A Model of Bank Failures: Funding Frictions and the Dynamics Before Collapse*

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October 30, 2025

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Abstract

This paper develops and quantifies a model of bank failures to study how funding frictions shape the dynamics of balance sheet deterioration and default. Empirically, I document that in the years leading up to failure, U.S. banks progressively shift their funding structures toward time deposits and other costly liabilities, while profitability, leverage, and credit quality deteriorate. Motivated by these patterns, I build a model in which heterogeneous banks face limited commitment, capital requirements, and costly access to long-term funding. Banks issue both short- and long-term deposits to smooth cash flows and manage liquidity risk, but doing so exposes them to default risk. The model generates endogenous default thresholds and replicates the key empirical regularities observed prior to failure. Quantitatively, the framework highlights how the composition of liabilities governs banks' resilience to balance sheet shocks: institutions relying more heavily on time deposits can sustain higher leverage and smoother cash flows than in an environment without such funding sources. This relaxation of funding constraints allows them to expand lending and maintain solvency for longer. The results underscore that funding structure is a central dimension of bank fragility and a key determinant of financial stability.

*I am grateful to Yan Bai for her guidance and support. This project benefited from numerous conversations with George Alessandria and Matias Moretti, as well as from valuable comments received at the Society for Economic Dynamics (SED) Meeting.

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1. Introduction

Banks rarely fail overnight. In the years preceding collapse, their balance sheets deteriorate gradually as funding costs rise, leverage increases, and loan performance weakens. A striking feature of these episodes is the progressive shift in banks' funding composition toward time deposits and other costly liabilities. This paper argues that such funding adjustments are not merely symptoms of distress, but rather key amplifiers and buffers that shape the path to failure. I develop and quantify a model of bank failures in which funding frictions—particularly the cost and maturity of liabilities—govern the buildup of fragility and the timing of default.

Empirically, I document evidence on how U.S. banks' funding structures evolve before failure. Using data from the FFIEC *Call Reports* and the FDIC's list of failed institutions between 2001 and 2025, I show that banks approaching failure rely increasingly on time deposits, while core deposits shrink and net interest margins compress. At the same time, leverage rises, profitability declines, and credit losses accelerate. These patterns reveal a consistent reallocation from stable to illiquid funding, accompanied by a deterioration in earnings and asset quality—suggesting that funding is a central dimension of banks' fragility.

Motivated by these findings, I build a quantitative model in which heterogeneous banks face limited commitment, capital regulation, and costly access to iliquid funding. Banks issue both deposits and time deposits to smooth cash flows and manage rollover risk, but doing so exposes them to default through higher leverage and debt-servicing costs. Default arises endogenously when equity buffers fall below regulatory thresholds, and the model generates a stationary distribution of banks across solvency states. In equilibrium, time deposits play a dual role: they relax funding constraints by providing stable liquidity, but also increase exposure to credit losses and amplify balance-sheet risk.

The model replicates the key empirical regularities observed in the data: the gradual rise in leverage, the shift toward time deposits, the compression of net interest margins, and the spike in charge-offs as failure approaches. It thereby provides a framework linking banks' funding choices, profitability, and default risk over the life cycle of distress. Quantitatively, the model highlights that iliquid funding serves as both a stabilizing and risky force: it allows banks to smooth liquidity needs and sustain lending, but increases vulnerability once earnings and asset quality deteriorate.

A counterfactual analysis further illustrates the role of time deposits in stabilizing the banking sector. When banks lose access to long-term funding, they deleverage preemptively and operate with smaller balance sheets, reducing average default rates but also curtailing lending and aggregate liquidity. Thus, long-term liabilities mitigate rollover risk yet sustain leverage, shaping the overall resilience and size of the financial system.

Related Literature

This paper contributes to several strands of research on bank fragility, funding structure, and financial frictions.

First, it connects to the empirical literature on bank failures and funding composition. Recent work has documented that deteriorating banks experience a progressive shift in their liabilities toward costlier and less stable sources of funding (Correia et al., 2023; Chen et al., 2024; Drechsler et al., 2021). This paper complements these findings by providing a rationale for the joint evolution of leverage, funding structure, and profitability in the years preceding default. In contrast to existing studies that focus primarily on depositor behavior or run dynamics, I emphasize how banks' own funding choices—particularly the reliance on time deposits—shape their resilience to shocks and the timing of default.

Second, it contributes to the theoretical and quantitative literature on financial frictions and default risk. Building on the tradition of limited-commitment models (e.g., Arellano et al., 2019; Ottonello and Winberry, 2020; Amador and Bianchi, 2024), the model developed here features banks that issue both short- and long-term liabilities under regulatory and liquidity constraints. As in Gertler and Kiyotaki (2015) and related frameworks, default arises endogenously when leverage and cash-flow risk interact with capital requirements. The novel feature is the role of liability composition: banks use long-term funding to smooth liquidity shocks and reduce rollover risk, but this same mechanism amplifies balance-sheet fragility when profitability deteriorates. In this respect, the model bridges the gap between theories of financial intermediation with default risk and the empirical patterns of pre-failure deterioration documented in the data.

Third, this paper contributes to the literature on liquidity management and debt maturity. A large body of work has examined how borrowers choose the maturity of debt to balance rollover risk and flexibility (Chatterjee and Eyigungor, 2012; Bocola, 2016; Crouzet et al., 2016; Diamond and He, 2014). In the banking context, Choudhary and Limodio (2022) show that liquidity shocks drive banks' maturity choices, consistent with the mechanism in this paper. Here, the emphasis is on how the liability structure itself becomes a determinant of financial fragility: time deposits serve as a hedge against liquidity risk but increase exposure to default once earnings weaken.

Finally, this work relates to research on bank regulation and financial stability (Corbae and D'Erasmo, 2021; Begenau and Landvoigt, 2022; Lee et al., 2024). These studies highlight how capital requirements and safety nets affect banks' risk-taking and credit supply. My framework complements theirs by introducing endogenous default and funding choices within a general equilibrium setting, showing how regulatory constraints interact with banks' liquidity management motives. The analysis thus provides a unified view of how regulation, funding composition, and default risk jointly determine the resilience of the banking sector.

Overall, this paper unifies empirical evidence and quantitative modeling to show that banks' funding structures are not merely reflections of market conditions but active determinants of financial fragility. By endogenizing the evolution of funding composition within a model of limited commitment and default, it provides a framework for understanding the buildup of vulnerabilities that precede banking crises.

2. Empirical Analysis

This section provides empirical evidence on the patterns of bank behavior and performance that motivate the model developed in Section 3. I begin by describing the construction of the dataset and the sources used to measure bank-level characteristics and failures. I then document how banks' funding structures and balance sheet fundamentals evolve in the years leading up to failure, using an event-study approach that compares failing and surviving institutions. The analysis highlights two key dimensions that guide the modeling framework: the shift in funding composition toward time deposits and the joint deterioration in profitability, leverage, and credit quality preceding failure.

Data Description

I use U.S. bank-level data from the quarterly *Call Reports* filed by all insured commercial banks, and I standardize several bank-specific ratios according to the definitions provided by the Uniform Bank Performance Report (UBPR).[1] The use of the UBPR ensures consistency across banks and over time. The sample covers quarterly observations from March 2001 through March 2025.

I complement the Call Report data with the FDIC's *List of Failed Banks*, which documents all failures of FDIC-insured institutions over the same period. A bank failure is defined as either the closure of a bank by regulators or an instance of open bank assistance. Throughout my sample period, I observe 500 bank failures as reported by the FDIC.[2]

Fundamentals Around Bank Failures

In this section, I replicate the empirical analysis of Correia et al. (2023) to document how banks' fundamentals evolve in the periods leading up to failure, relative to banks that remain solvent. This exercise serves two purposes. First, it provides a benchmark for understanding the patterns of balance sheet deterioration that typically precede bank failures in the United States. Second, it allows me to assess how the behavior of key variables—such as capital ratios, loan growth, and funding composition—relates to the heterogeneity in banks' funding emphasized in my analysis.

To study the dynamics of funding, losses, and insolvency risk in the years preceding failure, I estimate variants of the following specification:

$$y_{j,t} = \alpha_j + \alpha_t + \sum_{k=-40}^{0} \mathbb{I}_{k=t}\,\beta_k + \varepsilon_{j,t}, \tag{1}$$

where $y_{j,t}$ denotes a bank-level outcome, k measures the number of quarters to failure, and α_j and α_t are bank and time fixed effects, respectively. The benchmark period is set to $k = -40$, corresponding to ten years before failure, so all coefficients are measured relative to that date. The sequence of coefficients $\{\beta_k\}$ captures the average deviation of failing banks from solvent

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

[2]For more detailed information checking my Appendix section

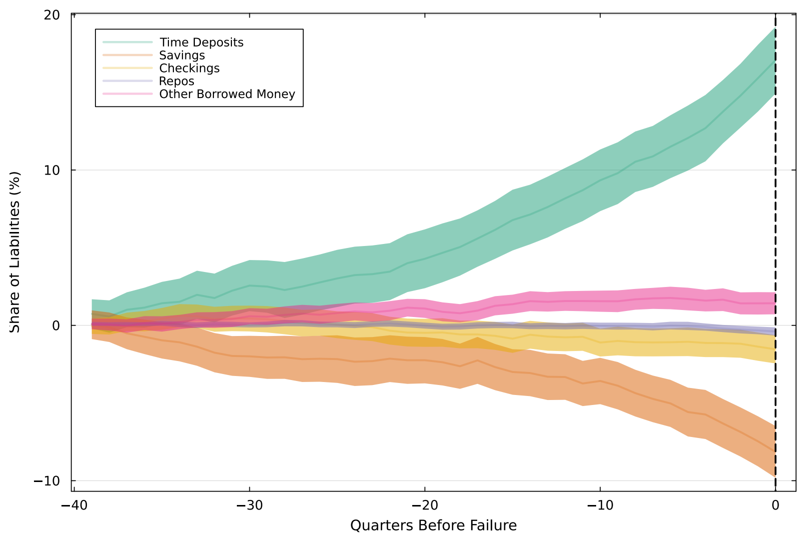

Figure 1: Funding Share Before Bank Failure

ones over time, holding constant bank-specific heterogeneity and aggregate shocks.

Funding. Figure 1 plots the evolution of banks' funding composition in the ten years preceding failure. The figure displays the estimated event-study coefficients for different categories of liabilities—checking deposits, savings deposits, time deposits, repos, and other borrowed money—relative to solvent banks, controlling for bank and time fixed effects. A clear pattern emerges: as banks approach failure, the share of time deposits rises sharply, indicating a shift toward illiquid and higher-yield liabilities. In contrast, the shares of checking and savings deposits decline steadily, reflecting a contraction in core retail funding. Repos exhibit a gradual decline, suggesting reduced use of secured short-term borrowing. Meanwhile, other borrowed money increases modestly closer to failure, reflecting a partial substitution toward unsecured wholesale funding. Together, these patterns show that as financial distress intensifies, banks substitute away from stable core deposits toward costlier and less stable wholesale funding sources.

Time Deposits. Figure 2 plots the evolution of banks' reliance on time deposits in the ten years preceding failure. The figure reports event-study coefficients for the share of time deposits in total liabilities, distinguishing between deposits above and below the FDIC insurance limit. A clear pattern emerges: as banks approach failure, the overall share of time deposits rises sharply, with the increase particularly pronounced for deposits below the in-

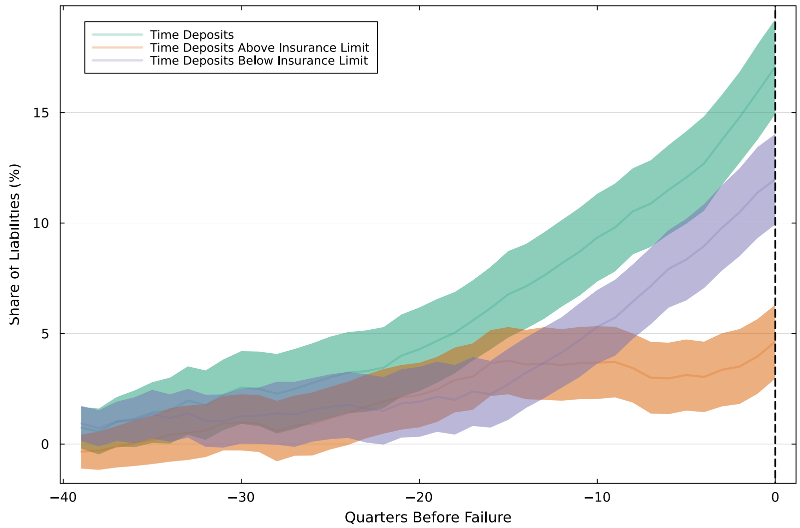

Figure 2: Funding Share of Time Deposits Before Bank Failure

surance limit. This pattern indicates that distressed banks increasingly rely on insured retail depositors, offering higher yields to retain funding as their financial conditions deteriorate. In contrast, the share of uninsured time deposits grows more modestly, suggesting limited access to large wholesale depositors. Taken together, these results reveal a systematic shift in the composition of liabilities toward insured, longer-maturity deposits, reflecting banks' attempts to lock in stable funding as default risk rises.

Deposit Rates. Figure 3 plots the evolution of deposit rates in the ten years preceding failure. The figure reports event-study coefficients for the interest rates paid on savings and checking accounts (core deposits), time deposits, and the spread between the two. Two distinct patterns emerge. First, while both rates exhibit moderate upward trends prior to failure, the increase is markedly stronger for time deposits, whose rates rise by roughly five basis points per quarter—about twenty basis points on an annualized basis—relative to solvent banks. In contrast, interest rates on core deposits remain largely flat and eventually decline, suggesting that banks do not pass higher funding costs through to retail depositors. Second, the spread between time and core deposit rates widens substantially in the years leading up to failure, reaching over ten basis points by the quarter of failure. This widening reflects a sharp deterioration in the marginal cost of funding, as troubled banks increasingly rely on costly time deposits to attract and retain liquidity. These results highlight rising

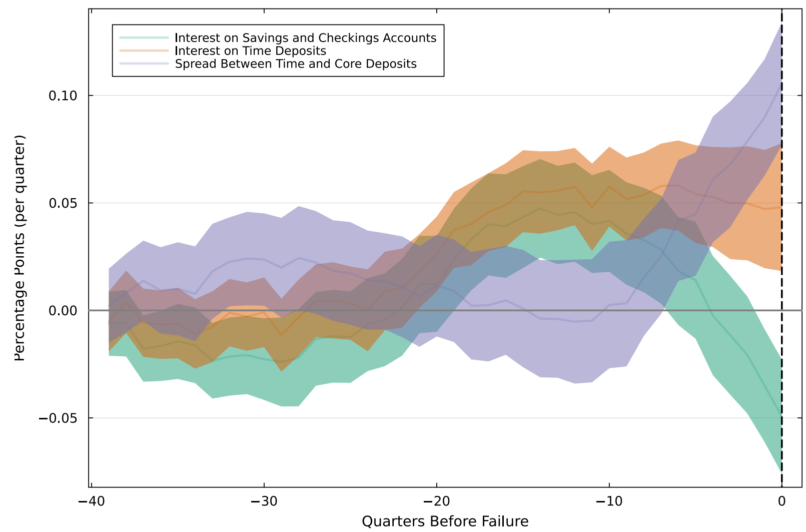

Figure 3: Deposit Rates Before Bank Failure

funding costs—especially for time deposits—as a key precursor to bank distress, mirroring the compositional shifts in liabilities shown in Figure 2.

Because of these patterns, my modeling analysis focuses on the distinction between time deposits and checking and savings deposits, which represent two distinct forms of retail funding. Time deposits tend to increase in the periods leading up to failure, reflecting reliance on illiquid and higher-yield liabilities, while checking and savings deposits decline as banks adjust their funding structure. This distinction captures the heterogeneity in funding maturity and pricing across retail liabilities—a central mechanism in the model's transmission of shocks to bank balance sheets.

Losses and Solvency. Figure 4 summarizes the dynamics of key bank fundamentals in the ten years preceding failure. The figure reports event-study coefficients for the net interest margin, leverage ratio, net charge-offs, and net income, estimated relative to solvent banks after controlling for bank and time fixed effects. The patterns indicate a progressive deterioration in profitability and asset performance as failure approaches. The net interest margin begins to decline about two years before failure, reflecting a narrowing gap between lending and funding rates. Leverage rises steadily throughout the period, pointing to an increase in liabilities relative to assets. Net charge-offs remain stable early on but rise sharply in the final quarters before failure, signaling mounting loan losses. Finally, net

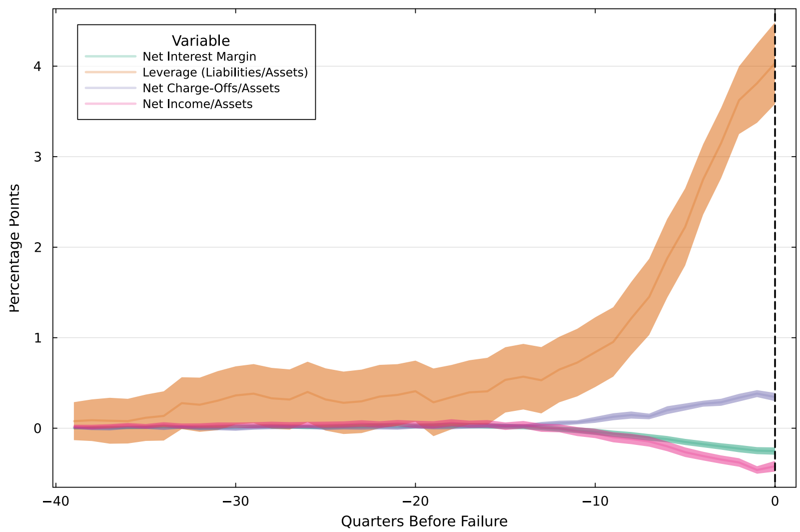

Figure 4: Losses and Solvency Before Bank Failure

income declines persistently and turns negative several quarters before failure. Together, these patterns document a gradual weakening of earnings and asset quality leading up to bank failure.

Taken together, these findings motivate a framework in which banks' solvency evolves endogenously with profitability, funding costs, and credit losses. The steady increase in leverage and charge-offs, combined with the decline in net interest margins and net income, suggests that both earnings compression and loss realization play central roles in the buildup to failure. In the model that follows, I formalize these mechanisms by allowing banks' balance sheets to respond to shocks that affect their funding costs and loan returns, shaping the evolution of their net worth and default risk.

The empirical evidence presented in this section reveals two central patterns that guide the theoretical analysis. First, banks approaching failure experience a marked reallocation of funding toward time deposits and other costly liabilities, accompanied by a decline in core deposits. Second, profitability, leverage, and credit performance deteriorate steadily in the years preceding failure, with losses and higher funding costs jointly eroding net income. These findings point to a close interaction between banks' funding structures and their solvency dynamics. In the next section, I develop a model that formalizes these mechanisms, allowing funding composition, lending returns, and default risk to co-evolve within a unified framework.

3. Model

This section develops a model of financial intermediation to study how banks' financial frictions interact with their endogenous default decisions. The framework features entrepreneurs seeking external financing for risky projects, competitive households allocating savings across assets, and banks that intermediate funds between the two sectors. The interplay between imperfect competition, regulatory constraints, and wholesale funding frictions generates the dynamics observed in the periods preceding bank failure.

Entrepreneurs face a static discrete choice problem when deciding whether to finance a risky project through bank borrowing. Households are competitive and can save either in deposits or in long-term bank liabilities. Banks act as intermediaries by accepting funds from households and extending loans to entrepreneurs. The economy produces a single final good, and all variables are expressed in units of consumption of this good.

Banks face several frictions that govern their funding life cycle. First, imperfect competition in the loan market allows banks to set lending rates to maximize profits. Second, regulatory constraints impose capital requirements that compel banks to manage their lending and funding decisions intertemporally, maintaining sufficient cash buffers against potential capital shortfalls. Third, time deposits represent a more costly funding source, reflecting both their longer maturity and greater exposure to default risk.

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 supplies labor to firms at wages W_t and rents capital via entrepreneurs. The household has a limited supply of labor $\bar{L} = 1$. It also saves by buying deposits, D, and certificates of deposits, B, from banks. They receive dividends from the banks and are taxed lump-sum. They fund new banks by transferring some equity, denoted by $\bar{n}$, so they can start their operation.

Firms

The economy is populated by a representative final-good firm that rents capital from entrepreneurs at rate $R_{K,t}$ and hires labor at wage W_t to operate a constant-returns-to-scale production technology:

$$Y_t = \bar{p}_t K_t^{\alpha} L_t^{1-\alpha}, \tag{2}$$

where $\bar{p}_t$ represents an aggregate *capital-quality shock* that affects both the productivity of capital and the expected success rate of entrepreneurial projects.

The firm's static profit-maximization problem is

$$\max_{K_t, L_t} \; \bar{p}_t K_t^{\alpha} L_t^{1-\alpha} - W_t L_t - R_{K,t} K_t. \tag{3}$$

The first-order conditions imply:

$$W_t = (1-\alpha)\bar{p}_t \left(\frac{K_t}{L_t}\right)^{\alpha}, \tag{4}$$

$$R_{K,t} = \alpha \bar{p}_t \left(\frac{L_t}{K_t}\right)^{1-\alpha}. \tag{5}$$

Assuming labor supply is normalized to $L_t = 1$, equilibrium wages and the rental rate of capital are

$$W_t = (1-\alpha)\bar{p}_t K_t^{\alpha}, \tag{6}$$

$$R_{K,t} = \alpha \bar{p}_t K_t^{\alpha-1}. \tag{7}$$

The rental rate $R_{K,t}$ determines the aggregate return to capital paid to entrepreneurs. Consistent with the entrepreneurial problem described below, the gross return on entrepreneurs' capital claims is given by:

$$R_{E,t+1} = \frac{R_{K,t+1}}{\bar{p}_t} + (1-\delta) = \alpha K_t^{\alpha-1} + (1-\delta), \tag{8}$$

where $(1-\delta)$ denotes the resale value of undepreciated capital. This formulation captures that when the quality of capital, $\bar{p}_t$, is high, the effective return received by entrepreneurs—normalized by capital quality—remains unchanged. Hence, only the firm's production technology depends on the aggregate capital-quality shock $\bar{p}_t$.

This relationship arises because entrepreneurs are subject to limited liability and may default on their obligations. As a result, the aggregate return to entrepreneurial capital is determined solely by the production technology and the effective depreciation of assets, rather than by the realized capital quality itself. The role of limited liability in implying this outcome will become clearer in the next subsection.

Entrepreneurs

The entrepreneurial sector consists of two-period entrepreneurs who finance investment through bank loans. Each entrepreneur belongs to a distinct bank pool, and there is no interbank competition or mobility across pools. The set of entrepreneurs linked to bank j constitutes its *client pool*, capturing the bank's local market power, consistent with recent empirical evidence.

Each pool contains a unit mass of entrepreneurs indexed by $i \in [0,1]$. Entrepreneurs are risk-neutral and maximize expected profits, which are ultimately transferred to the household sector.

In period t, each entrepreneur borrows $\bar{k}$ units of the final good from a bank to purchase risky capital claims priced at Q_t. Hence,

$$k_t^i = \bar{k}.$$

The capital claim yields a stochastic return per unit of loan given by:

$$R_{E,t+1} = \alpha K_t^{\alpha-1} + (1-\delta),$$

where $\alpha K_t^{\alpha-1}$ is the aggregate rental rate of capital determined by firms—abstracting from the quality shock—and $(1-\delta)$ represents the resale value of undepreciated capital. If the project succeeds, entrepreneurs receive this gross return; if it fails, the payoff is zero due to limited liability. Thus, the realized return on entrepreneurs' capital claims depends on the project's success state, while the expected return reflects both the production technology and the probability of repayment.

Each entrepreneur draws an idiosyncratic return x_t^i upon investment success, which is private information and expressed as a share of the borrowed amount $\bar{k}$. Banks cannot observe x_t^i ex ante and therefore charge a uniform loan rate within each pool. The realization of x_t^i is known to entrepreneurs at the beginning of period t.

Suppose entrepreneur i belongs to bank j's client pool, which faces a common project success probability $p_{t+1}^j(z_{t+1}, x_t^\star)$. The variable z_{t+1} denotes a *bank-specific state*, capturing idiosyncratic credit risk conditions or shocks to bank j's balance sheet. The function $p_{t+1}^j(z_{t+1}, x_t^\star)$ represents the probability that projects financed by bank j succeed, conditional on its state z_{t+1} and on the cutoff entrepreneur $x_t^\star$. The cutoff $x_t^\star$ reflects the risk composition of the bank's loan portfolio: when the marginal project offers higher expected returns, it also entails greater risk, thereby lowering the pool's overall success probability. Suppose entrepreneur i belongs to bank j's client pool, which faces a common project success probability $p_{t+1}^j(z_{t+1}, x_t^\star)$. The variable z_{t+1} denotes a *bank-specific state*, capturing idiosyncratic credit risk conditions or shocks to bank j's balance sheet. The function $p_{t+1}^j(z_{t+1}, x_t^\star)$ represents the probability that projects financed by bank j succeed, conditional on its state z_{t+1} and on the cutoff entrepreneur $x_t^\star$. The cutoff $x_t^\star$ reflects the risk composition of the bank's loan portfolio: when the marginal project offers higher expected returns, it also entails greater risk, thereby lowering the pool's overall success probability. Aggregating across the continuum of banks, the economy-wide success probability is given by the mass-weighted average

$$\bar{p}_{t+1} = \int_0^1 p_{t+1}^j(z_{t+1}^j, x_t^{j\star}) d\mu^j,$$

which represents the expected share of successful projects in the aggregate banking system.

The project's gross return per unit of loan is therefore:

$$\begin{cases} R_{E,t+1} + x_t^i, & \text{with probability } p_{t+1}^j(z_{t+1}, x_t^\star), \\ 0, & \text{with probability } 1 - p_{t+1}^j(z_{t+1}, x_t^\star). \end{cases} \tag{9}$$

The gross return is $R_{E,t+1} + x_t^i$ in the successful state and 0 in failure, implying full loss of capital.[3] The success probability $p_{t+1}^j(z_{t+1}, x_t^\star)$ is i.i.d. across entrepreneurs within a pool but correlated across time through the evolution of z_{t+1}.[4] The failure rate within each pool is $1-p_{t+1}^j(z_{t+1}, x_t^\star)$, and aggregation across all banks yields the unconditional failure probability $\bar{p}_{t+1}$.

Entrepreneurs cannot switch across banks. Given the loan rate $R_{\ell,t}^j$, each entrepreneur decides whether to borrow and invest. They must repay $R_{\ell,t}^j$ if they borrow, and due to limited liability, their payoff is bounded below by zero. Table 1 summarizes the payoff structure.

Table 1: Entrepreneur's Problem (conditional on investing)

State	Receive	Pay	Probability
Success	$R_{E,t+1} + x_t^i$	$R_{\ell,t}^j$	$p_{t+1}^j(z_{t+1}, x_t^\star)$
Failure	0	0	$1 - p_{t+1}^j(z_{t+1}, x_t^\star)$

Since $R_{\ell,t}^j > 1$, entrepreneurs cannot repay if their project fails, and the bank seizes the remaining capital claim, which has zero value.

The expected payoff of entrepreneur i conditional on borrowing at rate $R_{\ell,t}^j$ is

$$\pi_t(R_{\ell,t}^j) = E_t\big[p_{t+1}^j(z_{t+1}, x_t^\star)\big(R_{E,t+1} - R_{\ell,t}^j + x_t^i\big)\bar{k}\big].$$

[3] This setup follows Coimbra and Rey (2024), where the gross capital return equals $R_{K,t} + (1-\delta)$. I interpret $\bar{p}_t$ as the aggregate capital-quality shock. While the increased credit component follows Corbae and D'Erasmo (2021).

[4] This structure parallels Vasicek (2002), often used in regulatory credit-risk modeling.

If entrepreneurs do not invest, they forgo x_t^i. Hence, their decision rule is

$$U^e = \max_{h\in\{0,1\}} h\,\pi_t(R_{\ell,t}^j),$$

where h is the binary investment choice. An entrepreneur invests if and only if

$$R_{E,t+1} + x_t^i \geq R_{\ell,t}^j, \tag{10}$$

i.e., when the expected project return exceeds the loan rate.

Loan Demand. With no interbank competition or mobility, each bank j faces a unique loan demand function. From the investment rule in Equation 10 and the distribution of x_t^i, loan demand per unit of capital is

$$\ell^d(R_{\ell,t}^j, R_{E,t+1}) = \Pr\big(x_t^i \geq R_{\ell,t}^j - R_{E,t+1}\big)\bar{k}. \tag{11}$$

The marginal entrepreneur is defined by the indifference condition $x_t^\star = R_{\ell,t}^j - R_{E,t+1}$. Since x_t^i follows a known distribution, the loan demand corresponds to the complementary cumulative distribution function of x_t^i evaluated at $x_t^\star$. Thus, loan demand increases with $R_{E,t+1}$ and decreases with $R_{\ell,t}^j$: higher project returns or lower lending rates raise the share of entrepreneurs willing to invest.

Banks

There is a continuum of banks of measure one, indexed by $j \in [0,1]$, all owned by the representative household. Each bank is operated by a manager who makes decisions regarding entry, default, lending, and funding. The manager seeks to maximize the expected discounted stream of dividend payments, div_t, according to the objective function:

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

where Λ_t denotes the household's stochastic discount factor and $\sigma \in (0,1]$ captures the manager's degree of myopia. When $\sigma < 1$, managerial myopia introduces a potential agency friction between the bank manager and the household, as in Corbae and D'Erasmo (2021). To ensure a well-defined cross-sectional distribution of banks, I impose the condition $\sigma \Lambda_{t+1} R_{f,t} < 1$, which is standard in incomplete market environments. Here, $R_{f,t}$ denotes the risk-free rate.

Assets. To model bank solvency risk, I begin by characterizing the composition of bank assets. Each bank invests in loans that yield an agreed-upon gross interest rate $R^j_{\ell,t}$. Let ℓ^j_{t-1} denote the stock of loans extended by bank j in period $t-1$ at rate $R^j_{\ell,t-1}$. The value of bank j's assets at time t is given by:

$$a^j_t = p(z^j_t, R^j_{\ell,t-1} - R_{E,t+1}) R^j_{\ell,t-1} \ell^j_{t-1}, \tag{12}$$

where $p(\cdot)$ is the fraction of performing loans that are repaid. Defaulted loans are realized as losses on the bank's balance sheet, and $1 - p(\cdot)$ represents the share of charge-offs. I assume that z^j_t follows a persistent AR(1) process, capturing cyclical variation in credit risk across banks.

Resources. Bankers use their cash-on-hand (n), deposits (d), and time deposits (b) to finance new loans $\ell(R^j_{\ell,t}, R_{E,t+1})$ at the interest rate $R^j_{\ell,t}$.

Time deposits are long-term instruments that do not fully mature within a single period. A fraction λ of their principal is repaid each period, while the remaining share $1-\lambda$ remains outstanding. Debt holders receive a coupon payment c on the outstanding amount. Deposits, in contrast, are short-term contracts that fully mature each period.

Given their liabilities and loan portfolio, a bank's cash-on-hand evolves according to:

$$n^j_t = a^j_t - \omega^j_t \ell^j_t - d^j_t - (\lambda + c) b^j_t. \tag{13}$$

Here, a^j_t denotes the value of bank j's assets, ω^j_t is an idiosyncratic shock affecting the revenue generated from those assets, d^j_t represents deposit payouts inherited from the previous period, and $(\lambda + c) b^j_t$ corresponds to repayments on maturing time deposits plus coupon payments.

The shock ω^j_t introduces cross-sectional heterogeneity across banks, following the approach of Ottonello and Winberry (2020). It also helps match the empirical distribution of default rates observed in the data. I assume that ω^j_t is i.i.d. across banks and time and follows a normal process, $\omega^j_t \sim N(0, \eta^2_\omega)$. Intuitively, this shock captures fluctuations in asset returns, such as revenue losses from non-performing loans that have not yet been realized on the balance sheet.

Equity. At the beginning of each period, the bank's book equity is defined as the value of its cash-on-hand net of the outstanding amount of long-term debt, discounted at its present value:

$$e_t^j = n_t^j - q_{b,t}^{rf}(1-\lambda)b_t^j, \tag{14}$$

where $q_{b,t}^{rf}$ denotes the risk-free price of long-term liabilities.

This specification implies that when equity is evaluated at fair value, the bank's liabilities are also marked to fair value rather than to market value. This assumption is consistent with the regulatory treatment of Tier 1 capital, under which banks may include unrealized gains from changes in the fair value of their liabilities, excluding those arising from their own credit risk. Consequently, discrepancies can emerge between the fair value and the market value of equity.

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

$$div_t^j + \ell^d(R_{\ell,t}^j, R_{E,t+1}) = n_t^j + (q_{d,t} - \zeta)d_{t+1}^j + q_{b,t}\big(b_{t+1}^j - (1-\lambda)b_t^j\big) - \psi. \tag{15}$$

Equation (15) represents the bank's per-period resource constraint. On the left-hand side, dividends div_t^j and lending $\ell^d(R_{\ell,t}^j, R_{E,t+1})$ capture the uses of funds. The loan demand function $\ell^d(R_{\ell,t}^j, R_{E,t+1})$ is derived from the entrepreneurs' problem and links the bank's lending rate $R_{\ell,t}^j$ to the expected return on entrepreneurial projects $R_{E,t+1}$ (see Equation 11). On the right-hand side, n_t^j denotes the bank's net worth, while the terms $(q_{d,t} - \zeta)d_{t+1}^j$ and $q_{b,t}\big(b_{t+1}^j - (1-\lambda)b_t^j\big)$ represent new funding obtained through deposits and time deposits, respectively. The expression $b_{t+1}^j - (1-\lambda)b_t^j$ corresponds to the net issuance of time deposits, with λ denoting the maturity parameter that governs the fraction of long-term liabilities rolled over each period. The parameters $\zeta > 0$ and $\psi > 0$ capture, respectively, the marginal cost of issuing deposits and a fixed operating cost associated with maintaining banking operations. Together, these terms describe how each bank finances its lending activity, meets its operating expenses, and distributes dividends to shareholders.

In addition, I assume that banks cannot repurchase their outstanding stock of time deposits, i.e.,

$$b^j_{t+1} - (1-\lambda)b^j_t > 0.$$

Using the cash-on-hand equation 13 and fair value equity 14, we can determine next period equity by [5]

$$e^j_{t+1} = a^j_{t+1} - d^j_{t+1} - (\lambda + c + (1-\lambda)q^{rf}_{b,t+1})b^j_{t+1}.$$

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:

$$div^j_t \geq 0.$$

This constraint prevents banks from raising equity to substitute deposits or long-term 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.

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

$$e^j_{t+1} \geq \kappa a^j_{t+1}. \tag{16}$$

Equation 16 implies that the bank's fair value 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 stipulates that proposed dividends cannot exceed a bank's net income. Accordingly, dividends are restricted by

$$div^j_t \leq \bar{r}\,\ell^d(R^j_{\ell,t}, R_{E,t+1}),$$

where $\bar{r}$ represents the maximum permissible payout rate on the loan portfolio. A similar

[5] Here I am implicitly assuming that revenue shock, for example, unrealized losses from non-performing loans, does not interact with the requirements over capital tomorrow. This is in line with the reporting on capital tier ratio from Schedule RC-R, for which only unrealized losses on securities and debt securities are accounted.

assumption is made by Corbae and D'Erasmo (2021). In this setup, the restriction ensures that the bank's value function remains bounded and concave. I set $\bar{r} = 0.02$, corresponding to a maximum dividend payout of 2% per quarter.

Lastly, notice that all constraints are linear on the constant $\bar{k}$. Therefore, we can normalize all variables at the bank level by $\bar{k}$. Consequently, to solve the bank problem, we are only required to know aggregate variable $R_{E,t+1}$ in the steady state. As a simplification to speed up the computational process, I calibrate the steady $R_{E,t+1}$ to match the banks' net interest margins, while $\bar{k}$ is obtained as a residual of the entrepreneur return.

Debt Pricing

Households competitively lend resources to banks at the price schedules $q_d(z_t, R_{\ell,t}, d_{t+1}, b_{t+1})$ and $q_b(z_t, R_{\ell,t}, d_{t+1}, b_{t+1})$.

Banks cannot distinguish between the types of debt on which they default. If they default on deposits, they must also default on time deposits, and vice versa. The default decision of bank j is denoted by $h(z_t, n_t, b_t)$, where (z_t, n_t, b_t) are the bank's state variables.

A key distinction between deposits and time deposits arises from the presence of deposit insurance. Since, on average, roughly half of time deposits exceed the insurance limit, they are more exposed to default risk. To capture this feature, I assume a repayment hierarchy that guarantees the repayment of depositors before time deposit holders in the event of default.[6]

The process unfolds as follows. Whenever a bank defaults, debt holders take control of the bank's assets. Assets are liquidated with a recovery rate $\gamma \in (0, 1)$. Depositors are paid first, and any remaining funds after covering deposits are distributed to time deposit holders, who receive

$$\max\{0, \, \gamma(a_t - \omega_t \ell_t) - d_t\}.$$

Banks are required to pay insurance premiums to a regulator, net of the expected recovery on assets. The insurance premium is fairly priced, taking into account the bank's lending, debt, and default decisions. Consequently, deposits are priced net of this insurance premium.

[6]This assumption follows the hierarchy of claims established by the FDIC.

After liquidation, any unrecovered portion of assets is transferred lump-sum to the household sector; thus, there is no aggregate welfare loss from default.

Since households hold these liabilities, they discount them using the stochastic discount factor Λ_t. The price of deposits, net of the insurance premium, is therefore given by:

$$\begin{aligned} q_d(z_t, R_{\ell,t}, d_{t+1}, b_{t+1}) = E_t\{\Lambda_{t+1}[1 - h(z_{t+1}, n_{t+1}, b_{t+1}) \\ + h(z_{t+1}, n_{t+1}, b_{t+1}) \min\{1, \gamma(a_{t+1} - \omega_{t+1} l_{t+1})/d_{t+1}\}]\}. \end{aligned}$$

Similarly, the price of time deposits is given by:

$$\begin{aligned} q_b(z_t, R_{\ell,t}, d_{t+1}, b_{t+1}) = E_t\{\Lambda_{t+1}[(1 - h(z_{t+1}, n_{t+1}, b_{t+1}))(\lambda + c + (1-\lambda) q_{b,t+1}) \\ + h(z_{t+1}, n_{t+1}, b_{t+1}) \min\left\{c + \lambda + (1-\lambda) q_{b,t}^{rf}, \frac{\max\{0, \gamma(a_{t+1} - \omega_{t+1} l_{t+1}) - d_{t+1}\}}{b_{t+1}}\right\}\Bigg]\Bigg\}, \end{aligned}$$

where $q_{b,t+1}$ denotes the price of time deposits next period.

Bankers' Recursive Problem

Since the banker's problem is identical across banks, I drop the index j. The state vector (z, n, b) summarizes the bank's relevant variables: the idiosyncratic shock to the share of performing loans z, cash-on-hand n, and outstanding wholesale debt b. Bankers lack commitment and may default on their debt obligations. The value of operating the bank is therefore given by:

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

where h is the default indicator, $h(z, n, b)$ denotes the corresponding default rule, and $V^c(\cdot)$ represents the continuation value of remaining solvent. If the banker defaults, the value is zero.

The continuation value satisfies the following recursive problem:

$$V^c(z,n,b) = \max_{R_\ell,\, d',\, b'} \left\{ div + E_{z'|z}[\sigma\Lambda_{t+1}V(p',n',b')] \right\}$$

$$\begin{aligned}
\text{s.t. } & div = n - \ell^d(R_\ell, R_E') - \psi + (q_d - \zeta)d' + q_b(b' - (1-\lambda)b) \geq 0, \\
& a' = p(z', R_\ell - R_E')R_\ell\, \ell^d(R_\ell, R_E'), \\
& e' \geq \kappa a', \\
& e' = a' - d' - (\lambda + c + (1-\lambda)q_b^{rf})b', \\
& n' = a' - \omega'\ell^d(R_\ell, R_E') - d' - (\lambda + c)b', \\
& b' - (1-\lambda)b \geq 0, \\
& div \leq \bar{r}\ell^d(R_\ell, R_E')\,.
\end{aligned}$$

The bank chooses its loan rate R_ℓ, deposit issuance d', and long-term debt b' to maximize its expected discounted value, subject to the non-negativity of dividends, regulatory capital requirements, and the law of motion for assets and equity. All expectations are conditional on the current loan-performance state z.

Default Characterization

Banks face the possibility of default whenever their continuation value becomes non-positive. Because dividend payments must be non-negative, the continuation value $V^c(z,n,b)$ is positive for any feasible combination of (z,n,b) that satisfies the resource and feasibility constraints. When these constraints cannot be met—due to insufficient net worth or excessive leverage—the bank optimally defaults.

Formally, let Ω denote the set of feasible states. The *default region* is defined as:

$$\mathcal{H} = \{(z,n,b) \in \Omega : V^c(z,n,b) \leq 0\}.$$

In this region, the value of continuing operations falls below zero, and the banker chooses to default. Default implies liquidation of the bank and a payoff of zero to the banker, reflecting limited liability.

Hence, the bank's overall value function satisfies:

$$V(z, n, b) = \max\{V^c(z, n, b),\, 0\},$$

where $V^c(z, n, b)$ denotes the value of continuing operations and the zero value represents default. The boundary between the continuation and default regions defines the *endogenous default threshold*, which determines the states under which a bank remains solvent.

Finally, default occurs only when the continuation value $V^c(z, n, b)$ is *not feasible*, i.e., when no combination of (R_ℓ, d', b') satisfies the resource and feasibility constraints while maintaining non-negative dividends. In such cases, the bank cannot continue operations, and default becomes the only admissible outcome.

Exit and Entry

Exit from the market is endogenous and depends on the bank's default decision. In each period, the mass of entering banks, μ_e, equals the mass of exiting banks. Each entrant is endowed with initial equity $\bar{n}$ and begins operation with zero debt.

New banks inherit the pool of entrepreneurs previously served by exiting banks, thereby preserving the distribution of idiosyncratic shocks in the economy. This assumption captures the idea that entrants fill the market positions vacated by failed banks, maintaining a stable competitive environment.

Monetary Authority

The final component of the model is the monetary authority, which determines the real interest rate.

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

$$\log(R_{f,t}) = -\log(\beta), \tag{17}$$

implying a constant steady-state real rate consistent with the household's intertemporal discount factor.

Equilibrium

I now define the competitive equilibrium in both the steady state and during the transition following an unexpected aggregate shock to the interest rate, assuming perfect foresight along the transition path.

Law of Motion for the Distribution of Banks. Before defining the equilibrium, I first characterize the evolution of the bank distribution in steady state, with an analogous structure during the transition.

Let the optimal policies conditional on states (z, n, b) be:

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

where $R_\ell^\star(z, n, b)$ is the optimal lending rate, $d^{\star\prime}(z, n, b)$ the optimal deposit issuance, and $b^{\star\prime}(z, n, b)$ the optimal long-term liability policy.

These policies may be empty when the non-negative dividend constraint is violated, in which case the bank defaults. Upon default, a new bank enters the economy with initial equity $\bar{n}$, no long-term liabilities, and inherits the exiting bank's client pool, characterized by the same p. In equilibrium, the mass of entrants equals the mass of defaulting banks, maintaining a constant measure of active banks over time.

Let μ denote the cross-sectional distribution of banks over (z, n, b). The mass of exiting (defaulting) banks is given by:

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

where $\delta^\star$ is the bank's default policy.

Define the law of motion for net worth as:

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

and let the indicator function for next-period states be:

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

The distribution of incumbent banks evolves according to:

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

where $G(\omega')$ and $F(z' \mid p)$ are the transition probabilities of the exogenous shocks ω and p, respectively.

Similarly, the distribution of entrant banks evolves as:

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

Since entrants inherit the client pools of exiting banks, the entrant distribution depends on the same loan-performance state p.

The overall law of motion of the bank distribution is:

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

A stationary distribution satisfies:

$$\mu^\star(z, n, b) = \mu'(z, n, b) = \mu(z, n, b),$$

implying that the inflow and outflow of banks are balanced, and the cross-sectional distribution of banks remains constant over time.

Capital Market Clearing. Consider the distribution of operating banks $\mu(p, n, b)$. Let $R_\ell^\star(p, n, b)$ denote the optimal loan rate policy. Each bank's loan supply is given by $\ell^s(z, n, b) = \ell^d(R_\ell^\star(p, n, b), R_E')$.

Since banks may default, aggregate loan supply also accounts for new entrants:

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

where the first term represents incumbent banks and the second represents entrants. Given the normalization of the capital price to one, market clearing in the capital market requires:

$$K' = L^s, \tag{18}$$

where K' denotes aggregate capital next period.

Definition 1. *A stationary competitive equilibrium consists of value functions $V(p,n,b)$; decision rules $R_\ell(p,n,b)$, $d'(z,n,b)$, $b'(p,n,b)$; a measure of banks $\mu(p,n,b)$; debt price schedules $q_d(p,R_\ell,d',b')$ and $q_b(p,R_\ell,d',b')$; a borrowing decision $\ell(R^j_\ell, R'_E)$; and a set of prices P such that:*

- *Entrepreneurs maximize expected utility given the loan rate R^j_t, consistent with their borrowing decision and utility function;*
- *Banks choose $R_\ell(p,n,b)$, $d'(z,n,b)$, and $b'(p,n,b)$ to maximize their value functions;*
- *Households price default risk competitively and optimize their portfolio decisions;*
- *Firms maximize profits given factor prices;*
- *The distribution of banks $\mu(p,n,b)$ is consistent with individual policy functions and the law of motion above;*
- *All markets clear.*

One of the key state variables of interest is the cross-sectional distribution of banks across (z,n,b).

4. Quantitative Analysis

In this section, I explore the quantitative implications of my model. First, I calibrate my model to match the targeted moments of distribution in the U.S. banking sector. I then show how the model can match additional moments of the cross-section of banks. Third, I show that the model can replicate the heterogeneous response to an unexpected interest rate shock. Lastly, I conduct counterfactual analyses with the model, highlighting the importance of maturity for the transmission of monetary policy.

Computation

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).

Even after reducing the problem to a stationary equilibrium, the model features three individual state variables at the bank level: (z, n, b) and three choice variables (R_ℓ, d', b') and is therefore subject to the curse of dimensionality. [7] The algorithm for solving the model relies on graphics processing units (GPUs) to highly parallelize the solution.

Parameterization

The model calibration proceeds in two steps. First, a subset of parameters is directly obtained from the data, while the remaining parameters are estimated using the Simulated Method of Moments (SMM). As discussed later, the selected set of moments is chosen to capture the key financial frictions faced by banks. Throughout, one model period corresponds to a quarter, so all parameters and targets are expressed at a quarterly frequency.

The primary data source is the FFIEC *Call Reports*. I begin by parameterizing the stochastic process for loan losses.[8] Let $\text{nco}_{j,t}$ denote net loan charge-offs divided by total loans for bank j at time t, and define the implied loan-survival share

$$p_{j,t} \equiv 1 - \text{nco}_{j,t} \in (0, 1].$$

I estimate a right-censored Tobit for the latent process of $\log p_{j,t}$:

$$\log p^*_{j,t} = \mu_p + \rho_p \log p_{j,t-1} + \rho_R \hat{I}_{j,t-1} + u_{j,t}, \qquad u_{j,t} \sim \mathcal{N}(0, \eta_p^2),$$

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

[8] For consistency with the model, I truncate net loan charge-offs at zero (so that net recoveries are set to zero) and cap extreme values to avoid undefined logarithms.

observing $\log p_{j,t} = \min\{\log p^*_{j,t}, 0\}$, since $p_{j,t} \leq 1$ implies $\log p_{j,t} \leq 0$. Given (μ_p, ρ_p, η_p), I discretize the latent AR(1) process using Tauchen (1986) on the $\log p$ scale and map back to $p = \exp(\cdot)$, truncating the support to $p \leq 1$ and $p \geq \varepsilon$.

An essential parameter for the model is the average maturity of time deposits. Following the literature, I assume a maturity of one year, which implies $\lambda = 1/4$ in quarterly terms.

The loan demand function is parameterized by assuming that the idiosyncratic component x^i_t follows a logistic distribution, yielding

$$\ell^d(R_{\ell,t}, R_{E,t+1}) = \frac{1}{1 + \exp[\theta(R_{\ell,t} - R_{E,t+1})]}, \tag{19}$$

where θ captures the sensitivity of loan demand to the lending rate and $R_{E,t+1}$ is the expected return on capital.[9] Parameters θ and $R_{E,\star}$ are endogenously determined in the steady state, while $\bar{k}$ is recovered residually from the steady-state capital return condition using the aggregate loan supply.

Intuitively, higher asset returns increase the incentive to invest, raising the demand for loans. Under the logistic specification, loan demand becomes less sensitive to loan rates when lending rates are already high. Because the aggregate loan supply is tied to the asset price, a contraction in loan supply—such as that induced by a monetary tightening—reduces the asset price and shifts loan demand upward, partially offsetting the initial decline.

The remaining parameters are calibrated directly from macro-financial data. The aggregate risk-free rate is set to the average effective federal funds rate between 2002 and 2023, excluding observations below 20 basis points per year. The recovery rate on assets is set to $\gamma = 0.65$, slightly higher than the 51–55% range reported by Correia et al. (2023), but consistent with Corbae and D'Erasmo (2021). The coupon payment is chosen to generate a 50-basis-point annual spread between deposit and time-deposit rates in a risk-free environment.[10] The capital requirement ratio is fixed at $\kappa = 0.06$, matching the average Tier 1 capital ratio. The capital share α is set to 0.35, following standard values in the macro-finance literature,

[9]This representation of loan demand is similar to those in Wang et al. (2022) and Jiang (2023), with the difference that the return on capital is aggregate rather than idiosyncratic. A similar form can be obtained under linear utility with a GEV shock.

[10]This spread captures both the liquidity premium of deposits and the term premium.

and the depreciation rate $\delta = 0.05$ implies an average loan maturity of five years.[11] Table 2 summarizes the externally calibrated parameters.

Table 2: Fixed Parameters

Parameter	**Symbol / Value**	**Source / Target**
Capital share	$\alpha = 0.35$	Standard in literature
Depreciation rate	$\delta = 0.050$	Implies average loan maturity of 5 years
Risk-free rate (quarterly)	$R_f = 1.006$	Avg. Fed Funds rate (2001–2025)
Recovery rate on assets	$\gamma = 0.65$	Corbae and D'Erasmo (2021)
Coupon rate	$c = 0.004$	50 bp deposit–time deposit spread
Capital requirement ratio	$\kappa = 0.06$	Tier 1 capital ratio
Time deposit maturity	$\lambda = 1/4$	One-year maturity assumption

Notes: Parameters in this table are externally fixed prior to the simulated method of moments (SMM) estimation. One model period corresponds to a quarter. The coupon implies a 50-basis-point annualized difference between deposit and time deposit rates in a risk-free environment.

Targeted Moments

In this subsection, I assess whether the model can accurately approximate the targeted and untargeted moments. I begin by describing the endogenously calibrated parameters in the steady state, then discuss the targeted moments and their mapping to key bank frictions, and finally evaluate the model's fit and external validity.

Table 3 reports the parameters calibrated within the model. Because competition across banks is limited, the parameter governing the interest rate sensitivity of loan demand, θ, is higher than the value estimated by Wang et al. (2022). The steady-state entrepreneurial return, $R_{E,\star}$, plays a key role in matching the net interest margin, as it determines the level of the average lending rate. The myopia parameter, σ, is close to the value in Corbae and D'Erasmo (2021), which helps generate leverage ratios consistent with those observed in the data. The fixed operating cost, ψ, corresponds to approximately 0.02% of average lending in the steady state, or about 0.2% of banks' equity. Since the coupon rate, c, also affects the spread between deposit and time deposit rates, it is jointly calibrated with the other parameters that influence banks' default behavior, such as ψ and η_ω. Finally, the issuance cost of deposits, ζ, governs the equilibrium share of time deposits in total funding.

[11] Geelen et al. (2024) document that debt maturity is positively correlated with asset life, as firms tend

Table 3: Targeted Parameters

Parameter	**Description**	**Calibrated Value**
θ	Interest rate sensitivity	301
$\eta\omega$	Std. dev. of loan shock	0.03
σ	Manager myopia	0.975
ψ	Fixed operating cost (as share of $\bar{k}$)	1×10^{-4}
ζ	Issuance cost of deposits	7×10^{-4}
$R_{E,\star}$	Steady-state entrepreneurial return	1.085
c	Coupon rate	0.004

Note: Parameters are calibrated to match the empirical moments reported in Table 4. $R_{E,\star}$ denotes the steady-state equilibrium return on equity, and c corresponds to the coupon rate on time deposits. All parameters are expressed in quarterly terms unless otherwise noted.

The targeted moments are chosen to reflect the key frictions that banks face in the model. Because banks operate in imperfectly competitive markets, their lending rates depend on the elasticity of loan demand. To capture this relationship, I target the empirical net interest margin (NIM), defined as the difference between interest income and interest expense divided by total assets. This moment summarizes banks' average markup over funding costs and disciplines the parameter θ, which governs the sensitivity of loan demand to interest rate changes—particularly when banks adjust their funding composition toward more costly time deposits.

A second key friction arises from the banks' exposure to default risk. While insured deposits are protected by the FDIC, time deposits are not, and thus carry an endogenous default premium. I measure this premium as the spread between rates on time deposits and savings and checking accounts, which serves as a moment capturing the equilibrium default risk in the model. Additionally, the observed failure rate of banks provides an aggregate indicator of default risk and is included among the targets.

The final set of moments captures banks' funding and leverage decisions. Banks can finance themselves through retained earnings or external liabilities, subject to regulatory and market constraints. I therefore target the average leverage ratio and its standard deviation, which provide information about the tightness of these constraints. To discipline the model's

to match the maturity of assets and liabilities.

Table 4: Targeted Moments: Data vs. Model

Moment	**Data (%)**		**Model (%)**	
	Mean	Std. Dev.	Mean	Std. Dev.
Share of failing banks	0.079	—	0.075	—
Leverage (Liabilities/Assets)	89.53	2.53	88.48	2.40
Share of time deposits	36.70	15.88	32.11	10.74
Net interest margin (NIM)	0.89	—	1.00	—
Spread between time and core deposit rates	0.37	—	0.41	—

Note: Empirical moments are computed from FFIEC Call Reports (2001–2025). Model moments correspond to the stationary equilibrium of the calibrated economy. All variables are expressed as percentages. Standard deviations are in percentage points.

funding structure, I target the mean and dispersion of the share of time deposits in total liabilities, which reflects banks' composition between iliquid and liquid funding.

Table 4 compares the model-implied and empirical moments. Overall, the model fits the data well. It closely matches the margins observed in the data and reproduces the average leverage ratio and its volatility. The spread between time and core deposit rates is slightly larger in the model—about 4 basis points above the data—consistent with possibly a smaller coupon in the model. The share of time deposits funding and its standard deviation are also well captured, indicating that the model successfully reproduces the heterogeneity in banks' funding composition.

The model's ability to match both the average levels and dispersion of leverage, funding composition, and pricing spreads supports its quantitative relevance. In the next subsection, I evaluate the model's untargeted moments, which provide an additional validation of its capacity to capture banks' dynamic responses to shocks.

Untargeted Moments - Dynamics Around Default

The analysis of untargeted moments provides a complementary validation of the model's performance beyond the steady-state calibration. While the targeted moments ensure that the model matches key cross-sectional averages, the untargeted moments assess whether it can replicate the dynamic patterns observed in the data as banks approach default. In particular, I examine how leverage, profitability, and funding composition evolve in the simulated economy around episodes of bank failure. These dynamics are then compared to the empirical event-study patterns documented in Section 2, providing a test of whether the model captures the buildup of fragility that precedes default.

Leverage Dynamics. Figure 5 compares the evolution of leverage ratios in the data and in the simulated model around episodes of bank failure. Both series display a gradual and persistent increase in leverage in the years preceding default, reflecting the buildup of balance-sheet risk as banks accumulate liabilities relative to assets. The model closely tracks the empirical pattern, reproducing both the slow upward drift and the acceleration in leverage in the final quarters before failure. This close alignment suggests that the mechanisms governing funding decisions and default in the model successfully capture the gradual deterioration in banks' solvency observed in the data.

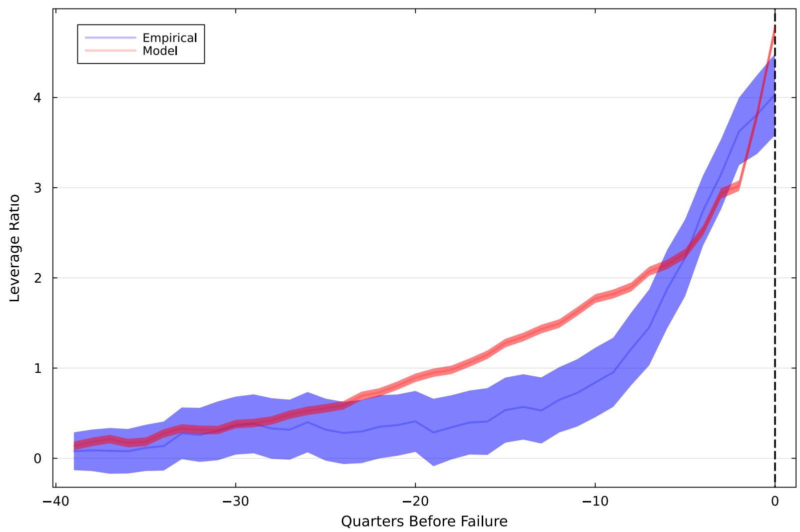

Figure 5: Leverage (Total Liabilities/Total Assets) Before Bank Failure

Funding Dynamics. Figure 6 compares the evolution of time deposits, expressed as a share of total liabilities, in the data and in the simulated model around episodes of bank failure. Both series show a gradual and sustained increase in the share of time deposits as default approaches, indicating that banks progressively shift toward illiquid and higher-yield funding sources when facing distress. The model captures both the timing and magnitude of this buildup, closely mirroring the empirical pattern. This alignment suggests that the mechanisms linking funding costs, maturity choice, and solvency in the model successfully reproduce the compositional changes in liabilities observed prior to failure.

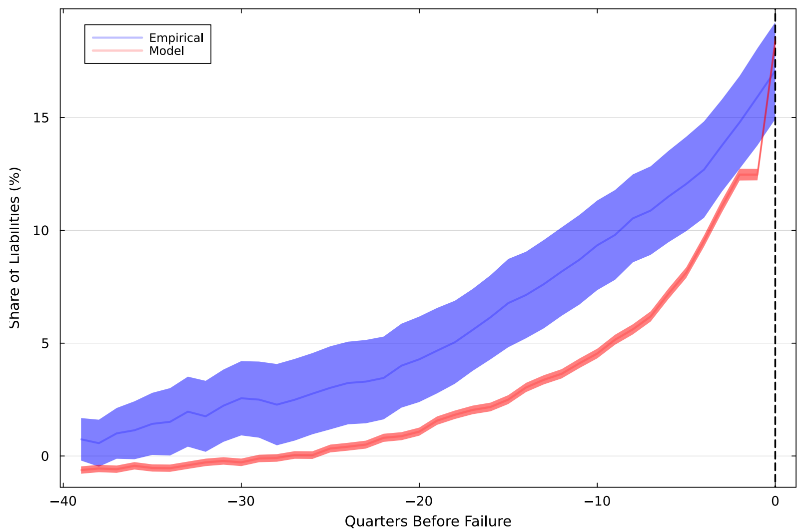

Figure 6: Time Deposits as a Share of Total Liabilities Before Bank Failure

Profitability Dynamics. Figure 7 compares the evolution of the net interest margin (NIM) in the data and in the simulated model around episodes of bank failure. Both series display a pronounced and sudden decline in NIM beginning roughly ten quarters before default, reflecting a sharp compression of lending margins as funding costs rise and profitability deteriorates. The model closely replicates this nonlinear pattern, matching the timing and intensity of the drop observed in the data. This sharp contraction in margins highlights how, late in the distress cycle, rising deposit rates and greater reliance on costly time deposits erode banks' profitability, ultimately precipitating default.

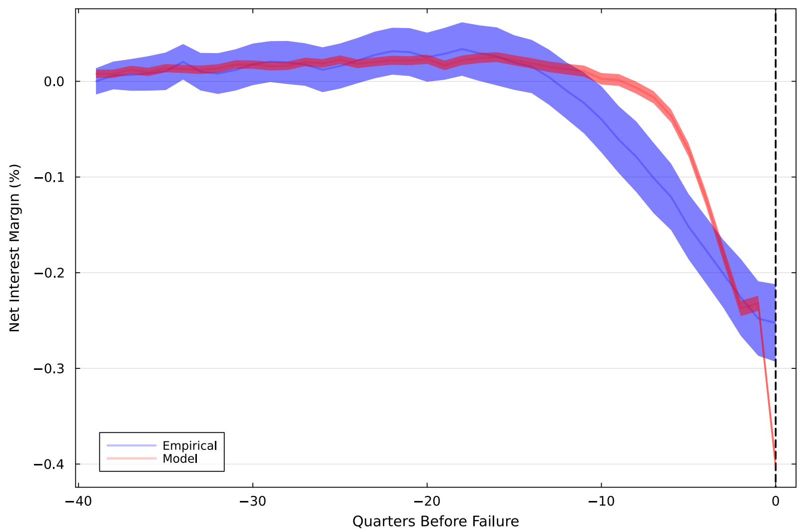

Figure 7: Net Interest Margin Before Bank Failure

Credit Losses. Figure 8 compares the evolution of net charge-offs in the data and in the simulated model around bank failures. Both series show a noticeable increase in charge-offs beginning roughly fifteen quarters before default, indicating a progressive deterioration in loan performance as banks approach distress. The model successfully reproduces the timing and trajectory of this increase, though it understates the final magnitude of losses observed in the data. This pattern reflects the buildup of credit risk that accompanies the funding and profitability pressures documented above: as margins compress and leverage rises, weaker balance sheets amplify exposure to loan defaults, eventually triggering bank failure.

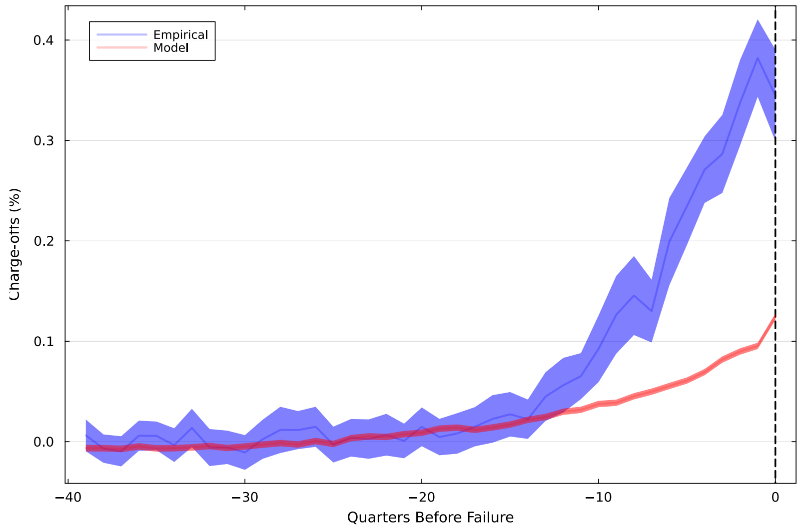

Figure 8: Net Charge-Offs Before Bank Failure

Taken together, these untargeted moments show that the model successfully reproduces the sequence of deterioration that precedes bank failure. It captures the gradual buildup of leverage, the shift toward illiquid and costly funding, and the sharp compression in profitability that ultimately culminate in rising loan losses and default. Although the model understates the final magnitude of charge-offs, it closely matches the timing and co-movement of key variables observed in the data. Overall, these results indicate that the mechanisms governing funding, risk-taking, and solvency in the model provide a coherent quantitative account of the dynamics of financial distress in the banking sector.

Counterfactual – The Role of Time Deposits

The model allows me to isolate the mechanism through which time deposits affect banks' balance-sheet dynamics. In this general equilibrium counterfactual, I eliminate the option to issue time deposits, forcing banks to rely solely on short-term deposit funding. All prices and aggregates adjust endogenously, allowing the comparison with the benchmark economy to reveal how the availability of time deposits relaxes funding constraints, alters the cost of liquidity, and reshapes bank failures.

General Equilibrium. Table 5 summarizes the general equilibrium differences between the benchmark model and the counterfactual economy without time deposits. Removing the option to issue time deposits leads to a substantial decline in the share of failing banks—from 0.075 percent to 0.042 percent—as banks deleverage and operate more conservatively. Average leverage falls from 88.5 percent to 86.3 percent, with higher dispersion, reflecting greater heterogeneity in balance-sheet adjustments as institutions manage rollover risk without access to illiquid funding. In turn, the net interest margin (NIM) rises from 1.00 to 1.18 percent, as the absence of costly time deposits lowers average funding costs and increases the spread between lending and deposit rates. Despite these higher margins, overall lending contracts slightly, from 12.30 to 12.16, as banks reduce balance-sheet size to mitigate liquidity risk. Together, these results illustrate the key general equilibrium trade-off: while the removal of time deposits reduces average default rates and raises profitability in the short run, it compresses credit supply and amplifies rollover risk, leading to a smaller and more fragile banking sector.

Table 5: Targeted Moments: Data, Model, and Counterfactual

Moment	**Data (%)**	**Model (%)**	**Counterfactual (%)**
Share of failing banks	0.079	0.075	0.042
Leverage (Liabilities/Assets)	89.53 (2.53)	88.48 (2.40)	86.30 (4.64)
Share of time deposits	36.70 (15.88)	32.11 (10.74)	—
Net interest margin (NIM)	0.89	1.00	1.18
Spread between time and deposit rates	0.37	0.41	—
Lending	—	12.30	12.16

Note: Standard deviations are shown in parentheses. Empirical moments are computed from FFIEC Call Reports (2001–2025). Model and counterfactual moments correspond to the stationary equilibria of the benchmark and no–time–deposit economies, respectively. Lending values are reported in model units (not percentages).

Leverage Dynamics. Figure 9 compares the evolution of leverage ratios in the data and in the simulated model around episodes of bank failure, when time deposits are no longer available. Unlike in the benchmark economy, where leverage rises gradually as banks rely on illiquid liabilities to smooth funding shocks, in this counterfactual the absence of time deposits amplifies rollover risk. Without access to long-term funding, banks are forced to rely exclusively on short-term deposits, making them more vulnerable to liquidity shocks, as captured by ω_t. As a result, they actively deleverage in anticipation of rollover risk, leading to a steady decline in leverage well before default. This pattern highlights that time deposits play a critical stabilizing role in the benchmark economy: by reducing debt repayment pressure, they mitigate rollover risk and allow banks to sustain higher leverage levels without immediate default.

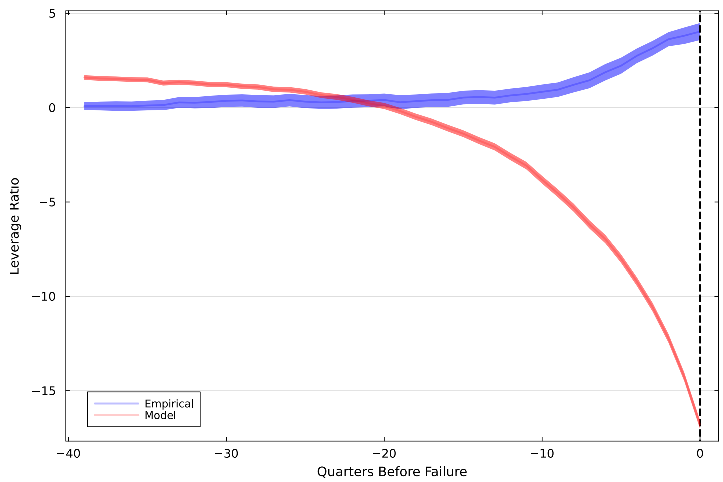

Figure 9: Leverage (Total Liabilities/Total Assets) Before Bank Failure Counterfactual

Profitability Dynamics. Figure 10 compares the evolution of the net interest margin (NIM) in the counterfactual economy, where time deposits are unavailable, to the empirical pattern. In contrast to the benchmark case, where NIM declines sharply prior to failure due to rising funding costs and a shift toward costly time deposits, the counterfactual shows a significant increase in NIM in the periods leading up to default. This occurs because banks rely exclusively on core deposits, whose rates are less sensitive to default risk and remain relatively stable as conditions deteriorate. As a result, funding costs do not rise as sharply, and the spread between lending and deposit rates temporarily widens. However, this apparent improvement in margins masks underlying fragility: without access to stable illiquid funding, rollover risk intensifies, forcing banks to deleverage and ultimately default despite higher measured profitability.

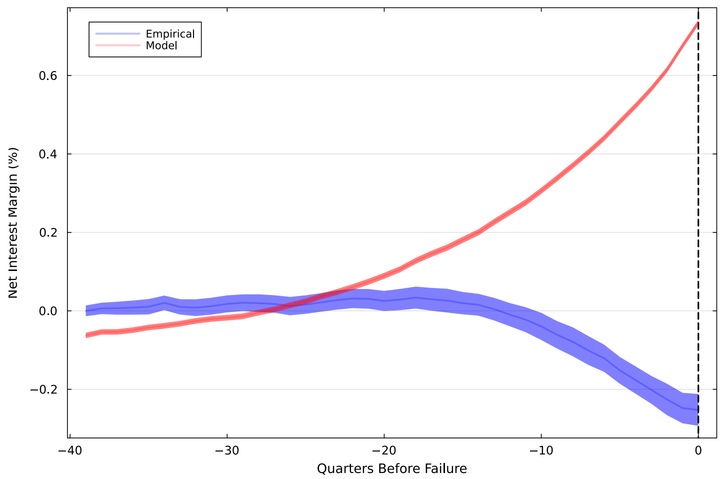

Figure 10: Net Interest Margin Before Bank Failure Counterfactual

Credit Losses. Figure 11 compares the evolution of net charge-offs in the counterfactual economy—where time deposits are unavailable—to the empirical pattern. The dynamics of credit losses remain broadly consistent across both settings: charge-offs begin to rise roughly thirty quarters before default, signaling a gradual deterioration in loan performance as banks approach distress, though the onset occurs earlier than in the benchmark model. In the absence of time deposits, however, the increase in charge-offs is somewhat more muted, as banks deleverage sooner and maintain smaller balance sheets. This close correspondence in dynamics, despite differences in leverage and profitability, highlights that deteriorating asset quality is a robust precursor to failure, largely driven by worsening borrower fundamentals rather than by the specific composition of bank funding.

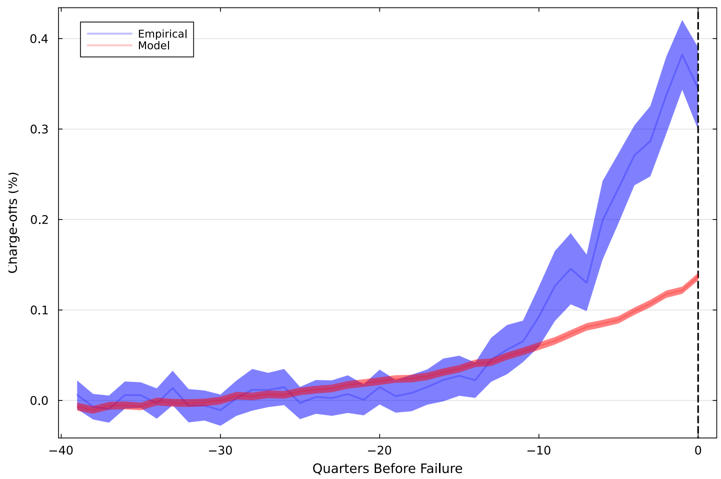

Figure 11: Net Charge-Offs Before Bank Failure Counterfactual

Taken together, these counterfactual results highlight the central role of time deposits in stabilizing banks' balance sheets and mitigating liquidity risk. When banks lose access to this form of illiquid funding, their exposure to rollover risk increases sharply, prompting earlier deleveraging and a contraction in balance-sheet size. Although profitability initially improves because core deposit rates are less sensitive to default risk, this gain is short-lived: the absence of stable funding amplifies vulnerability to liquidity shocks and accelerates default. In general equilibrium, time deposits therefore act as a crucial buffer that enables banks to sustain higher leverage and smoother funding conditions, ultimately reducing the frequency and severity of balance-sheet crises.

5. Conclusion

This paper developed and quantified a model of bank failures to study how funding frictions shape the buildup of balance-sheet fragility and default. Empirically, I showed that in the years preceding failure, banks progressively shift their funding composition toward time deposits and other costly liabilities, while leverage and credit losses rise and profitability deteriorates. These patterns indicate that funding structure is not only a reflection of balance-sheet risk but also an active margin of adjustment during financial distress.

Motivated by these facts, I built a quantitative model in which heterogeneous banks face limited commitment, capital regulation, and costly access to time deposits, due to default risk. Banks issue both deposits and time deposits to smooth cash flows and manage liquidity risk, but doing so exposes them to default risk through higher debt service and leverage. The model generates endogenous default thresholds and replicates the gradual buildup in leverage, the compression in net interest margins, and the increase in charge-offs observed in the data.

A counterfactual exercise highlights the stabilizing role of time deposits. When banks lose access to iliquid liabilities, they deleverage earlier and operate with smaller balance sheets to hedge rollover risk. Although their margins temporarily rise due to lower funding costs, lending contracts and liquidity risk becomes more acute. This general equilibrium adjustment illustrates that iliquid funding both amplifies leverage and mitigates the fragility arising from short-term refinancing exposure.

Together, these results show that the composition of liabilities are central determinants of financial stability. Time deposits, while costly, act as a buffer that allows banks to sustain lending and delay distress when shocks tighten funding conditions. The analysis thus provides a framework for understanding how the structure of bank funding governs the dynamics of crises—and underscores that the resilience of the banking system depends critically on the availability and design of stable, iliquid funding instruments.

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A. Appendix Additional Plots

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 bank subsidiaries at the Bank Holding Company (BHC) level. The FFIEC's National Information Center provides the relationship table between BHC and bank subsidiaries. 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 (**RCON2948**) and total assets (**RCON2170**).

Net Interest Margin. I define the Net Interest Margin by

$$\text{NIM}_{j,t} = 100 * \frac{RIAD4107_{j,t} - RIAD4073_{j,t}}{RCON3368_{j,t}}$$

where I transform interest income (**RIAD4107**) and interest expense (**RIAD4073**) in per quarter flows, and divide them by the quarterly average of assets (**RCON3368**).

C. Quantitative Appendix

C.1. Algorithm for Steady State

The bank 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 201, 111, and 101 grids for the endogenous choice variables, R_ℓ, d', and b', respectively. Additionally, I use 7 grid points for z, 101 for n, and 11 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^{-6}. Then, I store the policies for each grid point of (z, n, b).

The algorithm to solve the steady-state mass of banks according to their variables (z, n, b) follows Young (2010). 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', it generates a faster convergence speed than if I were to have (z, ℓ, d, b, ω) as state variables. Therefore, my vector for the steady state distribution is given by (z, n, b), which has more than 70 thousand grid points. Finally, I compute a transition matrix for (z, n, b), iterating with an initial guess for μ 5.000 times, which guarantees a convergence of the distribution.