Heterogeneous Banks and Transmission of Monetary Policy *

João Pedro Rudge Leite †
University of Rochester

October 30, 2024

[Click here for latest version]

Abstract

This paper analyzes the importance of heterogeneity in banks' funding on the transmission of monetary policy shocks. Banks fund themselves with liabilities that differ in their maturity. For example, deposits are short-maturity liabilities, and certificates of deposit are long-maturity liabilities. Empirically, I find that banks whose liabilities have longer maturity are less responsive to monetary shocks. I interpret this finding using a heterogeneous-banks macroeconomic model with endogenous default and funding choices. Funding decisions are primarily influenced by credit risk shocks and constraints on debt financing. Long-term liabilities enable cash flow smoothing but are more costly to issue. Using this framework, I assess the aggregate implications of monetary shocks and provide quantitative evidence that the effect of a monetary policy depends on the distribution of banks' funding structure, which varies over time and depends on the interest level.

*I am grateful to Yan Bai for her guidance and support. This project benefited from numerous conversations with George Alessandria, Matias Moretti, Gaston Chaumont, Rafael Guntin, and Mark Bils. I thank the workshop participants at the University of Rochester for their comments and suggestions.

†Department of Economics, University of Rochester. E-mail jrudgele@ur.rochester.edu

1. Introduction

The financial crisis of 2007-2008 has raised questions about our understanding of banks' role in the economy, especially on how they transmit aggregate shocks; see, for example, Coimbra and Rey (2024); Goldstein et al. (2024). In particular, understanding the underlying mechanism of monetary policy transmission through banks is crucial to assessing its magnitude (Kashyap and Stein, 1995, 2000; Drechsler et al., 2017; Wang et al., 2022). While existing literature has extensively recognized banks' central role in transmitting monetary policy, much of the focus has been on their asset compositions and market structures. By shifting attention to the liability side —specifically, the funding structure of U.S. commercial banks— I provide novel evidence that bank funding maturity has significant implications for monetary policy transmission, both empirically and quantitatively.

In this paper, I examine how banks' funding structure, particularly their maturity, influences monetary policy transmission. Empirically, I find evidence that the maturity of banks' liabilities matters for the heterogeneous transmission of monetary policy. Banks with shorter liability maturity are more responsive to changes in monetary policy, as they reduce their lending more than banks with longer liability maturity. To assess the aggregate implications of bank funding and, thus, their maturity, I develop a novel quantitative macro-finance framework in which banks dynamically choose their funding and monopolistically set their lending rates. From the model's perspective, these funding choices are driven by financial frictions that directly influence how banks manage their cash flows.

First, I provide empirical evidence on the heterogeneous funding structure of banks. For this, I construct a panel of banks' maturity using U.S. commercial banks' Call Reports data. The literature usually calls non-reservable borrowing any liability that is not a deposit. [1] Around 40% of banks' funding is from non-reservable liabilities, and these funds are different from deposits in three ways: first, as the name implies, they are not subject to reserve requirements; second, they are much longer-term contracts than deposits; third, a majority of them is not FDIC insured.[2] [3] I document that, on average, U.S. commercial banks'

[1]The Call Reports define reservable borrowing, such as savings and checking accounts, as having zero maturity.

[2]See Figure A.1 in the Appendix.

[3]Although the quantitative literature focuses on these reserve requirements as frictions, I abstract from them, as since 2008, there are interest payments on these reserves, diminishing their importance.

non-reservable liabilities have a maturity of around 13 months, which banking regulation categorizes as long-term liabilities. I also document that due to their higher maturity and lack of insurance, this funding is more expensive, with an average annual rate of 1.36 percentage points higher than deposits.

Second, I empirically test the heterogeneous response on bank lending with respect to the maturity of their liabilities. The empirical exercise is motivated by the bank-lending channel, where the Federal Reserve can shift loan supply schedules simply by conducting open market operations. In comparison to the empirical findings of Kashyap and Stein (2000) for liquidity and Drechsler et al. (2017) for market power, liabilities' maturity dampens the transmission of monetary policy to lending at the bank level. The intuition for this dampening comes from the fact that these liabilities have their future cash payments locked in before the shock, thus relatively decreasing interest payments afterward and "hedging" against the interest rate change.

I develop a novel macro-finance model to assess the aggregate implications of banks' liability structure with endogenous funding choices. The framework is a general equilibrium model populated by heterogeneous banks using internal resources and issuing liabilities to finance loans. There are four key ingredients to the model. First, banks are not committed to repaying their debt; thus, endogenous default risk limits their borrowing capacity. Second, banks can finance with deposits and non-reservable liabilities, which differ in maturity. The longer maturity of non-reservable funds allows banks to smooth their cash payments over time. Third, imperfect competition among banks allows them to use their market power when setting their lending rate. Lastly, regulatory restrictions on leverage push banks to adopt dynamic funding strategies to ensure adequate cash holdings.

Maturity choice plays a central role in banks' funding decisions due to their inability to freely raise funds. In my model, this funding constraint can arise either exogenously, through regulatory requirements, or endogenously, driven by banks' default decisions. In both cases, maintaining stable cash flows becomes essential to ensure liquidity and reduce the probability of default.

Because short-term liabilities, such as deposits, are rolled over each period, banks facing funding constraints are more vulnerable to states with low liquidity. To mitigate this risk, constrained banks tend to favor non-reservable, long-term debt. By extending the maturity of their liabilities, banks effectively hedge against idiosyncratic liquidity shocks, ensuring smoother cash flows over time. Consequently, long-term debt serves as a key tool for managing liquidity risk, allowing banks to operate under tighter financial constraints while minimizing the likelihood of default.

The model is calibrated to capture key features of banks' behavior, including their markup, leverage, funding structure, and borrowing rate spreads. The model generates the rich heterogeneity in bank funding choices observed in the data, particularly with respect to the maturity of liabilities and the reliance on non-reservable borrowing. Notably, the model effectively explains two key empirical correlations that were not explicitly targeted during its calibration, both of which are crucial in the literature on banking frictions. First, it reproduces the positive correlation between leverage and non-reservable liabilities, aligning with the findings of Hahm et al. (2013) and Barattieri et al. (2021) regarding non-core liabilities. [4] Second, the model accounts for the observed positive relationship between loan losses and non-core funding, consistent with the results of Correia et al. (2023). These untargeted correlations highlight the model's capability to capture the interactions between banks' funding decisions and financial risks.

To explore the effects of monetary policy on lending and interest rates, I simulate the model's response to a 25-basis-point (1% annual) increase in the risk-free rate. The model successfully captures the empirical dynamics of lending and its rates following such policy shocks, yielding a semi-elasticity of loans to lending rates of -1.98 and an imperfect pass-through to lending rates of 0.84.

Beyond matching the aggregate responses, the model replicates the heterogeneous response of banks with different debt maturities, aligning with my empirical findings. Banks with longer-maturity debt are typically more financially constrained. Crucially, these banks experience a substantial decline in the present value of their outstanding liabilities as future interest payments are locked in. This "hedging" effect of long-term debt against interest rate shocks increases their equity, thereby relaxing their funding constraints. The relaxation of these constraints more than offsets the rise in funding costs, enabling banks with a higher share of long-term debt to expand their lending in response to the monetary policy shock. Since

[4] Non-reservable liabilities encompass non-core liabilities, with the only distinction being that non-core liabilities exclude small time deposits.

funding decisions are linked to interest rates (see, for example, Supera (2021)), they become essential to examine the impact of monetary policy at various interest rate levels.

To quantify the aggregate implications of balance sheet constraints, I perform a counterfactual experiment using the model. In this scenario, I remove banks' outstanding debt from their balance sheets, offsetting this by reducing their cash on hand by an equivalent amount. Essentially, the analysis focuses solely on banks' leverage, disregarding the impact of their outstanding debt when responding to a monetary shock. My results show that, in the counterfactual scenario, the decline in lending is 43% larger than the benchmark case. This highlights the critical role that a decrease in the present value of banks' debt plays in easing their funding constraints, enabling them to sustain higher lending levels in response to a monetary policy shock.

To illustrate the importance of accounting for banks' funding structures when evaluating regulatory changes, I analyze the effects of tighter capital requirements in the model. Under the benchmark scenario, such requirements lead to higher lending rates, reduced aggregate lending and leverage, and a significant reduction in bank failure rates. However, these effects are considerably weaker when banks are restricted to funding themselves exclusively through deposits. This demonstrates that the broader funding structure, beyond just deposits, plays a crucial role in determining the impact of regulatory changes on banking outcomes.

In summary, this paper highlights the critical role of banks' funding structures, particularly the maturity of their liabilities, in shaping their responses to monetary policy. By incorporating balance sheet constraints and heterogeneity in funding choices, the model not only replicates key empirical patterns but also provides new insights into the transmission of monetary policy through the banking sector. These findings emphasize the importance of considering the full range of banks' funding sources when designing monetary policy.

Related Literature

This paper provides an empirical and quantitative analysis of the role of banks' funding in transmitting monetary policy. The choice of funding, particularly its maturity, is endogenously determined by the frictions affecting banks, such as regulations, limited commitment, and imperfect competition. It thereby contributes to four strands of literature.

First, it adds to the vast literature on the interaction of banks and interest rates (Bernanke and Blinder, 1992; Van den Heuvel et al., 2002; Jiménez et al., 2014; Drechsler et al., 2017, 2021; Wang et al., 2022). While existing empirical evidence supports the link between monetary policy and bank lending, the traditional arguments for this transmission often focus on regulatory constraints such as bank reserves and capital requirements (Bernanke and Blinder, 1988; Kashyap and Stein, 1995). In Wang et al. (2022), they propose a structural estimation of the quantitative impact of banks' market power on monetary policy transmission. Building on their framework, I extend their model by adding heterogeneous banks with endogenous default decisions and characterizing non-reservable liabilities as long-term debt according to the data. In contrast to their setup, the stock of outstanding non-reservable liabilities is crucial to understanding the aggregate impact of monetary policy, not just because they are unsecured but because they "hedge" banks against interest rate risk.

Second, this paper contributes to the literature on financial frictions and the transmission of aggregate shocks. Beginning with the seminal work of Kiyotaki and Moore (1997) and Bernanke et al. (1999), the financial accelerator literature has emphasized the role of balance sheet constraints in amplifying shocks. Over the past decade, in response to the Great Recession, this framework has been extended to the financial sector (Gertler and Karadi, 2011; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Gertler and Kiyotaki, 2015). More recently, some papers have explored the heterogeneous responses of the financial sector to aggregate shocks (Coimbra and Rey, 2024; Goldstein et al., 2024). While my model shares their focus on the aggregate transmission of shocks, the key difference lies in the source of heterogeneity. Rather than arising from differences in leverage, as in their models, my model's heterogeneity stems from the composition of banks' debt, particularly the maturity structure.

More specifically, this paper relates to the subset of the literature that develops general equilibrium models with default risk (see, for example, Arellano et al. (2019); Gertler and Kiyotaki (2015); Ottonello and Winberry (2020); Amador and Bianchi (2024)). In these models, the absence of a commitment to repay debt constrains the amount of leverage firms or banks can take on. This leads to the amplification of aggregate shocks due to their inability to issue debt to smooth these shocks. My model shares this feature, as banks are subject to leverage constraints. However, it adds a novel dimension by emphasizing that banks' limited commitment also compels them to maintain liquidity buffers to absorb adverse shocks. In my model, these buffers are largely maintained through the issuance of long-term debt, highlighting that the composition of debt, rather than just its level, is central to understanding bank liquidity management.

Third, this paper contributes to the growing literature on the aggregate implications of bank regulation, particularly regarding capital requirements and financial stability (see, for example, Corbae and D'Erasmo (2021); Begenau and Landvoigt (2022)). They explore how bank regulation enhances financial stability by influencing banks' risk-taking and credit-creation activities. In Corbae and D'Erasmo (2021), although capital regulation enhances stability, it generates higher market concentration. While in Begenau and Landvoigt (2022), the change in capital regulation has a positive spillover on shadow banking markets by reducing their risk-taking, as it reduces the subsidies to commercial banks coming from deposit insurance.

Building on this literature, my contribution introduces endogenous default decisions and funding choices shaped by the frictions banks face. Unlike models that primarily emphasize deposits, my approach highlights the importance of banks' cash-flow smoothing motives and how these interact with capital regulation to shape their balance sheet decisions. This framework provides a more nuanced understanding of how regulatory changes are transmitted through the banking sector, with implications for both financial stability and credit markets.

Finally, this paper contributes to the literature on default risk and maturity choice (see, for example, Chatterjee and Eyigungor (2012); Bocola (2016)). In the sovereign default literature, the choice of debt maturity arises from a trade-off between rollover risk and debt dilution under limited commitment (Sánchez et al., 2018). In the context of firm dynamics, papers such as Diamond and He (2014); Crouzet et al. (2016); Crouzet (2017); Dangl and Zechner (2021) examine how firms manage their maturity structure.

In my model, the fact that deposits are rolled over each period makes banks' exposure to rollover risks a central factor in their decision to issue long-term debt. This model also contributes to the broader literature on how debt maturity shapes the transmission of aggregate shocks, building on examples such as Gomes et al. (2016) for inflation shocks and Jungherr et al. (2024) for monetary shocks. By focusing on banks' maturity choices, my model highlights the importance of debt composition in understanding the propagation of shocks through the banking sector.

2. Empirical Analysis

I document that banks with longer maturity liabilities are less responsive to changes in monetary policy.

This section is structured as follows: First, I show that borrowing interest rates are higher for non-reservable liabilities, which primarily consist of time deposits and other borrowed money. Second, I demonstrate that the average maturity of non-reservable liabilities exceeds one year, classifying them as long-term debt. The longer maturity of non-reservable liabilities may explain their higher interest rates, as they are not FDIC-insured and, under default risk, longer maturity contracts become a more expensive source of funding. Finally, I show that bank lending responds heterogeneously based on the maturity structure of their liabilities.

Data Description and Main Definitions

I use U.S. bank-level data from the Uniform Bank Performance Report (UBPR), which covers all FDIC-insured commercial banks, savings banks, and savings associations. The dataset includes quarterly Call Reports from each insured bank, standardizing several bank-specific ratios. [5] I rely on the UBPR for the consistency of its definitions, using quarterly data from December 2002 to March 2023.

Deposits, comprising checking and savings accounts, are subject to reserve requirements and are considered a traditional and reliable source of bank funding. Federal Deposit Insurance Corporation (2024) identifies these liabilities as stable and cost-effective, thanks to FDIC insurance and the nature of depositors.

Non-reservable liabilities include time deposits, other borrowed money, fed funds purchases, and repo operations. [6] These liabilities, except for small time deposits, are not FDIC-insured,

[5] For more details on the FFIEC's UBPR and the construction of these variables, see `https://cdr.ffiec.gov/public/DownloadUBPRUserGuide.aspx`.

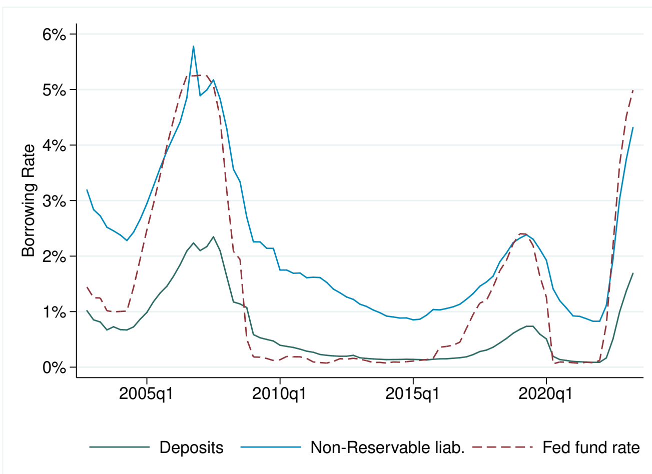
[6] Time deposits mainly include certificates of deposit and brokered deposits. Other borrowed money refers to bank funding sources apart from deposits, such as Federal Home Loan Bank advances and inter-bank loans that are not overnight. See FFIEC 031 and FFIEC 041 forms, Schedule RC-M item 5 for details.

making them more exposed to interest and credit risks, which contributes to their higher funding costs (Martin et al., 2018).

Aggregate Time Series of Banks Funding

To demonstrate that borrowing interest rates are higher for non-reservable liabilities, Figure 1 compares the average borrowing rates for deposits and non-reservable liabilities from 2003 to 2023. The average borrowing rate is calculated by dividing total interest expenses by the quarterly average stock of each liability type. For reference, the figure also includes the Fed funds rate.

Figure 1: Borrowing Rates

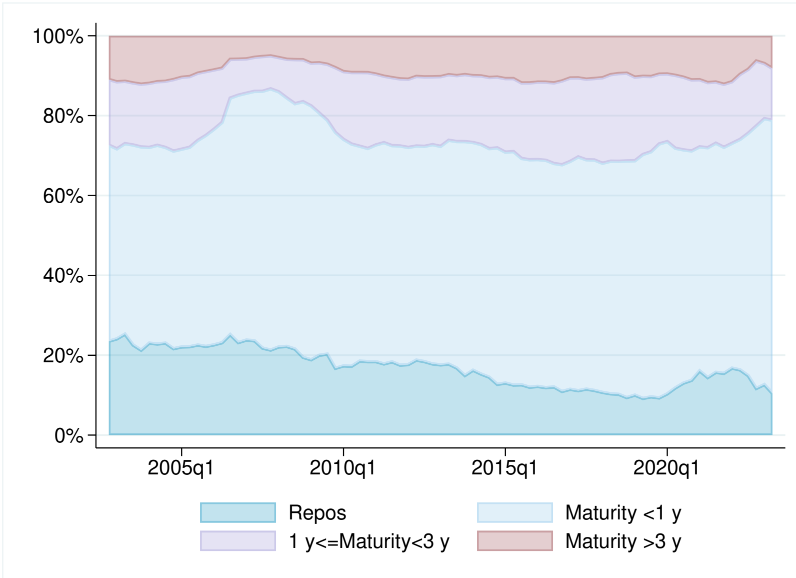


Notes: The figure plots the average borrowing rate by different liabilities and the Fed fund rate. The average borrowing rate is measured by the interest expense divided by the quarterly average stock of the liability. The data is from the U.S. Call Reports covering 2003 to 2023 at the quarterly frequency.

The figure indicates that interest rates for non-reservable liabilities are significantly higher than those for deposits, averaging 1.35% over the sample period. In Figure A.2 in the appendix, I further break down the borrowing rates for deposits and non-reservable liabilities, showing that the increased funding costs for non-reservable liabilities are largely due to time deposits and other borrowed money.

I analyze the maturity composition of non-reservable liabilities to show that the higher costs may stem from their uninsured status and longer maturities. Kashyap and Stein (1995) associates the higher borrowing costs of non-reservable liabilities with the uninsured status of large time deposits. In addition to default risk, longer maturity and banks' inability to commit to limiting future borrowing make long-term debt more expensive due to debt dilution. [7]

Figure 2: Non-Reservable Borrowing by Maturity



Notes: The figure plots bank liabilities' composition by the maturity bracket. The data is from the U.S. Call Reports covering 2003 to 2023 at the quarterly frequency.

Figure 2 illustrates the significant difference in the maturity profiles of deposits and non-reservable liabilities. For the period, non-reservable funds with maturities within one year make up roughly 50% of non-reservable borrowing, with 25% maturing in more than one year —a stark contrast to the shorter maturity profile of deposits. Figure A.3 in the appendix provides a more detailed breakdown of non-reservable liabilities by their components. The high proportion of long-term funding within non-reservable liabilities is driven by the prevalence of time deposits and other borrowed money, both of which typically feature longer maturities.

The longer maturity of non-reservable liabilities helps explain the observed difference in borrowing costs between deposits and non-reservable liabilities. Moreover, due to their

[7] Debt dilution is a well-known issue in the sovereign debt literature; see Chatterjee and Eyigungor (2012).

limited commitment, banks are incentivized to smooth their cash flows over time. This leads them to demand more long-term non-reservable funding to hedge against balance sheet shocks. In particular, when banks face tighter liquidity, they prefer issuing long-term debt to increase leverage and manage risks, as explained later on.

Commercial Banks Maturity

Having demonstrated that non-reservable borrowing predominantly consists of long-term liabilities, I now turn to calculating the average maturity of banks' balance sheets. This calculation reinforces the idea that non-reservable liabilities serve as a significant source of long-term funding for banks.

To do this, I utilize data from the Call Reports, which provide detailed information on banks' interest rate risk exposure. Banks are required to report the maturity distribution of their liabilities across several predefined brackets: liabilities maturing within one year, between one and three years, and beyond three years.

By assigning a midpoint to each bracket, I calculate the weighted average maturity of liabilities for each bank. Specifically, I use the following formula to capture the overall maturity profile:

$$M_{j,t} = \sum_{b \in \mathcal{B}} \frac{m_b \text{debt}_{b,j,t}}{\text{debt}_{j,t}} \tag{1}$$

where m_b denotes the mid-point of bracket b, $\text{debt}_{b,j,t}$ is the amount of debt in bracket b of bank j at time t, and $\text{debt}_{j,t}$ is the total debt of bank j and time t. This methodology is based on the approach proposed by English et al. (2018), with a slight modification: my series is reported in yearly terms, and for the upper brackets, I add a year to the lower bound of the bracket. [8]

I follow a similar procedure to estimate the average maturity of non-reservable liabilities, which allows for a direct comparison between overall bank liabilities and the subset of non-reservable liabilities.

Table 1 presents summary statistics for the maturities of both overall liabilities and non-reservable liabilities. A key takeaway is that while the average maturity of total bank li-

[8] For further details on the methodology, refer to English et al. (2018).

abilities is less than a year, non-reservable liabilities have a significantly longer maturity, averaging around 1.1 years (or approximately 13 months). This is a crucial distinction, as I will refer to liabilities with a maturity above one year as "long-term", consistent with banking regulations

Table 1: Summary Statistics Maturity

	mean	std dev	p5	p25	p50	p75	p95
Maturity of Liabilities	0.45	0.25	0.11	0.26	0.41	0.60	0.95
Maturity of Non-reservable	1.10	0.39	0.57	0.81	1.04	1.63	1.82

Notes: Moments for maturity are estimated using the full sample. Maturity construction follows English et al. (2018) but at yearly terms. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency.

How does funding maturity affect bank lending?

In this subsection, I investigate how the maturity structure of banks' liabilities influences their lending response to monetary policy shocks. Specifically, I study the heterogeneous pass-through of monetary policy via banks' funding decisions.

To estimate the dynamics of this heterogeneous response, I apply a Jordà (2005)-style local projections approach, specified as:

$$y_{j,t+1+h} - y_t = \alpha_{j,h} + \alpha_{t,h} + \beta_h (M_{j,t-1} - \bar{M}_j)\varepsilon_t^m + \Gamma_1 X_{j,t-1} + e_{j,t+h} \tag{2}$$

where $h \geq 0$ is the horizon of the local projection, $\alpha_{j,h}$ and $\alpha_{t,h}$ are bank and time fixed effects, respectively, and $M_{j,t}$ represents the maturity of bank liabilities. The term ε_t^m is the monetary policy shock constructed by Jarociński and Karadi (2020), purged of information shocks by zeroing out movements correlated with stock market responses.

By demeaning $M_{j,t}$ at the bank level, I control for permanent heterogeneity in bank responsiveness, ensuring that my results reflect the within-bank variation in liability maturity over time. This approach, inspired by Ottonello and Winberry (2020), allows me to isolate the effect of monetary policy on lending when banks face higher or lower liability maturity than usual.

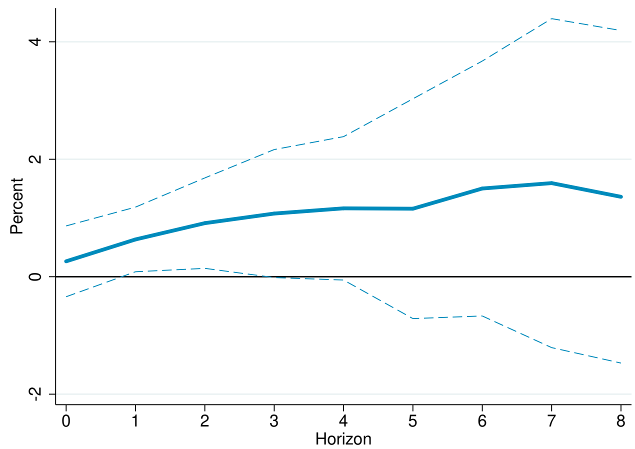
My coefficient of interest β_h captures the interaction effect of liability maturity on the average bank-level response to a monetary policy shock. I normalize the within-bank variation by the sample standard deviation for interpretability. The vector $X_{j,t-1}$ of bank-level controls contains log of total assets, return on assets, the non-reservable share of liabilities, leverage, the share of non-performing loans, the share of short-term investments, and the interacted variable $M_{j,t}$.

If banks exhibit a specific linear response to monetary policy, the typical approach of interacting$M_{j,t-1}$ and ε_t^m might reflect permanent heterogeneity across banks, as discussed in Ottonello and Winberry (2020). By demeaning the maturity variable within banks, my approach isolates the effects of changing liability maturity rather than differences in inherent bank characteristics. While my economic model assumes banks are ex-ante homogeneous (see Section 3), in reality, banks may exhibit ex-ante heterogeneity in their sensitivity to monetary policy. For instance, distinct market risks and differing levels of market power in loan markets can drive these differences in responsiveness.

In sum, demeaning the banks' maturity ensures that the estimated impact reflects how individual banks adjust their lending in response to monetary shocks when they experience atypical liability maturities. This allows for a more precise view of the role of funding maturity in monetary policy transmission.

Figure 3 summarizes the impulse response of loans to a 1% shock in the Fed funds rate over horizon h. The results of the local projection reveal a new finding in the literature regarding the maturity of banks' liabilities and their relationship with monetary policy. I find evidence that banks that fund their operations with more long-term liabilities are relatively less responsive to changes in monetary policy. This increase is around one percentage point for each percentage point of the shock. To put these numbers in perspective, using bank-firm loan data for Spain, Jiménez et al. (2012) and Ivashina et al. (2022) estimate the semi-elasticity of loans to the interbank rates of -1.39 and -1.88, respectively. While for the U.S. credit market, Bassett et al. (2014) estimates a demand elasticity of commercial and industrial loans of around -1.68. Therefore, a relative semi-elasticity that is 1 higher is significant in terms of dampening the transmission of monetary policy.

Figure 3: Heterogeneous Lending Response to Monetary Shock



Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

To check if my results are robust, I re-estimate the local projections under different specifications in Appendix B.3. Although with slight differences, the results are still robust at the 5% significance level. I further check if the maturity of banks' assets or the maturity gap also generates heterogeneous responses to lending with little to no significance. This points to the lesser significance of interest rate risk, which the evidence Drechsler et al. (2021) supports.

3. Model

The empirical evidence suggests a correlation between banks' funding structure and monetary policy transmission. However, it does not provide insight into the underlying mechanism behind these patterns observed in the data. To better understand this evidence, I consider an infinite-horizon equilibrium model of the banking industry with three sectors: entrepreneurs, households, and banks.

In this model, entrepreneurs face a static discrete choice problem when deciding whether to finance a risky project using bank loans. On the other hand, households are competitive and can save through deposits or non-reservable liabilities, which differ in maturity. Banks act as intermediaries between households and entrepreneurs by accepting funds and providing loans. The economy has a unique final good, and all variables are in consumption terms of the final good.

The model's richness relies on the banking sector, as banks face several frictions with different implications for transmitting monetary policy through their financial intermediation. First, imperfect competition in the loan market leads banks to choose their loan rates to maximize profits. Second, banks are subject to government regulation. Capital regulation requires banks to optimize their lending and funding intertemporally to preserve their cash reserves as a buffer against future capital inadequacy. Third, non-reservable liabilities are a costly funding source for banks. The higher cost of non-reservable liabilities is due to two factors: (i) they have longer maturity; (ii) they are more exposed to default risk.

The model borrows elements from Corbae and D'Erasmo (2021), which accounts for the regulatory constraints; Wang et al. (2022), which proposes a dynamic model of the bank's market power; and Ottonello and Winberry (2020) for the endogenous default decisions of banks.

Entrepreneurs

The entrepreneurial sector consists of two-period entrepreneurs who fund themselves through bank loans. Each entrepreneur belongs to a distinct bank pool, and there is no inter-bank competition or mobility. I call this pool the client pool of bank j.

Each pool contains a unit mass of entrepreneurs, and entrepreneurs are denoted $i \in [0, 1]$. Entrepreneurs are risk-neutral agents who maximize their expected profit, conditional on their project return. This assumption of market power is in line with recent empirical evidence that banks' market power affects the pass-through of monetary policy to the supply of loans (see, Scharfstein and Sunderam (2016); Drechsler et al. (2017)).

At period t, entrepreneurs borrow one unit of the final good from the banks to purchase risky projects. The project price is equal to P_t. Thus, the amount of the project purchased with the bank's loan equals

$$k_t^i = \frac{1}{P_t}.$$

The project might return x_t^i unit of dividends per unit of project purchased. x_t^i is the entrepreneur's private information and, thus, not observed by the bank. This implies that banks cannot set different interest rates for their client pool. x_t^i is known at the beginning of each period t.

Suppose this entrepreneur belongs to a client pool j affected by common probability p_{t+1}^j. Then, in the next period, the project returns (per unit of loan):

$$\begin{cases} 1 + x_t^i \text{ with prob } p_{t+1}^j \\ 0 \text{ with prob } 1 - p_{t+1}^j \end{cases} \tag{3}$$

in the successful and unsuccessful states, respectively. The entrepreneur's gross dividend return is $1 + x_t^i$ in the successful state and 0 in the unsuccessful state. The success of an entrepreneur's project, which occurs with probability p_{t+1}^j, is independent and identically distributed across entrepreneurs and captures the pool's not diversifiable risk. [9] After the project return is realized, the project fully depreciates.

In this environment, entrepreneurs within a bank pool j cannot move to another bank to borrow from them. Then, taking the gross lending rate $R_{\ell,t}^j$ as given, the entrepreneurs in that pool will decide whether to finance via bank loans. They must repay $R_{\ell,t}^j$ if they borrow from the bank.

The entrepreneur has limited liability at the project level, so the project return net of interest payment is bounded from below by zero. Table 2 summarizes the return and costs from the entrepreneur's investment problem. Since x_t^i is given for each entrepreneur, their expected payoff decreases on the loan rate $R_{\ell,t}^j$.

Table 2: Entrepreneur's Problem (conditional on investing)

	Receive	Pay	Probability
Success	$(1 + x_t^i)/P_t$	$R_{\ell,t}^j$	p_{t+1}^j
Failure	0	$\min\{0, R_{\ell,t}^j\}$	$1 - p_{t+1}^j$

Entrepreneurs cannot repay their debt fully if their projects fail. In this case, they will default on their loans. From the bank's perspective, these entrepreneurs become delinquent, and the bank realizes losses on that loan.

[9] The characterization of this failure rate is similar to Vasicek (2002), which is used for regulation motives.

Under these conditions, we have that the expected payoff of entrepreneur i, conditional that they borrow from the bank at rate $R^j_{\ell,t}$, is equal to:

$$\pi_t(R^j_{\ell,t}) = E_t\big\{p^j_{t+1}\big[(1/P_t)(1+x^i_t) - R^j_{\ell,t}\big]\big\}.$$

Assuming that if the entrepreneurs do not invest in the asset, their profit equals zero. Then, entrepreneurs maximize the following

$$U^e = \max_{h\in\{0,1\}} h\pi(R^j_{\ell,t}),$$

where h denotes the discrete choice of investing in the asset. Therefore, entrepreneurs invest in the asset if and only if

$$(1/P_t)(1+x^i_t) - R^j_{\ell,t} \geq 0, \tag{4}$$

the return per asset amount is higher than the lending rate.

Loan Demand. Since there is no inter-bank competition or mobility in the credit market, each bank j will face a unique loan demand function. Taking the entrepreneurs' investment decision from Equation 4, and the distribution of x^i, we can describe bank j's loan demand by:

$$\ell^d(R^j_t, P_t) = \text{Prob}\big(x^i_t \geq R^j_{\ell,t}P_t - 1\big). \tag{5}$$

This loan demand is characterized by the marginal entrepreneur, whose idiosyncratic dividend equals $x^\star = R^j_{\ell,t}P_t - 1$. Since x^i is independently distributed and follows a known distribution, the loan demand function is characterized by the complementary cumulative distribution function (ccdf) of x at the point $x^\star$. Due to this, the loan demand is decreasing in the asset price P_t and in the loan rate $R^j_{\ell,t}$. Intuitively, as asset prices increase or loan rates decrease, it becomes less attractive for entrepreneurs to invest independently of their idiosyncratic dividend.

Households

The economy features a representative household whose lifetime utility is given by

$$E_0\left[\sum_{t=0}^{\infty}\beta^t \log(C_t)\right].$$

where β is the discount factor and C_t is their consumption. The household owns all banks in the economy. I study the perfect foresight transition paths with respect to aggregate states, so the stochastic discount factor and the real interest rate are linked through the Euler equation for savings, $\Lambda_{t+1} = \frac{1}{R_{f,t}}$, where $R_{f,t}$ is the risk-free rate set by the monetary authority.

The household saves by buying deposits, D, and non-reservable liabilities, B, from banks. They receive dividends from the banks and are taxed lump-sum. They are also endowed with y units of goods each period. They fund new banks by transferring some equity, denoted by $\bar{n}$, so they can start their operation.

Banks

There is a constant unit measure of banks owned by the household. Banks are indexed by $j \in [0, 1]$. A manager operates at most one bank and decides entry, default, loans, and funding. The manager's objective is to maximize the lifetime stream of dividend payments div_t using the manager's discount factor

$$E_0\left[\sum_{t=0}^{\infty}\sigma^t \Lambda_t div_t\right],$$

where Λ_t represents the household stochastic discount factor at time t, and $\sigma \in (0, 1]$ is the myopia parameter from the bank manager. This assumption introduces the possibility of agency problems through managerial myopia when $\sigma < 1$ along the lines of Corbae and D'Erasmo (2021). To obtain a well-defined distribution of banks, I need a condition that guarantees $\sigma\Lambda_{t+1}R_f < 1$, a standard assumption in incomplete market models, where R_f is the risk-free rate .

Assets: To model the solvency risk of a bank, the first consideration is its assets. Bankers invest in loans with an agreed-upon interest, denoted by $R^j_{\ell,t}$. Let ℓ_{t-1} be the loan amount financed by bank j in the previous period at interest rate $R^j_{\ell,t-1}$. Then, bank j's assets are given by the equation:

$$a^j_t = p^j_t R^j_{\ell,t-1}\ell_{t-1} \tag{6}$$

In the above equation, p^j_t is the mass of repaying loans. Defaulted loans are realized as losses on the bank's balance sheet. The variable $1 - p^j_t$ captures the loan charges-offs. I assume that the process for $\log(p^j_t)$ is persistent and follows a truncated AR(1) process.

Resources. Bankers use their cash-on-hand (n), deposits (d) and non-reservable liabilities (b) to finance new loans $\ell(R^j_{\ell,t}, P_t)$ at interest rate $R^j_{\ell,t}$.

Assuming that non-reservable liabilities have a longer maturity than a period, a fraction λ of its principal is paid back every period while $1-\lambda$ remains outstanding. Debt holders receive a coupon payment of c for the outstanding amount. Deposits are short-term contracts that fully mature every period.

Conditional on their liabilities and loan portfolio, we can determine the bank's cash-on-hand at each period, which is given by:

$$n^j_t = a^j_t\omega^j_t - d^j_t - (\lambda + c)b^j_t - \psi. \tag{7}$$

Here, d^j is the deposit payout inherited from a previous period, $(\lambda + c)b^j_t$ is the payment on maturing non-reservable liabilities plus the coupon, a^j_t is the bank's assets, ω^j_t is an idiosyncratic shock affecting the bank's assets valuation, and ψ is a fix operating cost. [10] I assume this shock is i.i.d. across time and banks, and it follows a log-normal process, $\log(\omega^j_t) \sim N(0, \eta_\omega)$. This valuation shock is a simplified way of capturing the fact that banks have non-performing loans on their balance sheets that have yet to be realized as losses.

At the beginning of the period, the bank's equity is given by their cash-on-hand minus the amount outstanding of debt discounted at present value, i.e.,

$$e^j_t = n^j_t - q^{rf}_{b,t}(1-\lambda)b^j_t, \tag{8}$$

[10] This shock on assets return helps me generate cross-sectional heterogeneity, similar to Ottonello and Winberry (2020). It is also helpful to match the default rates observed in the data.

where $q_{b,t}^{rf}$ denotes the risk-free price of non-reservable liabilities. This assumption implies that when evaluating a bank's equity at book value, its liabilities are also considered at book value rather than at market value. This can create discrepancies between the book value and market value of equity.

Banks use their cash on hand and liabilities to finance new loans, which yields the following resource constraint:

$$div_t^j + \ell^d(R_{\ell,t}^j, P_t) = n_t^j + q_{d,t} d_{t+1}^j + q_{b,t}(b_{t+1}^j - (1-\lambda) b_t^j) \tag{9}$$

Here $\ell^d(R_{\ell,t}^j, P_t)$ is the loan demand of bank j, which comes from the entrepreneur's problem and is described by Equation 5, $b_{t+1}^j - (1-\lambda)b_t^j$ is the net issue of non-reservable liabilities and d_{t+1}^j is the amount of deposits raised. $q_{d,t}$ and $q_{b,t}$ are the pricing of deposits and non-reservable liabilities, respectively, endogenously determined as discussed in the following subsection.

Using the resource constraint 9 and book equity 8, we can determine next period equity by [11]

$$e_{t+1}^j = a_{t+1}^j - \ell^d(R_{\ell,t}^j, P_t) - \psi + e_t^{m,j} - div_t^j + (q_{d,t} - 1)d_{t+1}^j + (q_{b,t} - \lambda - c - (1-\lambda)q_{b,t+1}^{rf})b_{t+1}^j,$$

where $e_t^{m,j} = n_t^j - (1-\lambda)q_{b,t}$ denote the market equity value. This implies that today's market equity value determines tomorrow's book equity value, which is the net revenue on loans minus operating costs and the expenses on liabilities.

A key friction in the model is the assumption that banks are unable to issue equity, which necessitates that dividends must always be non-negative, expressed as:

$$div_t^j \geq 0.$$

This constraint prevents banks from raising equity to substitute deposits or non-reservable liabilities for funding their lending activities. Additionally, it highlights the limited liability of banks, as they have the option to default on their debt, resulting in equity holders losing their entire investment.

[11] Here I am implicitly assuming that valuation shock does not interact with the requirements over capital tomorrow.

The next important ingredient in my model is regulation, namely, capital requirement

$$e^j_{t+1} \geq \kappa a^j_{t+1}. \tag{10}$$

Equation 10 implies that the bank's book equity at the beginning of the next period has to be no smaller than a fraction κ of their total asset. Due to the no-equity investment and the capital constraints, banks will need to smooth their cash-holding to avoid states with low liquidity and, thus, default.

Lastly, I follow Title 12, "Banks and Banking," of the Code of Federal Regulations, which states that proposed dividends cannot exceed a bank's net income and restrict dividends to

$$div^j_t \leq E_t[a^j_{t+1} - \ell^d(R^j_{\ell,t}, P_t)].$$

A similar assumption is made by Corbae and D'Erasmo (2021). In my setup, it guarantees that the value function is bounded and concave.

Insurance, Liquidation, Debt Pricing

Households competitively lend resources to banks at the price schedules $q_d(p_t, r_{l,t}, d_{t+1}, b_{t+1})$ and $q_d(p_t, r_{l,t}, d_{t+1}, b_{t+1})$.

Banks cannot distinguish between the types of debt on which they default. If they default on deposits, they must also default on non-reservable liabilities, and vice versa. The default decision of the banker is denoted by $\delta(p_t, n_t, b_t)$, where (p_t, n_t, b_t) is the bank's state variables.

One of the differences between deposits and non-reservable liabilities is due to the lack of insurance for the latter. To account for the insurance, I assume there is a priority for guaranteeing the repayment of banks' debt holders in case of default, particularly for deposits. [12] The process occurs as follows: whenever a bank defaults, the deposit holders gain control of the bank's assets. In this case, assets are liquidated with a recovery rate given by a parameter $\gamma \in (0, 1)$.

Banks are required to pay insurance premiums to a regulator, net the recovery on the assets. The premium is fair and considers the bank's lending, debt, and default decisions. Conse-

[12] This assumption respects the hierarchy of debt holders according to the FDIC.

quently, we have a net price on deposits. After the liquidation, the remaining assets are transferred lump-sum to the household; thus, there is no welfare loss on default.

Since the household holds these liabilities, they are discounted by Λ_t. Consequently, the price of deposits, net insurance premium, is

$$\begin{aligned} q_d(p_t, R_{\ell,t}, d_{t+1}, b_{t+1}) = E_t\{\Lambda_{t+1}[1 - \delta(p_{t+1}, n_{t+1}, b_{t+1}) \\ + \ \delta(p_{t+1}, n_{t+1}, b_{t+1}) \min(1, \gamma\omega_{t+1}a_{t+1}/d_{t+1})]\} \end{aligned}$$

Similarly, the price of non-reservable liabilities is equal to

$$q_b(p_t, R_{\ell,t}, d_{t+1}, b_{t+1}) = E_t\{\Lambda_{t+1}[1 - \delta(p_{t+1}, n_{t+1}, b_{t+1})][\lambda + c + (1-\lambda)q_{b,t+1}]\}, \tag{11}$$

where $q_{b,t+1}$ is the price next period.

I allow for non-reservable liabilities to be bought back by the banks. In this case, their price is equal to the risk-free price.

Bankers' Recursive Problem

Since the banker's recursive problem is the same across banks, I drop the index j to denote the bank's j problem. The variables (p, n, b) summarize the banker's state space. Bankers lack commitment, as they can default on their debt obligations. Then, the value of the bank's operation is given by:

$$V(p, n, b) = \max_{\delta \in \{0,1\}} (1-\delta)V^c(p, n, b)$$

where δ is the default decision of the bank, $V^c(\cdot)$ is the continuation value of the banking operation, and the value for the banker of the banker defaults equals zero.

The continuation value is associated with the following recursive problem in the run state:

$$
\begin{aligned}
V^c(p,n,b) = \max_{R_\ell, d', b'} \; & div + E[\sigma \Lambda_{t+1} V(p',n',b')] \\
\text{s.t. } & div = n - \ell^d(R_\ell, P) + q_d d' + q_b(b' - (1-\lambda)b) \geq 0 \\
& a' = p' R_\ell \ell^d(R_\ell, P) \\
& e' \geq \kappa a' \\
& e^m = n - q_b(1-\lambda)b \\
& e' = a' - \ell^d(R_\ell, P) - \psi + e^m - div + (q_d - 1)d' + (q_b - \lambda - c - (1-\lambda)q_b^{rf})b' \\
& n' = a'\omega' - d' - (\lambda + c)b' - \psi \\
& div \leq E[a' - \ell^d(R_\ell^j, P)]
\end{aligned}
$$

Exit and Entry

Exit from the market is endogenous, depending on the bank's default decision. The mass of entrant banks μ_e equals the mass of exiting banks in each period. A banker is endowed with $\bar{n}$ initial equity to start the banking operation and zero debt.

Each new bank inherits a previous bank's pool of entrepreneurs, thus maintaining the same distribution of shocks in the economy. This captures that these new banks enter the markets left vacant by an incumbent bank's exit.

Project Producer and Monetary Authority

Project Producer. A representative project producer produces a new aggregate project using a linear technology, where I_t is the amount of final goods used to create the project. Notice that there is a departure from the standard capital producer of Ottonello and Winberry (2020) as there is no aggregate stock of the project in period t as it fully depreciates. They also face some convex adjustment cost given by $F(I_t)$. The project producer solves

$$\max_{I_t} P_t I_t - I_t - F(I_t)$$

where P_t denotes the price of the project.

The first-order condition of the problem is such that

$$P_t = 1 + F'(I_t).$$

Moreover, I assume a variation of the standard function form such that

$$F'(I_t) = \frac{1}{\chi}\left(\frac{L_t}{L_\star} - 1\right)$$

where $L_\star$ is the steady state loan amount. This characterization guarantees that the project price equals one in the steady state.

Monetary Authority. The monetary authority sets the real risk-free interest rate $R_{f,t}$ according to

$$\log(R_{f,t}) = -\log(\beta) + \varepsilon_t^m, \quad \varepsilon_t^m \sim N(0, \eta_m^2), \tag{12}$$

and ε_t^m is the monetary policy shock.

Equilibrium

I define the equilibrium for this economy in the steady state and the transition to an unexpected aggregate shock to interest rate, with perfect foresight on the transition path.

Law of motion of distribution of banks. Before defining the equilibrium, I characterize the law of motion of the distribution of banks in the steady state, with an analogous characterization for the transition path.

Consider the set of optimal policies conditional on the states (p, n, b):

$$R_\ell^\star(p, n, b), d^{\star\prime}(p, n, b), b^{\star\prime}(p, n, b),$$

where $R_\ell^\star(p, n, b)$ is the optimal lending rate, $d^{\star\prime}(p, n, b)$ is the optimal deposit policy, and $b^{\star\prime}(p, n, b)$ is the optimal non-reservable liability policy.

Notice that $R_\ell^\star(p, n, b), d^{\star\prime}(p, n, b), b^{\star\prime}(p, n, b)$ can be empty as banks might not satisfy the non-negative dividend constraint, and, thus, default. If the banker defaults on their debt, a new bank enters this economy with initial equity $\bar{n}$ and no non-reservable liabilities while keeping the same pool of clients, i.e., the same p. In equilibrium, the mass of entering banks equals the mass of defaulting, keeping the mass of banks equal to one over time.

Let μ denote the bank distribution of this economy with respect to (p, n, b). The mass of exiting banks is equal to

$$\mu^e = \int \delta^\star(p, n, b) d\mu(p, n, b),$$

where $\delta^\star$ is the default strategy of the bank.

Consider the following notation for the law of motion of net worth:

$$n'(p', \omega', p, n, b) = n'(p', \omega', R_\ell^\star(p, n, b), d^{\star\prime}(p, n, b), b^{\star\prime}(p, n, b)),$$

which is described in the bank's problem. I denote the indicator function for the next period states as

$$\mathbb{I}(p', \omega', n', b'|p, n, b) = \begin{cases} 1, & \text{if } (p', \omega', n', b') = (p', \omega', n'(p', \omega', p, n, b), b^{\star\prime}(p, n, b)) \\ 0, & \text{otherwise} \end{cases}$$

We can describe the subsequent period distribution of incumbent banks according to:

$$\mu_i'(p', n', b') = \int (1 - \delta^\star(p, n, b))\mathbb{I}(p', \omega', n', b'|p, n, b)G(\omega')F(p' \mid p)d\mu(p, n, b),$$

where $\mathbb{I}$ is an indicator function I described before, $G(\omega')$ and $F(p' \mid p)$ are the transition probabilities of the exogenous states ω and p, respectively. Similarly, the subsequent period distribution of entrant banks evolves according to:

$$\mu_e'(p', n', b') = \int \delta^\star(p, n, b)\mathbb{I}(p', \omega', n', b'|p, \bar{n}, 0)G(\omega')F(p' \mid p)d\mu(p, n, b).$$

Notice that since the new bank inherits the pool of exiting banks, the entrant distribution depends on the shock p. Lastly, this economy's distribution of banks evolve according to:

$$\mu'(p', n', b') = \mu_i'(p', n', b') + \mu_e'(p', n', b').$$

In this economy, a stationary bank distribution is such that:

$$\mu^{\star}(p,n,b)=\mu'(p,n,b)=\mu(p,n,b).$$

The stationary distribution $\mu^{\star}(p,n,b)$ remains unchanged over time, satisfying the equilibrium condition where the inflow and outflow of banks balance out.

Project Market Clearing. The last step before defining the equilibrium is characterizing the market clearing on the project market. Consider a distribution of operating banks $\mu(z,n,b)$. Like before, denote $R_{\ell}^{\star}(z,n,b)$ the lending rate policy conditional on (z,n,b). Denote the loan supply of each bank as $\ell^{s}(p,n,b)=\ell^{d}(R_{\ell}^{\star}(z,n,b),R_{K}^{E})$. Since banks can default, the loan supply mass also accounts for entrant banks. Therefore, we can define the aggregate loan supply by

$$L^{s}=\int[1-\delta^{\star}(p,n,b)]\ell^{s}(p,n,b)d\mu(p,n,b)+\int\delta^{\star}(p,n,b)\ell^{s}(z,\bar{n},0)d\mu(p,n,b),$$

the first term is the loan supply of incumbent banks, and the second is the loan supply of entrant banks.

Finally, the price of the asset today, P_t, must be such that

$$P_tK'=L^{s}, \tag{13}$$

which is the market clearing condition. Notice that since the economy is in a steady state, the price of assets is constant and equal to one.

Definition 1. *A stationary competitive equilibrium is a set of value functions $V(p,n,b)$; decision rules $R_{\ell}(p,n,b),d'(p,n,b),b'(p,n,b)$, measure of banks; debt price schedules $q_d(p,R_{\ell},d',b')$, $q_b(p,R_{\ell},d',b')$; borrowing decision $\ell(R_{\ell}^{j},P)$; and prices P such that*

- *Entrepreneurs maximize their utility, given the interest of their bank R_t^{j}, consistent with their utility function and borrowing decision;*
- *Banks policies for loan rates $R_{\ell}(p,n,b)$, deposits $d'(p,n,b)$, and non-reservable liabilities $d'(p,n,b)$, consistent with their maximization problem;*
- *Household price defaults competitively and optimizes its decision;*

- *The distribution of banks is consistent with their decision rules;*
- *All market clears.*

One of the state variables of interest in the distribution of banks according to their state variables (p, n, b). As previously highlighted during my empirical exercise, banks' lending responses are heterogeneous depending on their share of non-reservable funding. Therefore, according to it, the distribution of banks will have aggregate implications for monetary policy transmission.

4. Model Mechanism

Before delving into the quantitative analysis, I examine the transmission mechanism of monetary policy through banks' liabilities maturity. This is done by looking at the bank's dynamic decisions. The problem is formulated around a bank's choices of three key decision variables: the loan interest rate R_ℓ, deposits d', and non-reservable liabilities b'. I characterize the equilibrium behavior of banks in terms of the three associated first-order conditions.

For simplicity, I focus on two main constraints, the no-equity and capital constraints, while abstracting from any debt dilution effects on future bond prices and the iid shock.

Deposits. The first-order condition with respect to the deposits d' is

$$\left(q_d + \frac{\partial q_d}{\partial d'} d_{t+1} + \frac{\partial q_b}{\partial d'}(b' - (1-\lambda)b)\right)(1 + \upsilon_{\text{div}}) - \upsilon_{\text{cap}} - E_{p'|p}\big[(1 - \delta(p', n', b'))(1 + \upsilon'_{\text{div}} + \upsilon'_{\text{cap}})\sigma\Lambda'\big] = 0 \quad (14)$$

where υ_{div} and υ_{cap} are the Lagrangian multipliers associated with the dividend and capital constraints, respectively.

This condition illustrates the trade-off between the costs and benefits of deposit funding. Deposits expand banks' available resources, thereby relaxing both the resource and dividend constraints. However, they reduce the equity value in the following period, tightening the capital constraint. This effect, captured by $-\upsilon_{\text{cap}}$, can offset the initial relaxation of resources. As the capital constraint tightens, the Lagrange multiplier $-\upsilon_{\text{cap}}$ limits deposit growth. Examining the first-order condition for non-reservable liabilities reveals why banks facing stricter financial constraints favor longer-term debt instruments.

Non-reservable Liabilities. The first-order condition with respect to the non-reservable Liabilities b' is

$$\left(q_b + \frac{\partial q_d}{\partial b'}d' + \frac{\partial q_b}{\partial b'}(b' - (1-\lambda)b)\right)(1+\upsilon_{\text{div}}) - \upsilon_{\text{cap}}\left(c + \lambda + (1-\lambda)q_b^{rf'}\right) \\ - E_{p'|p}\left[(1-\delta(p', n', b'))(1+\upsilon'_{\text{div}} + \upsilon'_{\text{cap}})(c+\lambda+q'_b)\sigma\Lambda'\right] = 0 \quad (15)$$

Like deposits, non-reservable liabilities ease the resource and dividend constraints but have a smaller impact on the capital constraint. This difference arises because non-reservable liabilities aren't entirely rolled over, as shown by $c + \lambda + (1-\lambda)q_b^{rf'} \leq 1$. Consequently, banks with tighter capital constraints are more inclined to finance operations through non-reservable liabilities despite their higher cost.

Loan rate. The first-order condition with respect to the loan rate R_ℓ is

$$\left(-1 + \frac{\partial q_d}{\partial \ell^d(R_\ell, P)}d' + \frac{\partial q_b}{\partial \ell^d(R_\ell, P)}(b' - (1-\lambda)b)\right)(1+\upsilon_{\text{div}}) \\ + \upsilon_{\text{cap}}(1-\kappa)p'_{\text{low}}R_\ell\left(1 + \frac{1}{\frac{\partial \ell^d(R_\ell,P)}{\partial R_\ell}\frac{R_\ell}{\ell^d(R_\ell,P)}}\right) \\ + E_{p'|p}\left[(1-\delta(p', n', b'))(1+\upsilon'_{\text{div}} + \upsilon'_{\text{cap}})\sigma\Lambda' p' R_\ell\left(1 + \frac{1}{\frac{\partial \ell^d(R_\ell,P)}{\partial R_\ell}\frac{R_\ell}{\ell^d(R_\ell,P)}}\right)\right] = 0. \quad (16)$$

here, banks just need to consider the worst-case scenario of credit repayment for the capital requirement to be valid for all other states; thus, explicitly, I consider the collateral constraint in the state p'_{low}.

The first component of the equation captures the tightening of the resource and dividend constraint coming from increasing the bank's lending, netting the benefit on debt pricing. Because banks are monopolistic, whenever setting loan rates, they take into account the effect on their loan demand, as captured by the elasticity $\frac{\partial \ell^d(R_\ell,P)}{\partial R_\ell}\frac{R_\ell}{\ell^d(R_\ell,P)}$. This elasticity also influences capital constraints, as a larger asset base will relax them. Finally, the last term captures the bank's expected marginal revenue along with the associated markup.

To understand the heterogeneous impact of monetary policy on banks, it's essential to identify which banks are more dependent on non-reservable long-term liabilities. The first-order conditions suggest that banks with tighter collateral constraints rely more heavily on such liabilities for funding. When a monetary shock occurs, a portion of this debt—specifically $1 - \lambda$ - remains outstanding. This debt, issued initially at lower rates with fixed coupon payments, loses value even without default risk. Consequently, banks experience a positive equity effect as the market value of their debt obligations declines.

For constrained banks, the combination of holding long-term debt and this equity improvement more than compensates for the rise in funding costs. This dynamic enables these banks to expand their lending in response to the monetary shock.

5. Quantitative Analysis

The model described in Section 3 features heterogeneity across banks and important nonlinearities. All nonlinearities arise from the bank's problem due to the endogenous default decision and the sometimes binding constraints. Due to these nonlinearities, I rely on global methods to solve the model (value function iteration). In the transition dynamics, the aggregate state variables, such as asset prices, depend on the distribution of banks μ, an infinite dimensional object. Therefore, I focus on the transition with perfect foresight, following the approach of Boppart et al. (2018). The reason is that for banks to make their decisions, they just need to know the aggregate price for projects P_t, which depends on the distribution of banks.

Even after reducing the problem to a perfect foresight transition, the model features three individual state variables at the bank level: (p, n, b) and three choice variables (R_ℓ, d', b') and is therefore subject to the curse of dimensionality. [13] The algorithm for solving the model relies on graphics processing units (GPUs) to highly parallelize the solution.

Parameterization

The model calibration involves two steps. Initially, a set of parameters is directly obtained from the data, followed by estimating a second set using the Simulated Method of Moments

[13] In Appendix, I cover how I compute the policies and steady state distribution of banks.

(SMM). As detailed later, the chosen set of moments aims to align with the financial frictions encountered by banks. It's important to note that in the model, one period corresponds to a quarter, meaning that all information presented from this point on is quarterly.

The Uniform Bank Performance Report (UBRP) is my primary source for calibrating the model. I aggregate commercial bank-level data to the Bank Holding Company (BHC) level. [14] Data on bank failures is collected from FDIC.

I first parameterize the stochastic process of loan losses. [15] I obtain the bank-level gross loan losses over total loans and then create a variable equal to one minus the gross losses while removing both time and bank fixed effects. I then estimate the following autoregressive equation: $\log(p_{j,t}) = \mu_p + \rho_p \log(p_{j,t-1}) + u_{j,t}$, with $u_{j,t} \sim N(0, \eta_p^2)$. Once the parameters μ_p, ρ_p, and η_p are estimated, I discretize the process using the method proposed by Tauchen (1986), truncating the value for p in such a way that is never above one.

An essential parameter for the model is the average maturity of non-reservable liabilities. To obtain this, I use the share of non-reservable liabilities with a maturity of less than a year, a combination of time deposits and other borrowed money. For maturities above one year, I use the total liabilities information. [16] I construct the weighted average maturity at the bank level and use the asset-weighted average maturity obtained.

I parametrize the loan demand function by assuming that x_t^i follows a logistic distribution, resulting in the following functional form for the loan demand:

$$l^d(R_{\ell,t}, P_t) = \frac{1}{1 + \exp(\alpha(R_{\ell,t}P_t - 1 + \nu))}, \tag{17}$$

α is the sensitivity of loan demand to interest rate, and ν is the median return on these projects. [17] α and ν are endogenously calibrated, while P_t is endogenously estimated on the transition dynamics.

[14] Note that the matching between commercial banks and the BHC is done using the relationship table from the FFIEC. Additional information about the merger process is provided in the Appendix.

[15] For this part, I utilize the realized gross loan losses, and net loan losses can be negative, which does not align with the model setup.

[16] This approach is not an issue as any other liability with maturity above a year is non-reservable.

[17] This representation of loan demand is similar to the ones in Wang et al. (2022); Jiang (2023), with the difference being the aggregate asset price. A similar functional form for loan demand is obtained if I assume a linear utility function with GED shock.

Intuitively, investing becomes more attractive when the asset returns increase. In turn, this increases the demand for loans, and under this logistic distribution, the demand becomes less sensitive to loan rates for a given interest rate $R_{\ell,t}$. Since aggregate loan supply is directly associated with the asset's price, if the loan supply decreases due to a monetary policy, the loan demand shifts upwards due to the decrease in the asset's price, offsetting the initial drop.

The last five parameters are the aggregate risk-free rate, recovery rate on assets, coupon rate, and capital requirement ratio. Because interest rates have implications for the distribution of non-reservable liabilities, I take the average Fed fund rates between 2002 and 2023, excluding observations where the rate was below 20 basis points per year. I take the recovery rate from the Correia et al. (2023), which finds a recovery for depositors equal to 0.40. The coupon payment is chosen to match a 5-basis-point interest rate spread between deposits and non-reservable liabilities in a risk-free environment. [18] The capital requirement ratio is taken to match the tier 1 capital ratio of 6%. Table 3 presents the externally calibrated parameters.

Table 3: Fixed Parameters

Parameter	Name	Source	Value
$R-1$	Interest Rate	Mean Fed Fund Rates	0.6%
μ_p	Mean of Repayment Share	Mean of Gross Loans Charge-offs	-0.09%
ρ_p	Repayment Share Persistence	AC Gross Loans Charge-offs	0.59
η_p	SD Repayment Share	SD Gross Loans Charge-offs	0.28%
$1/\lambda$	Maturity	Maturity of non-reservable Liab.	4.40
γ	Recovery rate on Assets	Correia et al. (2023)	40%
c	Coupon Payment	Term Premium	0.45%

Notes: Parameters exogenously fixed in the calibration

Targeted and Untargeted Moments

In this subsection, I assess whether the model can accurately approximate the targeted and untargeted moments. I start with the endogenously calibrated parameters in the steady state. I then describe the targeted moments and their relationships with the banks' frictions and present the model fit. Lastly, I present the untargeted moments as external validity of the model.

[18] This choice for the 5-basis point is associated with both the liquidity premium of deposits and their term premium.

Table 4 shows the estimated parameters inside the model. Due to the lack of competition across banks, the parameter dictating the interest rate sensitivity of the loan demand, α, is higher than the one estimated by Wang et al. (2022). The myopia parameter estimated by the model is close to the one in Corbae and D'Erasmo (2021), which generates the high leverage in the banks' balance sheet. Finally, the fixed operating cost corresponds to around 0.2% of average lending in a steady state.

Table 4: Endogenous Parameters

Parameter	Name	Value
α	Interest rate sensitivity	181
ν	Median return of project	2.05%
σ	Manager Myopia	98%
ψ	Fix Operation Cost	0.15%
η_ω	Std of asset shock	1.95%
$\bar{n}$	New bank equity	3%

Notes: Parameters are chosen to match the moments in Table 5.

The moments chosen align with each friction that banks face. For example, as banks operate in imperfectly competitive markets, their lending rate reflects the elasticity of their loan demand. Thus, I estimate the data equivalent to the markup and use its mean and standard deviation as targeted moments.

Also, in the model, an essential factor to consider is the endogenous default decision of banks. Due to the lack of insurance, non-reservable liabilities are exposed to default risk, and as a result, their borrowing rates include default premiums. In contrast, the FDIC insures deposits, so they do not necessarily face the same default risk.

I measure default risk by focusing on the difference between deposits and non-reservable liabilities rates. Additionally, the failure rate of banks is another indicator of default risk.

Lastly, I focus on banks' funding decisions. Banks can fund themselves using retained earnings or debt. I target the average leverage and its standard deviation, as they provide insight into the regulatory constraints that determine how much leverage banks can take A critical aspect of the calibration is the share of non-reservable liabilities over total debt, corresponding to the banks' maturity. I target both the mean and standard deviation of non-reservable

Table 5: Moments

Moment (all in percentage)	Description	Data		Model	
		Mean	SD	Mean	SD
Interest rates (quarterly)					
$E[R_\ell/R_{\text{borrow}} - 1]$	Markup	1.25	0.23	1.42	0.23
$E[q_b^{-1} - q_d^{-1}]$	Spread btwn deposits and non-reservable	0.33		0.23	
Funding					
$E[\frac{q_b b'}{q_b b' + q_d d'}]$	Non-reservable Share of funding	40.77	16.59	34.27	20.67
$E[\frac{q_b b' + q_d d'}{l}]$	Leverage	89.49	2.74	89.91	3.32
Risk					
$E[\delta]$	Default rate	0.14		0.05	

Notes: Moments are estimated using the full sample. $R_{\text{borrow}} = \frac{d' q_d^{-1} + b' q_b^{-1}}{d' + b'}$ is the weighted average borrowing rate. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. See Appendix B.3 for the definition of the variables.

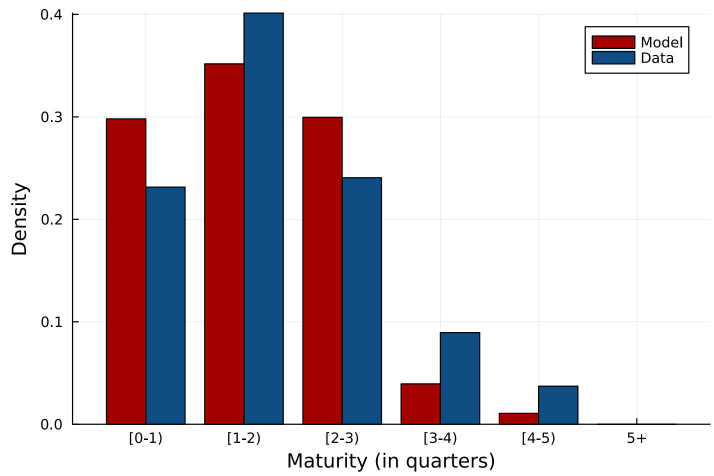
liabilities share.

Table 5 presents the model fit compared to the data moments. Overall, the model does a good job of matching the markup's standard deviation but overestimates its mean. The spread between non-reservable and deposit borrowing rates is higher in the data, around ten basis points. This discrepancy is due to the nine basis point differences in my model's default rate from the data, plus the effect non-reservable buybacks have on the model. The model almost matches the average leverage and its standard deviation. The model matches the share of non-reservable funding and its standard deviation.

Now, I look at the untargeted moments regarding non-reservable funding. First, I check how well my model matches the maturity distribution across banks and time. Figure 4 compares the model implied maturity distribution with the distribution of the panel of commercial banks. The model does an excellent job of matching the distribution of maturities. As explained in Section 2, banks with a higher maturity are the ones to cut their lending less when there is a positive monetary shock. Thus, matching the maturity distribution is crucial to understanding the pass-through of monetary policy through banks.

An established empirical pattern is the positive association between non-reservable liabilities — particularly non-core liabilities — and higher leverage, as documented by Hahm et al. (2013). To verify if my model replicates this relationship, I plot the model-generated correlation between leverage and the log of liability maturity, which serves as a proxy for

Figure 4: Banks' Distribution

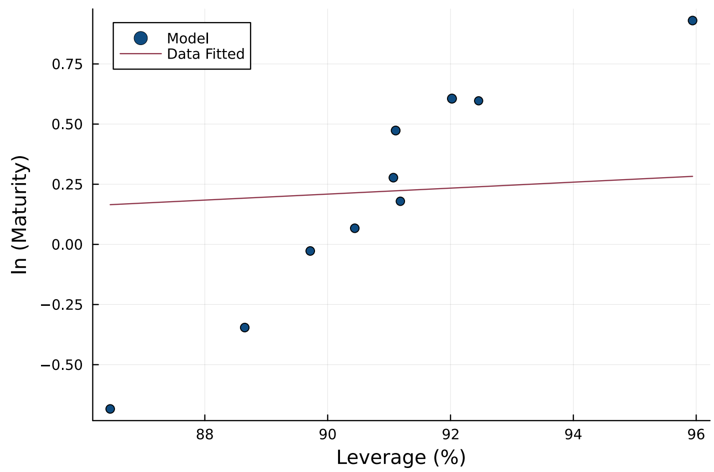


Notes: The figure compares the maturity distribution implied by the model to that for the panel of commercial banks. The data is from the U.S. Call Reports covering 2002-2023, using quarterly data.

non-reservable liabilities. As shown in Figure 5, the model captures this positive correlation between leverage and non-reservable liabilities, although with a four times steeper slope than observed empirically.

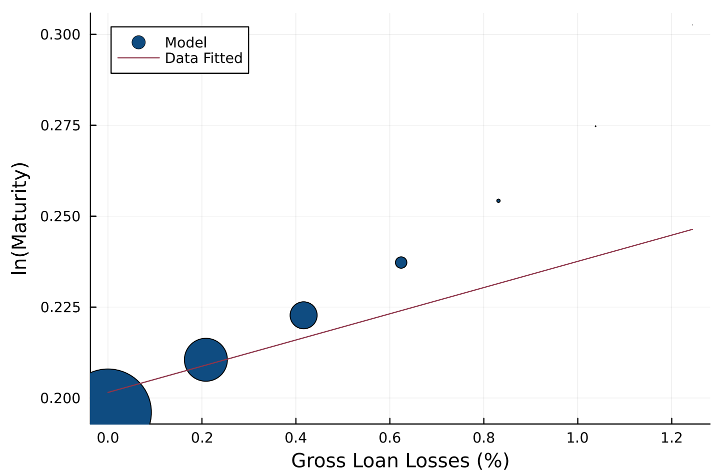
Lastly, I examine the relationship between liability maturity and loan losses. In sovereign debt literature, long-term debt is often argued to serve as a hedge against adverse shocks, and rollover risk. Similarly, from a bank's perspective, the persistence of loan losses suggests that a bank experiencing losses today is likely to face them in the near future. If the hedging rationale applies, banks might respond to potential losses by increasing their reliance on non-reservable funding. Figure 6 shows the model-generated scatter plot between gross loan losses and log maturity, with a linear regression line for comparison with empirical data. The model aligns well with the observed positive correlation, suggesting that long-term debt may indeed serve as a hedge against idiosyncratic risks.

Figure 5: Scatter leverage and maturity



Notes: The figure plots the model-generated log maturity for each binned level of leverage. The slope is obtained by regressing log maturity on leverage, controlling for size, non-performing loans, return on assets, and liquidity, using bank and time-fixed effects. The data is from the U.S. Call Reports covering 2003-2023 at the quarterly frequency. The slope is centered to match the model level. Dot sizes represent the frequency of model generated moment.

Figure 6: Scatter gross loan losses and maturity



Notes: The figure plots the model-generated log maturity for each grid point of gross loan losses. The slope is obtained by regressing log maturity on gross loan losses, controlling for size leverage, return on assets, and liquidity, using bank and time-fixed effects. The data is from the U.S. Call Reports covering 2003-2023 at the quarterly frequency. The slope is centered to match the model level. Dot sizes represent the frequency of model generated moment.

Aggregate Transmission of Monetary Policy

The previous subsection showed that the model successfully replicates key cross-sectional facts about the financing choices of U.S. commercial banks. The model thus provides an appropriate quantitative framework for studying the role of liability maturity in the aggregate and heterogeneous effects of monetary policy. I now quantify the aggregate implications of the monetary policy shock.

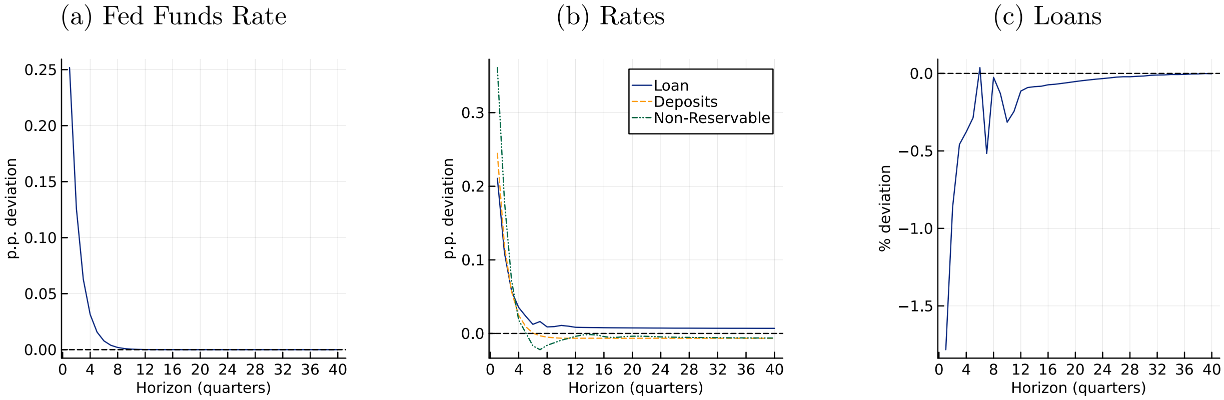
The economy is initially in the steady state and receives an unexpected shock of magnitude 25 basis points on Equation 12. In annual terms, this shock corresponds to an increase of one percentage point in the Fed funds rate. For any subsequent period, the shock follows a deterministic AR(1) process $\varepsilon_t = \rho_\epsilon \varepsilon_{t-1}$, with parameter ρ_ϵ equal to 0.5, eventually reverting back to the steady state. [19] The asset adjustment parameter is set to $\chi = 10$, and the model is simulated for 40 periods, sufficient for the interest rate to converge to the initial steady state.

Figure 7 shows the aggregate effects of this monetary policy shock. The model aggregate lending semi-elasticity to the lending rate is around -1.98 using annualized interest rates, in line with the micro-level evidence for Commercial and Industrial Loans of Bassett et al. (2014). [20] The bank-lending channel, as expressed by Kashyap and Stein (1995), occurs when the pass-through for loan rates is higher than one. In this model, loan rates respond less than one-to-one. The explanation for this incomplete pass-through is the increase in loan elasticity whenever banks increase their lending rate, which arises from their monopolistic behavior. The model's slope between the monetary policy and loan rates is around 0.84, which aligns with the incomplete pass-through monetary policy rate to lending rate of Scharfstein and Sunderam (2016), Drechsler et al. (2021), and Wang et al. (2022). Lastly, because non-reservable borrowing is long-term, the rate increase is significantly larger than the deposit rate, which matches their data behavior.

[19] The parameter ρ_ϵ comes from other papers in the literature.

[20] For the Fed funds rate of the model, the semi-elasticity of loans is around -1.66.

Figure 7: Aggregate Response to Contractionary Monetary Policy Shock



Notes: Aggregate impulse responses to a $\varepsilon_0^m = 0.0025$ innovation to the policy rate which decays at rat $\rho_m = 0.5$. Computed with perfect foresight transition in response to a series of unexpected innovations starting from the steady state.

Heterogeneous Effect of Maturity

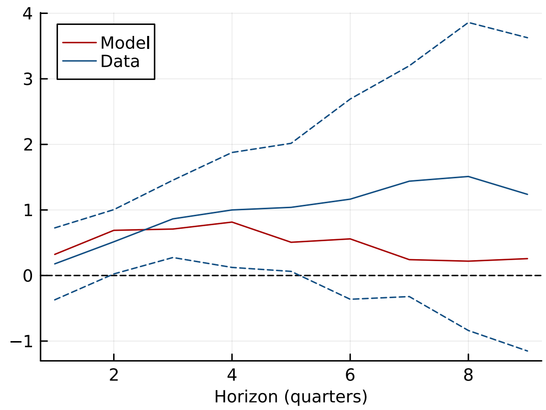
In order to compare my model to the data, I simulate the differential response between two groups in generated by the model. The groups are selected by the setup in the empirical exercise. I divide my model-generated bank distribution into two groups: (i) banks one standard deviation above the mean maturity and (ii) the complementary set. In terms of masses, this choice is close to the share above one standard deviation in the data, 13.24%, while in the model the mass is equal to 18.87%.

Because in the model, these banks with higher maturity are also the ones with more leverage and riskier, this would imply different pre-trends before the monetary shock. Therefore, I focus on the deviations from the group's specific transition using steady-state policies. [21] Then, I compare it to my baseline regression.

Figure 8 presents that the model can replicate the heterogeneous transmission of monetary policy with respect to banks' maturity. First, it matches the persistent discrepancies in the data. Second, on level, it remains within the 95% confidence interval for the empirical coefficients up to eight quarters after the shock.

[21] Notice that since the optimal policies in the steady state guarantee a unique bank distribution if the time interval is large enough, both sub-groups would eventually converge to the same points.

Figure 8: Heterogeneous Response to Contractionary Monetary Policy Shock



Notes: Heterogeneous impulse responses to a $\varepsilon_0^m = 0.0025$ innovation to the policy rate which decays at rat $\rho_m = 0.5$. Groups are selected according to their maturity. Blue line is the data point estimates. Dashed lines report 95% confidence interval. Computed with perfect foresight transition in response to a series of unexpected innovations starting from the steady state.

The model can accurately replicate the empirical heterogeneity as it captures the correlation between banks' maturity choice and their financial frictions. Consistent with the data, banks with longer-maturity debt tend to be more financially constrained. Importantly, these banks benefit from a significant decline in the present value of their outstanding liabilities, as their future interest payments are locked in. This "hedging" effect of long-term debt against interest rate shocks not only increases their equity but also alleviates their funding constraints. This mitigation more than compensates for any increase in funding costs, allowing banks with a greater proportion of long-term debt to increase their lending in response to monetary policy shocks.

Since monetary shocks influence the overall structure of bank funding, see, for example, Supera (2021), understanding the distribution of funding maturities becomes essential to fully grasp how banks' lending responses vary with interest rate changes and time. This exercise highlights that banks' funding structures — particularly liability maturity — play a significant role in determining the extent of their responses to monetary policy.

Counterfactual Analysis

To understand the overall impact of bank funding, I conduct two counterfactual analyses to assess the effects of banking policies. The first analysis, linked to our initial exercise, examines how monetary policy is transmitted when I eliminate the maturity channel of monetary policy.

The second analysis will explore the effects of changes in capital regulation.

On the Transmission of Monetary Policy. To shed role additional light on the role of funding maturity for the transmission of monetary policy, I conduct a model experiment where I eliminate maturity exogenously. This is done as follows. Let (p, n, b) be the bank state variable in the steady state. I rewrite the cash-on-hand of banks as their equity according to

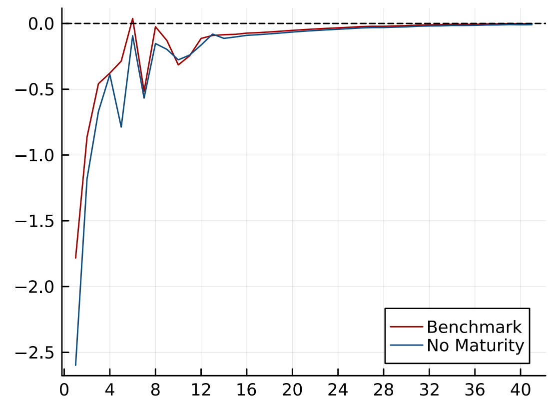
$$\tilde{n} = n_j - (1 - \lambda) q_b(p, n, b) b$$

where $q_b(p, n_j, b_j)$ denotes the non-reservable pricing with regard to the bank's optimal policies. Simultaneously, I set the new non-reservable liabilities level $\tilde{b}$ to zero. Intuitively, as the shock occurs, there won't be any effect on banks' equity coming from their stock of outstanding debt, and no interest rate "hedging". [22]

Figure 9 shows the benchmark impulse response and its counterfactual counterpart. Mirroring my empirical exercise and the heterogeneous response, by eliminating the effect of outstanding debt on my model, the decrease in lending is around one percentage point higher in my counterfactual at the shock. Over the 20 quarter horizon, the cumulative impact on the counterfactual experiment is 42% higher relative to the benchmark model. These results highlight the importance of accessing the funding distribution of banks whenever conducting monetary policy.

[22] Due to numerical approximation, the aggregate variables in this steady state do not exactly match those in the benchmark steady state. To address this, I control for the transition of this distribution while assuming the steady state policy. The distribution converges to the steady state by the second period.

Figure 9: Counterfactual of Response to Contractionary Monetary Policy Shock



Notes: Impulse responses to a $\varepsilon_0^m = 0.0025$ innovation to the policy rate which decays at rat $\rho_m = 0.5$ for benchmark and counterfactual distributions. In the counterfactual distribution, I eliminate the interest rate "hedging" effect on banks' balance sheets. Computed with perfect foresight transition in response to a series of unexpected innovations starting from the steady state.

On Capital Regulation. The model establishes a direct relationship between long-term funding choices and banks' leverage. Therefore, I argue that accounting for the heterogeneity in bank funding is crucial when estimating the impact of regulatory changes on the banking market. For this reason, I begin by studying the impact of capital regulation in my benchmark model. Similar to Corbae and D'Erasmo (2021), I set the new capital requirement for banks at $\kappa = 10\%$ and compare both steady-state moments. I then compare the benchmark implications with the alternative, where deposits are the only funding source, by setting the maturity of non-reservable liabilities equal to one.

Table 6 presents the aggregate implications of a change in capital regulation in my benchmark model. The first result is that regulatory changes directly affect the lending market by tightening the banks' balance sheets. The tightening drives loan rates up and, thus, decreases lending. Interestingly, banks' average leverage does not decrease by the same magnitude as the change in capital regulation. This occurs as other frictions, such as default risk and dividend smoothing, mainly drive it. In terms of the effectiveness of generating stability, the policy is impactful, decreasing the default rate significantly. Finally, because banks' idiosyncratic risk and leverage drive maturity, such change causes an overall shift towards deposit.

Table 6: Counterfactual of Capital Regulation

	κ_{low}	κ_{high}	$\%\Delta$
Loans	48.09	46.57	-3.16
Loan rates (%)	2.09	2.12	0.03
Leverage (%)	89.91	88.19	-1.72
Default rate (%)	0.05	0.01	-0.04
Maturity	1.53	0.96	-37

Notes: Moments of steady-state equilibrium at different parameterization. κ_{low} is the benchmark capital requirement equal to 6%, and κ_{high} is the counterfactual requirement set to 10%.

To address the implications of funding structure on the banking policy, I compare my benchmark model counterfactual with the alternative where only deposits are used. [23] Table 7 compares the aggregate implications of the regulatory changes between the benchmark model and a model with only deposits. Overall, when we account for banks' funding structure, it generates much more variations in aggregate outputs than the alternative specifications. In particular, under my benchmark model, the capital requirement is much more effective in decreasing banks' default rates, which are mainly driven by the sharper decrease in leverage.

Table 7: Counterfactual of Capital Regulation Comparison

	Benchmark	Deposits-only	Difference
Loans (%)	-3.16	-2.11	-1.05
Loan rates (%)	0.03	0.02	0.01
Leverage (%)	-1.72	-0.23	-1.49
Default rate (%)	-0.04	-0.01	-0.03

Notes: Changes in moments of steady-state equilibrium at different parameterization. Deposits-only denotes the parametrization of the model where λ is set to one, which implies that only deposits will be used due to their lower cost.

[23] Table 9 presents the full comparison between these moments.

6. Conclusion

In this paper, I have argued that banks' maturity dampens lending response to monetary policy. My argument had two components. First, I showed in the bank-level data that banks with higher maturity in their liabilities are less responsive to monetary policy shocks, i.e., they decrease their lending relatively less. Second, I built a heterogeneous bank model with default risk, market power, and capital regulation that is quantitatively consistent with these empirical results. In the model, banks that tend to fund their lending with long-term debt have either more leverage or face larger loan losses. I interpret these connections through the financial frictions banks face. Due to capital requirements, banks must smooth their cash flow over time, and this is done by funding their operations with non-reservable liabilities. Although more financially constrained, these banks are less responsive to monetary policy because they locked in the future cash payments on their liabilities before the shock. This alleviates their leverage and allows them to increase their lending relatively more. Finally, in my counterfactual analyses, I highlighted that accessing the distribution of funding structure is crucial to understanding the aggregate effects of policies.

In summary, this paper emphasizes the critical role of banks' funding structures, especially the maturity of their liabilities, in influencing their responses to monetary policy. By incorporating balance sheet constraints and heterogeneity in funding choices, the model not only replicates key empirical patterns but also provides new insights into the transmission of monetary policy through the banking sector. These findings emphasize the importance of considering the full range of banks' funding sources when designing monetary policy.

References

Amador, M. and Bianchi, J. (2024). Bank runs, fragility, and credit easing. *American Economic Review*, 114(7):2073–2110.

Arellano, C., Bai, Y., and Kehoe, P. J. (2019). Financial frictions and fluctuations in volatility. *Journal of Political Economy*, 127(5):2049–2103.

Barattieri, A., Moretti, L., and Quadrini, V. (2021). Banks funding, leverage, and investment. *Journal of Financial Economics*, 141(1):148–171.

Bassett, W. F., Chosak, M. B., Driscoll, J. C., and Zakrajšek, E. (2014). Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics*, 62:23–40.

Begenau, J. and Landvoigt, T. (2022). Financial regulation in a quantitative model of the modern banking system. *The Review of Economic Studies*, 89(4):1748–1784.

Bernanke, B. S. and Blinder, A. S. (1988). Credit, money, and aggregate demand. *The American Economic Review*, 78(2):435–439.

Bernanke, B. S. and Blinder, A. S. (1992). The federal funds rate and the channels of monetary transmission. *The American Economic Review*, 82(4):901–921.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, 1(PART C):1341–1393.

Bocola, L. (2016). The pass-through of sovereign risk. *Journal of Political Economy*, 124(4):879–926.

Boppart, T., Krusell, P., and Mitman, K. (2018). Exploiting mit shocks in heterogeneous-agent economies: the impulse response as a numerical derivative. *Journal of Economic Dynamics and Control*, 89:68–92.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

Chatterjee, S. and Eyigungor, B. (2012). Maturity, indebtedness, and default risk. *American Economic Review*, 102(6):2674–2699.

Coimbra, N. and Rey, H. (2024). Financial cycles with heterogeneous intermediaries. *Review of Economic Studies*, 91(2):817–857.

Corbae, D. and D'Erasmo, P. (2021). Capital buffers in a quantitative model of banking industry dynamics. *Econometrica*, 89(6):2975–3023.

Correia, S., Luck, S., and Verner, E. (2023). Failing banks. *Available at SSRN 4650834*.

Crouzet, N. (2017). Aggregate Implications of Corporate Debt Choices. *The Review of Economic Studies*, 85(3):1635–1682.

Crouzet, N. et al. (2016). Default, debt maturity, and investment dynamics. In *2016 Meeting Papers, Society for Economic Dynamics*, volume 533, pages 1635–1682.

Dangl, T. and Zechner, J. (2021). Debt Maturity and the Dynamics of Leverage. *The Review of Financial Studies*, 34(12):5796–5840.

Diamond, D. W. and He, Z. (2014). A theory of debt maturity: the long and short of debt overhang. *The Journal of Finance*, 69(2):719–762.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, 132(4):1819–1876.

Drechsler, I., Savov, A., and Schnabl, P. (2021). Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance*, 76(3):1091–1143.

English, W. B., Van den Heuvel, S. J., and Zakrajšek, E. (2018). Interest rate risk and bank equity valuations. *Journal of Monetary Economics*, 98:80–97.

Federal Deposit Insurance Corporation (2024). Risk management manual. Manual.

Gertler, M. and Karadi, P. (2011). A model of unconventional monetary policy. *Journal of monetary Economics*, 58(1):17–34.

Gertler, M. and Kiyotaki, N. (2015). Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review*, 105(7):2011–2043.

Goldstein, I., Kopytov, A., Shen, L., and Xiang, H. (2024). Bank heterogeneity and financial stability. *Journal of Financial Economics*, 162:103934.

Gomes, J., Jermann, U., and Schmid, L. (2016). Sticky leverage. *American Economic Review*, 106(12):3800–3828.

Hahm, J.-H., Shin, H. S., and Shin, K. (2013). Noncore bank liabilities and financial vulnerability. *Journal of Money, Credit and Banking*, 45(s1):3–36.

He, Z. and Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, 103(2):732–770.

Ivashina, V., Laeven, L., and Moral-Benito, E. (2022). Loan types and the bank lending channel. *Journal of Monetary Economics*, 126:171–187.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43.

Jiang, E. X. (2023). Financing Competitors: Shadow Banks' Funding and Mortgage Market Competition. *The Review of Financial Studies*, 36(10):3861–3905.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5):2301–2326.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2):463–505.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182.

Jungherr, J., Meier, M., Reinelt, T., Schott, I., et al. (2024). Corporate debt maturity matters for monetary policy. *Working Paper*.

Kashyap, A. K. and Stein, J. C. (1995). The impact of monetary policy on bank balance sheets. *Carnegie-Rochester Conference Series on Public Policy*, 42:151–195.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of political economy*, 105(2):211–248.

Martin, C., Puri, M., and Ufier, A. (2018). Deposit inflows and outflows in failing banks: The role of deposit insurance. Technical report, National Bureau of Economic Research.

Ottonello, P. and Winberry, T. (2020). Financial heterogeneity and the investment channel of monetary policy. *Econometrica*, 88(6):2473–2502.

Paul, P. (2023). Banks, maturity transformation, and monetary policy. *Journal of Financial Intermediation*, 53:101011.

Scharfstein, D. and Sunderam, A. (2016). Market power in mortgage lending and the transmission of monetary policy. *Unpublished working paper. Harvard University*, 2.

Supera, D. (2021). Running out of time (deposits): Falling interest rates and the decline of business lending, investment and firm creation. *Unpublished manuscript*.

Sánchez, J. M., Sapriza, H., and Yurdagul, E. (2018). Sovereign default and maturity choice. *Journal of Monetary Economics*, 95:72–85.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics letters*, 20(2):177–181.

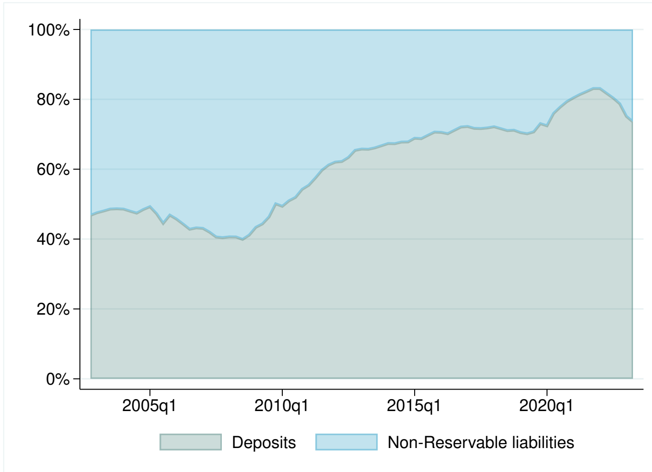
Van den Heuvel, S. J. et al. (2002). The bank capital channel of monetary policy. *The Wharton School, University of Pennsylvania, mimeo*, pages 2013–14.

Vasicek, O. (2002). The distribution of loan portfolio value. *Risk*, 15(12):160–162.

Wang, Y., Whited, T. M., Wu, Y., and Xiao, K. (2022). Bank market power and monetary policy transmission: Evidence from a structural estimation. *The Journal of Finance*, 77(4):2093–2141.

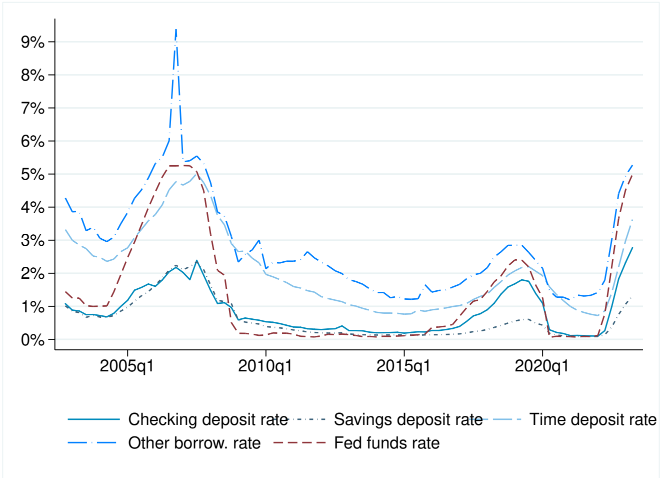
A. Appendix Additional Plots

Figure A.1



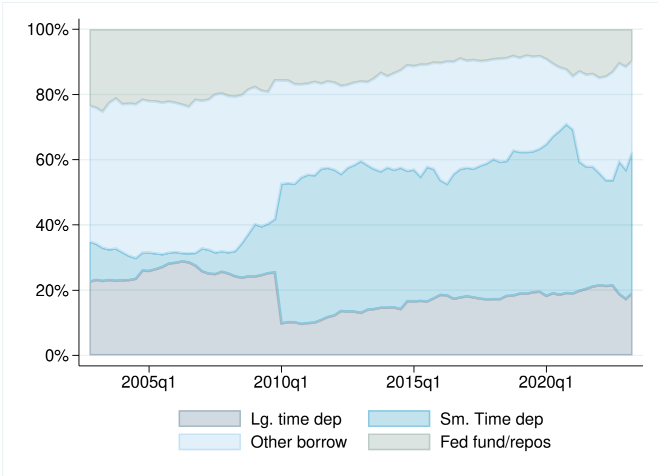
Notes: The figure plots the composition of debt funding for the commercial banking sector. The data is from the U.S. Call Reports covering 2003 to 2023 at the quarterly frequency.

Figure A.2



Notes: The figure plots the average borrowing rate by different liabilities and the Fed fund rate. The average borrowing rate is measured by the interest expense divided by the quarterly average stock of the liability. The data is from the U.S. Call Reports covering 2003 to 2023 at the quarterly frequency.

Figure A.3



Notes: The figure plots the composition of non-reservable liabilities for the commercial banking sector. The data is from the U.S. Call Reports covering 2003 to 2023 at the quarterly frequency.

B. Empirical Appendix

B.1. Data Sources

Uniform Bank Performance Reports. Data from the Call reports is obtained from the Uniform Bank Performance Reports, which is supplied by the FFIEC, for years between 2002 and 2023. The UBPR covers all FDIC-insured commercial banks, savings banks, and savings associations. The dataset compiles quarterly call reports from each insured bank and constructs standardized measurements for several bank-specific ratios. All definition are provided by the UBPR. I follow the approach of Paul (2023) to aggregate ban subsidiaries at the Bank Holding Company (BHC) level. The relationship table between BHC and bank subsidiaries is provided by the FFIEC's National Information Center. I only include institutions where the average loan to asset ratio is above 25%.

Interest Rate Shocks. My measure of interest rate shock is the series of Jarociński and Karadi (2020) due to their decomposition between information and monetary shock.

B.2. Variable Definitions

Bank Leverage. I define leverage as the ratio between total liabilities (**UBPR2948**) and total assets (**UBPR2170**).

Markup. I define the markup as follows

$$\text{markup}_{j,t} = \frac{1 + \text{Int. Rate Loan}/400}{1 + \text{Int. Rate Expense}/400} - 1$$

where I transform interest rate expense (**UBPRE666**) and loan interest rate (**UBPRE686**) in per quarter rates.

Deposits. Deposits are define as Demand, NOW, ATS and MMDA and Deposits Below Insurance Limit (**UBPRK431**) minus Deposits Below Insurance Limit (**UBPRK426**).

Non-reservable Liabilities. I define non-reservable liabilities as non-core liabilities (**UBPRK445**) plus small non-brokered deposits (**UBPRK426** minus **UBPR2366**).

Non-reservable share. I define non-reservable share of liabilities as non-reservable liabilities divided by total liabilities (**UBPR2948**).

Short term investments over total assets. To proxy for liquidity of the assets, I use the variable short term investments over total assets (**UBPRE589**).

Return on assets. To proxy for return on assets I use the net income over total assets (**UBPRE013**).

Gross Loan Losses. To capture banks' credit risk, I use the gross loan losses (**UBPRE390**).

Non-perfoming Loans. I use the UBPR constructed non-performin loans (**UBPR7414**).

Interest Expense on Non-reservable Liabilities. I construct the interest expense on non-reservable liabilities by summing the expenses on time deposits (**UBPRHR59**), Federal Funds Purchased & Repos (**UBPRD370**), and Other Borrowed Money (**UBPRD479**).

Quarterly average of Non-reservable Liabilities. To compute the borrowing rates on non-reservable liabilities, I need to compute their quarterly average stocks, analogous to the approach on the UBPR. For these I sum the quarterly average of time deposits (**UBPRHR65**), Federal Funds Purchased & Repos (**UBPR3353**) , and Other Borrowed Money (**UBPRD443**).

Interest Expense on Deposits. I construct the interest expense on deposits by summing the expenses savings accounts (**UBPRD372**) and transaction accounts (**UBPRD513**).

Quarterly average of Non-reservable Liabilities. To compute the borrowing rates on deposits, I need to compute their quarterly average stocks, analogous to the approach on the UBPR. For these I sum the quarterly average of savings accounts (**RCONB563**) and transaction accounts (**RCON3485**).

Interest Rate on Liabilities. Interest rate on any type of liability is measured as the interest rate expense, divided by the quarterly average stock.

B.3. Empirical Robustness

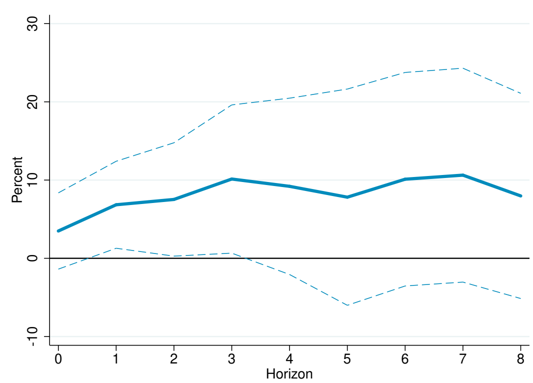
As a robustness to my baseline specification, I re-estimate the Jordà (2005) under the following specification:

$$y_{j,t+1+h} - y_t = \alpha_{j,h} + \alpha_{t,h} + \beta_h M_{j,t-1}\varepsilon_t^m + \gamma^j \varepsilon_t^m + \Gamma_1 X_{j,t-1} + e_{j,t+h} \tag{A.1}$$

where γ^j is the bank-specific permanent heterogeneous response to monetary policy, the rest is the same as the benchmark specification.

Figure B.1 shows the result of estimating the specification of Equation A.1. Similar to the benchmark, my results are significant at the 5% significance level for the same interval. Because maturity is not normalized, the point estimates are different.

Figure B.1: Heterogeneous Lending Response to Monetary Shock Alternative 1



Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. Maturity is constructed by using time-to-maturity brackets. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

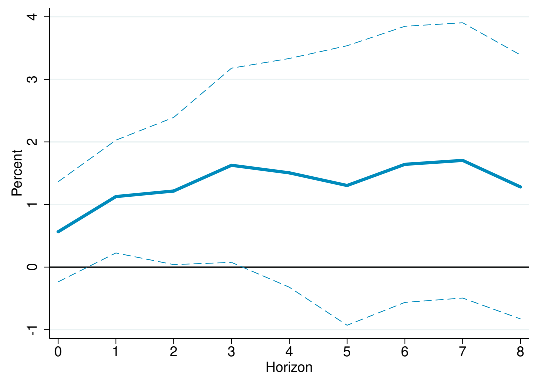
To understand how the estimation of the within-bank variation and the permanent heterogeneous response (γ^j) are related, I re-estimate the projections under the following speciation:

$$y_{j,t+1+h} - y_t = \alpha_{j,h} + \alpha_{t,h} + \beta_h (M_{j,t-1} - \bar{M}_j)\varepsilon_t^m + \gamma^j \varepsilon_t^m + \Gamma_1 X_{j,t-1} + e_{j,t+h} \tag{A.2}$$

all the variables are the same as specified before.

Figure B.2 shows the result of estimating the specification of Equation A.2. Similar to the previous specification, my results do not change. This is expected because the estimation of γ^j captures the bank-specific ex-ante heterogeneity. The different point estimates arise from the standardization of the within-bank maturity differences.

Figure B.2: Heterogeneous Lending Response to Monetary Shock Alternative 2



Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. Maturity is constructed by using time-to-maturity brackets. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

Now, I check if my results are robust to the fed funds shock of Jarociński and Karadi (2020) without the "purging" of the information shock. I re-estimate the projections under the following speciation:

$$y_{j,t+1+h} - y_t = \alpha_{j,h} + \alpha_{t,h} + \beta_h(M_{j,t-1} - \bar{M}_j)\varepsilon_t^{\text{fed}} + \Gamma_1 X_{j,t-1} + e_{j,t+h} \tag{A.3}$$

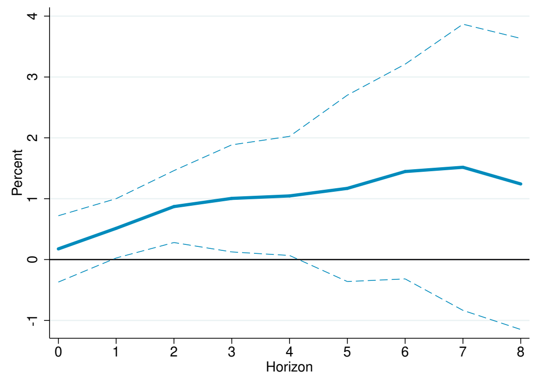
where $\varepsilon_t^{\text{fed}}$ is the fed fund shock.

Figure B.3 shows the result of estimating the specification of Equation A.3. Similar to the benchmark specification, the alternative of the interest rate shock behaves similarly to the monetary shock, as identified by Jarociński and Karadi (2020).

I also check if the responses are the same if I use the variations of the fed funds rate instead. Under this alternative, I re-estimate the projections under the following speciation:

$$y_{j,t+1+h} - y_t = \alpha_{j,h} + \alpha_{t,h} + \beta_h(M_{j,t-1} - \bar{M}_j)\Delta_t^{\text{fed}} + \Gamma_1 X_{j,t-1} + e_{j,t+h} \tag{A.4}$$

Figure B.3: Heterogeneous Lending Response to Monetary Shock Alternative 3

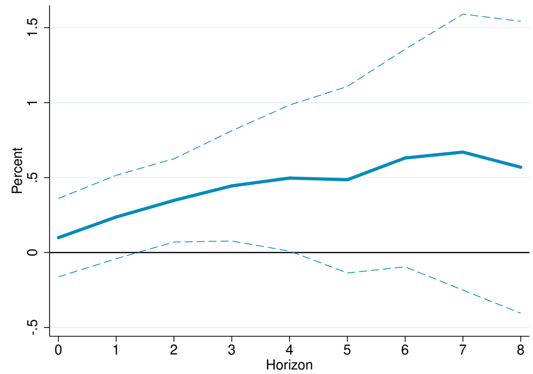


Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. Maturity is constructed by using time-to-maturity brackets. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

where Δ_t^{fed} is the variation of the fed funds rate. I instrumentalize the variation using the monetary policy shocks.

Figure B.4 shows the result of estimating the specification of Equation A.4. Although with smaller values, my results are significant at the 5% significance level for the same interval.

Figure B.4: Heterogeneous Lending Response to Monetary Shock Alternative 4



Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. Maturity is constructed by using time-to-maturity brackets. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

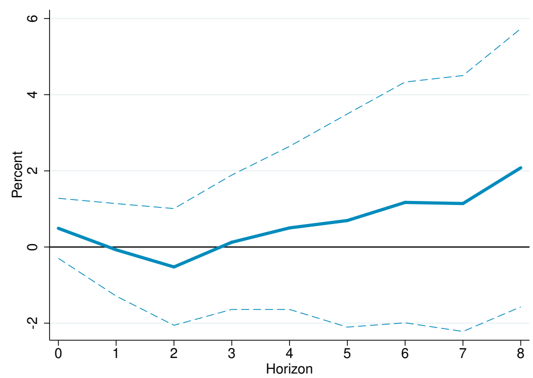
Finally, I turn my attention to the maturity of assets and the maturity gap. The rationale for this is to check if interest rate risk affects banks' lending heterogeneously. The construction for the variables follows English et al. (2018).

$$y_{j,t+1+h} - y_t = \alpha_{j,h} + \alpha_{t,h} + \beta_h(M^k_{j,t-1} - \bar{M^k}_j)\varepsilon^m_t + \Gamma_1 X_{j,t-1} + e_{j,t+h} \tag{A.5}$$

where $k \in \{\text{Assets}, \text{Gap}\}$ denotes if it is the maturity of the assets or the maturity gap between assets and liabilities.

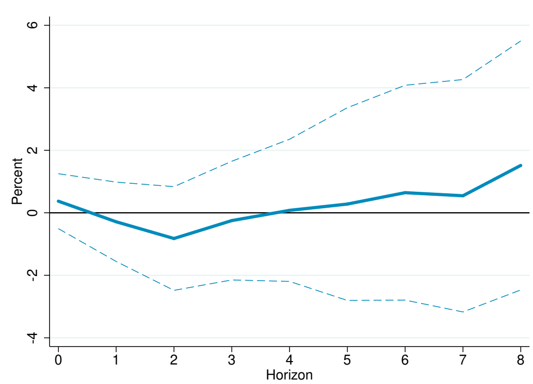
Figures B.5 and B.6 present the local projections for the heterogeneous response with respect to the maturity of assets and the maturity gap, respectively. Different from the maturity of liabilities, neither presents a significant heterogeneous effect on bank lending. This might suggest that the maturity mismatch, or for that matter, interest rate risk, is not statistically significant enough to explain the heterogeneous response at the bank level.

Figure B.5: Heterogeneous Lending Response to Monetary Shock Maturity of Assets



Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. Maturity is constructed by using time-to-maturity brackets. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

Figure B.6: Heterogeneous Lending Response to Monetary Shock Maturity Gap



Notes: The figure presents the impulse response of a 1% monetary shock, constructed by Jarociński and Karadi (2020), based on the local projection approach. The data is from the U.S. Call Reports covering 2002 to 2023 at the quarterly frequency. Maturity is constructed by using time-to-maturity brackets. The cumulative growth of loan growth is plotted with a 95 percent confidence interval shown using standard errors clustered at the bank and time level.

C. Quantitative Appendix

C.1. Algorithm for Steady State

The banks problem is solved using value function iteration (VFI) due to the existence of two defaultable liabilities, which might cause indeterminacy. In the benchmark setup, I have 101, 101, and 61 grids for the endogenous choice variables, R_ℓ, d', and b', respectively. Additionally, I use 7 grid points for p, 150 for n, and 5 for ω. After each iteration, I update both liability prices to speed up the computational time. I stop the process if the distance between iterations is below a tolerance of 10^{-5}. Then, I store the policies for each grid point of (p, n, b).

The algorithm to solve the steady-state mass of banks according to their individual variables (p, n, b) is as follows. Since the number of grid points for the endogenous variables for the cash-on-hand (n) is significantly smaller than the number of grid points for R_ℓ, d', 150 versus 10,201, I generate a finer grid for the steady state n 30 times larger than the number of grid points for the VFI, which I denote n_{fine}. Also, for the steady state, I account for the distribution of shocks ω. Therefore, my vector for the steady state distribution is given by $(p, n_{\text{fine}}, b, \omega)$, which has dimension $9,607,500$. For each grid in n_{fine} I linear interpolate the policies from the VFI, doing the same interpolation for next period cash-on-hand. This allows me the approximate the steady distribution of banks as if I were to compute $(p, R_\ell, d, b, \omega)$, without the computationally costly procedure of getting the policies for these grid points. Finally, I compute a transition matrix for $(p, n_{\text{fine}}, b, \omega)$, iterating with a initial guess for μ until the distribution converges.

C.2. Algorithm for Impulse Response Functions

As explained in the text, I use the method proposed by Boppart et al. (2018) to solve this Heterogeneous banks model. Intuitively, for banks to solve their problem, they only need the sequence of asset prices $\{P_k\}_{k=0}^{T}$, similar to their argument.

Due to the problem's non-linearity, my dampening parameter depends on the size of the shock to avoid instability of the convergence. The parameter is given by

$$\delta_t = \bar{\delta}\rho_\delta^t$$

where δ_t is the dampening parameter at period t of the transition, $\bar{\delta}$ is a constant dampener, and ρ_δ is a exponentially decaying parameter. After computing the prices using the functional form of the asset producer, I construct the new price as

$$P_{new,t} = \delta_t(1 + (1/\chi) * (L_t/L_\star - 1)) + (1 - \delta_t)P_{old,t}.$$

This step gives less weight to observations that would not be updated significantly. I stop my interaction whenever $|P_{new} - P_{old}|_{max} < 2.5 \times 10^{-6}$. This approach allows me to approximate the aggregate prices without instability.

As a test to check my approach, I regress the model-generated prices against the model-generated loans to see if they match the parametrization. The estimation follows:

$$P_t = \alpha + \beta(L_t/L_\star - 1) + \varepsilon_t \tag{A.6}$$

which β is the coefficient of interest, which should be equal to 1/10.

Table 8 presents the results of my estimation. Although the prices have a slightly higher intercept (1 basis point), we cannot reject the null hypothesis that the parameter beta is equal to the set in the model. Therefore, the approach for the computation of the asset prices seems to be reasonable.

Table 8: Price Check

Parameter	Estimation
α	1.0000
	(0.0000)
β	0.0960
	(0.0049)
R^2	0.9064
Null-Hypothesis	p-value
$\beta = 0.1$	0.4229

Notes: Estimation of the transition linear equation between prices and deviations from the steady state of loans.

C.3. Counterfactual Appendix

Table 9: Counterfactual of Capital Regulation

	Benchmark			Deposits-only			
	κ_{low}	κ_{high}	$\%\Delta$	κ_{low}	κ_{high}	$\%\Delta$	Difference
Loans	48.09	46.57	-3.16	47.44	46.44	-2.11	-1.15
Loan rates (%)	2.09	2.12	0.03	2.11	2.13	0.02	0.01
Leverage (%)	89.91	88.19	-0.72	88.14	87.90	-0.23	-0.39
Default rate (%)	0.05	0.01	-0.04	0.05	0.04	-0.01	-0.03
Maturity	1.53	0.96	-37				

Notes: Moments of steady-state equilibrium at different parameterization. κ_{low} is the benchmark capital requirement equal to 6%, and κ_{high} is the counterfactual requirement is set to 10%.