\cdot)$. The formula is such that the average default rate is p. In turn, $\rho \in [0,1]$ is a correlation parameter, which increases dispersion, and dictates how the underlying portfolio-level risk factor affects individual loan defaults. We opt for this specification as this distribution is used as a statistical foundation for the capital requirement formulas (IRB approach) of Basel II (Gordy, 2003).[11]

Entrepreneurs' entry cost. The entrepreneurs' cost of starting an investment project is assumed to be given by

$$a(N_t) = \zeta_1 N_t^{\zeta_2}, \tag{20}$$

with $\zeta_1 > 0$ and $\zeta_2 > 0$. These parameters govern the loan-demand elasticity.

3.2 Calibration

The notion of a time period is one quarter. Parameter values are either set externally or set internally to deliver a target moment of the data. Table 1 reports all parameter values corresponding to both groups.

Pre-set parameters. The first block of Table 1 corresponds to the parameters set either following the calibration of other papers or set directly to their observed regulatory

[11] See, e.g., Repullo and Suarez (2004) for details.

counterparts. We follow Mendicino et al. (2020) and set the average loan default rate p to 2.65% (annualized) and the loan-loss given default λ to 0.3. The average maturity of loans is set to 0.05, consistent with an average loan duration of 5 years reported by Cortina et al. (2018), which corresponds to the maturity observed for syndicated loans in developed economies from 1991 to 2014. The corporate tax rate τ is set at the average effective tax rate of 20% for European banks.[12]

Policy parameters are set based on Basel III regulatory levels: The capital requirement γ encompasses the minimum Common Equity Tier 1 (CET1) requirement, 4.5%, plus a capital conservation buffer, 2.5%, that must also be maintained with CET 1 capital. The parameter α in equation (4), which determines the share of deposits in banks' balance sheet, is set to match the observed ratio of deposits-to-total-assets of 0.78, while the liquidity requirement θ matches the reserve-to-total-liabilities ratio of 0.118, both ratios are consistent with the consolidated balance sheet of monetary financial institutions in the euro area.[13] The steady-state value of the policy rate r^M (i.e., the rate of remuneration on central bank reserves) is set to the historical average of the nominal deposit facility rate in the euro area (1%). Similarly, the steady-state deposit rate r^D is set to 0.5% according to the historical average of the nominal overnight deposit rate in the euro area.

Jointly calibrated parameters. The second block of Table 1 corresponds to parameters calibrated jointly to deliver target moments. The targets for banks' return on equity (ROE) of 6.4 percent and the bank failure probability of 0.66 percent are taken directly from Mendicino et al. (2020). These targets are key to identifying the bankers' discount factor β and the volatility of a bank's portfolio default rate ρ, respectively. Similarly, the scale parameters η of the loan-origination cost in (18), ζ_2 and ζ_1 of the loan demand in (20) are jointly estimated to target the historical average loan rates of 3%, the peak response of the logarithm of new lending, -0.38, to a monetary policy shock of 100 basis points (see Figure 4 below), and the average voluntary capital buffer of 5.1 percent, a target consistent with the mean CET1 buffer for supervised banks reported by the

[12]See http://www.stern.nyu.edu/~adamodar/pc/datasets/taxrateEurope.xls

[13]See Appendix B, Figure 13, for a detailed composition of MFIs and a description of the time series used. We cannot distinguish MMF from the deposit-taking institutions for the entire time series, but this does not distort the data much as the size of MMFs is very small compared to deposit-taking institutions. In 2024Q2, for instance, MMF aggregate size was 1.8 tn euros, less than 5% the size of deposit-taking institutions, which amounts to 38 tn.

Table 1: Parameter values

Pre-set parameters

	Parameter	Value	Target/Source
p	Loan default rate, mean (%)	0.6625	Mendicino et al. (2020)
λ	Loan loss-given-default	0.30	Mendicino et al. (2020)
δ	Loan maturity	0.05	Cortina et al. (2018)
τ	Corporate tax rate	0.20	Damodaran database.
γ	Min. capital requirement (%)	7.0	Basel III CET1 + Buffer requirement.
α	Deposits-to-loans ratio	0.78	Consolidated EA banks balance sheet.
θ	Liquidity requirement (%)	11.8	Liquid asset to deposit ratio.
r^M	Steady-state policy rate (pp)	1.0	Avg. EA deposit facility rate, 1999-2019.
r^D	Steady-state deposit rate (pp)	0.5	Avg. EA overnight deposit rate, 2003-2023.

Jointly calibrated parameters

	Parameter	Value	Target	Data	Model
β	Subjective discount factor	0.933	Banks' return on equity (%)	6.4	6.4
ρ	Loan default correlation	0.51	Bank failure probability (%)	0.66	0.66
η	Loan origination cost	0.22	Voluntary capital buffer (%)	5.1	4.8
ζ_1	Ent. entry cost (level)	5.78	Avg. lending rates (%)	3.0	3.0
ζ_2	Ent. entry cost (power)	0.50	Response of new lending (%)	-0.38	-0.37
$\bar{\pi}$	Fixed operating cost	0.012	Non-interest expenses to assets (%)	0.34	0.22
χ	Bank's exit rate (pp)	2.00	Slope of log-log asset distribution	-1.56	1.56

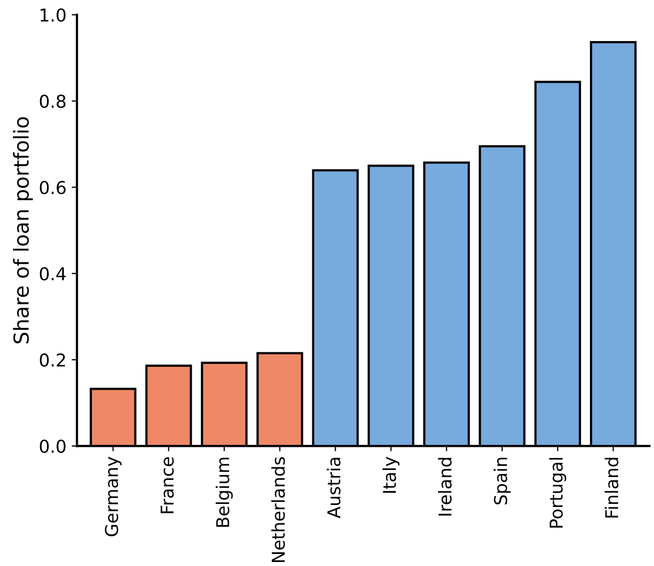
Note: Interest rates and probabilities are reported in annualized terms.

European Banking Authority for 2021.[14]

The bank's fixed operating cost parameter $\bar{\pi}$ is informative about the average net non-interest expenses-to-assets ratio, and the bank's exit rate χ is disciplined by targeting the slope of the log-log regression coefficient (tail coefficient) of the asset-size distribution. As discussed in Section 3.3, this moment allows the model to replicate a power-law distribution of bank asset sizes, a salient feature of the data.

[14] We calibrate the model based on the CET1 estimates for Supervised banks, as it represents the most accurate available estimate for capital buffers. See Appendix B.3 for a comparison of different estimates of CET 1 ratios and buffers.

Figure 1: Share of variable-rate loans.



Note: Average share of the aggregate total outstanding loans issued at variable rates from 2014 to 2020. Includes loans to non-financial corporations and loans to households– mortgage loans, consumer loans, and other loans. Orange bars corresponds to our classification of fixed-rate countries and Blue bars to variable-rate ones. *Source*: ECB MFI Statistics.

Fixed ex-ante heterogeneity. As anticipated above, we study two versions of the model, one with variable-rate (VR) and the other with fixed-rate (FR). This feature is motivated by cross-country institutional patterns in the observed countries of the euro area. Figure 1 presents the share of variable-rate loan contracts in each country. Variable-rate loans are defined as those with original and remaining maturity over 1 year and interest rate reset within the next 12 months.[15] We observe that in a first group of countries, Germany, France, Belgium, and the Netherlands, banks issue around 80% of their contracts as FR contracts and 20% as VR. In contrast, in a second group, Finland, Portugal, Spain, Ireland, Italy, and Austria, issue above 60% of their loans in VR contracts. We label the first and second groups as FR and VR banking systems, respectively. Appendix B.4 provides additional analysis of this categorization across households and non-financial corporate loans. In particular, we establish that these

[15]At the country-consolidated level, the time series for loans are not exclusively categorized by the type of interest rate fixation but rather by their maturity. We also approximate the share of variable-rate loans by categorizing loans with a maturity of up to a year, which produces similar results. The categorization in Figure 1 aligns with the results reported by Core et al. (2025) using Anacredit (a confidential database of the European Central Bank) for non-financial corporate loans in the euro area.

patterns have remained stable and extend across loan categories, affecting both household and corporate lending. We employ these definitions in Section 5, where we study the aggregate response of banks' balance sheet variables by groups to monetary shocks.

3.3 Cross-sectional moment fit

Bank balance sheet composition. We begin by comparing the consolidated balance sheet of monetary financial institutions (MFIs) operating in the euro area to our model's counterpart.[16] Table 2 shows that the model's steady-state consolidated balance sheet closely aligns with the composition of assets and liabilities in the data.

Table 2: Consolidated bank balance sheet composition: euro area 2013–2023 vs. model

Assets		**Liabilities**	
Loans	88% (89%)	Deposits	78% (81%)
ST securities and reserves	12% (11%)	Wholesale funding	14% (9%)
		Equity capital	8% (10%)

Note: The composition is expressed as percentages to total assets. Model counterparts are shown in parentheses. The data corresponds to the consolidated balance sheet of euro area Monetary Financial Institutions (MFIs), excluding the Eurosystem, reported by the European Central Bank. *Loans* include loans to the private sector, to the general government, and other risky assets. *ST securities and reserves* include short-term securities holdings, operations with national central banks (repos and securities lending), and other short-term external assets. *Deposits* include retail deposits of different maturities, external and other liabilities. *Wholesale funding* corresponds to debt securities issued. *Equity capital* comprises capital and reserves.

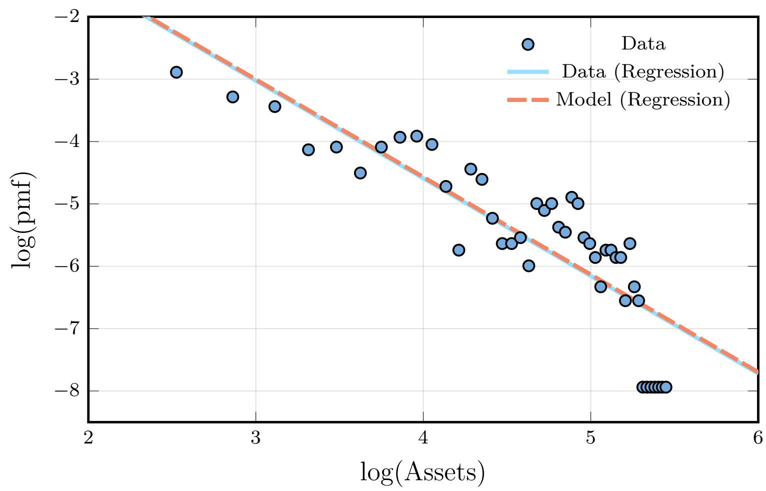
Asset-size distribution. The model generates a steady-state distribution of bank assets that closely mirrors the asset distribution observed for euro area banks with only the exit parameter.[17] Figure 2 compares the model's and the empirical right tails of the asset distribution in the log-log space, illustrating the substantial heterogeneity in bank sizes produced by the model. As explained in Gabaix (2009), growth independence and an exit

[16] MFIs includes deposit-taking institutions (banks) and money market funds (MMFs). We cannot distinguish MMF from the deposit-taking institutions for the entire time series, but the presence of MMFs is immaterial given their size. For example, in 2024Q2, MMFs totaled €1.8 trillion—less than 5% of deposit-taking institutions (€38 trillion). Appendix B details on the composition of MFIs and the time series used.

[17] We construct an unbalanced bank-level dataset using balance-sheet data from S&P Global, a proprietary source. The quarterly dataset covers the period from 2013 to 2020 and includes information on common equity tier 1 (CET1) capital levels, risk-weighted assets, and total assets. We fit a power law distribution of the form $f(x) = \bar{A}x^{\psi}$, where ψ denotes the slope of the fitted curve and captures the tail behavior of the asset distribution.

rate coefficient, both features of the model, yield power laws. This empirical regularity is observed in many datasets, and the bank-size distribution is not an exception. While we target the exit rate to match the corresponding Pareto tail, the fact that we can fit the data well indicates that the model effectively captures the statistical properties of bank-level dynamics .

Figure 2: Banks' asset size — Tail distribution (steady state).



Note: The blue dots represent equally spaced bins in the right tail of the empirical distribution of banks' assets. The light blue line is a regression based on the log of these bins. The dashed red line is the model-equivalent to the light blue line based on the steady-state distribution. To make model and data distributions comparable, we have scaled the asset values to have the same mean in the model and the data.

Capital-ratio distribution. Table 3 reports the distribution of capital ratios in the data and the model.[18]

The model distribution captures its empirical counterpart well. The capital ratio of banks in the first percentile of the distribution is 9.7 percent in the model and 9.4 in the data, slightly above the regulatory limit of 7 percent. Both in the model and in the data, a substantial part of the mass is close to the constraint imposed by capital regulation: banks try to operate above the constraint to avoid being liquidated. The capital ratio of banks in the 40th percentile is 12.7 in the model and 13.5 in the data. For those banks in the upper half of the distribution, the average capital ratio is 13.1 in the model and

[18]Since the gradual implementation of Basel III in 2013, capital ratios for euro area banks have increased steadily. This adds additional dispersion to the distribution. To adjust the empirical distribution for time trends, we normalize each period by subtracting its mean and then re-centering the data using the mean capital ratio in 2019.

18.7 in the data, reflecting the fact that the model underestimates the mass of banks with high leverage levels.

To understand this, we also compare the model with the distribution of capital in large banks, defined as XXX, in the second column of Table 3. The model's fit improves for the entire capital distribution. The average for the mass of banks in the upper half, for instance, is now 14.7 in the data (compared with 13.1 in the model). We attribute this fact, among other things, to additional regulatory constraints that our model is not able to capture. In particular, banks should satisfy a Minimum Requirement for Own Funds and Eligible Liabilities (MREL).[19] While medium and large banks typically issue contingent liabilities to satisfy this requirement, small local banks typically satisfy this constraint by issuing additional CET1 capital, which may explain the CET1 levels well above 15%.

In any case, the underestimation of the right tail is inconsequential for our results. As we show next, the behavior of banks far away from the constraint is pretty much homogeneous. Therefore, aggregate dynamics are affected by the left tail and not by the right one.

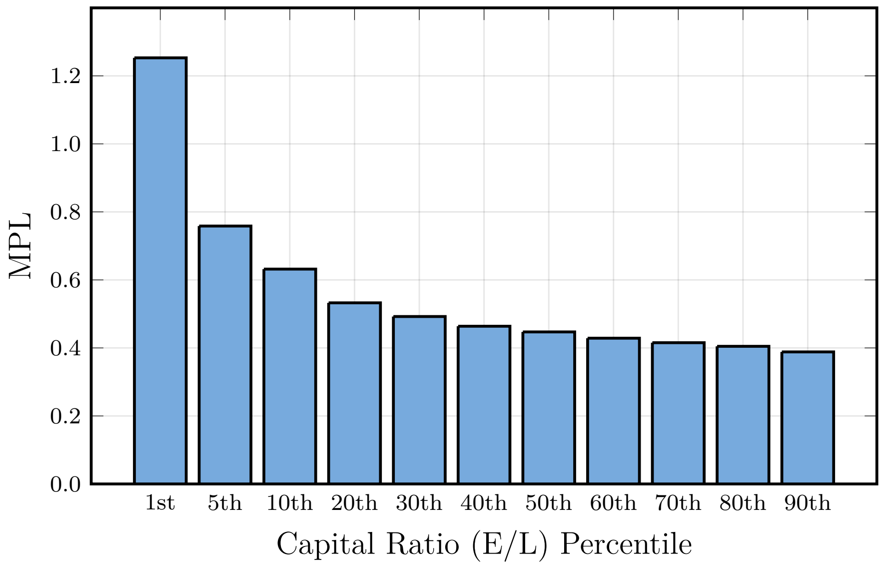
Table 3: Capital-ratio distribution

	All Banks	Large Banks	Model
1st Percentile	9.36	9.68	9.71
5th Percentile	11.22	10.91	11.10
10th Percentile	11.68	11.28	11.66
20th Percentile	12.31	11.67	12.18
30th Percentile	13.03	12.00	12.46
40th Percentile	13.54	12.41	12.65
Avg. Top 50%	18.71	14.73	13.13

Sources: S&P Global and ESRB supervisory data on European banks' capital requirements. Capital ratios are defined as CET1 capital over risk-weighted assets. The sample corresponds to 60 large and medium-sized European banks from 2013 to 2020.

[19] This is a regulatory framework that requires financial institutions to hold a sufficient amount of own funds and eligible liabilities to absorb losses and potentially recapitalize in case of failure.

Figure 3: Distribution of marginal propensity to lend (MPL).



Note: The figure displays the MPL for different percentiles of the capital ratio distribution.

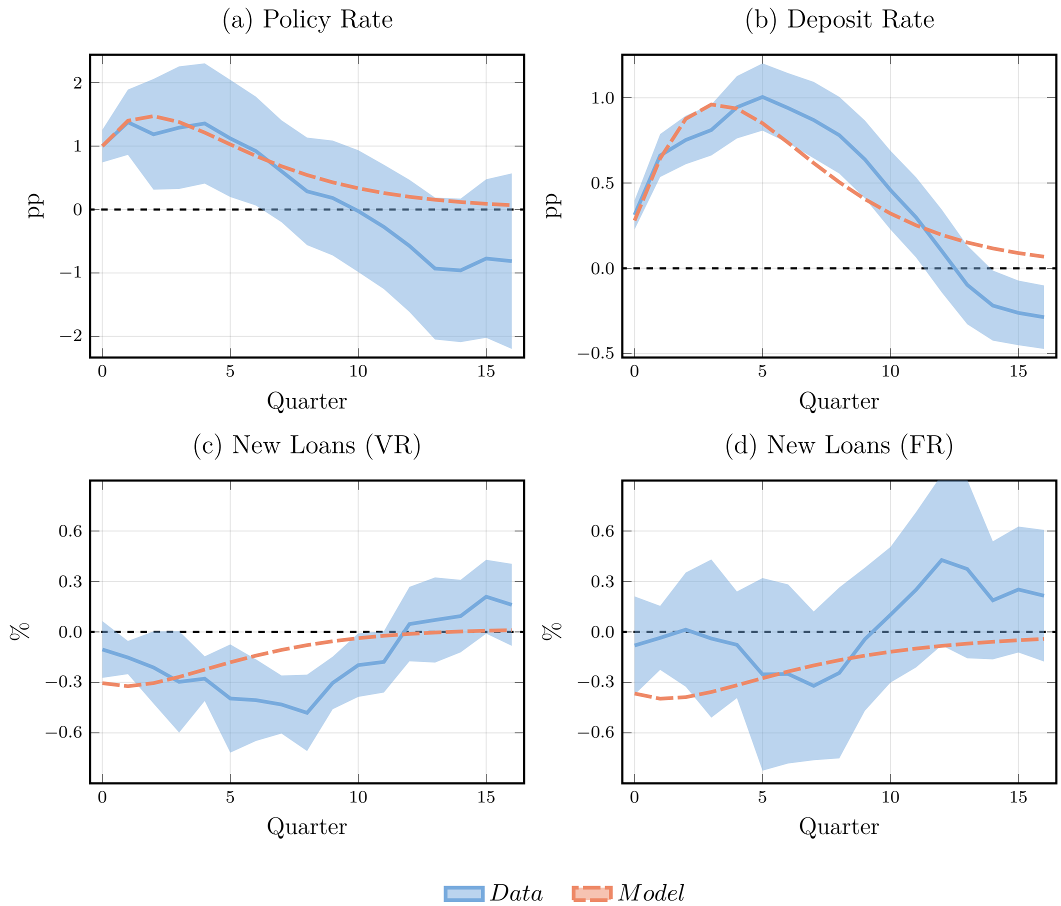
Marginal propensity to lend. We define the marginal propensity to lend (MPL) as a statistic that summarizes a bank's increase in lending out of a marginal increase in equity capital, a concept we adopt from Jamilov and Monacelli (2025). The MPL is defined as

$$MPL(l) = \frac{dN(l,E)}{dE} = \frac{dn(l)}{dl}\frac{dl}{dE}E + n(l) = -l\frac{dn(l)}{dl} + n(l),$$

where $N(l,E) = n(l)E$ is the policy function for new loans of a bank with leverage $l = L/E$ and equity E. Thus, the marginal propensity to lend only depends on a bank's leverage.

Figure 3 shows the model's distribution of MPLs, ranging from 1.2 to 0.4. There is significant heterogeneity in MPLs. We obtain that banks with lower capital ratios (i.e., those closer to the regulatory constraint) feature a higher MPL. The intuition is clear: adding an extra unit of equity for a bank allows it to move further from the regulatory constraint. Although, to the best of our knowledge, there are no empirical estimations of a bank's MPL—of new lending— in the literature, these values are broadly consistent with Gambacorta and Shin (2018)'s bank-level elasticity of loan growth to equity ratio (0.66).

Figure 4: Targeted IRFs



Note: Solid blue lines show the empirical impulse responses to a monetary policy shock and dashed red lines compute the model counterparts. Light blue bands show the 95% confidence intervals. Panels (a) and (b) report the responses of the policy rate and the deposit rate. Panels (c) and (d) report the response of new loans, distinguishing between FR and VR countries in the data and in the model. See Appendix B.5 for details.

3.4 Time-series moment fit

Responses to a monetary tightening. The main focus of interest is on how heterogeneous banks respond to monetary policy shocks, along various dimensions. To evaluate the model's ability to account for the bank lending channel, we compare the model-generated impulse response functions (IRFs) with their empirical counterparts. All the empirical IRFs are estimated using a local projections approach (Jordà, 2005; Jordà et al., 2015) (Appendix B.5 presents the estimation details).

To obtain the model's response of new loans to an unexpected increase in the

Figure 5: Untargeted impulse responses: Loan rates and volumes

Note: Solid blue lines show the empirical impulse responses to a monetary policy shock and dashed red lines compute the model counterparts. Light blue bands show the 95% confidence intervals. Panels (a) and (b) report the response of the interest rate on new loans, and panels (c) and (d) of the volume of legacy loans, distinguishing between FR and VR countries in the data and in the model. See Appendix B.5 for details.

policy rate r^M, we compute the transitional dynamics after an unanticipated (MIT) shock following an algorithm similar to Boppart et al. (2018).[20] The loan rates and quantities in the model are determined through equilibrium via market-clearing. We also introduce preference shocks on the deposit side to induce similar deposit-rate paths as observed in the empirical IRF. Thus, for new loans, quantities and prices are jointly determined by demand and supply. For deposits, rates are de facto exogenous with quantities determined by the demand for funding by banks. All in all, the model takes as exogenous inputs the projected paths for both the policy rate and the deposit

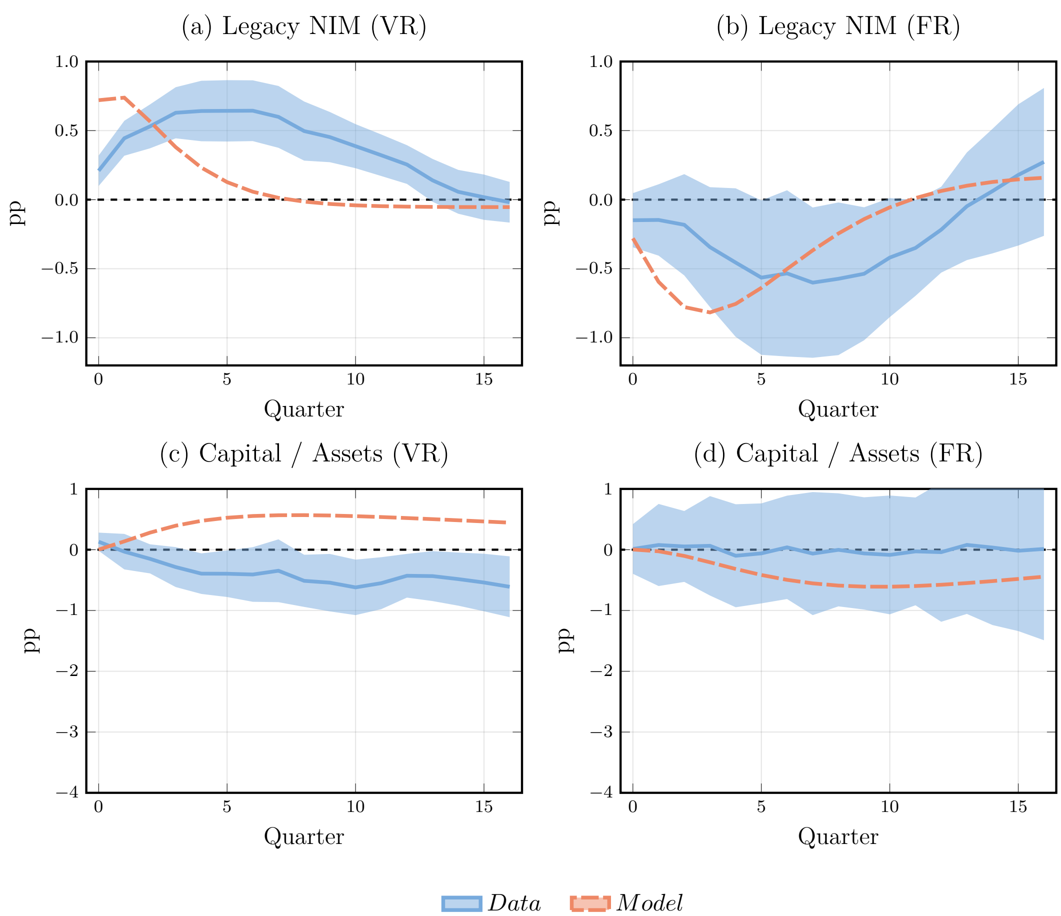
[20]This is equivalent to solving a model with aggregate risk by a first-order perturbation method.

rate after a 1 percentage point increase in the policy rate, r^M, estimated from the data.

The upper row of panels in Figure 4 presents the IRFs of the exogenous rate processes. Panel (a) displays the estimated trajectory of the policy rate, and Panel (b) shows the corresponding path for the deposit rate. The solid blue line and the blue shaded areas correspond to the point estimates and confidence bands of the IRFs. The dashed lines in those top panels are the exogenous rate paths induced into the model. The figure shows how the shocks are calibrated to roughly match the dynamics in the data.

The bottom rows in Figure 4 report the response of the quantities of new loans for variable- and fixed-rate countries, both in the model and the data. The model matches

Figure 6: Untargeted impulse responses: NIM and capital ratio



Note: Solid blue lines show the empirical impulse responses to a monetary policy shock and dashed red lines compute the model counterparts. Light blue bands show the 95% confidence intervals. Panels (a) and (b) report the response of the legacy NIM, and panels (c) and (d) of the capital ratio, distinguishing between FR and VR countries in the data and in the model. See Appendix B.5 for details.

reasonably well the pass-through of shocks to quantities.[21] In both cases the volume of new loans decreases after a monetary policy tightening.

We further analyze in Figures 5 and 6 the IRFs of variables that are not calibration targets. These figures allow us to assess the model's fit along other bank-balance sheet variables. In both figures, the panels on the left represent VR countries, whereas the panels on the right represent FR counterparts.

Figure 5 reports the responses of the rate charged on new loans and of the amount of legacy loans over time. The fit to the data is also good in these cases.

The model captures well the fact that the passthrough to new loan rates is higher in VR economies than in FR ones (panels a and b). The model also captures how the decline in the volume of legacy loans is larger and more persistent in FR economies (panels c and d).

Figure 6 displays the IRFs of the net interest margin (NIM) for legacy loans, as well as the response of capital ratio.[22] Regarding the NIM (panels a and b), the model IRFs are in the order of magnitude of those in the data, but miss the dynamics, which are more persistent in the data. Panels (a) and (b) also show how the response of the NIM in legacy loans is positive for VR countries and negative for FR ones both in data and model, a feature that we explain in the next section. Likewise, the model is able to produce much larger reductions in capital ratios for FR countries than VR ones (panels c and d).

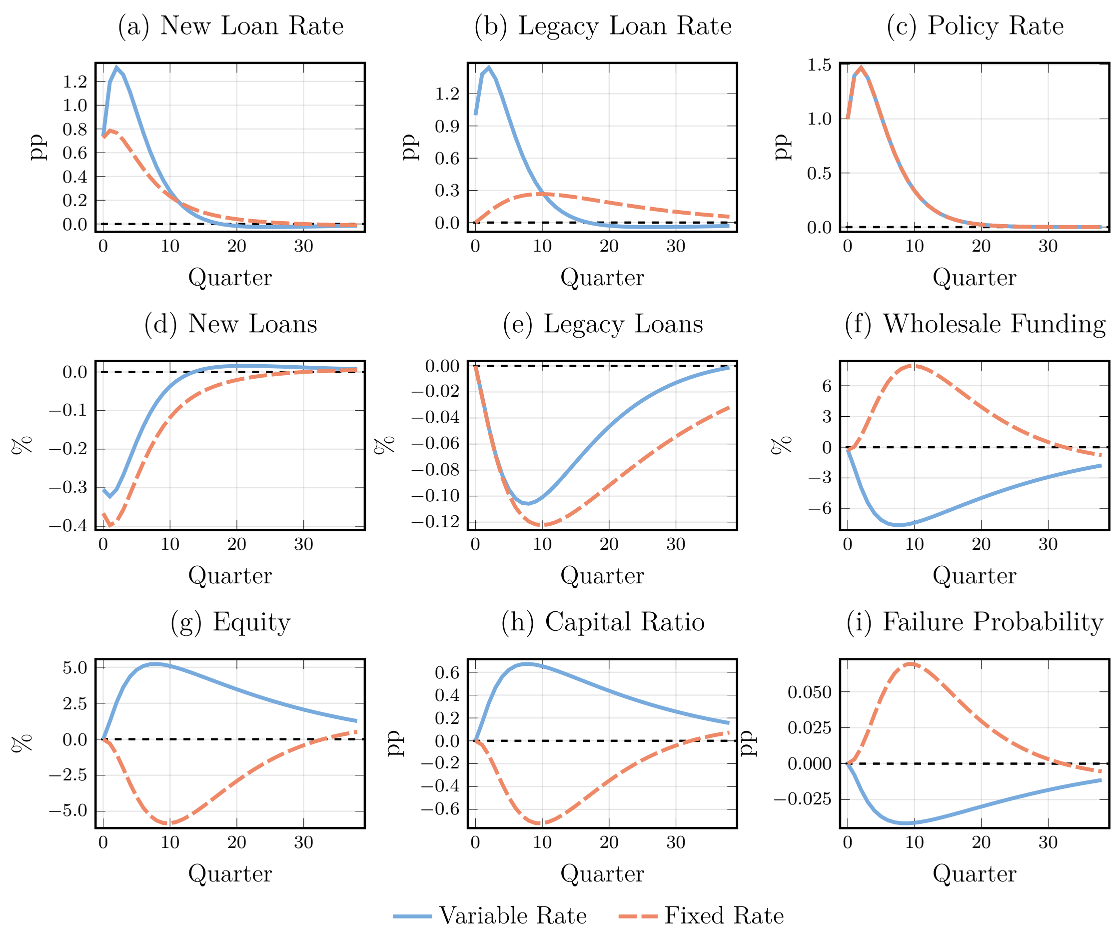
4. Inspecting the mechanism

In this section, we use the model to analyze how ex-ante and ex-post heterogeneity impact the bank-lending channel. We first consider the role of ex-ante heterogeneity by comparing the IRFs in FR and VR economies—to a one percentage point increase in the policy rate (the remuneration rate of central bank reserves). Then, we evaluate the role of ex-post heterogeneity by looking at the IRFs of different banks in different points of the capital-ratio distribution. Finally, we contrast the model with a version without idiosyncratic shocks.

[21]We should note that we use only one parameter, the elasticity of the loan demand ζ_2, to try to approximate the response of new loans averaged across both countries.

[22]The NIM for legacy loans as the difference between average interest rate on the stock of legacy loans and the average deposit rate.

Figure 7: Aggregate impulse response functions



Note: Impulse responses to a 1 p.p. increase in the policy rate. Solid blue lines show the economy with fixed interest rate loans and the dashed red lines the economy with variable interest rate loans.

Ex-ante heterogeneity. Figure 7 contrasts the aggregate-level IRFs to a one percentage point contractionary monetary policy shock for VR and FR economies. Following the same path of a policy shock (Panel c), banks' funding costs rise as the interest rate on wholesale debt increases in tandem. In contrast, the pass-through to deposit rates remains gradual, by construction (recall the explanation of Figure 4). This asymmetric response causes the marginal cost of funding to increase sharply, depressing new-loan originations, while the average funding cost remains more contained. The average funding cost is mainly driven by the more gradual increase in deposit rates, due to deposits representing the lion share of banks' liability mix, and, together with loan rates, determines the impact on profitability.

For variable-rate banks (blue solid line), the initial pressure on funding costs is offset by a rapid pass-through of the policy rate to both new and legacy loans (Panels a and b). This widens their net interest margin (NIM), translating into higher profitability, which in turn increases their equity and capital ratios (Panels g and h). In stark contrast, fixed-rate banks experience a severe and prolonged compression in their NIM, as their funding costs rise while income from their fixed-rate legacy portfolio remains stagnant (the higher interest rate on new loans only increases the average rate in the banks' portfolio as new loans slowly replace maturing legacy ones). This dynamic precipitates an erosion of their equity and capital ratios. The asymmetry in the response of equity represents the main amplification channel explaining the diverging responses across the two types of banking sectors. Ultimately, the deterioration in bank capitalization under a fixed-rate regime leads to a significantly sharper and more prolonged contraction in new loan origination compared to the variable-rate system (Panel d), as well as an increase in their reliance on wholesale funding (Panel f).

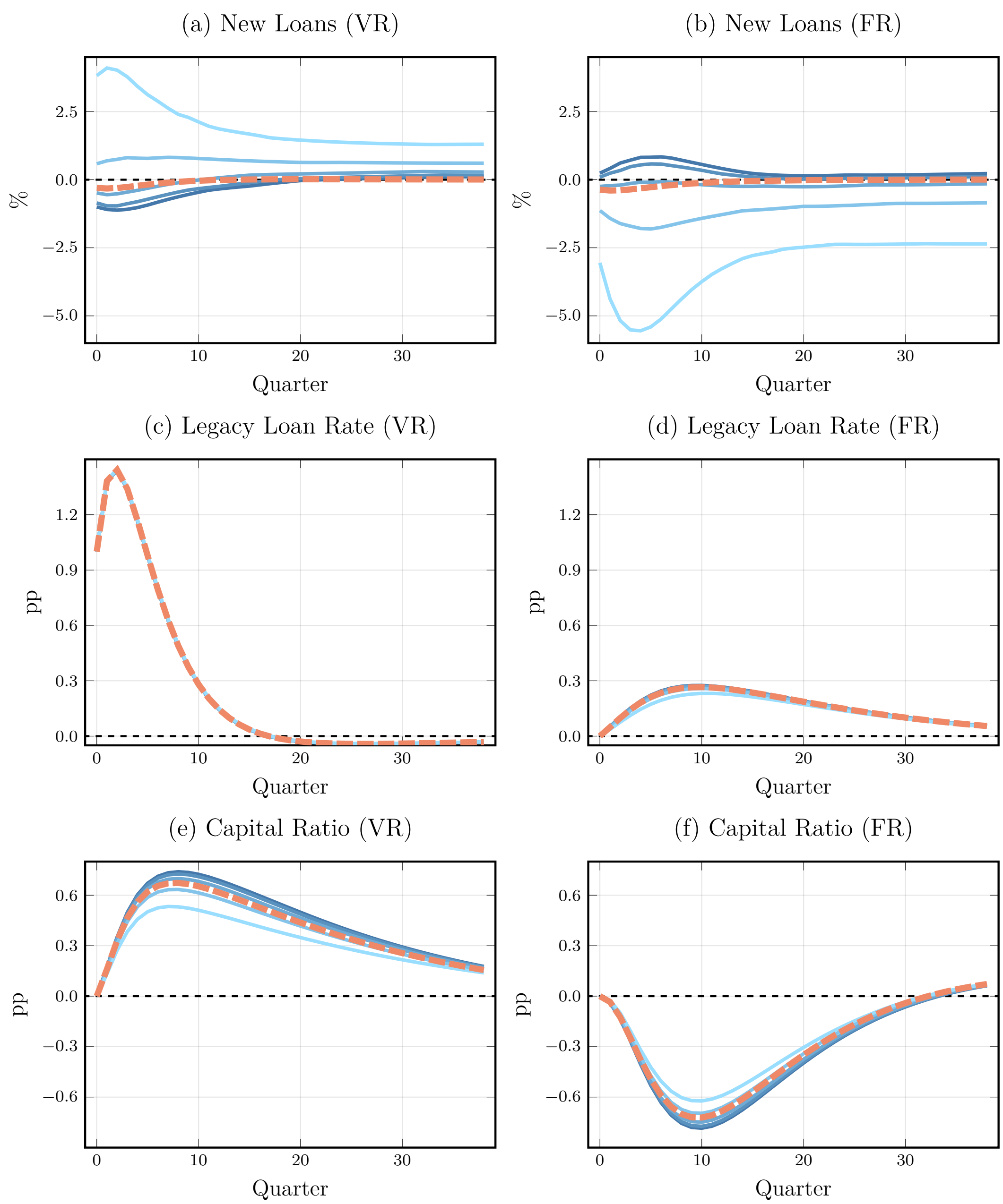
Finally, the monetary tightening has opposing effects on financial stability: the probability of bank failure increases markedly in the fixed-rate system, owing to the decrease in banks' capitalization, whereas it declines for variable-rate banks for the opposite reason (Panel i). This heterogeneity in loan rate fixation patterns is therefore a critical determinant of both the amplification of monetary policy and its consequences for financial stability.

All in all, we can conclude that ex-ante heterogeneity leads to a quantitative difference in the bank lending channel: the elasticity of new lending is about 1/3 larger in fixed-rate economies. Beyond this significant quantitative difference, the implications of bank capital, critical for financial stability, go in opposite directions.

Ex-post heterogeneity. The aggregate responses mask a substantial degree of heterogeneity in the transmission of monetary policy to bank lending. To show this, we disaggregate the responses to explore the role of ex-post heterogeneity in bank leverage. Figure 8 presents the impulse responses for banks in different quantiles of the steady-state capital-ratio distribution, where lighter shades represent more highly leveraged institutions.

The results highlight two key findings. First, consistent with the empirical literature, higher-leverage banks are a key margin of transmission. In both fixed-rate (FR) and variable-rate (VR) systems, these banks exhibit a stronger lending response to the

Figure 8: Individual impulse response functions



Note: The dashed red line shows the aggregate impulse response for the respective variable. The solid blue lines show the impulse responses of banks that are at the 1st, 10th, 50th, 90th, or 99th percentile of the capital ratio distribution. The lightest shade of blue corresponds to the 1st percentile, i.e., the bank that is closest to the capital requirement in the steady state, while the other percentiles are shown with increasingly darker shades of blue.

monetary policy shock.

Second, ex-post heterogeneity is substantially amplified within a fixed-rate system. For FR banks, the shock-induced capital erosion (Panel f) is most severe for institutions that are already highly leveraged. Consequently, these banks are forced into a starkly more profound and more prolonged contraction in new lending (Panel b) as they move to restore their capital buffers. In contrast, while all VR banks see their capital ratios improve (Panel e), higher-leverage institutions exhibit a stronger marginal propensity to lend (as shown in Figure 3), leading to a more aggressive expansion in new loans (Panel a). The heterogeneity in lending responses is therefore driven by proximity to capital constraints of high- and low-leverage institutions. All in all, the interaction between high leverage and fixed-rate loan portfolios acts as a powerful amplifier of monetary policy shocks.

Interactions between both types of heterogeneity. Figure 9 compares the responses of loan quantities (bank-lending channel) and financial stability variables in both economies (FR and VR) against a counterpart where we significantly reduce the level of idiosyncratic risk.

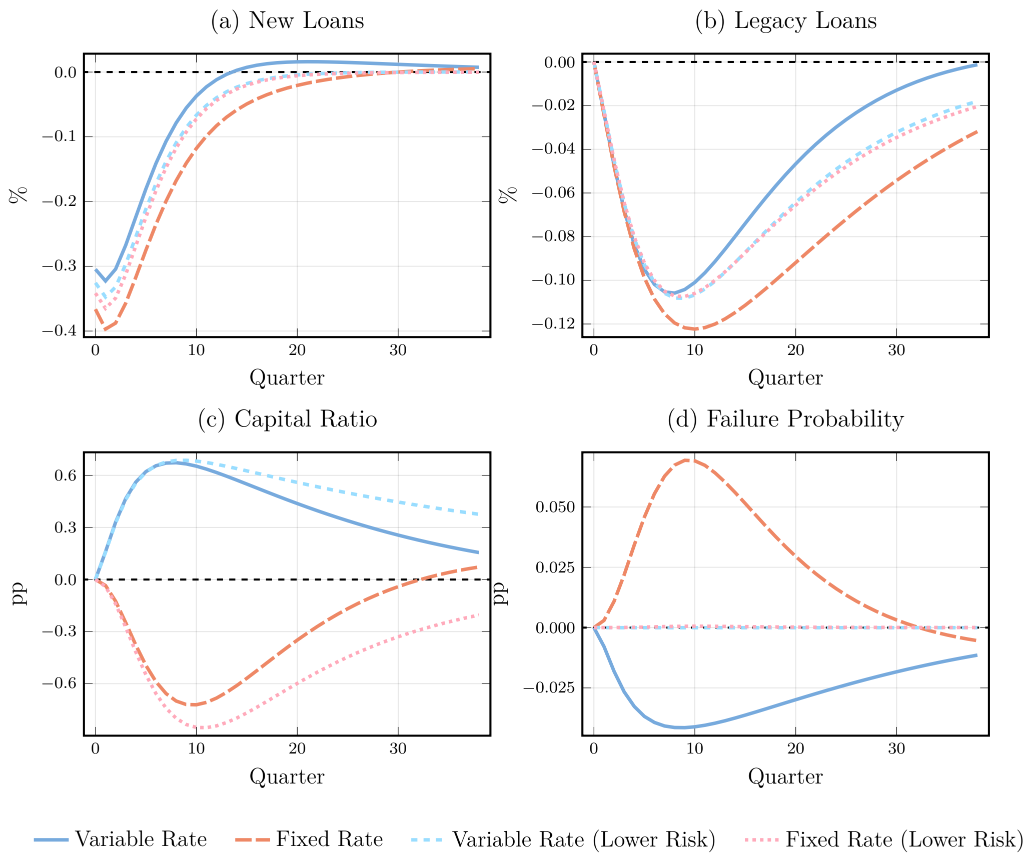
Regarding the bank-lending channel, differences in ex-ante heterogeneity disappear when ex-post risk is reduced. Moreover, bank failure rates disappear entirely even though the effects on capital ratios remain the same.

Why is this interaction so stark? First, we clarify that this answer critically depends on the calibration. Second, and most importantly, loan origination costs play a fundamental role: Without idiosyncratic risk, banks would ideally want to maximize leverage as there is no risk-return tradeoff. However, the loan-origination costs that, together with the observed default risk rationalize the capital buffer, are relatiely large in our calibration. For that reason, even without idiosyncratic risk, bank remain substantially far from their regulatory capital limits.

For this reason, IRFs across FR and VR countries are identical once idiosyncratic risk is muted. Since, when the volatility of idiosyncratic shocks is small enough, no bank risks liquidation, their new lending responds exclusively to changes in the NIM of new loans, even though the policy rate shock moves their capital ratios in opposite directions.

The key lesson of this section is that ex-ante heterogeneity is relevant only because there is ex-post heterogeneity.

Figure 9: Impulse response functions — Lower idiosyncratic risk

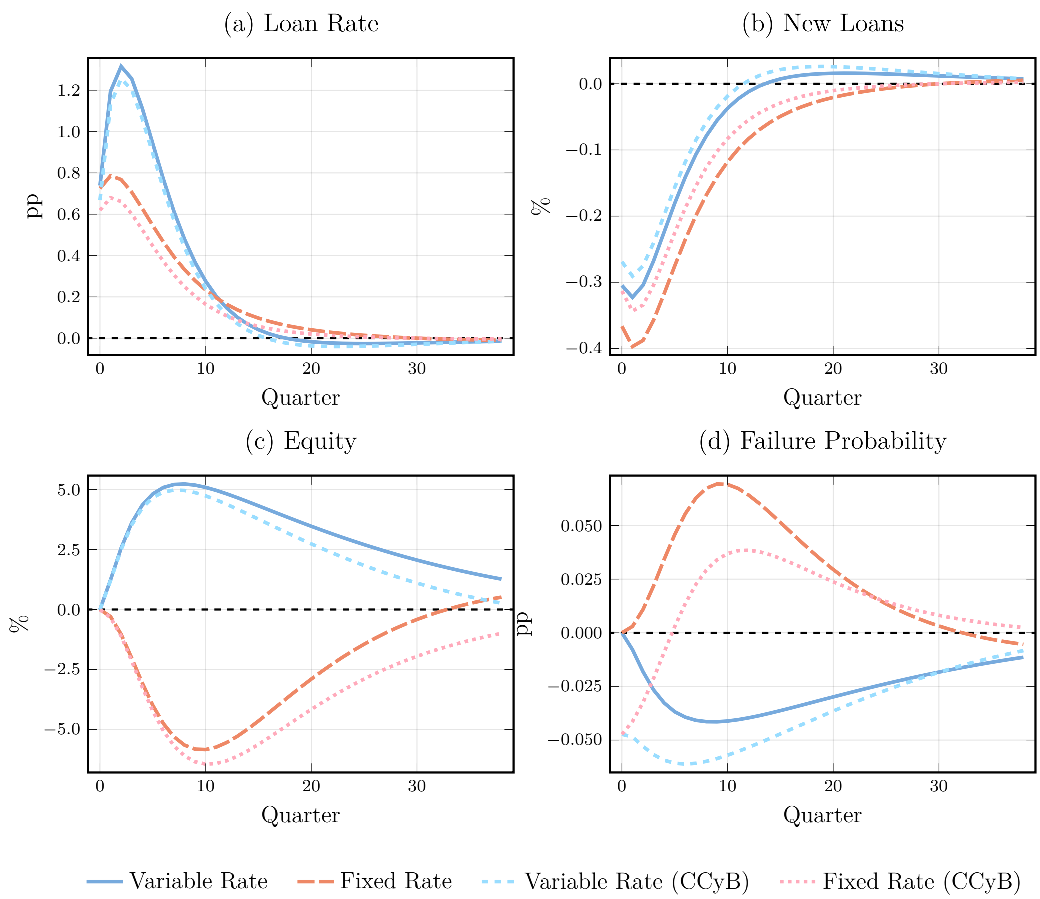


Note: The impulse responses denoted "Variable Rate" and "Fixed Rate" correspond to the baseline calibration. "Variable Rate (Lower Risk)" and "Fixed Rate (Lower Risk)" denote alternative parameterizations where we reduce ρ from 0.51 to 0.1, meaning that in these economies there is substantially lower idiosyncratic risk.

5. Implications: a discussion

Financial stability and monetary policy conflicts. Our findings have important implications for the design and coordination of bank regulation and monetary policy. Changes in capital requirements can amplify the differential effects of monetary policy across banking systems: tighter capital requirements increase the fraction of banks operating near regulatory constraints, making fixed-rate economies even more vulnerable to monetary tightening while having little effect on variable-rate systems. This asymmetry makes the trade-offs facing monetary policymakers in a monetary union more acute, as regulatory changes can inadvertently increase the divergence in regional responses to uniform policy. Figure 10 shows the impulse response functions after an interest rate increase by the central bank with a concurrent release of the CCyB by 1pp. The CCyB release is modeled as a changed in capital requirement γ, where $\gamma_t - \bar{\gamma} = \rho(\gamma_{t-1} - \bar{\gamma})$ and $\rho = 0.95$.

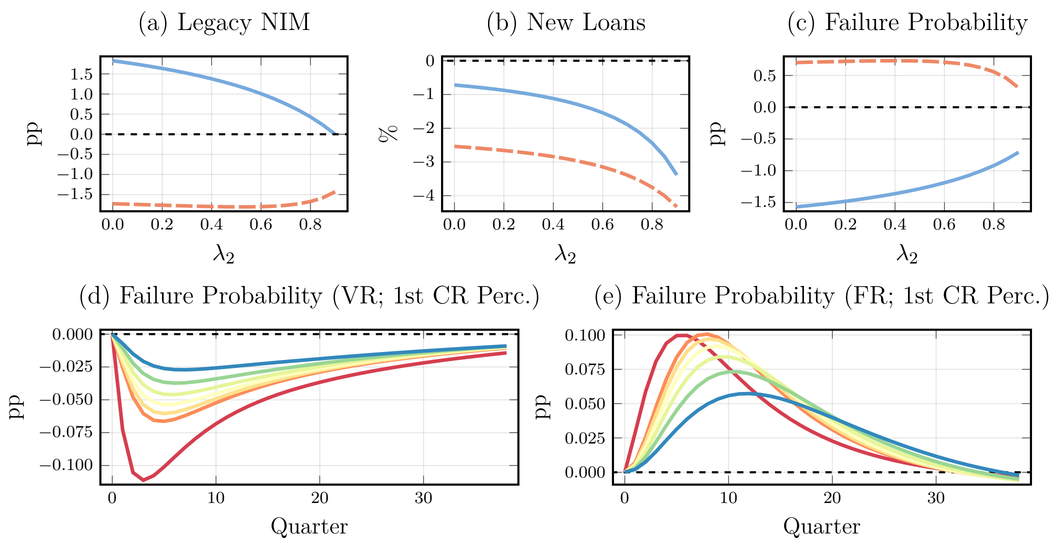
Figure 10: Impulse response functions — Interest rate increase + CCyB release



Note: The impulse responses denoted "Variable Rate" and "Fixed Rate" correspond to the baseline calibration. "Variable Rate (CCyB)" and "Fixed Rate (CCyB)" denote alternative parameterizations where γ is reduced by 1pp on impact of the policy rate increase and then gradually reverts to its steady state value.

Gradualism doctrine. Our analysis provides, in principle, a theoretical foundation for gradualism in monetary policy conduct. Rapid policy rate increases prevent banks from anticipating and preparing for regulatory pressures, forcing abrupt deleveraging that amplifies the contractionary effects. In contrast, gradual and well-communicated policy adjustments allow banks to rebuild capital buffers and adjust their portfolios more smoothly, reducing the severity of the lending contraction while achieving the same cumulative policy stance. These insights suggest that effective macroeconomic stabilization requires careful coordination between monetary and prudential authorities, with particular attention to the timing and sequencing of policy interventions across these domains.

Figure 11: Effects of Gradualism



Note: Panels (a), (b), and (c) show the cumulative response of the respective variable for the variable rate economy (solid blue) and the fixed rate economy (dashed red) under different degrees of gradualism as captured by the parameter λ_2. Panels (d) and (e) show the impulse responses for the failure probability of bank that is at the 1st percentile of the capital ratio distribution in the steady state. The colors from red to blue correspond to different degrees of gradualism as captured by λ_2, where $\lambda_2 \in \{0.0, 0.65, 0.7, 0.75, 0.85, 0.9\}$, i.e., red corresponds to an AR(1) process, while blue is the most gradual AR(2) process.

The model can be used to study experiments to shed light on these questions, by comparing different levels of capital requirements and more gradual policy hikes.

6. Conclusion

This paper investigates how bank heterogeneity shapes the transmission of monetary policy.

Our central finding is that the ex-ante heterogeneity between loan-pricing regimes is quantitatively important for the bank lending channel. In a fixed-rate system, banks are unable to reprice legacy assets to offset rising funding costs after a monetary tightening, reducing their profitability and their capital positions. This forces a sharper credit contraction relative to variable-rate systems, in which loan repricing combined with a gradual pass-through to deposit rates makes the effect of a monetary tightening positive for profitability. Furthermore, the shock also also raises the probability of bank failure in fixed-rate systems, highlighting the financial stability risks.

Furthermore, the model demonstrates that banks' leverage acts as a powerful amplifier, but its effects are contingent on the loan-pricing regime. Consistent with the literature, high-leverage banks are the primary margin of transmission. However, in a fixed-rate system, their proximity to regulatory constraints forces them to cut lending most aggressively in response to capital depletion. Conversely, in a variable-rate system where monetary tightening boosts profitability, these same high-leverage banks, exhibiting a higher marginal propensity to lend out of equity, expand their loan origination most. Our analysis thus reveals that the interplay between loan pricing and bank capitalization is fundamental to understanding both the aggregate strength of the transmission and the heterogeneous impact of monetary policy.

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Appendices

A. Model derivations

A.1 A microfundation for aggregate deposits demand

TBC.

A.2 Bank problem

TBC.

A.3 Conditions for risk-free wholesale debt

The balance sheet of the bank, after substituting for the binding constraints (4) and (8), reads:

$$L_t + N_t + \theta\alpha L_t = \alpha L_t + B_t + E_t.$$

Solving for B_t:

$$B_t = [1 + \alpha(\theta - 1)]L_t + N_t - E_t.$$

Consider the worst possible realization for the iid shock ($\omega_{t+1} = 1$). Then debt holders recover at most:

$$(1 + r_t^M)M_t + (1 - \lambda)(L_t + N_t).$$

For debt to be risk free, we need:

$$(1 + r_t^B)\underbrace{\{[1 + \alpha(\theta - 1)]L_t + N_t - E_t\}}_{B_t} \leq (1 + r_t^M)\theta\alpha L_t + (1 - \lambda)(L_t + N_t),$$

which, imposing the equilibrium condition $r_t^B = r_t^M$, simplifies to the following condition:

$$(1 + r_t^B)[(1 - \alpha)L_t + N_t - E_t] \leq (1 - \lambda)(L_t + N_t).$$

A.4 Law of motion of a bank's equity

TBC.

A.5 Derivation of Resource Constraint

TBC.

A.6 Portfolio credit risk

It is assumed that individual banks face limits in fully diversifying their loan portfolio and that loan defaults in the portfolio of bank j are correlated according to the *single risk factor* model of Vasicek (2002), in which the failure of the loan i from bank j is driven by the realization of a latent random variable:

$$\xi_{ijt+1} = -\Phi^{-1}(p) + \sqrt{\rho} z_{jt+1} + \sqrt{1-\rho}\varepsilon_{it+1}, \tag{21}$$

where $\Phi(\cdot)$ denotes the cdf of a standard normal random variable and $\Phi^{-1}(\cdot)$ its inverse, z_{jt+1} is a bank-idiosyncratic risk factor that affects all projects in bank's j portfolio, ε_{it+1} is a project-idiosyncratic risk factor that only affects the loan i, and $\rho \in [0,1]$ determines the extent of correlation in loan failures. It is assumed that z_{jt+1} and ε_{it+1} are standard normal random variables, independently distributed from each other, as well as across time, banks, and loans.

The loan i fails when $\xi_{ijt+1} < 0$. The deterministic term $-\Phi^{-1}(p)$ in (21) ensures that the unconditional probability of failure of project i satisfies:

$$\Pr(\xi_{ijt+1} < 0) = \Pr\left[\sqrt{\rho} z_{jt+1} + \sqrt{1-\rho}\varepsilon_{it+1} < \Phi^{-1}(p)\right] = \Phi\left[\Phi^{-1}(p)\right] = p. \tag{22}$$

Notice that for $\rho = 0$ the bank-idiosyncratic risk factor does not play any role and loan failures are statistically independent, while for $\rho = 1$ the entrepreneur-idiosyncratic risk factor does not play any role and loan failures are perfectly correlated within each bank. By the law of large numbers, the failure rate ω_{jt+1} (the fraction of loans within a bank's portfolio that fail) for a given realization of the bank-idiosyncratic risk factor z_{jt+1} coincides with the probability of failure of a (representative) project i conditional on z_{jt+1}; that is,

$$\begin{aligned}\omega_{jt+1} =&\xi(z_{jt+1}) = \Pr\left(-\Phi^{-1}(p) + \sqrt{\rho} z_{jt+1} + \sqrt{1-\rho}\varepsilon_{it+1} < 0 | z_{jt+1}\right)\\ =&\Phi\left(\frac{\Phi^{-1}(p) - \sqrt{\rho} z_{jt+1}}{\sqrt{1-\rho}}\right).\end{aligned} \tag{23}$$

From here it follows that the cdf of the loans' failure rate is

$$\begin{aligned}F(\omega_{jt+1}) =&\Pr\left[\xi(z_{jt+1}) \leq \omega_{jt+1}\right] = \Pr\left[z_{jt+1} \geq \xi^{-1}(\omega_{jt+1})\right]\\ =&\Phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(\omega_{jt+1}) - \Phi^{-1}(p)}{\sqrt{\rho}}\right).\end{aligned} \tag{24}$$

A.7 Proofs

We start with the problem of the fixed-rate bank. First we will assume, and verify later, that, in the absence of idiosyncratic risk, the regulatory constraint is never binding (and, thus, the bank never fails). In that case, the problem of the bank is:

$$\max_{\{N_t, M_t, D_t, B_t\}} \sum_{t=0}^{\infty} \beta^{t+1} (1-\chi)^t \chi E_{t+1}, \tag{25}$$

subject to

$$L_{t+1} = (1-p)(1-\delta)(L_t + N_t), \tag{26}$$

$$E_{t+1} = E_t + (1-\tau)\Pi_{t+1}, \tag{27}$$

$$r^L_{t+1} = \frac{r^L_t L_t + r^N_t N_t}{L_t + N_t}, \tag{28}$$

$$\begin{aligned}\Pi_{t+1} = &(1-p)\left(r^L_t L_t + r^N_t N_t\right) + r^M_t M_t - r^D_t D_t - r^B_t B_t\\ &- \lambda p(L_t + N_t) - f\left(N_t / L_t\right) L_t,\end{aligned} \tag{29}$$

$$L_t + N_t + M_t = D_t + B_t + E_t, \tag{30}$$

$$D_t \leq \alpha L_t, \tag{31}$$

$$M_t \geq \theta(B_t + D_t). \tag{32}$$

Assuming the deposit constraint (31) and the liquidity requirement (32) are always binding, the problem can be simplified. The choice variables D_t, M_t, and B_t can be expressed as functions of the single choice variable for new loans, N_t, and the state variables L_t and E_t.

The bank's problem is reduced to:

$$\max_{\{N_t\}} \sum_{t=0}^{\infty} \beta^{t+1}(1-\chi)^t \chi E_{t+1}, \tag{33}$$

subject to the laws of motion:

$$L_{t+1} = (1-p)(1-\delta)(L_t + N_t), \tag{34}$$

$$E_{t+1} = E_t + (1-\tau)\Pi_{t+1}, \tag{35}$$

$$r^L_{t+1} = \frac{r^L_t L_t + r^N_t N_t}{L_t + N_t}, \tag{36}$$

where bank profits, Π_{t+1}, are given by:

$$\begin{aligned} \Pi_{t+1} = (1-p)\left(r^L_t L_t + r^N_t N_t\right) + r^M_t \left[\frac{\theta}{1-\theta}(L_t + N_t - E_t)\right] \\ - r^D_t(\alpha L_t) - r^B_t \left[\frac{(1-\alpha(1-\theta))L_t + N_t - E_t}{1-\theta}\right] \\ - \lambda p(L_t + N_t) - f\left(N_t/L_t\right) L_t. \end{aligned} \tag{37}$$

We can now iterate forward the law of motions of the state variables:

Stock of loans L_t. To find the expression for L_t as a function of L_0 and the sequence of new loans $\{N_s\}_{s=0}^{t-1}$, we can solve the law of motion for loans by forward iteration. The law of motion for L_t is given by:

$$L_{t+1} = (1-p)(1-\delta)(L_t + N_t).$$

Let's define a constant $\varrho = (1-p)(1-\delta)$. The equation becomes $L_{t+1} = \varrho(L_t + N_t)$. Then, for any time t:

$$L_t = \varrho^t L_0 + \varrho^t N_0 + \varrho^{t-1} N_1 + \cdots + \varrho N_{t-1}.$$

This can be written more compactly using summation notation:

$$L_t = \varrho^t L_0 + \sum_{s=0}^{t-1} \varrho^{t-s} N_s.$$

Average loan rate r_t^L. To find the expression for r_t^L, we start with its law of motion:

$$r_{t+1}^L = \frac{r_t^L L_t + r_t^N N_t}{L_t + N_t}.$$

This equation states that the average interest rate on the loan portfolio next period, r_{t+1}^L, is the weighted average of the rate on existing loans, r_t^L, and the rate on new loans, r_t^N.

We can rearrange the equation to better understand the dynamics of the total interest income from loans. Let's define the total interest income at the beginning of period t as $I_t = r_t^L L_t$. From the law of motion for r_{t+1}^L:

$$r_{t+1}^L (L_t + N_t) = r_t^L L_t + r_t^N N_t.$$

We know from the law of motion for loans that $L_{t+1} = (1-p)(1-\delta)(L_t + N_t)$. Let $\varrho = (1-p)(1-\delta)$. Then $L_t + N_t = L_{t+1}/\varrho$. Substituting this into the rearranged equation gives:

$$\begin{aligned} r_{t+1}^L \frac{L_{t+1}}{\varrho} &= r_t^L L_t + r_t^N N_t, \\ r_{t+1}^L L_{t+1} &= \varrho(r_t^L L_t + r_t^N N_t). \end{aligned}$$

This gives us a law of motion for the total interest income, $I_{t+1} = \varrho(I_t + r_t^N N_t)$. We can solve this by forward iteration, similar to how we solved for L_t:

$$\begin{aligned} I_1 &= \varrho(I_0 + r_0^N N_0) = \varrho(r_0^L L_0 + r_0^N N_0), \\ I_2 &= \varrho(I_1 + r_1^N N_1) = \varrho^2(r_0^L L_0 + r_0^N N_0) + \varrho r_1^N N_1, \\ &\vdots \\ I_t = r_t^L L_t &= \varrho^t r_0^L L_0 + \sum_{s=0}^{t-1} \varrho^{t-s} r_s^N N_s. \end{aligned}$$

To find the expression for r_t^L, we simply divide the total interest income, $r_t^L L_t$, by the total loan stock, L_t. Using the expression for L_t from the previous step:

$$L_t = \varrho^t L_0 + \sum_{s=0}^{t-1} \varrho^{t-s} N_s,$$

we get:

$$r_t^L = \frac{\varrho^t r_0^L L_0 + \sum_{s=0}^{t-1} \varrho^{t-s} r_s^N N_s}{\varrho^t L_0 + \sum_{s=0}^{t-1} \varrho^{t-s} N_s}.$$

This expression shows that r_t^L is a weighted average of the interest rates on the initial loan stock and all new loans issued up to time $t-1$, where the weights are determined by the surviving principal amounts of those loans.

Equity E_t. The expression for bank equity E_t is derived by solving its law of motion, which is a linear first-order recurrence relation. The final expression is a function of the initial states (E_0, L_0, r_0^L), the history of the bank's choices for new loans $(\{N_s\}_{s=0}^{t-1})$, and the given path of exogenous interest rates.

The law of motion for bank equity is given by:

$$E_{t+1} = E_t + (1-\tau)\Pi_{t+1}.$$

The profit function Π_{t+1} depends linearly on the current equity stock E_t. We can rewrite the profit function from the problem description to isolate the terms involving E_t:

$$\Pi_{t+1} = \Upsilon_t + E_t \left(\frac{r_t^B - r_t^M \theta}{1-\theta} \right),$$

where

$$\begin{aligned} \Upsilon_t = (1-p)\left(r_t^L L_t + r_t^N N_t\right) + r_t^M \left[\frac{\theta}{1-\theta}(L_t + N_t) \right] \\ - r_t^D(\alpha L_t) - r_t^B \left[\frac{(1-\alpha(1-\theta))L_t + N_t}{1-\theta} \right] \\ - \lambda p(L_t + N_t) - f(N_t/L_t)\, L_t. \end{aligned} \tag{38}$$

Substituting this into the law of motion for equity gives:

$$E_{t+1} = E_t + (1-\tau)\left[\Upsilon_t + E_t \left(\frac{r_t^B - r_t^M \theta}{1-\theta} \right) \right].$$

Rearranging this equation yields a standard linear recurrence relation of the form

$E_{t+1} = \Psi_t E_t + \Phi_t$, where:

$$\Psi_t = 1 + (1-\tau)\left(\frac{r_t^B - r_t^M \theta}{1-\theta}\right),$$

$$\Phi_t = (1-\tau)\Upsilon_t.$$

This type of equation can be solved by forward iteration. Given an initial value E_0, the solution at time t is:

$$E_t = \left(\prod_{s=0}^{t-1} \Psi_s\right) E_0 + \sum_{k=0}^{t-1} \left(\prod_{s=k+1}^{t-1} \Psi_s\right) \Phi_k. \tag{39}$$

This formula holds with the convention that an empty product is equal to one (i.e., $\prod_{s=t}^{t-1} \Psi_s = 1$). To complete the expression, we write out Φ_k in terms of the model's fundamental variables by substituting the expressions for L_k and $r_k^L L_k$ derived in the previous steps. Let $\varrho = (1-p)(1-\delta)$.

The additive term Φ_k is:

$$\Phi_k = (1-\tau)\Big\{(1-p)(r_k^L L_k + r_k^N N_k) + \frac{r_k^M \theta}{1-\theta}(L_k + N_k) - r_k^D \alpha L_k - \frac{r_k^B\left[(1-\alpha(1-\theta))L_k + N_k\right]}{1-\theta} - \lambda p (L_k + N_k) - f(N_k/L_k) L_k\Big\}.$$

Substituting $L_k = \varrho^k L_0 + \sum_{j=0}^{k-1} \varrho^{k-j} N_j$ and $r_k^L L_k = \varrho^k r_0^L L_0 + \sum_{j=0}^{k-1} \varrho^{k-j} r_j^N N_j$ everywhere, including inside the function $f(\cdot)$, we get:

$$\Phi_k = (1-\tau)\Bigg\{(1-p)\left(\varrho^k r_0^L L_0 + \sum_{j=0}^{k-1} \varrho^{k-j} r_j^N N_j + r_k^N N_k\right) + N_k \left[\frac{r_k^M \theta - r_k^B}{1-\theta} - \lambda p\right] + \left(\varrho^k L_0 + \sum_{j=0}^{k-1} \varrho^{k-j} N_j\right)\Bigg[\frac{r_k^M \theta - r_k^B(1-\alpha(1-\theta))}{1-\theta} - r_k^D \alpha - \lambda p - f\left(\frac{N_k}{\varrho^k L_0 + \sum_{j=0}^{k-1} \varrho^{k-j} N_j}\right)\Bigg]\Bigg\}.$$

The final expression for E_t is given by equation (39) where Ψ_k and Φ_k are defined as above.

To find the optimal N_0, we now take the derivative of the objective function with respect to N_0 and set it to zero. This gives the first-order condition (FOC):

$$\sum_{t=0}^{\infty} \beta^{t+1}(1-\chi)^t \chi \frac{\partial E_{t+1}}{\partial N_0} = 0.$$

Since β and χ are non-zero constants, we can simplify this to:

$$\sum_{t=0}^{\infty} \beta^{t+1}(1-\chi)^t \frac{\partial E_{t+1}}{\partial N_0} = 0.$$

The core of the problem is to find the derivative of equity at all future dates, $\frac{\partial E_{t+1}}{\partial N_0}$, with respect to the choice of new loans today.

Deriving the impact of N_0 on future equity. From the expression for E_{t+1}, and noting that E_0 and the interest rates in Ψ_s are independent of N_0, the derivative is:

$$\frac{\partial E_{t+1}}{\partial N_0} = \sum_{k=0}^{t} \left(\prod_{s=k+1}^{t} \Psi_s \right) \frac{\partial \Phi_k}{\partial N_0}.$$

Substituting this back into the FOC and changing the order of summation gives:

$$\sum_{k=0}^{\infty} \frac{\partial \Phi_k}{\partial N_0} \left(\sum_{t=k}^{\infty} \beta^{t+1}(1-\chi)^t \prod_{s=k+1}^{t} \Psi_s \right) = 0.$$

Let's define the term in the parenthesis as S_k, which represents the stochastic discount factor for profits generated at time k:

$$S_k = \sum_{t=k}^{\infty} \beta^{t+1}(1-\chi)^t \left(\prod_{s=k+1}^{t} \Psi_s \right).$$

The FOC can now be written more compactly as:

$$\sum_{k=0}^{\infty} S_k \frac{\partial \Phi_k}{\partial N_0} = 0.$$

This can be split into the immediate impact at $k = 0$ and the impact on all future periods $k \geq 1$:

$$S_0 \frac{\partial \Phi_0}{\partial N_0} + \sum_{k=1}^{\infty} S_k \frac{\partial \Phi_k}{\partial N_0} = 0.$$

Calculating the derivatives of Φ_k. We now need to calculate how Φ_k changes with N_0. The derivatives with respect to N_0 for any $k \geq 1$ are:

$$\frac{\partial L_k}{\partial N_0} = \varrho^k \quad \text{and} \quad \frac{\partial (r_k^L L_k)}{\partial N_0} = \varrho^k r_0^N.$$

Case 1: The immediate impact ($k = 0$). Φ_0 is a function of the state variables at $t = 0$ (L_0, E_0, r_0^L) and the choice N_0. Differentiating Φ_0 with respect to N_0 yields:

$$\frac{\partial \Phi_0}{\partial N_0} = (1-\tau)\left[(1-p)r_0^N + \frac{r_0^M\theta - r_0^B}{1-\theta} - \lambda p - f'\left(\frac{N_0}{L_0}\right)\right].$$

This term represents the marginal profit from new loans in the first period, including the marginal adjustment cost $f'(N_0/L_0)$.

Case 2: The future impact ($k \geq 1$). For any period $k \geq 1$, Φ_k depends on N_0 indirectly through its effect on the future stock of loans L_k and the future interest income $r_k^L L_k$. The derivative is:

$$\frac{\partial \Phi_k}{\partial N_0} = (1-\tau)\Big\{(1-p)\frac{\partial (r_k^L L_k)}{\partial N_0} + \left[\frac{r_k^M\theta - r_k^B(1-\alpha(1-\theta))}{1-\theta} - r_k^D\alpha - \lambda p\right]\frac{\partial L_k}{\partial N_0} - \frac{\partial}{\partial N_0}\big(f(N_k/L_k)L_k\big)\Big\}.$$

Using the chain rule for the adjustment cost term:

$$\frac{\partial}{\partial N_0}\big(f(N_k/L_k)L_k\big) = \left[f(N_k/L_k) - f'(N_k/L_k)\frac{N_k}{L_k}\right]\frac{\partial L_k}{\partial N_0}.$$

Substituting the derivatives of L_k and $r_k^L L_k$:

$$\frac{\partial \Phi_k}{\partial N_0} = (1-\tau)\varrho^k\left\{(1-p)r_0^N + \frac{r_k^M\theta - r_k^B(1-\alpha(1-\theta))}{1-\theta} - r_k^D\alpha - \lambda p - \left[f\left(\frac{N_k}{L_k}\right) - f'\left(\frac{N_k}{L_k}\right)\frac{N_k}{L_k}\right]\right\}.$$

This expression captures how an additional unit of new loans at time 0 affects the bank's profits at a future time k. The effect comes from the additional loans surviving on the balance sheet, generating revenue and incurring funding costs.

The final expression for optimal N_0. Substituting the derivatives of Φ_0 and Φ_k back into the first-order condition $S_0 \frac{\partial \Phi_0}{\partial N_0} + \sum_{k=1}^{\infty} S_k \frac{\partial \Phi_k}{\partial N_0} = 0$, and solving for the marginal cost term $f'(N_0/L_0)$, we obtain the final expression that characterizes the optimal choice of N_0:

$$
\begin{aligned}
f'\left(\frac{N_0}{L_0}\right) &= (1-p) r_0^N + \frac{r_0^M \theta - r_0^B}{1-\theta} - \lambda p \\
&+ \frac{1}{S_0} \sum_{k=1}^{\infty} S_k \varrho^k \Bigg\{ (1-p) r_0^N + \frac{r_k^M \theta - r_k^B (1-\alpha(1-\theta))}{1-\theta} - r_k^D \alpha - \lambda p \\
&- \left[f\left(\frac{N_k}{\varrho^k L_0 + \sum_{s=0}^{k-1} \varrho^{k-s} N_s}\right) - f'\left(\frac{N_k}{\varrho^k L_0 + \sum_{s=0}^{k-1} \varrho^{k-s} N_s}\right)\left(\frac{N_k}{\varrho^k L_0 + \sum_{s=0}^{k-1} \varrho^{k-s} N_s}\right) \right] \Bigg\},
\end{aligned}
\tag{40}
$$

where:

$$
\begin{aligned}
\varrho &= (1-p)(1-\delta), \\
S_k &= \sum_{t=k}^{\infty} \beta^{t+1} (1-\chi)^t \left(\prod_{s=k+1}^{t} \left[1 + (1-\tau) \left(\frac{r_s^B - r_s^M \theta}{1-\theta} \right) \right] \right).
\end{aligned}
$$

This equation is the Euler equation for the bank's problem. It states that the marginal cost of issuing new loans today, $f'(N_0/L_0)$, must equal the marginal benefit. The marginal benefit consists of the immediate net return on new loans (the first line) plus the discounted sum of all future net returns generated by the surviving portion of these new loans (the summation term).

We can proceed in a similar way to obtain the expression that characterizes the optimal choice of N_0 for the variable-rate bank:

$$
\begin{aligned}
f'\left(\frac{N_0}{L_0}\right) &= (1-p)(s_0^N + r_0^M) + \frac{r_0^M \theta - r_0^B}{1-\theta} - \lambda p \\
&+ \frac{1}{S_0} \sum_{k=1}^{\infty} S_k \varrho^k \Bigg\{ (1-p)(s_0^N + r_k^M) + \frac{r_k^M \theta - r_k^B (1-\alpha(1-\theta))}{1-\theta} - r_k^D \alpha - \lambda p \\
&- \left[f\left(\frac{N_k}{\varrho^k L_0 + \sum_{s=0}^{k-1} \varrho^{k-s} N_s}\right) - f'\left(\frac{N_k}{\varrho^k L_0 + \sum_{s=0}^{k-1} \varrho^{k-s} N_s}\right)\left(\frac{N_k}{\varrho^k L_0 + \sum_{s=0}^{k-1} \varrho^{k-s} N_s}\right) \right] \Bigg\}.
\end{aligned}
\tag{41}
$$

In the fixed-rate economy, the equilibrium is characterized by a combination of new loans, N_0, and an interest rate on these new loans, r_0^N, that simultaneously satisfies the bank's loan supply condition (40) and the borrower's loan demand condition:

$$a(N_0) = \sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1} \left(A - r_0^N\right). \tag{42}$$

Let's define the present value factor from the demand equation as $K \equiv \sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1}$. We can solve the demand equation for r_0^N:

$$r_0^N = A - \frac{a(N_0)}{K} \tag{43}$$

Substituting this expression for r_0^N into the supply equation (40) yields a single equation that determines the equilibrium value of N_0 in the fixed-rate economy.

Similarly, the equilibrium in the variable-rate economy is characterized by a combination of new loans, N_0, and an spreads on these new loans, s_0^N, that simultaneously satisfies the bank's loan supply condition (41) and the borrower's loan demand condition:

$$a(N_0) = \sum_{k=1}^{\infty} \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1} \left[A - \left(r_{0+k-1}^M + s_0^N\right)\right]. \tag{44}$$

We can solve the demand equation for s_0^N:

$$s_0^N = A - \frac{a(N_0) + \sum_{k=1}^{\infty} Z_k r_{k-1}^M}{K} \tag{45}$$

where $Z_k \equiv \beta^k (1-p)^k (1-\delta)^{k-1} (1-\tilde{\chi})^{k-1}$. Substituting this expression for s_0^N into the supply equation (41) yields the equilibrium condition for N_0 in the variable-rate economy.

To prove that N_0 is the same in both economies, we must show that the final equilibrium condition for N_0 is identical in both cases. From the FR supply equation (40), we can write:

$$\mathscr{F}(N_0, N_k) = (1-p) r_0^N \left(S_0 + \sum_{k=1}^{\infty} S_k \varrho^k\right) \tag{46}$$

where $\mathscr{F}(\cdot)$ is a function containing all other terms, which are common to both supply equations (i.e., f', funding costs, and adjustment cost terms). From the VR supply equation (41), we can similarly write:

$$\mathscr{F}(N_0, N_k) = (1-p)s_0^N\left(S_0 + \sum_{k=1}^{\infty} S_k\varrho^k\right) + (1-p)\left(S_0 r_0^M + \sum_{k=1}^{\infty} S_k\varrho^k r_k^M\right) \tag{47}$$

By equating the right-hand sides of (46) and (47), we find the relationship between r_0^N s_0^N that must hold on the supply side for a given N_0:

$$(r_0^N - s_0^N)\left(S_0 + \sum_{k=1}^{\infty} S_k\varrho^k\right) = S_0 r_0^M + \sum_{k=1}^{\infty} S_k\varrho^k r_k^M \tag{48}$$

Now, let's establish the relationship on the demand side. For the same level of N_0, the value to the borrower, $a(N_0)$, must be the same. Equating the right-hand sides of the two demand equations (42) and (44) gives:

$$\sum_{k=1}^{\infty} Z_k(A - r_0^N) = \sum_{k=1}^{\infty} Z_k(A - (r_{k-1}^M + s_0^N)) \tag{49}$$

This simplifies to:

$$r_0^N K = s_0^N K + \sum_{k=1}^{\infty} Z_k r_{k-1}^M \implies r_0^N - s_0^N = \frac{\sum_{k=1}^{\infty} Z_k r_{k-1}^M}{K} \tag{50}$$

This equation shows the relationship between the fixed rate and the variable-rate spread that makes the borrower indifferent between the two contracts. Substituting the demand-side relationship (50) into the supply-side relationship (48) gives:

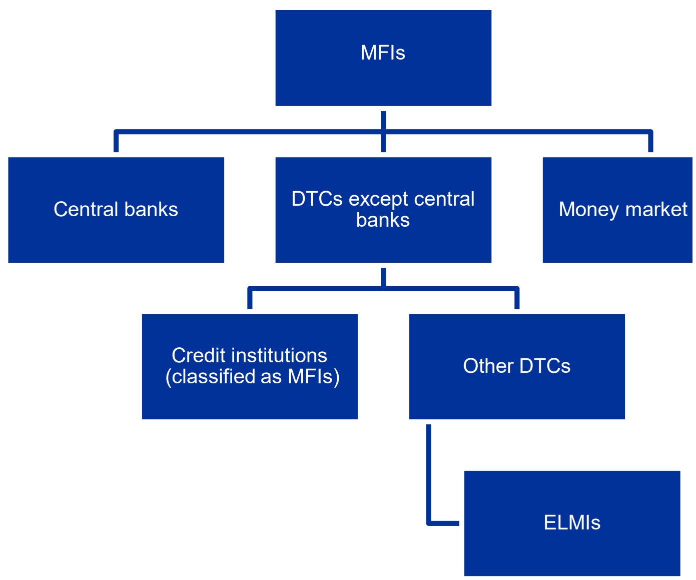
$$\left(\frac{\sum_{k=1}^{\infty} Z_k r_{k-1}^M}{K}\right)\left(S_0 + \sum_{k=1}^{\infty} S_k\varrho^k\right) = S_0 r_0^M + \sum_{k=1}^{\infty} S_k\varrho^k r_k^M \tag{51}$$

B. Data Appendix

B.1 Consolidated banks balance sheet: Data sources

This section explains how we map the Consolidated Balance Sheet of the Euro Area MFIs (excluding the Eurosystem) to the banks' balance sheet in the model.

Figure 12: Components of the MFIs sector



Note: DTC stands for deposit-taking corporation. ELMI stands for electronic money institution.

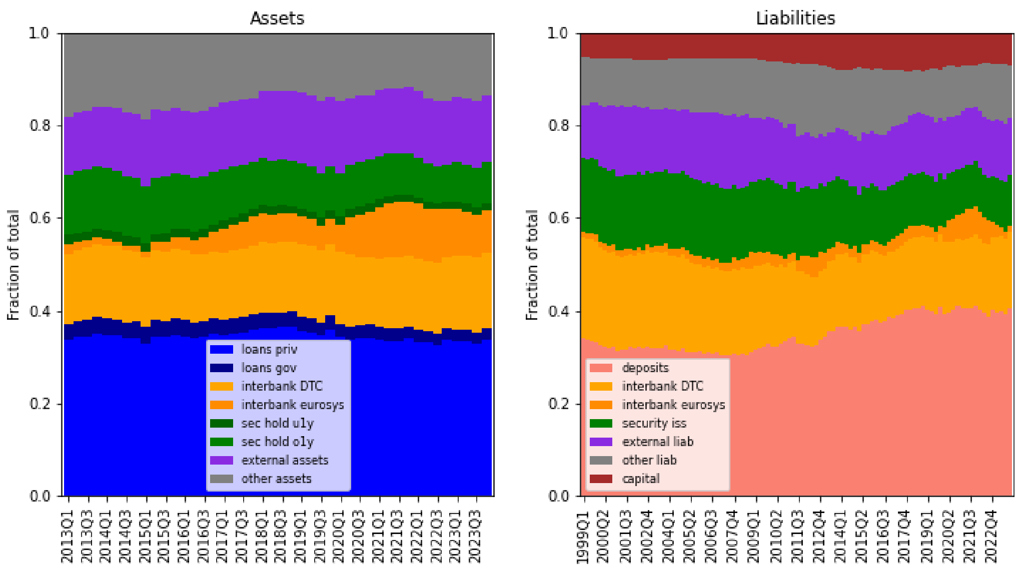
The main source is the Statistical Data Warehouse (SDW) of the ECB. We use monthly or quarterly data subject to availability and transform the series to quarterly frequency. The period of analysis starts corresponds to 01/1999 - 01/2024. Datasets:

- Consolidated balance sheet of the MFIs (excluding the Eurosystem). https://data.ecb.europa.eu/publications/money-credit-and-banking/3031821
- MFI holdings of securities breakdown by maturity and types: Debt securities, equity, and non-MMF investment fund shares. https://data.ecb.europa.eu/publications/money-credit-and-banking/3031889
- Sectoral breakdown of MFI loans vis-à-vis the private sector. https://data.ecb.europa.eu/publications/money-credit-and-banking/3031822

B.2 Euro Area MFIs Balance Sheet

This section summarizes the salient features of the aggregated balance sheet of monetary financial institutions (MFIs) operating in the euro area, excluding the Eurosystem.[23] These MFIs include deposit-taking institutions (banks), and money market funds (MMFs).

Figure 13: MFIs Consolidated Balance Sheet in the Euro Area, 2013-2023



Source: ECB SDW. Aggregated Balance Sheet of Euro Area Monetary Financial Institutions (MFIs) excluding the Eurosystem. MFIs are comprised of deposit-taking corporations, money market funds, and central banks.

An inspection of the asset side of Monetary and Financial Institutions (MFIs) in the euro area from 1999 to 2023, in Figure 13, shows that their asset composition has been remarkably stable. On average, the lending portfolio to households, firms, and the government accounts for 62% of assets. Interbank loans—which include repurchase agreements (repos), securities lending, and similar operations with other MFIs and national central banks—account for about 15% of assets. Security holdings, both short and long-term, account for the remaining 23%.[24] On the liabilities side, most liabilities

[23]The Eurosystem includes the European Central Bank (ECB) and the national central banks of the countries of the euro area.

[24]We assign external assets and other assets proportionally to the loans and short-term security holdings

(60%) are deposits and interbank deposits (17%). The remaining liabilities are securities (16 %) and capital (7%).[25] See the breakdown below in the Table 4.

Table 4: MFIs Balance Sheet Composition (2013–2023)

Assets		**Liabilities**	
Loans	0.62	Deposits	0.63
Interbank loans	0.15	Interbank deposits	0.15
Short-term security holdings	0.12	Security issuance	0.14
long-term security holdings	0.11	Capital	0.08

Source: ECB Statistical Data Warehouse. Aggregated Balance Sheet of Euro Area MFIs, excluding the Eurosystem. Time series averages across periods. Loans: include loans to the private sector, loans to government, a fraction (85%) of external assets (i.e. operations with non-euro area residents) and other assets. Interbank loans: includes interbank loans with other DTCs. Short-term security holdings: include security holdings with a maturity of less than a 1 year plus interbank operations with NCBs (repos and security lending). Long-term security holdings: include security holdings with a maturity greater than 1 year. Deposits: include retail deposits of different maturities, external liabilities with non-euro area residents, and other liabilities. Interbank deposits refer to interbank deposits with other DTCs. Security Issuance includes the issuance of short and long-term securities plus interbank operations with NCBs.

B.3 Distribution of Capital Ratios

Table 5 reports the cross-sectional average CET1 capital ratios and capital buffers for euro area banks for the centered distribution grouped from 2013 to 2020. For each bank in the sample, we calculate the capital buffer as the difference between its CET1 ratio and the applicable Combined Buffer Requirement (CBR) in each quarter.

The CBR is defined as the sum of the Capital Conservation Buffer (CCoB), the Countercyclical Capital Buffer (CCyB), and the maximum of the following institution-specific components: the Systemic Risk Buffer (SRB), the Global Systemically Important Institution (G-SII) buffer, and the Other Systemically Important Institution (O-SII) buffer.

The third column presents CET1 ratios and capital buffer estimates for Supervised Banks as of 2021:Q4. These estimates incorporate Pillar 2 requirements for CET1 capital

categories. External assets are holdings of cash in currencies other than the euro, holdings of securities issued by non-residents of the euro area, and loans to non-residents of the euro area (including banks). For statistical purposes, these items are included indistinguishably in MFIs' external assets without identifying them separately.

[25] Notice that this aggregate measure of capital and reserves does not coincide with the regulatory capital that we present in Appendix B.3, which is the Core Equity Tier 1 (CET1) capital expressed as a percentage of risk-weighted assets.

in addition to the combined buffer requirements. As expected, the average CET1 capital buffer is slightly lower once Pillar 2 requirements are included. Nonetheless, the overall distribution retains a similar shape and statistical properties.

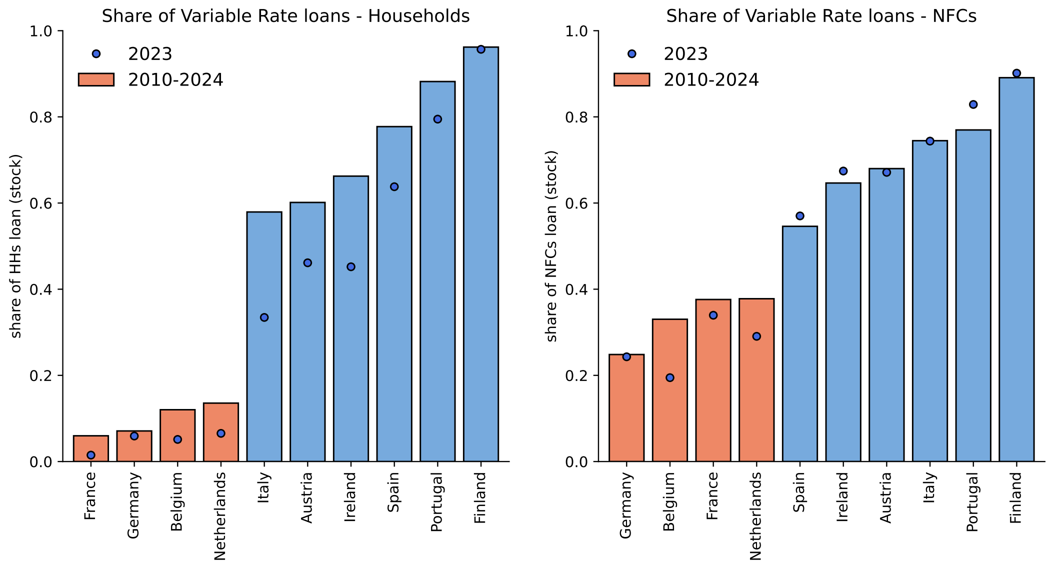
Table 5: Average capital ratios for Euroarea banks

	All banks	Large	Supervised
CET 1 capital ratio	15.62	13.23	14.45
CET 1 management buffer ratio	7.97	6.16	5.12

Note: All numbers are in percentage points. The first two columns correspond to the cross-sectional means of the centered distribution grouped from 2013 to 2020. *All banks* refers to all euro area banks in our sample, approximately 70 per quarter. *Large banks* refer to banks with total assets larger than 100 billion euros. *Supervised banks* refer to 64 banks supervised by the European Banking Authority (EBA) in 2021.Q4. *Sources:* Regulatory requirements (GSII, OSI, SRB) are obtained from the European Systemic Risk board (ESRB). Data for the Pillar 2 requirements of CET1 capital from ECB supervisory data. Bank-level data for CET 1 ratios and Total Risk Weighted Assets from *S&P* Global Pro.

B.4 Loan Rate Fixation Patterns

Figure 14: Composition of lending stocks by interest rate fixation period.



Authors elaboration. Data sources: ECB Statistical Data Warehouse. The left panel presents the share of the stock of aggregate lending to households (including mortgage loans, consumer loans, and other loans) issued at variable rates. The right panel presents the share of stock of aggregate lending to non-financial corporations issued at variable rates. The bars display the average for 2010Q1-2024Q1. Orange bars corresponds to our classification of fixed-rate countries and blue bars to variable-rates. Blue circles depict the average for the year 2023.

B.5 Estimating Local Projections

We estimate Local Projections a là Jordà (2005) and Jordà et al. (2015). As it is standard in the literature, we instrument the first differences in the deposit facility rate (DFR) with a measure of monetary surprises. Our instrument is the monetary policy component from Jarociński and Karadi (2020). We built a balanced panel for ten largest euro are countries (Austria, Belgium, Germany, Finland, France, Italy, Ireland, Netherlands, Portugal, and Spain) using data on lending rates, deposit rates, among others, from 2000 to 2023. For these estimations, we aggregate the data to quarterly frequency.

We classify countries as variable-raters (VR) if their share of variable-rate lending is above 50%. VR countries are Spain, Portugal, Italy, Finland, Ireland, and Austria. Fixed-raters (FR) are Germany, France, Belgium, and the Netherlands.

Prices. For interest rates, we estimate the following local projection specification:

$$r_{c,t+h} = \alpha_{c,h} + \beta_{1h}\varepsilon_t^{MP} + \beta_{2h}\left[\varepsilon_t^{MP} \times I_c^{FR}\right] + \Gamma_h X_{c,t} + e_{c,t+h} \tag{52}$$

where $r_{c,t+h}$ denotes the variable of interest (lending rates, deposit rates, NIM) at time t, and horizon h ranging from 0 to 16 quarters. The variable ε_t^{MP} denotes the monetary policy shock at time t. I_c^{FR} is a dummy variable that takes the value of one if country belongs to the FR category.

$X_{c,t}$ represents the set of controls. As it is common in the literature, we include the first lag of the dependent variable and the first lag of the deposit facility rate. We also use the contemporaneous and the first lag of inflation and the quarterly growth rate of the industrial production index. As well as the first lag of the yield on a BBB corporate bond index for the euroarea, and the first lag of the yield on the one-year German government debt bond since these variables have been found relevant for the euro area (Jarociński and Karadi (2020)).

Quantities. In a similar fashion, our econometric specification for the volume of lending:

$$\log Y_{c,t+h} = \alpha_{c,h} + \beta_{1h}\epsilon_t^{MP} + \beta_{2h}\left[\epsilon_t^{MP} \times I_c^{FR}\right] + \Gamma_h X_{c,t} + e_{c,t+h}. \tag{53}$$

For these IRFs, we directly use the monetary surprises (ϵ_t^{MP}) without instrumenting the DFR since for log-volumes the monetary surprise series yields smoother IRFs. The set of controls is the same used for interest rates but expressing variables in logarithms: first lag of the dependent variable $\log Y_{c,t-1}$. The contemporaneous and the first lag of HICP and the log of the industrial production index. We also include the first lag of the yield on a BBB corporate bond index for the euroarea, and the first lag of the yield on the one-year German government debt bond.

C. Solution Algorithm

Preliminaries. For the solution algorithm, we define a new choice variable

$$k_t^{gap} = 1 - \gamma(l_t + n_t),$$

which captures how slack the capital constraint is. Note that given this definition, the capital constraint simplifies to $k_t^{gap} \geq 0$. Using the choice variable k_t^{gap} and the state l_t, we can then compute n_t as

$$n_t = \frac{1 - \gamma l_t - k_t^{gap}}{\gamma}$$

Given the expression for n_t, all other model variables can be computed using the expressions presented in the main text and the appendix.

The solution algorithm then aims to find a policy function for k_t^{gap} that maximizes the value function such that $k_t^{gap}, n_t, d_t, b_t, m_t \geq 0$. Note that the constraint on d_t is always satisfied since $l_t \geq 0$ and $d_t = \alpha l_t$. If, additionally, $b_t \geq 0$ then the constraint on m_t is also satisfied since $m_t = \theta(b_t + d_t)$. Therefore, we only need to ensure

$$\begin{aligned} n_t &= \frac{1 - \gamma l_t - k_t^{gap}}{\gamma} \geq 0, \\ b_t &\frac{l_t + n_t + m_t + (\theta - 1)d_t - 1}{} \geq 0, \end{aligned}$$

which implies two upper bounds on k_t^{gap}

$$\begin{aligned} 1 - \gamma l_t &\geq k_t^{gap}, \\ 1 - \gamma(1 + (1 - \theta)\alpha l_t) &\geq k_t^{gap}. \end{aligned}$$

The constraints define a maximum feasible value for k_t^{gap}

$$k_t^{gap,max} = \min\{1 - \gamma l_t, 1 - \gamma(1 + (1 - \theta)\alpha l_t)\},$$

In the implementation of Algorithm 1, it is ensured that these constraints are not violated.

Steady State. Solving for the model's steady state comprises two main steps: First, solving for the individual bank policy functions using value function iteration. Second, computing the steady-state bank distribution over equity E_t, leverage l_t, and the average loan rate/spread x_t^L using the method of Young (2010). These steps must then be executed iteratively to find the equilibrium loan rate r^L which clears the loan market.

We discretize the state space for $l_t \in [0, 1/\gamma]$, $x_t^L \in [x^L - \sigma, x^L + \sigma]$, where σ is the size of the MIT shock, and $\log(E_t) \in [\log(0.13), \log(3000)$ using equally spaced grids.[26] Algorithm 1 describes the value function iteration algorithm used to solve the problem of an individual bank which, due to size-independence, only depends on (l_t, x_t^L). Algorithm 2 describes the algorithm to compute the bank distribution. Finally, Algorithm 3 describes the complete algorithm used to solve for the steady state.

Algorithm 1 (Individual Problem)

1. *Make a guess for the capital gap policy function* $k_0^{gap}(l, x^L)$ *and the value function* $V_0(l, x^L)$.

2. *Taking the value function for next period* $V_i(l, x^L)$ *as given, use an optimization routine to find the value of* $k_{i+1}^{gap}(l, x^L)$ *that maximizes todays value* $V_{i+1}(l, x^L)$ *for each grid point* (l, x^L). *Note that we use cubic interpolation to interpolate the value function if* (l_{t+1}, x_{t+1}^L) *are off-grid.*

3. *Optional "Howard Improvement": Keeping the capital gap policy function* $k_{i+1}^{gap}(l, x^L)$, *update the value function by iterating on it* N *times.*

Iterate on steps 2 & 3 until the maximum absolute difference between $V_{i+1}(l, x^L)$ *and* $V_i(l, x^L)$ *is less than a given degree of precision.*

Algorithm 2 (Bank Distribution)

1. *Make a guess for the bank distribution* $H(l, x^L, \log(E))$ *in the form of a matrix* $\mathscr{H}_0$ *where each element corresponds to the mass associated with a particular grid point* $(l, x^L, \log(E))$.

2. *Given the individual policy function and the distribution* $\mathscr{H}_i$, *determine the closest grid points to which banks move in the next period and redistribute mass using the method of Young (2010) yielding* $\mathscr{H}_{i+1}$.

[26]Note that, technically, there is no need for the x^L grid in the steady state, since it stays constant for all banks. However, computing the steady-state policies for $x_t^L \neq x^L$ is required when computing the transition after an MIT shock, such that bank behavior is well-defined when interest rates are back at their steady-state value, even if the average loan rate/spread at individual banks x_t^L has not yet converged back to the steady state.

Iterate on steps 2 until the maximum absolute difference between $\mathcal{H}_{i+1}$ and $\mathcal{H}_i$ is less than a given degree of precision.

Algorithm 3 (Steady State)

1. *Make an initial guess for the loan rate r^N.*

2. *Solve the individual bank problem as described in Algorithm 1.*

3. *Solve for the bank distribution as described in Algorithm 2.*

4. *Check whether r^N clears the loan market. If the loan market does not clear, update the guess for r^N and go to step 2.*

Transition. We use an algorithm similar to the one described in Boppart et al. (2018) to solve for the transitional dynamics after an MIT shock. The approach is similar in spirit to the steady-state algorithm presented above. However, in this case, we are not trying to find a single value for the loan rate r^L to clear the loan market but a path $\{r_t^N\}_{t=0}^T$ to clear the loan market in each period.

Algorithm 4 (Transition)

1. *Choose a time T at which the economy is assumed to have reached the steady state.*

2. *Guess a path for the loan rate $\{r_t^N\}_{t=0}^T$.*

3. *Solve the value and policy functions backward from $t = T-1, \ldots, 1$ assuming that time T value and policy functions correspond to the ones in the steady state.*[27]

4. *Update the paths for the distribution $\{\mathcal{H}_t(l, x^L, \log(E))\}_{t=0}^T$ by iterating forwards from $t = 1, \ldots, T$ using the updated path of policy functions from the previous step.*

5. *Given the path for the distribution, the policy functions, and the loan demand schedule, compute the implied path for the loan rate.*

6. *Compute the maximum difference between the implied paths for $\{r_t^N\}_{t=0}^T$ and its guess. Stop the algorithm if the maximum difference is less than a given degree of precision.*

[27]This part of the algorithm proceeds analogously to solving for the steady state.

7. *Update the guess* $\{r_t^N\}_{t=0}^T$ *by taking a weighted average of the old guess and the implied paths. Go to step 3.*