Bank Heterogeneity, Deposits, and the Pass-through of Interest Rates *

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Abstract

We present two new stylized facts regarding the setting of deposit rates by US banks. First, deposit-rate pass-through is greater at highly leveraged banks: they overshoot the average bank both when policy tightens and when financial stress forces rates downward. Second, large banks (once we control for other bank characteristics) display state-dependent pass-through: they under-react to policy rate hikes but over-react to rate cuts, pushing their deposit rates further below the average in both cases. To explain these two stylized facts, we develop a continuous-time general equilibrium heterogenous bank model, in which banks face an occasionally binding leverage constraint, have monopolistic power in the market for household deposits, and importantly, households have deep habits with regard to their demand for banking services.

Keywords: Balance sheet channel, Interest rate margin, Financial frictions, Customer capital

JEL Classifications: C63, E44, E52, G21

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"You're more likely to be divorced than to change your bank account"—Ed Balls (Shadow Chancellor of the Exchequer) on the BBC Andrew Marr Show, 8 July 2012

"Regulators warn UK banks over miserly savings rates for loyal customers"—The Guardian, 21 April 2023

1 Introduction

Central banks across the world have sharply raised policy rates in recent years in response to rising inflation. Yet, deposit rates offered to savers have risen much more slowly. This sluggish pass-through has raised policy and political concerns. In the UK, for instance, regulators have warned banks about perceived exploitation of market power in deposit pricing.

A key feature of retail banking markets is depositor inertia: households rarely change their primary banking relationship. In the U.S., adults keep the same checking account for an average of 17 years and annual switching rates remain low, between 6–9%, despite modest recent increases Bankrate (2021). Depositors have a preference for adding new relationships over replacing old ones. For instance, over 50% of depositors split their direct deposits across banks and among switchers more than half hold four or more checking accounts (see Pinwheel, 2024; Curinos, 2024). In the UK, the Current Account Switch Service (CASS) was introduced in 2013 to eliminate frictions to switching. The service automates the transfer of standing orders and guarantees completion within seven days. Yet, despite these efforts, switching rates remain low, at about 3–4% annually, driven more by promotional offers than by a shift in depositor behavior (see Hartfree et al., 2016; Blakey, 2025). While the banking landscape is evolving, inertia remains a defining feature.

The monetary policy implications of market power and deposit inertia are increasingly recognized. When the Federal Reserve raises the policy rate, banks widen the spread between lending and deposit rates, and deposits flow out of the banking system. This mechanism, known as the "deposit channel of monetary policy", has been formalized and empirically tested by Drechsler et al. (2017). However, less is known about the heterogeneity across banks in how they set deposit rates in response to policy changes.

We use two US data sets, one with bank level balance sheet data and the other with branch-level posted interest rates on a wide variety of savings products, for the period 2000 to 2023. We identify two stylized empirical facts regarding heterogeneity in the setting of deposit rates across US banks. One, deposit-rate pass-through is greater at highly leveraged banks: they adjust more than the average bank in both directions, raising deposit rates by more when policy tightens and cutting them by more during episodes of financial stress. Two, large banks behave differently, they display state-dependent pass-through: they under-react to policy rate hikes but over-react to rate cuts, driving their deposit rates further below the cross-section mean in both cases.

To explain these two stylized facts, we develop a continuous-time general equilibrium heterogeneous bank model, in which banks face idiosyncratic investment return shocks, an occasionally binding leverage constraint, and have monopolistic power in the market for household deposits. Moreover, households have "deep" habits with regard to their demand for banking services.

Deep habits refer to households forming habits over individual varieties of bank deposit-liquidity services. This causes deposit demand to depend on past holdings, which banks internalize when setting interest rates. Deep habits affect the equilibrium dynamics of deposit rates via an intertemporal channel: banks recognize that raising rates today can boost future demand by building customer habits. When expected future spreads are high, banks have a stronger incentive to invest in their customer base now, even at the cost of lower current profits. Because substitution across banks is slow under deep habits, the customer base is more persistent. The interaction between financial frictions and deep habits thus introduces time and state variation in interest rate pass-through. In this environment, banks differ not only in their net worth but also in the habit stock they've built with depositors. Unconstrained banks can more readily exploit the dynamic trade-off between current rates and future profits, unlike leverage-constrained banks, leading to heterogeneity in deposit rate pricing across banks.

Related literature A growing literature studies how heterogeneity and micro-level frictions shape monetary policy transmission. This includes Ottonello and Winberry (2020), Gödl-Hanisch (2021), Jamilov and Monacelli (2021), Bellifemine et al. (2022), Cloyne et al. (2023), Perez-Orive et al. (2024), Gonzalez et al. (2024) and Vats (2025).

For instance, Jamilov and Monacelli (2021), which shares similarities with our work, develop a Bewley-style model where dispersion in returns and bank size amplifies aggregate shocks. In contrast, our paper shows that heterogeneity can also dampen financial shocks. We allow banks to endogenously switch between being constrained and unconstrained, a feature absent from most models.[1] This mechanism extends the logic of Manea (2020), who finds that a fixed share of unconstrained firms stabilizes aggregate dynamics via reallocation. Unlike Manea, our framework allows this stabilizing share to emerge endogenously. This stands in contrast to the representative-bank structure of Bocola (2016) and complements insights from Crouzet and Mehrotra (2020), who show that the skewed size distribution of firms can reduce

[1]A common simplifying assumption in financial friction models is that all borrowers (firms or banks) are constrained at all times (e.g., Gertler and Karadi, 2011; Gonzalez et al., 2024). Bocola (2016) and Manea (2020) depart from this approach; the former with a representative bank that can switch types and the latter by fixing the constrained/unconstrained distribution exogenously. Vats (2025) goes further by allowing the constraint status to evolve endogenously at the individual level and shows that endogenously evolving firm-level constraints shape the aggregate response to monetary policy.

macro volatility.

Empirically, Cloyne et al. (2023) show that investment responses to monetary shocks are stronger for financially constrained firms, providing direct evidence that firm-level balance sheet heterogeneity matters for monetary transmission. Together, these strands show that heterogeneity across financial intermediaries, on both the asset and liability sides, can significantly shape the aggregate effects of monetary and financial shocks. Our work shares with these papers the insight that monetary transmission depends on the evolving distribution of financial constraints. Whereas most of the aforementioned works examine heterogeneity across firms, our analysis emphasizes heterogeneity across banks.

Other recent papers on bank heterogeneity include Corbae and D'Erasmo (2021), who model large banks with market power interacting with small competitive banks. Scharfstein and Sunderam (2016) find that mortgage market concentration weakens the pass-through of monetary policy. Wang (2018) shows that as bond rates have fallen, the pass-through of monetary shocks to loan and deposit rates has weakened while the spread on U.S. bank loans has risen. Levieuge and Sahuc (2021) document downward rigidity in lending rates, motivating an asymmetric bank lending rate adjustment cost in a DSGE model calibrated to the euro area. Altavilla et al. (2020) show that during 2008–14, the pass-through of standard monetary policy measures to lending rates was low for banks with a weak capital position and that non-standard measures were effective in lowering lending rates for banks with a low capital ratio.

Building on the idea that heterogeneity shapes monetary transmission, recent work has also shifted attention to the liability side of banks' balance sheets and how differences in banks' funding structures and deposit market power affect policy pass-through. Drechsler et al. (2017) identify the deposit channel. Recent work underscores that banks differ systematically in deposit pricing. Kundu et al. (2023) show that "low-rate" banks with sticky deposits behave differently from "high-rate" banks that operate like money-market funds. This heterogeneity in pass-through is tied to differences in funding models, branch networks, and customer loyalty. Our paper captures this bifurcation via monopolistic competition and deep habits in deposit demand, linking deposit rate stickiness with financial constraints and intertemporal bank optimization.

Further related work includes Gödl-Hanisch and Pandolfo (2025), who show that banks with more deposit market power offer lower rates and exhibit lower pass-through. Begenau and Stafford (2022) emphasize that internal pricing rigidity across products can create aggregate deposit stickiness even without traditional market power. Choi and Rocheteau (2023) model deposit competition in a search framework, highlighting how frictions in depositor-bank matching generate endogenous margins. Our contribution to the deposit market and pass-through literature is threefold: we document two new stylized facts about bank-level deposit rate setting, estimate heterogeneous pass-through using local projections, and build a structural model to account for the observed patterns.

The evidence on heterogeneous deposit pricing naturally raises the question of what underpins such stickiness. One explanation is the presence of habits or relationship capital that tie depositors to specific banks. Gilchrist et al. (2017) was the first paper to interact habits with financial constraints and showed that non-financial firms that were financial unconstrained during the 2007-08 financial crisis lowered prices relative to constrained competitors in order to grab market share.[2] Our model embeds deep habits (à la Ravn et al., 2006), building on Dempsey and Faria-e Castro (2021), who apply habits to bank lending. We show that deposit-side habits interact with financial frictions to create rich state dependence: banks with strong habit stocks and slack constraints use deposit rate increases to build and exploit customer capital, while constrained banks are limited in their ability to do so. This creates endogenous variation in pass-through and stabilizes financial shocks. Our mechanism parallels the results in Eichenbaum et al. (2025), who show that deposit inattention affects net interest margins and policy pass-through. But while their model emphasizes household inertia, we focus on bank-side constraints and strategic pricing in the presence of deep habits. Both frameworks reveal that the distributional structure of the banking sector affects aggregate dynamics.

The rest of the paper proceeds as follows. Section 2 presents two stylized empirical facts. Section 3 describes the full model and Section 4 its calibration. Section 5 presents the results and Section 6 concludes.

2 Empirical results

Section 2.1 describes the data and Section 2.2 presents the regression analysis.

2.1 Data

Our first data source is RateWatch, a branch-level survey of deposit rates that was acquired by S&P Global in 2018. This is a weekly panel of branch-level data on newly offered deposit rates for various standardized savings products. The data ranges from January 2001 to December 2023. However, gaps in data coverage mean we restrict our analysis to a shorter time period that goes from January 2003 to December 2023. We aggregate data to a monthly frequency. For the results in the main part of the paper we focus on the $10k USD 6-month and 12-month certificates of deposit (henceforth, 6m CD 10k and 12m CD 10k, respectively), which is the most ubiquitous product.[3] Appendix A presents result for other products.

[2] Gilchrist et al. (2023) apply the same logic to explain the different dynamics of mark ups in the core and periphery of the euro area during the sovereign debt crisis.

[3] Our results still hold for certificates of deposits of different maturities and amounts. Moreover, similar results are found with money market accounts of different amounts. Others in the literature have focused on certificates of deposits and money market accounts of similar amounts, as these are the most commonly offered savings

Table 1: Long-run statistics

	Data	**95% CI**
Mean		
Leverage	10.10	[8.76, 11.99]
Deposits/Assets	0.83	[0.81, 0.87]
Deposit rate (6m CD 10k)	1.13	[0.15, 3.83]
Deposit rate (12m CD 10k)	1.38	[0.23, 4.19]
Standard deviation		
Leverage	2.77	[2.05, 4.73]
Deposits/Assets	0.07	[0.06, 0.09]
Deposit rate (6m CD 10k)	0.37	[0.11, 1.15]
Deposit rate (12m CD 10k)	0.42	[0.16, 1.35]
Skewness		
Leverage	1.34	[-0.23, 3.32]
Deposits/Assets	-2.19	[-3.45, -1.63]
Deposit rate (6m CD 10k)	0.62	[-0.60, 1.73]
Deposit rate (12m CD 10k)	0.28	[-0.87, 1.24]
Correlation		
Leverage & Assets	0.01	[-0.02, 0.06]
Leverage & Equity	-0.00	[-0.02, 0.04]
Leverage & Deposits	0.01	[-0.02, 0.05]
Other		
$r^f - r^d$ ‡	1.94	[0.42, 3.23]
$r^f - r^d$ †	1.70	[0.23,2.94]
r^k (% ann)	5.00	

Note: r^f is the 10 year Treasury yield; r^d is the interest rate on the 6m CD or 12m CD for ‡ or †, respectively; and CI is the 95% confidence interval.

We link this data, via the Summary of Deposits, to the Call Reports that all FDIC-insured financial institutions are required to complete on a quarterly basis. Call Reports contain bank-level income and expenditure accounts and balance sheet statements. We use this data to construct a separate gauge of deposit rates as follows

$$r^d_{j,t} = 400\frac{i_{j,t}}{d_{j,t}}, \tag{1}$$

where $i_{j,t}$ and $d_{j,t}$ denote bank j's total interest expense on time deposits and the total amount of time deposits on the balance sheet, respectively. This approach yields an implied annualized deposit rate, allowing us to compare pricing behavior across banks that complements the RateWatch observations. We also use balance sheet items from the Call Reports, such as total assets and equity, to construct a measure of leverage. Because Call Reports are filed quarterly, we interpolate these data to a monthly frequency to match our RatheWatch interest rate data.

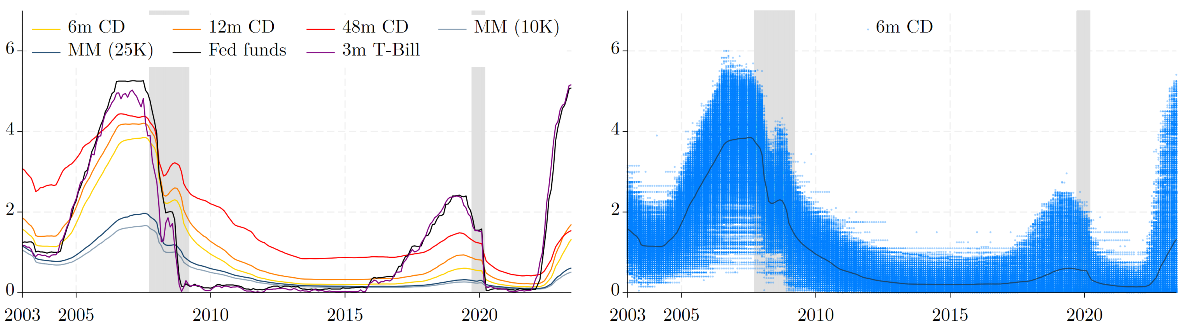
We construct our estimation sample by applying several filters. First, we exclude banks with negative equity or with leverage above the 99th percentile of the within-period distribution. Second, we trim deposit rate outliers by removing the top 1% of the implied rate distribution in each month. The resulting sample contains 1,788,692 observations.

products (see Drechsler et al., 2017; Gödl-Hanisch, 2021)

Table 1 shows descriptive statistics of the main variables of interest, which serves as our calibration target in the structural model. Model-based moments are discussed in a Section 4. Leverage is defined as total assets over equity, which has a mean of 10.1, a cross-sectional standard deviation of 2.8 and a modest positive skew. Deposits are the dominant funding source for these banks, with deposits as a share of total assets equaling 0.83 with a standard deviation of only 0.07 and a strong negative skew. The mean deposit rate for 6m CD 10k is 1.13% which amounts to a spread below the 10 year Treasury rate of 1.94%. These deposit rates show quite sizable cross-sectional variation with a standard deviation of 0.37ppt and a small positive skew. Finally, the table shows that leverage and bank size are uncorrelated, emphasizing our finding that each characteristic is independently important in explaining heterogeneity in deposit interest rate dynamics.

Figure 1 provides a visualization of the heterogeneity in interest rates. The left panel shows the mean interest rate for five different savings products: $10k certificates of deposit of 6-month, 12-month, and 48-month maturity; and $10k and $25k money market accounts alongside the Fed funds rate and the 3 month Treasury Bill rate. The panel shows that, on average, deposit rates adjust more slowly than changes in the fed funds rate or 3-month T-bill rate. The right panel displays the 10k 6-month CD rates at the bank branch level, highlighting the extent of the variation across individual banks. This is variation is striking given that this savings product is a fairly homogenous product.

Figure 1: Interest rates

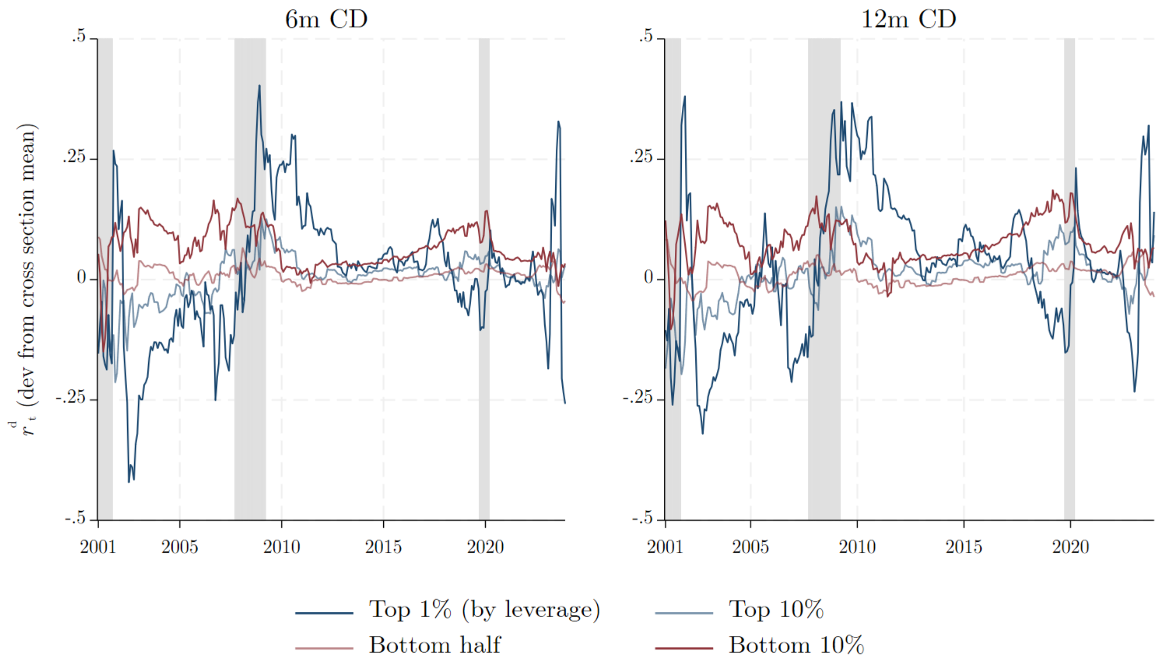


Note: Annualized percent. The CDs are 6 and 12 month certificates of deposit (10k); MMs are money market savings with account sizes of $10k and $25k in size, respectively.

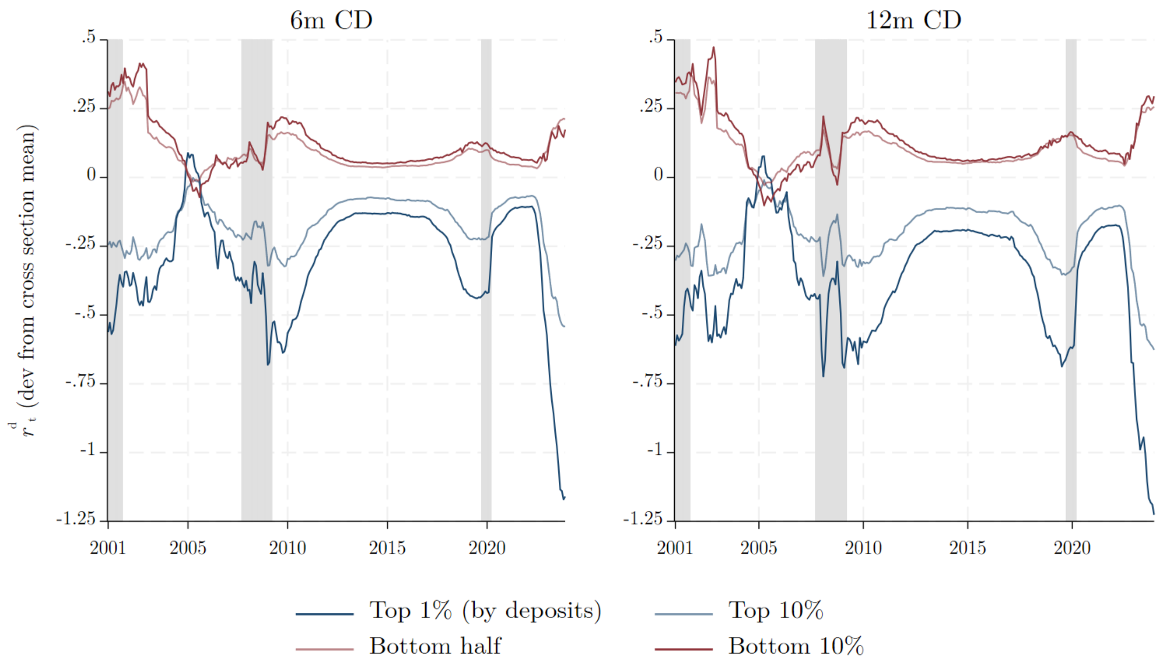
Next, we look at the interest rate dynamics across the distribution of banks. Figure 2 plots the mean interest rate spread (relative to the cross-section mean) of 6m CD 10k and 12m CD 10k, respectively, for different quantile groups of the bank distribution. Panel (a) shows the average spreads for banks in the top 1%, top 10%, bottom half, and bottom 10% of the leverage distribution. The shaded regions denote NBER recession periods. This plot shows that different segments of the bank distribution set deposit interest rates differently. The clearest pattern we observe is that more leveraged banks have been slower in increasing interest rates when policy rates are high and vice-versa.

Figure 2: Deposit rate heterogeneity across the size and leverage distribution of banks

(a) Deposit rate spreads of banks in different segments of the leverage distribution



(b) Deposit rate spreads of banks in different segments of the size distribution



Note: Annualized percent. For example, the darkest blue line in the top-left panel plots the difference between the mean interest rate on a 6 month CD offered by banks in the top 1% by leverage and the cross-section mean. Thus, a positive value indicates that these banks are offering above average interest rates. Shaded area denotes NBER recession dates.

Similarly, Panel (b) shows the same picture but based on the size distribution of banks as measured by the quantity of deposits. In this case, the timing is different, with the largest banks (by deposits) offering interest on a 10k 6m-CD in 2007 around 40bp below the mean. The gap shrunk over the coming years but remained around 15bp below average in the period 2013-17. In the two subsequent fed funds hiking cycles (in 2017-19 and 2022-23) the largest banks have again been slow to increase interest rates on savings, with the gap, relative to the cross-sectional mean, widening each time. The spreads are also persistent. Note that the cross-sectional correlation between leverage and bank size (as measured by deposits) is approximately 0.01, which suggests that leverage and size reflect largely independent dimensions of bank heterogeneity, and that the two panels illustrate distinct behavioral patterns across the bank distribution.

When examining deposit rate deviations from the monthly cross-sectional mean, a pronounced size gradient emerges. Branches of large banks (top decile of the deposit distribution) consistently offer deposit rates below the market average, whereas branches of small banks (bottom decile) offer above-average rates. Conditional on leverage, size remains the dominant determinant of pricing: among large banks, leverage makes little difference, while among small banks, high leverage is associated with slightly lower deposit rates. This pattern strengthens during the Great Recession, when low-leverage small banks maintained relatively high deposit rates, whereas highly leveraged small banks compressed rates more aggressively. Overall, these results confirm that bank size drives the bulk of cross-sectional variation in deposit pricing, with leverage playing a secondary but asymmetric role that becomes more pronounced under financial stress.

Overall, Figures 1 and 2 show that deposit rate setting is heterogeneous across bank size, with small banks paying a premium and large banks enjoying a discount relative to the cross-sectional mean. This reflects persistent market power asymmetries, customer inertia, and potentially funding risk differences. However, these time-series plots are only indicative of heterogeneity in the pass-through of interest rates. We next turn to a formal empirical analysis.

2.2 Local projections

To study the dynamic effects of bank deposit rates setting behavior, we apply local projections (Jordà, 2005) as follows

$$\tilde{r}^d_{i,t+h} = \alpha_i + \sum_{j=1}^{3} \beta_{h,j} x_{t,j} + \gamma_{\mathbf{h}} \mathbf{X_{i,t}} + \delta_{\mathbf{h}} \mathbf{X_t} + \epsilon_{i,t+h} \tag{2}$$

where $\tilde{r}^d_{i,t+h} = r^d_{i,t+h} - \bar{r}^d_{t+h}$ denotes the deviation of bank i's deposit rate from the cross-sectional mean $\bar{r}^d_{t+h}$ in month $t+h$, where $h = 0, 1, \ldots, 24$. The constant α_i is the branch-fixed effect and $\mathbf{X_{i,t}}$ & $\mathbf{X_t}$ are vectors of time-variant control variables at the bank-and aggregate-level. Bank-level controls include deposit-asset ratio, cash ratio and leverage (assets-equity ratio).[4] Aggregate controls include PCE Inflation, recession dummies and Industrial Production as a measure of economic activity.

The $x_{t,j}$ terms are our exogenous variations of interest. We consider two different shocks. The first one is the z-score of the financial uncertainty index of Ludvigson et al. (2021). The second shock is the change in the federal funds rate. Since the right-hand side of the regression also controls for inflation and economic activity, the change in the federal funds rate can be considered the residuals in a Taylor-type monetary policy rule.[5]

In terms of identification, we are interested in the impulse responses, $\beta_{h,j}$ (for each horizon h) of the deviation of banks' deposit rates (from the cross-sectional mean) to $x_{t,j}$. The key identifying assumption that allows causal interpretation is that (controlling for macroeconomic conditions) $x_{t,j}$ does not respond to bank-level deposit rates. The value of granular bank-level data as the dependent variable means we plausibly avoid simultaneity bias.

To test for heterogeneous effects, we rank the banks each period by either leverage or the size of their deposit base. We then define dummy $D^d_{it} = 1$ for bank i in decile d in year t. We use these dummies to estimate decile-specific coefficient estimates, following de Groot et al. (2020).

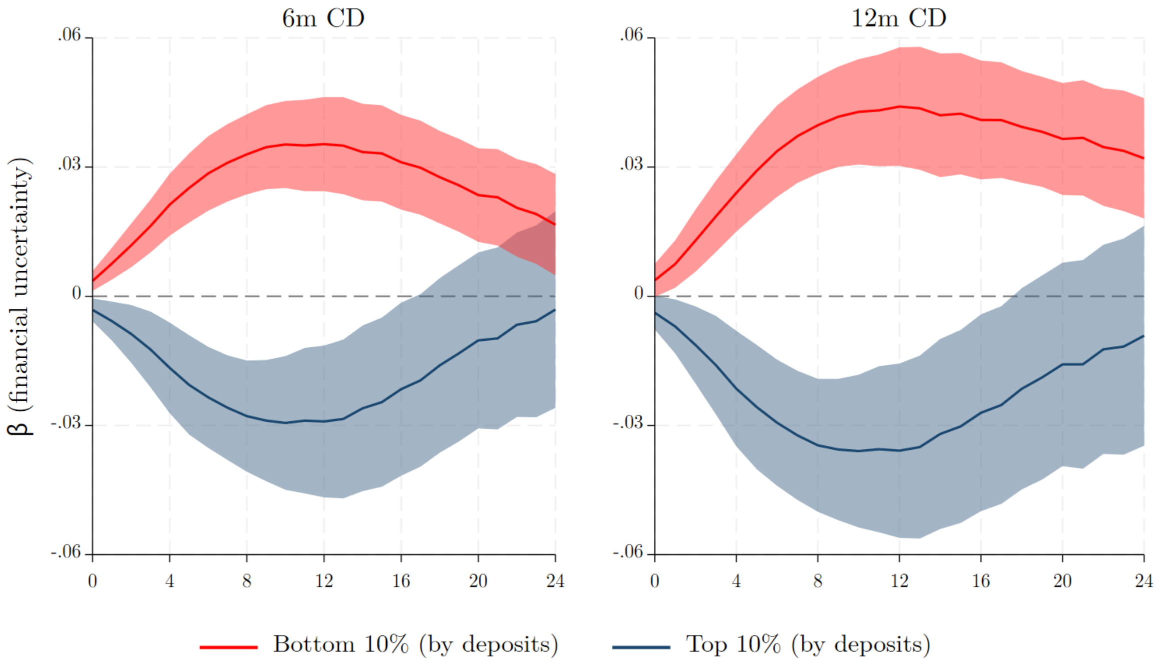
Figures 3 to 6 plot the impulse responses. Figure 3 plots the response of the top and bottom 10% of banks by deposit size to a positive one standard deviation shock of the financial uncertainty index. In response to the financial shock, the largest banks cut their deposits rate faster relative to the average bank while smaller banks do so at a slower pace. As large (small) banks tend to offer lower (higher) rates relative to the mean, their spreads widen realtive to the cross-section mean. Figure 4 plots the response of the top and bottom 10% of banks by leverage. Highly leveraged banks cut their deposits rate relative to the average bank (increasing their risk-free rate-deposit rate margin) while the less leveraged banks increase their relative deposit rates (decreasing profitability).

Figure 5 and 6 plot the impulse responses to an increase in the federal funds rate. Large banks lower their relative deposit rates whereas small banks go in the opposite direction, once again widening spreads. The response of the leverage deciles is different. Low leverage banks move first in raising rates, initially increasing the spread with the mean before returning to their initial state. High leverage banks display an initial weaker response before finally narrowing their spread relative to the mean. This result becomes more patent as the maturity of the CD increases. To provide a structural interpretation of these heterogeneous responses,

[4]The cash ratio is a measure of liquidity and is defined as the sum of cash and securities available for sale, divided by liabilities.

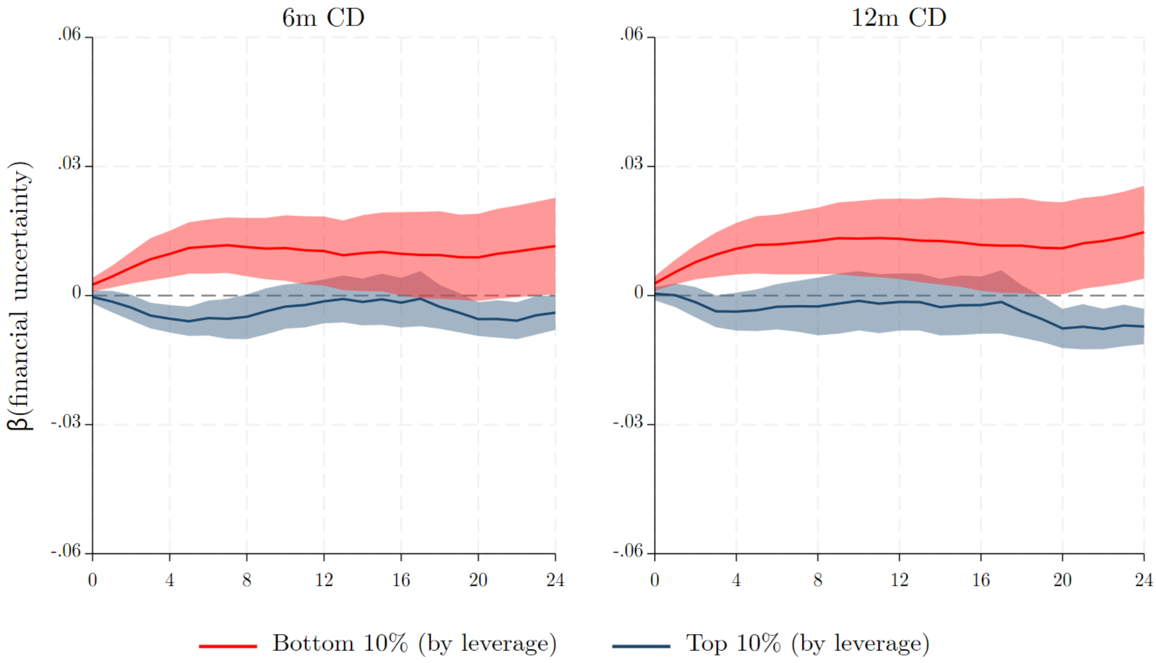
[5]We also tested the monetary policy surprise from Jarociński (2024), which yielded no notable effects.

Figure 3: Response to financial uncertainty (by deposit base)



Note: Local projections. 95% confidence bands. Time in months.

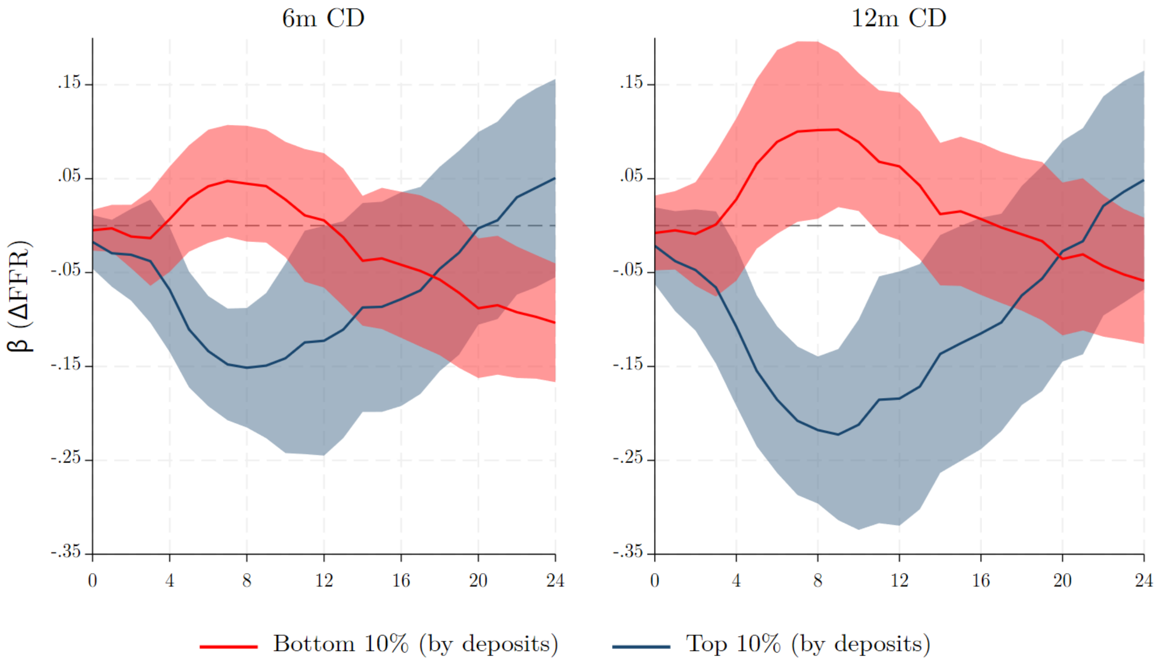
Figure 4: Response to financial uncertainty (by leverage)



Note: Local projections. 95% confidence bands. Time in months.

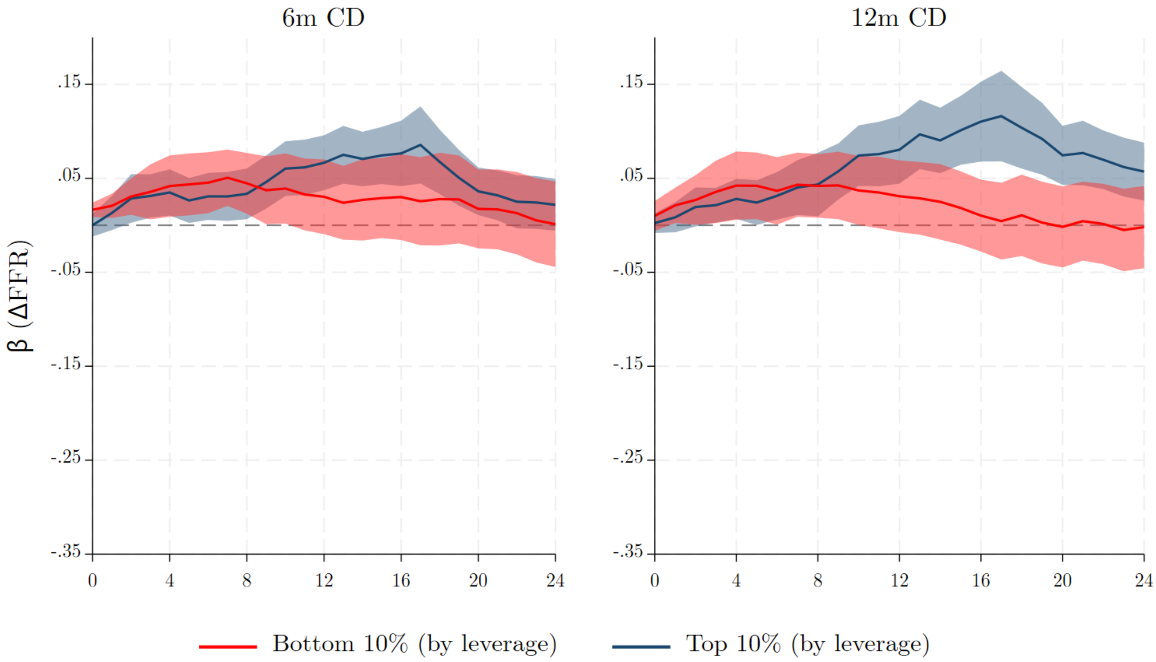
we build a heterogenous bank model in the next section.

Figure 5: Response to increase in fed funds rate (by deposit base)



Note: Local projections. 95% confidence bands. Time in months.

Figure 6: Response to increase in fed funds rate (by leverage)



Note: Local projections. 95% confidence bands. Time in months.

3 The model

Time is continuous with no aggregate uncertainty. The representative household comprises workers and bankers. Workers supply labor. Bankers use internal funds (net worth) and external funds (deposits) to finance the purchase of firms' physical capital. Banks are perfectly competitive in the lending market and monopolistically competitive in the deposit market, with households exhibiting external deep-habits over liquidity services. Additionally, banks experience idiosyncratic return shocks. Upper case letters denote aggregate variables and lower case letters denote individual bank variables. For a stylized three-period version of the model, see Appendix C.

3.1 Households

The representative household chooses consumption C_t, labor, L_t, risk-free bonds, B_t, and deposits at bank i, denoted d_{it}, to solve the following problem:

$$V_0 = \max_{C_t,\{d_{it}\}} \int_0^\infty e^{-\rho t} \left[u\left(C_t, L_t\right) + \vartheta \left(\int_0^1 \left(\frac{d_{it}}{s_{it}^\theta} \right)^\varepsilon \mathrm{d}i \right)^{\frac{1}{\varepsilon}} \right] \mathrm{d}t, \tag{3}$$

where $u\left(\cdot\right)$ is a separable utility function of constant-relative-risk-averse (CRRA) form with coefficient of relative risk aversion, η and Frisch elasticity of labor supply $1/\gamma$, that is, $u(C_t, L_t) = \frac{C_t^{1-\eta}}{1-\eta} - \Upsilon \frac{L_t^{1+\gamma}}{1+\gamma}$. The subjective discount rate is denoted ρ. The second term in the square brackets represents the utility value of liquidity services provided by banks, where $1/(1-\varepsilon)$ is the elasticity of substitution across banks ($0 < \varepsilon < 1$), and s_{it} is the bank-specific (external) habit stock, where $\theta < 0$. Household asset holdings evolve according to

$$\frac{\mathrm{d}B_t}{\mathrm{d}t} = w_t L_t + r_t B_t - \int_0^1 f_{it}\mathrm{d}i + \Pi_t - T_t - C_t, \tag{4}$$

$$\frac{\mathrm{d}d_{it}}{\mathrm{d}t} = r_{it}^d d_{it} + f_{it} \quad \text{for} \quad i \in [0,1], \tag{5}$$

where r_t is the risk-free rate, r_{it}^d is the return on deposits at bank i, W_t is the wage earned from supplying labor, Π_t are net transfers from bankers and profits from capital production, T_t are lump sum taxes, and f_{it} are the flow of deposits.[6] The risk-free bond will be in zero net supply. Defining wealth as $A_t = B_t + \int_0^1 d_{it}\mathrm{d}t$, the evolution of wealth is given by

$$\frac{\mathrm{d}A_t}{\mathrm{d}t} = w_t L_t + r_t A_t - \int_0^1 \left(r_t - r_{it}^d\right) d_{it}\mathrm{d}i + \Pi_t - T_t - C_t. \tag{6}$$

[6] Each bank $i \in [0,1]$ is characterized by type $(n(i), s(i))$, inducing a density $g(n,s)$ over characteristics (net worth and habits, explained further below).

The optimality conditions of the household problem are given by

$$\frac{\mathrm{d}C_t}{\mathrm{d}t} = \frac{1}{\eta}\left(r_t - \rho\right) C_t, \tag{7}$$

$$w_t = \frac{\Upsilon L_t^{\gamma}}{C_t^{-\eta}}, \tag{8}$$

$$r_{it}^d = r_t - \frac{\vartheta}{u'(C_t)} \left(\frac{d_{it}}{\tilde{D}_t}\right)^{\varepsilon-1} s_{it}^{-\theta\varepsilon}, \tag{9}$$

where

$$\tilde{D}_t \equiv \left(\int_0^1 \left(\frac{d_{it}}{s_{it}^{\theta}}\right)^{\varepsilon} \mathrm{d}i\right)^{\frac{1}{\varepsilon}}, \tag{10}$$

is the habit-adjusted liquidity aggregator. Equation (7) is the standard consumption Euler equation. Equation (9) is the demand curve for deposit contracts at bank i. The demand curve has three key properties. One, the return on deposits is always below the return on the risk-free bond, reflecting the liquidity value of deposits over bonds. Two, the demand curve is upward sloping; the demand for deposits in bank i are increasing in the interest rate offered on those deposits. The demand curve is not flat, reflecting monopolistic competition. Three, habits shift the demand curve. When s_{it} is larger, the household is willing to accept a lower deposit rate for the same quantity of deposits, all else equal. The parameter $\vartheta > 0$ allows us to match the steady state mean risk-free rate to deposit-rate spread in the data.

Finally, the stock of habits evolve as follows

$$\mathrm{d}s_{it} = (1-h)\left(s_{it}^{p} d_{it}^{1-p} - \delta_s s_{it}\right)\mathrm{d}t + \sigma_s \mathrm{d}W_t, \tag{11}$$

where $0 < h < 1$ captures the persistence of habits and habit shocks are captured by the Wiener process, W_t. Notice, however, that these habits are external, meaning that the household does not take them into account when solving its dynamic optimization problem. Banks, however, will internalize the effects of habits when setting deposit rates.

3.2 Banks

There is a unit continuum of banks. Bankers exit the market at a exogenous rate $0 < \zeta < 1$ and return net worth to the household. New bankers enter the market, keeping the mass of bankers unchanged. During operation, bankers maximize the expected present discount value of future net worth, n_t, given by

$$V_0 = \max_{\phi_t} \mathbb{E}_0 \int_{t=0}^{\infty} \zeta n_t e^{-\left(\int_0^t r_s ds + \zeta s\right)} \mathrm{d}t. \tag{12}$$

For ease of exposition, we drop the bank i subscript in this section. A bank's balance sheet is given by $Q_t k_t = d_t + n_t$, where k_t and Q_t are capital and the price of capital, respectively, d_t are deposits and n_t is net worth. We define bank leverage as $\phi_t \equiv Q_t k_t / n_t$.

Bankers face a Gertler and Karadi (2011)-type incentive constraint (IC), given by

$$V_t \geq \lambda \phi_t n_t, \tag{13}$$

where V_t is the bank's value. The banker can, at any time, abscond with a fraction $0 < \lambda < 1$ of the bank's assets. Thus, to continue operating the bank, the continuation value must weakly exceed the payoff from absconding.

The bank's net worth evolves according to

$$\mathrm{d}n_t = \left(r_t^K \phi_t - r_t^d \left(\phi_t - 1 \right) - \frac{c\left(d_t\right)}{n_t} \right) n_t \mathrm{d}t + \phi_t n_t \sigma_n \mathrm{d}Z_t, \tag{14}$$

where r_t^K is the return on capital, which is taken as given and common across banks. While the return is common, realized outcomes for net worth are bank-specific due to individual shocks, captured by the Wiener process, Z_t, and that are scaled by the banks asset position.[7] $c\left(\cdot\right) > 0$ are convex deposit costs with the functional form

$$c\left(x\right) = \frac{\zeta_1}{1+\zeta_2} x^{1+\zeta_2}, \tag{15}$$

where $\zeta_1, \zeta_2 \geq 0$. The optimization problem facing a banker is described by the following Hamiltonian-Jacobi-Bellman (HJB) equation

$$(r+\zeta)V = \max_{\phi} \zeta n + \frac{\partial V}{\partial n} S_n + \frac{\partial V}{\partial s} S_s + \frac{(n\phi\sigma_n)^2}{2} \frac{\partial^2 V}{\partial n^2} + \frac{(s\sigma_s)^2}{2} \frac{\partial^2 V}{\partial s^2}, \tag{16}$$

where, for ease of exposition, we have dropped time, t, subscripts. S_n is the drift in net worth: $\left(r^K \phi - r^d \left(\phi - 1\right) - c\left(d\right)/n \right) n$ and S_s is the drift in habits: $\left(1-h\right)\left(s^p d^{1-p} - \delta_s s\right) \mathrm{d}t$. In practice, we reformulate the expression above as

$$(r+\zeta)\upsilon = \max_{\phi} \ \zeta + \left[\frac{\partial \upsilon}{\partial n} + \frac{\upsilon}{n} \right] S_n + \frac{\partial \upsilon}{\partial S} S_s + \frac{(n\phi\sigma_n)^2}{2} \left[\frac{\partial^2 \upsilon}{\partial n^2} + \frac{2}{n}\frac{\partial \upsilon}{\partial n} \right] + \frac{(s\sigma_s)^2}{2} \frac{\partial^2 \upsilon}{\partial s^2}, \tag{17}$$

where $\upsilon \equiv V/n$. A banker's incentive constraint (13) occasionally binds. When it does bind, (13) holds with equality. When it does not, the first-order condition of the HJB equation

[7] This is an idiosyncratic version of the return shock used in Fernández-Villaverde et al. (2023).

with respect to leverage is given by

$$\left(\frac{\partial \upsilon}{\partial n}+\frac{\upsilon}{n}\right)\left(r^K-r^d-\frac{\partial r^d}{\partial \phi}(\phi-1)-c'(d)\right)+\frac{\partial \upsilon}{\partial s}(1-h)(1-p)\left(\frac{s}{d}\right)^p$$
$$+\phi(n\sigma_n)^2\left[\frac{\partial^2 \upsilon}{\partial n^2}+\frac{2}{n}\frac{\partial \upsilon}{\partial n}\right]+(s\sigma_s)^2\frac{\partial^2 \upsilon}{\partial s^2}=0. \tag{18}$$

Equation (18) tells us the effects of an increase in leverage. First, profits rise because the interest margin, $r^K - r^d$, is positive. Two, an increase in ϕ drives the bank to offer a higher deposit rate, $\partial r^d/\partial\phi > 0$, which pushes down on profits. In addition, deposit costs, $c(\cdot)$, rise with leverage, putting further downward pressure on profits. Finally, higher leverage today increases habits and future profits and thus pushes up the continuation value of the bank, $\partial\upsilon/\partial s > 0$.

Finally, new bankers enter at a rate ζ and are endowed with $(n^0, s^0) = (\omega_n N_t, \omega_s S_t)$, where $\omega_n > 0, \omega_s > 0$ are parameters, N_t is aggregate net worth, and $\omega_s S_t$ is the initial stock of habits. Let $\mathbf{x}_t = [n_t, s_t]'$ and let $g(\mathbf{x}_t, t)$ be the distribution of $\mathbf{x}_t$. The Kolmogorov Forward Equation (KFE) that describes the evolution of the distribution is given by

$$\begin{aligned}\frac{\partial g(\mathbf{x}_t,t)}{\partial t} =& -\frac{\partial}{\partial n}\left(S_n g(\mathbf{x}_t,t)\right)-\frac{\partial}{\partial s}\left(S_s g(\mathbf{x}_t,t)\right)\\ &+\frac{1}{2}\frac{\partial^2}{\partial n^2}\left((\phi n\sigma_n)^2 g(\mathbf{x}_t,t)\right)+\frac{1}{2}\frac{\partial^2}{\partial s^2}\left((s\sigma_s)^2 g(\mathbf{x}_t,t)\right)\\ &-\zeta g(\mathbf{x}_t,t)+\zeta\delta(n-\omega N_t)(s-\omega_s S_t),\end{aligned} \tag{19}$$

where $\delta(\cdot)(\cdot)$ is the Dirac delta. The stationary equilibrium is defined as $\partial g(\mathbf{x}_t,t)/\partial t = 0$.

3.3 Production

The production side of the economy is standard. A representative firm produces intermediate output, Y_t, with technology

$$Y_t = A_t K_t^{\alpha} L_t^{(1-\alpha)} \tag{20}$$

where K_t is the aggregate capital stock. The aggregate capital stock evolves according to

$$\dot{K}_t = (\iota_t - \delta) K_t \tag{21}$$

where ι_t is the investment rate. Investment that differs from replacement is subject to a deadweight convex adjustment costs, $\chi(\iota_t) \equiv \frac{\psi}{2}(\iota_t-\delta)^2$ per unit of capital. The optimality condition for capital producers is given by

$$r_t = \iota_t - \delta + \frac{\dot{Q}_t - (Q_t-1)\iota_t + \chi(\iota_t) - \chi''(\iota_t)\dfrac{\mathrm{d}\iota_t}{\mathrm{d}t}}{Q_t - 1 - \chi'(\iota_t)}, \tag{22}$$

where Q_t is the price of capital. When $\psi = 0$ then $\dot{Q}_t = 0$ and $Q_t = 1$. The return on capital is given by

$$r_t^k = \frac{MPK_t - \delta Q_t + \dot{Q}_t}{Q_t}, \tag{23}$$

where MPK_t is the marginal product of capital. Intermediate output is sold to monopolistically competitive final goods producers that face deadweight convex price adjustment costs (Rotemberg, 1982) of the form $\frac{\theta^\pi}{2}\left(\dot{P}_t/P_t\right)^2 Y_t$, where $\pi_t = \dot{P}_t/P_t$. The optimal pricing decision of the final goods firms delivers the following Phillips curve

$$\left(r_t - \dot{Y}_t/Y_t\right)\pi_t = \frac{\epsilon}{\theta^\pi}\left(m_t - \frac{\epsilon - 1}{\epsilon}\right) + \dot{\pi}_t, \tag{24}$$

where ϵ is the elasticity of substitution across goods, π_t is the inflation rate, and m_t is the inverse of the mark-up over marginal cost. The marginal product of capital is given by $MPK_t \equiv \alpha m_t \tau_m A_t (L_t/K_t)^{\alpha-1}$. The term $\tau_m = \epsilon/\left(\epsilon - 1\right)$ ensures that the steady state is undistorted by the presence of monopolistic competition in the goods market. Similarly, the wage rate is given by $w_t = (1-\alpha) m_t \tau_m A_t (K_t/L_t)^\alpha$

3.4 Closing the model

The government runs a balanced budget in every period. It has expenditures proportional to output $G_t = \varpi Y_t$ that are funded by lump sum T_t taxes on the household such that $T_t = G_t = \varpi Y_t$. The central bank sets the nominal risk-free rate via a simple Taylor rule given by

$$\mathrm{d}r_t^n = -\nu_m(r_t^n - [\rho + \phi_m \pi_t])\mathrm{d}t, \tag{25}$$

where ϕ_m is the responsiveness of the policy rate to deviations of inflation and where ν_m governs the speed of adjustment. The nominal rate is linked to the real rate via the Fischer relation: $r_t = r_t^n - \pi_t$. Finally, we have the following aggregation identities: $K_t = \int n\phi_t\left(\mathbf{x}\right) g_t\left(\mathbf{x}\right) \mathrm{d}\mathbf{x}$, $N_t = \int n g_t\left(\mathbf{x}\right) \mathrm{d}\mathbf{x}$, and

$$\tilde{D}_t^\varepsilon = \int \left(\left(\phi_t\left(\mathbf{x}\right) - 1\right) n s^{-\theta}\right)^\varepsilon g_t\left(\mathbf{x}\right) \mathrm{d}\mathbf{x}. \tag{26}$$

The aggregate resource constraint is given by

$$Y_t = C_t + \iota_t K_t + G_t + PC_t + AC_t, \tag{27}$$

where PC_t are the aggregated deposit costs. Finally, the sum of investment adjustment and inflation costs is defined as $AC_t \equiv \frac{\psi}{2}(\iota_t - \delta)^2 K_t + \frac{\theta^\pi}{2}\pi_t^2 Y_t$. The model is solved numerically using the finite differences approach outlined in Achdou et al. (2022), on non-uniform grids.

4 Parameterization

The set of model parameters is split into two subsets. The first subset are given standard values in the literature. The second subset are calibrated to minimize the distance between the data and model moments as presented in Table 3.

In the first subset of parameters, the subjective discount rate, ρ, gives a steady steady annualized risk-free rate of 3.02%, which we take from the average 10-year Treasury rate from January 2003 to December 2023. The coefficient of relative risk aversion, $\eta = 1$, implies log-preferences and the inverse Frisch elasticity is set to 1 as in Kaplan et al. (2018). The constant in labor disutility, Υ, is set such that steady state labor L is equal to 1. The capital share of income, α is set to $1/3$, the depreciation rate of capital, δ is set to 0.025 and the government spending share of output is set at 0.2. We also assume that the habit persistence, h, is 0.95, following Gilchrist et al. (2017) and set banker exit at an exogenous rate of 0.0433. We also adopt standard values from the literature for monetary policy and nominal rigidities. The persistence parameter in the Taylor rule, ν_m, is set to 0.2, and the responsiveness of the nominal interest rate to inflation, ϕ_m, is set to 1.5, following Gonzalez et al. (2024). The elasticity of substitution across goods, ϵ, is fixed at 10, following Kaplan et al. (2018), which implies a steady-state markup of approximately 11%. Finally, the price adjustment cost parameter, $theta^{\pi}$, is set to 100, also based on Kaplan et al. (2018).

The second subset of (twelve) parameters $\{\vartheta, \varepsilon, \theta, \lambda, \omega, \zeta, \zeta_1, \zeta_2, \sigma_n, \sigma_s, p, \delta_s\}$, are chosen to minimize the distance to (fourteen) data moments. These include the mean, standard deviation and skewness of the distribution of leverage, deposits-assets ratio and deposit interest rates, respectively, and the average of the per-period correlations of leverage with assets, equity and deposits. These moments are based on RateWatch, US Call Report and FDIC data. In addition, we aim for roughly ninety percent of banks to be constrained in the ergodic distribution, match the rate of return on capital and the long-run spread between the average deposit rate and the risk-free rate.

The final calibration matches most moments relatively well. We match the mean annualized interest rate on deposits is 1.38% (12m CD 10k), which gives a 165bp liquidity premium relative to the risk-free rate. However, the model slightly unpredicts the cross-sectional standard deviation of deposit rates and overpredicts the skewness of deposit rates. In the data, there is a cross-sectional standard deviation of 42bp (and skewness of 0.28) versus 39bp and 0.56, respectively, in the model. We match the mean leverage, at 10.1, overpredict its cross-sectional standard deviation at 3.39 versus 2.77 in the data, and underpredict skewness (1.34 in the data vs 0.91 in the model). While we get low correlation between leverage and deposits, assets and equity, we get values outside of the 95 % confidence interval. Otherwise we do relatively well at matching the remaining moments.

Table 2: Parameterization

Parameter	Name	Value	Notes
Real economy			
ρ	Subjective discount rate	0.0302	10-year treasury rate 01/03-12/23
η	Coefficient of RRA	1	Log-preferences
γ	Inverse Frisch elasticity	1	Kaplan et al. (2018)
Υ	Labor disutility constant	1.2159	Normalisation $L = 1$
α	Share of capital	1/3	Standard value
δ	Depreciation	0.025	Gertler and Karadi (2011)
ϖ	Gov. spending share	0.2	Gertler and Karadi (2011)
ψ	Capital adjustment cost	7	Gonzalez et al. (2024)
Liquidity preferences			
ϑ	Liquidity weight	0.0024	Simulated method of moments
$1/(1-\varepsilon)$	Substitution elasticity	10	Simulated method of moments
θ	Habit strength	-0.10	Simulated method of moments
h	Habit persistence	0.95	Gilchrist et al. (2017)
δ_s	Habit depreciation	1	Simulated method of moments
p	Habit formation elasticity	0.2	Simulated method of moments
Financial sector			
ζ	Banker exit rate	0.0433	Simulated method of moments
λ	Incentive constraint	0.2278	Simulated method of moments
ω_n	n tsf. to new bankers	0.1578	Simulated method of moments
ω_s	s tsf. to new bankers	0.0010	New banks start at $\underline{s}$
ζ_1	Deposit adj. cost fn.	0.0015	Simulated method of moments
ζ_2	Deposit adj. cost fn.	0.5	Simulated method of moments
σ_n	St.Dev. risk shock	0.0125	Simulated method of moments
σ_s	St.Dev. s shock	0.0125	Simulated method of moments
Monetary policy and inflation			
ν_m	Persistence Taylor rule	0.2	Gonzalez et al. (2024)
ϕ_m	Slope Taylor rule	1.5	Gonzalez et al. (2024)
ϵ	Goods elasticity of substn.	10	Kaplan et al. (2018)
θ^{π}	Price adjustment costs	100	Kaplan et al. (2018)

In terms of the implied parameters values, the moment matching exercise delivers an elasticity of substitution across banks of 10 and an incentive constraint parameter that implies that bankers can abscond with 23% of assets. The estimated elasticity of substitution between habits and deposits in (11), $p = 0.2$, suggests that the evolution of habits is highly responsive to deposit choices. Given $\theta = -0.1$ and $0 < \varepsilon < 1$, the elasticity of the deposit rate markdown with respect to habits is positive but small, meaning that a 1% increase in the habit stock widens the spread by roughly $0.1\varepsilon\%$. Finally, the estimated standard deviations of the idiosyncratic shocks ($\sigma_n = \sigma_s = 0.0125$) are moderate, additionally increasing to some extent heterogeneity across banks.

In the stationary equilibrium, the model reproduces the established empirical ranking of deposit rate spreads relative to the cross-section mean across bank types. When banks are sorted by deposits, the top decile (large banks) offers an average deposit rate that lies about 54bps below the cross-section mean, whereas the bottom decile (small banks) offers a rate approximately 59bps above the mean. Although these spreads are not calibration targets,

Table 3: Long-run statistics for leverage, deposits/assets ratio and deposit rates.

	Data	**95% CI**	**Model**
Mean			
Leverage	10.10	[8.76, 11.99]	10.1
Deposits/Assets	0.83	[0.81, 0.87]	0.88
Deposit rate (12m CD 10k)	1.38	[0.23, 4.19]	1.38
Standard deviation			
Leverage	2.77	[2.05, 4.73]	3.39
Deposits/Assets	0.07	[0.06, 0.09]	0.06
Deposit rate (12m CD 10k)	0.42	[0.16, 1.35]	0.39
Skewness			
Leverage	1.34	[-0.23, 3.32]	0.91
Deposits/Assets	-2.19	[-3.45, -1.63]	-3.58
Deposit rate (12m CD 10k)	0.28	[-0.87, 1.24]	0.56
Correlation			
Leverage & Assets	0.01	[-0.02, 0.06]	-0.15
Leverage & Equity	-0.00	[-0.02, 0.04]	-0.16
Leverage & Deposits	0.01	[-0.02, 0.05]	-0.14
Other			
$r^f - r^d$ †	1.65	[0.23,2.94]	1.65
r^k (% ann)	5.00		5.00
Constrained banks	?		93.62%

Note † 10 year treasury yield - 12m CD 10k, % ann.

their magnitudes are of the same order as those observed empirically in normal times, albeit somewhat larger in the model. Sorting instead by leverage yields a mirror ordering: low-leverage banks (bottom decile) post rates about 52bps below the mean, while high-leverage banks (top decile) offer rates roughly 32bps above it. Thus, in steady state, large and low-leverage banks price deposits at a discount relative to the average bank, while small and high-leverage banks compensate depositors with a premium. Figure B.2 in the appendix shows the annualized average deviation at each decile of the leverage and deposits distribution. This pattern is consistent with the interpretation that market power and balance-sheet tightness jointly shape deposit pricing in the model.

We quantify the overlap in steady state between size- and leverage-sorted tails with the ratio $J(A,B) = |A \cap B|/|A \cup B|$, computed with model weights. The top-decile by deposits and the bottom-decile by leverage almost coincide ($J = 0.937$), whereas their complements are essentially disjoint.[8] The bottom-decile by deposits overlaps moderately with the top-decile by leverage ($J = 0.307$). A similar exercise confirms that the banks driving these tails are overwhelmingly unconstrained. The overlap between the unconstrained set and the top-deposit decile is 0.637, and 99.9% of unconstrained banks lie in that decile, while 63.7% of the top-deposit mass is unconstrained. Likewise, the overlap between unconstrained banks and the bottom-leverage decile is 0.657. Once again 99.9% of unconstrained banks fall in this bin, and 65.7% of the bottom-leverage mass is unconstrained. The mass of unconstrained banks in

[8]That is, $J(\text{top deposits, top leverage}) = 0$ and $J(\text{bottom deposits, low leverage}) = 0$.

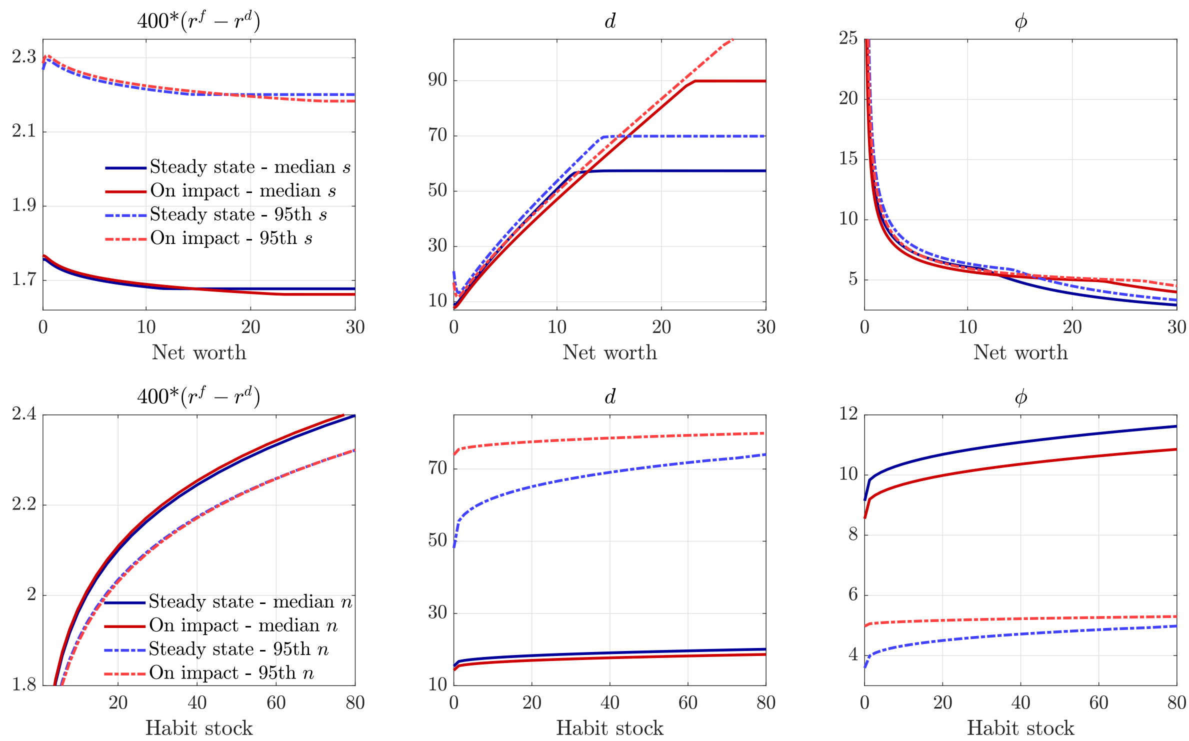
the stationary distribution is 6.38%. These figures reinforce that large and low-leverage banks tend to be composed of unconstrained institutions.

5 Results

5.1 Financial shocks

We present results from a series of shocks to the model in Section 3. In particular, we consider shocks to the incentive constraint, capital quality, monetary policy and the aggregate habit stock. We first explore a financial shock modeled as an unanticipated 5% increase in λ.[9] We first focus on this shock as it is illustrative of the many mechanisms driving results in all shocks. An increase in λ is an increase in the proportion of assets that a banker can abscond with. As such, it tightens the incentive compatibility constraint of bankers and reduce households' willingness to hold deposits. We assume the rise in λ decays with a half-life of approximately 6 quarters.

Figure 7: Policy functions



Policy response of an unexpected rise of 5% in λ.

[9]The computational approach used in this paper is commonly referred to as 'MIT shocks'. See Achdou et al. (2022).

Figure 7 plots banks' policy functions at the ergodic steady state (blue) and on impact of the financial shock (red). Since the state of an individual bank is two-dimensional, described by its net worth, n, and habit stock, s, we present two cuts of the policy function: the top row plots different levels of n, for a given s (median and 95th percentile) while the bottom row plots policies at different levels of s for a given n (median and 95th percentile).

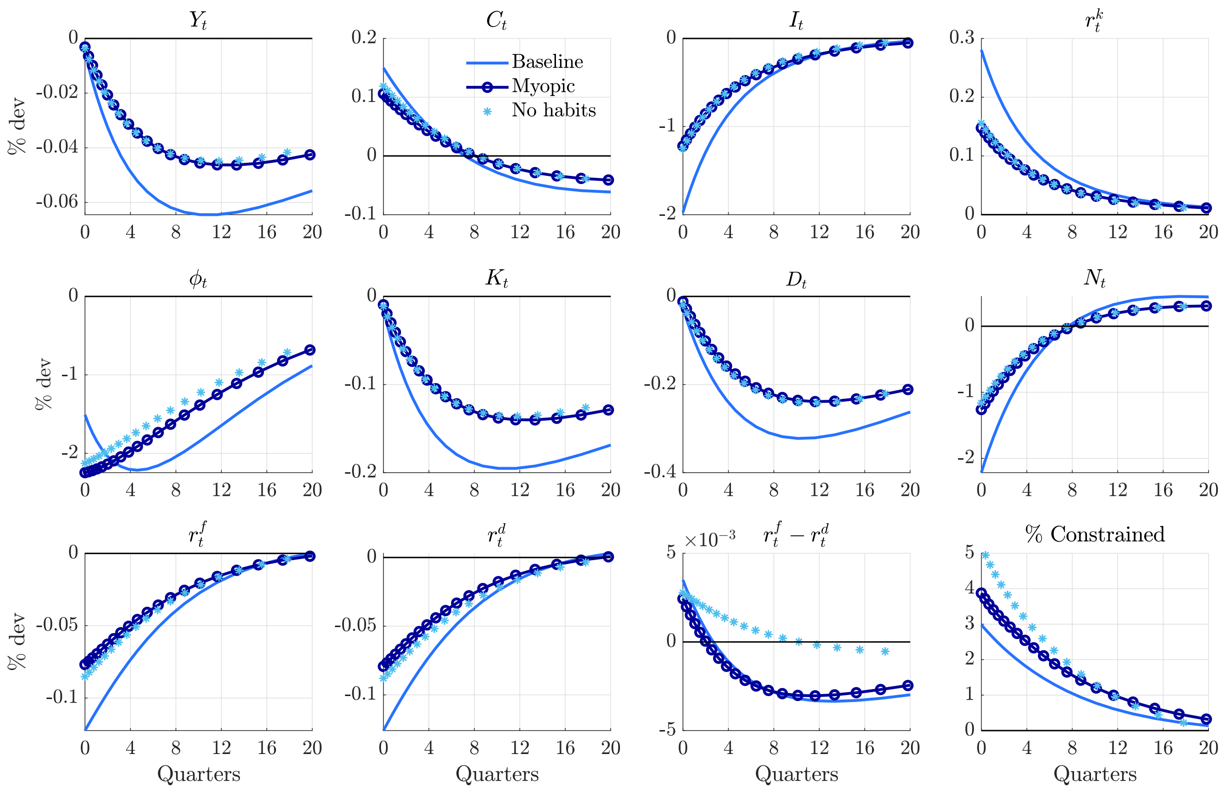
The policy functions in the top row display a kink, which demarcates the constrained from the unconstrained banks. At the median habit, the kink is around $n = 12$ in steady state and $n = 15$ on impact of the shock. The kink shifts to the right at the 95th percentile of habits, capturing that as the habit stock grows interest margins and leverage increase. For a bank with low n, a marginal increase in n raises its equilibrium deposit stock and lowers its leverage. The former is because an increase in n eases the incentive constraint, which makes households more willing to hold deposits at that bank. The latter (drop in leverage) is because of the convex costs associated with larger deposits and the elasticity of substitution across banks, ε. Due to the demand curve for deposits, for a given level of habits, an increase in deposits requires a higher equilibrium deposit interest rate and hence a lower $r^f - r^d$ spread. Hence, for a given level of habit, a bank will be able to attract more depositors with a higher deposit rate, narrowing the spread. As such, banks expand their assets by less than one-for-one with the increase in net worth.

In contrast, when net worth is large (and to the right of the kink in the policy function), banks are unconstrained. Any marginal increase n means the bank needs less external funding (deposits) to maintain the same balance sheet. As the bank grows its habit stock it gains more market power and reduces the deposit rate, widening the spread. On impact of the financial shock, constrained and unconstrained banks behave differently. For a given level of s, constrained (low n) banks are forced to cut deposits and shrink the balance sheet while unconstrained (high n) banks significantly expand the balance sheet. As a result, constrained banks deleverage while unconstrained ones leverage up. Moreover, constrained banks increase their near-term interest rate margins (raising $r^f - r^d$) while unconstrained bank lower their near-term margins.

We now explore how the presence of habits amplifies the financial shock. Figure 8 presents impulse responses functions (IRFs) to the λ shock, focusing on a few key aggregates. The solid-dark blue line presents the baseline model. The dark-blue line with circles presents IRFs in a version of the model where banks do not internalize the effect of their $\{r^d, \phi\}$ decision on the evolution of the habit stock, which we refer to as the myopic case.[10] For comparison we set $\theta = 0$ and compute the IRFs (starred), thereby switching off habits.

[10]In essence the bank does not see $\partial v / \partial s$ by setting $h = 1$, although we still track the evolution of habits with its original value $h < 1$.

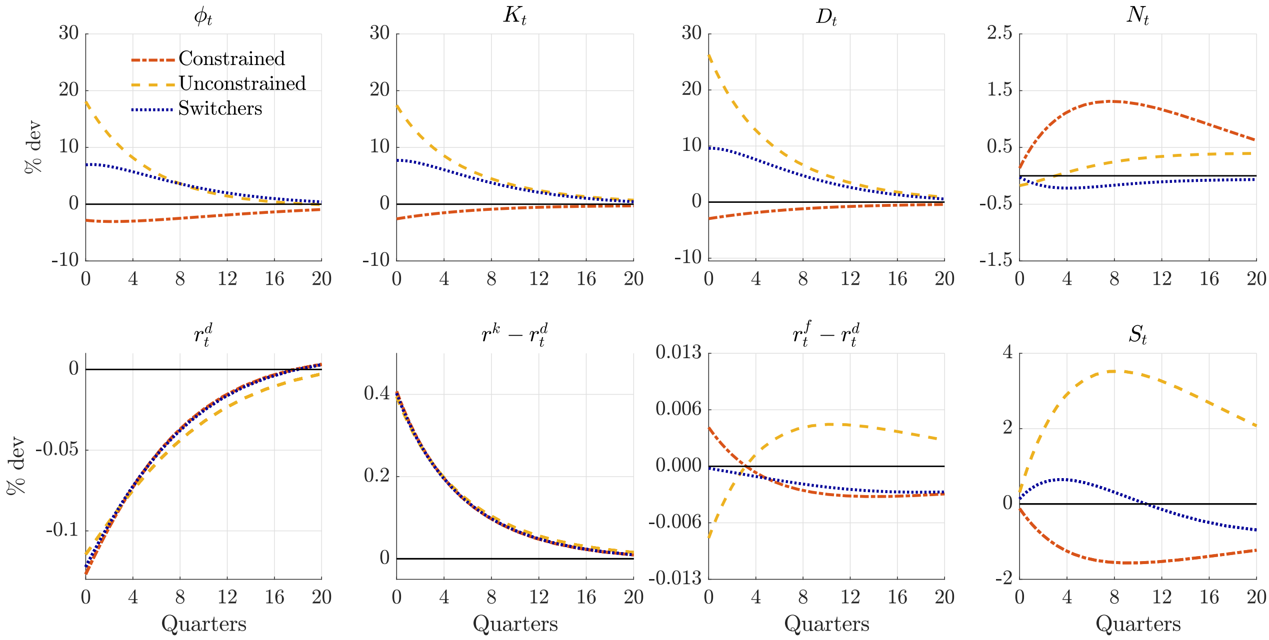
Figure 8: Aggregate response to a 5% λ shock



The tightening of financial conditions following a rise in the incentive constraint leads banks to deleverage. Constrained banks are forced to cut back sharply on investment, and asset prices fall, reducing net worth across the banking sector. The simultaneous loss of net worth and deleveraging pressure causes a contraction in aggregate investment, a decline in the capital stock and a widening of the credit spread (the spread between the aggregate return on capital and the risk-free rate). The risk-free rate and consumption growth both fall in tandem, reflecting lower intertemporal returns. The presence of habits amplifies shocks although the real effects of the financial shock are relatively mild in this scenario; a 5% increase in λ results in only a 0.2% fall in the capital stock. This is because unconstrained banks cushion most of the deleveraging of constrained banks. In general, as the share of unconstrained banks grows, the milder the impact of the shock on aggregates.[11] In the myopic case, when banks do not internalize the effect of their decisions on the evolution of habits, the fall in output, capital stock, risk free rate and investment spending dampens. The no-habits IRFs are broadly similar despite the larger increase int he share of constained banks and the milder but more persistent increase in the deposit rate spread. To understand this result, we need to look more closely at

[11] A share of unconstrained banks of just 0.1% is enough for IRFs to exhibit a considerably milder response to a financial shock.

Figure 9: Behavior of constrained vs unconstrained banks (λ shock)



the heterogeneous behavior of different banks in the model economy.

Figure 9 presents the differential behavior of constrained and unconstrained banks in response to the aggregate financial shock. To construct this figure we group the distribution of banks into three subsets: those that are always constrained (orange) until time t, those that are always unconstrained (yellow) up to time t, and the residual, those that switch at some point during the transition (purple). The IRFs of the constrained and unconstrained subset of banks is quite different. Initially, constrained banks shrink in size and deleverage whereas the unconstrained banks grab market share and become more leveraged. In terms of deposit rates, constrained banks initially cut deposit rates by more than unconstrained banks, resulting in a rise in $r^f - r^d$. Unconstrained banks in contrast see an initial fall followed by a persistent increase, relative to steady state, in $r^f - r^d$. This is inline with our empirical results when we split the distribution into high and low-leverage banks.[12]

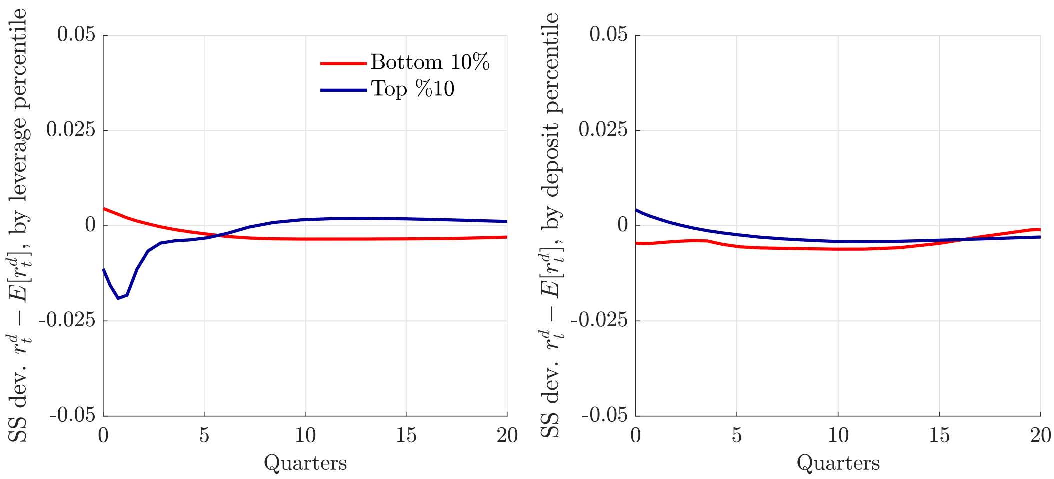
To understand more clearly the role of habits, Figure B.3 in the appendix compares the baseline IRFs to those when banks are myopic and do not internalize the effects of their $\{r^d, \phi\}$ decisions on the dynamics of their habit stock. This figure shows that with myopic banks, the heterogeneity of response is much more muted. The unconstrained banks vary deposit rates less in the myopic case since they do not internalize the effect on long-term profits of cutting deposit rates today and grabbing market share in exchange for a larger habit stock and greater

[12]The correlation between bank size and leverage is close to zero in the data. In the model, there is a weak negative correlation. Thus, in the model, "unconstrained" is synonymous with "low levarage" but not necessarily with "large banks".

profits in the future.

Finally, we examine the response of deposit rate spreads (relative to the cross-sectional mean) to the financial shock, to assess whether the model replicates the empirical patterns shown in Figures 4 and 3. The impulse responses in Figure 10 indicate that a temporary tightening of the incentive constraint only partially reproduces the dynamics observed in the data. While the spread responses by leverage are qualitatively consistent with the local-projection estimates, their magnitude is noticeably weaker. Moreover, the responses by deposit base differ qualitatively from the empirical evidence, suggesting that an incentive-constraint shock alone cannot account for the full cross-sectional adjustment observed during financial crises.

Figure 10: Response of $r_t^d - E[r_t^d]$ spread to a 5% λ shock

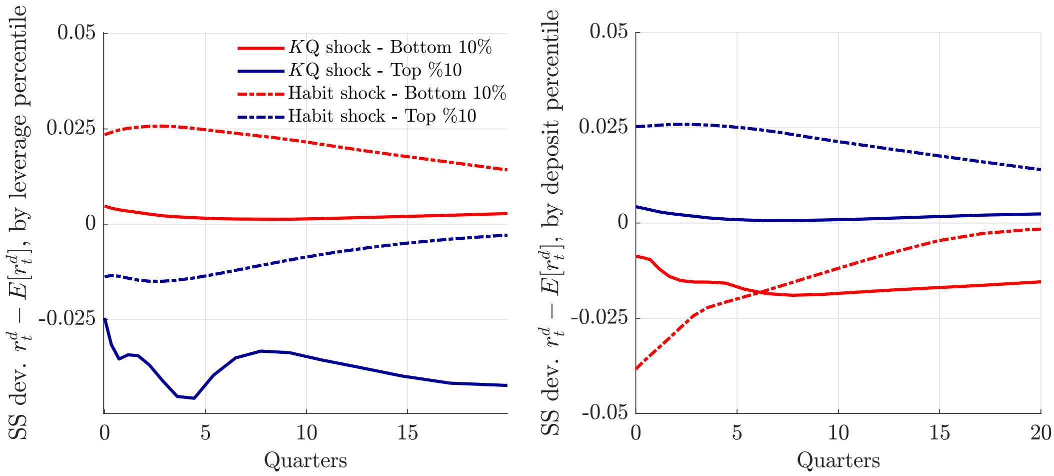


We consider three additional sources of variation that capture financial crises: a capital-quality shock, following the spirit of Gertler and Karadi (2011) and Jamilov and Monacelli (2021), an aggregate habit-stock shock and shock to liquidity preferences.

5.1.1 Response to capital quality and habit shocks

Figure 11 shows the IRF of the deviation of deposit rate spreads from the cross-sectional mean, for the top and bottom deciles of leverage and deposit, following a 1% negative capital quality shock. The figure also overlays the IRF of a negative 25% aggregate habit stock shock. The IRFs on the left panel (leverage distribution) following the capital quality shock and the habit shock align relatively well with the local projections of 12 month CDs (for financial uncertainty) seen in Figures 3 and 4. On the other hand, we still see the opposite order (top/bottom) on the right panel (deposit distribution), relative to the data.

Figure 11: IRF of $r_t^d - E[r_t^d]$ by bottom/top deciles



The capital quality shock (KQ) and aggregate habit shock

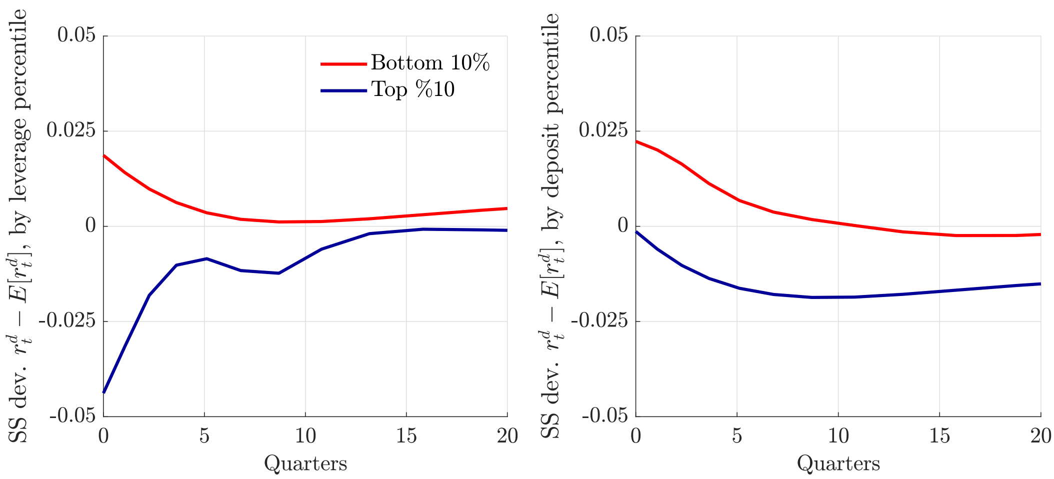
The impulse responses highlight how banks with different balance sheet characteristics adjust their deposit rates relative to the cross-sectional average following a financial shock. The mechanism behind these results is the same as in the λ shock. For leverage heterogeneity, the IRF shows that both the top/bottom banks (by leverage) experience a more pronounced narrowing of their deposit rate spread relative to the mean. Note that most (least) levered banks have a positive (negative) spread. Once again, the least levered banks begin offering relatively more attractive rates to gain market share although with more persistance and amplitude relative to the λ shock.

Next, we examine whether liquidity-preference shocks (ϑ) can reproduce the deposit-sorted IRFs. We introduce a shock that raises ϑ for habit-rich banks and lowers it for habit-poor banks, generating a reallocation of deposits from small to large institutions and allowing the latter to reduce deposit rates. The shock is such that banks above (below) the median value of habits of unconstrained banks see a temporary and decaying increase (decrease) of ϑ. Figure B.5 in the appendix shows the results. High habit banks simultaneously increase deposits and reduce deposit rates, widening their spread relative to the cross-section mean. This comes at the cost of no longer matching the IRFs in the leverage dimension and triggering a small increase in output. However, the exercise shines light on how we can get closer to the empirical IRFs in the deposits dimension. We need to generate a tightening of lending conditions and simultaneously capture a flight of funds towards more established banks.

5.1.2 Matching both panels simultaneously

We can simultaneously match both panels by combining the lambda and liquidity preference shocks. During the Great Financial Crisis, not only did lending conditions tighten sharply, but there was also flight of funds away from small, weaker banks toward larger, more established institutions. To capture this dual dynamic, we now combine the λ shock (tightening financial frictions) with a ϑ shock that tilts deposit demand in favor of large banks, reflecting the observed flow of funds.

Figure 12: IRF of $r_t^d - E[r_t^d]$ by bottom/top deciles

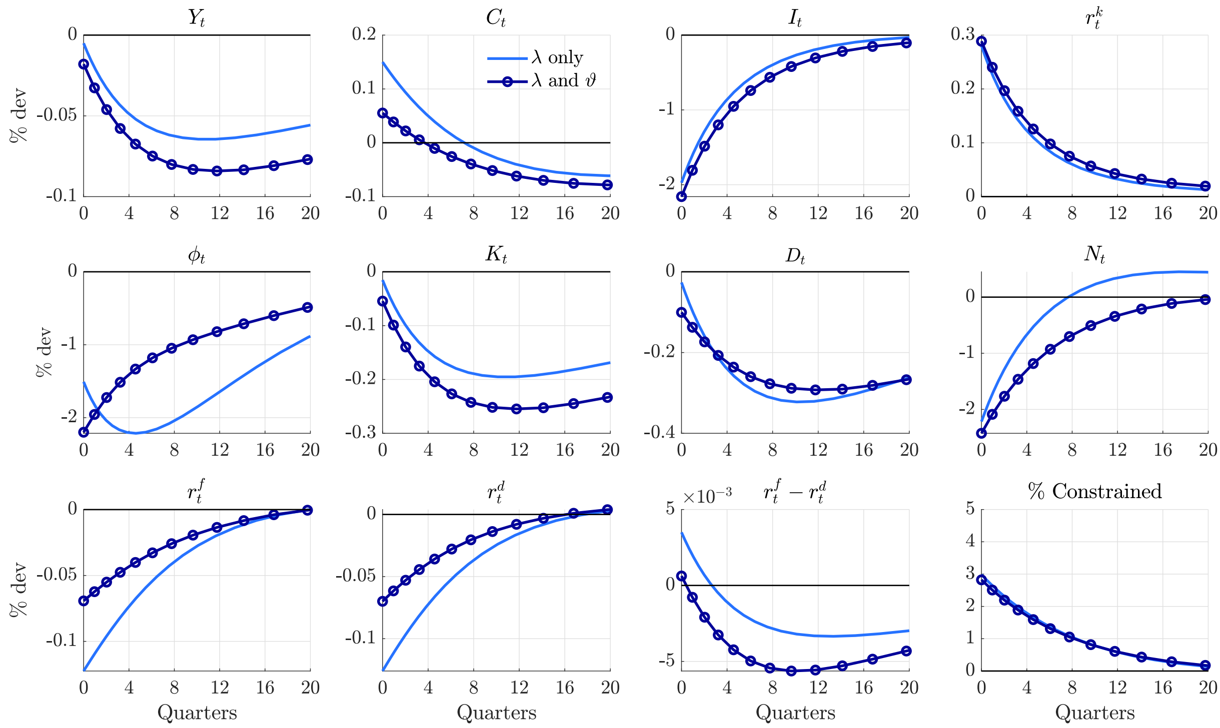


λ and ϑ shock.

When we focus on the response by deposit base, we now see that large banks cut deposit rates faster than the mean, widening spreads. Large banks, which have greater market power and more dispersion in habits, now do not unambiguously increase leverage and raise deposit rates. Figure 13 shows that the shock generates a much more pronounced drop in net worth and a smaller rise in the share of constrained banks.[13] Overall, banks at the very top cut rates faster than the mean, widening their spreads.

[13] Figure B.4 in the appendix compares the baseline IRF of constrained and unconstrained banks with the combined λ and ϑ shocks.

Figure 13: IRF of $r_t^d - E[r_t^d]$ by bottom/top deciles



λ and ϑ shock.

These model predictions align well with the empirical evidence shown in Sections 2.1 and 2.2. The local projection estimates show that, following a financial crisis, the least levered banks initially compress their deposit rates relative to the mean before widening the spread, while large banks reduce their deposit rates relative to the mean, widening an already negative spread. The model thus captures the key empirical fact although the magnitude of these adjustments is smaller than in the data, especially when looking at responses by bank size. The model produces more muted and gradual responses; while it captures the direction of adjustment, it underpredicts the intensity of these cross-sectional dynamics observed during crises.

5.2 Response to a monetary policy shock

We now turn to the effects of a contractionary monetary policy shock. The qualitative responses are similar in the two model variants we consider, the baseline with deep habits and a counterfactual without habits ($\theta = 0$), but their magnitudes differ in important ways. In the baseline, habits make the downturn more pronounced: banks internalize the interaction between market power and the intertemporal trade-off between short-run margins and long-run customer capital, which amplifies the fall in real activity. When habits are removed, this channel disappears and the recession is noticeably milder.

While habits amplify the downturn, they dampen the immediate pass-through to deposit rates because unconstrained banks trade off current margins against building customer capital. As a result, the average deposit rate declines by roughly half of the drop observed in the no-habits economy. Notably, in both cases, the nominal rate increase is more than offset by the fall in inflation, resulting in a temporary negative real interest rate. [14].

Figure 14: Aggregate response to a contractionary 10bp monetary policy shock

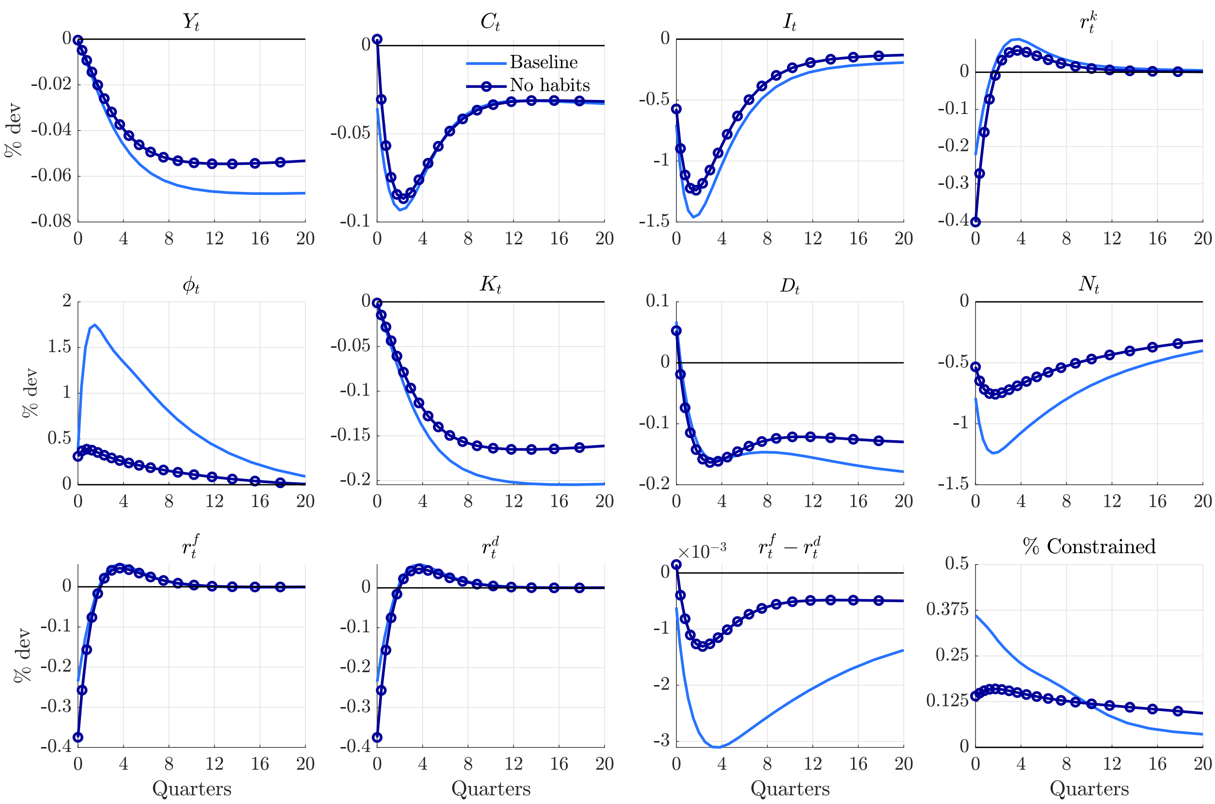


Figure 15 breaks out the response by bank type. Once again we can see that unconstrained banks pick up the slack and cushion the downturn triggered by the contractionary monetary policy shock. Unconstrained banks initially reduce their interest margins and build up their stock of habits, which later translates into higher and more persistent profits. To do so they substantially increase deposits and investment, while constrained banks move in the opposite direction. While unconstrained banks cushion aggregates, they also dilute the pass-through

[14]This behavior is consistent with the findings of Rupert and Šustek (2019), who show that in New-Keynesian models with capital and investment dynamics, the real interest rate can rise or fall, depending on calibration, following a contractionary monetary policy shock.

to the aggregate deposit rate.

Figure 15: Constrained/unconstrained bank response to a contractionary 10bp monetary policy shock

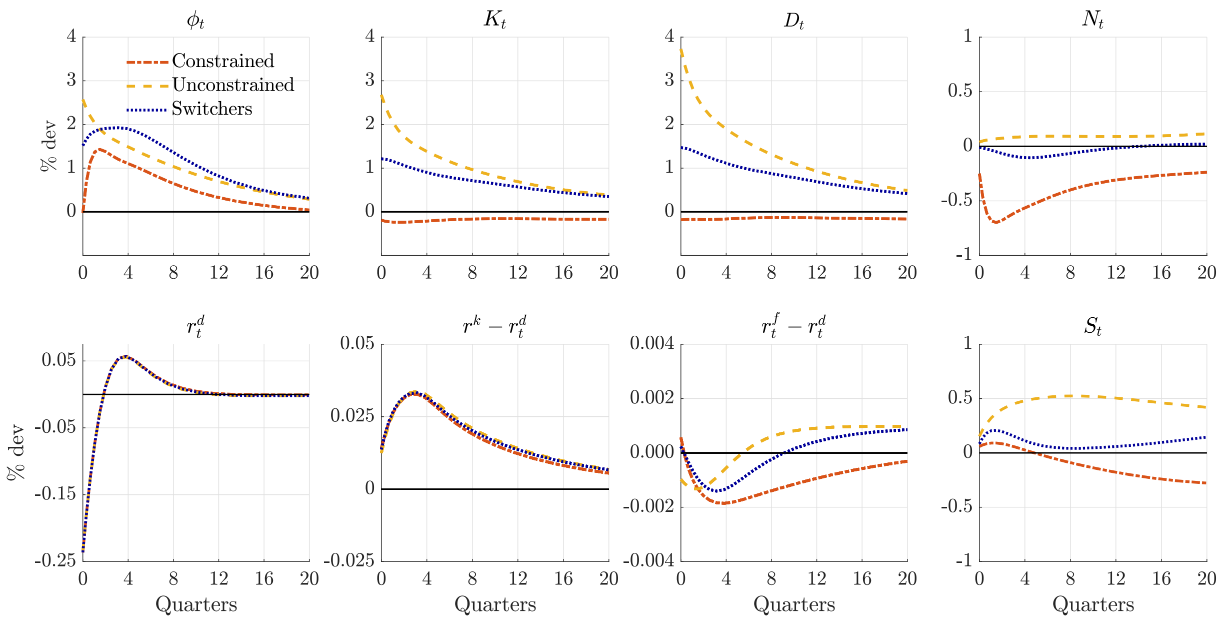
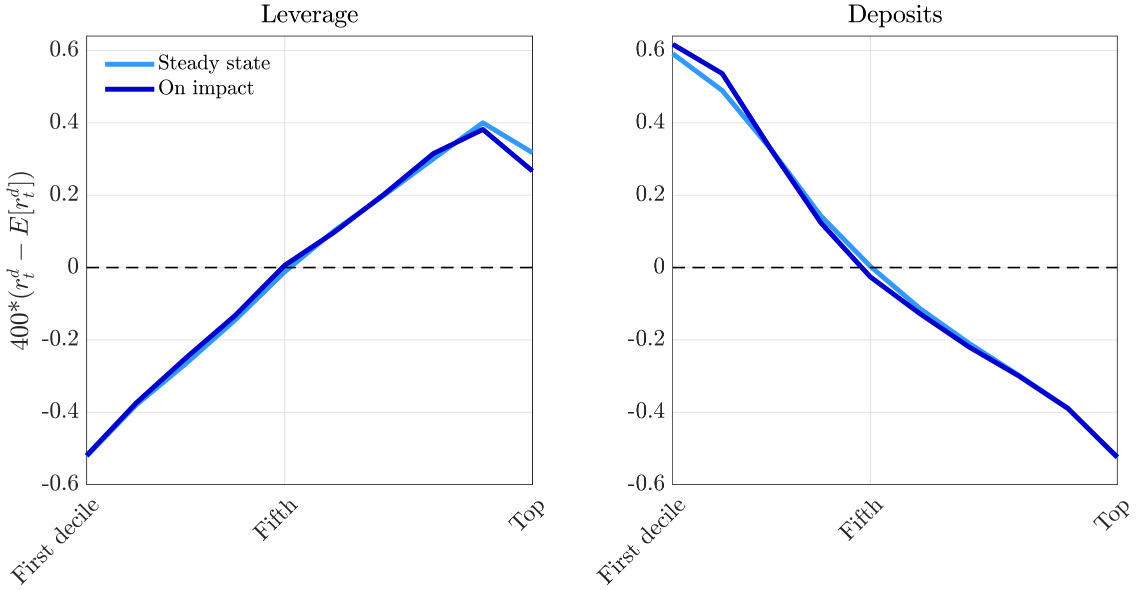


Figure 17 plots the impulse responses of deposit-rate deviations from the cross-section mean for banks in the top and bottom deciles of deposits and leverage. The responses line up with the empirical local projections for 12-month CDs in Figures 5 and 6.[15] The deposit-sorted responses show how spreads widen since large banks lower their relative deposit rates faster than the mean, while small banks do not fall as fast as the mean. Note that the top decile (by deposits) group is mostly unconstrained but 40–50% are constrained, so the top decile by deposits (and bottom one by leverage) has a mixed constraint status. In the model, unconstrained banks initially cut margins to build habits, while constrained banks do the opposite; the net large-bank response that we see is the weighted outcome of those two behaviors within the top-decile, explaining the rather muted response of spreads in the model.

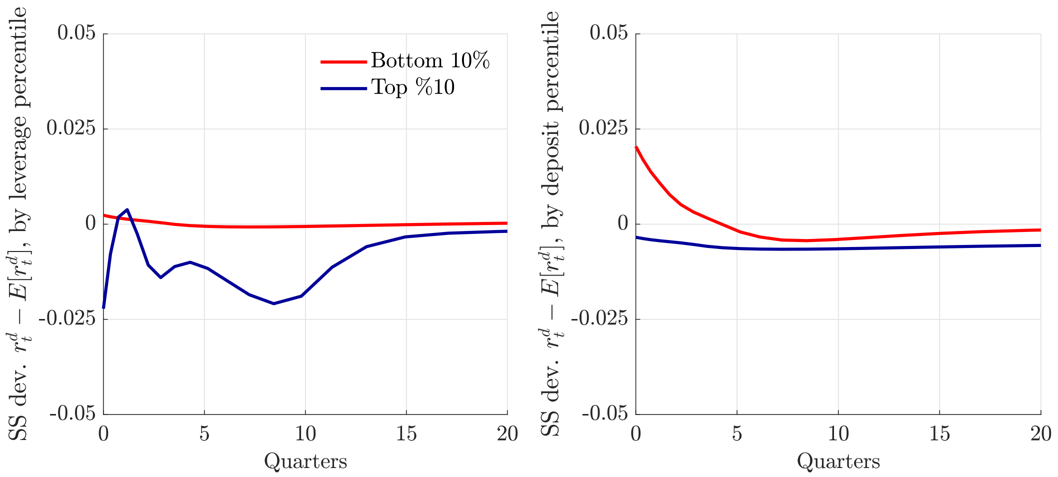
[15] Note that the empirical IRFs correspond to a 100 bp change in the federal funds rate, so they should be divided by 10 to make them comparable to the 10 bp shock used in the model.

Figure 16: Deposit rate deviation from cross-section mean



The left (right) panel shows the annualized average deposit rate deviation from the cross section mean at each decile of the leverage (deposit) distribution.

Figure 17: IRF of $r_t^d - E[r_t^d]$ by bottom/top deciles



6 Conclusion

This paper demonstrates that deposit rate pass-through in the United States is systematically heterogeneous across banks. Empirically, we find two consistent forms of heterogeneity in deposit pricing. (i) Relative to the average bank, highly leveraged banks display greater pass-through: they raise deposit rates by more following monetary tightenings and cut them by more during financial stress. (ii) Large banks exhibit a different, state-dependent pattern: they under-react to policy rate hikes but over-react to rate cuts, pushing their deposit rates further below the average in both cases. These results reveal distinct and systematic patterns in banks' deposit pricing behavior.

To interpret these patterns, we develop a continuous-time heterogeneous bank model featuring occasionally binding leverage constraints and deep habits in deposit demand. The model clarifies the interaction between bank balance sheet strength and depositor inertia: leverage-constrained banks are unable to exploit the dynamic gains from expanding their depositor base when funding costs fall, whereas unconstrained banks invest in customer capital by temporarily raising deposit rates. This mechanism generates endogenous variation in pass-through and explains why deposit rate adjustments differ systematically across banks.

Our quantitative analysis shows that this interaction between financial frictions and deep habits not only accounts for the direction of observed heterogeneity but also dampens the aggregate effects of financial shocks. Unconstrained banks absorb part of the deleveraging pressure from constrained banks, stabilizing the overall response of credit and output. However, the model underpredicts the magnitude of deposit rate dispersion observed during crises, suggesting that additional mechanisms—such as shifts in liquidity preferences or flight-to-quality dynamics—amplify observed cross-sectional differences.

Taken together, the evidence and model imply that monetary transmission depends critically on the evolving distribution of financial constraints and relationship capital across banks. Policies that alter the composition of constrained versus unconstrained intermediaries, or that affect depositor mobility, can therefore materially change the speed and strength of monetary policy pass-through.

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A Additional empirical results

A.1 Data

There are three types of Call Report FFIEC 031, FFIEC 041, and FFIEC 051 which are for a Bank with Domestic and Foreign Offices; for a Bank with Domestic Offices Only; and for a Bank with Domestic Offices Only and Total Assets Less that $\$5$billion, respectively.

From the Income Statement, we take information on Interest expenses on deposits, which are on Transaction accounts (RIAD4508), Savings deposits (RIAD0093), Time deposits of $\$250$k or less (RIADHK03), and Time deposits of more than $\$250$k (RIADHK04).

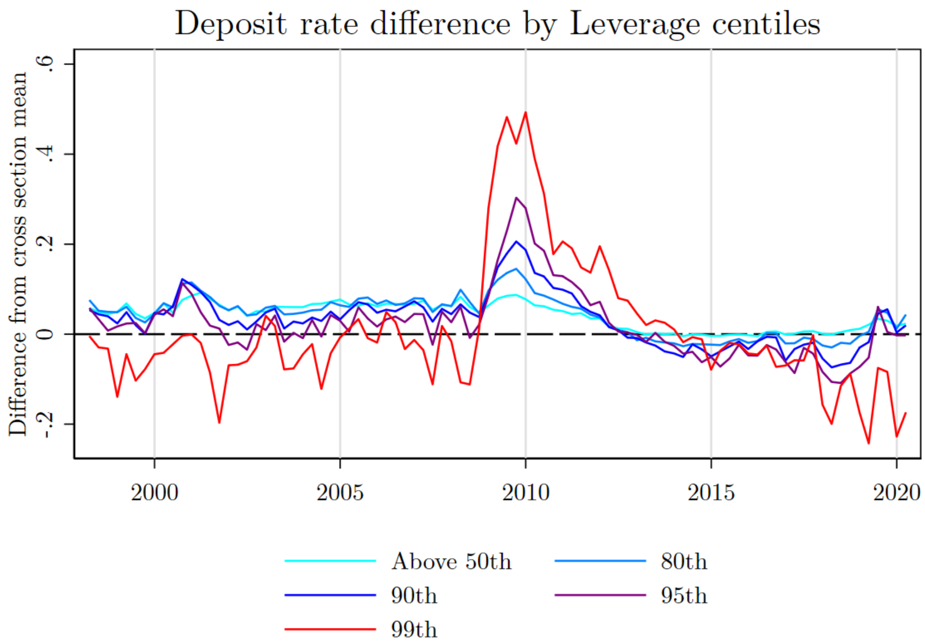
From the Balance Sheet, we take Total Assets (RCFD2170/RCON2170), Deposits (RCON2200), split between Noninterest-bearing (RCON6631) and Interest-bearing (RCON6636), and Total equity capital (RCFDG105/RCONG105).

A.2 Call Report implied interest rates

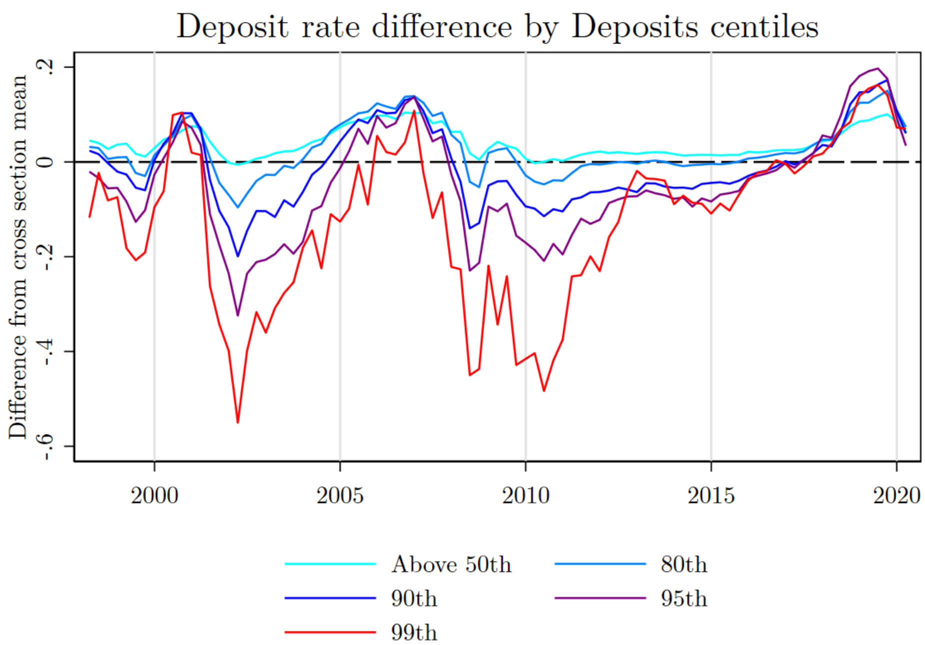
Figure A.1 plots the implied deposit interest rate based on Call Report interest expenses. Panel (a) plots the difference between the mean interest rate of a given centile of the leverage distribution and the cross-sectional mean. Panel (b) plots the same but for different centiles of the bank size distribution as measured by quantity of deposits.

Figure A.1: Call Report implied interest rates

(a)



(b)



In Panel (a), for example, the red line shows the difference between the average (weighted) deposit rate of banks in the top percentile and all banks. A negative value indicates that the top banks have a lower than average deposit rate.

B Additional figures

Figure B.1

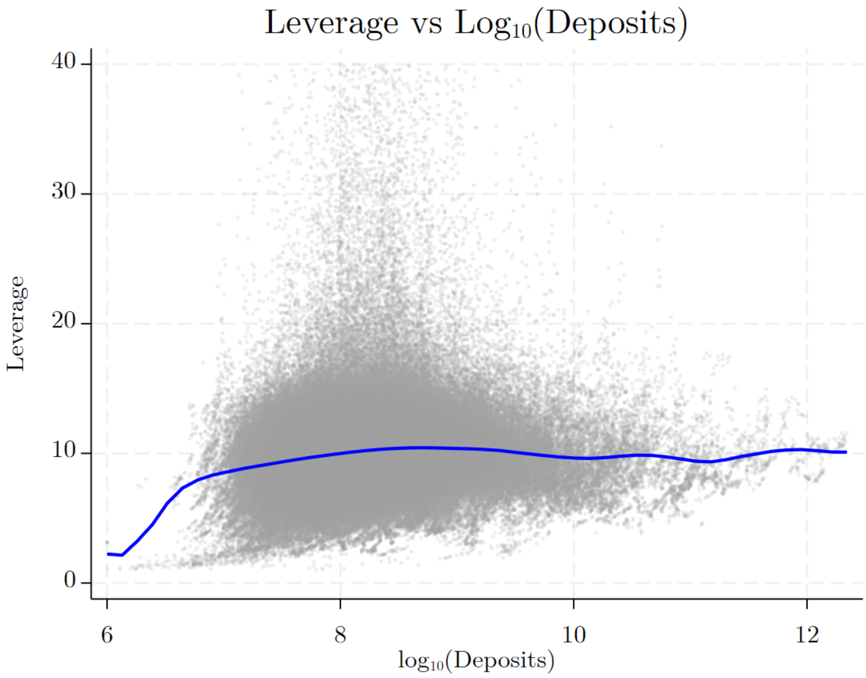
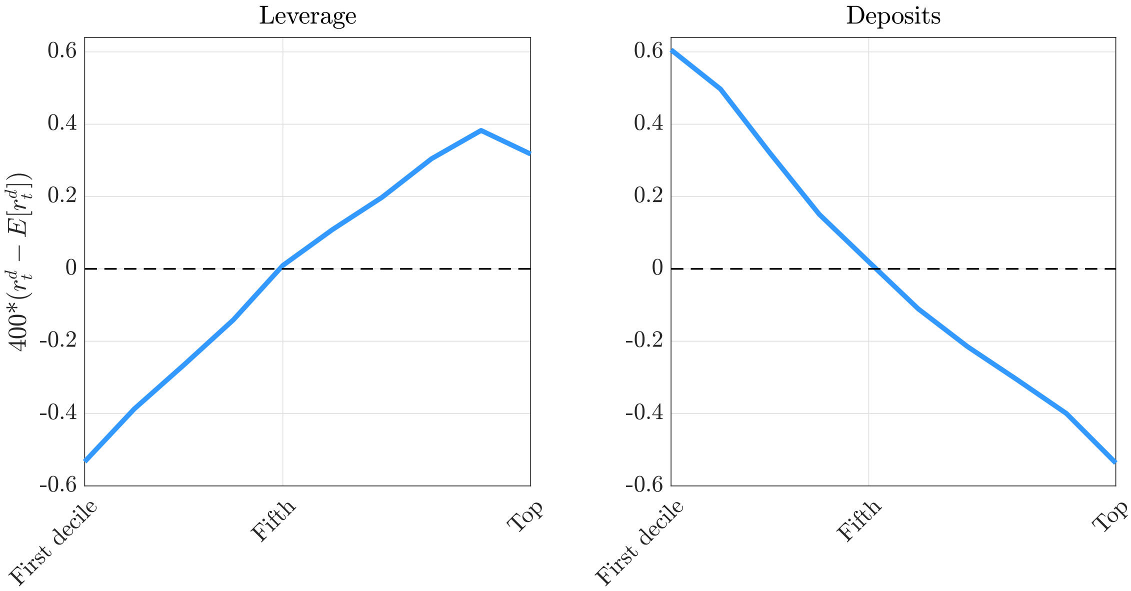


Figure B.2: Deposit rate deviation from cross-section mean



The left (right) panel shows the annualized average deposit rate deviation from the cross section mean at each decile of the leverage (deposit) distribution.

Figure B.3: Behavior of myopic banks (financial shock)

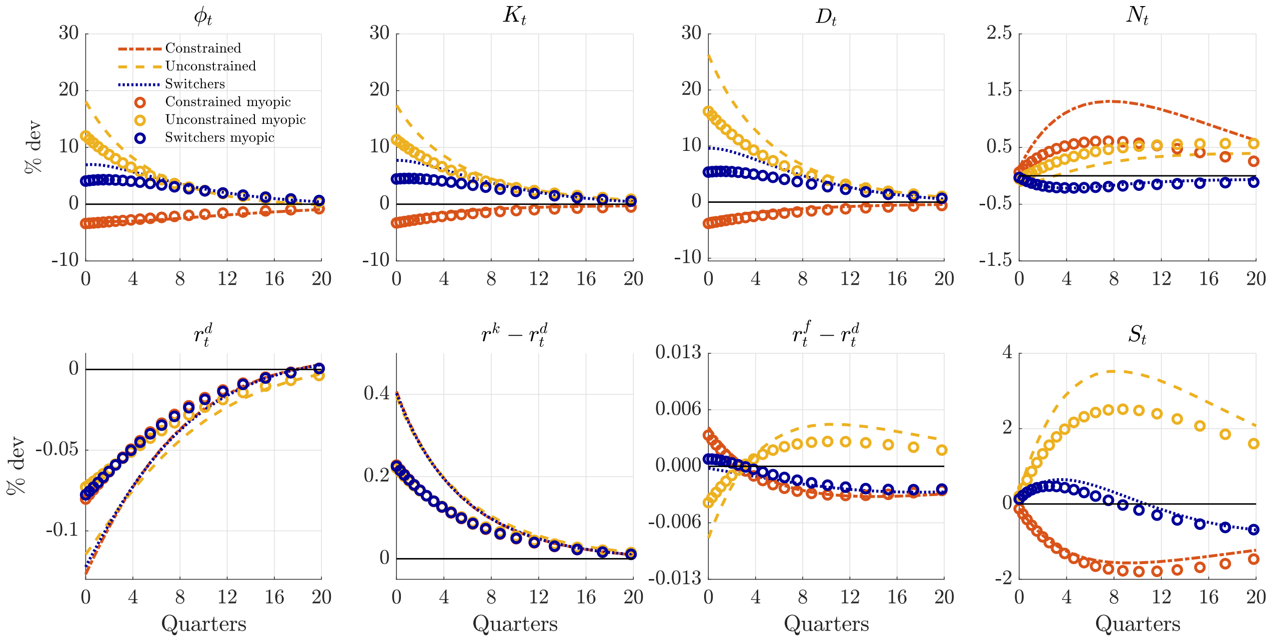


Figure B.4: Behavior of myopic banks (financial shock)

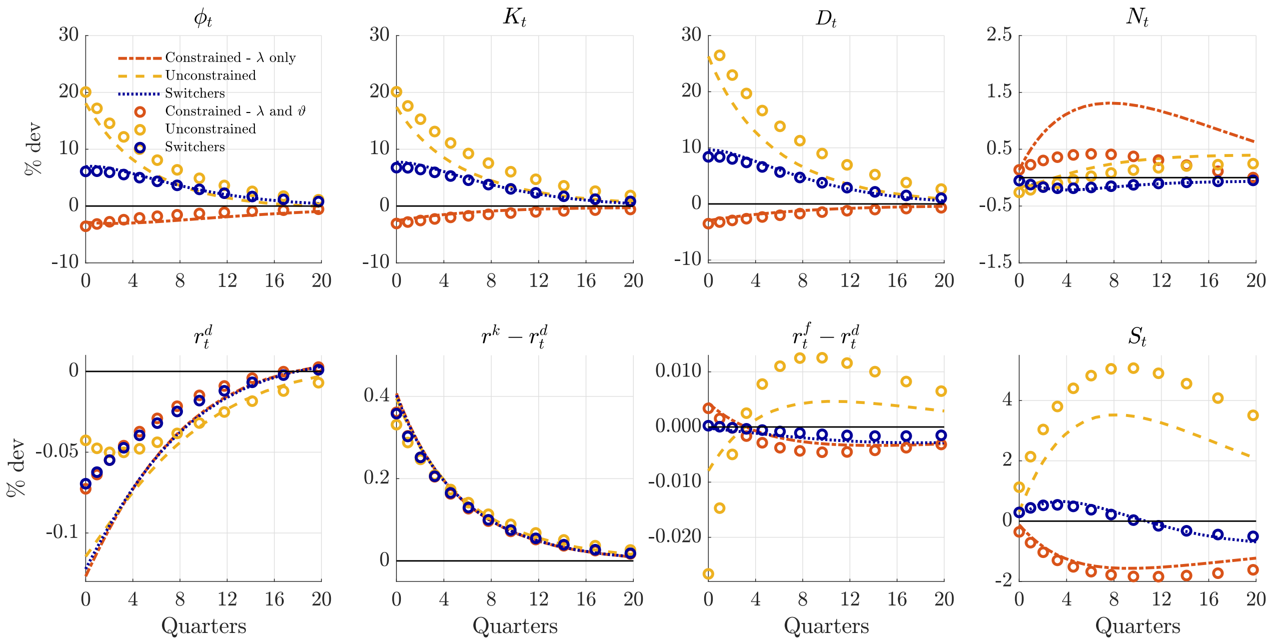
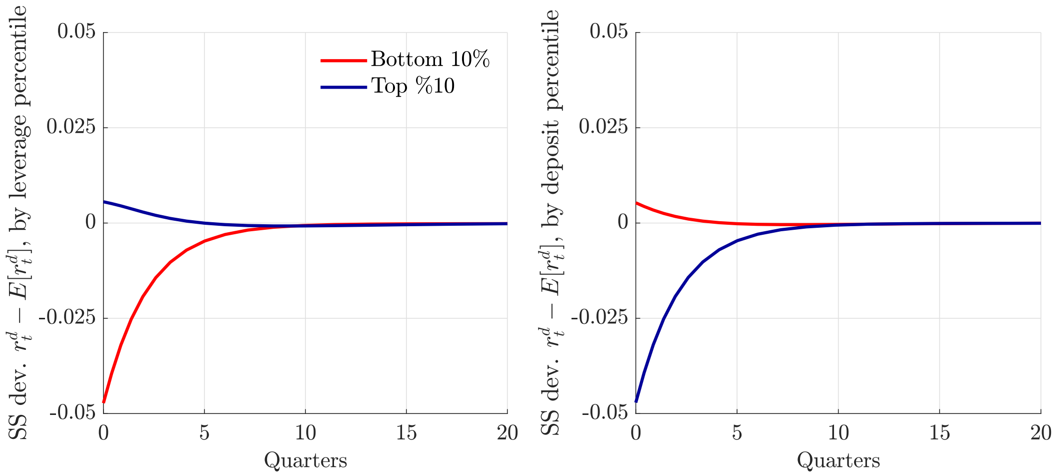


Figure B.5: IRF of $r_t^d - E[r_t^d]$ by bottom/top deciles



1% ϑ shock.

C Stylized model

Time is discrete, indexed t, $t+1$, and $t+2$. There is no uncertainty. Aggregate variables are denoted with upper case letters. Bank specific variables are denoted with lower case letters.

C.1 Households

A representative household chooses $\left\{C_t, C_{t+1}, C_{t+2}, B_t, B_{t+1}, \{d_t\}_0^1, \{d_{t+1}\}_0^1\right\}$ to maximize

$$V = u(C_t) + \beta u(C_{t+1}) + \beta^2 u(C_{t+2}) + \vartheta \left(\int_0^1 \left(\frac{d_t}{s_t^\theta}\right)^\varepsilon\right)^{\frac{1}{\varepsilon}} + \beta\vartheta \left(\int_0^1 \left(\frac{d_{t+1}}{s_{t+1}^\theta}\right)^\varepsilon\right)^{\frac{1}{\varepsilon}} \quad \text{(C.1.1)}$$

subject to

$$C_t + B_t + \int_0^1 d_t = Y_t - N_t \quad \text{(C.1.2)}$$

$$C_{t+1} + B_{t+1} + \int_0^1 d_{t+1} = Y_{t+1} + R_t B_t + \int_0^1 r_{d,t} d_t + \Pi_{t+1}, \quad \text{(C.1.3)}$$

$$C_{t+2} = R_{t+1} B_{t+1} + \int_0^1 r_{d,t+1} d_{t+1} + \Pi_{t+2}, \quad \text{(C.1.4)}$$

where $\varepsilon < 1$. The variables Y_t, N_t, and Y_{t+1} are exogenous.

The equilibrium conditions are given by

$$1 = \Lambda_{s,s+1} R_s, \quad \text{(C.1.5)}$$

$$r_{d,s} = R_s \left(1 - \frac{1}{u'(C_s)} \vartheta \left(\frac{d_s}{\tilde{D}_s}\right)^{\varepsilon-1} s_s^{-\theta\varepsilon}\right) \quad \text{for} \quad s = t, t+1, \quad \text{(C.1.6)}$$

where

$$\Lambda_{t,t+1} \equiv \frac{\beta u'(C_{s+1})}{u'(C_s)} \quad \text{and} \quad \tilde{D}_t \equiv \left(\int_0^1 \left(\frac{d_t}{s_t^\theta}\right)^\varepsilon\right)^{\frac{1}{\varepsilon}}. \quad \text{(C.1.7)}$$

We denote the supply (of loanable funds) curves (C.1.6) as $r_d(d_t, s_t)$.

C.2 Banks

An individual bank wants to maximize

$$v_t = \Lambda_{t,t+1} \pi_{t+1} + \Lambda_{t,t+1} \Lambda_{t+1,t+2} \pi_{t+2} \quad \text{(C.2.1)}$$

subject to the following constraints

$$n_{t+1} + \pi_{t+1} = R_k k_t - r_{d,t} d_t - \frac{\varphi}{2} d_t^2, \tag{C.2.2}$$

$$\pi_{t+2} = R_k k_{t+1} - r_{d,t+1} d_{t+1} - \frac{\varphi}{2} d_{t+1}^2, \tag{C.2.3}$$

$$s_{t+1} = s_t^h d_t^{1-h}, \tag{C.2.4}$$

$$v_{t+1} = \Lambda_{t+1,t+2} \pi_{t+2}, \tag{C.2.5}$$

and

$$v_s \geq \lambda k_s, \tag{C.2.6}$$

$$k_s = d_s + n_s, \tag{C.2.7}$$

$$r_{d,s} = r_d \left(d_s, s_s\right) \quad \text{for} \quad s = t, t+1. \tag{C.2.8}$$

The problem reduces to

$$\begin{aligned} \max_{d_t, d_{t+1}, n_{t+1}, \zeta_t, \zeta_{t+1}} & \left(1+\zeta_t\right) \Lambda_{t,t+1} \left(R_k \left(d_t + n_t\right) - r_d \left(d_t, \cdot\right) d_t - n_{t+1} - \frac{\varphi}{2} d_t^2\right) \\ & \left(1+\zeta_t+\zeta_{t+1}\right) \Lambda_{t,t+1} \Lambda_{t+1,t+2} \left(R_k \left(d_{t+1} + n_{t+1}\right) - r_d \left(d_{t+1}, s_t^h d_t^{1-h}\right) d_{t+1} - \frac{\varphi}{2} d_{t+1}^2\right) \\ & - \zeta_t \lambda \left(d_t + n_t\right) - \zeta_{t+1} \Lambda_{t,t+1} \lambda \left(d_{t+1} + n_{t+1}\right). \end{aligned} \tag{C.2.9}$$

The first-order conditions are given by

$$\begin{aligned} 0 = & \left(1+\zeta_t\right) \Lambda_{t,t+1} \left(R_k - r_{d,t}^{(1)} d_t - r_{d,t} - \varphi d_t\right) \\ & - \left(1+\zeta_t+\zeta_{t+1}\right) \Lambda_{t,t+1} \Lambda_{t+1,t+2} r_{d,t+1}^{(2)} d_{t+1} (1-h) \left(s_t / d_t\right)^h - \zeta_t \lambda, \end{aligned} \tag{C.2.10}$$

$$0 = \left(1+\zeta_t+\zeta_{t+1}\right) \Lambda_{t+1,t+2} \left(R_k - r_{d,t+1}^{(1)} d_{t+1} - r_{d,t+1} - \varphi d_{t+1}\right) - \zeta_{t+1} \lambda, \tag{C.2.11}$$

$$\left(1+\zeta_t\right) = \left(1+\zeta_t+\zeta_{t+1}\right) \Lambda_{t+1,t+2} R_k - \zeta_{t+1} \lambda, \tag{C.2.12}$$

where $r_{d,t}^{(2)}$, for example, is the derivative with respect to the second argument.

Profits in period 1 In an unconstrained world, the condition for profits to be paid after period 1 is that $1 > \Lambda_{t+1,t+2} R_k$. i.e., return on the risk-free rate is greater than return on K. For an individual bank, this restriction is never more stringent. since $\frac{1+\zeta_t+\zeta_{t+1}}{1+\zeta_t+\lambda\zeta_{t+1}} > 1$. Hence, if we can rule it out in aggregate, we can rule it out individually.

There are four potential scenarios for banks: $\{C, C\}$, $\{C, U\}$, $\{U, C\}$ and $\{U, U\}$.

Case 1 $\{U, U\}$: In this case, $\zeta_t = \zeta_{t+1} = 0$. The FOCs reduce to:

$$R_k = r_{d,t} + r_{d,t}^{(1)} d_t + \varphi d_t + \Lambda_{t+1,t+2} r_{d,t+1}^{(2)} d_{t+1} (1-h) \left(s_t / d_t\right)^h, \tag{C.2.13}$$

$$R_k = r_{d,t+1} + r_{d,t+1}^{(1)} d_{t+1} + \varphi d_{t+1}, \tag{C.2.14}$$

$$1 = \Lambda_{t+1,t+2} R_k. \tag{C.2.15}$$

The third equation implies that either $n_{t+1} = 0$ or $\pi_{t+1} = 0$, depending on whether the gross discount rate adjusted return in period 2 is greater than 1.

Case 2 $\{C, C\}$: In this case, $\zeta_t = \zeta_{t+1} > 0$. The FOCs reduce to:

$$v_t = \lambda k_t, \tag{C.2.16}$$
$$v_{t+1} = \lambda k_{t+1}. \tag{C.2.17}$$

Case 3 $\{U, C\}$: In this case, $\zeta_t = 0, \zeta_{t+1} > 0$. The FOCs reduce to:

$$R_k = r^{(1)}_{d,t} d_t + r_{d,t} + \varphi d_t + \Lambda_{t+1,t+2} r^{(2)}_{d,t+1} d_{t+1} (1-h) (s_t/d_t)^h. \tag{C.2.18}$$
$$v_{t+1} = \lambda k_{t+1}. \tag{C.2.19}$$

Case 4 $\{C, U\}$: In this case, $\zeta_t > 0, \zeta_{t+1} = 0$. The FOCs reduce to:

$$v_t = \lambda k_t, \tag{C.2.20}$$
$$R_k = r_{d,t+1} + r^{(1)}_{d,t+1} d_{t+1} + \varphi d_{t+1}. \tag{C.2.21}$$

C.3 Calibration

We set the aggregate endowments as follows: $N_0 = 1$, $Y_0 = 1$, $Y_1 = 0.5$, and $Y_2 = 0$. The household subject discount factor is $\beta = 0.9524$. The aggregate gross return on capital is 1.09. The fraction of assets that a banker can abscond with is $\lambda = 0.2$. Furthermore, we set $\nu = 0.075$, $\epsilon = 0.8$, $h = 0$ and $\theta = -2$. The portfolio cost parameter $\varphi = 0.1$. $s_0 = 0.45$ for all banks. n_0 is distributed exponentially with $n_0^{\min} = 0.01$ and $n_0^{\max} = 0.25$ with 52 grid points.

C.4 Results

Figure C.1 plots the equilibrium outcomes under the baseline and under a myopic alternative. In the myopic alternative, the first-order conditions, (C.2.13) and (C.2.18) are replaced by

$$R_k = r^{(1)}_{d,t} d_t + r_{d,t} + \varphi d_t. \tag{C.4.1}$$

In each panel, the x-axis is the level of net worth. Panel(1,1), for example, plots the level of assets in period 0. Think kink is indicative of the boundary between the financially constrained banks (to the left of the kink) and the financially unconstrained banks. The dashed line in the R_d 0 and R_d 1 plots show the level of the risk-free rate. The dashed line in the s_1 plot shows s_0 which is common across banks. The panels marked n_1/n_0 and π_2/n_0 show the first period return on equity and the total (two-period) return on equity, respectively. In Panel(4,3), the dashed line is the distribution of n_0. The solid line is an indicator function: $(5+20+70)/4 = 23.75$ indicates the bank is constrained in both period 0 and 1; $(5+20)/4 = 6.25$ indicates the bank is constrained in period 0 only; $(5+70)/4 = 18.75$ indicates the bank is constrained in period 1 only; and $5/4 = 1.25$ indicates the bank is unconstrained in both period 0 and 1.

Figure C.1: Effects of deep habits

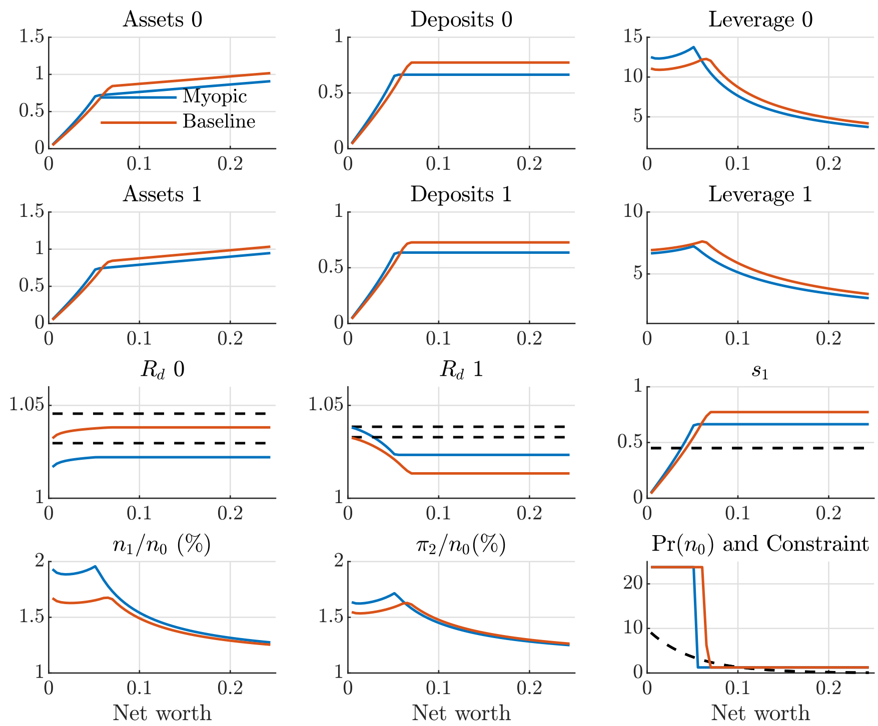


Figure C.2 Shows the effect of an increase in λ. That is, $\lambda = 0.225$, up from $\lambda = 0.2$. This tightens the incentive compatibility constraint on banks and a larger fraction of banks become constrained.

Figure C.3 Shows the effect of a temporarily high β. That is, $\beta_0 = 1.0526$ and $\beta_1 = \beta = 0.9524$. This means the household is more patient, which means the equilibrium risk-free rate falls.

Figure C.2: Effects of an increase in λ

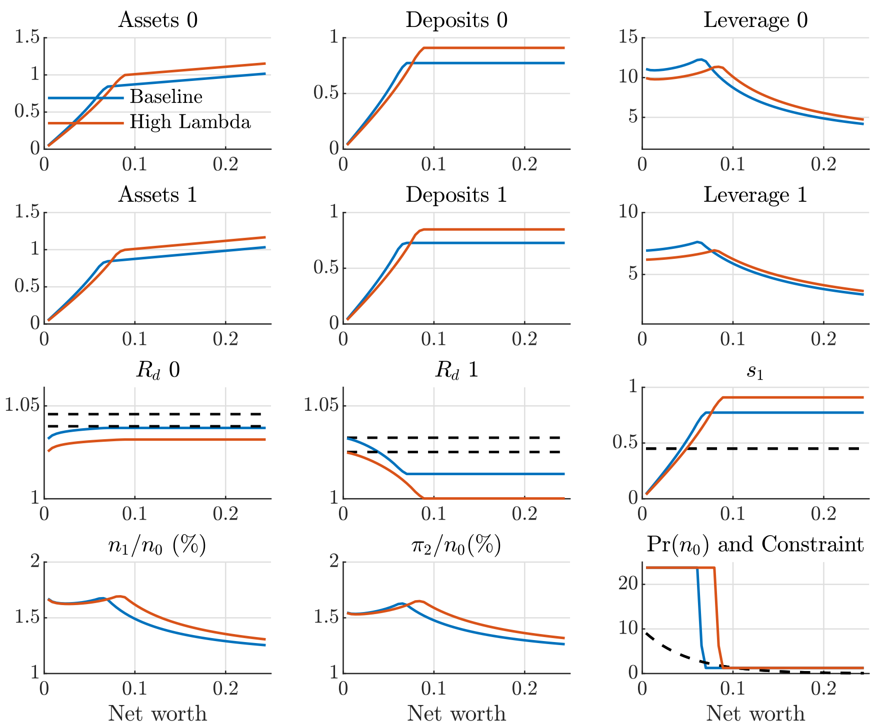


Figure C.3: Effects of an increase in β