Interest Rate Risk and Cross-Sectional Effects of Micro-Prudential Regulation [*]

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Abstract

This paper investigates the financial stability consequences of banks' interest rate risk exposure and uninsured deposit funding share. We develop a model of heterogeneous banks, with a portfolio choice between interest rate-sensitive securities and credit-risky loans, a funding choice between insured and uninsured deposits, and endogenous run risk on uninsured deposits to *jointly* analyze banks' portfolio and funding fragility decisions. The model delivers the concentration of uninsured deposits in larger banks and the U-shaped relationship between the portfolio allocation to cash and securities and bank size. We study the effects of Federal Reserve rate hikes on banks and analyze micro-prudential policy tools to enhance the banking sector's resilience. Tightening a conventional capital requirement substantially lowers run risk and improves capital allocation, but lowers the banking sector's ability to provide liquidity. A higher liquidity requirement targeting uninsured deposits reduces run risk at large banks but also causes misallocation in the lending market. A size-dependent capital requirement reduces run-risk by more than the liquidity requirement, with minimal unintended consequences.

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1 Introduction

Banks hold portfolios of fixed-income assets—such as loans and securities—whose values decline when the yield curve shifts upward. These assets are primarily funded with insured and uninsured deposits, exposing banks to run risk. The Federal Reserve's interest rate hike in 2022 revealed significant heterogeneity in banks' exposure to interest rate and run risk, highlighting the need for a framework to assess the effectiveness of microprudential policies in mitigating financial fragility in the banking sector.

This paper builds a framework to *jointly* analyze portfolio and funding choices and the resulting run-fragility exposure across the bank size distribution. We first study and quantify the forces that drive differences in banks' risk exposure choices. We then use the model to analyze which regulatory policies reduce financial fragility at large banks since they impact financial sector stability the most. We show that a size-dependent capital requirement is most effective at lowering financial fragility, without changing the allocation of bank loans and provision of liquidity services.

Three stylized facts about differences in banks' portfolio choices and funding characteristics guide our model setup. First, the banking sector is highly concentrated, with over half of aggregate assets owned by banks in the top percentile of assets. Second, larger banks choose a higher share of uninsured deposit funding. These two facts imply that uninsured deposit funding is also very concentrated: the top 10% of banks issue 90% of aggregate uninsured deposits. Third, the portfolio share of cash and securities is decreasing in bank size except for the top-percentile banks, whose share is as large as that of a median-sized bank.

We build a two-period model with a cross-section of banks and a representative household to analyze the economic drivers of differences in portfolio and funding choices across banks. Households derive utility from consumption in both periods and liquidity services from banks. Banks are ex-ante heterogeneous in their lending and deposit productivity. In the first period, banks choose investments in credit-risky loans and interest-rate risky bonds. Banks fund their assets with insured and uninsured deposits that are differentiated products and offer liquidity services valued by the household and equity issued to the household. We model liquidity services as a constant elasticity of substitution (CES) aggregator over quantities of insured and uninsured deposits scaled by banks' deposit productivity. A capital requirement and a liquidity requirement constrain bank leverage and portfolio choices. In the second period, the lending technology is subject to decreasing returns to scale and is hit by an idiosyncratic and aggregate productivity shock. Bonds expose banks to interest rate risk. Banks can default when they cannot repay depositors in the second period. Bank default causes bankruptcy costs that lower aggregate consumption. While insured deposits are fully covered by deposit insurance, funded with lump-sum taxes on households, uninsured depositors are not necessarily repaid in full, providing uninsured depositors with an incentive to run.

We calibrate the model to U.S. commercial banks, focusing on the post-Great Financial Crisis (GFC) period after 2009. Our calibration uses standard data from bank regulatory filings (FFIEC 031/041) on asset and uninsured deposit concentration, bond shares, and realized deposit rates. We jointly calibrate three parameter sets that govern loan productivity, deposit productivity, and liquidity preferences.

The loan return technology parameters determine the concentration within the banking sector. Our model differentiates between asset concentration and loan concentration, which are influenced by the curvature of the loan production function and the parameter that governs ex-ante loan productivity differences across banks. Our calibration of these parameters targets the standard deviation of the loan and asset distribution, the aggregate loan return, and asset productivity estimates implied by Egan, Lewellen, and Sunderam (2022). We assume that a bank's deposit productivity is proportional to its lending productivity, which captures complementarities between banks' assets and liabilities. We calibrate the parameter that governs how much deposit productivity rises with a bank's lending productivity separately for banks below and above the loan productivity median. We target the bond share of the smallest 20% and the top 1% largest banks by assets, respectively.

We calibrate the liquidity preferences parameters as follows. We target the average time deposit rate for the parameter that governs the overall weight on liquidity services in the utility, and the average share of uninsured deposits in overall deposits for the weight on insured deposits.[1] For the parameters that govern the degree of deposit product differentiation between

[1]Due to data limitations, transaction and time deposit rates are used as proxies for insured and uninsured deposit rates.

banks within the insured and the uninsured deposit market, our calibration targets the average transaction deposit rate and the Gini coefficient of uninsured deposits, respectively. Our calibration finds that insured deposits are more differentiated than uninsured deposits.

The model rationalizes the cross-section of bank portfolio and funding choices as follows. Its lending and deposit technology optimally determines a bank's scale. It can fund its assets with insured and uninsured deposits. Our calibration implies that the bank's profit margins are higher in the insured deposit market. The deposit business mainly drives the balance sheet size of a less loan-productive bank. Such a bank invests in bonds to back its insured deposit business. In contrast, a more loan-productive bank has a larger optimal size than what it can optimally fund with insured deposits, without giving away too much of the profit margin in the insured market. Therefore, it also issues uninsured deposits to fund its profitable loan business. In our model, small banks hold bonds to support a relatively more profitable deposit business, generating a security share that declines with bank size. However, as in the data, the largest banks—with more uninsured deposit funding and hence higher run risk exposure—hold optimally more bonds compared to slightly smaller banks whose lower uninsured share means they have less precautionary incentives to hold bonds.

We then study bank default decisions. The model distinguishes between two types of defaults: solvency defaults and run defaults. Low fundamental asset return realizations characterize both types of defaults. In addition to a terrible asset return realization, run defaults require some assets to be illiquid. We find that solvency defaults are more common in less productive small banks, with a solvency default probability of up to 1.5%. Run defaults only affect banks with uninsured deposits, hence only large bank risk run defaults. In the baseline calibration, run defaults only happen for the lowest realization of the asset returns, increasing the probability of run-driven failures to just over 5%. Large banks hold enough bonds to hedge against run risk for all other asset return realizations. If an unanticipated rate hike shock hits banks' bond portfolios, small banks' default rates increase by roughly 10 basis points, while the run default probability of the largest banks nearly doubles. These findings illustrate that the combination of uninsured deposit funding and unexpectedly low bond return realizations can significantly increase the financial fragility of large banks.

Building on previous analysis, we solve a version of the model in which banks anticipate highly volatile bond returns to allow them to internalize the effects of raising interest rates on their optimal decisions. Interestingly, we find that rather than choosing safer portfolios as a precaution, the default probability of banks increases across the size distribution, especially run defaults for the larger banks. The increase in run-induced defaults is partly driven by lower realized bond returns but also reflects large banks' choice to no longer hold bonds to guard against runs. For large banks whose loans are very productive and whose uninsured deposit rates reflect some asset risk, an increase in bond risk makes bonds much less attractive as an investment and as a means to hedge liquidity (run) risk. For smaller banks whose balance sheet size is primarily determined by their insured and, therefore, mispriced deposit business, the increased bond risk is not reflected in insured deposit rates. Together with their relatively more profitable deposit business, small banks choose a similar balance sheet scale and, therefore, a similar amount of bonds to back their deposit business. This analysis suggests that the rational anticipation of interest rate risk can increase bank fragility.

Finally, we use the model as a laboratory to evaluate the microprudential effects of several policy interventions. We show that increasing the capital requirement effectively reduces run-induced default risk among large banks, thereby lowering aggregate deadweight losses from bankruptcies. It also improves capital allocation by addressing distortions in banks' size choices caused by mispriced insured deposits. However, an across-the-board tighter capital requirement constrains the banking sector's ability to provide liquidity through deposit funding.

Given that default risk is concentrated among large banks in our model, we examine a policy that scales capital requirements with bank size. Imposing stricter capital requirements on large banks reduces their leverage and mitigates their run risk. Unlike a uniform increase in capital requirements across all banks, this targeted approach achieves a meaningful reduction in default risk without significantly diminishing the liquidity services provided by the banking sector.

Since runs trigger most defaults among large banks, our third policy experiment considers tightening the liquidity requirement by explicitly conditioning on the amount of uninsured deposit funding. This policy compels large banks to hold more liquid (but interest rate-sensitive) bonds. Although it does reduce run-induced defaults, its effectiveness is less than half that of the size-dependent capital requirement, as increased bond holdings heighten banks' exposure to interest rate risk. Not only is the policy less successful at mitigating run risk, it also distorts portfolio choices across banks of different sizes, leading to misallocation in the loan market. Thus, our framework suggests that size-dependent capital regulation is more effective at limiting the run exposure of large banks than liquidity requirements that do not distinguish between the duration risk of bonds.

Related literature Our work is at the intersection of banking, asset pricing, and macro-finance. The model captures several forces emphasized in prior literature, including banks' interest rate risk exposure, asset and deposit productivity heterogeneity across banks, and the risk of runs on uninsured deposits.

The maturity transformation inherent in banks' business models exposes them to interest rate risk, defined as changes in a bank's value due to fluctuations in interest rates. Long-standing literature has examined how to measure the extent of banks' exposure to this risk (e.g., Flannery, 1981; Choi, Elyasiani, and Kopecky, 1992; Hirtle, 1997; Landier, Sraer, and Thesmar, 2013; English, Van den Heuvel, and Zakrajšek, 2018; Paul, 2023; Haddad and Sraer, 2020; Greenwald, Krainer, and Paul, 2024; Begenau, Piazzesi, and Schneider, 2025; Jiang et al., 2024; DeMarzo, Krishnamurthy, and Nagel, 2024). In our model, banks endogenously choose how much interest rate risk they seek exposure to in conjunction with credit risk and deposit funding choices.

Our model builds on the quantitative macro-banking literature with heterogeneous banks (e.g., Robatto, 2019; Elenev, Landvoigt, and Van Nieuwerburgh, 2021; Jamilov, 2021; Begenau and Landvoigt, 2022; Begenau et al., forthcoming; Coimbra and Rey, 2024), capturing banking sector concentration—the first stylized fact—highlighted by Corbae and D'Erasmo (2020) and quantitatively modeled in Corbae and D'Erasmo (2021). Compared to much of the existing macro-banking literature, our model incorporates endogenous run risk driven by uninsured deposit funding. While some notable macro-banking models also incorporate run risk (e.g., Ennis and Keister, 2003; Gertler and Kiyotaki, 2015; Robatto, 2019), our approach emphasizes cross-sectional heterogeneity across banks. In line with the IO-banking literature, differences in product offerings and productivity levels across banks help account for the observed concentration in the banking sector.

Our paper also connects to the IO-banking literature that has long modeled product- and productivity differences on banks' asset side (for recent examples see Benetton, 2021; Benetton and Buchak, 2024; Egan, Lewellen, and Sunderam, 2022; Jiang, 2023; Buchak et al., 2024) and deposit side (e.g., Egan, Hortaçsu, and Matvos, 2017; Egan, Lewellen, and Sunderam, 2022; d'Avernas et al., 2024; Jiang et al., 2023, 2024). The fragility from uninsured deposits and potential policy responses has been extensively analyzed by Egan, Hortaçsu, and Matvos (2017), and more recently in Chang, Cheng, and Hong (2023), Jiang, Matvos, Piskorski, and Seru (2023), Pancost and Robatto (2023) and Jiang, Matvos, Piskorski, and Seru (2024). Jiang, Matvos, Piskorski, and Seru (2023) also show that larger banks rely more on uninsured deposit funding compared to smaller banks, the second stylized fact the model aims to capture. We contribute to this literature by adding portfolio choice and endogenous run risk to a model of heterogeneous banks with insured and uninsured funding choices. We model run decisions of uninsured depositors as in Dávila and Goldstein (2023).

Our model reflects the deposit-centric view of banking (e.g., Hanson et al., 2015; Drechsler, Savov, and Schnabl, 2017; Egan, Hortaçsu, and Matvos, 2017; Egan, Lewellen, and Sunderam, 2022; d'Avernas et al., 2024), recognizing that a core aspect of the banking business model revolves around deposit-taking. In our model, households derive utility from deposits (Van den Heuvel, 2008; Krishnamurthy and Vissing-Jorgensen, 2012; Begenau, 2020; Krishnamurthy and Li, 2023) and deposits are differentiated products (Egan, Hortaçsu, and Matvos, 2017). Our model shows that deposits drive banks' portfolio decisions, particularly banks' choice to invest in interest rate sensitive bonds to back a profitable deposit business when lending opportunities are weak, which is consistent with the empirical evidence in (e.g., Stulz, Taboada, and Van Dijk, 2022; Begenau, Piazzesi, and Schneider, 2025).

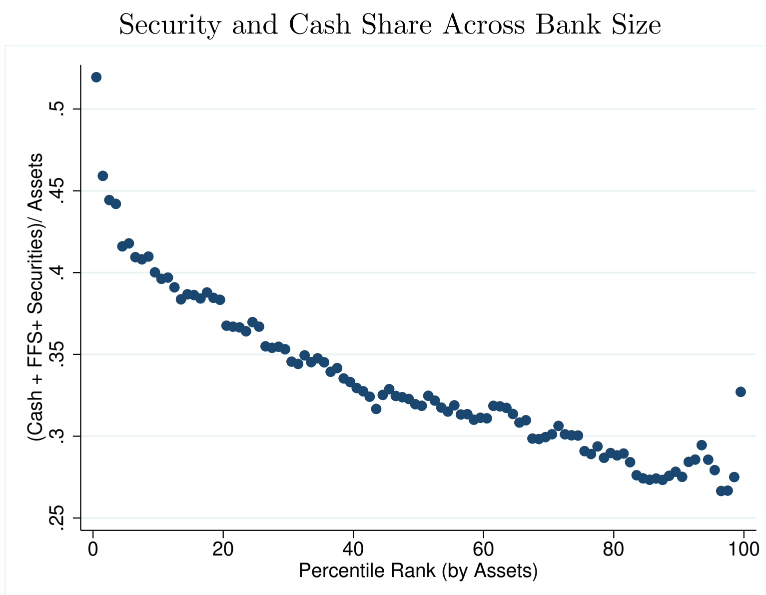
The following section presents stylized facts that guide our modeling choices. Section 3 presents our model. We discuss the model's calibration in Section 4. Section 5 analyzes the model mechanism and discusses policy experiments.

2 Stylized Facts

This section summarizes stylized facts about the cross-section of US commercial bank securities and uninsured deposit funding central to our modeling framework. We use bank call report data from 2010Q1 to 2022Q4 to capture the post-GFC era changes in banks' regulatory environment.[2]

Securities Share We study differences in banks' portfolio choices over the size distribution. Smaller banks hold more cash and securities on their balance sheet compared to larger banks. Figure 1 presents a binned scatter plot of the securities and cash shares over bank size as measured by logged assets. To construct this plot, we compute each bank's asset share in securities, cash, and federal funds sold and repo assets for each quarter between 2010Q1 and 2022Q4. We calculate the average cash and securities share for each log asset percentile. The security share is generally declining in size but increases slightly for the largest banks.

Figure 1: **Stylized Facts of the Cross-Section of Banks**



Notes: This figure presents the average securities share (Panel A) and the average maturity of securities as a binscatter plot, with 100 bins. The securities share is the ratio of the sum of cash, federal funds sold, repo assets, and securities over assets. The data are from bank call reports, filing forms FFIEC 031/041 using a bank-quarter panel from 2010Q1 to 2022Q4.

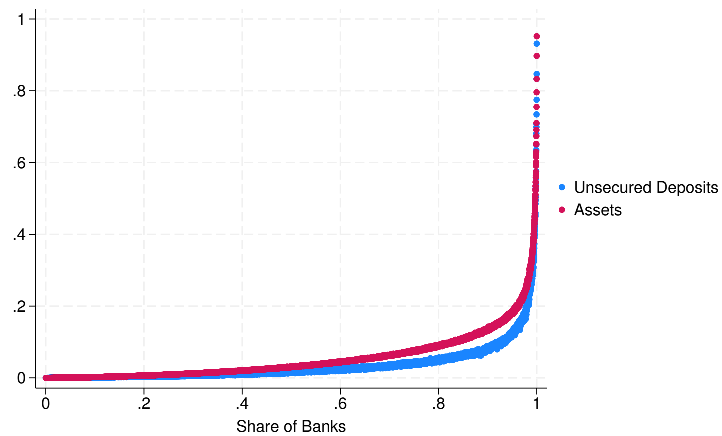
Asset and Uninsured Deposits Concentration The banking sector is highly concentrated (see Panel A of Figure 2 and Corbae and D'Erasmo (2020); Begenau, Piazzesi, and Schneider (2025). As a result, most assets and uninsured deposits are held by a small fraction of banks. In addition, Panel B of Figure 2 shows that uninsured deposits represent a larger fraction of large

[2]The data are from bank level call forms FFIEC 031 and FFIEC 041.

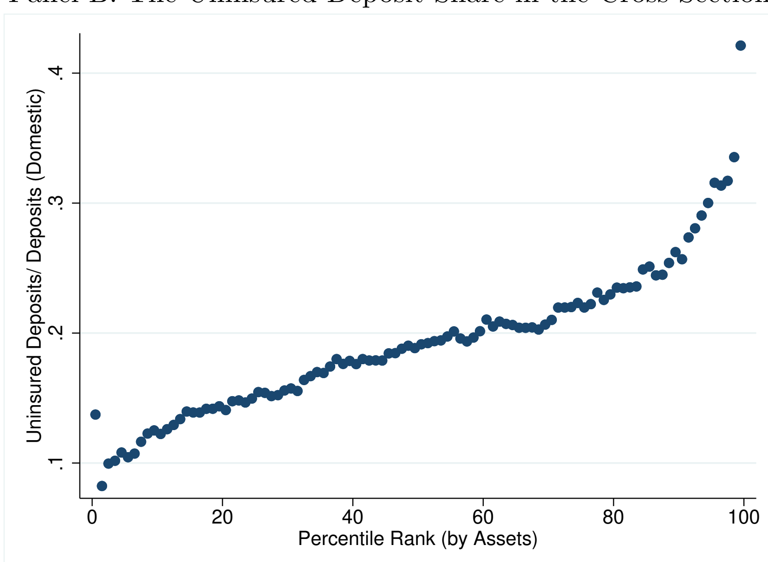
banks' domestic deposit funding, confirming the earlier findings by Jiang, Matvos, Piskorski, and Seru (2023). The average uninsured deposit share increases from about 10% for the smallest banks to about 40% for the largest banks. Since the banking sector is very concentrated, uninsured deposits dollars are disproportionately concentrated in the largest banks (Panel A).

Figure 2:

Panel A: Concentration of Uninsured Deposits and Assets



Panel B: The Uninsured Deposit Share in the Cross-Section

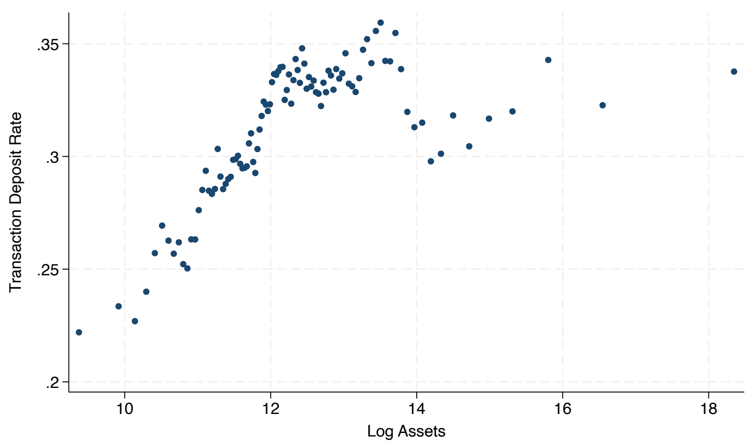


Notes: Panel A shows the concentration of unsecured deposits and assets. We compute the cumulative aggregate share of each held by a given share of banks and plot the curves. Panel B presents the uninsured share over the bank size distribution as a binscatter plot, with 100 bins. The uninsured share is the ratio of uninsured domestic deposits over domestic deposits. Uninsured deposits are deposit accounts with more than $250 thousands. The data are from bank call filing forms FFIEC 031/041 using a bank-quarter panel from 2010Q1 to 2022Q4.

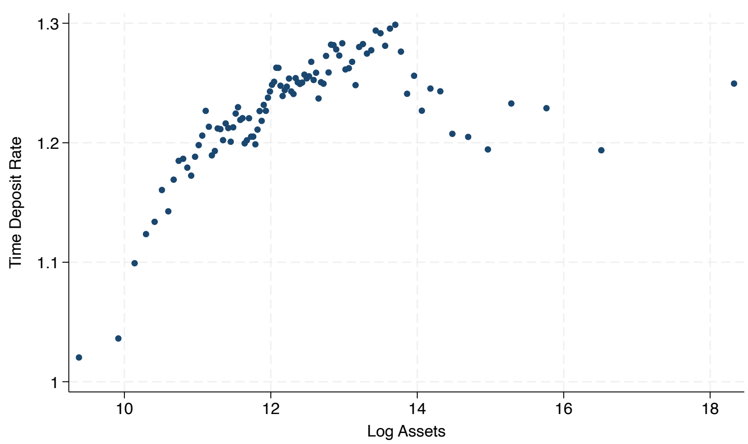
Deposit Rates Figure 3 presents a scatter plot of transaction deposit rates in Panel A and time deposit rates in Panel B. The largest banks pay higher deposit rates compared to the smallest banks, but the largest banks pay less than large mid-size banks consistent with the findings in d'Avernas, Eisfeldt, Huang, Stanton, and Wallace (2024). We choose transaction and time deposit rates as data on realized interest expenses on insured and uninsured deposits are unfortunately not available for transaction accounts and are very limited for time deposits.

Figure 3:

Panel A: Transaction Deposit Rates



Panel B: Time Deposit Rates



Notes: This figure shows binned scatter plots of deposit rates in percentage points over bank size as measured by log assets. The data are from bank call reports, filing forms FFIEC 031/041 using a bank-quarter panel from 2010Q1 to 2022Q4. Transaction deposit rates (Panel A) are computed as the sum of domestic deposit interest rate expense less domestic time deposit expense divided by transaction deposits at the beginning of the period. Transaction deposits are domestic deposits less domestic time deposits. Time deposit rates (Panel B) are computed as the interest expense on time deposits divided by the beginning of period time deposits.

In the next section, we build a model that is consistent with the concentration of assets and uninsured deposits and the cross-sectional differences in the security share and deposit rates.

3 Model of the Cross-section of Banks

3.1 Environment and Timing

There are two types of agents, households and banks. Households are identical, and we solve the problem of a representative household. Banks are heterogeneous in their productivity of lending and providing deposits to households. Banks are indexed by i on the continuum $[0, 1]$. The model has two dates, 0 and 1. At date 0, households invest in bank liabilities, and banks decide on lending and capital structure. At date 1, there are two subperiods. First, aggregate and idiosyncratic bank productivity shocks are realized, and uninsured depositors decide whether to "run" on the bank and demand their balances to be paid. In case of a run, banks have to liquidate assets to pay out these early withdrawals.

Thereafter, banks can decide to default, in which case they are liquidated by the deposit insurance agency. Insured deposit payoffs are safe and backed by taxation. Uninsured deposits are risky and only receive a stochastic recovery value depending on bank assets.

3.2 Households

There is a unit mass of identical households. Households maximize utility over consumption C_t in both periods $t \in \{0, 1\}$, and over liquidity services at time 0 that are provided by bank deposits. They maximize the utility function

$$U(C_0, C_1, \{D_i^I\}, \{D_i^U\}) = \log(C_0) + \psi \log\left(H\left(\{D_i^I\}, \{D_i^U\}\right)\right) + \beta \log\left(\mathrm{E}\left[C_1^{1-\varphi}\right]^{1/(1-\varphi)}\right) \tag{1}$$

with the liquidity preference function

$$H\left(\{D_i^I\}, \{D_i^U\}\right) = \left[\alpha \left(\int_0^1 (A_i^D D_i^I)^{\rho_I} di\right)^{\eta/\rho_I} + (1-\alpha) \left(\int_0^1 (A_i^D D_i^U)^{\rho_U} di\right)^{\eta/\rho_U}\right]^{1/\eta}, \tag{2}$$

where $\{D_i^I\}_{i\in[0,1]}$ are insured, and $\{D_i^U\}_{i\in[0,1]}$ are uninsured deposits. Household enjoy liquidity services provided by both types of deposits, with α being the relative weight on insured deposits and η governing the elasticity of substitution between types. Banks have different productivity in liquidity services provision given by A_i^D. Further, banks have local monopolies in deposit markets, implying that their deposits are not perfect substitutes within the insured and uninsured categories. The degree of substitutability in each type is governed by ρ_j, for $j \in \{I, U\}$, respectively.

At date 0, households are endowed with initial wealth W_0, and they choose how much of this wealth to consume and how much to invest in equity $\{S_i\}$ and deposits $\{D_i^I\}, \{D_i^U\}$ of all banks. The household budget constraint at date 0 is

$$C_0 = W_0 - T + \int_i \Pi_i di - \int_i p_i S_i di - \int_i q_i^I D_i^I di - \int_i q_i^U D_i^U di, \tag{3}$$

where p_i is the price of equity and q_i^j for $j \in \{I, U\}$ is the price of insured and uninsured deposits of bank i. Households pay lump-sum taxes T that are needed to pay for bailouts of insured deposits. They further receive time-0 profits of all banks Π_i. Consumption at time 1 consists of the payoff of all securities bought at time 0:

$$C_1 = \int_i D_i^I di + \int_i \mathbb{I}_{\text{nd}_i} S_i \text{Div}_i di + \int_i D_i^U \mathcal{P}_i^U di. \tag{4}$$

Insured deposits pay off with certainty, while only non-defaulting banks, indicated by the binary variable $\mathbb{I}_{\text{nd}_i}$, pay dividends to equity holders. The payoff of uninsured deposits depends on both aggregate and idiosyncratic risk through banks' default decision and the potential realization of runs. These factors are encapsulated in $\mathcal{P}_i^U$ defined in equation (23) below. Time-1 consumption is exposed to aggregate risk and hence a random variable at time 0.

3.3 Banks

There is a continuum of banks of mass one, indexed by i. Banks are ex-ante heterogeneous in their cost of producing deposits and in their lending productivity, denoted by the pair of parameters $(A_i^D, A_i^K) \sim G$. Banks can invest in two types of assets, bonds and loans (= capital).

The capital price at time 0 is normalized to 1 and the aggregate return to capital R_K is risky: $R_K \in \{R_{K,1}, \ldots, R_{K,n_K}\}$ with probability vector π_K. Bonds are also exposed to aggregate risk, with bond return realizations $R_B \in \{R_{B,1}, \ldots, R_{B,n_B}\}$ and probability vector π_B, analogous to capital. We allow the payoffs banks earn on their bond holdings to have limited exposure to bond return risk. Banks have tools to reduce this exposure, for example by holding bonds to maturity or by hedging using derivatives, that are outside of our model. Specifically, the bond payoff in the final period is

$$\bar{R}_B = \omega R_B + (1 - \omega)(1 + r), \tag{5}$$

where r is the riskfree rate, and ω governs exposure to interest rate risk.

The aggregate payoffs of both assets are independent. Banks further receive multiplicative i.i.d. shocks ϵ_i to their loan production at time 1. A bank that extends K_i loans at time zero therefore receives total loan payoff

$$R_K A_i^K \epsilon_i K_i^{1-\kappa}, \tag{6}$$

where κ governs the degree of decreasing returns in lending.

Banks can decide to default. If a bank defaults, its pays out a dividend of zero and a fraction ξ of its output is lost in the bankruptcy proceedings. The remaining output $(1-\xi)A_i^K \epsilon_i K_i^{1-\kappa}$ is allocated proportionally to the recovery of insured and uninsured deposits. Uninsured deposits pay out this recovery value to households, while insured deposits pay out 1. Payouts of insured deposits for defaulting banks are funded by the government, which raises lump-sum taxes on households at date 0 to cover the shortfall between recovery and full payout in expectation.

Banks' uninsured deposits are subject to runs. In particular, we assume that fraction $1-\phi$ of uninsured deposits is "runnable," while remaining fraction ϕ is not.[3] Banks can pay out early withdrawals by liquidating bonds or loans to outside investors.

When a run occurs, bonds are always liquidated at their market value R_B. The measures banks take to mitigate bond return risk in their final payoff, reflected by ω in equation (5), are irrelevant when the bank experiences a run. Further, capital can only be liquidated with fire-sale discount $\delta < 1$.

[3]The non-runnable fraction ϕ represents other bank liabilities that are junior to deposits. This share of uninsured deposits is only senior to bank equity and will receive the residual recovery value of bank assets in bankruptcy. We will also consider too-big-too-fail guarantees for these deposits.

To summarize, the timing of events is

0. Time 0: Banks choose portfolio $\{K_i, B_i, D_i^U, D_i^I\}$. Households choose portfolio of bank securities.

1a. Time 1: Aggregate and idiosyncratic productivity shocks are realized and observed. Uninsured depositors decide whether to run. Banks subject to runs choose quantity of capital and bonds to sell in order to cover deposit outflow D_i^U.

1b. Bank default decision. All assets pay out.

3.4 Bank Problem

We will solve the bank problem backwards, starting at the run stage 1a. in the time line above.

Problem with run. We consider the problem of a bank that experiences a run. The bank needs to decide on the quantities of loans $\hat{K}_i$ and bonds $\hat{B}_i$ to liquidate in order to pay out running depositors. We summarize the portfolio of the bank by $\mathcal{A}_i = (B_i, K_i, D_i^I, D_i^U)$. The aggregate state $\mathcal{R} = (R_K, R_B)$ consists of the realized loan and bond returns. The bank solves the optimization problem

$$V(\mathcal{A}_i, \epsilon_i, \mathcal{R}) = \max_{0\leq \hat{K}_i \leq K_i, 0 \leq \hat{B}_i \leq B_i} \max\{0, A_i^K \epsilon_i R_K (K_i - \hat{K}_i)^{1-\kappa} + \bar{R}_B(B_i - \hat{B}_i) - D_i^I - \phi D_i^U\} \quad (7)$$

subject to

$$\delta R_K \hat{K}_i + R_B \hat{B}_i \geq (1-\phi) D_i^U. \quad (8)$$

The bank maximizes its post-run dividend to shareholders in (7). However, if this dividend is negative, banks take advantage of limited liability and go into bankruptcy. The constraint in (8) states that the bank must pay out balances of running depositors $(1-\phi)D_i^U$ by selling capital or bonds. Comparison between the bond payoffs in equations (7) and (8) clarifies that bonds always have full risk exposure R_B during the run stage when bonds are liquidated to pay out depositors, while their risk exposure in the bank objective $\bar{R}_B$ depends on the effective exposure ω. We assume that banks always choose portfolios such that they can fully pay out running depositors, i.e. the constraint (8) can always be met.

Assumption 1. *All banks choose portfolios $\mathcal{A}_i$ that satisfy constraint* (8)*.*

This assumption is not restrictive. If $\kappa > 0$, banks have decreasing returns in loan payoffs with an Inada condition in the production function. For a hypothetical bank that has sold off its complete loan portfolio in a fire sale such that $K_i - \hat{K}_i = 0$, the inframarginal unit of loans has an infinite marginal payoff. This is not compatible with optimality for fairly general conditions, implying that banks will have enough assets to avoid selling all capital. To simplify the solution to the problem given by (7) – (8), we further make the following assumption.

Assumption 2. *Conditional on a run, banks first liquidate their bond holdings to pay out running depositors. Only if bond holdings are insufficient to cover deposit withdrawals, banks also liquidate capital holdings.*

This assumption implies that banks will choose $\hat{B}_i = \min\left\{\frac{(1-\phi)D_i^U}{R_B}, B_i\right\}$ and only resort to selling capital at fire sale discount δ if $(1-\phi)D_i^U > R_B B_i$. While we outright assume this liquidation pecking order for simplicity, we should note that it is also optimal for banks for a wide range of parameters.[4]

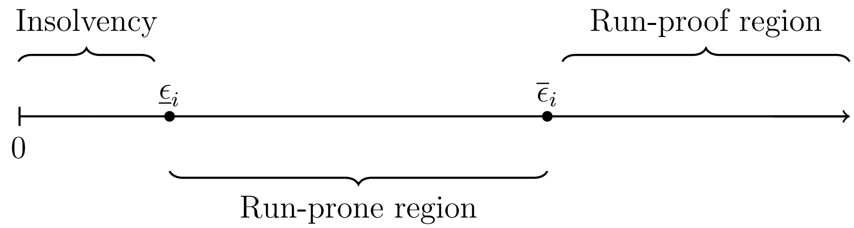
A key property of our model is that banks choose their exposure to run risk by issuing uninsured deposits. A bank that issues only insured deposits does not experience any runs. Furthermore, it is important to note that even though banks have sufficient assets to pay out running uninsured depositors, the remaining assets after these payouts may be insufficient to pay out the bank's remaining debts. These consist of non-running uninsured and insured deposits, $\phi D_i^U + D_i^I$. We define optimal policy functions $\hat{B}_i^* = \hat{B}_i(\mathcal{A}_i, \epsilon_i, \mathcal{R})$ and $\hat{K}_i^* = \hat{K}_i(\mathcal{A}_i, \epsilon_i, \mathcal{R})$ for fire sale quantities characterized in Appendix C.2. Inserting these optimal choices into the bank dividend in (7) implies the existence of the default threshold

$$\bar{\epsilon}_i = \frac{D_i^I + \phi D_i^U - \bar{R}_B(B_i - \hat{B}_i^*)}{A_i^K R_K (K_i - \hat{K}_i^*)^{1-\kappa}}, \tag{9}$$

such that banks with $\epsilon_i > \bar{\epsilon}_i$ do not default even conditional on experiencing a run.

[4]For a given δ, deviations from this pecking order can arise for banks with large capital holdings K_i, but low loan productivity realizations ϵ_i. For such banks, the effective marginal product of loans after the run, $A_i^K \epsilon_i (1-\kappa) K_i^{-\kappa}$, can be lower than the fire sale price δ.

Figure 4: Endogenous run-prone region as function of idiosyncratic risk



Problem without run. Now we consider a bank that does not experience a run. This bank's dividend payment to households is

$$\max\{0, A_i^K \epsilon_i R_K K_i^{1-\kappa} + \bar{R}_B B_i - D_i^U - D_i^I\},$$

which implies a threshold

$$\underline{\epsilon}_i = \frac{D_i^U + D_i^I - \bar{R}_B B_i}{A_i^K R_K K_i^{1-\kappa}}. \tag{10}$$

Banks with idiosyncratic shocks $\epsilon_i < \underline{\epsilon}_i$ will default even if they do not experience a run.

Run coordination. Consistent with the thresholds for idiosyncratic productivity in (9) and (10), we assume that uninsured depositors do not run on banks with $\epsilon_i > \bar{\epsilon}_i$, since these banks are always solvent. Further, we assume that the regulator shuts down banks with $\epsilon_i < \underline{\epsilon}_i$ before depositors can run. This leaves banks in the interval $\bar{\epsilon}_i \geq \epsilon_i \geq \underline{\epsilon}_i$ vulnerable to runs. These banks will default if they experience a run, but not otherwise. We assume that depositors choose to run on such banks conditional on realization of a bank-specific Bernoulli variable ς_i that takes on value 1 with probability π (a sunspot).[5]

Time-0 Problem. Define the household SDF M, derived in Appendix C.1. Then at time 0, bank i solves

$$\max_{K_i, B_i, D_i^U, D_i^I} \Pi_i + \mathrm{E}\left[M\left(\mathbb{I}_{\epsilon_i \geq \bar{\epsilon}_i} + \mathbb{I}_{\bar{\epsilon}_i \geq \epsilon_i \geq \underline{\epsilon}_i} \mathbb{I}_{\varsigma_i = 0}\right)\left(A_i^K \epsilon_i R_K K_i^{1-\kappa} + \bar{R}_B B_i - D_i^U - D_i^I\right)\right] \tag{11}$$

[5]The run game follows the structure laid out in Dávila and Goldstein (2023).

subject to the budget constraint

$$p_i + q_i^I(D_i^I)D_i^I + q_i^U(\mathcal{A}_i)D_i^U = K_i + B_i + \Pi_i, \tag{12}$$

the leverage constraint

$$D_i^I + D_i^U \leq \theta^K K_i + \theta^B B_i, \tag{13}$$

and the liquidity constraint

$$\theta^D(D_i^I + D_i^U) \leq B_i. \tag{14}$$

Banks choose their portfolio of assets to maximize the sum of time-0 profits and the present value of time-1 dividends to their shareholders, the households. The bank maximizes dividends for states of the world in which the bank does not default, which are selected by the indicator functions based on the thresholds in (9) and (10). The objective (11) highlights that banks suffering a run always default. The budget constraint in (12) states that banks raise funds through sales of equity p_i and both types of deposits. Deposit prices are bank-specific, since banks have market power and idiosyncratic default risk. Banks internalize the effects of their portfolio choice on these bond prices, a key mechanism that shapes their optimal choices. Banks spend the funds raised on purchases of loans and bonds, and on profit payouts. The model contains two features giving rise to non-zero economic profits, which are decreasing returns to scale in lending and market power in deposit markets. The leverage constraint in (13) captures real-world bank equity capital requirements, allowing for different risk weights on loans and bonds. Finally, constraint (14) reflects liquidity regulation such as the liquidity coverage ratio (LCR) that requires banks to hold a fraction of their assets in liquid assets (bonds).

3.4.1 Recovery Value

When a bank defaults, creditors have a claim on the remaining value of bank assets. A fraction ξ of assets is lost in the bankruptcy process. The remainder is allocated proportionally to insured and uninsured deposits. The recovery value for insured deposits is used by the insurance fund to partially cover its expenses for paying out insured depositors. The recovery value of uninsured deposits is paid out to uninsured deposit holders. We separately derive recovery values conditional on whether a bank experienced a run.

No Run. In this case, assets after bankruptcy are $(1-\xi)(\epsilon_i R_K A_i^K K_i^{1-\kappa} + \bar{R}_B B_i)$. Fractions $D_i^I/(D_i^I + D_i^U)$ and $D_i^U/(D_i^I + D_i^U)$, respectively, are allocated to the recovery value of insured and uninsured bonds. The recovery value per dollar of deposits is thus for both insured and uninsured deposits

$$r_i^{nr} = \frac{(1-\xi)(\epsilon_i R_K A_i^K K_i^{1-\kappa} + \bar{R}_B B_i)}{D_i^I + D_i^U}. \tag{15}$$

Run. If there is a run, assets after bankruptcy are

$$(1-\xi)(\epsilon_i A_i^K R_K (K_i - \hat{K}_i)^{1-\kappa} + \bar{R}_B (B_i - \hat{B}_i)).$$

Since fraction $1-\phi$ of uninsured deposit holders have been paid out already after a run, the recovery value applies to insured deposits and the non-running uninsured deposits:

$$r_i^r = \frac{(1-\xi)\left(\epsilon_i A_i^K R_K (K_i - \hat{K}_i)^{1-\kappa} + \bar{R}_B (B_i - \hat{B}_i)\right)}{D_i^I + \phi D_i^U}. \tag{16}$$

3.5 Equilibrium

Expected insurance payouts for insured deposits are for each bank

$$T_i = D_i^I \mathrm{E}\left[F(\underline{\epsilon}_i)(1 - \mathrm{E}(r_i^{nr})) + \pi\left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right)(1 - \mathrm{E}(r_i^r))\right].$$

Total taxes are $T = \int_i T_i di$. The government raises the amount of revenue needed to pay for bailouts in expectation.[6]

Bonds are supplied elastically by the government at price p. Loans are supplied by borrowers elastically at a price of 1. Insured deposit, uninsured deposit, and equity markets clear for each bank: supply of these securities by banks must equal demand by households at prices q_i^I, q_i^U, and p_i, respectively.

[6]Depending on the aggregate state, actual bailout expenses may deviate from this expected expenditure.

3.6 Equilibrium Conditions

We provide a full derivation of all equilibrium conditions in the model appendix. Below we summarize the model's implications for the drivers of bank runs, choices of insured and uninsured deposits by households and banks.

Drivers of runs. Each bank has idiosyncratic run risk given by $\pi(F(\overline{\epsilon}_i) - F(\underline{\epsilon}_i))$. Thus, run risk depends on $\overline{\epsilon}_i - \underline{\epsilon}_i$; if this difference is large, bank i is subject to high run risk.

While the size of the interval $[\underline{\epsilon}_i, \overline{\epsilon}_i]$ generally depends on many model parameters, we can gain some intuition for the drivers of runs by considering a simplified case, in which all uninsured depositors are alert, $\phi = 0$, and bonds have equal exposure to risk at the run and final payoff stages, $\omega = 1$. We further define the fraction of uninsured deposit withdrawals that can be satisfied from bond liquidations

$$x_i = \min\left\{1, \frac{R_B B_i}{D_i^U}\right\}. \tag{17}$$

If a bank has large bond holdings relative to uninsured deposits, then it can meet all uninsured redemptions during a run, implying $x_i = 1$. A value of $x_i < 1$ in turn implies that the bank needs to liquidate capital to pay out running uninsured depositors. Given this definition we can write the thresholds as

$$\overline{\epsilon}_i = \frac{D_i^I + x_i D_i^U - R_B B_i}{A_i^K R_K K_i^{1-\kappa}\left(1 - \frac{(1-x_i)D_i^U}{\delta R_K K_i}\right)^{1-\kappa}}, \tag{18}$$

$$\underline{\epsilon}_i = \frac{D_i^I + D_i^U - R_B B_i}{A_i^K R_K K_i^{1-\kappa}}. \tag{19}$$

We can gauge the factors that drive run risk by inspecting the difference $\overline{\epsilon}_i - \underline{\epsilon}_i$. A high ratio of bonds to uninsured deposits yields $x_i = 1$, implying $\overline{\epsilon}_i - \underline{\epsilon}_i = 0$ and zero run risk. This includes the case of a bank that issues no uninsured deposits, $D_i^U = 0$. Thus, banks can always choose to completely avoid run risk by issuing no uninsured deposits.

Consider instead the case of a bank that has zero bond holdings and strictly positive uninsured deposits, $D_i^U > 0$, such that $x_i = 0$. This bank needs to liquidate capital to pay out uninsured depositors who run. We show in Appendix C.4 that under the additional assumption of a binding leverage constraint (13), $D_i^I + D_i^U = \theta^K K_i$, the condition for run risk $\bar{\epsilon}_i - \underline{\epsilon}_i > 0$ becomes

$$\frac{u_i}{1-(1-u_i)^{\frac{1}{1-\kappa}}} > \frac{\delta R_K}{\theta^K}, \tag{20}$$

where $u_i = D_i^U/(D_i^U + D_i^I)$ is the fraction of deposits that is uninsured. Condition (20) clarifies that absent bond holdings and at a binding leverage constraint, the only bank specific variable contributing to run risk is the uninsured deposit share. The LHS of condition (20) is strictly increasing in u_i, such that for any parameters run risk is increasing in the uninsured share. The condition also clarifies that even for a bank with an uninsured share of $u_i = 1$, run risk could be zero. If $u_i = 1$, the LHS of the condition is 1. Suppose banks have tight capital requirements, with $\theta^K < 1$ and capital returns are bounded by the lowest return $\underline{R}_K$. Then if capital is sufficiently liquid, with $\delta > \frac{\theta^K}{\underline{R}_K}$, the RHS is greater than 1 and runs occur with zero probability. Conversely, if capital is more illiquid (smaller δ), leverage constraints are lax (higher θ^K), or capital returns are more volatile (lower $\underline{R}_K$), the run region expands. In the unrestricted case that does not satisfy the simplifying assumptions underlying condition (20), banks' leverage choice, the fact that bonds have different risk exposure in runs and final payoffs ω, the share of non-alert depositors ϕ, and the distribution of idiosyncratic shocks F affect run risk in addition.

This analysis highlights that the fundamental sources of run risk in our model are capital illiquidity, high leverage, and low capital payoffs.[7] Banks can avoid this liquidity risk associated with capital by issuing few uninsured deposits or holding fully liquid bonds. However, since bonds are also exposed to market risk, low realizations of R_B raise run risk for those banks who hedge their uninsured deposit issuance through bond holdings.

[7]Our model thus features runs driven by asset illiquidity and strategic complementarities as in Diamond and Dybvig (1983) and Dávila and Goldstein (2023), and differs, therefore, from deposit franchise runs as modeled in recent work (e.g., Jiang et al., 2024; Haddad, Hartman-Glaser, and Muir, 2023).

Households. Households purchase insured and uninsured deposits of all banks. In Appendix C.1, we derive household first-order conditions for deposits of bank i as

$$q_i^I = \psi \mathcal{H}^I(D_i^I)C_0 + \mathrm{E}[M], \tag{21}$$

$$q_i^U = \psi \mathcal{H}^U(D_i^U)C_0 + \mathrm{E}\left[M\mathcal{P}^U(\mathcal{A}_i)\right], \tag{22}$$

where the payoff to uninsured deposits is

$$\begin{aligned}\mathcal{P}^U(\mathcal{A}_i) =& 1 - F(\bar{\epsilon}_i) + F(\underline{\epsilon}_i)\mathrm{E}[r_i^{nr}|\epsilon_i < \underline{\epsilon}_i] \\ &+ (1-\pi)\left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right) + \pi\left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right)\left(1 - \phi + \phi\mathrm{E}[r_i^r|\underline{\epsilon}_i \leq \epsilon_i \leq \bar{\epsilon}_i]\right),\end{aligned} \tag{23}$$

with F being the c.d.f. of ϵ_i. Insured deposit prices in (21) have a certain payoff of 1 at time 1. In addition, they deliver a liquidity benefit $\mathcal{H}^I(D_i^I)$ given in equation (30) in Appendix C.1 to households that depends on their quantity – deposits have diminishing marginal benefits. Uninsured deposits in (22) deliver an analogous liquidity benefit $\mathcal{H}^U(D_i^U)$ contained in equation (29) in the appendix. Furthermore, uninsured deposits have a stochastic payoff at date 1 given in equation (23) that depends on aggregate risk and banks' idiosyncratic shock ϵ_i. The first line of (23) accounts for banks that are either run-proof with a shock realization $\epsilon_i > \bar{\epsilon}_i$, or fundamentally insolvent even absent a run $\epsilon_i < \underline{\epsilon}_i$. In the former case, uninsured deposits pay out in full, and in the latter case they pay the no-run recovery value in (15). The second line of (23) accounts for banks in the run-prone region with $\epsilon_i \in [\underline{\epsilon}_i, \bar{\epsilon}_i]$: these banks do not experience a run with probability $1-\pi$, in which case uninsured deposits pay out in full. A run occurs with probability π, in which case the fraction $1-\phi$ of running uninsured depositors is paid out in full, but fraction ϕ of inactive depositors only receives the post-run recovery value from (16). Equation (23) clarifies that the uninsured payoff depends on the complete portfolio $\mathcal{A}_i = (K_i, B_i, D_i^I, D_i^U)$ of the bank, since these choices impact default thresholds and recovery values.

Banks. When banks choose their portfolios, they internalize the effects of their choices on the prices of insured and uninsured deposits. Taking bank first-order conditions for (K_i, B_i, D_i^I, D_i^U) therefore involves differentiating (21) and (22). For example, the the FOC of bank i for insured deposits is

$$q_i^I = \mu_i + \theta^D \lambda_i - \frac{\partial q^I(D_i^I)}{\partial D_i^I} D_i^I - \frac{\partial q^U(\mathcal{A}_i)}{\partial D_i^I} D_i^U + \mathrm{E}\left[M(1 - F(\underline{\epsilon}_i) - \pi(F(\overline{\epsilon}_i) - F(\underline{\epsilon}_i))\right]. \tag{24}$$

In this expression, μ_i is the Lagrange multiplier on the bank's leverage constraint and λ_i is the multiplier on the liquidity constraint. The rightmost term reflects that bank equity owners only care about payoffs in states without bank default. The two partial derivatives in the middle arise as banks take into account the effect of their insured deposit issuance on the household valuation of insured and uninsured deposits – these terms differentiate the household demand functions in (21) and (22). Specifically, each bank internalizes that issuing more insured deposits will decrease households' marginal liquidity benefit and thus raise the interest rate it has to pay on insured deposits ($\frac{\partial q^I(D_i^I)}{\partial D_i^I} < 0$). Further, each bank internalizes that issuing more insured deposits will raise its leverage and default risk, which in turn means that it must pay higher interest on its *uninsured* deposits ($\frac{\partial q^U(\mathcal{A}_i)}{\partial D_i^I} < 0$). All other bank first-order conditions and the derivatives of household demand functions are in Appendix C.2.

4 Calibration

4.1 Parameters

We calibrate the model to bank-level data from regulatory filings (FFIEC 031/041) from 2010q1 to 2022q4. We jointly calibrate the key parameters in Panel A of Table 1 as they shape how bank productivity and size distribution interact with households' liquidity demand. We can structure this description around how and which parameters affect (1) banks' production technology, (2) banks' deposit productivity, (3) and households' liquidity preference.

The production technology parameters are helpful for capturing the concentration of the banking sector. Our model allows for a distinction between asset concentration and loan concentration. Both the loan production function curvature κ and the parameter Z_{shape}, which governs the loan productivity distribution across banks, influence how concentrated the banking sector is. We target both the standard deviation of log loans (1.521) and log assets (1.427). The parameter μ_{RK} determines the average aggregate return on capital R^K, which scales the average aggregate loan return. Note that given the concentration in the banking sector and decreasing returns to scale, the average loan return is distinct from the average aggregate return on capital R^K. We compute a value-weighted loan return in the data as the ratio of the sum of aggregate interest income on loans and leases and loan sale income minus provisions for loan losses and the loan operating expense share over the beginning of period aggregate loans.

The second set of parameters governs heterogeneity in banks' deposit productivity. We assume that deposit productivity is correlated with loan productivity, with a loading that can depend on the position of the bank in the productivity distribution. Specifically,

$$A_i^D = \bar{a} + A^{-}\min\{A_i^K - \text{med}(A_i^K), 0\} + A^{+}\max\{A_i^K - \text{med}(A_i^K), 0\}.$$

This specification allows a different loading for banks below and above median loan productivity. To calibrate A^- and A^+, we target the bond share of the bottom 20% smallest banks by asset size and the bond share of the top 0.1% of banks. This leads to a higher sensitivity for below-median banks with $\mathrm{A}^- = 1.05$, implying that these banks are roughly equally unproductive in deposit creation and lending. For above-median banks, we set $\mathrm{A}^+ = 0.4$. The high value of A^- causes small banks to reduce their holdings of bonds relative to a calibration with constant deposit productivity, since their deposit franchise is less valuable. At the same time, the moderately positive value for A^+ means that the most loan-productive banks also have high deposits productivity, which causes them to have higher bond holdings. We define the bond share as the ratio of the sum of cash, federal funds sold, repo assets, and securities over assets. Bank size is determined by assets.

The final set of jointly calibrated parameters governs liquidity preferences. The parameter ψ is the weight of liquidity in the household utility function. As such, it scales the liquidity premium that drives a wedge between the risk-free rate and deposit rates. The CES elasticity of substitution parameter ρ, which governs the degree to which insured deposits are differentiated products, also matters for the level of deposit rates (ceteris paribus). When insured deposits are relatively more differentiated relative to uninsured deposits, households accept a lower interest rate on insured deposits relative to uninsured deposits. The ideal empirical targets for ψ and ρ would, therefore, be the insured and uninsured deposit rates. Unfortunately, rates

Table 1: Key Parameters

Panel A: Name	Jointly Calibrated Parameters Description	Value	Data	Model
	Production technology			
κ	Production fct curvature	0.125	Std(Log Loans) = 1.521	1.560
μ_{RK}	Mean capital return	1.0875	Agg Loan Return = 2.742%	2.204%
Z_{shape}	Shape of loan prd dist std = shape $\times$ scale	0.13	Std(Assets) =1.427	1.436
	Deposit technology			
A_{-}^{D}	Slope of Deposit Productivity $-$	1.05	Bottom 20% bond share= 0.410	0.398
A_{+}^{D}	Slope of Deposit Productivity $+$	0.4	Top 0.1% bond share = 0.328	0.213
	Liquidity preference			
ψ	Weight on liquidity	0.048	Time deposit rate = 1.228%	0.936%
α	Weight on insured deposits	0.65	Uninsured deposit share = 0.419	0.376
ρ	EoS b/w insured deposits	0.855	Transaction deposit rate = 0.312%	0.234%
ρ_U	EoS b/w uninsured deposits	0.96	Gini uninsured = 0.963	0.894

Panel B: Name	Externally Calibrated Parameters Description	Value	Data Source
β	Discount factor	0.99	1% risk-free return
φ	Risk aversion	2	Standard value in literature
Z_{mean}	Mean loan productivity	1	Normalization
Z_{loc}	Minimum loan productivity	0.6	ELS implied 0.48
Z_{scale}	Max - min loan productivity	1.55	ELS implied 1.54
σ_{RK}	Deviation of capital return	0.045	Vol of corporate bond portfolio
$\sigma_{\epsilon \ln}$	Volatility of idio. capital shocks	0.11	Vol of idio. bank equity return
r	Bond return	0.0123	Avg. bond return
μ_{RB}	Avg. bond payoff	$1 + r$	Normalization
σ_{RB}	Volatility of bond return	0.035	Vol of 5-year UST
ϕ	Fraction of sleepy uninsured depositors	0.03	Long term debt share = 0.074
δ	1 - Firesale costs of capital	0.78	Literature
ξ	1 - share lost in recovery	0.25	Moody's recovery
ω	long-horizon IR risk	0.4	Greenwald, Krainer, and Paul (2024)

Notes: This table presents the internally (jointly) calibrated model parameters (Panel A) and the parameters set directly to external moments in the data (Panel B). Uninsured share is the share of uninsured deposits in total domestic deposits. ELS stands for Egan, Lewellen, and Sunderam (2022). Details on Panel A parameters are in the text. The sample period is from 2010 to 2022 unless otherwise stated. Data sources are bank call report filings. Details on Panel B parameters are in Appendix Section A1.

by insurance status are only available for time deposits and only before 2009 or after 2016 when bank call reports reported the interest expense on time deposits broken out by deposit insurance limit.[8] Given the data limitation, we choose to target the transaction deposit rates and time deposit rates to roughly capture insured and uninsured deposit rates. We compute the transaction deposit rate as interest expenses on domestic deposits less domestic time deposit interest expense over beginning of period transaction deposit accounts, which are domestic non-time deposit accounts. The time deposit rate is the interest expense on domestic time deposits divided by the beginning of period domestic time deposit accounts. Both rates are annualized. The parameter α is the weight on insured deposits in the liquidity aggregator, and therefore determines the insured deposit share, and likewise our target the uninsured deposit share. We compute the uninsured share as the share of uninsured domestic deposits over total domestic deposits. Uninsured deposits are deposit account values with balances over $250,000 minus the number of uninsured accounts times $250,000. We choose the Gini coefficient of uninsured deposits as a target for the elasticity of substitution parameter for uninsured deposits ρ_U. When households perceive uninsured deposits as relatively undifferentiated, only the most productive banks will find it profitable to issue uninsured deposits. As a result, uninsured deposits will be only issued by the largest banks since large banks are the most productive banks in our model, leading to the Gini coefficient as a natural target for ρ_U.

We discuss the externally calibrated parameters listed in Panel B in Appendix Section A.

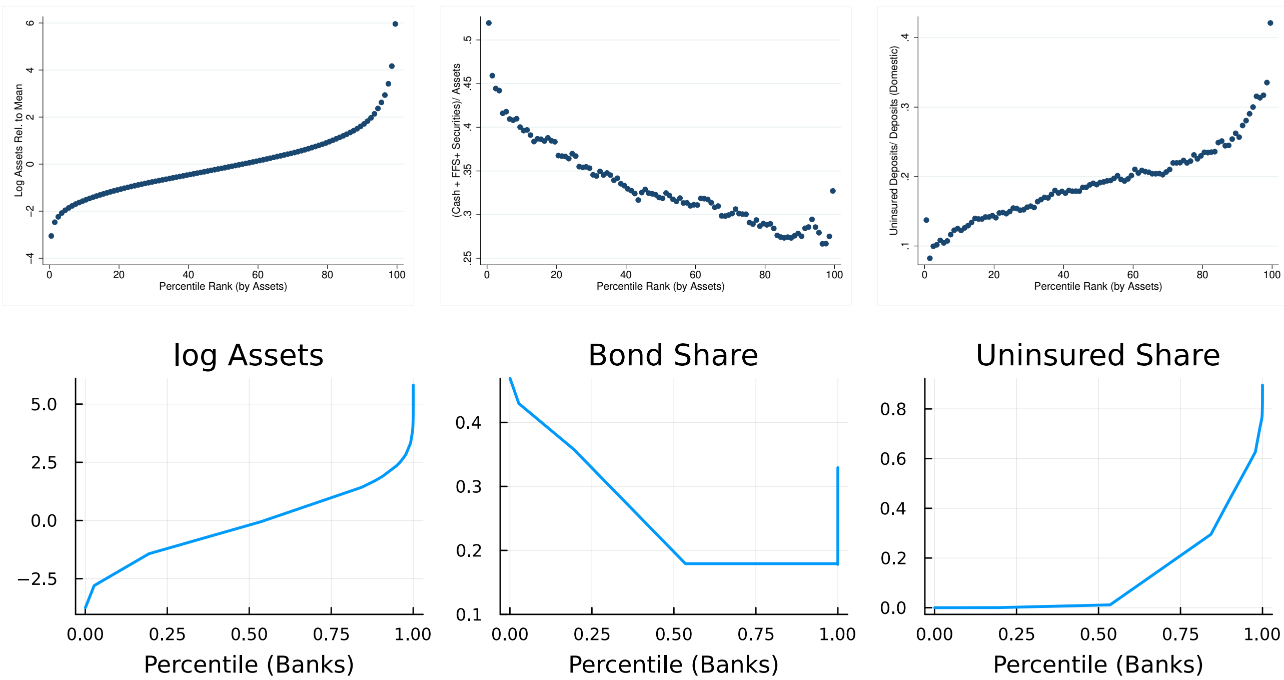
4.2 Model Fit

When compared to the cross-sectional stylized facts documented in Section 2, the model produces the right qualitative and quantitative patterns, as can be seen in Figure 5. The asset size distribution is as dispersed and as skewed as it is in the data, with the largest percentile of banks more than 5 orders of magnitude larger than the median. As in the data the bond share is U-shaped in log assets, decreasing for small and medium banks and higher for the largest

[8] Between 2009 and 2016, interest expenses were reported for time deposits with balances above and below $100,000, but the deposit insurance limit had increased to $250,000 at the end of 2008. In addition, large demand or savings deposits accounts may also exceed the deposit insurance limit. RateWatch reports banks offer rates by deposit products, but offer rates on select products are not informative about what banks actually pay overall on their deposit accounts.

banks than for the medium-large ones. The uninsured share is small for small and large for large banks. The model overstates this pattern somewhat relative to the data, but captures the particularly rapid increase in uninsured deposit share in the right tail of the bank size distribution.

Figure 5: Model Fit



Notes: X-axis: percentile rank of banks ordered by assets, e.g., a value of 0.5 represents the median bank. Left column: "log Assets" is the logarithm of the sum of capital and bonds. Middle column: "Bond Share" is the fraction of bonds in the asset portfolio. Right column: "Uninsured Share" is the fraction of uninsured deposits in all deposits. Top row: data; bottom row: baseline calibration of the model.

5 Results

In this section, we first describe the model mechanism, then discuss how an unanticipated interest rate shock and a partial bailout guarantee affect the banking system, and finally, we discuss policy implications.

5.1 Key Model Mechanisms

We now describe the key mechanisms that allow the model to match the empirically observed high concentration of uninsured deposits among the largest banks. High shares of uninsured deposits expose the largest banks to the possibility of runs.

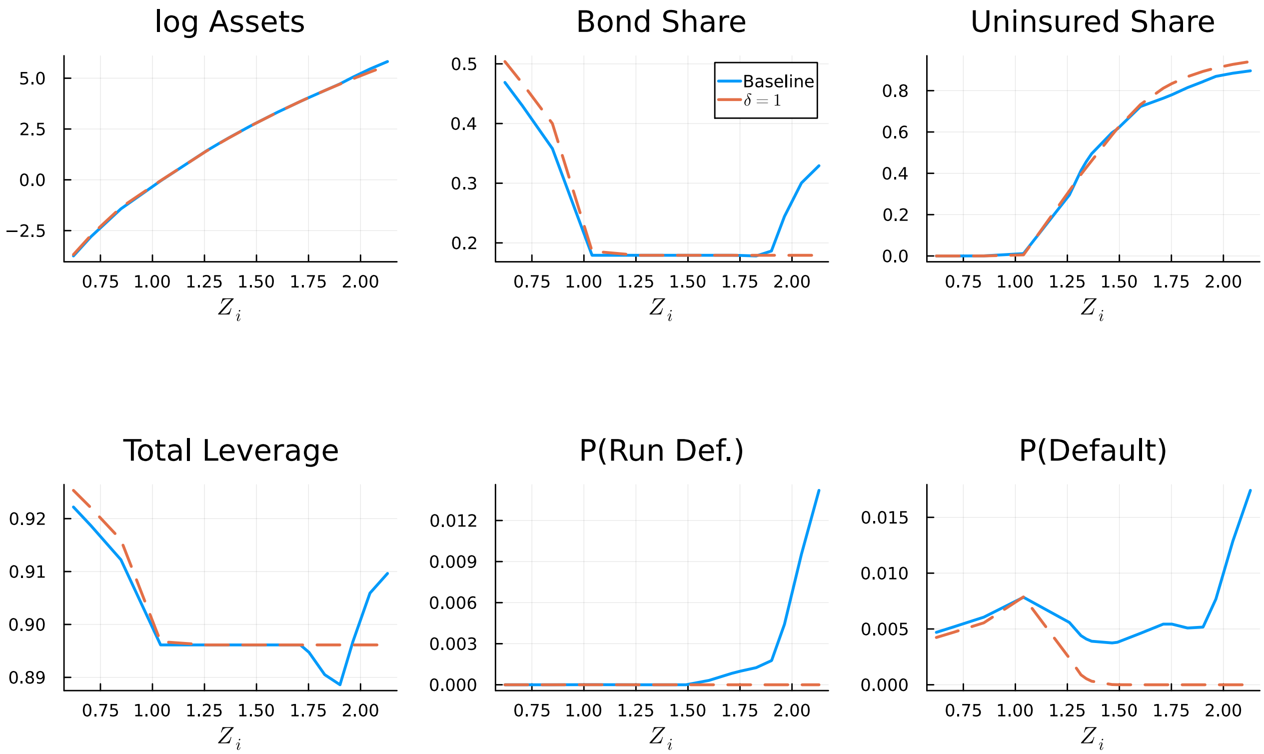
5.1.1 The Role of Runs

We first analyze how run risk affects bank choices and the industry equilibrium, both ex-ante and in terms of realized risks. To do so, we consider a counterfactual version of the model where capital can be sold without a firesale discount during runs ($\delta = 1$), allowing banks to fully repay depositors in case of a run. In this special case, runs do not induce banks to realize losses. Thus, with $\delta = 1$, depositors have no reason to run in the first place, and runs will not occur in equilibrium irrespective of banks' portfolio composition.[9]

Figure 6 shows six outcome variables in the cross-section of banks, indexed by asset productivity Z_i on the x-axis. The blue line shows the calibrated model "Baseline," while the red dashed line shows a counterfactual model with no fire sale discount, $\delta = 1$. Banks choose similar scales in terms of total assets, although the largest, most productive banks are smaller in the $\delta = 1$ model without run risk as a result of general equilibrium forces. The presence of run risk has a noticeable effect on banks' bond share: absent this risk, small banks choose to hold more bonds, while large banks only hold bonds mandated by liquidity regulation. This is contrary to the baseline model, where the largest banks voluntarily hold more bonds than required. The share of uninsured bonds is most strongly affected by the presence of run risk. While the least productive banks do not issue any uninsured deposits in either model, the uninsured share is more steeply increasing in the $\delta = 1$ equilibrium, and it is higher for the largest banks. Without run risk, all banks are at a binding leverage constraint. In the baseline model, the largest banks leave a buffer to the constraint – this is despite the fact that their greater bond share would allow them higher leverage compared to the $\delta = 1$ model. These effects on bond holdings, uninsured deposits, and leverage reflect precautionary portfolio decisions of banks to insure against the risk of runs.

[9] Alternatively, we could set the probability of the sunspot for runs π to zero. Results look almost identical to the ones for $\delta = 1$. Varying δ is computationally more convenient.

Figure 6: Equilibrium in Baseline and Without Runs



Notes: Top row: "log Assets" is the logarithm of the sum of capital and bonds; the plot shows the difference "$\delta = 1$" minus "Baseline", "Bond Share" is the fraction of bonds in the asset portfolio, and "Uninsured Share" is the fraction of uninsured deposits in all deposits. Bottom row: "Total Leverage" is the sum of insured and uninsured deposits divided by assets, "P(Run Def.)" is the unconditional probability of banks experiencing a run and defaulting as a result, and "P(Default)" is the unconditional probability of default across all aggregate payoff states.

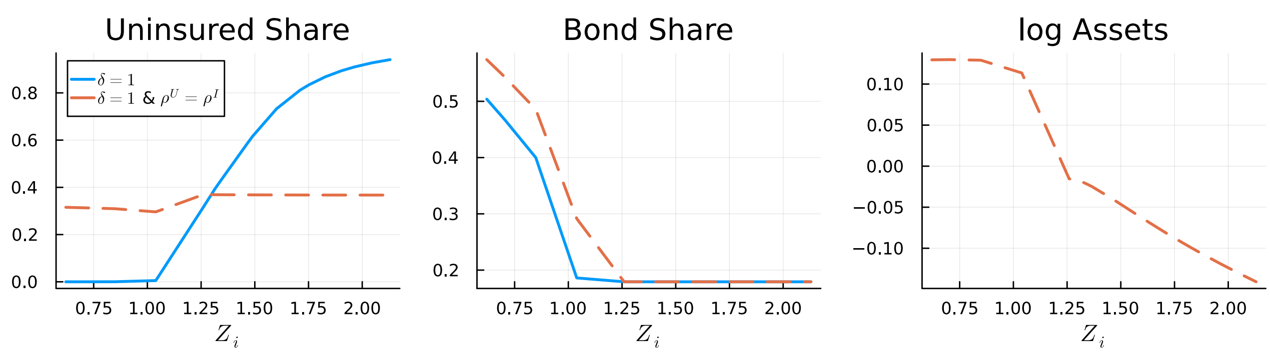
The mid panel of the bottom row shows that runs occur for the largest banks in the baseline economy with an unconditional probability of 1.2%. With $\delta = 1$, the absence of runs is an immediate consequence of the fundamental lack of a run motive. However, $\delta = 0.75$ in the baseline model implies substantial fire sale losses in case of a run. The fact that few runs occur even in this model is due to banks' precautionary behavior: they issue fewer uninsured deposits (to reduce run exposure) and hold more bonds (to hedge fire sale losses in capital). A few medium to large banks reduce leverage (to limit default risk).

Total realized defaults shown in the bottom right panel are the sum of run- and solvency-driven defaults. Small banks do not have run risk exposure, since they issue no uninsured deposits. However, they have worse performing loan assets, raising their risk of solvency default relative to large banks.

5.1.2 Differential Market Power in Insured versus Uninsured

The model generates a realistic concentration of uninsured deposits among the largest banks. As in the data, the uninsured share is strongly increasing in bank size. To isolate the role of product differentiation in generating this cross-sectional pattern, we consider a simple counterfactual economy in which the degree of production differentiation is identical in both deposit types, i.e. $\rho^U = \rho^I = 0.855$.

Figure 7: Equilibrium With Symmetric Deposit Market Power



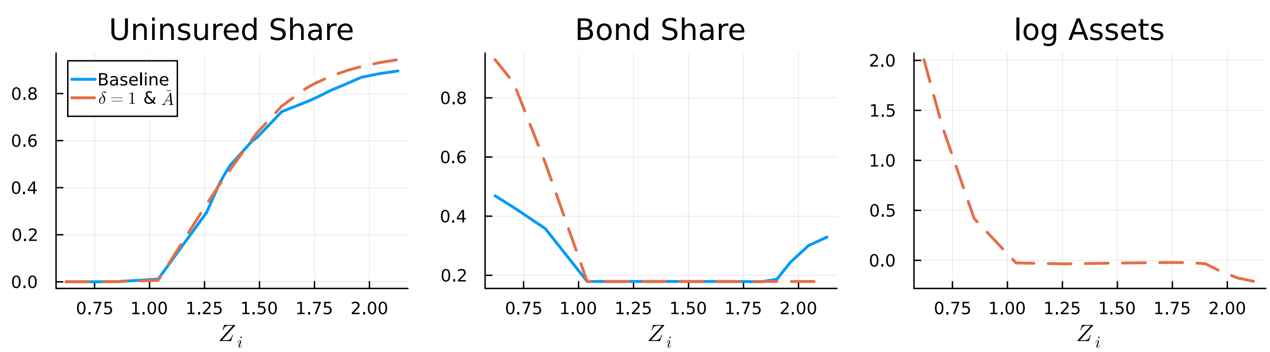
Notes: “Uninsured Share” is the fraction of uninsured deposits in all deposits. “Bond Share” is the fraction of bonds in the asset portfolio. “log Assets” is the logarithm of the sum of capital and bonds.

Figure 7 shows the effects of this parameter change. As we can see in the top left panel, the uninsured share is almost flat at 30% across the size distribution when $\rho^U = \rho^I$. The different nature of competition in the uninsured market, in turn, affects bond shares, leverage, profits, and default rates. The right panel shows log assets of the model with equal ρ^j minus log assets in the $\delta = 1$ baseline. This difference shows that with symmetric market power in both deposit types, the bank size distribution is more equal: low-productivity banks are relatively larger, and high-productivity banks are smaller compared to the baseline with more differentiation in insured deposits. This comparison highlights that the cross-sectional pattern in uninsured deposits generated by the model is not due to run risk or bailout guarantees, since neither of these channels are present in the $\delta = 1$ economy. Rather by comparing the one-parameter change in ρ^U relative to the high-delta economy, we can clearly see that the differential degree of market power in markets for insured and uninsured deposits is at the core of the model's ability to create the right cross-sectional allocation of uninsured deposits.

5.1.3 Deposit Productivity Heterogeneity

The baseline model features heterogeneity in deposit productivity that is perfectly correlated with loan productivity. However, the loading of deposits on loan productivity is asymmetric above and below the median. Deposit productivity of below-median banks is $\bar{A}^- = 1.05$ times their loan productivity, while for above-median banks the loading is $\bar{A}^+ = 0.4$.

Figure 8: Equilibrium With Symmetric Deposit Productivity



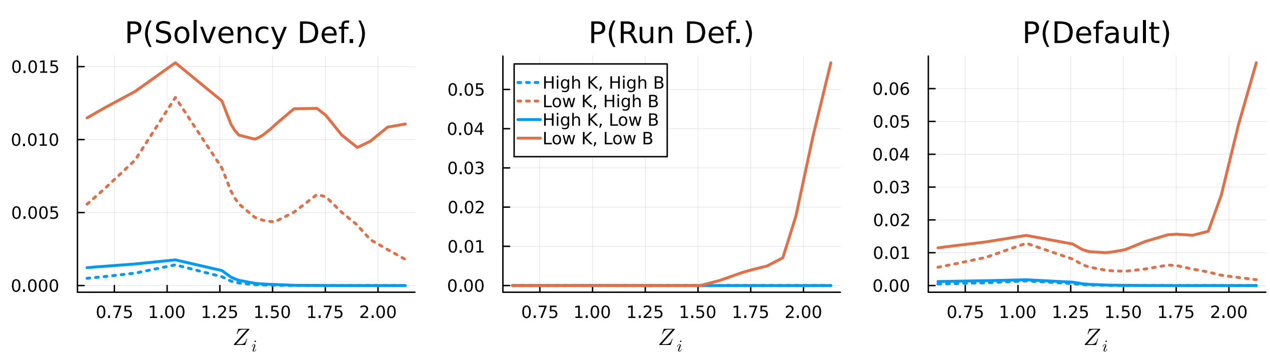
Notes: 'Uninsured Share" is the fraction of uninsured deposits in all deposits. "Bond Share" is the fraction of bonds in the asset portfolio. "log Assets" is the logarithm of the sum of capital and bonds.

Figure 8 compares the baseline calibration to a model in which the deposit productivity loading is symmetric below and above the mean at $\bar{A}^- = \bar{A}^+ = 0.4$. The direct consequence of this parameter change is that the deposit productivity of banks below the median is now declining much less rapidly in loan productivity than in the baseline. The rightmost plot in Figure 8 shows that low-productivity banks are much smaller in the baseline economy as a result. In the counterfactual economy with $\bar{A}^- = 0.4$, banks with low loan productivity have relatively much higher deposit productivity. It is optimal for them to issue larger quantities of insured deposits to exploit their market power. Since these banks only have access to low productivity loans, they instead rely on bonds to scale up their balance sheet, resulting in a much higher bond share as can be seen in the middle panel of Figure 8. The main effect of lower $\bar{A}^-$ on large banks is in the uninsured deposit share depicted in the left panel. Even though the above-median banks are not directly affected by the parameter change, general equilibrium forces cause them to increase their uninsured deposit share. In the symmetric $\bar{A}^j$ model, low-productivity banks are much larger, and they supply substantially more insured deposits in total. Since insured and uninsured deposits are imperfect substitutes in aggregate, greater insured supply from small banks creates demand for greater uninsured supply from large banks.

5.2 Effects of Aggregate Shocks on Bank Defaults

We next analyze the role of aggregate loan and interest rate risk on the fragility of the banking sector. Figure 9 displays bank default rates, by type of default, across the bank size distribution. Each line corresponds to a combined realization of the two aggregate shocks. Blue lines represent high aggregate loan productivity (R^K) while red represent low. Likewise, dotted lines represent high bond returns (R^B), while solid lines represent low bond returns, which realize when bond yields go up, e.g., when the central bank hikes rates.

Figure 9: Default Probabilities by Aggregate State



Notes: "P(Solvency Def.)" is the default rate due to insolvency ($\epsilon_i < \underline{\epsilon}_i$). "P(Run Default)" is the default rate caused by runs. "P(Default)" is the sum of insolvency and run-induced defaults. Blue (red) lines correspond to high (low) realizations of R^K. Dotted (solid) lines correspond to high (low) realizations of R^B.

As the left panel shows, small banks default for solvency reasons. Solvency default is highly sensitive to aggregate loan risk. Low loan returns increase solvency risk across the board (blue to red), which is amplified further by low bond returns (dotted to solid).

For large banks, a low bond return realization poses an additional threat, given their role as a precautionary buffer against run risk. Low bond returns cause an expansion of the run-prone region and lead to a substantial increase in the likelihood of run-driven defaults, approximately 5% for the largest banks (middle panel). In this state of the world, run defaults account for the vast majority of overall bank failures (right panel).

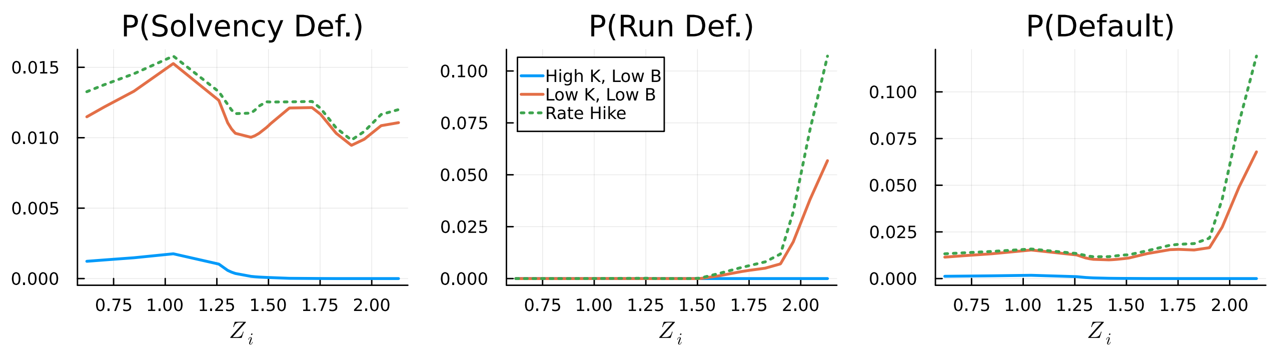
Agents in the model anticipate substantial interest rate return risk: the return on bonds has a standard deviation of 3.5%. What if bond returns drop lower than agents anticipate, for example, following a surprising interest rate hike by the central bank? To answer this question, we study how default risk across the bank size distribution is affected by an unanticipated low return realization of 5% below the mean.[10]

Figure 10 displays bank default rates across the size distribution for different realizations of aggregate returns on loans and bonds. The left panel shows defaults purely based on solvency risk, i.e., when $\epsilon_i < \underline{\epsilon}_i$. When the loan return is high and the bond payoff is low, as shown by the solid blue line, solvency defaults are small and slightly declining in size. When both asset returns are low, as depicted by the red line, solvency default rates are around 1.5% for the smallest banks and decline to around 1% for the largest banks. When interest rates unexpectedly increase such that the return on bonds is -5% (dashed green line), solvency defaults for the smallest banks rise noticeably; solvency defaults for banks above the 25th percentile of the asset distribution, however, are hardly changed relative to the low anticipated value of bond returns. This is because smaller banks hold a substantially larger fraction of their assets in interest-rate-sensitive bonds.

Run defaults in the middle panel jump to 5% for low realizations of both returns (red line). The low unexpected return of -5% causes run risk among the largest banks to spike at over 10% since these banks have issued most uninsured deposits. Total defaults in the right panel are the sum of both components. After a rate hike, defaults are higher at all points in the size distribution. These results demonstrate that the combination of uninsured deposits and low bond returns greatly amplifies the default risk of large banks.

[10] The numerical implementation discretizes the bond return with two equal-probability realizations. The lowest return realization in the expectation set is thus 3.5% below the mean.

Figure 10: Default Probabilities After Rate Hike



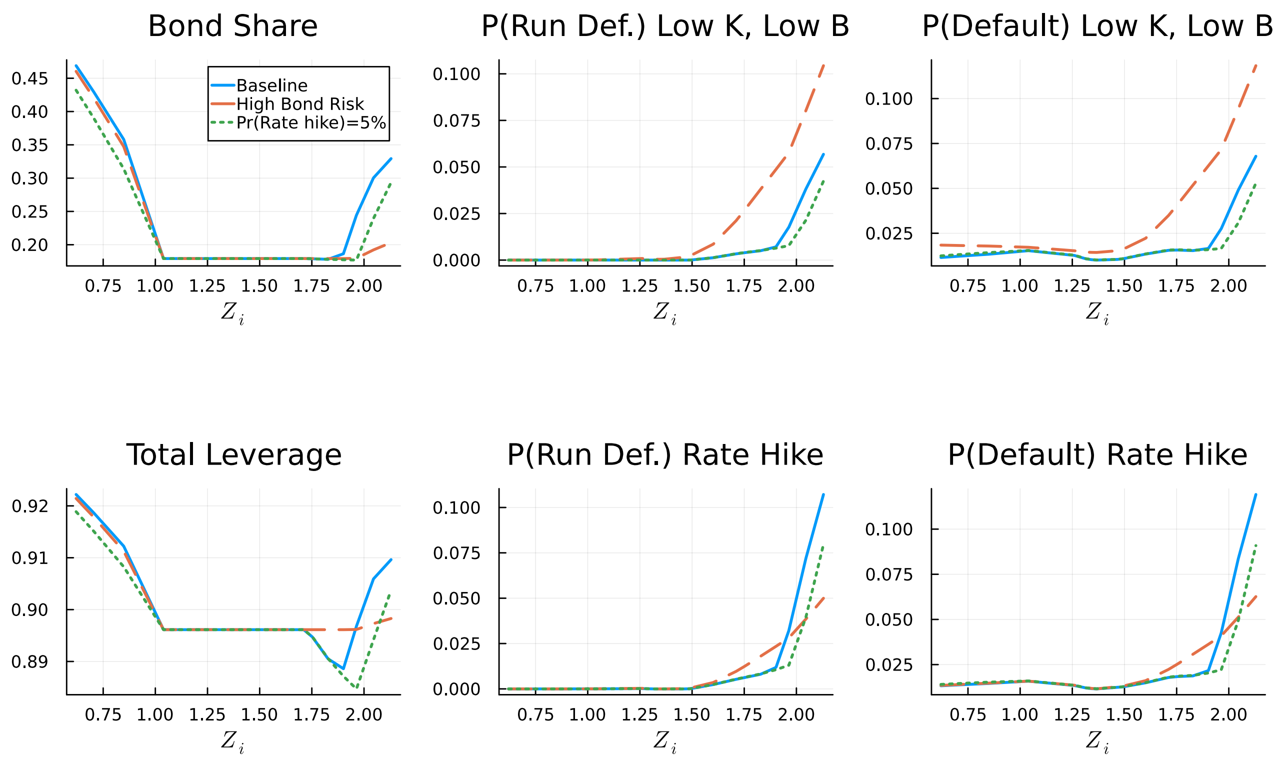
Notes: "P(Solvency Def.)" is the default rate due to insolvency ($\epsilon_i < \underline{\epsilon}_i$). "P(Run Default)" is the default rate caused by runs. "P(Default)" is the sum of insolvency and run-induced defaults. Blue and red solid lines show the effect of an *anticipated* low bond return R^B, conditional on high and low loan productivity realization R^K, respectively. The green-dotted line shows the effect of an *unanticipated* rate hike, leading to an especially low realization of R^B, conditional on low R^K.

5.3 Were Banks "Surprised" By Rate Hikes?

Do these results hold up if banks anticipate greater bond return risk, or more technically, if lower (and higher) bond return realizations are in the expectation set of banks, rather than arriving as "MIT shocks?"

Symmetric Bond Return Risk. We explore this question in Figure 11, which compares the baseline economy to one in which bond returns are much more volatile at 8.5% standard deviation (compared to 3.5% in the baseline), in the red line labeled "High Bond Risk." The middle and right panels of the top row show default rates conditional on an anticipated low loan/low bond return shock. In the baseline model (blue line labeled "Baseline"), this shock causes run defaults. In the economy with high bond risk, however, this anticipated shock causes a doubling of run defaults for large banks. This rise in run-induced defaults is, of course, partially due to a much lower realization of bond returns, but it is also caused by different ex-ante portfolio choices of banks. In particular, large banks in the high bond risk economy have negligible voluntary bond holdings (top left) and do not keep a precautionary buffer to their maximum allowed leverage (bottom left). Furthermore, small banks in the high-risk economy do not decrease their bond share despite much riskier returns. Small banks' optimal size is mainly driven by the insured deposit market profitability. Since insuring deposits severs the link between asset risk and deposit rates, small banks maintain similar bond portfolio shares compared to the baseline economy, even with high bond risk. This behavior results in slightly higher solvency default rates for small banks.

Figure 11: Default Probabilities After Rate Hike With Higher Bond Risk



Notes: "Bond Share" is the fraction of bonds in the asset portfolio. "Total Leverage" is the sum of insured and uninsured deposits divided by assets."P(Run Default)" is the default rate caused by runs. "P(Default)" is the sum of insolvency and run-induced defaults. The middle and right panels of the top row present default rates for low aggregate capital and bond returns. The middle and right panels of the bottom row present default rates for the rate hike experiment. The blue line represents the baseline economy, the red line represents the economy with higher anticipated bond risk, and the green-dotted line represents the economy where rate hikes are expected with a 5% probability.

The middle and right panels in the bottom row show how these different portfolio choices affect the probability of run defaults and defaults overall when the unanticipated rate hike occurs. As for the top row that displays the anticipated shock, overall defaults are mainly driven by run defaults. When banks anticipate bonds to be much more volatile (the red-line in the bottom panels), the rate hike leads to only half the run defaults compared to the baseline economy, where banks expect bond return volatility to be just 3.5%. This makes sense since the worst-case scenario of bond returns in the high bond risk economy spans the rate hike.

These results highlight that rational anticipation of higher symmetric bond return risk by banks does not necessarily lead to safer portfolios that can absorb greater interest rate fluctuations without incurring solvency and run risk.

Downside Bond Return Risk. What if banks instead anticipate the actual rate hike with a 5% probability? The green dotted line labeled "Pr(Rate Hike)=5%" shows this scenario. Relative to the high bond risk economy, banks now anticipate asymmetric downside risk in bond returns that is equal in size to the realized rate hike. This change in expectations shifts the mean bond return, causing both small and large banks to downscale their bond shares relative to the baseline economy. Especially large banks reduce leverage substantially in this economy, which works to reduce run and overall default risk. Since bonds are less useful as insurance for runs, banks instead use leverage to manage their risk.

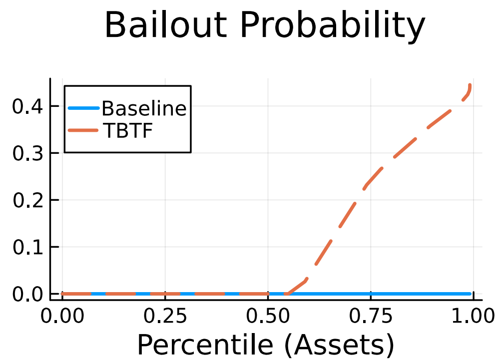
Taken together, both scenarios imply that bank exposure to interest rate risk is consistent with rational portfolio choice that anticipates high bond return volatility. Only if banks have expectations of asymmetric downside (but not upside) bond return risk, our model implies that they would optimally choose slightly safer portfolios compared to the baseline economy.

5.4 Partial Guarantees for Uninsured Deposits

Implicit bailout guarantees for large banks that are deemed "too big too fail" (TBTF), are commonly considered as explanation for uninsured deposit concentration at these large banks (O'Hara and Shaw, 1990). The intuition is straightforward: if the "uninsured" deposits of large banks also enjoy significant government guarantees, then depositors should be more willing to hold them. As we established in Section 5.1.2, the baseline version of our model does not rely on this explanation. However, we can easily incorporate probabilistic bailout guarantees of uninsured deposits that are increasing in bank size.

In Figure 12, we show the size-dependent bailout probability that we feed into the model. The probability is zero for banks below the asset median and then increases in balance sheet

Figure 12: Size-dependent Bailout Probability

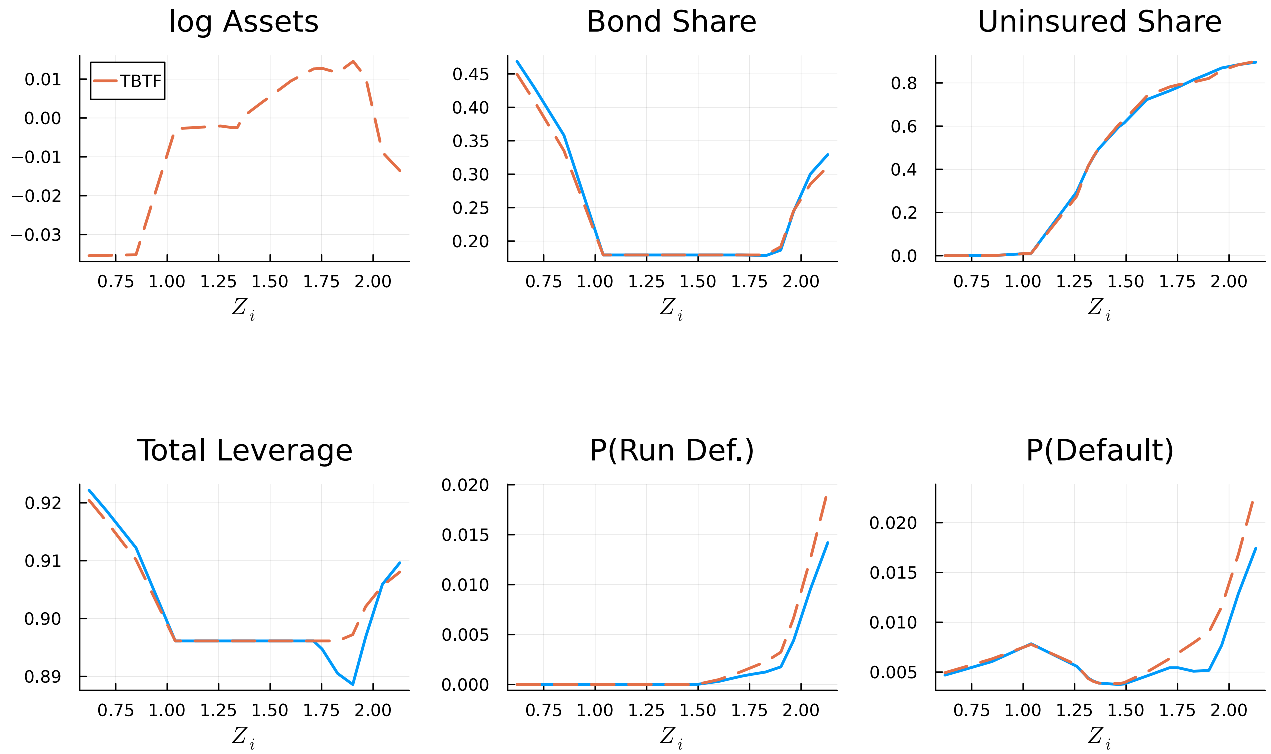


Notes: Left panel: size-dependent bailout probability for uninsured deposits by bank productivity Z_i. Right panel: size-dependent bailout probability for uninsured deposits by bank asset distribution percentile.

size until topping out at 45% for the largest banks. In Figure 13, we see how this bailout probability affects bank choices and outcomes. Most strikingly, too-big-too-fail bailouts raise the run risk of large banks significantly, as the bottom mid-panel shows. This is despite large banks choosing fewer uninsured deposits – the increase in risk happens as a result of a lower bond share and higher leverage. While bailout guarantees do not explain the allocation of uninsured deposits, they are a powerful source of risk-taking for large banks.

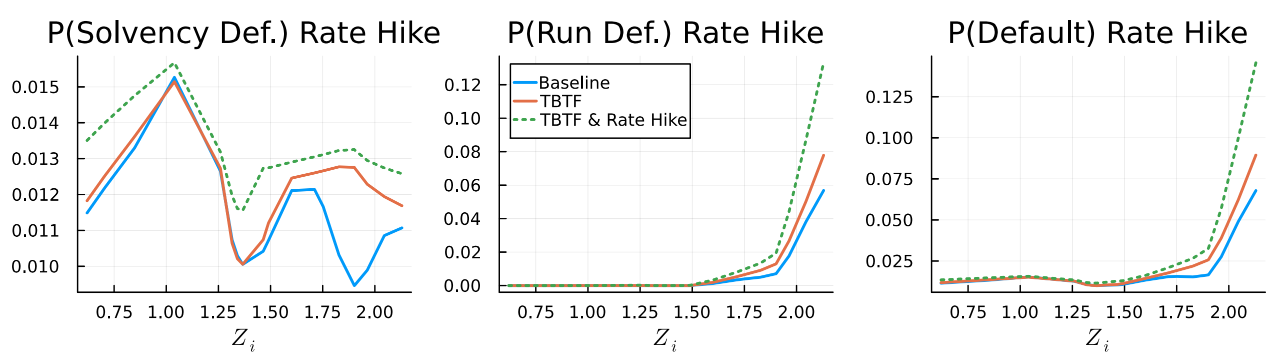
We further decompose the increase in default risk in Figure 14, which also displays the effect of an unanticipated rate hike combined with too-big-to-fail guarantees. The red and blue solid lines in the graph show the default probability in the baseline and TBTF versions of the model, respectively, for the worst possible aggregate payoff state. As we know from previous results, low aggregate return realization for loans and bonds cause run-based defaults in the baseline model. However, in the model with bailout guarantees, the run default rate in the bad (expected) state is close to 8%. The dashed green line shows default probabilities to the unanticipated rate hike in the model with bailouts. Run-default rates for the largest banks go above 12% in this model; from Figure 10, we recall that this default rate only rises to 10% in the baseline model. Thus, TBTF bailout guarantees amplify the run risk of big banks in case of a large surprise rate increase.

Figure 13: Equilibrium in Baseline and With Bailouts



Notes: Top row: "log Assets" is the logarithm of the sum of capital and bonds, "Bond Share" is the fraction of bonds in the asset portfolio, and "Uninsured Share" is the fraction of uninsured deposits in all deposits. Bottom row: "Total Leverage" is the sum of insured and uninsured deposits divided by assets, "P(Run Def.)" is the unconditional probability of banks experiencing a run and defaulting as a result, and "P(Default)" is the unconditional probability of default across all aggregate payoff states.

Figure 14: Bank Default Risk With Bailouts



Notes: "P(Solvency Def.)" is the default rate due to insolvency ($\epsilon_i < \underline{\epsilon}_i$). "P(Run Default)" is the default rate caused by runs. "P(Default)" is the sum of insolvency and run-induced defaults.

5.5 Policy Implications

We use the model as a laboratory for evaluating various policy proposals. In the following subsections, we will consider standard size-independent regulation and policies that explicitly condition on bank size. For all policy counterfactuals, we use the model with TBTF guarantees as baseline.

Unconditional capital requirements. Equity capital requirements for risky assets are widely regarded as a powerful tool for mitigating risk-taking by banks and have been studied extensively in the literature. We begin our policy analysis by studying variations in the equity capital requirement for loans, which is captured by the maximum leverage parameter θ in the model. Table 2 shows different aggregate outcomes for different values of θ around the baseline value of 0.88 (corresponding to a 12% risk-weighted capital charge on loans).

Table 2: Varying the capital requirement on loans

Outcome	θ					θ(size)
	85%	86%	87%	**88%**	89%	
Loans	-0.529	-0.268	-0.022	1.571	-0.007	0.005
C0	-0.015	-0.005	0.004	2.073	-0.010	0.000
E(C1)	0.095	0.063	0.030	2.201	-0.032	0.001
E(DWL)	-68.510	-53.966	-30.007	0.002	42.668	-1.137
SD(MPK)	-24.002	-17.147	-9.760	0.003	12.571	-0.007
Liquidity	-2.527	-1.712	-0.876	0.927	0.861	-0.038
HH Utility	-0.114	-0.074	-0.035	1.509	0.028	-0.001
Run Def. top 0.1%	-99.983	-60.192	-44.006	0.020	52.801	-41.414
C1 (Rate Hike)	0.065	0.040	0.014	2.118	-0.043	0.002
HH Utility (Rate Hike)	-0.138	-0.092	-0.047	1.472	0.022	-0.001

Notes: This table shows changes in aggregate model outcomes as the maximum allowed leverage on loans θ is varied around its baseline value of 88%. The last columns shows the effects of size-dependent capital requirements. The *levels* of listed outcomes for the baseline model are shown in the $\theta = 88\%$ column of the table. The columns to the left and right show *percentage changes* of the same moments relative to baseline. Moments: 1. Loans – aggregate lending $\mathrm{E}_i[K]$, 2. C_0 – time-0 consumption, 3. $\mathrm{E}[C_1]$ – time-1 expected consumption, 4. E[DWL] – time-1 aggregate expected DWL, including default bankruptcy costs and firesale losses during runs, 5. SD[MPK] – expected standard deviation in marginal product of capital across banks at time 1, 6. Liquidity – liquidity utility H, 7. HH Utility – total time-0 expected utility, 8. C1 (Rate Hike) – Time-1 consumption conditional on unanticipated rate hike. 9. HH Utility (Rate Hike) – Time-0 utility conditional on unanticipated rate hike at time 1.

In line with other studies, capital requirements govern a trade-off between consumption and liquidity provision. Row 1 shows that tightening the capital requirement by 3% (to $\theta = 85\%$) restricts lending by 0.5%, while relaxing the requirement by 1% (to $\theta = 89\%$) also reduces lending slightly. At the same time, a tighter requirement reduces bankruptcy-induced deadweight losses by 69% (row 4), while a relaxation by 1% causes deadweight losses to rise by 43%. These changes in bankruptcy losses affect consumption in an intuitive way – lower losses mean higher consumption; see rows 2 and 3 of the table. However, since baseline losses are small, so are the corresponding changes in consumption. The benefit of a tighter capital requirement is thus higher consumption, which is traded off against lower liquidity provision. Row 6 displays this effect on utility from liquidity services, which declines by 2.5% with a 3% tighter capital requirement. In row 5, which shows the dispersion in the marginal product of lending, we can see how capital requirements affect the efficiency of capital allocation in the banking sector. In a frictionless model, the marginal product of capital should be equalized across banks. Row 5 shows that dispersion in MPK declines with a tighter capital requirement in the model, which is an additional source of welfare gain from tighter regulation that is not directly linked to avoiding bankruptcy losses.[11]

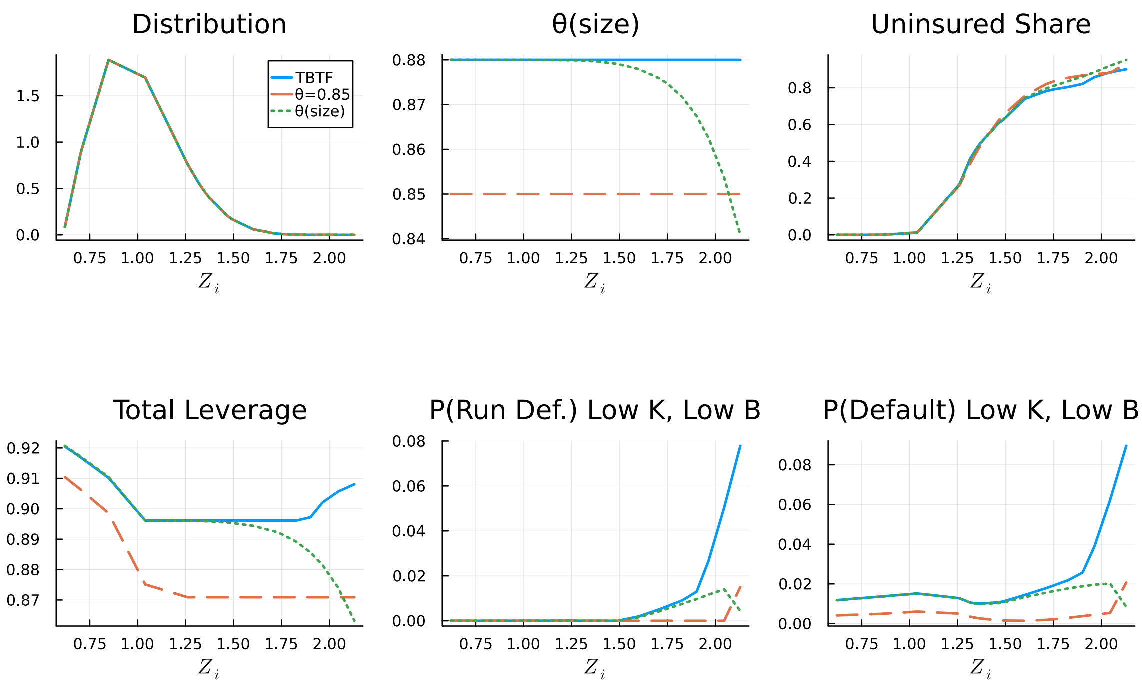
Row 7 shows that household utility is roughly maximized at the baseline value of θ at 88%, although a slight relaxation of the requirement would imply 2bp higher utility. A tighter capital requirement increases consumption in both periods but also lowers liquidity services, with the second effect dominating. Looser capital requirements, in turn, cause an increase in liquidity utility but simultaneously reduce consumption through greater defaults and misallocation. Note that our model only captures the micro-prudential effects of bank capital requirements and that macro-prudential considerations such as larger consumption losses during a systemic crisis may warrant a tighter capital charge on loans.

The focus of our analysis in on run default risk among the largest banks. Here, tighter capital requirements are a highly effective tool. A 3% tighter requirement almost eliminates run defaults among the top 0.1% banks by assets completely.

[11] Better loan allocation measured by lower dispersion in MPK materializes in higher consumption, same as lower bankruptcy losses.

Size-dependent capital requirements. Size-dependent capital requirements that explicitly condition on assets are designed to account for the systemic importance of large banks. Since the model captures the cross-sectional distribution of banks, we can use it to evaluate size-dependent policies.

Figure 15: Size-dependent Capital Requirements



Notes: Effects of size dependent capital requirements in an economy with bailout guarantees.

Figure 15 compares the baseline model with TBTF guarantees, to the same model with a tighter unconditional capital requirement (red line), and a third model in which the capital requirement is increasing in bank size (green line). The resulting level of maximum leverage θ is plotted in the middle panel of the top row. The bottom row displays how this policy affects leverage, run-driven defaults, and total defaults. The size-dependent requirement is as effective in curbing run-driven defaults among the largest banks as the unconditionally tighter requirement.

However, as we can see in Table 2, unconditional increase in θ cause a decline in welfare, since they reduces bank leverage throughout the whole distribution, and cause a decline in liquidity supply. The size-dependent requirement in the final column, on the other hand, only reduces leverage of the largest banks and leads to a much smaller reduction in liquidity supply. The overall welfare impact of an unconditional tightening of θ is negative, while the size-dependent requirement is roughly welfare-neutral. Thus, size-dependent capital requirements are an effective tool to reduce run exposure of large banks. At the same time, they have a minimal negative impact on other aspects of bank portfolios. We conclude that size-contingent capital requirements are an effective targeted regulation to address run risk caused by concentration of uninsured deposits.

Liquidity requirements. Liquidity requirements are meant to ensure that banks have liquid assets which can be sold without loss in case of large deposit withdrawals or runs. Our model captures both runs and the heterogeneous exposure of banks to run risk through their endogenous choice of uninsured deposits. A natural policy to mitigate the risk stemming from runs are liquidity requirements tied to uninsured deposits. We implement this policy in the model through a modified liquidity constraint (see equation (14)):

$$\theta^D D_i^I + (\theta^D + \theta^U) D_i^U \leq B_i, \tag{25}$$

where θ^U is a new parameter that requires banks to hold bonds in proportion to their uninsured deposits.

Table 3 shows how the same aggregate outcomes studied in Table 2 respond to an increase in θ^U relative to its baseline value of 0% in the first column. The run risk of the largest banks is listed in row 8 of the table, and one can see that small additional liquidity requirements work as intended: they reduce this risk by 20% at the 2% value for θ^U. Interestingly, the effect is non-monotonic – at $\theta^U = 8\%$, run defaults of the largest banks are higher by 17%, highlighting the importance of general equilibrium effects.

While the liquidity requirement makes large banks less vulnerable to runs, it also distorts their asset portfolio away from loans and towards bonds. The result is increased dispersion in the marginal product of capital listed in row 5. This causes capital misallocation. Higher liquidity requirements are effective at reducing run risk, but they do this at the expense of lending efficiency.

Table 3: Varying liquidity requirements for uninsured deposits

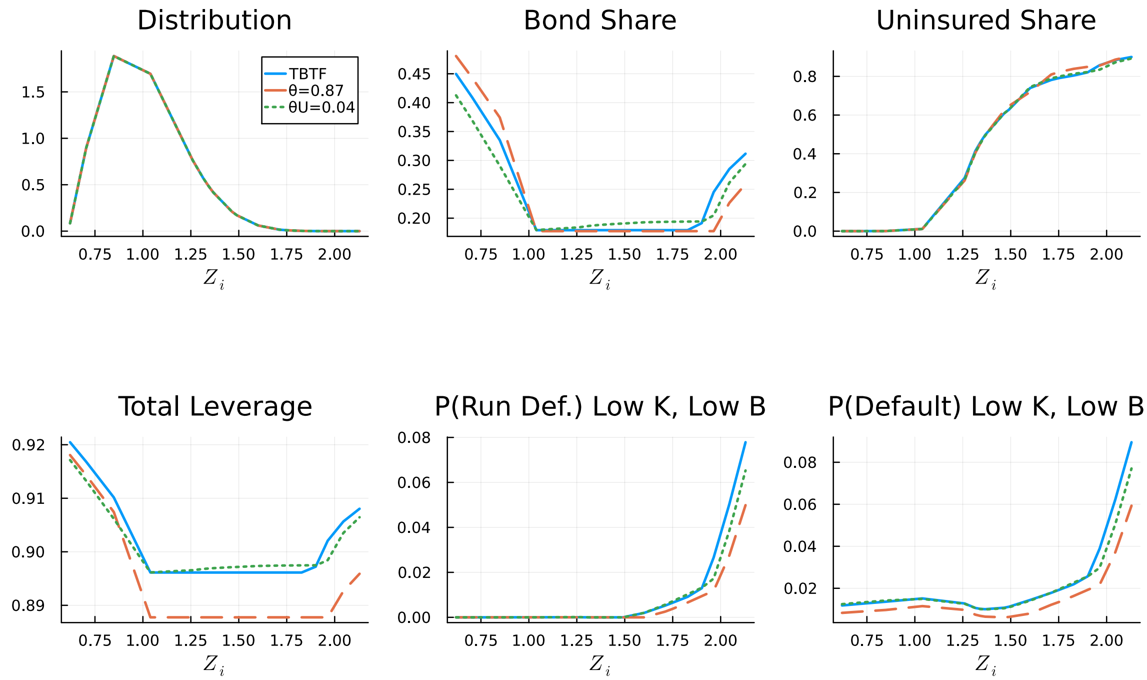
Outcome	θ^U				
	0%	2%	4%	6%	8%
Loans	1.571	-0.536	-1.089	-1.645	-2.379
C0	2.073	-0.028	-0.056	-0.085	-0.122
E(C1)	2.201	0.025	0.050	0.075	0.107
E(DWL)	0.002	2.883	6.015	9.488	10.276
SD(MPK)	0.003	6.175	13.156	20.739	24.313
Liquidity	0.927	0.043	0.087	0.130	0.223
HH Utility	1.509	0.002	0.003	0.005	0.008
Run Def. top 0.1%	0.020	-20.395	-14.692	-1.011	17.546
C1 (Rate Hike)	2.118	0.032	0.064	0.096	0.138
HH Utility (Rate Hike)	1.472	0.006	0.011	0.017	0.026

Notes: This table shows changes in aggregate model outcomes as the additional liquidity requirement for uninsured deposits θ^U is raised from its baseline value of 0%. The *levels* of listed outcomes for the baseline model with TBTF guarantees are shown in the $\theta^U = 0\%$ column of the table. The columns to the right show *percentage changes* of the same moments relative to baseline. Moments: 1. Loans – aggregate lending $\mathrm{E}_i[K]$, 2. C_0 – time-0 consumption, 3. $\mathrm{E}[C_1]$ – time-1 expected consumption, 4. E[DWL] – time-1 aggregate expected DWL, including default bankruptcy costs and firesale losses during runs, 5. SD[MPK] – expected standard deviation in marginal product of capital across banks at time 1, 6. Liquidity – liquidity utility H, 7. Welfare – total time-0 expected utility, 8. Run Def. top 0.1% – Run-induced default rate of top 0.1% largest banks in worst aggregate payoff state.

In Figure 16, we analyze the causes for the non-monotonic effects of higher liquidity requirements targeted specifically at uninsured deposits. We compare the baseline TBTF economy to one with a 1% tighter capital requirement $\theta = 0.87$ (red dashed) and a third economy with $\theta^U = 0.04$ (green dotted). The liquidity requirement works as intended, forcing a higher bond share for banks with uninsured deposits. It is as effective at reducing run defaults among the largest banks as a 1% tighter capital requirement, yet it accomplishes this task without reducing leverage and thus liquidity provision. Quite contrary, we see in Table 3 that higher θ^U actually increases liquidity provision. However, we can also see that the liquidity requirement causes a pronounced reallocation of bond holdings across the size distribution.

Furthermore, while reducing run defaults among the largest banks, the policy slightly raises run default among among banks with productivity above 1.5, explaining the non-monotonic effects in Table 3.

Figure 16: Comparing tighter capital and liquidity requirements



Notes: The figure compares the baseline economy with TBTF guarantees to policy counterfactuals with (i) a 1% tighter capital requirement ($\theta = 0.87$) and (ii) a liquity requirement of 4% for uninsured deposits ($\theta^U = 0.04$).

In summary, our policy experiments show that both size-dependent capital requirements and liquidity requirements targeted at uninsured deposits are highly effective tools at reducing run risk among the very top banks. However, our experiments also demonstrate that different policies cause substantially different cross-sectional allocations of loans, bonds, and deposits. Banks in our model face a realistic set of portfolio choices both on the asset and liability sides. Once we take into account this wide range of choices, it is difficult to find a "one-size-fits-all" policy that reduces risk exposure without side effects on lending and liquidity provision.

6 Conclusion

In this study, we develop a model to investigate the complex interplay between banks' portfolio and funding choices–particularly the reliance on uninsured deposits and investment in interest rate sensitive securities–and the resulting in cross-sectional differences between banks. We then examine their impact on financial stability in the face of interest rate- and run risk.

Our analysis reveals that large banks' reliance on uninsured deposit funding exposes them to greater financial instability, especially during periods of rising interest rates. The model shows that large banks–while benefiting from greater loan and deposit productivity–face heightened run-risk, while small banks are more vulnerable to solvency risk.

Our model underscores the importance of considering the heterogeneous impact of regulatory policies. Uniform regulations may not adequately address the unique challenges faced by banks of varying sizes and risk profiles. Therefore, a more nuanced regulatory approach that differentiates between the risks posed by smaller versus larger institutions is essential for maintaining financial stability in a dynamic economic environment.

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A Calibration

Panel B of Table 1 lists the externally calibrated parameters. Related to households' preferences, the discount factor β is set to match a 1% risk-free return. The risk-aversion parameter φ is set to 2, a standard value in the literature.

The ex-ante bank loan productivity Z_i follows an affine function of a Beta-distributed random variable. Specifically,

$$Z_i = Z_{loc} + (Z_{loc} + Z_{scale})\,\tilde{Z}_i,$$

with $\tilde{Z}_i \sim B\left(\beta_1, Z_{shape}\right)$. We choose β_1 such that the $E[Z_i] \equiv Z_{mean} = 1$. We follow Egan, Lewellen, and Sunderam (2022) to estimate cross-sectional statistics of banks' loan productivity using quarterly bank call report data from 2010 to 2022.

We match the volatility of the aggregate loan productivity σ_{RK} to the volatility of a portfolio consisting of BBB-rated corporate bonds and mortgage-backed securities. We match the volatility of banks' idiosyncratic capital shocks to the volatility of bank equity returns. To this end, we take the equity return of publicly traded banks over our sample period and residualize them vis-a-vis the Fama-French 3-Factor model. We then compute the annualized cross-sectional standard deviation of the residuals. We match the bond return r to the annualized real return on a constant 5-year maturity Treasury portfolio and σ_{RB} to its volatility.

We match the fraction of uninsured depositors that are sleepy, i.e., that do not run, to roughly the fraction of long-term unsecured debt funding of banks. These are the uninsured depositors are exposed to losses during a run. The fire-sale discount parameter $1-\delta$ is consistent with the literature Campbell, Giglio, and Pathak (2011) and Franks, Seth, Sussman, and Vig (2021). The recovery ratio is from Moody's. To parameterize the long-horizon interest rate risk of banks' security portfolio we target the AFS security share as documented by Greenwald, Krainer, and Paul (2024).

Table A1 lists all parameter values used in the model.

B Empirical Support for Model Assumption

B.1 Liquidity Converage Ratio

The liquidity coverage ratio does not differentiate between short and long duration assets as Figure A1 below shows. The tables are from Roberts, Sarkar, and Shachar (2023).

$$\text{LCR} = \frac{\text{HQLA}}{\text{30 day net outflow rate}} \geq 1$$

Figure A1: Roberts, Sarkar, and Shachar (2023) LCR

(a) Liquidity Coverage ratio

Table 1: Categories of High-Quality Liquid Assets under the Liquidity Coverage Ratio Standard

Category	Cap	Discount	Included Assets
Level 1	None	0%	◆ Unrestricted Federal Reserve balances ◆ U.S. Treasury securities ◆ Liquid and marketable securities issued by other U.S. government agencies whose obligations are explicitly guaranteed by the U.S. government ◆ Unrestricted reserves held at foreign central banks ◆ Low-risk securities issued or guaranteed by a foreign sovereign entity, the Bank for International Settlements, the International Monetary Fund, the European Central Bank, European Community, or a multilateral development bank and that meet certain criteria
Level 2A	40%	15%	◆ Certain securities issued by a U.S. government-sponsored enterprise such as Fannie Mae or Freddie Mac ◆ Higher-risk securities issued or guaranteed by a foreign sovereign entity or a multilateral development bank and that meet certain criteria
Level 2B	15%	50%	◆ Liquid and marketable corporate debt securities that meet certain criteria ◆ Liquid and marketable publicly traded common stocks that meet certain criteria

Source: Based on Davis Polk & Wardwell LLP, "U.S. Basel III Liquidity Coverage Ratio Final Rule: Visual Memorandum," September 23, 2014

Notes: The "cap" is the maximum percentage of a bank's high-quality liquid assets that can come from each category. The values of Level 2A and Level 2B assets are discounted to reflect assumptions about their lower liquidity and higher risk.

(b) Assumed Outflow Rate

Table A.1: (Continued) The Liquidity Coverage Ratio (LCR): Asset- and Liability-Side Requirements

Abbreviations for secured funding collateral are for levels of High Quality Liquid Assets: L1 = Level 1, L2a = Level 2a and L2b = Level 2b. Abbreviations for funding counter-parties are: SB = small business; NFin = non-financial; Fin = financial.

Panel B: LCR Outflow Categories, Inflow and Outflow Rates

LCR Outflow Category	Y-9C item	LCR Outflow Rate	LCR Inflow Rate
Secured Funding	ON Repo Sold Securities Lent	L1 & L2A collateral: 0-15% L2B & non-HQLA collateral: $25-100\%$[1]	L1 & L2A collateral: 0-15% L2B & non-HQLA collateral: $50-100\%$
Unsecured Funding	ON fed funds purchased Deposits Trading Liabilities Commercial Paper Other Borrowed Money Subordinated Debt Other Liabilities Equity	Retail & SB: $3-40\%$[2] Insured retail deposits: 3% Uninsured retail deposits: 10% Wholesale: 5-100%	
Commitments	Unused Commitments Standby Letters of Credit	Retail & SB non-mortgage: 5% NFin Wholesale: 10-30% Fin Wholesale: 40-100%	
Derivatives	Net Derivatives	100%	

1. Borrowings from exempted central banks have rate=0%.
2. Brokered deposits maturing less than or equal to 30 days have a 100% runoff rate.

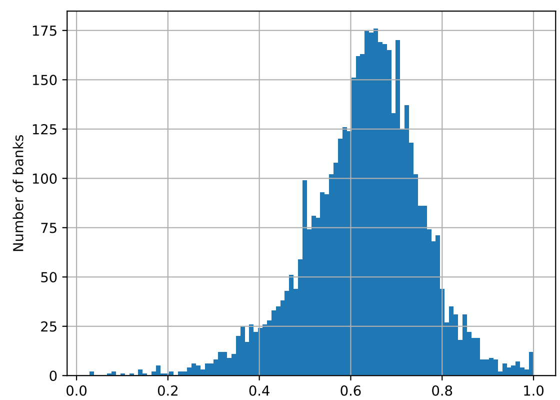
Notes: These figures are excerpts from the internet Appendix of "Liquidity Regulations, Bank Lending and Fire-Sale Risk" by Roberts, Sarkar, and Shachar (2023)

B.2 Uninsured versus insured deposits as different products

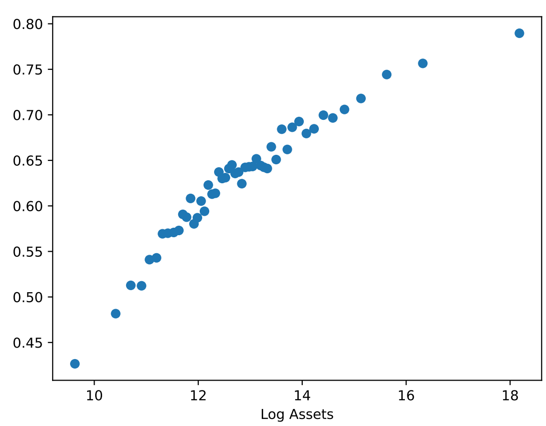
Section 3 assumes insured and uninsured deposits are separate products. We now show that this is largely consistent with the data. Note that in the data, banks report how many accounts are above the deposit insurance limit of $250K$ and how many dollars are in these ”large” accounts. Figure A2a presents a histogram of the fraction of uninsured dollars in large accounts. Most large accounts are indeed uninsured accounts.

Figure A2: Uninsured Deposits

(a) Fraction Uninsured In Large Accounts($\geq 250K$)



(b) Fraction of uninsured in large ($\geq 250K$) accounts by bank size



Notes: Data source: Call reports

Figure A2b shows this relationship by size. For the largest banks, which in our model are those with the highest uninsured share, roughly 80% of large accounts are uninsured.

B.3 Interest rate risk in unmarked assets

Mark-to-Market Losses and Bank Equity It is rare for interest rate risk to be visibly realized in bank portfolios since they are mainly unmarked. The interest rate hike period after the pandemic has allowed a rare glimpse into the interest rate sensitivity of bank portfolios. For securities, bank call reports require banks to fill in the fair value of their unmarked securities (hold-to-maturity securities). When we revalue assets by subtracting the book value of securities and adding back their fair value, we can recalculate an implied market value of equity. Panel A of Figure A3 shows the aggregate market value of equity normalized by the aggregate book equity since 2010. The rate hike period led to large unrealized losses in banks' securities portfolio, leading to a drop in the market value equity due to security losses alone of nearly 20%.[12]

Panel B shows the mark-to-market losses of the 50 largest banks in 2022 Q3, calculated similarly to for Panel A but expressed as a share of assets. For comparison, we also plot the regulatory book value of equity as a fraction of assets. Most of the large banks sustained losses on their securities portfolios, leading to large unrealized losses in equity.

C Derivations

C.1 Household Problem

Denoting equity shares of bank i that are in unit supply as S_i, households solve

$$\max_{\{S_i\},\{D_i^I\},\{D_i^U\},C_0,C_1} \log(C_0) + \psi \log\left(H\left(\{D_i^I\},\{D_i^U\}\right)\right) + \beta \log\left(\mathrm{E}\left[C_1^{1-\varphi}\right]^{1/(1-\varphi)}\right) \tag{26}$$

subject to

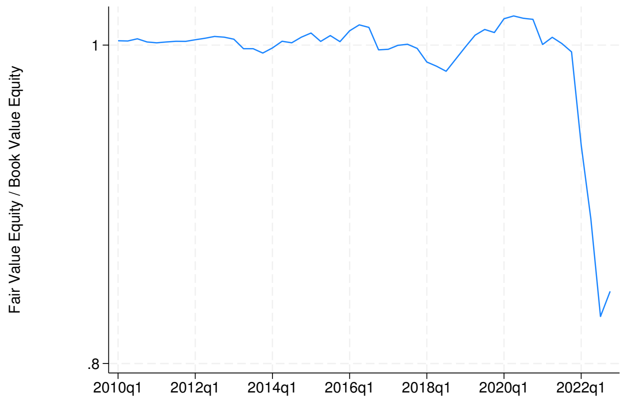
$$C_0 = W_0 + \int_i \Pi_i di - T - \int_i p_i S_i di - \int_i q_i^I D_i^I di - \int_i q_i^U D_i^U di, \tag{27}$$

$$C_1 = \int_i D_i^I di + \int_i \left(\mathbb{I}_{\epsilon_i \geq \bar{\epsilon}_i} + \mathbb{I}_{\bar{\epsilon}_i \geq \epsilon_i \geq \underline{\epsilon}_i} \mathbb{I}_{\varsigma_i = 0}\right) S_i \mathrm{Div}_i di + \int_i D_i^U \mathcal{P}_i^U di. \tag{28}$$

[12]Granja, Jiang, Matvos, Piskorski, and Seru (2024) show how banks attempted to insulate themselves from the interest rate shock by shifting more securities into the held-to-maturity portfolio.

Figure A3: Interest Rate Shock and Portfolio Revaluation

Panel A: Security Revaluation at Market Prices: Time Series



Panel B: Mark-to-Market Losses of the 50 Largest Banks in 2022 Q3

Notes: The data are from bank call reports, filing forms FFIEC 031/041 using a bank-quarter panel from 2010Q1 to 2022Q4.

At time 0, households purchase all securities issued by banks: debt of both types and equity. Household funds consist of initial wealth W_0 and bank profits, net of taxes raised to cover expected deposit insurance payouts. At time 1, households receive insured deposit payouts. They also receive the dividend payouts of non-defaulting banks, with the survival rate being

$$1 - \hat{F}(\underline{\epsilon}_i, \bar{\epsilon}_i) \equiv \mathrm{E}\left[\mathbb{I}_{\epsilon_i \geq \bar{\epsilon}_i} + \mathbb{I}_{\bar{\epsilon}_i \geq \epsilon_i \geq \underline{\epsilon}_i} \mathbb{I}_{\varsigma_i = 0}\right] = 1 - F(\bar{\epsilon}_i) - \pi \left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right).$$

The payoff on uninsured deposits depends on the realization of banks' idiosyncratic productivity shocks ϵ_i. As explained in the main text, the payoff to uninsured deposits is given in (23):

$$\begin{aligned}\mathcal{P}_i^U =& 1 - F(\bar{\epsilon}_i) + F(\underline{\epsilon}_i)\mathrm{E}[r_i^{nr} | \epsilon_i < \underline{\epsilon}_i] \\ &+ (1-\pi)\left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right) + \pi \left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right)\left(1 - \phi + \phi \mathrm{E}[r_i^r | \underline{\epsilon}_i \leq \epsilon_i \leq \bar{\epsilon}_i]\right).\end{aligned}$$

Marginal liquidity value. First, we compute marginal value of liquidity of each type.

$$\mathcal{H}_i^U = \frac{\partial \log\left(H\left(\{D_i^I\},\{D^U\}\right)\right)}{\partial D_i^U} = (1-\alpha)\left(\frac{A_i^D D_i^U}{D^U}\right)^{\rho_U}\left(\frac{D^U}{H}\right)^{\eta}\frac{1}{D_i^U} \tag{29}$$

$$\mathcal{H}_i^I = \frac{\partial \log\left(H\left(\{D_i^I\},\{D^U\}\right)\right)}{\partial D_i^I} = \alpha\left(\frac{A_i^D D_i^I}{D^I}\right)^{\rho_I}\left(\frac{D_I}{H}\right)^{\eta}\frac{1}{D_i^I} \tag{30}$$

where $D^j = \left(\int_i (A_i^D D_i^j)^{\rho_j} di\right)^{1/\rho_j}$, for $j = I, U$.

Consumption-savings choice. Denote total household wealth at time 0 as $W = W_0 + \int_i \Pi_i di - T$, and the total value of the household portfolio for time 0 (=savings) as $Z = \int_i p_i S_i di + \int_i q_i^I D_i^I di + \int_i q_i^U D_i^U di$. The return on this portfolio is

$$R_1 = C_1/Z = \int_i d_i^I di + \int_i \mathbb{I}_{\mathrm{nd}_i} s_i \mathrm{Div}_i di + \int_i d_i^U \mathcal{P}_i^U di,$$

where $d_i^I = D_i^I/Z$, $d_i^U = D_i^U/Z$, and $s_i = S_i/Z$. We can rewrite the HH problem as

$$\max_{\{s_i\},\{d_i^I\},\{d_i^U\},Z} \log(W-Z) + \psi \log\left(ZH\left(\{d_i^I\},\{d_i^U\}\right)\right) + \beta \log\left(\mathrm{E}\left[(R_1 Z)^{1-\varphi}\right]^{1/(1-\varphi)}\right).$$

The FOC for Z is

$$\frac{1}{W-Z} = \frac{\psi}{Z} + \frac{\beta}{\mathrm{E}\left[(R_1 Z)^{1-\varphi}\right]^{1/(1-\varphi)}}\frac{1}{1-\varphi}\left(\mathrm{E}\left[(R_1 Z)^{1-\varphi}\right]^{1/(1-\varphi)-1}\right)\mathrm{E}\left[R_1^{1-\varphi}(1-\varphi)Z^{-\varphi}\right]$$

which reduces to

$$Z = \frac{\beta+\psi}{1+\beta+\psi}W,$$

and therefore

$$C_0 = \frac{1}{1+\beta+\psi}W.$$

SDF. To derive the representative household's stochastic discount factor, we consider the first-order condition for a hypothetical riskfree bond without any liquidity benefits, with price $\tilde{q}$. The FOC would be

$$\frac{\tilde{q}}{C_0} = \frac{\beta}{\mathrm{E}\left[C_1^{1-\varphi}\right]^{1/(1-\varphi)}}\frac{1}{1-\varphi}\left(\mathrm{E}\left[C_1^{1-\varphi}\right]^{1/(1-\varphi)-1}\right)\mathrm{E}\left[(1-\varphi)C_1^{-\varphi}\right].$$

Canceling and multiplying by C_0

$$\tilde{q} = \beta\frac{C_0^{1-\varphi}}{\mathrm{E}\left[C_1^{1-\varphi}\right]}\mathrm{E}\left[\left(\frac{C_1}{C_0}\right)^{-\varphi}\right].$$

We can thus define

$$M = \beta \frac{C_0^{1-\varphi}}{\mathrm{E}\left[C_1^{1-\varphi}\right]} \left(\frac{C_1}{C_0}\right)^{-\varphi}, \tag{31}$$

such that $\tilde{q} = \mathrm{E}[M]$.

Deposits. Then HH FOCs for deposits are

$$q_i^I = \psi \mathcal{H}_i^I C_0 + \mathrm{E}[M], \tag{32}$$

$$q_i^U = \psi \mathcal{H}_i^U C_0 + \mathrm{E}\left[M \mathcal{P}_i^U\right]. \tag{33}$$

Bank equity. The FOC for bank equity shares is

$$p_i = \mathrm{E}\left\{M\left((1 - F(\bar{\epsilon}_i))\mathrm{E}_\epsilon[\mathrm{Div}_i | \epsilon_i > \bar{\epsilon}_i] + (1-\pi)(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i))\mathrm{E}_\epsilon[\mathrm{Div}_i | \bar{\epsilon}_i > \epsilon_i > \underline{\epsilon}_i]\right)\right\}. \tag{34}$$

C.2 Bank Problem

Stage 1a. We start with the optimization problem at the run stage 1a. Given Assumptions 1 and 2, banks will sell bonds at market price R_B until they have either paid out all running depositors, or they have liquidated all bonds

$$\hat{B}_i = \min\left\{B_i, \frac{(1-\phi)D_i^U}{R_B}\right\}.$$

Banks do not want to sell more capital than necessary at fire sale prices, and the constraint (8) is always binding. Thus capital fire sales are

$$\hat{K}_i = \frac{(1-\phi)D_i^U - R_B \hat{B}_i}{R_K \delta}.$$

We can write the post-run dividend more compactly defining the function

$$x(B_i, D_i^U) = \min\left\{1, \frac{R_B B_i}{(1-\phi)D_i^U}\right\}. \tag{35}$$

Using this definition, we have that

$$R_B \hat{B}_i = x(B_i, D_i^U)(1-\phi)D_i^U,$$

since either the bond portfolio is (weakly) more valuable than the amount that needs to be paid out, $R_B B_i \geq (1-\phi)D_i^U$, in which case $x(B_i, D_i^U) = 1$, or the full bond portfolio is liquidated but insufficient, in which case $x(B_i, D_i^U) < 1$ and $\hat{B}_i = B_i$. We can thus express the key terms in the bank payoff as

$$\bar{R}_B(B_i - \hat{B}_i) - \phi D_i^U = \bar{R}_B B_i - D_i^U \left[x(B_i, D_i^U)(1-\phi)\frac{\bar{R}_B}{R_B} + \phi \right].$$

This in turn allows us to write the upper default threshold as

$$\bar{\epsilon}_i = \frac{D_i^I + \phi D_i^U + (1-\phi) D_i^U x(B_i, D_i^U) \frac{\bar{R}_B}{R_B} - \bar{R}_B B_i}{A_i^K R_K \left(K_i - \frac{(1-\phi) D_i^U (1 - x(B_i, D_i^U))}{R_K \delta} \right)^{1-\kappa}}. \tag{36}$$

Recall that the lower default threshold is

$$\underline{\epsilon}_i = \frac{D_i^I + D_i^U - \bar{R}_B B_i}{A_i^K R_K K_i^{1-\kappa}}. \tag{37}$$

Stage 0. The dividend for the time-0 problem becomes

$$\mathrm{E}[M \max\{0, \mathrm{Div}_i^*\}] = \mathrm{E}\left[M \left(\mathbb{I}_{\epsilon_i \geq \bar{\epsilon}_i} + \mathbb{I}_{\bar{\epsilon}_i \geq \epsilon_i \geq \underline{\epsilon}_i} \mathbb{I}_{\varsigma_i = 0} \right) \left(A_i^K R_K \epsilon_i K_i^{1-\kappa} + \bar{R}_B B_i - D_i^I - D_i^U \right) \right],$$

which we can write as

$$\begin{aligned} &\mathrm{E}\left[M(1 - F(\bar{\epsilon}_i)) \left(A_i^K R_K \bar{\epsilon}_i^+ K_i^{1-\kappa} + \bar{R}_B B_i - D_i^I - D_i^U \right) \right] \\ &+ \mathrm{E}\left[M(1-\pi)(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)) \left(A_i^K R_K \underline{\bar{\epsilon}}_i^+ K_i^{1-\kappa} + \bar{R}_B B_i - D_i^I - D_i^U \right) \right] \end{aligned}$$

with the the conditional expectations

$$\begin{aligned} \bar{\epsilon}_i^+ &= \mathrm{E}[\epsilon_i | \epsilon_i > \bar{\epsilon}_i], \\ \underline{\bar{\epsilon}}_i^+ &= \mathrm{E}[\epsilon_i | \bar{\epsilon}_i > \epsilon_i > \underline{\epsilon}_i]. \end{aligned}$$

Given this definition of the bank dividend, the optimization problem in (11) only needs to be solved at time 0, with the function (35) reflecting optimal choices at the run stage, and the default thresholds (36) and (37) capturing the optimal default decision.

In problem (11), $x(B_i, D_i^U)$ is a non-differentiable function of B_i and D_i^U. For the numerical implementation, we define

$$Q(z) = \int \min\{\nu, z\} \, dF(\nu) = F_\nu(z) \, \mathrm{E}[\nu \mid \nu < z] + (1 - F_\nu(z)) \, z.$$

where ν is a random variable with positive support, c.d.f F_ν, and $\mathrm{E}[\nu] = 1$. We then define the function

$$\tilde{x}(B_i, D_i^U) = Q\left(\frac{R_B B_i}{(1-\phi)D_i^U}\right)$$

and approximate

$$x(B_i, D_i^U) \approx \tilde{x}(B_i, D_i^U).$$

First-order conditions. We attach multiplier μ_i to the leverage constraint (13) and λ_i to the liquidity constraint (14). The bank FOC for capital is

$$1 = \mu_i \theta^K + \frac{\partial q_i^U(\mathcal{A}_i)}{\partial K_i} D_i^U + \mathrm{E}\left[M\left((1-F(\bar{\epsilon}_i))\,\bar{\epsilon}_i^+ + (1-\pi)(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i))\underline{\bar{\epsilon}}_i^+\right)(1-\kappa)R_K A_i^K K_i^{-\kappa}\right]. \tag{38}$$

The bank FOC for bonds B_i is

$$p = \mu_i \theta^B + \lambda_i + \frac{\partial q^U(\mathcal{A}_i)}{\partial B_i} D_i^U + \mathrm{E}\left[M(1-\hat{F}(\underline{\epsilon}_i, \bar{\epsilon}_i))\bar{R}_B\right]. \tag{39}$$

The FOCs for deposits are

$$q_i^I = \mu_i + \lambda_i \theta^D - \frac{\partial q^I(D_i^I)}{\partial D_i^I} D_i^I - \frac{\partial q^U(\mathcal{A}_i)}{\partial D_i^I} D_i^U + \mathrm{E}\left[M(1-\hat{F}(\underline{\epsilon}_i, \bar{\epsilon}_i))\right], \tag{40}$$

$$q_i^U = \mu_i + \lambda_i \theta^D - \frac{\partial q^U(\mathcal{A}_i)}{\partial D_i^U} D_i^U + \mathrm{E}\left[M(1-\hat{F}(\underline{\epsilon}_i, \bar{\epsilon}_i))\right]. \tag{41}$$

The FOCs in (38) – (41) contain derivatives of the deposit demand functions from households in (21) and (22). In the next section, we provide expressions for these terms.

C.3 Derivatives of q^I and q^U

C.3.1 Insured

To compute the derivative of $q^I(D_i^I)$ given by (21) with respect to D_i^I, we apply the same assumptions as in the usual monopolistic competition setup. Banks internalize the effect on D_i^I in household demand, but not the effect on the aggregate D^I.

$$\frac{\partial q^I(D_i^I)}{\partial D_i^I} = C_0 \psi (\rho_I - 1)\alpha \frac{(A_i^D)^{\rho_I}}{(D_i^I)^2}\left(\frac{D^I}{D_i^I}\right)^{-\rho_I}\left(\frac{H}{D^I}\right)^{-\eta} = -C_0\psi \frac{1-\rho_I}{D_i^I}\mathcal{H}_i^I. \tag{42}$$

C.3.2 Uninsured

Recall the household FOC for uninsured deposits

$$q^U(\mathcal{A}_i) = \psi \mathcal{H}_i^U C_0 + \mathrm{E}\left[M\mathcal{P}^U(\mathcal{A}_i)\right],$$

with the payoff $\mathcal{P}^U(\mathcal{A}_i)$ provided in (23),

$$\begin{aligned}\mathcal{P}_i^U =& 1 - F(\bar{\epsilon}_i) + F(\underline{\epsilon}_i)\mathrm{E}[r_i^{nr}|\epsilon_i < \underline{\epsilon}_i] \\ &+ (1-\pi)\left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right) + \pi\left(F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i)\right)\left(1 - \phi + \phi\mathrm{E}[r_i^r|\underline{\epsilon}_i \le \epsilon_i \le \bar{\epsilon}_i]\right).\end{aligned}$$

We want to calculate the derivative of this function with respect to bank choices in $\mathcal{A}_i$. The derivatives of the deposit demand function are

$$\begin{aligned}\frac{\partial q^U(\mathcal{A}_i)}{\partial D_i^U} &= -\psi\frac{1-\rho_U}{D_i^U}\mathcal{H}_i^U + \mathrm{E}\left[M\frac{\partial \mathcal{P}^U(\mathcal{A}_i)}{\partial D_i^U}\right], \\ \frac{\partial q^U(\mathcal{A}_i)}{\partial D_i^I} &= \mathrm{E}\left[M\frac{\partial \mathcal{P}^U(\mathcal{A}_i)}{\partial D_i^I}\right], \\ \frac{\partial q^U(\mathcal{A}_i)}{\partial B_i} &= \mathrm{E}\left[M\frac{\partial \mathcal{P}^U(\mathcal{A}_i)}{\partial B_i}\right], \\ \frac{\partial q^U(\mathcal{A}_i)}{\partial K_i} &= \mathrm{E}\left[M\frac{\partial \mathcal{P}^U(\mathcal{A}_i)}{\partial K_i}\right].\end{aligned}$$

Computing the derivatives of q^U therefore comes down to computing the derivatives of $\mathcal{P}^U$ for each $Z_i \in \{D_i^I, D_i^U, K_i, B_i\}$. In what follows, denote the derivatives of the default probability weighted recovery values as

$$\mathcal{R}_i^{Z,nr} = \frac{\partial(F(\underline{\epsilon}_i)\mathrm{E}[r_i^{nr}|\epsilon_i < \underline{\epsilon}_i])}{\partial Z_i}$$

for the no-run states, and

$$\mathcal{R}_i^{Z,r} = \frac{\partial((F(\bar{\epsilon}_i) - F(\underline{\epsilon}_i))\,\mathrm{E}[r_i^r|\underline{\epsilon}_i \le \epsilon_i \le \bar{\epsilon}_i])}{\partial Z_i}$$

for run states. The derivative of the payoff $\mathcal{P}^U(\mathcal{A}_i)$ takes the general form

$$\frac{\partial \mathcal{P}^U(\mathcal{A}_i)}{\partial Z_i} = -\left(\pi\phi f(\bar{\epsilon}_i)\frac{\partial \bar{\epsilon}_i}{\partial Z_i} + (1-\pi\phi)f(\underline{\epsilon}_i)\frac{\partial \underline{\epsilon}_i}{\partial Z_i}\right) + \mathcal{R}_i^{Z,nr} + \pi\phi\mathcal{R}_i^{Z,r}.$$

We thus need to calculate the derivatives of both default thresholds with respect to all bank choices. To do so, we define the marginal product of capital for bank i, conditional on the outcome of the run game as

$$\mathrm{MPK}_i^{nr} = (1-\kappa)R_K A_i^K K_i^{-\kappa}, \tag{43}$$

$$\mathrm{MPK}_i^{r} = (1-\kappa)R_K A_i^K \left(K_i - \frac{(1-\phi)D_i^U(1-\tilde{x}_i)}{\delta R_K}\right)^{-\kappa}. \tag{44}$$

Solvency default threshold. First, for $\underline{\epsilon}_i$ given in (37) we get

$$\frac{\partial \underline{\epsilon}_i}{\partial D_i^U} = \frac{1}{\underline{\mathcal{D}}_i}, \quad \frac{\partial \underline{\epsilon}_i}{\partial D_i^I} = \frac{1}{\underline{\mathcal{D}}_i}, \quad \frac{\partial \underline{\epsilon}_i}{\partial K_i} = -\frac{\mathrm{MPK}_i^{nr} \underline{\epsilon}_i}{\underline{\mathcal{D}}_i}, \quad \frac{\partial \underline{\epsilon}_i}{\partial B_i} = -\frac{\bar{R}_B}{\underline{\mathcal{D}}_i}$$

where

$$\underline{\mathcal{D}}_i = R_K A_i^K K_i^{1-\kappa}.$$

Run default threshold. For the threshold $\bar{\epsilon}_i$ provided in (36), we obtain similar expressions for capital and insured deposits

$$\frac{\partial \bar{\epsilon}_i}{\partial D_i^I} = \frac{1}{\overline{\mathcal{D}}_i}, \quad \frac{\partial \bar{\epsilon}_i}{\partial K_i} = -\frac{\mathrm{MPK}_i^{r} \bar{\epsilon}_i}{\overline{\mathcal{D}}_i},$$

where

$$\overline{\mathcal{D}}_i = A_i^K R_K \left(K_i - \frac{(1-\phi) D_i^U (1-x_i)}{\delta R_K} \right)^{1-\kappa}.$$

For the derivative w.r.t. D_i^U, we get

$$\frac{\partial \bar{\epsilon}_i}{\partial D_i^U} = \frac{(\phi + \frac{\bar{R}_B}{R_B}(1-\phi) F_{\nu,i} \nu_i^-) \overline{\mathcal{D}}_i + \frac{1-\kappa}{\delta} A_i^K \left(K_i - \frac{(1-\phi) D_i^U (1-\tilde{x}_i)}{\delta R_K} \right)^{-\kappa} (1 - F_{\nu,i} \nu_i^-) \mathcal{N}_i}{(\overline{\mathcal{D}}_i)^2}$$

$$\mathcal{N}_i = D_i^I + \phi D_i^U + \tilde{x}_i \frac{\bar{R}_B}{R_B} (1-\phi) D_i^U - \bar{R}_B B_i,$$

and we have further defined the conditional expectations $\nu_i^- = \mathrm{E}\left[\nu \mid \nu < \frac{R_B B_i}{(1-\phi) D_i^U} \right]$. To calculate the expression above we have used the fact that

$$\frac{\partial \tilde{x}(B_i, D_i^U)}{\partial D_i^U} = -\frac{(1 - F_{\nu,i}) R_B B_i}{(1-\phi)(D_i^U)^2},$$

and the definition of $\tilde{x}$ as

$$\tilde{x} = Q(z) = F_\nu(z) \nu_i^- + (1 - F_\nu(z)) z.$$

We can simplify the expression to get

$$\frac{\partial \bar{\epsilon}_i}{\partial D_i^U} = \frac{\phi + (1-\phi) \left(\frac{\bar{R}_B}{R_B} F_{\nu,i} \nu_i^- + (1 - F_{\nu,i} \nu_i^-) \frac{\mathrm{MPK}_i^r}{\delta R_K} \bar{\epsilon}_i \right)}{\overline{\mathcal{D}}_i}. \tag{45}$$

Similarly, we take the derivative w.r.t. B_i

$$\frac{\partial \bar{\epsilon}_i}{\partial B_i} = \frac{\left(-R_B + \bar{R}_B (1 - F_\nu, i) \right) \overline{\mathcal{D}}_i - \frac{1-\kappa}{\delta} A_i^K \left(K_i - \frac{(1-\phi) D_i^U (1-\tilde{x}_i)}{\delta R_K} \right)^{-\kappa} R_B (1 - F_{\nu,i}) \mathcal{N}_i}{(\overline{\mathcal{D}}_i)^2}$$

where we use the fact that

$$\frac{\partial x(B_i, D_i^U)}{\partial B_i} = \frac{R_B(1 - F_{\nu,i})}{(1-\phi)D_i^U}.$$

This reduces to

$$\frac{\partial \overline{\epsilon}_i}{\partial B_i} = -\frac{R_B + (1 - F_{\nu,i})\left(R_B \frac{\mathrm{MPK}_i^r}{\delta R_K}\overline{\epsilon}_i - \bar{R}_B\right)}{\overline{\mathcal{D}}_i}. \tag{46}$$

Combining. We can now combine the expressions above to obtain the complete derivatives. First, for D_i^U

$$\begin{aligned}\frac{\partial q_i^U}{\partial D_i^U} = & -\psi\frac{1-\rho_U}{D_i^U}\mathcal{H}_i^U - \mathrm{E}\left[M\left((1-\pi\phi)f(\underline{\epsilon}_i)\frac{1}{\underline{\mathcal{D}}_i} - \mathcal{R}_i^{D^U,nr}\right)\right] \\ & -\pi\phi\mathrm{E}\left[M\left(\frac{\phi + (1-\phi)\left(\frac{\bar{R}_B}{R_B}F_{\nu,i}\nu_i^- + (1-F_{\nu,i}\nu_i^-)\frac{\mathrm{MPK}_i^r}{\delta R_K}\overline{\epsilon}_i\right)}{\overline{\mathcal{D}}_i} - \mathcal{R}_i^{D^U,r}\right)\right].\end{aligned} \tag{47}$$

For insured deposits we get

$$\frac{\partial q_i^U}{\partial D_i^I} = -\mathrm{E}\left[M\left((1-\pi\phi)f(\underline{\epsilon}_i)\frac{1}{\underline{\mathcal{D}}_i} - \mathcal{R}_i^{D^I,nr} + \pi\phi f(\overline{\epsilon}_i)\frac{1}{\overline{\mathcal{D}}_i} - \pi\phi\mathcal{R}_i^{D^I,r}\right)\right]. \tag{48}$$

For capital, the derivative is

$$\frac{\partial q_i^U}{\partial K_i} = \mathrm{E}\left[M\left((1-\pi\phi)f(\underline{\epsilon}_i)\frac{\mathrm{MPK}_i^{nr}\underline{\epsilon}_i}{\underline{\mathcal{D}}_i} + \mathcal{R}_i^{K,nr} + \pi\phi f(\overline{\epsilon}_i)\frac{\mathrm{MPK}_i^r\overline{\epsilon}_i}{\overline{\mathcal{D}}_i} + \pi\phi\mathcal{R}_i^{K,r}\right)\right]. \tag{49}$$

Finally, for bonds we calculate

$$\begin{aligned}\frac{\partial q_i^U}{\partial B_i} = & \mathrm{E}\left[M\left((1-\pi\phi)f(\underline{\epsilon}_i)\frac{\bar{R}_B}{\underline{\mathcal{D}}_i} + \mathcal{R}_i^{B,nr}\right)\right] \\ & + \pi\phi\mathrm{E}\left[M\left(f(\overline{\epsilon}_i)\frac{R_B + (1-F_{\nu,i})\left(R_B\frac{\mathrm{MPK}_i^r}{\delta R_K}\overline{\epsilon}_i - \bar{R}_B\right)}{\overline{\mathcal{D}}_i} + \mathcal{R}_i^{B,r}\right)\right].\end{aligned} \tag{50}$$

Inserting the derivatives in (47) – (50) into the first-order conditions in (38) – (41) completes the bank's optimality conditions. Note that the expressions above contain unresolved derivatives of the recovery values, $\mathcal{R}_i^{Z_i,j}$, for $Z_i \in \{D_i^U, D_i^I, K_i, B_i\}$ and $j \in \{nr, r\}$. Calculating these derivatives explicitly requires substantial algebra, but provides little additional insight. The derivatives of the recovery values can be signed unambiguously, with

$$\mathcal{R}_i^{D_i^U,j} < 0, \;\; \mathcal{R}_i^{D_i^I,j} < 0$$

and

$$\mathcal{R}_i^{K_i,j} > 0, \;\; \mathcal{R}_i^{B_i,j} > 0,$$

for $j \in \{nr, r\}$. This in turn implies that we can sign the derivatives of all assets but bonds as

$$\frac{\partial q_i^U}{\partial D_i^U} < 0, \quad \frac{\partial q_i^U}{\partial D_i^I} < 0, \quad \frac{\partial q_i^U}{\partial K_i} > 0.$$

The sign of bond derivative $\frac{\partial q_i^U}{\partial B_i}$ depends on parameter values; the term $R_B \frac{\text{MPK}_i^r}{\delta R_K} \bar{\epsilon}_i - \bar{R}_B$ compares the value of bonds during runs to the final portfolio payoff. In our calibrated model, we have $\frac{\partial q_i^U}{\partial B_i} > 0$, since fire sale losses on capital are sufficiently large (δ is sufficiently small), and a fraction of bonds is held in the AFS account (such that R_B and $\bar{R}_B$ are correlated). These signs are intuitive: on the margin, issuing more deposits of either kind increases the bank's default risk and thus the required interest paid to households, equivalent to a lower issuance price at time 0. By the same logic, holding more assets either in the shape of loans or bonds reduces the bank's default risk and the interest rate required on uninsured deposits.

C.4 Condition for $\bar{\epsilon}_i > \underline{\epsilon}_i$

Setting $B_i = 0$ and $x_i = 0$, the condition becomes

$$\bar{\epsilon}_i - \underline{\epsilon}_i = \frac{D_i^I}{\left(1 - \frac{D_i^U}{\delta R_K K_i}\right)^{1-\kappa}} - (D_i^I + D_i^U) > 0. \tag{51}$$

A binding leverage constraint implies that

$$K_i = \frac{D_i^I + D_i^U}{\theta^K},$$

which we can substitute into (51) to get

$$\frac{D_i^I}{\left(1 - \frac{\theta^K D_i^U}{\delta R_K (D_i^I + D_i^U)}\right)^{1-\kappa}} > D_i^I + D_i^U.$$

Defining $u_i = D_i^U/(D_i^U + D_i^I)$ as in the main text and dividing both sides by $D_i^U + D_i^I$ then gives

$$\frac{1 - u_i}{\left(1 - \frac{\theta^K u_i}{\delta R_K}\right)^{1-\kappa}} > 1.$$

Note that bank choices in combination with the power production function give rise to an Inada condition that guarantees $1 - \frac{\theta^K u_i}{\delta R_K} > 0$. We can thus rewrite the condition as

$$(1 - u_i)^{\frac{1}{1-\kappa}} > 1 - \frac{\theta^K u_i}{\delta R_K},$$

and some additional algebra yields the expression in the main text in equation (20).

Table A1: Model Calibration Parameters

Name	**Description**	**Value**
κ	production function curvature	0.125
β	discount factor	0.99
μ_{RK}	mean capital return	1.0875
σ_{RK}	deviation of capital return	0.045
π_K	probability of high capital return	0.5
r	bond return	0.0123
μ_{RB}	mean bond return	1
σ_{RB}	deviation of bond return	0.035
ω	Afs share	0.4
π_B	probability of high bond return	0.5
ψ	liquidity preference	0.048
α	insured deposit share	0.65
ρ	elasticity of substitution between insured deposits	0.855
ρ_U	elasticity of substitution between uninsured deposits	0.96
η	elasticity of substitution between uninsured and insured deposits	0.025
θ	leverage constraint	0.88
π	run probability	0.25
ϕ	uninsured deposit haircut in runs	0.03
δ	1 - firesale costs of capital	0.78
φ	risk aversion	2
$\sigma_{\epsilon ln}$	volatility of idiosyncratic capital shocks	0.11
Zmean	mean loan productivity	1
Zloc	minimum loan productivity	0.6
Zscale	max - min loan productivity	1.55
Zshape	shape of loan productivity distribution std = shape * scale	0.13
bailKmin	size of bank below which no bailout	7.5
bailα	rate of bailout probability increase	0.8
ξ	1 - share lost in recovery	0.25
A^-	for below median loan productivity	1.05
A^+	for above median loan productivity	0.4
W_0	initial wealth set to ensure $K_{agg} = 1$	4