Why Bank Net Interest Margins Are Stable - Insights from the Asset Side

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Abstract

Net interest margin (NIM) measures net interest income per dollar of assets and remains remarkably stable for most US banks despite large fluctuations in the federal funds rate. I show that an important reason for this stability is changes in credit spreads on new assets. To derive the credit spreads, I construct a bank-specific risk-free benchmark rate for assets and infer the implied spread as the difference between the interest income rate and this benchmark. For most banks, the risk-free benchmark responds more to policy rate changes than interest expenses. Consequently, without changes in credit spreads, a 100 bp decline in the policy rate would compress average NIM by about 28 bp and expose banks to interest rate risk. NIM stability implies that most banks add new assets to their balance sheets at higher credit spreads when the policy rate falls and at lower spreads when it rises. Increases in implied credit spreads are associated with greater exposure to credit and duration risk, consistent with banks reaching for yield. The results provide a novel asset-side explanation of how NIM stability is achieved.

JEL-Classification: G21, E43, G28

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1 Introduction

Commercial banks derive most of their net income from interest, typically investing in higher-yield, long-term interest-earning assets and funding them with lower-cost, short-term deposits. This asset-liability structure allows them to cater to the time preferences of borrowers and depositors while earning the spread between rates received and paid, the net interest margin (NIM). Because of this maturity transformation, a widely held belief is that banks are exposed to interest rate risk: Deposit rates are assumed to react to policy rate changes almost immediately, whereas only a smaller fraction of asset yields responds. Consequently, NIM is expected to decline when policy rates rise.[1] A persistent decline in net interest margin, in turn, can erode bank equity, constrain lending, and increase default risk.[2]

Yet prior work documents that NIM has remained remarkably stable over time for many banks despite large fluctuations in short-term policy rates (e.g., Flannery (1981), English (2002) and Drechsler et al. (2021)). This stability implies that interest income and interest expense rates respond similarly to changes in policy rates, leaving their spread largely unchanged (Figure 1).

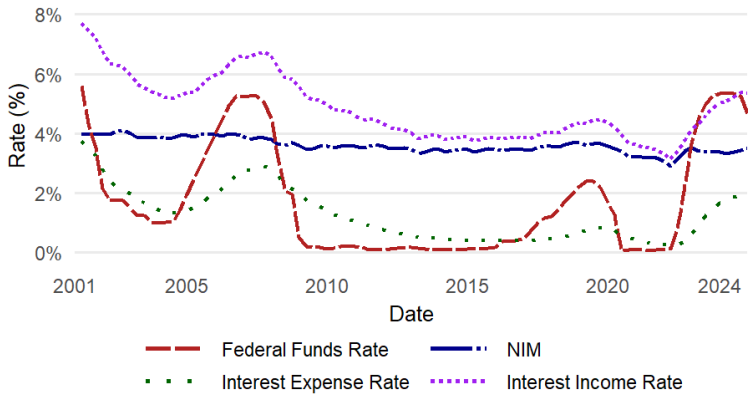


Figure 1: Time-series of the average net interest margin (NIM), interest income rate, interest expense rate, and the federal funds rate. Data: US commercial bank Call Reports and and the effective federal funds rate from the Federal Reserve's H.15 release, 2001-2024.

The stability of NIM despite the substantial maturity mismatch between banks' assets and

[1]This belief is routinely presented in textbook discussions of interest rate risk, e.g., Saunders et al. (2024) and Mishkin (2021), who also emphasize the conditions under which the prediction holds.

[2]For evidence linking policy rate changes and levels to bank profitability, equity, and lending, see Bernanke et al. (1991), Claessens et al. (2018), English et al. (2018), Kashyap and Stein (2000).

liabilities may appear puzzling. Drechsler et al. (2021), hereafter DSS, emphasize the role of deposit market power, which allows banks to keep deposit rates low even as the policy rate rises. As a result, interest expenses adjust much more modestly to policy rate changes than the widely held belief would suggest. I complement their liability-side findings with a novel asset-side explanation and show that NIM remains stable for most banks because they add new assets to their balance sheets at higher credit spreads when the federal funds rate falls and at lower spreads when it rises. I provide evidence that these changes in credit spreads are associated with shifts in lending risk, consistent with banks reaching for yield when policy rates decline. Absent credit spread adjustments, interest income would respond more strongly to policy rate changes than interest expenses, so that a decline in the policy rate would compress average NIM, contrary to the widely held belief that NIM compresses when rates increase. This implication arises because banks' market power keeps deposit rates low even when policy rates are high, leaving limited scope for deposit rates to decline when policy rates fall. By contrast, risk-free returns on new and floating-rate assets fall one-for-one with a policy rate decline, and such assets account on average for about one-third of total assets in each quarter. In response, banks invest in new assets with higher credit spreads when policy rates fall, stabilizing NIM while increasing their exposure to risks associated with these assets.

To derive the credit spreads, I develop a novel methodology that decomposes at the bank level the interest income rate on assets into a risk-free benchmark rate and an implied credit spread. I construct the bank-specific risk-free benchmark rate using quarterly Call Reports for 6,150 US commercial banks from 1997 to 2024 with detailed asset repricing maturity information and the quarterly average effective federal funds rate from the Federal Reserve's H.15 release.[3] The methodology attaches to each asset the federal funds rate prevailing at its most recent pricing date. For fixed-rate assets, the attached rate is the federal funds rate prevailing at origination or purchase, while for floating-rate assets it is the rate prevailing at the most recent rate reset. The bank-specific risk-free benchmark rate for a given quarter is the value-weighted average of these attached federal funds rates across all outstanding assets. Intuitively, this benchmark captures the risk-free return determined by the federal funds rate prevailing at each asset's last

[3]For fixed-rate instruments, repricing maturity equals contractual maturity. For floating-rate instruments, it is the earlier of the next rate reset date or contractual maturity.

pricing and therefore represents the risk-free rate currently earned on the bank's outstanding assets. The implied credit spread in a given quarter is the difference between the interest income rate and this risk-free benchmark rate. It captures the value-weighted average markup over the federal funds rate prevailing at each asset's initial pricing, reflecting the credit spread currently earned on the bank's assets. The credit spread captures all non-risk-free premia embedded in asset returns, including credit risk, duration risk, and other markups. Figure 2 displays the federal funds rate and the average interest income rate along with averages of the estimated risk-free benchmark rate and implied credit spread. The average risk-free benchmark rate (black solid line) tracks the federal funds rate (red dashed line) with a lag and is smoother, because it averages current and historical federal funds rates. The average interest income rate (purple dotted line) responds more slowly to policy rate changes than the average risk-free benchmark rate. Hence, the difference between the interest income rate and risk-free benchmark rate, the average implied credit spread (gold solid line) is broadly countercyclical to the policy rate.

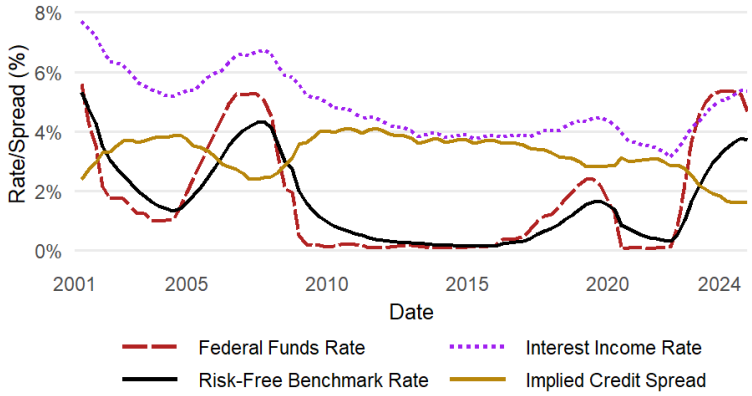


Figure 2: Time-series of the average interest income rate, risk-free benchmark rate, implied credit spread and the federal funds rate. Data: US commercial bank Call Reports and and the effective federal funds rate from the Federal Reserve's H.15 release, 2001-2024.

In a second step, I analyze the sensitivity of NIM and its components to changes in the federal funds rate. Intuitively, NIM is insensitive to policy rate changes when the sensitivities of interest income and interest expense are equal. Using the decomposition of the interest income rate into a risk-free benchmark rate and an implied credit spread, this condition is equivalent to the sum of the risk-free benchmark and credit spread sensitivities matching the interest expense sensitivity. For comparison, I estimate sensitivities following the methodology in DSS.

That is, for each bank, I regress the quarterly change in NIM and each of its components on the contemporaneous and three lagged quarterly changes in the federal funds rate. A variable's sensitivity is the sum of the four coefficients. The first results align with DSS: Estimating sensitivities at the bank level and summarizing across banks, I find that the mean NIM sensitivity is about 4 bp per 100 bp change in the federal funds rate. Moreover, for 76% of banks, NIM sensitivity is not statistically different from zero at the 5% level, indicating that most banks' profitability is not significantly exposed to interest rate risk. Within-bank NIM volatility averages 0.53%, only 14% of the mean NIM level, and the correlation with the policy rate is only 11%. By construction, NIM stability reflects closely matched sensitivities of the interest income and interest expense rates, 35 bp vs. 31 bp on average.

I provide new evidence for why NIM remains stable by focusing on the interest income rate and separately estimating the sensitivities of its two components. The risk-free benchmark rate rises (falls), on average, by 58 bp for a 100 bp increase (decrease) in the policy rate. This sensitivity reflects the substantial share of assets that adjust within a quarter, on average 33.4%, and a catch-up effect, arising when long-term assets whose risk-free rates were set in the past exit and are replaced by new assets priced at the current federal funds rate, or when new assets are added through growth at the current rate while the average risk-free benchmark lags behind the current rate. If credit spreads were constant, a 100 bp decrease in the policy rate would thus compress NIM by about 28 bp on average (and vice versa) and 91% of banks would exhibit statistically significant NIM sensitivity, indicating exposure to interest rate risk. An important reason why NIM remains stable is that implied credit spreads move counter to policy rates: a 100 bp decrease (increase) in the policy rate is associated with an average 24 bp increase (decrease) in credit spreads, and the relation is negative and statistically significant for about 90% of banks. As spreads are set at asset origination or purchase, the average credit spread changes when new assets replace exiting positions at different spreads, or when balance sheet growth adds assets at spreads different from the portfolio average.[4] The results are robust to estimating responses to positive and negative federal funds rate changes separately, restricting the sample to the largest banks, using the full 1997-2024 window, estimating

[4]With negative growth, average spreads change when exiting assets' spreads differ from the portfolio average. Some loan contracts also allow spreads to increase following covenant breaches.

responses separately in good and bad aggregate financial conditions, alternative constructions of the risk-free benchmark rate, variations in the algorithm's underlying assumptions and estimating sensitivities at the bank holding company level. The results also hold within loans and within securities, with average credit spreads moving inversely with the policy rate, indicating that the bank-level pattern is not only driven by shifts between these asset classes.[5]

To assess whether increases in implied credit spreads are associated with greater risk-taking, I study the relation between credit spread changes driven by policy rate movements and measures of credit and duration risk. I first show that increases in implied credit spreads are related to higher borrower default risk, proxied by subsequent increases in the share of non-performing loans and credit-impaired securities. To allow default risk to materialize with a lag, I document this relationship using local projections as in Jordà (2005), exploiting both within-bank and cross-bank variation in credit spread changes and controlling for bank and time fixed effects. Second, I show that increases in implied credit spreads are associated with higher exposure to duration risk, reflected in contemporaneous increases in average asset maturities and a widening of the one-year repricing gap, defined as the difference between the shares of liabilities and assets repricing within one year. This increase in duration risk arises from shifts in balance-sheet composition toward a higher share of loans and a lower share of interbank assets, with loans having longer maturities than interbank assets on average. It does not reflect a lengthening of maturities within loans or securities and is not driven by balance-sheet growth. Overall, the findings indicate that increases in credit spreads help stabilize NIM when policy rates fall, thereby reducing interest rate risk, but are associated with greater exposure to credit and duration risk. This pattern aligns with Hellwig (1994), who argues that when a banking system engages in maturity transformation, it cannot fully diversify interest rate risk without shifting exposure to other risks.

My findings suggest that most banks smooth NIM, which may be due to various motives. One potential motive is Earnings at Risk (EaR) management, in which banks monitor how net interest income (= NIM $\times$ assets) responds to interest rate shocks and set internal limits

[5]Throughout this paper, loans include leases.

reviewed by supervisors.[6] Other motives are consistent with the broader earnings-smoothing literature. Acharya and Lambrecht (2015) develop a dynamic agency model in which pressure to meet the market's earnings expectations induces income smoothing. Managers with little or no equity ownership underproduce today to keep tomorrow's expected earnings lower, sacrificing value to maintain earnings stability and protect their future rents. Consistent with this theory, Graham et al. (2005) report survey evidence that 78% of CFOs would sacrifice long-term value to meet earnings targets, with CFOs most frequently citing the high cost of negative earnings surprises that can trigger market turmoil and tighter financing conditions. Because analysts forecast NIM and banks routinely provide NIM guidance on earnings calls, it is a salient target for potential smoothing by managers.[7] For banks, negative earnings surprises may contribute to higher funding stress and run risk, consistent with the mechanisms in classic bank-run models and related empirical evidence on runs (e.g., Diamond and Dybvig (1983), Gorton (1988), Jacklin and Bhattacharya (1988), Goldstein and Pauzner (2005), Gorton and Metrick (2012), Iyer and Puri (2012), Dietrich and Gehrig (2025)).

Taken together, this paper provides an asset-side explanation for why NIM is stable for most banks. To align movements in interest income with movements in interest expense, thereby reducing interest rate risk, banks increase credit and duration risk on the asset side when policy rates decline. These findings imply that interest rate risk should not be assessed in isolation from other balance-sheet risks in stress testing and capital frameworks. My findings are consistent with the risk-taking channel of monetary policy (e.g. Dell'Ariccia et al. (2017), Ioannidou et al. (2015), Jiménez et al. (2014), Maddaloni and Peydró (2011), Paligorova and Santos (2017)), whereby banks expand credit to riskier borrowers and ease lending standards in low policy rate environments. While part of the observed increase in credit spreads could, in principle, reflect higher markups conditional on risk, this interpretation is difficult to reconcile with the risk-taking channel, which documents that prices for risk tend to decline, rather than increase, when policy rates are low.

[6] Banks sometimes state this motive explicitly, for example Bank of America in its 2017 annual report: "Our overall goal is to manage interest rate risk so that movements in interest rates do not significantly adversely affect earnings and capital."

[7] For example, S&P Global's Visible Alpha reports NIM forecasts for commercial banks among its top KPI.

The remainder of the paper is organized as follows. Section 2 reviews related work on interest rate risk. Section 3 presents a simple bank balance sheet model of NIM stability. Section 4 describes the data and the methodology for decomposing interest income rates into risk-free benchmark rates and implied credit spreads. Section 5 contains the results from the sensitivity analysis. Section 6 and Section 7 analyze how increases in implied credit spreads relate to banks' exposure to credit and duration risk, respectively. Section 8 concludes.

2 Related Literature

This study adds to the literature on how changes in the policy rate affect banks' profitability and stability, a topic that gained renewed attention following the 2023 US regional banking turmoil. The literature offers two distinct perspectives. The cash-flow perspective, in which this paper is situated, studies how banks' income-statement cash flows respond to changes in the policy rate. In contrast, the market-value perspective evaluates the impact of policy rate changes on the market values of banks' balance sheet items, many of which are not marked to market. These approaches imply different definitions of interest rate risk.

Under the cash-flow perspective, as long as changes in interest income and expense cash flows match, net interest margins remain stable and banks' profitability is not impacted by interest rate risk. Prior work documents stable net interest margins: Flannery (1981) is among the first to show that banks maintain stable NIM, and English (2002) finds that commercial banks in ten industrial countries tend to keep NIM stable with respect to policy rate changes. A prominent contribution to the cash-flow perspective is Drechsler et al. (2021), who show that interest income and interest expense sensitivities to the federal funds rate closely match, leaving NIM and, by extension, return on assets (ROA) mostly insensitive to policy rate changes. They emphasize the role of deposit market power on the liability side, which dampens the response of interest expenses to policy rate movements. Related work highlights uniform rate setting by large banks (Begenau and Stafford 2025) and heterogeneity in consumer preferences and bank technologies across bank sizes (d'Avernas et al. 2025) as additional mechanisms reducing interest expense rate sensitivities. My paper complements this evidence by focusing on the interest income side of NIM. I show how movements in risk-free benchmark rates and implied

credit spreads keep interest income and expense cash-flows aligned as policy rates change and that reductions in interest rate risk are accompanied by increased exposure to credit and duration risk when policy rates fall. A related strand within the cash-flow perspective examines cross-sectional heterogeneity in the sensitivity of NIM and ROA to policy rate changes, rather than how those sensitivities arise. Williams (2020) documents that sensitivities vary with business models and that ROA is about one-third less sensitive than NIM because banks offset part of the interest-rate effect on ROA by adjusting non-interest expenses. She interprets these findings as consistent with earnings management to report stable profits. My paper supports this interpretation by showing that banks stabilize NIM in part through active asset management. Hoffmann et al. (2019) examine European banks and attribute cross-country differences in NIM sensitivity to fixed- versus floating-rate mortgage conventions. They find that banks in jurisdictions with predominantly floating-rate mortgages exhibit NIM that fluctuates more strongly with short-term interest rates. These findings are consistent with my mechanism, as risk-free benchmark rates adjust more quickly when a larger share of assets has rates that reset within the quarter, increasing the need for adjustments in credit spreads to stabilize NIM.

From a market-value perspective, interest rate risk arises when policy rate changes alter the market values of banks' assets and liabilities. Even if NIM is stable, policy rate increases can depress asset market values and diminish franchise value. In this context, interest rate risk is often described as duration risk. Begenau et al. (2025) fall within this perspective, constructing banks' net fixed-income positions - the market value of fixed-income assets minus fixed-income liabilities - and use public data to stress-test the impact of rate changes on market values. Begenau and Stafford (2022) use long-short positions in US Treasuries to show that spreads, analogous to NIM, can be stable while the positions remain highly exposed to duration risk, illustrating that cash-flow stability need not imply market-value stability. This distinction matters because rising rates generate unrealized losses, i.e. declines in market, not book, values. These losses become problematic if deposit outflows force banks to liquidate assets and realize them. Jiang et al. (2024) estimate that during the 2022:Q1 to 2023:Q1 monetary tightening, the market value of US bank assets fell by roughly 10% on average (about $2 trillion in aggregate),

roughly equal to aggregate bank equity. They further demonstrate that sufficiently large unrealized losses, such that the market value of assets falls below liabilities, can trigger deposit runs, linking this mechanism to the March 2023 failure of Silicon Valley Bank. Drechsler et al. (2025) provide a duration-based analysis, estimating aggregate unrealized losses of about $1.7 trillion over the year preceding the 2023 bank failures, and emphasize that uninsured depositors are prone to run when they perceive that asset values no longer fully cover their claims. Flannery and Sorescu (2023) arrive at a slightly lower estimate of $1.1 trillion in before-tax unrealized mark-to-market losses on securities and loans. Together, these papers underscore that substantial unrealized losses accumulated during the 2022-2023 monetary tightening, leaving banks vulnerable to duration risk. Haddad et al. (2023) complement this view by showing that even insured depositors may run when rising rates erode asset values and depositors believe the bank is likely to fail, highlighting that market-value losses can trigger runs beyond the uninsured depositor base as uninsured depositors also value the conitnuation of banking relationships. Moreover, DeMarzo et al. (2025) develop a framework to measure bank franchise value, the present value of future net interest income net of operating costs, and show that it declines when policy rates rise, as higher discount rates reduce the value of stable cash flows. My paper contributes to the market-value perspective by showing that NIM stability implies banks manage cash flows through credit spreads, which results in longer asset maturities when policy rates fall. This increase in duration exposure becomes particularly problematic when policy rates subsequently rise.

3 Theoretical Framework

This section presents a simple, discrete-time balance sheet model of a representative bank. I develop this model to isolate the asset-side mechanisms that shape the sensitivity of NIM to the short-term policy rate. At each time t, the bank finances its assets A_t with deposits D_t, wholesale funding W_t and equity E_t, such that $A_t = D_t + W_t + E_t$. The model allows for time-varying maturity mismatches and asset growth. In each period, a fraction η_t of assets adjusts their rates, comprising floating-rate assets and new assets. Deposits and wholesale funding have a maturity of one period. The bank faces no financing frictions and can borrow

and lend any amount risk-free at the federal funds rate f_t. Throughout, $\Delta x_t \equiv x_t - x_{t-1}$ denotes the change in variable x from period $t-1$ to t. This setup allows for a clear decomposition of the components of net interest margin (NIM) that are sensitive to changes in the policy rate.

3.1 Net Interest Margin

The bank earns interest income on its assets and pays interest expenses on its liabilities. The interest income rate r_t^{inc} is defined as total interest income divided by assets and the interest expense rate r_t^{exp} as total interest expenses divided by assets. The net interest margin at time t is defined as the difference of the two rates:

$$\text{NIM}_t = r_t^{\text{inc}} - r_t^{\text{exp}} \tag{1}$$

The *NIM sensitivity* is defined as the one-period change in net interest margin relative to the change in the federal funds rate, $\frac{\Delta \text{NIM}_t}{\Delta f_t}$. The *NIM sensitivity* is zero if the sensitivity of the interest income rate to changes in the federal funds rate, hereafter *interest income sensitivity*, equals the sensitivity of the interest expense rate to changes in the federal funds rate, hereafter *interest expense sensitivity*. These sensitivities are defined equivalently. The condition for insensitive NIM is:

$$\frac{\Delta \text{NIM}_t}{\Delta f_t} = 0 \quad \text{if} \quad \frac{\Delta r_t^{\text{inc}}}{\Delta f_t} = \frac{\Delta r_t^{\text{exp}}}{\Delta f_t} \tag{2}$$

3.2 Interest Expense Rate

Funding consists of a fraction δ in deposits, γ in wholesale funding and $(1-\delta-\gamma)$ in equity, with $\delta > 0, \gamma \geq 0$ and $\delta + \gamma < 1$.[8] The deposit rate r_t^d is defined as interest paid on deposits relative to those deposits. Wholesale funding is obtained at the federal funds rate f_t. The interest expense rate can be expressed as:

$$r_t^{\text{exp}} = \delta \; r_t^d + \gamma \; f_t \tag{3}$$

[8] As I focus on the interest income side, assuming constant shares of deposits, wholesale funding, and equity entails no loss of generality, while simplifying the calculation of the *interest expense rate* sensitivity.

The *interest expense sensitivity* is:

$$\begin{aligned}\frac{\Delta r_t^{\text{exp}}}{\Delta f_t} &= \delta \, \frac{\Delta r_t^d}{\Delta f_t} + \gamma \, \frac{\Delta f_t}{\Delta f_t} \\ &= \delta \, \frac{\Delta r_t^d}{\Delta f_t} + \gamma\end{aligned} \tag{4}$$

This sensitivity satisfies

$$\frac{\Delta r_t^{\text{exp}}}{\Delta f_t} < 1 \tag{5}$$

for two reasons. First, deposit rates are sticky, i.e. $\frac{\Delta r_t^d}{\Delta f_t} < 1$. Second, the bank is partly equity-funded and equity does not generate any interest expense.

3.3 Interest Income Rate

To analyze how the interest income rate responds to policy rate changes, it is decomposed into a risk-free benchmark rate and a credit spread. Changes in the interest income rate are decomposed into contributions from the assets whose rates adjust to identify which assets drive the change. The bank holds both interest-earning assets $A_t^I > 0$ and non-interest-earning assets $A_t^N \geq 0$, with total assets $A_t = A_t^I + A_t^N$. Let $\lambda_t = \frac{A_t^I}{A_t}$ denote the share of interest-earning assets and let $\overline{r}_t^{\text{inc}}$ be the interest income rate on interest-earning assets.

The interest income rate is:

$$r_t^{\text{inc}} = \lambda_t \, \overline{r}_t^{\,\text{inc}} \tag{6}$$

Among interest-earning assets, a fraction $\eta_t \in [0, 1]$ adjusts its rate between $t-1$ and t, while the remaining share $1 - \eta_t$ is carried over from the previous period without a change in the rate. Let $\hat{r}_t^{\,\text{inc}}$ denote the interest income rate on adjusting assets, and $\tilde{r}_t^{\,\text{inc}}$ the interest income rate on non-adjusting assets. The interest income rate on interest-earning assets at time t is:

$$\overline{r}_t^{\,\text{inc}} = \eta_t \, \hat{r}_t^{\,\text{inc}} + (1 - \eta_t) \, \tilde{r}_t^{\,\text{inc}} \tag{7}$$

η_t can be decomposed into three components, each expressed as a fraction of A_t^I:

(i) pre-existing floating-rate assets that reset between $t-1$ and t, $\eta_t^{\text{floating}} \geq 0$

(ii) newly added assets that replace maturing ones, $\eta_t^{\text{replacement}} \geq 0$;[9] and

(iii) newly added assets due to growth in interest-earning assets, $\eta_t^{\text{growth}} = \frac{A_t^I - A_{t-1}^I}{A_t^I} \geq 0$.[10]

The interest income rate on interest-earning assets can thus be expressed as:

$$\overline{r}_t^{\,\text{inc}} = \eta_t^{\text{floating}}\, r_t^{\text{floating}} + \eta_t^{\text{replacement}}\, r_t^{\text{replacement}} + \eta_t^{\text{growth}}\, r_t^{\text{growth}} + (1-\eta_t)\, \tilde{r}_t^{\,\text{inc}} \tag{8}$$

Here, r_t^{floating}, $r_t^{\text{replacement}}$, and r_t^{growth} denote the interest income rates on floating-rate assets, newly added assets that replace maturing ones and newly added assets due to growth, respectively, and $\eta_t = \eta_t^{\text{floating}} + \eta_t^{\text{replacement}} + \eta_t^{\text{growth}}$.

The one-period change in the interest income rate on interest-earning assets is:

$$\Delta\overline{r}_t^{\,\text{inc}} = \eta_t^{\text{floating}}\, \Delta r_t^{\text{floating}} + \eta_t^{\text{replacement}}\, \Delta r_t^{\text{replacement}} + \eta_t^{\text{growth}}\, \Delta r_t^{\text{growth}} \tag{9}$$

as the rate on carried-over assets remains unchanged, $\Delta\tilde{r}_t^{\,\text{inc}} = 0$.

As any interest rate can be expressed as a risk-free benchmark rate plus a credit spread, each interest rate change in the decomposition above can be written as the sum of changes in its risk-free benchmark rate and credit spread.

Floating-rate assets adjust between period $t-1$ and t but remain on the balance sheet, so their rate change reflects only movements in the risk-free benchmark:

$$\Delta r_t^{\text{floating}} = f_t - r_{f,t-1}^{\text{bench,floating}} \tag{10}$$

where $r_{f,t-1}^{\text{bench,floating}}$ is the weighted average federal funds rate set at the instruments' last reset

[9] Empirically, (ii) includes new assets replacing positions that exit via amortization or premature sale.

[10] In the empirical analysis, I allow for $\eta_t^{\text{growth}} < 0$ and $\eta_t < 0$ to capture contractions in interest-earning assets. If $\eta_t^{\text{replacement}} + \eta_t^{\text{growth}} \geq 0$, I assume not all maturing assets are reinvested. If $\eta_t^{\text{replacement}} + \eta_t^{\text{growth}} < 0$, I assume some assets are sold prematurely without replacement.

prior to t, or at their initial pricing if they had not yet reset, and the new risk-free benchmark rate is the current federal funds rate f_t.

The rate change for newly added assets that replace maturing ones is:

$$\Delta r_t^{\text{replacement}} = \left(f_t - r_{f,t-1}^{\text{bench,maturing}}\right) + \left(s_t^{\text{replacement}} - s_{t-1}^{\text{maturing}}\right) \tag{11}$$

where $r_{f,t-1}^{\text{bench,maturing}}$ is the risk-free benchmark rate of the maturing assets, that is, the weighted average of the federal funds rates prevailing at their initial pricing or at the most recent reset. And $s_{t-1}^{\text{maturing}}$ is the weighted average credit spread of the maturing assets. Replacement assets are priced at the current policy rate f_t with spread $s_t^{\text{replacement}}$.

The rate change for newly added assets due to growth is:

$$\Delta r_t^{\text{growth}} = \left(f_t - r_{f,t-1}^{\text{bench,average}}\right) + \left(s_t^{\text{growth}} - s_{t-1}^{\text{average}}\right) \tag{12}$$

where $r_{f,t-1}^{\text{bench,average}}$ is the risk-free benchmark rate of the prior period's interest-earning assets, that is, the weighted average of the federal funds rates prevailing at their initial pricing or at the most recent rate reset. And s_{t-1}^{average} is the corresponding weighted average credit spread. New assets arising from growth in interest-earning assets are priced at the current policy rate f_t with spread s_t^{growth}.

Substituting these expressions into Equation (9) yields:

$$\begin{aligned}\Delta \overline{r}_t^{\text{inc}} =& \eta_t^{\text{floating}} \left(f_t - r_{f,t-1}^{\text{bench,floating}}\right) \\ &+ \eta_t^{\text{replacement}} \left[\left(f_t - r_{f,t-1}^{\text{bench,maturing}}\right) + \left(s_t^{\text{replacement}} - s_{t-1}^{\text{maturing}}\right)\right] \\ &+ \eta_t^{\text{growth}} \left[\left(f_t - r_{f,t-1}^{\text{bench,average}}\right) + \left(s_t^{\text{growth}} - s_{t-1}^{\text{average}}\right)\right]\end{aligned} \tag{13}$$

This expression decomposes into (i) changes in the risk-free benchmark $\Phi_t^{r_f^{\text{bench}}}$:

$$\begin{aligned}\Phi_t^{r_f^{\text{bench}}} &= \eta_t^{\text{floating}} \left(f_t - r_{f,t-1}^{\text{bench,floating}}\right) + \eta_t^{\text{replacement}} \left(f_t - r_{f,t-1}^{\text{bench,maturing}}\right) \\ &\quad + \eta_t^{\text{growth}} \left(f_t - r_{f,t-1}^{\text{bench,average}}\right) \end{aligned} \tag{14}$$

And (ii) changes in credit spreads Φ_t^{spread}:

$$\Phi_t^{\text{spread}} = \eta_t^{\text{replacement}} \left(s_t^{\text{replacement}} - s_{t-1}^{\text{maturing}}\right) + \eta_t^{\text{growth}} \left(s_t^{\text{growth}} - s_{t-1}^{\text{average}}\right) \tag{15}$$

The one-period change in the interest income rate on total assets can be decomposed into a change in the interest income rate on interest-earning assets and a change in the share of interest-earning assets in total assets:[11]

$$\Delta r_t^{\text{inc}} = \Delta \left(\lambda_t \overline{r}_t^{\,\text{inc}}\right) = \lambda_{t-1}\, \Delta \overline{r}_t^{\,\text{inc}} + \overline{r}_t^{\,\text{inc}}\, \Delta \lambda_t \tag{16}$$

Using $\overline{r}_t^{\,\text{inc}} = \frac{r_t^{\text{inc}}}{\lambda_t}$ this can be further expressed as:

$$\Delta r_t^{\text{inc}} = \lambda_{t-1}\, \Phi_t^{r_f^{\text{bench}}} + \lambda_{t-1}\, \Phi_t^{\text{spread}} + \Delta \lambda_t\, \frac{r_t^{\text{inc}}}{\lambda_t} \tag{17}$$

Define $\Delta r_{f,t}^{\text{bench}} = \lambda_{t-1}\, \Phi_t^{r_f^{\text{bench}}}$, $\Delta s_t = \lambda_{t-1}\, \Phi_t^{\text{spread}}$ and $\Delta \mathcal{A}_t = \Delta \lambda_t\, \frac{r_t^{\text{inc}}}{\lambda_t}$ as the one-period change in the risk-free benchmark rate, the credit spread and the asset composition, respectively. Then the *interest income sensitivity* is:

$$\frac{\Delta r_t^{\text{inc}}}{\Delta f_t} = \frac{\Delta r_{f,t}^{\text{bench}}}{\Delta f_t} + \frac{\Delta s_t}{\Delta f_t} + \frac{\Delta \mathcal{A}_t}{\Delta f_t} \tag{18}$$

[11] This follows from the expansion: $\Delta(\lambda_t\, \overline{r}_t^{\,\text{inc}}) = \lambda_t\, \overline{r}_t^{\,\text{inc}} - \lambda_{t-1}\, \overline{r}_{t-1}^{\,\text{inc}} = \lambda_t\, \overline{r}_t^{\,\text{inc}} - \lambda_{t-1}\, \overline{r}_t^{\,\text{inc}} + \lambda_{t-1}\, \overline{r}_t^{\,\text{inc}} - \lambda_{t-1}\, \overline{r}_{t-1}^{\,\text{inc}} = \lambda_{t-1}\, \Delta \overline{r}_t^{\,\text{inc}} + \overline{r}_t^{\,\text{inc}}\, \Delta \lambda_t$. As the expression is symmetric in λ and $\overline{r}^{\,\text{inc}}$, I verify in robustness tests that empirical results are quantitatively and qualitatively equivalent to using the alternative expansion $\Delta r_t^{\text{inc}} = \lambda_t\, \Delta \overline{r}_t^{\text{inc}} + \overline{r}_{t-1}^{\text{inc}}\, \Delta \lambda_t$.

The expression consists of three sensitivities. First, the ***risk-free benchmark sensitivity*** $\beta^{r_f^{\text{bench}}}$, which captures how the average risk-free benchmark rate responds to changes in the federal funds rate is:

$$\beta^{r_f^{\text{bench}}} \equiv \frac{\Delta r_{f,t}^{\text{bench}}}{\Delta f_t} \tag{19}$$

Second, the ***credit spread sensitivity*** β^{spread}, which captures how average credit spreads respond to changes in the federal funds rate is:

$$\beta^{\text{spread}} \equiv \frac{\Delta s_t}{\Delta f_t} \tag{20}$$

And third, the ***asset composition sensitivity*** β_t^{λ}, which reflects how the share of interest-earning assets in total assets responds to changes in the federal funds rate is:

$$\beta_t^{\mathcal{A}} \equiv \frac{\Delta \mathcal{A}_t}{\Delta f_t} \tag{21}$$

The sum of these three sensitivities determines the total *interest income sensitivity*, defined as $\beta_t^{\text{inc}} \equiv \frac{\Delta r_t^{\text{inc}}}{\Delta f_t}$:

$$\beta_t^{\text{inc}} = \beta_t^{r_f^{\text{bench}}} + \beta_t^{\text{spread}} + \beta_t^{\mathcal{A}} \tag{22}$$

3.4 Matching Interest Income and Interest Expense Sensitivities

For NIM to be insensitive to policy rate changes, the condition in Equation (2) must hold, that is, *interest income* and *interest expense sensitivities* must match. Substituting $\beta_t^{\text{NIM}} \equiv \frac{\Delta \text{NIM}_t}{\Delta f_t}$, $\beta_t^{\text{exp}} \equiv \frac{\Delta r_t^{\text{exp}}}{\Delta f_t}$ and the decomposition of Equation (22), this condition becomes:

$$\beta_t^{\text{NIM}} = 0 \quad \text{if} \quad \beta^{r_f^{\text{bench}}} + \beta^{\text{spread}} + \beta_t^{\mathcal{A}} = \beta_t^{exp} \tag{23}$$

That is, NIM is insensitive to policy rate changes when the combined sensitivities of the risk-free benchmark, credit spread, and asset composition match the interest expense sensitivity.

4 Data

4.1 Data Sources and Preparation

Data sources. Bank data comes from US Call Reports (Forms 031/041/051), regulatory filings submitted by all FDIC-insured institutions. I focus on commercial banks (charter type 200) over 1997:Q2 to 2024:Q4, the period for which detailed repricing-maturity information is available.[12] The data is accessed via WRDS and constructed by merging two series, prioritizing the Federal Financial Institutions Examination Council (FFIEC) series from 2001:Q1 onward and filling gaps with the Federal Reserve Bank of Chicago (Chicago FED) series from 1997:Q2 to 2021:Q2. The policy rate is the daily effective federal funds rate of the Federal Reserve's H.15 release, averaged to quarters. For analyses focusing on the largest banks, I use the monthly, seasonally adjusted Consumer Price Index for All Urban Consumers (CPI-U) from the US Bureau of Labor Statistics, averaged to quarters, to compute inflation-adjusted assets. For analyses at the fully consolidated level, I aggregate banks to top-tier bank holding companies (BHCs) and standalone commercial banks using relationship links from the National Information Center (NIC) and using holding company data from Form FR-Y-9C.

Repricing maturity data. I primarily use Call Report schedules RI (income statement) and RC-K (quarterly average balance sheet), and for repricing maturities RC-B (securities), RC-C (loans) and RC-E (deposits). For fixed-rate instruments, repricing maturity equals contractual maturity. For floating-rate instruments, it is the earlier of the next rate reset date or contractual maturity. Repricing maturities are reported as end-of-quarter values and for loans and securities in six buckets:

$$<3 \text{ months, 3-12 months, 1-3 years, 3-5 years, 5-15 years, and } >15 \text{ years.}$$

These are provided for two loan and three security subgroups.[13] To separate floating-rate

[12] Commercial banks include depository trust companies, credit card banks with commercial bank charters, private banks, development banks, and limited charter banks.

[13] For non-residential, non-pass-through mortgage-backed securities (MBS), only two buckets are reported: "$\leq$ 3 years" and "$>$ 3 years". On average, these account for less than 10% of total securities. I allocate them proportionally to the distribution of other securities with more granular repricing information. When no such information is available, I allocate them linearly across quarters.

from maturing instruments, I use the reported volumes of loans and securities scheduled to mature within one year. I proxy the amount of loans and securities maturing within three months as the lesser of one-fourth of the amount scheduled to mature within a year and the amount scheduled to reprice within three months. The remainder of the "< 3 months" bucket is classified as floating-rate. The remaining volume scheduled to mature within one year is then assigned to the next repricing maturity bucket, with any residual amount in that bucket classified as floating-rate. Interest-earning assets without repricing maturity data (e.g. cash, federal funds sold, reverse repurchase agreements, and trading assets) are assumed to reprice each quarter.

Accounting basis. Under US GAAP, interest income is recognized using the effective interest method on amortized cost assets, i.e., it is accrued as earned over time, including for semiannual or annual coupon instruments and for zero-coupon bonds. Net interest margins and related interest rates use quarterly average total assets as the denominator. Loan and securities interest rates use quarterly average loans and quarterly average securities, respectively. Because interest is recognized on an amortized-cost basis, all rate calculations use amortized-cost amounts as denominators. Quarterly average loan and debt-security items in Schedule RC-K are reported at amortized cost. Repricing maturity buckets in schedules RC-B and RC-C report loans and held-to-maturity (HTM) securities at amortized cost but available for sale (AFS) securities at fair value. At the portfolio level, AFS securities are reported at both amortized cost and fair value. I impute repricing maturity bucket-level amortized cost amounts by scaling each bucket's fair value by the portfolio-level amortized-cost-to-fair-value ratio.

Additional details on data construction and harmonization are reported in Appendix A.

Sample. The main sample begins in 2001, both to avoid initialization effects from treating all loans and securities as newly added in 1997 and to align with the period when Call Reports are electronically filed and collected by the FFIEC, improving data quality and consistency. I restrict the sample to banks with at least 40 quarterly observations. The final sample includes 6,150 commercial banks and 495,439 bank-quarter observations, which map to 2,449 top-tier BHCs and standalone commercial banks with 187,564 bank-quarter observations.

4.2 Risk-Free Benchmark Rate and Implied Credit Spread Estimation

This subsection explains how risk-free benchmark rates and implied credit spreads are estimated in the data. The estimation builds on the decomposition of one-period changes in NIM:

$$\Delta \text{NIM}_t = \Delta r_t^{\text{inc}} - \Delta r_t^{\text{exp}}$$

$$\Delta r_t^{\text{inc}} = \underbrace{\Delta r_{f,t}^{\text{bench}}}_{\substack{\text{Risk-Free Benchmark} \\ \text{Change}}} + \underbrace{\Delta s_t}_{\substack{\text{Credit Spread} \\ \text{Change}}} + \underbrace{\frac{r_t^{\text{inc}}}{\lambda_t} \Delta \lambda_t}_{\substack{\text{Asset Composition} \\ \text{Change } (\Delta \mathcal{A}_t)}}$$

Required Variables. The following variables and their one-period changes are directly calculated from the Call Reports:

$r_{i,t}^{\text{inc}}$ Interest income rate, defined as interest income divided by quarterly average assets.

$r_{i,t}^{\text{exp}}$ Interest expense rate, defined as interest expense divided by quarterly average assets.

$\text{NIM}_{i,t}$ Net interest margin, $r_{i,t}^{\text{inc}} - r_{i,t}^{\text{exp}}$.

$\lambda_{i,t}$ Share of interest-earning assets in quarterly average total assets.

The changes in the risk-free benchmark rate $\Delta r_{f,t}^{\text{bench}}$ and in credit spreads Δs_t are not directly observed. I construct $\Delta r_{f,t}^{\text{bench}}$ using the algorithm described below and compute Δs_t as $\Delta s_t = \Delta r_t^{\text{inc}} - \Delta r_{f,t}^{\text{bench}} - \frac{r_t^{\text{inc}}}{\lambda_t} \Delta \lambda_t$. The detailed algorithmic steps are reported in Appendix B.

The construction of the risk-free benchmark rate proceeds as follows. Each quarter, I observe loans and securities that exit the balance sheet through scheduled maturity, loan amortization, and premature sale. Loan amortization is assumed to be linear. Premature sales are identified when outstanding amounts fall below the level implied by rolling forward the previous quarter's positions by one quarter, net of amortization. I also observe the volume of loans and securities added to the balance sheet, equal to those exits plus net growth, which may be negative. I assign the quarter's federal funds rate to (i) newly added loans and securities, (ii) floating-rate assets that reset in that quarter, and (iii) all interbank assets.[14] Preexisting loans and securities

[14] Interbank assets comprise deposits at other banks, federal funds sold, and reverse repurchase agreements.

that remain on the balance sheet retain the federal funds rate from their most recent pricing date, either at initial pricing or at the most recent rate reset. I treat all positions as newly added to the balance sheet in 1997 and, in each subsequent quarter, move outstanding positions one quarter closer to maturity or the next rate reset, broadly following the algorithmic steps in Begenau et al. (2025).[15]

The bank-specific risk-free benchmark rate for a given quarter is the value-weighted average of the attached federal funds rates across outstanding assets. Intuitively, this benchmark reflects the risk-free return determined by the policy rate prevailing at each asset's last pricing and thus indicates the risk-free rate currently earned on the bank's asset portfolio. The implied credit spread in a quarter is the difference between the interest income rate and this risk-free benchmark rate. It captures the value-weighted average markup over the policy rate prevailing at each asset's initial pricing, reflecting the credit spread currently earned on the bank's assets.

To estimate changes in the risk-free benchmark rate, credit spread and asset composition, I follow the direct decomposition outlined in Section 3 rather than taking first differences of the levels of risk-free benchmark rates and credit spreads. The decomposition resolves a timing mismatch in the data, as repricing volumes are reported as of quarter-end, whereas rates are based on quarterly average values. It also helps to clarify which assets drive the change in the risk-free benchmark rate. Appendix C shows that the difference between the decomposition-based risk-free benchmark rate change and the average-asset-based estimate is minor.

The next subsection presents summary statistics on repricing maturities and on the estimated variables introduced here.

[15]The authors use a similar algorithm to transform loans into portfolios of zero-coupon bonds and to map their face values to appropriate discount rates; see their Appendix B.

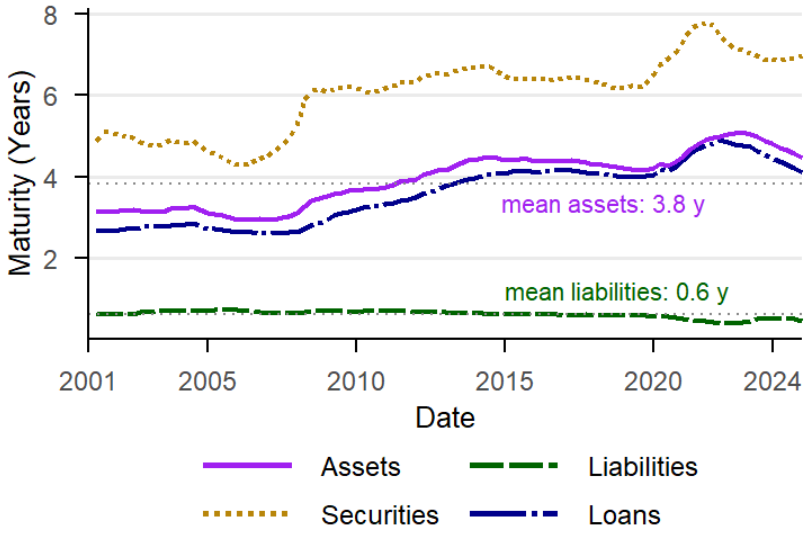
4.3 Summary Statistics

Repricing maturities of assets and liabilities. Table 1 reports the distribution of repricing maturities for total assets and total liabilities from US Call Reports. Liabilities have a larger share repricing within the first year, whereas assets carry more weight at longer maturities. On average, 24.8% of total assets are scheduled to mature or reset floating rates within three months, based on contractual repricing maturities. Because this measure excludes amortization, balance-sheet growth, and premature sales, it is a lower bound on the fraction of assets whose rates adjust within three months. The average share of non-interest-earning instruments is higher for liabilities (27.5%) than for assets (7.1%), reflecting equity (11%) and non-interest-earning deposits (16.5%). Figure 3 compares average repricing maturities for interest-earning assets, loans, securities and interest-paying liabilities over time. The average repricing maturity gap between assets and liabilities is large and persistent: The time-series average is 3.8 years for assets versus 0.6 years for liabilities. Over 2001-2024, asset repricing maturity lengthens from 3.1 to 4.5 years, while liability maturity remains short. Securities have relatively long maturities, rising from about 4.9 to 7.0 years, whereas loans are of relatively shorter maturity, increasing from about 2.7 to 4.1 years. Taken together, the table and figure show that, despite the high average repricing maturity of assets, a substantial share is scheduled to adjust their rates within three months, consistent with a right-skewed distribution of asset repricing maturities. In particular, the average repricing maturity of 3.8 years for assets does *not* imply that $1/3.8$ of assets adjust their rates each year.

Table 1: Average shares of total assets and liabilities by repricing maturity. This table presents average shares of total assets and total liabilities (including equity) by repricing maturity bucket and the share of non-interest-earning assets and liabilities. Means are calculated first by bank and then across banks. Standard deviations across banks in parentheses. Data: US commercial bank Call Reports, 2001-2024.

Repricing maturity bucket	Total assets	Total liabilities
$<$ 3 months	24.8% (11%)	45.8% (9.3%)
3 months – 1 year	12.1% (5.4%)	15.6% (6%)
1 – 3 years	17.8% (6.2%)	6.7% (3.8%)
$>$ 3 years	38.2% (12.8%)	4.4% (4%)
Non-interest-earning	7.1% (3.1%)	27.5% (7.9%)
of which: equity	–	11.0% (3.7%)

Figure 3: Average repricing maturities over time. The figure plots quarterly cross-bank averages of repricing maturity (years) for interest-earning assets, loans, securities, and interest-paying liabilities. Dotted horizontal lines mark time-series averages for assets and liabilities. Within each bank and quarter, the average repricing maturity is computed from repricing maturity bucket means. For liabilities, the highest bucket (> 3 years) is set to a mean of 5 years. For assets, the two longest buckets use exponentially declining weights, implying mean maturities of 7.5 years for the second-longest bucket and 18 years for the longest bucket. Data: US commercial bank Call Reports, 2001-2024.



Repricing maturities of interest-earning assets. Table 2 reports the distribution of repricing maturities for securities, loans and total interest-earning assets, that is, the shares scheduled to mature or to reset floating rates within each repricing maturity bucket. Shares are averaged over time within bank and then across banks. Loans have shorter average repricing maturities than securities and place more mass in early buckets. Within the first year, 40.4% of loans are scheduled to mature or reset, compared with 17.5% for securities. For loans, this first-year share comprises 28.3% scheduled maturities and 10.4% floating-rate resets. For securities, the corresponding components are 10.8% and 6.7%, respectively. Overall, total interest-earning assets exhibit substantial short-maturity mass within the first year (39.7%), driven by scheduled maturities (21.6%), floating-rate resets (10.0%), and interbank assets (8.2%). This composition shows that a sizable share of portfolios adjusts frequently despite long average maturities. Figure 4 visualizes the right-skewed distributions for loans, securities and total interest-earning assets. Each departs from a uniform distribution, placing substantial mass in the early years. Figure 5 plots aggregate amounts of securities, loans and interest-earning assets by repricing maturity over time. Aggregate holdings expand over the sample period, and the shares discussed below are computed from these aggregates and are therefore value-weighted. The maturity mix of securities shifts markedly: the share with maturity ≥ 15 years rises from 19% in 2001:Q1 to 42% by 2024:Q4, comprising almost entirely mortgage-backed securities (not shown). Loans remain predominantly short-dated, with about half repricing within one year (56% in 2001:Q1, 53% in 2024:Q4), and a clear majority within five years throughout. Total interest-earning assets likewise show substantial short-maturity mass: the share repricing within one year is 53% in 2001:Q1 and 50% in 2024:Q4.

Table 2: Average shares of interest-earning assets by repricing maturity. This table presents average shares of securities, loans and total interest-earning assets by repricing maturity bucket, the average and median repricing maturity in years and the number of banks used to calculate the shares (last row). Means are calculated first by bank and then across banks. The median is calculated by bank and then averaged across banks. Maturities are uniformly distributed within buckets up to 5 years, and exponentially declining weights are used in the 5–15 and >15 year buckets. Standard deviations across banks in parentheses. Data: US commercial bank Call Reports, 2001-2024.

Repricing maturity bucket	Securities	Loans	Interest-earning assets
< 3 months (total)	7.6% (7.4%)	24.2% (13.1%)	26.7% (11.9%)
maturing < 3 months	3.5% (4.6%)	13.8% (9%)	10.3% (9.3%)
floating < 3 months	4.1% (6.1%)	10.4% (9.5%)	8.2% (7.4%)
interbank assets	–	–	8.2% (6.5%)
3 months – 1 year (total)	9.9% (7.3%)	16.2% (8.2%)	13% (5.8%)
maturing 3 months – 1 year	7.3% (6.8%)	14.5% (7.3%)	11.3% (5.4%)
floating 3 months – 1 year	2.6% (3.9%)	1.7% (3.9%)	1.7% (2.7%)
1 – 3 years	19.9% (11.2%)	21.4% (8.2%)	19.2% (6.6%)
3 – 5 years	14.7% (7.4%)	19.2% (7.6%)	16.6% (5.9%)
5 – 15 years	34.4% (16.4%)	13.2% (9.1%)	17.6% (9.2%)
> 15 years	11.7% (12.6%)	5.7% (7.2%)	6.8% (6.7%)
Average (years)	5.9 (2.4)	3.5 (1.5)	3.8 (1.5)
Median (years)	5.0 (2.6)	2.2 (1.4)	2.4 (1.4)
Number of banks	6134	6142	6150

Figure 4: Asset shares by repricing maturities. The figure plots asset shares by repricing maturity for securities, loans and total interest-earning assets. Within buckets up to 5 years, mass is allocated uniformly across the quarters those buckets spans; for higher-maturity buckets, mass is allocated using exponentially declining weights. The final bucket is truncated at a 30-year horizon. Averages are computed first by bank and then across banks. Data: US commercial bank Call Reports, 2001-2024.

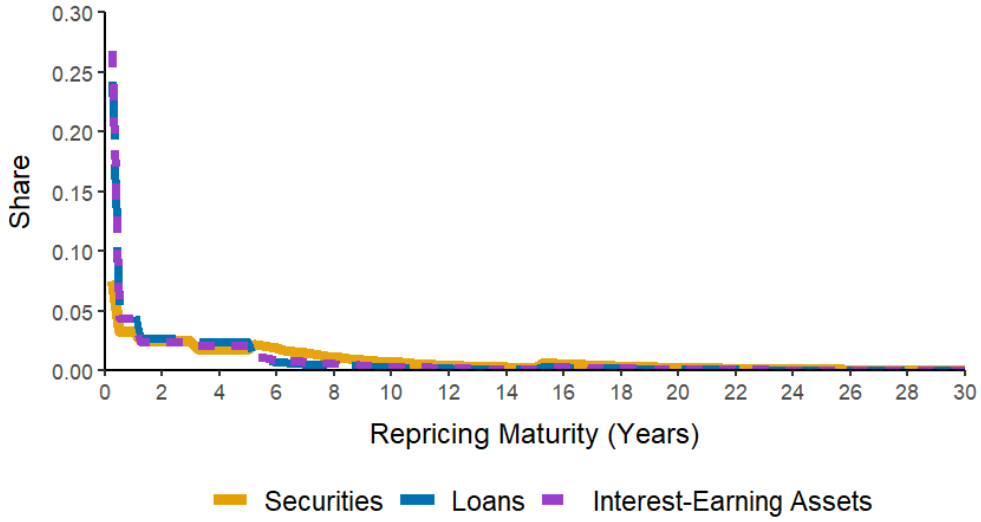
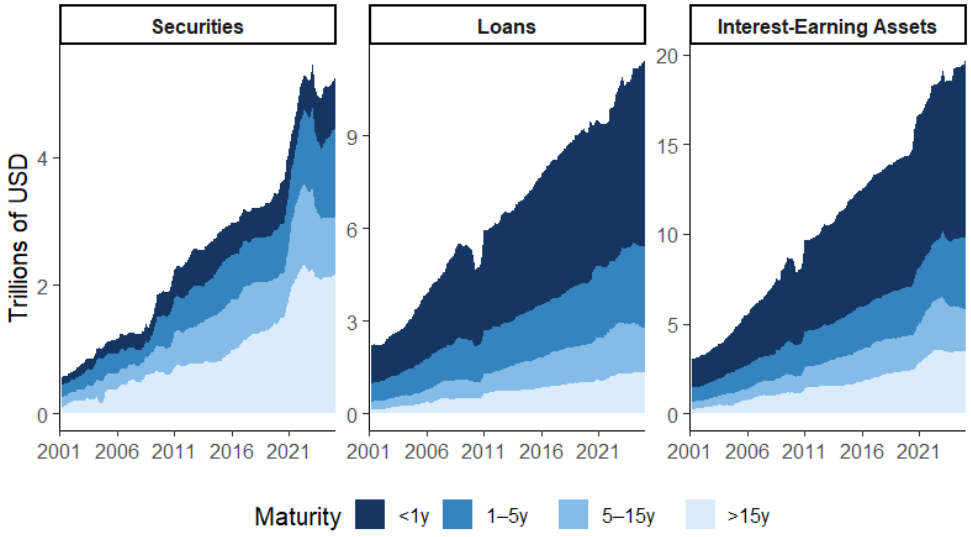


Figure 5: Aggregate Holdings by Repricing Maturity. Aggregate holdings of securities, loans and interest-earning assets of US commercial banks at amortized cost by repricing maturities across time. Volumes are in trillions of US dollars and grouped by repricing maturities of <1y, 1-5y 5-15y, and >15y. Data: US commercial bank Call Reports, 2001-2024.



Estimated Variables. Table 3 reports the average share of interest-earning assets that adjust to policy rates each quarter, η, and its components. On average, $\eta = 36.74\%$. Within interest-earning assets, replacements of exiting positions are the largest component (18.83%), followed by floating-rate resets of loans and securities (8.04%) and interbank assets (8.24%), while balance sheet growth contributes modestly (1.6%). Within replacements, scheduled maturities account for 9.87%, amortization for 6.23% and premature sales for 2.73% of interest-earning assets. With an average interest-earning asset share of $\lambda \approx 93\%$, roughly 34% of total assets adjust their rates each quarter. Figure 6 shows the equally weighted average of $\lambda\eta$ (the share of total assets that reset within the quarter), and, for comparison, the share of total assets in the $<$3-month repricing maturity bucket, alongside the federal funds rate (right axis). The $<$3-month measure reflects positions contractually scheduled to reprice within three months (floating-rate assets, scheduled maturities, and interbank assets). $\lambda\eta$ also includes amortization, premature sales, and balance-sheet growth, and is therefore higher on average. Both series exhibit little co-movement with the federal funds rate. However, both shares declined during the 2022-2023 policy tightening cycle. Figure 7 plots the federal funds rate (red dashed line) alongside equally weighted bank averages of the net interest margin (blue dash-dotted line), interest expense rate (green dotted line), interest income rate (purple dotted line), estimated risk-free benchmark rate (black solid line) and implied credit spread (gold solid line). The risk-free benchmark rate tracks the federal funds rate with a lag and is smoother, because it averages current and historical policy rates. The interest income rate adjusts more gradually than the risk-free benchmark rate. As a result, the implied credit spread moves countercyclically with the policy rate. The interest expense rate co-moves with the interest income rate, leaving their difference, the net interest margin, remarkably stable despite the large swings in the federal funds rate.

Table 3: Mean shares of interest-earning assets adjusting per quarter (%). This table provides summary statistics of the average interest-earning asset shares adjusting per quarter. Means are first computed by bank, then across banks. Cross-sectional standard deviations in parentheses. Data: US commercial bank Call Reports, 2001-2024.

η **(in %)**			
η (total)	$\eta^{\text{replacement}}$	η^{growth}	η^{floating}
36.74 (11.12)	**18.83** (6.90)	**1.60** (1.18)	**16.28** (9.24)

Decomposition of $\eta^{\text{replacement}}$ (in %)		
Scheduled maturity	Amortization	Premature sales
9.87 (6.49)	**6.23** (2.27)	**2.73** (1.21)

Decomposition of η^{floating} (in %)	
Loans & securities	Interbank assets
8.04 (7.12)	**8.24** (6.48)

Figure 6: Shares of assets adjusting or repricing within the quarter. The figure plots the federal funds rate (right axis, dashed red) and equally weighted bank averages of (i) $\lambda\eta$, the share of assets that adjust their rates within the quarter, and (ii) the share of assets in the <3-month repricing maturity bucket (left axis). Data: US commercial bank Call Reports, 2001-2024.

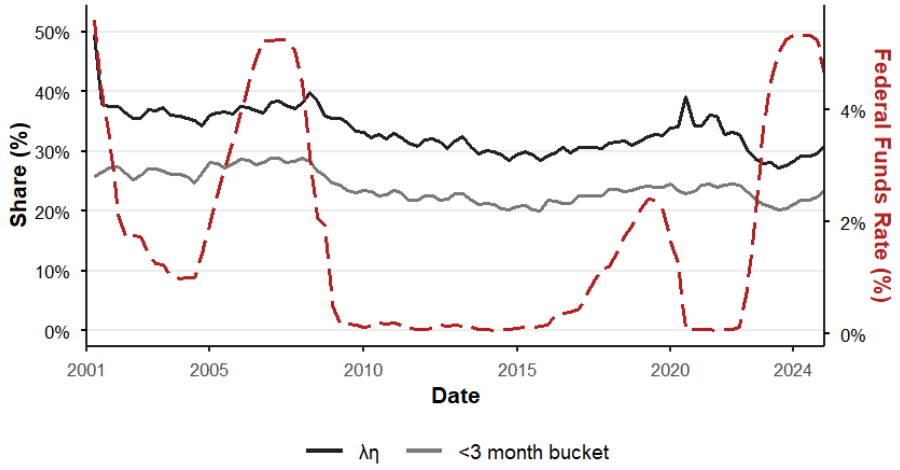
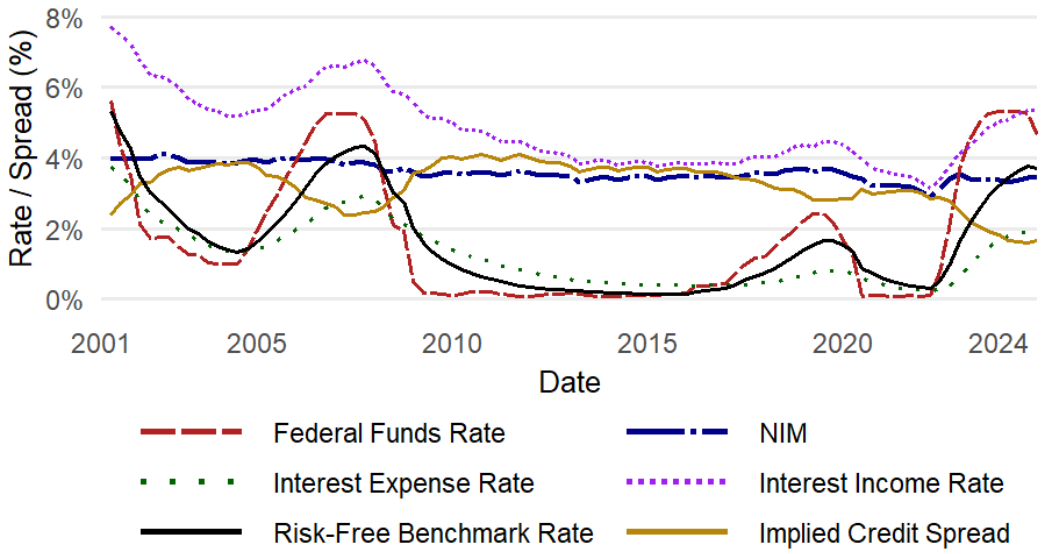
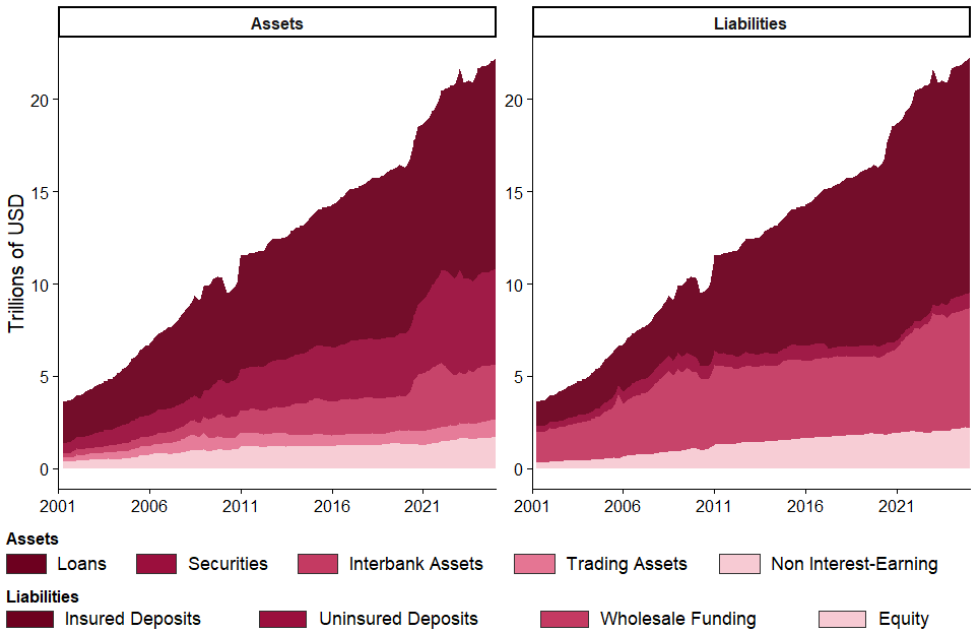


Figure 7: NIM and related rates. The figure plots the federal funds rate and equally weighted averages of the net interest margin (NIM), the interest income rate, the interest expense rate, the risk-free benchmark rate and the implied credit spread. Data: US commercial bank Call Reports, 2001-2024.



Bank summary statistics. Figure 8 plots the aggregate composition of US commercial bank balance sheets from 2001 to 2024. Loans are the largest asset class throughout, declining from 62% to 51%, while securities and interbank assets rise from 16% to 23% and from 7% to 14%, respectively. The share of trading assets remains around 6% and non-interest-earning assets around 8%.[16] On the liability side, insured deposits grow from 38% to 57%, uninsured deposits decline from 9% to 4%, wholesale funding shrinks from 45.3% to 29.1% and equity remains near 10%. Because these shares are expressed relative to total assets, the resulting averages are value-weighted. Appendix D reports summary statistics. NIM averages 3.63% (SD 0.66%) and bank size is highly skewed (mean $2.22 bn; median $0.17 bn). The remaining variables follow the patterns shown in the preceding figures and tables.

Figure 8: Aggregate balance sheet composition, 2001-2024. Aggregate assets (left) and liabilities (right) of US commercial banks by type. Assets are grouped into loans (incl. leases), securities, interbank assets, trading assets and non-interest-earning assets. Liabilities into insured deposits, uninsured deposits, wholesale funding (excl. uninsured deposits) and equity. Volumes are in trillions of US dollars. Data: US commercial bank Call Reports, 2001-2024.



[16]Trading assets are negligible for most banks (cross-sectional mean 0.03%; median 0.00%) and are concentrated in few large banks. For brevity, I reclassify them to interbank assets. Call Reports record their returns under interest income, so this affects only classification, not results.

5 Sensitivities of NIM and its Components to Policy Rate Movements

This section analyzes how NIM and its components respond to changes in the policy rate. NIM is insensitive if the interest income and interest expense sensitivities match. Equivalently, NIM is insensitive if the sum of the interest income-side sensitivities (risk-free benchmark, credit spread, and asset composition) equals the interest expense sensitivity. Formally, for bank i:

$$\frac{\Delta \text{NIM}_i}{\Delta f} = 0 \quad \text{if} \quad \underbrace{\frac{\Delta r_i^{\text{exp}}}{\Delta f}}_{\beta_i^{\text{exp}}} = \underbrace{\frac{\Delta r_i^{\text{inc}}}{\Delta f}}_{\beta_i^{\text{inc}}} = \underbrace{\frac{\Delta r_{f,i}^{\text{bench}}}{\Delta f}}_{\beta_i^{r_f^{\text{bench}}}} + \underbrace{\frac{\Delta s_i}{\Delta f}}_{\beta_i^{\text{spread}}} + \underbrace{\frac{\Delta \mathcal{A}}{\Delta f}}_{\beta_i^{\mathcal{A}}} \tag{24}$$

The sensitivity analysis follows Drechsler et al. (2021): For each bank i, and variable $\Delta X \in \left\{\Delta \text{NIM},\ \Delta r^{\text{exp}},\ \Delta r^{\text{inc}},\ \Delta r_f^{\text{bench}},\ \Delta s,\ \Delta \mathcal{A}\right\}$ I estimate

$$\begin{aligned} \Delta X_{it} &= \alpha_i + \sum_{\tau=0}^{3} \beta_{i,\tau}^{X} \Delta f_{t-\tau} + \epsilon_{it} \\ \beta_i^X &= \sum_{\tau=0}^{3} \beta_{i,\tau}^{X} \end{aligned} \tag{25}$$

This yields $\beta_i^{\text{NIM}},\ \beta_i^{\text{exp}},\ \beta_i^{\text{inc}},\ \beta_i^{r_f^{\text{bench}}},\ \beta_i^{\text{spread}},\ \beta_i^{\mathcal{A}}$ corresponding to the listed ΔX variables.

To allow for asymmetric responses, I also estimate separate sensitivities for increases and decreases in the policy rate:

$$\begin{aligned} \Delta X_{it} = \alpha_i &+ \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,+}\, \Delta f_{t-\tau}\, \mathbf{1}\{\Delta f_{t-\tau} > 0\} \\ &+ \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,-}\, \Delta f_{t-\tau}\, \mathbf{1}\{\Delta f_{t-\tau} \leq 0\} + \epsilon_{it}, \\ \beta_i^{X,+} = \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,+}, &\qquad \beta_i^{X,-} = \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,-}. \end{aligned} \tag{26}$$

Additionally, I construct a counterfactual NIM with credit spreads held constant:

$$\Delta \text{NIM}_{i,t}^{\text{counter}} = \Delta r_{f,i,t}^{\text{bench}} + \Delta \mathcal{A}_{i,t} - \Delta r_{i,t}^{\text{exp}} \tag{27}$$

and estimate its sensitivities analogously to obtain $\beta_i^{\text{NIM}^{\text{counter}}}$, $\beta_i^{\text{NIM}^{\text{counter},+}}$ and $\beta_i^{\text{NIM}^{\text{counter},-}}$.

For the sensitivity estimates, defined as sums of four coefficients $\beta_i^X \equiv \sum_{\tau=0}^{3} \beta_{i,\tau}^X$, statistical significance is assessed using a joint Wald test on the coefficient sum with Newey-West SEs.

Subsection 5.1 reports aggregate bank-level sensitivity estimates. Subsection 5.2 examines cross-sectional relationships among the estimates and Subsection 5.3 reports loan- and security-level sensitivity estimates.

5.1 Aggregate Bank-Level Sensitivities

Panel A of Table 4 reports aggregate bank-level sensitivity estimates to changes in the federal funds rate. On average, the NIM sensitivity is small (0.037), and for more than three-quarters of banks it is not statistically different from zero at the 5% level, implying limited exposure of net interest margins to interest rate risk. This reflects nearly matching interest expense and interest income sensitivities, on average 0.311 and 0.348, respectively. On the asset side, for nearly all banks the risk-free benchmark is strongly sensitive to the policy rate (mean 0.579). This sensitivity reflects the fraction $\lambda\eta$ of assets that adjust their rates within a quarter, on average 34%, and a catch-up effect arising when long-term assets whose risk-free rates were set in the past exit and are replaced by new assets priced at the current federal funds rate, or when new assets are added through growth at the current rate while the average risk-free benchmark lags behind that rate. The implied credit spread moves in the opposite direction (mean -0.238), with one-sided significance tests indicating that credit spread sensitivities are statistically significantly negative for about 90% of all banks but almost never significantly positive. Asset composition sensitivities are close to zero on average (0.007) and mostly insignificant, suggesting little contemporaneous adjustment in the interest-earning share of assets when policy rates move. Holding credit spreads fixed, the counterfactual NIM responds

strongly to policy rates: the mean sensitivity is 0.271, and the one-sided tests at the 5% level indicate that the sensitivity is significantly positive for 93% of banks and almost never significantly negative. Thus, the near-zero NIM sensitivity of most banks is in large part attributable to credit spreads moving inversely with the policy rate, offsetting what would otherwise be material exposure of NIM to interest rate risk.

Panel B of Table 4 indicates broad symmetry across policy rate increases and decreases. Interest expense and interest income sensitivities are modestly higher for positive than for negative federal funds rate changes (interest expense 0.405 vs. 0.265, interest income 0.478 vs. 0.288), suggesting that interest rates on both assets and liabilities respond more strongly to policy rate increases than to decreases. The pattern for interest expense is consistent with rising funding costs when policy rates increase, as deposits flow out and banks partly replace them with more expensive wholesale funding, in line with the deposit channel of Drechsler et al. (2017) and evidence that policy rate increases induce substitution from retail deposits into wholesale funding (Choi and Choi 2021). The risk-free benchmark sensitivity is also higher for positive than for negative changes (0.637 vs. 0.561). By contrast, the credit spread sensitivity is slightly more negative for policy rate decreases (-0.253) than for increases (-0.244) and is significant for a larger share of banks (71% vs. 40%). This pattern suggests that banks widen credit spreads slightly more when policy rates fall than they compress them when policy rates rise. NIM sensitivity remains small across both policy rate increases and decreases (0.073 vs. 0.023), as in both cases interest income and interest expense sensitivities remain closely aligned. The lower significance in the subsample estimates is consistent with reduced statistical power from splitting the sample (fewer observations and larger Newey-West standard errors per subsample).

Figure 9 shows density distributions of bank-level sensitivities for interest expense (top panel) and interest income, risk-free benchmark and credit spread (bottom panel). The patterns accord with the table evidence. Interest expense sensitivities cluster tightly around 0.311 (SD 0.086), indicating moderate responsiveness to policy rate changes. Interest income sensitivities are somewhat more dispersed, centered at 0.348 (SD 0.141). Within interest income, the risk-free benchmark sensitivities center above zero around 0.579 (SD 0.113), while the credit spread

sensitivities center well below zero with a mean of −0.238 (SD 0.128). Taken together, these distributions show that interest income and interest expense sensitivities are closely aligned, while the risk-free benchmark sensitivity lies well above the interest expense sensitivity and the credit-spread sensitivity is negative for the vast majority of banks. Figure 10 shows density distributions of bank-level sensitivities for NIM and for a counterfactual NIM that holds credit spreads constant. Most counterfactual NIM sensitivities are above zero, clustered around 0.272, whereas NIM sensitivities cluster near zero. The gap between the two distributions indicates that credit spread sensitivities offset much of the wedge between the risk-free benchmark and interest-expense sensitivities, leaving NIM largely insensitive on average.

Appendix E reports robustness checks for the sensitivity analysis using (i) alternative constructions of the risk-free benchmark and implied credit spread, (ii) only the largest 10% and 5% of banks by real assets (iii) estimation over the full sample (1997-2024), (iv) splits by aggregate financial conditions, (v) alternative assumptions in the algorithm, and (vi) estimation at the top-tier bank holding company and standalone commercial bank level. The results are quantitatively and qualitatively similar across specifications with one notable exception: when loan amortization is suppressed, the mean credit spread sensitivity falls to about −0.149 and the share of banks with a significant credit spread sensitivity decreases to 60.8%. This setting, however, imposes a very strong assumption, as no balance-sheet component amortizes.

Table 4: Summary statistics for sensitivity regressions. This table reports summary statistics of bank-level sensitivities for US commercial banks using quarterly data from 2001–2024. For each variable, a bank's sensitivity equals the sum of coefficients from a regression of its quarterly change on the contemporaneous and three lagged quarterly changes in the federal funds rate. Panel A reports sensitivities over the full sample; Panel B reports sensitivities estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, and "% Sig." is the share of banks with a statistically significant two-sided sensitivity at 5% (Newey–West SEs). In Panel A, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. Sample: 6,150 banks; 495,439 bank-quarter observations.

Panel A: Full Sample

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Net interest margin (NIM)	**0.037**	0.140	24%	23%	9%	0.114
Interest expense	**0.311**	0.086	99%	99%	0%	0.600
Interest income	**0.348**	0.141	96%	97%	0%	0.308
Risk-free benchmark	**0.579**	0.113	100%	100%	0%	0.875
Credit spread	**−0.238**	0.128	86%	0%	90%	0.179
Asset composition	**0.007**	0.037	5%	6%	3%	0.086
Counterfactual NIM	**0.275**	0.119	91%	93%	0%	0.338

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.073**	0.237	25%	**0.023**	0.184	16%
Interest expense	**0.405**	0.156	98%	**0.265**	0.100	93%
Interest income	**0.478**	0.237	93%	**0.288**	0.186	80%
Risk-free benchmark	**0.637**	0.204	100%	**0.561**	0.115	100%
Credit spread	**−0.244**	0.262	40%	**−0.253**	0.199	71%
Asset composition	**0.085**	0.150	4%	**−0.019**	0.072	6%
Counterfactual NIM	**0.317**	0.243	68%	**0.277**	0.160	77%

Figure 9: Distribution of bank-level interest income and expense sensitivities to the federal funds rate. The figure plots kernel densities of bank-level sensitivity estimates (β_i) from regressions of quarterly changes in each variable (interest expense rate, interest income rate, risk-free benchmark rate, and implied credit spread) on the contemporaneous and three lagged quarterly changes in the federal funds rate; a variable's sensitivity equals the sum of the four coefficients. The top panel shows the interest expense sensitivity. The bottom panel shows the interest income sensitivity and its two components: the risk-free benchmark and the credit spread sensitivity. Dashed vertical lines mark cross-bank means; the solid vertical line marks zero. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001-2024.

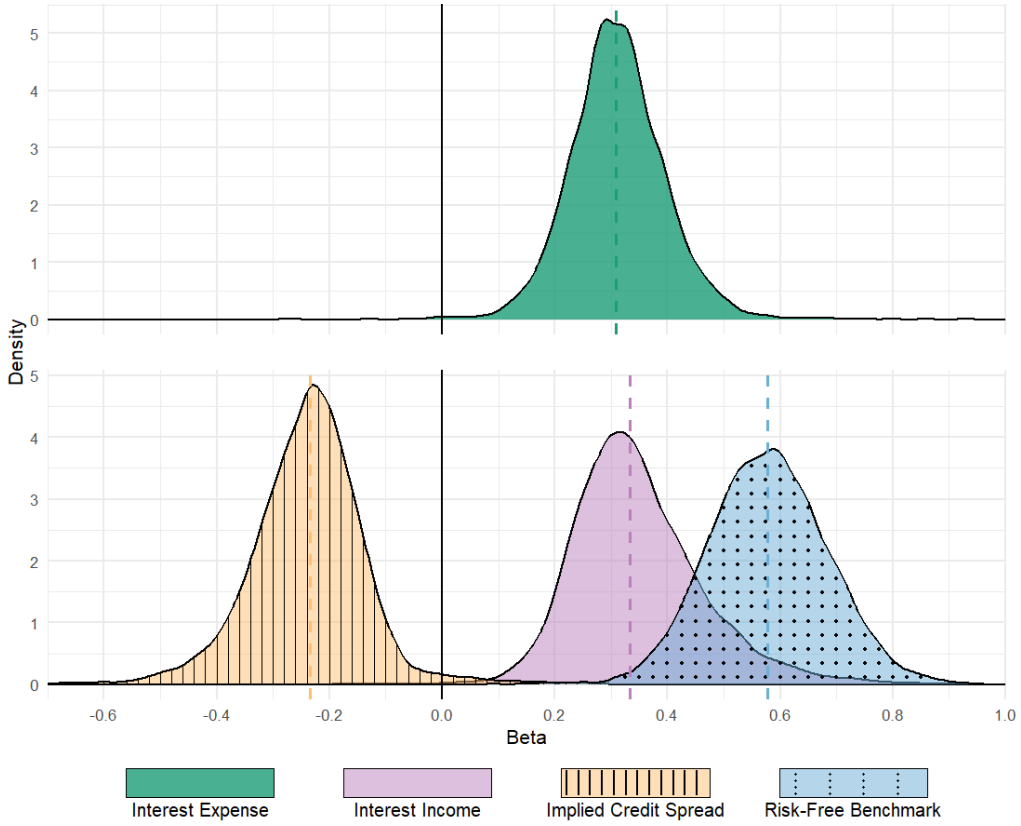
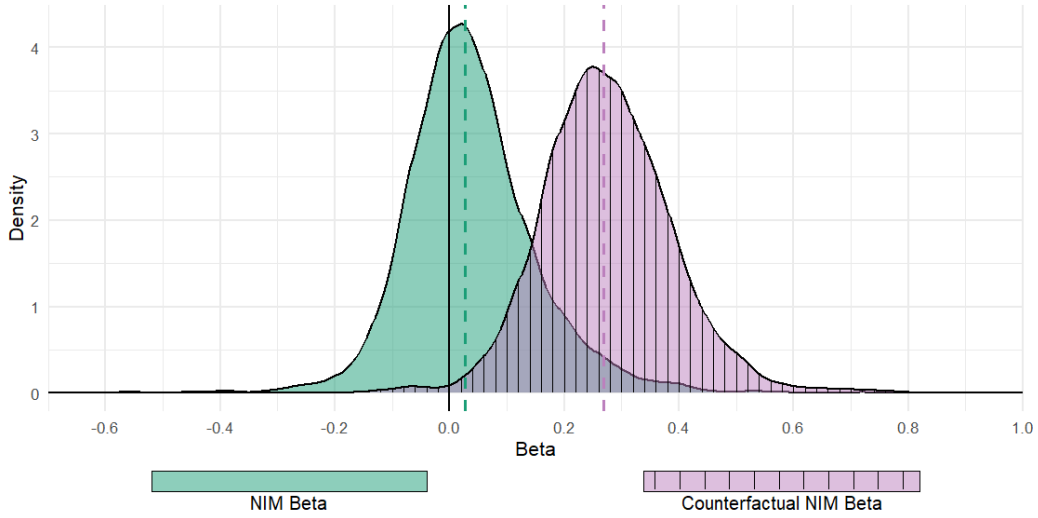


Figure 10: Distribution of bank-level NIM sensitivities to the federal funds rate. The figure plots kernel densities of bank-level sensitivity estimates (β_i) from regressions of quarterly changes in each variable (NIM and a counterfactual NIM that holds credit spreads constant) on the contemporaneous and three lagged quarterly changes in the federal funds rate; a variable's sensitivity equals the sum of the four coefficients. Dashed vertical lines mark cross-bank means; the solid vertical line marks zero. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001-2024.



5.2 Cross-Sectional Comparison of Bank-Level Sensitivities

Figure 11 plots bank-level pairs of sensitivities, with one sensitivity on the x-axis and another on the y-axis. Banks are sorted by the x-axis sensitivity and split into 100 equal-count bins, each point shows the within-bin means of the x- and y-axis sensitivities. Each panel also reports the fitted OLS slope from the cross-sectional regression $\beta_i^y = \alpha + \gamma\ \beta_i^x + \varepsilon_i$, where β^y is the y-axis and β^x the x-axis sensitivity, respectively, and stars indicate statistical significance at the 1% (***), 5% (**) and 10% (*) levels based on block-bootstrapped standard errors with 1000 repetitions. Appendix F provides the corresponding cross-sectional regression estimates.

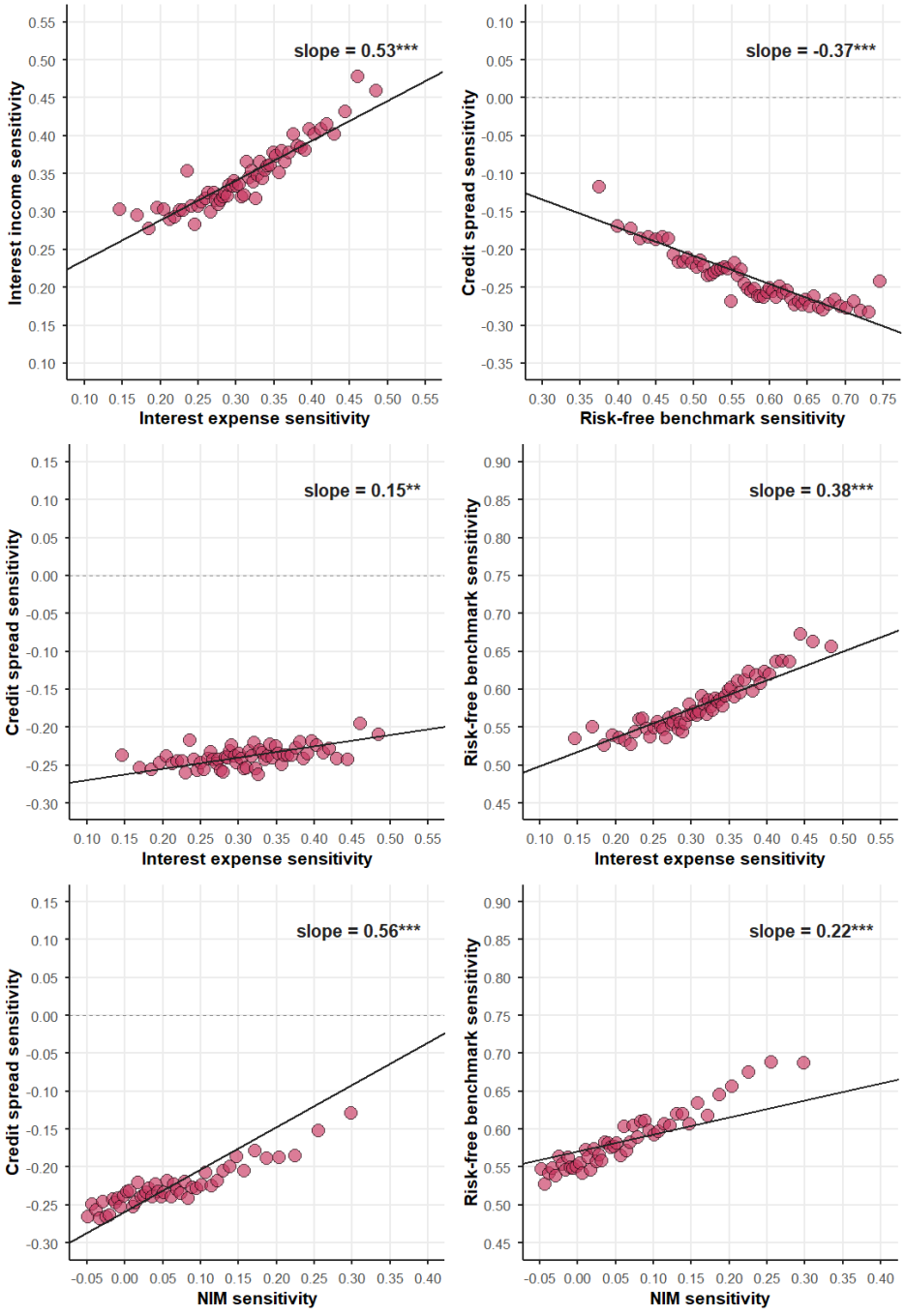
The top-left panel shows that banks with higher interest-expense sensitivities also exhibit higher interest-income sensitivities. Unlike Drechsler et al. (2021), I do not find a near one-to-one relationship as the slope is only 0.53, likely reflecting design and sample differences.[17] The

[17]For example, I do not winsorize sensitivities, use a different sample period, and apply less stringent data

slope captures cross-sectional co-movement and is not, by itself, evidence for or against NIM stability. NIM is stable if, within banks, income and expense sensitivities are close in levels. The top-right panel shows a negative cross-sectional relationship between risk-free benchmark and credit spread sensitivities, with banks that have stronger risk-free benchmark sensitivity also exhibiting more negative credit spread sensitivity, partly offsetting the former. The middle-left panel shows a positive but economically small relationship between credit spread sensitivities and interest expense sensitivities, implying that banks' spread adjustments are only weakly tied to how sensitive their interest expenses are to policy rate changes. By contrast, the middle-right panel shows a positive association between risk-free benchmark and interest expense sensitivities. This pattern is consistent with evidence that banks with greater deposit market power tend to both adjust deposit rates less if policy rates change, lowering interest expense sensitivities (DSS) and originate longer-term loans given more stable funding (Li et al. 2023), mechanically lowering risk-free benchmark sensitivities. In the bottom-left panel, bins with the most negative credit spread sensitivities coincide with NIM sensitivities clustered near zero (where most bins lie), suggesting that negative credit spread sensitivities help stabilize NIM. Cases where credit spread sensitivity is so negative that NIM sensitivity turns negative are rare, implying limited benefits from additional credit spread variability and likely higher costs. The bottom-right panel shows that banks with higher risk-free benchmark sensitivity also have higher NIM sensitivity, indicating that higher risk-free benchmark sensitivities are not fully offset by more negative credit spread sensitivities, so that NIM remains somewhat sensitive to policy rates for these banks.

cleaning. These choices better fit my setting, data coverage, and research question.

Figure 11: Cross-bank bin scatter plots of sensitivity estimates. Panels plot one sensitivity against another. Banks are sorted by the x-axis sensitivity and grouped into 100 equal-count bins, each bin reports the average x- and y-sensitivities for that bin. The fitted line in each panel is the OLS regression of the y-axis sensitivity on the x-axis sensitivity across banks, with the estimated slope reported. Significance levels: $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$ based on block-bootstrapped standard errors. Panels cover pairs among NIM, interest income, interest expense, the risk-free benchmark, and the credit spread sensitivity. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001-2024.



5.3 Aggregate Loan- and Security-Level Sensitivities

This subsection focuses on loan- and security-level risk-free benchmark rates and credit spreads to show that the aggregate bank-level patterns also hold within those asset classes.

Figure 12 plots the average loan- and security-level risk-free benchmark rates (black solid line for loans; gray dotted line for securities) and implied spreads (blue dash-dotted line for loans; yellow solid line for securities) alongside the federal funds rate (red dashed line). Both risk-free benchmark rates track the federal funds rate with a lag and are smoother. The security risk-free benchmark rate lags more and is smoother than the loan risk-free benchmark rate, consistent with longer repricing maturities and the lack of amortization on securities. Within each asset class, implied credit spreads move counter to policy rates: loan and security spreads widen when policy rates fall and compress when they rise, with securities showing the same pattern at lower levels. Taken together, the figure provides initial evidence that the aggregate bank-level results for risk-free benchmark and credit spread sensitivities also hold within loans and securities.

Next, I repeat the sensitivity analysis within asset classes. For each bank i and separately for loans and securities, I estimate sensitivities for the two components of the interest income rate, the risk-free benchmark and the implied credit spread, using Equation (25). To allow for asymmetry between policy rate increases and decreases, I also estimate subsample-specific sensitivities using Equation (26). Table 5 reports the corresponding sensitivity estimates. In Panel A, risk-free benchmark sensitivities are on average slightly larger for loans (0.699) than for securities (0.556), consistent with a higher share of loans scheduled to reprice within one quarter. Credit spread sensitivities are negative for both loans (-0.368) and securities (-0.364) on average. Interest income sensitivities average 0.331 for loans and 0.194 for securities. In Panel B, risk-free benchmark sensitivities are on average larger for policy rate increases than for decreases (loans: 0.776 vs. 0.668; securities: 0.615 vs. 0.543). Credit spread sensitivities are on average slightly less negative in increases for loans (-0.353 vs. -0.379) and much closer to zero in increases for securities (0.018 vs. -0.501), indicating that average credit spreads on new securities widen when policy rates fall but do not compress significantly when they

rise. Taken together, these results show that the countercyclical behavior of credit spreads and the relatively strong response of risk-free benchmark rates to policy rate changes are present within both loans and securities, indicating that the bank-level patterns are not solely driven by shifts between these asset classes.

Figure 12: Loan- and security-level risk-free benchmark rates and implied credit spreads. The figure plots the federal funds rate and equally weighted bank averages of the risk-free benchmark rates for loans and securities, and the implied credit spreads for loans and securities. Data: US commercial bank Call Reports, 2001-2024.

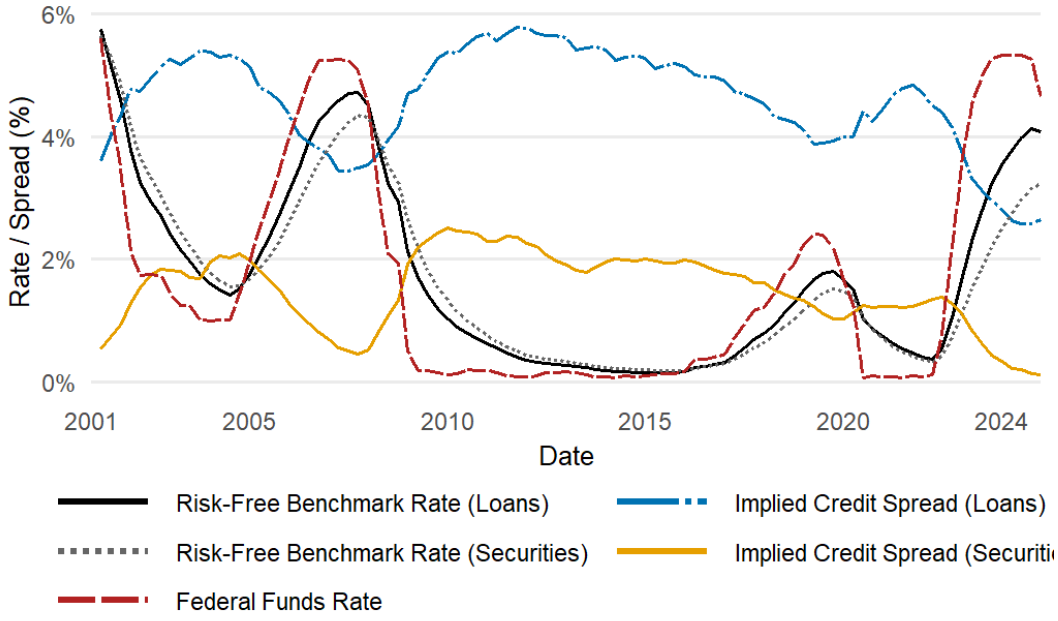


Table 5: Summary statistics for sensitivity regressions within loans and securities. This table reports bank-level sensitivities within loans and within securities for US commercial banks using quarterly data from 2001–2024. For each variable, a bank's sensitivity equals the sum of coefficients from a regression of its quarterly change on the contemporaneous and three lagged quarterly changes in the federal funds rate. The first panel reports sensitivities over the full sample; the second panel reports sensitivities estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, and "% Sig." is the share of banks with a statistically significant beta at the 5% level (Newey–West SEs). In Panel A, "% Sig.+" and "% Sig.−" are the corresponding one-sided tests, and $\overline{R}^2$ is the average R^2 across banks. Sample: 6,013 banks; 487,467 bank-quarter observations.

Panel A: Full Sample

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Loans						
Interest income	**0.331**	0.175	89%	91%	0%	0.243
Risk-free benchmark	**0.699**	0.102	100%	100%	0%	0.907
Credit spread	**−0.368**	0.152	94%	0%	96%	0.260
Securities						
Interest income	**0.194**	0.288	38%	48%	0%	0.131
Risk-free benchmark	**0.556**	0.146	100%	100%	0%	0.647
Credit spread	**−0.364**	0.298	80%	0%	86%	0.182

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Loans						
Interest income	**0.423**	0.297	80%	**0.289**	0.277	69%
Risk-free benchmark	**0.776**	0.134	100%	**0.668**	0.122	100%
Credit spread	**−0.353**	0.280	74%	**−0.379**	0.265	84%
Securities						
Interest income	**0.625**	1.291	35%	**0.043**	0.374	13%
Risk-free benchmark	**0.615**	0.209	100%	**0.543**	0.185	99%
Credit spread	**0.018**	2.270	26%	**−0.501**	0.431	76%

6 Implied Credit Spreads and Borrower Default Risk

In this section, I test whether increases in implied credit spreads predict subsequent increases in non-performing loans and credit-impaired securities using local projections (Jordà 2005). For each bank i, I first estimate the sensitivity of the implied credit spread as before,

$$R_{i,t} \;=\; \alpha_i \;+\; \sum_{\tau=0}^{3} \beta_{i,\tau}^{\text{spread}}\, \Delta f_{t-\tau} \;+\; \varepsilon_{i,t} \tag{28}$$

I then construct the fitted quarterly implied credit spread change,

$$\widehat{R}_{i,t} \;=\; \widehat{\alpha}_i \;+\; \sum_{\tau=0}^{3} \widehat{\beta}_{i,\tau}^{\text{spread}}\, \Delta f_{t-\tau}, \tag{29}$$

which I standardize within bank to obtain

$$z\widehat{R}_{i,t} = \frac{\widehat{R}_{i,t} - \overline{\widehat{R}}_{i,\cdot}}{\text{sd}(\widehat{R}_{i,\cdot})}. \tag{30}$$

I then test the effect of credit spread increases on non-performing loans and credit-impaired securities, which include non-accrual instruments and exposures past-due $\geq$ 90 days and still accruing.[18] I define

$$\text{NP}_{i,t}^{(L+S)} = \frac{\text{Non-Performing Loans}_{i,t} + \text{Credit-Impaired Securities}_{i,t}}{\text{Total Assets}_{i,t}} \tag{31}$$

Continuous-treatment local projections. Because non-performing exposures are defined at a 90-day threshold, default risk cannot materialize contemporaneously and may emerge with a lag as underlying borrower risk becomes observable in delinquency and non-accrual outcomes (Kim et al. 2024). Accordingly, I estimate panel local projections for $\ell = 0, \ldots, 16$

[18] Non-accrual exposures are those for which interest accrual has been suspended. "Past-due $\geq$ 90 days and still accruing" are exposures at least 90 days past due on principal or interest but continue to accrue interest.

quarters, corresponding to up to four years ahead:

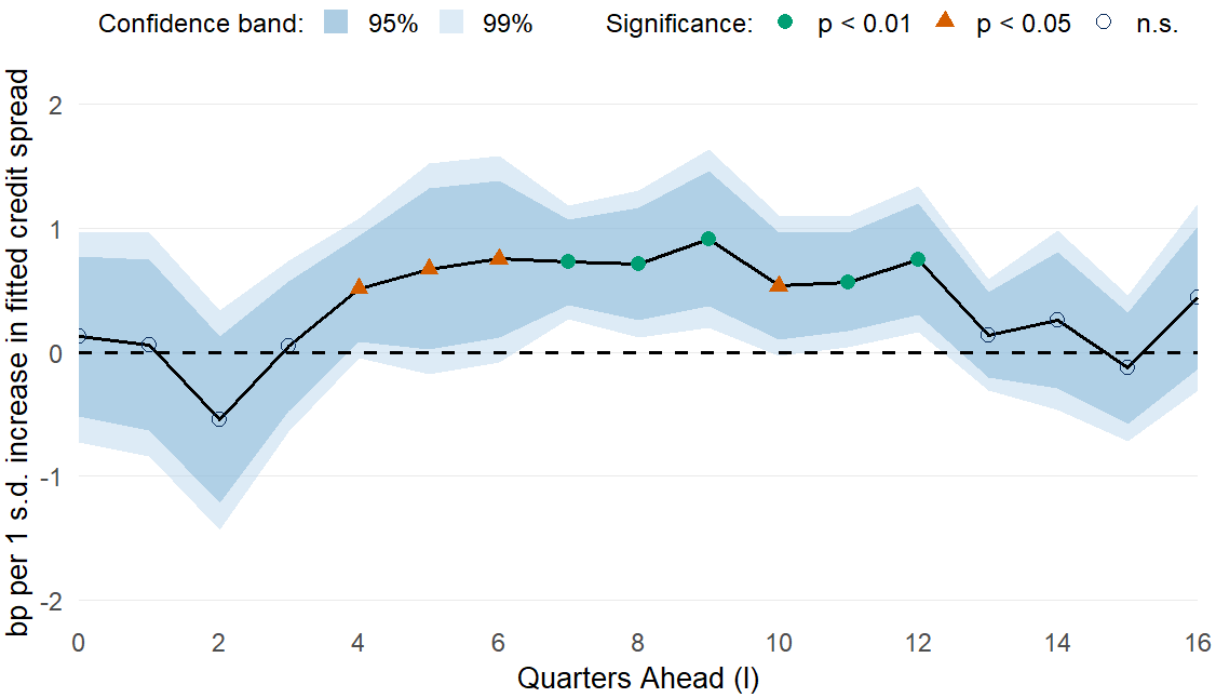
$$\Delta \log\Big(1 + \mathrm{NP}_{i,t+\ell}^{(L+S)}\Big) = \gamma_i + \psi_t + \delta_\ell \, z\widehat{R}_{i,t-1} + u_{i,t+\ell}, \tag{32}$$

Bank fixed effects γ_i and time fixed effects ψ_t absorb time-invariant cross-sectional heterogeneity and aggregate shocks, respectively. Standard errors are two-way clustered by bank and quarter.[19]

Figure 13 reports the continuous-treatment local-projection estimates showing that higher implied credit spreads are associated with subsequent increases in non-performing loans and credit-impaired securities. Following a within-bank one-standard-deviation increase in credit spreads, the average share of non-performing loans and credit-impaired securities increases by about 0.5 bp after one year. The response is statistically significant, persists for roughly nine quarters, and cumulates to about 6 bp at its peak before gradually returning toward zero. Given that the mean share of non-performing loans and credit-impaired securities is only about 88 bp, this constitutes an economically meaningful increase. Since a one–standard deviation increase in credit spreads corresponds to roughly 13 bp, and a 100 bp decrease in the policy rate raises credit spreads by about 24 bp, such a policy easing implies an increase in the share of non-performing loans and credit-impaired securities by about 11 bp, or roughly 13 percent, after three years. The pattern suggests that when banks originate or purchase assets at higher credit spreads following policy rate decreases, they take on higher borrower default risk. Appendix G shows that the results are robust to asymmetric responses, using local projections that separately identify the effects of positive and negative fitted credit spread changes.

[19] I use $\log(1 + x)$ rather than $\log(x)$ because the mean ratio of non-performing loans and credit-impaired securities to total assets is only about 0.0088 and ratios can equal zero.

Figure 13: Local projections of future non-performing loans and credit-impaired securities. The figure plots the local projection on the within-bank standardized fitted credit spread change with bank and time fixed effects. Standard errors are two-way clustered by bank and time. Markers: • $p < 0.01$, ▲ $p < 0.05$, ■ $p < 0.10$, ∘ non-significant. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001-2024.



Binary-treatment local projection. To alleviate concerns that the baseline estimates could be mechanically tied to aggregate monetary and macro conditions that are related to federal funds rate increases and decreases, I re-estimate the local projections in a binary-treatment DiD: within each date, I contrast the top- and bottom-quartile banks by fitted risk, yielding a purely cross-sectional comparison under identical aggregate conditions.

For horizons $\ell = 0, \ldots, 16$, I estimate

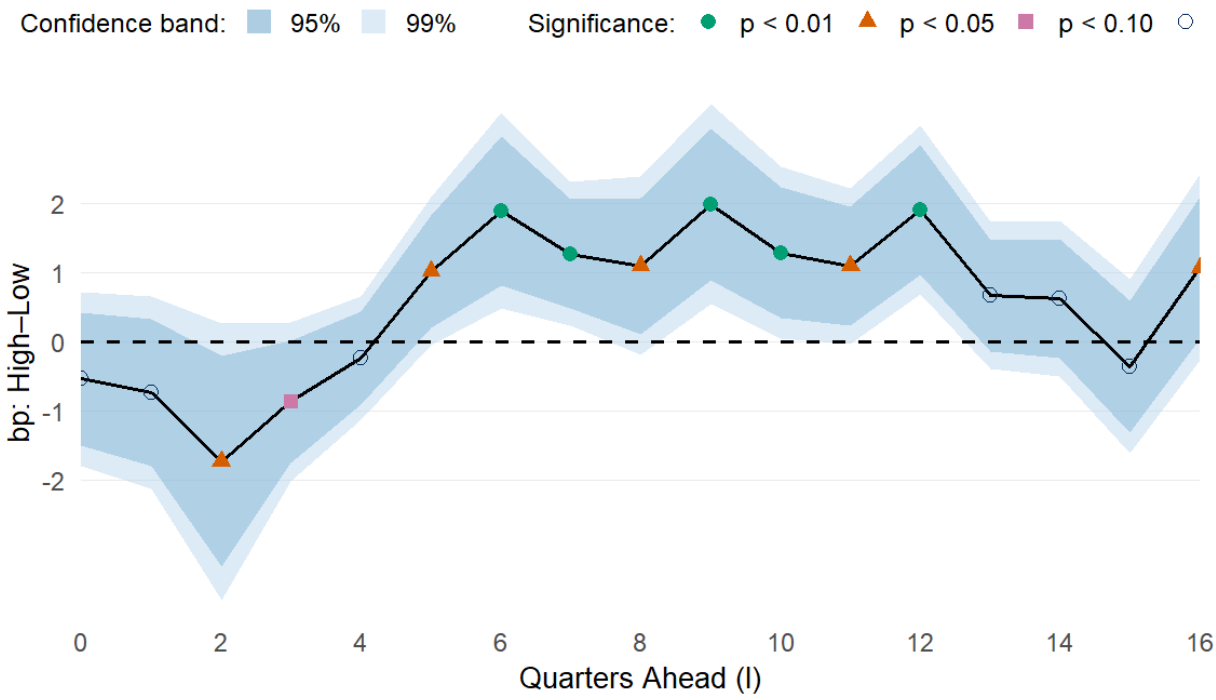
$$\Delta \log\Big(1 + \mathrm{NP}_{i,t+\ell}^{(L+S)}\Big) = \gamma_i + \psi_t + \beta_\ell \, H_{i,t-1} + u_{i,t+\ell}, \tag{33}$$

where γ_i and ψ_t are bank and time fixed effects. Standard errors are two-way clustered by bank and quarter. The treatment indicator $H_{i,t}$ is defined cross–sectionally within date t from the fitted risk $z\widehat{R}_{i,t}$ as

$$H_{i,t} = \begin{cases} 1, & \widehat{R}_{i,t} \geq Q_{0.75}\big(\widehat{R}_{\cdot,t}\big), \\ 0, & \widehat{R}_{i,t} \leq Q_{0.25}\big(\widehat{R}_{\cdot,t}\big), \end{cases} \qquad \text{and observations with } Q_{0.25} < \widehat{R}_{i,t} < Q_{0.75} \text{ are excluded.} \tag{34}$$

Figure 14 reports the binary-treatment local projection estimates. The High-Low gap turns positive after five quarters and cumulates to 12.6 bp after three years on average. Relative to the mean ratio of non-performing loans and credit-impaired securities to total assets (88 bp), this effect is economically meaningful in magnitude. The response remains positive for several horizons and is frequently significant at conventional levels, before gradually reverting toward zero. By defining treatment within date, this design relies on cross-sectional variation: banks in the top quartile of implied credit spread changes, relative to the bottom quartile on the same date, subsequently exhibit larger increases in the share of non-performing loans and credit-impaired securities, even if they start from lower levels at treatment.

Figure 14: Cross-sectional (High–Low) local projections of future non-performing loans and credit-impaired securities. The figure plots local projections of future non-performing loans and credit-impaired securities on a within-date High–Low indicator based on the fitted credit spread ($\widehat{R}_{i,t}$): High $\geq Q_{0.75}$, Low $\leq Q_{0.25}$. Standard errors are two-way clustered by bank and time. Markers: • $p < 0.01$, ▲ $p < 0.05$, ■ $p < 0.10$, ∘ non-significant. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001-2024.



7 Implied Credit Spreads and Duration Risk

In this section, I examine whether increases in implied credit spreads are associated with greater duration risk on bank balance sheets. I focus on contemporaneous changes in average asset maturities and in the one-year repricing gap between assets and liabilities as proxies for duration risk, following (Kim et al. 2024). As in the previous section, I use the fitted and within-bank standardized implied credit spread change $z\widehat{R}_{i,t}$, constructed in equations (28)–(30), to isolate variation in credit spreads driven by policy rate movements. I then estimate pooled panel regressions of the form:

$$\Delta Y_{i,t} = \gamma_i + \psi_t + \beta\, z\widehat{R}_{i,t} + \mathbf{X}'_{i,t}\theta + u_{i,t}, \tag{35}$$

where $Y_{i,t}$ captures measures of duration risk and balance-sheet composition. Bank fixed effects γ_i and time fixed effects ψ_t absorb time-invariant cross-sectional heterogeneity and aggregate shocks, respectively. $\mathbf{X}_{i,t}$ controls for profitability (return on assets), capitalization (equity to assets) and size (log total assets). Standard errors are two-way clustered by bank and quarter.

Table 6 shows that an increase in the fitted implied credit spread is associated with higher duration risk, proxied by average asset maturity and the repricing maturity gap between liabilities and assets. First, a one-standard-deviation increase in the fitted implied credit spread lengthens average asset maturities by about 0.45 weeks. Since a 100 bp decrease in the policy rate raises credit spreads by about 24 bp, such a policy easing implies a lengthening of average asset maturity by about 0.83 weeks. Second, a one-standard-deviation increase in the fitted implied credit spread widens the one-year repricing gap by roughly 22 basis points, where the gap is defined as the difference between the shares of liabilities and assets repricing within one year. As this difference is positive on average (see Table 1), the gap increase implies a greater mismatch between the repricing of liabilities and assets at short horizons. This widening is driven by both sides of the balance sheet. The share of liabilities repricing within one year increases by about 7 basis points, while the share of assets repricing within one year declines by about 15 basis points. Together, these results imply that credit spread increases following

policy rate declines are associated with shifts toward longer-term assets and a smaller share of assets repricing at short horizons. At the same time, policy rate declines are accompanied by inflows of short-term deposits into the banking sector, consistent with the evidence in Drechsler et al. (2017). The results are robust to controlling for bank profitability, capitalization, and size.

Table 6: Implied credit spreads and duration risk. This table reports pooled panel regression estimates of contemporaneous changes in measures of duration risk on changes in the fitted implied credit spread. Measures of duration risk include average asset maturity (measured in weeks), the one-year repricing gap (defined as the difference between the shares of liabilities and assets repricing within one year), the short-term liability share, and the short-term asset share, each defined as the share of liabilities or assets repricing within one year relative to total assets. Two-way clustered standard errors (bank and time) are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Sample: 6,150 banks, U.S. commercial bank Call Reports, 2001–2024.

	Δ Asset maturity (weeks)		Δ 1Y repricing gap (bp)		Δ 1Y short-term liabilities share (bp)		Δ 1Y short-term assets share (bp)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Credit Spread	0.451***	0.444***	22.343***	22.809***	7.176***	7.634***	-15.167***	-15.175***
	(0.099)	(0.097)	(3.420)	(3.595)	(2.367)	(2.550)	(1.896)	(1.902)
ROA		-6.320		-1009.832***		-588.001*		421.831***
		(4.491)		(343.842)		(323.816)		(107.322)
Equity/Assets		20.746***		504.635***		-20.531		-525.166***
		(2.489)		(161.742)		(130.811)		(55.123)
ln(Assets)		-0.516***		-2.925		11.307***		14.232***
		(0.132)		(5.796)		(4.181)		(4.343)
Bank and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	495k	494k	495k	494k	495k	494k	495k	494k
R^2	0.031	0.032	0.467	0.492	0.546	0.586	0.032	0.033

Table 7: Implied credit spreads and balance-sheet composition. This table reports pooled panel regression estimates of contemporaneous changes in measures of duration risk and balance-sheet composition on changes in the fitted implied credit spread. These measures include changes in the maturities of securities and loans (measured in weeks), changes in asset shares (measured in basis points of total assets) for loans, securities and interbank asset and asset growth. Two-way clustered standard errors (bank and time) are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Sample: 6,150 banks, U.S. commercial bank Call Reports, 2001–2024.

	Δ Sec maturity (weeks)		Δ Loan maturity (weeks)		Δ Loans/Assets (bp)		Δ Sec/Assets (bp)		Δ Interbank/Assets (bp)		Asset growth (bp)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Credit Spread	0.185	0.185	0.032	0.035	15.049***	14.287***	-31.476	-31.496	-28.333***	-27.757***	0.305	-2.116
	(0.125)	(0.121)	(0.048)	(0.048)	(2.005)	(1.909)	(29.241)	(29.325)	(2.643)	(2.604)	(3.290)	(3.310)
ROA		-1.935		-7.800*		160.155		28.699		-44.941		2298.162***
		(10.110)		(4.187)		(115.244)		(59.732)		(95.748)		(297.365)
Equity/Assets		21.959***		4.380***		982.222***		57.472		-891.027***		1542.066***
		(3.840)		(1.660)		(104.610)		(167.358)		(93.265)		(178.888)
ln(Assets)		-0.441		-0.169		-45.331***		23.176**		25.679***		-58.771***
		(0.317)		(0.110)		(4.167)		(9.959)		(4.160)		(10.851)
Bank and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	487k	486k	495k	493k	495k	494k	495k	494k	495k	494k	495k	494k
R^2	0.025	0.025	0.025	0.025	0.065	0.076	0.225	0.226	0.042	0.048	0.100	0.110

The increase in overall asset maturity and the reduction in the share of assets repricing at short horizons could arise from a lengthening of maturities within loans and securities, shifts in balance-sheet composition across asset classes, or balance-sheet growth. Table 7 distinguishes between these mechanisms and shows that a one–standard deviation increase in the fitted implied credit spread does not significantly affect the average maturity of loans or securities. Instead, the increase in overall asset maturity is driven by shifts in balance-sheet composition. In particular, the share of loans increases by about 15 basis points, while the share of interbank assets declines by roughly 28 basis points. This change in asset composition increases the average asset maturity as interbank assets, comprising federal funds sold, reverse repurchase agreements, and interest-bearing balances at depository institutions, reprice at very short maturities, while loans reprice on average at longer horizons (see Table 2).At the same time, total assets do not change significantly, indicating that banks reallocate assets rather than expand or shrink their balance sheets. The share of securities also remains unchanged. Together, these results imply that the increase in duration risk following credit spread increases arises primarily from a balance-sheet composition shift toward loans and away from interbank assets.

8 Conclusion

This paper documents that the stability of net interest margins despite large movements in the federal funds rate owes importantly to adjustments in credit spreads on new assets. I construct a bank-specific risk-free benchmark rate for assets and infer the implied credit spread as the difference between the observed interest income rate and this benchmark. The approach requires no instrument-level interest rate data and delivers credit spread estimates for banks' aggregate asset portfolios. My contribution shows that, absent adjustments in asset-side credit spreads, average NIM would expand when the federal funds rate rises and compress when it falls, exposing most banks to interest rate risk. NIM stability implies that most banks add new assets to their balance sheets at higher credit spreads when the policy rate falls and at lower spreads when it rises. The results are robust to a range of alternative

specifications and hold within both loans and securities. Higher implied credit spreads are associated with greater credit risk, measured by higher subsequent shares of non-performing loans and credit-impaired securities. They are also associated with greater duration risk, reflected in longer asset maturities driven by a reallocation from interbank assets toward loans, and in larger maturity mismatches between short-term assets and short-term liabilities. Together, these results show that reductions in interest rate risk are accompanied by shifts in exposure toward credit and duration risk, consistent with banks reaching for yield when policy rates decline.

These results raise the question whether current regulatory frameworks adequately capture how banks manage interest rate risk through balance-sheet adjustments. Stress tests and capital frameworks that treat interest rate risk and other risks embedded in credit spreads in isolation may understate their linkage. The evidence, therefore, supports tighter joint modeling in stress tests, linking interest rate risk and the broader risks associated with credit spread adjustments.

Apart from documenting that implied credit spread increases are associated with shifts in lending risk, this paper does not take a stand on the full set of mechanisms behind credit spread changes. Such changes may also reflect changes in liquidity, term premia, market power, or aggregate forces such as the price of risk or the demand for credit. Disentangling these mechanisms and the cross-sectional heterogeneity in banks' credit spread sensitivities awaits future work. This heterogeneity likely reflects differences in business models, funding mixes, maturity profiles, governance, local credit market conditions, binding constraints, and risk exposures.

Taken together, the evidence suggests that banks manage NIM stability by adjusting credit spreads on new assets in response to policy rate movements, providing a novel asset-side explanation of how NIM stability is achieved.

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Appendix

A Data Preparation Details

Call Report Schedules. Call Reports are organized into schedules. I primarily use quarterly average balance sheet data from schedule RC-K and income statement data from schedule RI. Repricing-maturity volumes are reported as memoranda items, within RC-B for securities, RC-C for loans, and RC-E for deposits. The WRDS Call Report extracts provide item-level fields rather than assembled schedules. For example, quarterly average total assets appear under codes RCFD3368 (Form 031) and RCON3368 (Forms 041/051). The codes can differ across forms, which form a bank files depends on its size and whether it has foreign offices. From these fields, I reconstruct the schedules in line with the FFIEC Call Report forms and instructions. I rely both on current and historical instructions to map items consistently over time and to handle definition changes.

Commercial Bank Filter. Call Reports are filed by various institutions, identified by charter type. I focus on commercial banks (charter type 200), which derive most of their income from interest (on average 88%). Because institutions' charter types can change over time, for example to respond to changing regulatory requirements, I use time-series charter data from the National Information Center (NIC)[20].

Bank Holding Company Data. In robustness tests, I estimate sensitivities on the fully consolidated level, where capital requirements apply. This includes top-tier BHCs and standalone commercial banks not owned by another domestic or foreign parent. Since key information on repricing maturities and certain accounting items is only available at the commercial bank level, I aggregate commercial banks to their corresponding top-tier BHCs using relationship data from the NIC. I supplement the aggregated Call Report data with holding company data from Form FR-Y-9C; the data sources and reporting periods for this form are the same as for the Call Report forms described above. I remove all observations

[20]The NIC is maintained by the FFIEC.

where the difference between aggregated Call Report assets and BHC-level assets exceeds 20%. After this adjustment, aggregated Call Report assets differ from BHC-level assets by about 1% on average.

B Algorithm Details

Sub-bucketing of repricing maturities. Repricing maturity buckets are split into quarterly sub-buckets following Begenau et al. (2025), assuming a maximum maturity of 30 years (120 quarters). The <3 months bucket is assigned entirely to the first quarter; the 3-12 months, 1-3 years, and 3-5 years buckets are allocated uniformly across the quarters they span. The longest buckets, 5-15 years and >15 years, use exponentially declining weights to place relatively more mass on nearer quarters. One-half of the mass is assigned to the first 25% and 20% of quarters within those buckets, respectively (versus 50% under uniform allocation).[21] Within the first year, floating-rate and maturing assets are treated separately.[22]

Algorithm to estimate risk-free benchmark rates. Quarterly sub-buckets are mapped to the federal funds rate prevailing at origination or purchase or at the last rate adjustment. The procedure follows Begenau et al. (2025), who use a similar algorithm to transform loans into portfolios of zero-coupon bonds and map their face values to discount rates. For simplicity, I assume linear amortization for loans rather than amortization via a constant annuity schedule.[23] The algorithm is initialized in t=1997:Q2, when repricing maturity data first becomes available. To limit the influence of this initialization, the empirical analysis begins in 2001:Q1, by which time about 95% (loans) and 97% (securities) of initially assigned risk-free benchmark rates have rolled out of the first sub-bucket, with even larger roll-off at longer maturities.

Algorithm setup and initialization. For each bank, and separately for loans and securities, and

[21] Results are robust to assuming uniform distributions within the two longest buckets.

[22] Distinguishing fixed- from floating-rate assets does not significantly impact the estimation but helps separate rate changes attributable to each type.

[23] A constant annuity schedule would require rate estimates within repricing maturity sub-buckets and asset-type risk estimates, adding complexity and additional assumptions not needed here. Results are however robust to implementing a constant-annuity schedule with bank-level loan and security rates that are constant across sub-buckets and asset subgroups.

within each, for fixed- and floating-rate assets, I maintain two $T \times M$ matrices:[24] volumes $V_{t,m,a}$, assets scheduled to reprice in m quarters at t for asset class $a \in \{$loans fixed, loans floating, securities fixed, securities floating$\}$, and attached risk-free benchmark rates $F_{t,m,a}$, the weighted average of the federal funds rates prevailing at the assets' initial pricing or last reset. I initialize the algorithm in 1997:Q2 by setting $F_{0,m,a} = f_{1997:Q2}$ for all m, with $f_{1997:Q2}$ being the federal funds rate for this quarter. Thus, for banks active in $t = 0$ all loans and securities are treated as newly originated or purchased at that quarter's policy rate.

Roll-down rules. Each quarter, positions move one sub-bucket closer to maturity or rate reset. Loans amortize linearly, securities do not.[25] I track amortization and premature sales in matrices $A_{t,m,a}$ and $P_{t,m,a}$ and their risk-free benchmark rates in $F^A_{t,m,a}$ and $F^P_{t,m,a}$, respectively.

Carried over balances and amortization. Between $t-1$ and t, balances shift one quarter closer to maturity or next rate reset. The carried-over balances $V^{\text{carry}}_{t,m,a}$, amortization volumes $A_{t,m,a}$ (loans only) and attached risk-free benchmark rates $F^{\text{carry}}_{t,m,a}$ and $F^A_{t,m,a}$ evolve as:

$$\textbf{Loans:} \quad V^{\text{carry}}_{t,m,a} = \frac{m}{m+1} V_{t-1,m+1,a}; \quad A_{t,m,a} = \frac{1}{m+1} V_{t-1,m+1,a}; \quad F^{\text{carry}}_{t,m,a} = F^A_{t,m,a} = F_{t-1,m+1,a}$$

$$\textbf{Securities:} \quad V^{\text{carry}}_{t,m,a} = V_{t-1,m+1,a}; \qquad F^{\text{carry}}_{t,m,a} = F_{t-1,m+1,a}$$

Total quarterly amortization and its associated risk-free benchmark rate for all m are given by:

$$A_{t,a} = \sum_{m=1}^{M-1} A_{t,m,a}; \qquad F^A_{t,a} = \frac{\sum_{m=1}^{M-1} A_{t,m,a} \times F^A_{t,m,a}}{A_{t,a}} \quad (\text{if } A_{t,a} > 0)$$

Premature sales. If the observed bucket volume is smaller than the carried-over volume, the shortfall is recorded as a premature sale. To avoid netting across subgroups, I compute premature sales separately for the two loan and three securities subgroups s.[26] Let $P^{\text{agg}}_{t,m,a}$ the observed premature sale from aggregate assets, $P^s_{t,m,a}$ the premature sale of subgroup s, and

[24] By construction from the Call Reports, floating-rate instruments have repricing maturity ≤ 1 year, hence $M \leq 4$.

[25] For securities, I assume bullet repayment, which closely matches the structure of treasury and agency securities.

[26] Risk-free benchmark rates are not constructed at subgroup levels because no matching interest income rate exists at that granularity.

$F^P_{t,m,a}$ the risk-free benchmark rate associated with premature sales:

$$P^{\text{agg}}_{t,m,a} \;=\; \left(V^{\text{carry}}_{t,m,a} - V_{t,m,a}\right)_+; \qquad P^{\text{s}}_{t,m} \;=\; \left(V^{\text{carry},s}_{t,m,a} - V^{a}_{t,m,a}\right)_+; \qquad F^P_{t,m,a} = F_{t-1,m+1,a}$$

The total premature sale for bucket m, $P_{t,m,a}$, the total premature sale for all m, $P_{t,a}$, and its associated risk-free benchmark rate $F^P_{t,a}$ are given by:

$$P_{t,m,a} = \sum_s (P^s_{t,m,a})_+; \qquad P_{t,a} = \sum_{m=1}^{M-1} P_{t,m,a}; \qquad F^P_{t,a} = \frac{\sum_{m=1}^{M-1} P_{t,m,a} \times F^P_{t,m,a}}{P_{t,a}} \quad (\text{if } P_{t,a} > 0)$$

The excess premature sale not captured by the aggregate estimate is $P^{\text{excess}}_{t,m,a} = P_{t,m,a} - P^{\text{agg}}_{t,m,a}$.

New assets. The incremental flow in (t, m, a), $V^{\text{new}}_{t,m,a}$, is the excess of the observed volume over the carried-over volume plus the excess premature sale and is priced at the current policy rate f_t. Formally:

$$V^{\text{new}}_{t,m,a} = \max\{\, V_{t,m,a} - V^{\text{carry}}_{t,m,a} + P^{\text{excess}}_{t,m,a},\, 0\,\}, \qquad F^{\text{new}}_{t,m,a} = f_t,$$

Risk-free benchmark rates. The risk-free benchmark rate for sub-bucket m is:

$$F_{t,m,a} = \frac{F^{\text{carry}}_{t,m,a}\left(V^{\text{carry}}_{t,m,a} - P^{\text{excess}}_{t,m,a}\right) + f_t\, V^{\text{new}}_{t,m,a}}{V_{t,m,a}} \quad (\text{if } V_{t,m,a} > 0)$$

The asset-class-level benchmark rate aggregates across sub-buckets:

$$r^{\text{bench}}_{f,t,a} = \frac{\sum_{m=1}^{M} V_{t,m,a}\, F_{t,m,a}}{\sum_{m=1}^{M} V_{t,m,a}} \quad \left(\text{if } \sum_{m=1}^{M} V_{t,m,a} > 0\right)$$

where $a \in \{\text{loans fixed, loans floating, securities fixed, securities floating}\}$. Let $A^{\text{bal}}_{t,a}$ denote the balance sheet amount of asset class a, $A^{\text{bal}}_{t,\text{oth}}$ the amount of interbank and $A^{\text{bal}}_{t,\text{total}}$ the amount of total assets. Because total assets include non-interest-earning items, $\sum_a A^{\text{bal}}_{t,a} + A^{\text{bal}}_{t,\text{oth}} \le A^{\text{bal}}_{t,\text{total}}$.

The bank-wide risk-free benchmark rate is:

$$r_{f,t}^{\text{bench, algo}} = \frac{\sum_a A_{t,a}^{\text{bal}}\, r_{f,t,a}^{\text{bench}} + A_{t,\text{oth}}^{\text{bal}}\, f_t}{A_{t,\text{total}}^{\text{bal}}}$$

Risk-free benchmark rate change. As outlined in Section 3, the change in the bank-wide risk-free benchmark rate equals the share of interest-earning assets times the change in their benchmark: $\Delta r_{f,t}^{\text{bench}} = \lambda_{t-1}\, \Phi_t^{r_f^{\text{bench}}}$. The change in the risk-free benchmark rate of interest-earning assets, $\Phi_t^{r_f^{\text{bench}}}$, is driven by: (i) the share of floating-rate assets that reset this quarter, η_t^{floating}; (ii) the share of newly added assets that replace exiting ones, $\eta_t^{\text{replacement}}$; and (iii) the share of newly added assets due to growth, η_t^{growth}. Following Equation (14):

$$\begin{aligned}
\Phi_t^{\text{r}_f\text{-update}} = \quad & \eta_t^{\text{floating}} \quad (f_t - r_{f,t-1}^{\text{bench,floating}}) \\
+ \ & \eta_t^{\text{replacement}}\, (f_t - r_{f,t-1}^{\text{bench,maturing}}) \\
+ \ & \eta_t^{\text{growth}} \quad (f_t - r_{f,t-1}^{\text{bench,average}})
\end{aligned}$$

In the data, $\eta_t^{\text{replacement}}$ aggregates replacements for three exit channels - scheduled maturity, amortization, and premature sale:

$$\eta_t^{\text{replacement}} = \eta_t^{\text{scheduled}} + \eta_t^{\text{amortization}} + \eta_t^{\text{premature}}$$

With $r_{f,t-1}^{\text{bench, scheduled}}$, $r_{f,t-1}^{\text{bench, amortization}}$ and $r_{f,t-1}^{\text{bench, premature}}$ denoting the associated $t-1$ risk-free benchmark rates for those channels, respectively. Additionally, η_t^{floating} comprises floating-rate loans and securities as well as interbank assets. Estimating $\Delta r_{f,t}^{\text{bench}}$ via this decomposition is numerically equivalent to constructing the level $r_{f,t}^{\text{bench, algo}}$ above and differencing. The decomposition, however, resolves a timing mismatch in the data: repricing volumes are reported as of quarter-end, whereas rates are based on quarterly average values. It also helps to clarify which assets drive the change. Appendix C shows that the difference between the decomposition-based risk-free benchmark rate change $\Delta r_{f,t}^{\text{bench}}$ and the average-asset-based estimate of $\Delta r_{f,t}^{\text{bench, algo}}$ is minor. For the time-series figures displaying rates, I use $r_{f,t}^{\text{bench, algo}}$.

Floating-rate and scheduled maturity shares. The shares of floating-rate (fixed-rate) assets that reset (mature) at t are identified from the previous periods' "$<$ 3 months" repricing-maturity buckets (i.e., $m = 1$) of floating-rate (fixed-rate) assets, divided by the total volume of quarterly interest-earning assets at t, $A^{\text{bal}}_{t,\text{int}} = \sum_a A^{\text{bal}}_{t,a} + A^{\text{bal}}_{t,\text{oth}}$. Define float = loans floating + securities floating and fixed = loans fixed + securities fixed and aggregate volumes and average rates across respective asset classes within a. Then:

$$\textbf{Float: } \eta^{\text{floating}}_t = \frac{0.5\, V_{t-1,1,\text{float}} + 0.5\, V_{t-2,1,\text{float}}}{A^{\text{bal}}_{t,\text{int}}};\ r^{\text{bench, floating}}_{f,t-1} = 0.5\, F_{t-1,1,\text{float}} + 0.5\, F_{t-2,1,\text{float}},$$

$$\textbf{Fixed: } \eta^{\text{scheduled}}_t = \frac{0.5\, V_{t-1,1,\text{fixed}} + 0.5\, V_{t-2,1,\text{fixed}}}{A^{\text{bal}}_{t,\text{int}}};\ r^{\text{bench, scheduled}}_{f,t-1} = 0.5\, F_{t-1,1,\text{fixed}} + 0.5\, F_{t-2,1,\text{fixed}}$$

Assuming the scheduled resets (exits) are uniformly distributed over the subsequent three-month window, one half of the amount scheduled to reprice within the next three months reported in $t-1$ and one half of that in $t-2$ affect rates at quarter t.[27]

Amortization and premature sale shares. The shares of amortizing loans and premature-sales are obtained by: [28]:

$$\eta^{\text{amortization}}_t = \frac{0.5\, A_t + 0.5\, A_{t-1}}{A^{\text{bal}}_{t,\text{int}}};\quad r^{\text{bench,amortization}}_{f,t-1} = \frac{0.5\, A_t\, F^A_t + 0.5\, A_{t-1}\, F^A_{t-1}}{0.5\, A_t + 0.5\, A_{t-1}};$$

$$\eta^{\text{premature}}_t = \frac{0.5\, P_t + 0.5\, P_{t-1}}{A^{\text{bal}}_{t,\text{int}}};\quad r^{\text{bench,premature}}_{f,t-1} = \frac{0.5\, P_t\, F^P_t + 0.5\, P_{t-1}\, F^P_{t-1}}{0.5\, P_t + 0.5\, P_{t-1}}$$

That is, quarterly averages are proxied by a 50% end-of-t and 50% end-of-$t-1$ weighting.

Growth share. The share of new assets due to growth in interest-earning assets and the risk-free benchmark rate on the pre-existing assets are given by:

$$\eta^{\text{growth}}_t = \frac{0.5(V_t - V_{t-1}) + 0.5(V_{t-1} - V_{t-2})}{A^{\text{bal}}_{t,\text{int}}} \quad r^{\text{bench,average}}_{f,t-1} = 0.5\, r^{\text{bench,algo}}_{f,t-1} + 0.5\, r^{\text{bench,algo}}_{f,t-2}$$

[27] For intuition, if all assets scheduled to reprice within three months reported in quarter t reprice on the last day of $t+1$, the repricing affect rates in $t+2$, not $t+1$.

[28] Aggregating across all asset classes a, i.e. $A_t \equiv \sum_a A_{t,a}$, $P_t \equiv \sum_a P_{t,a}$, $F^A_t \equiv \frac{\sum_a A_{t,a} F^A_{t,a}}{\sum_a A_{t,a}}$ and $F^P_t \equiv \frac{\sum_a P_{t,a} F^P_{t,a}}{\sum_a P_{t,a}}$

When growth is negative, I assume not all exiting assets are reinvested, i.e. $\eta_t^{\text{replacement}}$ declines accordingly. If negative growth exceeds $\eta_t^{\text{replacement}}$, I treat the remainder as premature sales.[29]

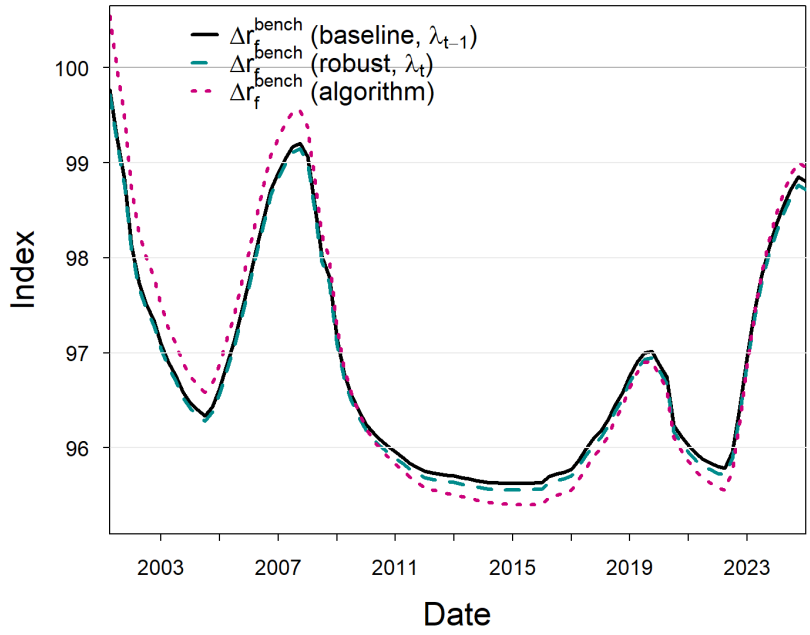
These components together yield the change in the risk-free benchmark on total assets, $\Delta r_{f,t}^{\text{bench}}$. The change in credit spreads is obtained residually, $\Delta s_t \equiv \Delta r_t^{\text{inc}} - \Delta r_{f,t}^{\text{bench}} - \frac{r_t^{\text{inc}}}{\lambda_t} \Delta \lambda_t$. For time-series figures on levels, I also report the algorithm-implied spread $s_t \equiv r_t^{\text{inc}} - r_{f,t}^{\text{bench, algo}}$.

C Comparison of Risk-Free Benchmark Rate Changes: Decomposition vs. Algorithm

Figure 15 plots level indices for three estimates of the quarterly change in the risk-free benchmark: baseline decomposition with lagged interest-earning asset weights λ_{t-1} (solid black), a robustness variant with contemporaneous weights λ_t (dashed teal), and the algorithmic average-asset estimate (dotted magenta). All three series move nearly indistinguishably over time; the algorithmic estimate is slightly more volatile. The figure shows that any difference between the algorithmic estimate and the decomposition estimates is minor.

[29]The second case is rare but can occur due to timing differences between repricing volumes recorded at quarter-end and the rates based on quarterly-average balances. I assess negative growth separately for loans and for securities so that any residual contraction is attributed to premature sales where they actually occur.

Figure 15: Decomposition vs. direct estimate of $\Delta r_{f,t}^{\text{bench}}$. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001-2024.



D Bank Summary Statistics

Table 8: Bank summary statistics. This table reports summary statistics for US commercial banks, 2001-2024, covering net interest margin, total assets (quarterly averages); balance-sheet shares (all over assets); repricing maturities (assets and liabilities); and the share of assets adjusting each quarter (η). Means are computed per bank and then averaged across banks. Medians and standard deviations are cross-sectional. 'Range' reports the 10th-90th cross-sectional percentiles. Sample: 6,150 banks; 495,439 bank-quarter observations.

	Central Tendency			Range	
	Mean	Median	St.Dev.	P10	P90
NIM (%)	3.62	3.58	0.66	3.00	4.26
Assets (USD bn)	2.22	0.17	38.67	0.04	0.95
Balance-Sheet Shares					
Loans	0.63	0.65	0.14	0.45	0.78
Securities	0.22	0.20	0.13	0.07	0.40
Insured Deposits	0.57	0.57	0.09	0.46	0.67
Uninsured Deposits	0.12	0.11	0.06	0.06	0.20
Wholesale Funding	0.20	0.19	0.07	0.12	0.29
Equity	0.11	0.10	0.04	0.08	0.14
Repricing Maturities					
Assets	3.80	3.57	1.48	2.16	5.74
Liabilities	0.62	0.59	0.28	0.30	0.98
Adjusting Share					
Total (η) (%)	36.74	35.15	11.12	24.08	51.19
Replacement of Exits (%)	18.83	17.85	6.90	11.10	27.77
Growth (%)	1.60	1.40	1.18	0.52	3.09
Floating (%)	16.28	14.38	9.24	7.02	27.80

E Sensitivity Analysis Robustness Tests

This appendix presents alternative specifications for the sensitivity analysis. As in Equation (25), I estimate per-bank sensitivities on the full sample, and as in Equation (26), I estimate them separately for policy rate increases and decreases.

Alternative construction of the risk-free benchmark and implied credit spread. I compare three constructions of the risk-free benchmark and implied credit spread. (i) Baseline uses Equation (16) with λ_{t-1}. (ii) A symmetric alternative replaces λ_{t-1} with λ_t. (iii) An "algorithm" construction computes benchmark rates and spreads directly from the algorithm's level estimates, bypassing the decomposition. The results are reported in Table 9. Across these alternatives, cross-bank means, standard deviations, and significance shares for the sensitivity estimates are similar.

Focusing on the largest 10% and 5% of banks. I report average sensitivities for the largest 10% and 5% of banks, measured by CPI-adjusted average assets. These banks manage 91% and 88% of aggregate assets, respectively. The results are reported in Table 10 and Table 11. As I focus on progressively larger banks, credit spread sensitivities decrease and interest expense sensitivities increase, but the results are qualitatively similar.

Entire sample window. I re-estimate all sensitivities on the full 1997-2024 sample (rather than 2001-2024), which allows early observations being affected by the initialization assumption. The results are reported in Table 12 and are close to the baseline.

Good vs. bad financial conditions. Table 13 reports sensitivity estimates obtained by splitting the sample between good and bad aggregate financial conditions. The National Financial Conditions Index (NFCI) and Adjusted National Financial Conditions Index (ANFCI) are obtained from the Chicago Fed. The NFCI aggregates information from money markets, debt and equity markets, and the shadow banking system to summarize overall financial conditions, while the ANFCI removes the influence of cyclical macroeconomic factors so that it reflects financial conditions independent of the business cycle. For each index, quarters are classified as being under "good" and "bad" financial conditions according to the index

definition, using quarterly averages of the weekly series, where positive values indicate relatively bad conditions and negative values indicate relatively good conditions. I estimate per-bank sensitivities separately in these two regimes as:

$$\Delta X_{it} = \alpha_i + \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,\text{good}} \, \Delta f_{t-\tau} \, \mathbf{1}\{\text{FC}_{t-\tau} \leq 0\} + \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,\text{bad}} \, \Delta f_{t-\tau} \, \mathbf{1}\{\text{FC}_{t-\tau} > 0\} + \epsilon_{it}, \tag{36}$$

$$\beta_i^{X,\text{good}} = \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,\text{good}}, \qquad \beta_i^{X,\text{bad}} = \sum_{\tau=0}^{3} \beta_{i,\tau}^{X,\text{bad}}, \tag{37}$$

The NFCI and ANFCI splits yield qualitatively similar results and are broadly consistent with the baseline estimates, while showing substantially higher cross-bank dispersion in sensitivities during periods of bad financial conditions.

Alternative algorithms. I also consider variants of the algorithm that reduce the effective share of assets adjusting their rates each quarter: (i) geometric loan amortization under a constant-annuity schedule, where loan and security rates are held fixed within sub-buckets and asset subgroups (ii) no loan amortization and (iii) uniform (rather than exponentially declining) weights in the longest repricing-maturity buckets. The results are reported in Table 14. Mechanically, these changes lower the risk-free benchmark sensitivity. Because credit spread sensitivities are negative for most banks, their magnitudes become less negative as well. In the most extreme case without loan amortization, the mean credit spread sensitivity falls to about -0.149 and the share of significant estimates declines to 61%. The qualitative conclusions are unchanged.

Top-tier bank holding company (BHC) and standalone commercial bank level. I estimate sensitivities at the top-tier bank holding company (BHC) and standalone commercial bank levels, aggregating subsidiary commercial banks to their highest-level parent BHC and treating standalone institutions individually. The results, reported in Table 15, are qualitatively and quantitatively consistent with the commercial-bank-level estimates.

Table 9: Robustness of risk-free benchmark and credit spread sensitivities to construction. This table reports summary statistics of bank-level sensitivities for US commercial banks using quarterly data from 2001–2024. For each variable, a bank's sensitivity equals the sum of coefficients from a regression of its quarterly change on the contemporaneous and three lagged quarterly changes in the federal funds rate. Baseline uses Equation (16) with (λ_{t-1}); the robust variant uses (λ_t); "algorithm" computes the risk-free benchmark and credit spread sensitivities directly from the algorithm levels without the decomposition. Panel A reports sensitivities over the full sample; Panel B reports sensitivities estimated separately for quarters with positive and negative changes in the federal funds rate. In Panel A, Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, "% Sig." is the share of banks with a statistically significant two-sided sensitivity at 5%, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. In Panel B, "% Sig." again refers to the two-sided 5% test. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001–2024.

Panel A: Full Sample

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Risk-free benchmark sensitivity						
Baseline (λ_{t-1})	**0.579**	0.113	100%	100%	0%	0.875
Robust (λ_t)	**0.579**	0.106	100%	100%	0%	0.874
Algorithm	**0.637**	0.094	100%	100%	0%	0.898
Credit spread sensitivity						
Baseline (λ_{t-1})	**−0.238**	0.128	86%	0%	90%	0.179
Robust (λ_t)	**−0.238**	0.126	87%	0%	90%	0.180
Algorithm	**−0.296**	0.122	93%	0%	95%	0.217

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Risk-free benchmark sensitivity						
Baseline (λ_{t-1})	**0.637**	0.204	100%	**0.561**	0.115	100%
Robust (λ_t)	**0.632**	0.157	100%	**0.562**	0.114	100%
Algorithm	**0.702**	0.129	100%	**0.614**	0.104	100%
Credit spread sensitivity						
Baseline (λ_{t-1})	**−0.244**	0.262	40%	**−0.253**	0.199	71%
Robust (λ_t)	**−0.240**	0.248	41%	**−0.255**	0.198	72%
Algorithm	**−0.309**	0.248	60%	**−0.307**	0.195	80%

Table 10: Summary statistics for sensitivity regressions, largest 10% of banks. This table reports summary statistics of bank-level sensitivities for US commercial banks using quarterly data from 2001–2024. For each variable, a bank's sensitivity equals the sum of coefficients from a regression of its quarterly change on the contemporaneous and three lagged quarterly changes in the federal funds rate. Panel A reports sensitivities for the 10% largest banks by average real assets; Panel B reports sensitivities for those banks estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations and "% Sig." is the share of banks with a statistically significant two-sided sensitivity at 5%. In Panel A, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. Sample: 615 banks; 49,699 bank-quarter observations from US commercial bank Call Reports, 2001–2024.

Panel A: Largest 10% Banks

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Net interest margin (NIM)	**0.027**	0.124	24%	21%	11%	0.131
Interest expense	**0.369**	0.099	98%	99%	0%	0.661
Interest income	**0.396**	0.134	96%	97%	0%	0.426
Risk-free benchmark	**0.582**	0.108	100%	100%	0%	0.896
Credit spread	**−0.185**	0.114	81%	1%	85%	0.213
Asset composition	**−0.000**	0.035	7%	4%	9%	0.080
Counterfactual NIM	**0.212**	0.117	84%	88%	1%	0.399

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.035**	0.171	23%	**0.039**	0.164	18%
Interest expense	**0.462**	0.141	97%	**0.315**	0.139	93%
Interest income	**0.497**	0.179	92%	**0.354**	0.208	88%
Risk-free benchmark	**0.626**	0.152	100%	**0.568**	0.117	99%
Credit spread	**−0.128**	0.161	35%	**−0.209**	0.305	74%
Asset composition	**−0.002**	0.086	5%	**−0.005**	0.131	10%
Counterfactual NIM	**0.163**	0.145	60%	**0.248**	0.257	82%

Table 11: Summary statistics for sensitivity regressions, largest 5% of banks. Bank-level sensitivities are sums of coefficients from regressions of quarterly changes on the contemporaneous and three lagged changes in the federal funds rate. Panel A reports sensitivities for the 5% largest banks by average real assets; Panel B reports sensitivities for those banks estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations and "% Sig." is the share of banks with a statistically significant two-sided sensitivity at 5%. In Panel A, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. Sample: 308 banks; 24,961 bank-quarter observations from US commercial bank Call Reports, 2001–2024.

Panel A: Largest 5% Banks

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Net interest margin (NIM)	**0.030**	0.139	19%	19%	10%	0.137
Interest expense	**0.388**	0.107	98%	100%	0%	0.663
Interest income	**0.418**	0.146	95%	96%	0%	0.445
Risk-free benchmark	**0.576**	0.109	100%	100%	0%	0.895
Credit spread	**−0.156**	0.124	74%	1%	79%	0.203
Asset composition	**−0.002**	0.043	9%	3%	13%	0.078
Counterfactual NIM	**0.186**	0.119	81%	85%	2%	0.374

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.054**	0.177	24%	**0.035**	0.198	18%
Interest expense	**0.461**	0.139	97%	**0.342**	0.167	94%
Interest income	**0.515**	0.177	92%	**0.378**	0.262	86%
Risk-free benchmark	**0.623**	0.144	99%	**0.559**	0.123	98%
Credit spread	**−0.098**	0.166	29%	**−0.172**	0.411	67%
Asset composition	**−0.010**	0.089	6%	**−0.010**	0.182	14%
Counterfactual NIM	**0.152**	0.140	59%	**0.207**	0.331	75%

Table 12: Summary statistics for sensitivity regressions, 1997–2024. This table reports summary statistics of bank-level sensitivities for US commercial banks using quarterly data from 1997–2024. For each variable, a bank's sensitivity equals the sum of coefficients from a regression of its quarterly change on the contemporaneous and three lagged quarterly changes in the federal funds rate. Panel A reports sensitivities over the full sample; Panel B reports sensitivities estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, and "% Sig." is the share of banks with a statistically significant sensitivity at 5% (Newey–West SEs). In Panel A, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. Sample: 6,795 banks; 591,267 bank-quarter observations from US commercial bank Call Reports, 1997–2024.

Panel A: Full Sample

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Net interest margin (NIM)	**0.036**	0.141	26%	23%	10%	0.111
Interest expense	**0.322**	0.089	99%	99%	0%	0.575
Interest income	**0.358**	0.143	96%	97%	0%	0.300
Risk-free benchmark	**0.584**	0.112	100%	100%	0%	0.867
Credit spread	**−0.237**	0.129	84%	0%	88%	0.161
Asset composition	**0.011**	0.042	5%	7%	2%	0.075
Counterfactual NIM	**0.273**	0.122	90%	93%	0%	0.292

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.072**	0.292	23%	**0.022**	0.193	17%
Interest expense	**0.414**	0.157	97%	**0.274**	0.103	93%
Interest income	**0.486**	0.296	91%	**0.296**	0.195	80%
Risk-free benchmark	**0.639**	0.189	100%	**0.564**	0.115	100%
Credit spread	**−0.237**	0.309	35%	**−0.258**	0.206	70%
Asset composition	**0.083**	0.161	3%	**−0.010**	0.076	5%
Counterfactual NIM	**0.308**	0.243	62%	**0.279**	0.162	76%

Table 13: Summary statistics for sensitivity regressions split by financial conditions. This table reports bank-level sensitivities estimated separately in quarters with relatively favorable and relatively unfavorable financial conditions. For each variable, a bank's sensitivity equals the sum of coefficients from a regression of its quarterly change on the contemporaneous and three lagged quarterly changes in the federal funds rate, estimated separately in "good" and "bad" financial conditions. Financial conditions are measured by the NFCI and the ANFCI. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, and "% Sig." is the share of banks with a statistically significant two-sided sensitivity at 5% (Newey–West SEs). Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank call reports 2001–2024.

Panel A: NFCI

	Good conditions			Bad conditions		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.033**	0.184	23.3%	**0.045**	0.516	21.2%
Interest expense	**0.361**	0.110	99.4%	**0.144**	0.240	33.7%
Interest income	**0.394**	0.189	94.9%	**0.189**	0.510	26.8%
Risk-free benchmark	**0.595**	0.130	99.9%	**0.557**	0.218	88.5%
Credit spread	**−0.191**	0.184	67.6%	**−0.373**	0.502	52.2%
Asset composition	**−0.011**	0.089	5.3%	**0.006**	0.263	20.0%

Panel B: ANFCI

	Good conditions			Bad conditions		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.034**	0.187	23.5%	**−0.013**	5.327	14.5%
Interest expense	**0.362**	0.115	99.5%	**0.207**	0.519	37.8%
Interest income	**0.396**	0.193	94.9%	**0.195**	4.860	31.0%
Risk-free benchmark	**0.595**	0.131	99.9%	**0.570**	0.383	95.2%
Credit spread	**−0.187**	0.190	66.7%	**−0.377**	5.066	49.0%
Asset composition	**−0.012**	0.097	5.4%	**0.001**	0.227	11.5%

Table 14: Robustness of risk-free benchmark and credit spread sensitivities to algorithm estimation choices. "Geometric amortization" uses geometric amortization of loans; "no loan amortization" estimates sensitivities without loan amortization; "no exponential weights" estimates sensitivities without exponentially declining weights. The first panel reports sensitivities over the full sample; the second panel reports sensitivities estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, and "% Sig." is the share of banks with a statistically significant sensitivity at 5% (Newey–West SEs). In Panel A, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. Sample: 6,150 banks; 495,439 bank-quarter observations from US commercial bank Call Reports, 2001–2024.

Panel A: Full Sample

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Risk-free benchmark sensitivity						
Geometric amortization	**0.575**	0.113	100%	100%	0%	NA
No loan amortization	**0.490**	0.117	100%	100%	0%	NA
No exponential weights	**0.577**	0.115	100%	100%	0%	NA
Credit spread sensitivity						
Geometric amortization	**−0.234**	0.128	86%	0%	85%	NA
No loan amortization	**−0.149**	0.123	61%	0%	60%	NA
No exponential weights	**−0.237**	0.129	86%	0%	86%	NA

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Risk-free benchmark sensitivity						
Geometric amortization	**0.633**	0.205	100%	**0.556**	0.115	100%
No loan amortization	**0.556**	0.205	100%	**0.465**	0.121	99%
No exponential weights	**0.638**	0.205	100%	**0.558**	0.117	100%
Credit spread sensitivity						
Geometric amortization	**−0.240**	0.262	38%	**−0.249**	0.198	70%
No loan amortization	**−0.164**	0.257	15%	**−0.157**	0.196	43%
No exponential weights	**−0.245**	0.262	40%	**−0.251**	0.199	70%

Table 15: Summary statistics for sensitivity regressions, top-tier BHC and standalone commercial banks. Bank-level sensitivities are sums of coefficients from regressions of quarterly changes on the contemporaneous and three lagged changes in the federal funds rate. The first panel reports sensitivities over the full sample; the second panel reports sensitivities estimated separately for quarters with positive and negative changes in the federal funds rate. Mean reports the average sensitivity estimate in bold, SD the cross-sectional standard deviations, and "% Sig." is the share of banks with a statistically significant sensitivity at 5% (Newey–West SEs). In Panel A, "% Sig.+" ("% Sig.−") is the corresponding one-sided test for $H_1: \beta > 0$ ($H_1: \beta < 0$), and $\overline{R}^2$ is the average R^2 across banks. Sample: 2,449 top-tier BHC and standalone commercial banks with 187,564 observations from US commercial bank Call Reports, 2001–2024.

Panel A: Full Sample

	Mean	SD	% Sig.	% Sig.+	% Sig.−	$\overline{R}^2$
Net interest margin (NIM)	**0.050**	0.134	27%	26%	8%	0.131
Interest expense	**0.311**	0.098	97%	98%	0%	0.595
Interest income	**0.361**	0.144	95%	96%	0%	0.340
Risk-free benchmark	**0.573**	0.118	100%	100%	0%	0.878
Credit spread	**−0.221**	0.131	83%	1%	86%	0.201
Asset composition	**0.008**	0.036	8%	9%	4%	0.087
Counterfactual NIM	**0.271**	0.130	90%	92%	0%	0.399

Panel B: Positive vs. Negative Federal Funds Rate Changes

	Positive Δf			Negative Δf		
	Mean	SD	% Sig.	Mean	SD	% Sig.
Net interest margin (NIM)	**0.068**	0.255	25%	**0.049**	0.197	18%
Interest expense	**0.418**	0.183	96%	**0.256**	0.119	90%
Interest income	**0.486**	0.264	90%	**0.305**	0.199	81%
Risk-free benchmark	**0.633**	0.187	100%	**0.556**	0.120	100%
Credit spread	**−0.198**	0.270	39%	**−0.246**	0.206	72%
Asset composition	**0.051**	0.132	6%	**−0.005**	0.056	8%
Counterfactual NIM	**0.266**	0.223	66%	**0.295**	0.160	82%

F Cross-Sectional Regression of Sensitivity Estimates

Table 16: Cross-sectional regressions of sensitivity estimates. This table reports estimates from cross-sectional regressions of the form $\beta_i^y = \alpha + \gamma\,\beta_i^x + \varepsilon_i$ for different pairs of bank-level sensitivity estimates. Each column corresponds to a separate regression, with the dependent variable shown at the top of the column and the regressor listed in the left-hand margin. Stars indicate statistical significance (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$) based on block-bootstrapped standard errors with 1000 repetitions (in parentheses). Sample: 6,150 US commercial banks.

	Interest income	Credit spread			Risk-free benchmark	
	(1)	(2)	(4)	(5)	(3)	(6)
Interest expense	0.53***	0.15**			0.38***	
	(0.05)	(0.07)			(0.04)	
Risk-free benchmark			-0.37***			
			(0.06)			
NIM				0.56***		0.22***
				(0.06)		(0.04)
R^2	0.10	0.01	0.11	0.37	0.08	0.08

G Local Projection Estimates with Asymmetric Responses

This appendix presents local projection estimates that allow for asymmetric responses to fitted credit spread changes. Specifically, I decompose the standardized fitted credit spread into its positive and negative components,

$$z\widehat{R}^{+}_{i,t} = \max\Big\{z\widehat{R}_{i,t},\, 0\Big\}, \qquad z\widehat{R}^{-}_{i,t} = \min\Big\{z\widehat{R}_{i,t},\, 0\Big\}.$$

and estimate equation (32) separately using $z\widehat{R}^{+}_{i,t}$ and $z\widehat{R}^{-}_{i,t}$ as the regressor. All other elements of the specification remain unchanged. The results are reported in Figure 16 and Figure 17. The cumulative response remains positive and statistically significant for both credit spread increases and decreases, amounting to roughly 5 bp following one-standard-deviation increases and about 15 bp following one-standard-deviation decreases.

Figure 16: Local projections of future non-performing loans and credit-impaired securities, positive credit spread changes. The figure plots local projections of future non-performing loans and credit-impaired securities on the within-bank standardized fitted credit spread change, restricting to positive fitted credit spread changes. Bank and time fixed effects are included. Standard errors are two-way clustered by bank and time. Markers: ● $p < 0.01$, ▲ $p < 0.05$, ■ $p < 0.10$, ○ non-significant. Sample: 6,150 banks; 495,439 bank-quarter observations from U.S. commercial bank Call Reports, 2001–2024.

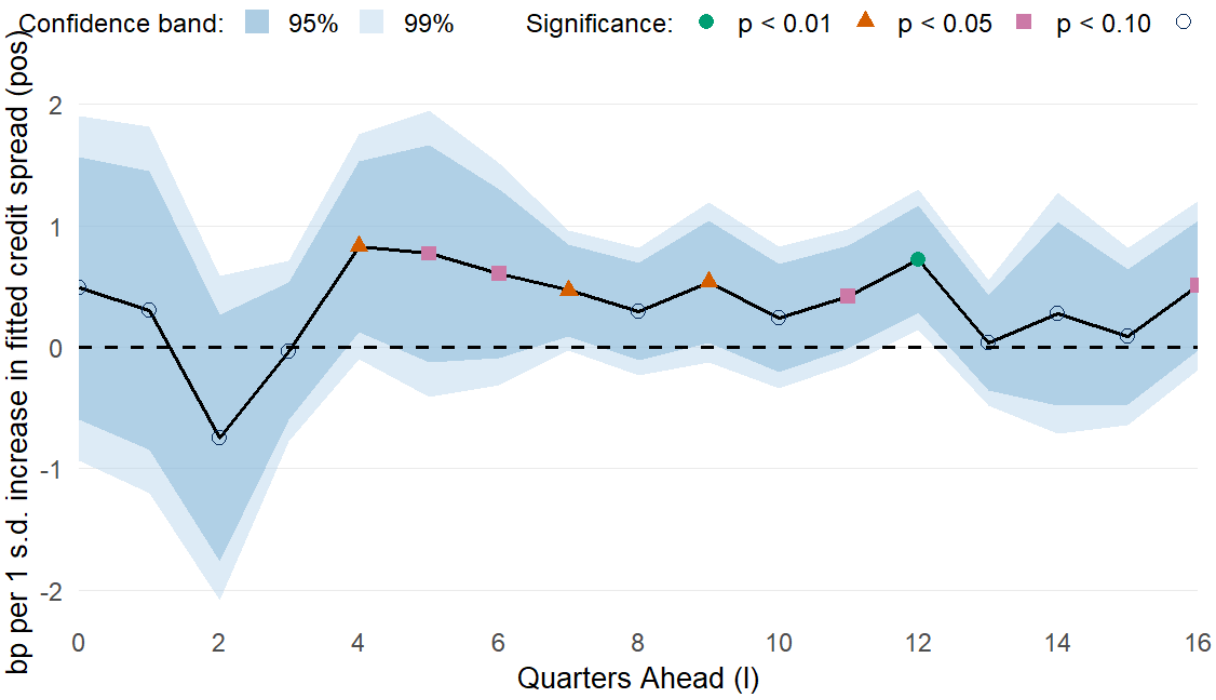


Figure 17: Local projections of future non-performing loans and credit-impaired securities, negative credit spread changes. The figure plots local projections of future non-performing loans and credit-impaired securities on the within-bank standardized fitted credit spread change, restricting to negative fitted credit spread changes. Bank and time fixed effects are included. Standard errors are two-way clustered by bank and time. Markers: • $p < 0.01$, ▲ $p < 0.05$, ■ $p < 0.10$, ∘ non-significant. Sample: 6,150 banks; 495,439 bank-quarter observations from U.S. commercial bank Call Reports, 2001–2024.

