The Impact of Risk Management Activities on Bank Valuation

Jin Ca

Michael S. Pagano

John Sedunov

Abstract

This paper examines how banks' hedging activities influence market valuation. Using U.S. commercial bank data from 2001Q1–2024Q3, we develop a two-stage estimation process that isolates bank-specific effects on the market-to-book (*MB*) ratio after controlling for macroeconomic and size-related factors. We find that derivatives-based interest rate hedging is significantly and positively associated with *MB*, particularly during monetary tightening and for banks with high uninsured deposits, large unrealized securities losses, more liquidity creation, or greater asset-related rate sensitivity. Interest rate hedging also positively affects bank valuation during periods of declining interest rates, though this effect is not as pervasive. In addition, credit risk hedging shows no significant impact. Overall, we observe that the level of interest rate hedging activity has more than doubled during the most recent portion of our sample (2019-2024) as a greater percentage of banks began using derivatives to manage their interest rate risk. Our findings highlight market conditions and bank hedging decisions under which interest rate risk management creates shareholder value.

June 2026

The Impact of Risk Management Activities on Bank Valuation

Abstract

This paper examines how banks' hedging activities influence market valuation. Using U.S. commercial bank data from 2001Q1–2024Q3, we develop a two-stage estimation process that isolates bank-specific effects on the market-to-book (*MB*) ratio after controlling for macroeconomic and size-related factors. We find that derivatives-based interest rate hedging is significantly and positively associated with *MB*, particularly during monetary tightening and for banks with high uninsured deposits, large unrealized securities losses, more liquidity creation, or greater asset-related rate sensitivity. Interest rate hedging also positively affects bank valuation during periods of declining interest rates, though this effect is not as pervasive. In addition, credit risk hedging shows no significant impact. Overall, we observe that the level of interest rate hedging activity has more than doubled during the most recent portion of our sample (2019-2024) as a greater percentage of banks began using derivatives to manage their interest rate risk. Our findings highlight market conditions and bank hedging decisions under which interest rate risk management creates shareholder value.

June 2026

1. Introduction

In terms of classic financial intermediation at a commercial bank, managers are entrusted with the assets of the financial institution (FI) and must generate revenue that will not only cover all funding and operational costs but also satisfy equity investors' expectations for an adequate return on their investment.[1] When managers fail in this task, investors will stop financing the FI and invest their money elsewhere. Without a continuous and stable source of financing, a financial firm will be unable to remain in operation for very long.[2]

It is well known that an FI's intermediation activities such as asset transformation, delegated monitoring, and brokerage services create numerous exposures to risk related to interest rates, lending, investing, and financing (e.g., see Saunders, Cornett, and Erhemjamts, 2024). Consistent with Stulz (2013), a firm's choices related to managing these risks are at the core of a bank's ability to maximize value for its equity investors. However, from an empirical perspective, it can be difficult to isolate how much of a bank's market value is affected by market-wide (or "macro") factors relative to management-specific choices. Accordingly, our study focuses on how a bank's market value of equity is affected by the firm's interest rate and credit risk management activities, after controlling for market-wide factors and other bank-specific effects. We show, in a variety of settings, that a bank's interest rate risk hedging is positively and significantly related to its market value, while its credit risk management activity is not.

We adopt this approach because prior work by Diamond (1984), Froot and Stein (1998), and Flannery and James (1984) has shown that a FI faces two main types of risk: 1) systematic (or "tradable")

---

[1] For an excellent, detailed treatment of various financial valuation techniques, please see Sopranzetti and Kiess (2024). In addition, Dermine (2015) examined the valuation of banks based on a non-traditional approach while Pagano and Sedunov (2025) apply a cost-benefit analysis to link risk management decisions and bank value.

[2] See the sudden failures by Lehman Brothers on September 15, 2008, and Silicon Valley Bank (SVB) on March 10, 2023, as extreme examples of how quickly investors can become skittish of lending to a financial firm that has growing risks and a high degree of uninsured debt. A thorough discussion of systemic risk and crises can be found in Berger and Sedunov (2024). Related to the rapid interest rate hikes in the U.S. during 2022-2023, Jiang, Matvos, Piskorski, and Seru (2024) estimate that the market value of industry-wide bank assets fell 10% and totaled about $2 trillion.

and 2) idiosyncratic (or "non-tradable") risks. For example, Diamond (1984) models banks as delegated monitors, exposing them to credit risks that, if unmanaged, amplify equity volatility. Flannery and James (1984) highlight the importance of a bank's interest rate risk by empirically estimating how unexpected interest rate changes can negatively affect bank stock returns via an FI's asset-liability maturity mismatches. This finding provides a rationale for how interest rate hedging can enhance a firm's market value of equity.

In addition, Froot and Stein (1998) integrate risk management within the firm's capital budgeting and financing choices and argue that hedging mitigates underinvestment from costly external financing. They model an FI that faces convex financing costs (e.g., due to liquidity constraints and moral hazard) and concave benefits (via diminishing returns to investing), yielding time-varying, bank-specific optimal hedging levels. Schrand and Unal (1998) extend this concept with "coordinated risk management," in which hedging some core risks (e.g., interest rates and credit risk) can free up equity capital to generate greater returns from other bank activities, thus increasing the bank's market value of equity.

Although there is a large literature describing bank derivatives usage and its relation to conventional banking functions, much less is known about the direct effects of a bank's interest rate and credit risk management actions on the firm's market value of equity.[3] Following prior literature, we standardize our comparison across banks by using the market-to-book value of equity ratio (*MB*). Our study is related to Egan, Lewellen, and Sundaram (2022), which takes a production function approach to estimating the impact of liquidity creation on a bank's *MB* ratio. Like the theoretical model of Froot and Stein (1998), Egan et al. (2022) decompose a bank's activities into systematic and idiosyncratic factors to focus on the valuation effects of bank-specific lending and deposit-taking. They find that deposit-taking efficiency and its positive impact on liquidity provision primarily explains cross-sectional differences in *MB* ratios for U.S. banks. Our study also builds upon the work of Minton, Stulz, and Taboada (2019) which analyzes the size-related effects of "Too Big to Fail" policies (TBTF) on U.S. bank market-to-book ratios

[3] Our valuation-based approach contrasts with prior work on bank risk management activities such as Sinkey and Carter (2000) and Kim (2023) which focus on identifying the bank attributes that are correlated with derivatives usage rather than directly assessing valuation effects.

(*MB*). They find that larger banks have lower *MB* and therefore their equity investors are not likely to benefit from TBTF policies.

Both Egan et al. (2022) and Minton et al. (2019), as well as Bogdanova, Fender, and Takats (2018), follow Calomiris and Nissim (2014) by examining time series and cross-sectional valuation effects related to variables such as bank size, dividends, and accounting-based measures of bank profitability. All the studies noted here indicate that a bank's *MB* ratio is affected by a bank's main economic functions related to lending, trading, and liquidity provision but do not explicitly analyze the impact of a bank's hedging decisions on firm value.

In contrast to the above studies, we examine the effects on *MB* due to a bank's risk management choices, as proxied by their exposures to derivatives-based interest rate and credit risk hedges. Recent related work emphasizes the effect of balance sheet constraints on hedging activity. Choi, Kim, and Kim (2016) provide positive but non-monotonic evidence about hedging effects, linking hedging derivatives to increased market values at lower and intermediate levels of interest rate hedging activity. In addition, Miloș and Miloș (2022) caution that high levels of derivatives usage at European banks negatively impacted *MB* ratios due to suboptimal hedging and increased volatility (e.g., a 1% increase in usage reduces *MB* by 0.11%-0.47% during crises).

In sum, these studies indicate optimal hedging levels might exist that maximize a bank's *MB* ratio by balancing risk reduction with opportunity costs (Delis and Karavias, 2015; Kim, 2023). Well-managed hedging can stabilize earnings (Schrand and Unal, 1998), reduce financial distress costs (Froot and Stein, 1998, Purnanandam, 2007), and enhance market value, but over-reliance on derivatives can lead to suboptimal outcomes (Choi et al., 2016; Milos and Milos, 2022). In addition, Drechsler, Savov, and Schnabl (2021) show that a bank can control its interest rate risk through the matching of interest rate sensitivities for assets and liabilities by setting their asset and deposit "betas" to similar but offsetting values, as measured by their "Net Interest Margin beta," which we refer to here as a bank's *NIM Beta*.[4] The *NIM Beta* concept of Drechsler et al. (2021) based on cash flow sensitivity and DeMarzo et al's (2024) alternative duration-based interpretation of the effects of deposit rate betas suggest that we must also account for on-balance sheet-based ways to engage in interest rate risk management.

We estimate the impact of bank hedging activity using a two-stage process and by including both derivatives- and balance sheet-based risk management variables. First, we use an asset pricing model to differentiate between market-wide factors affecting all banks and bank-specific idiosyncratic factors. Similar in spirit to Egan et al. (2022), we first control for market-wide and size-related effects and use the bank-specific component in a second stage to estimate how bank-specific choices affect the firm's market-to-book ratio. However, in contrast to the Egan et al. (2022) focus on lending and deposit-taking, we study how a bank's *MB* is affected by the firm's risk management activity related to interest rate and credit risks. To do this, we expand upon the Minton et al. (2019) empirical model by including proxies of hedging based on the existing literature for interest rate risk (Kim, 2023, and Drechsler et al., 2021) and credit risk management (Delis and Karavias, 2015), among others.[5]

In the second stage, we identify the key determinants of these bank-specific risk management choices, focusing on effects arising from the bank's on-balance-sheet operations and derivatives usage, after controlling for the firm's lending, investing, and financing activities. Similar in spirit to Froot and Stein (1998) and Pagano and Sedunov (2025), we assume that financing, trading, and hedging-related costs are convex in terms of hedging activity due to factors such as liquidity constraints and moral hazard while

[4] This *NIM Beta* is estimated by separately regressing changes in interest income and interest expense on changes in the Federal Funds rate. The authors find that the values are nearly identical with an average "interest income beta" of 0.351 and an average "interest expense beta" (or "deposit beta") of 0.345. The effect is a near-zero level of interest rate risk (i.e., *NIM Beta* = 0.351 - 0.345 = +0.006) and could help explain why many banks did not extensively engage in derivatives-related interest rate hedging in the past.

[5] We include estimates of bank credit risk management by including credit default swap usage as an additional control variable to isolate our interest rate hedging measures from these potential alternative hedging effects. In practice, most banks do not use credit derivatives extensively to manage credit risk.

the benefits of hedging are concave due to diminishing marginal returns to these bank activities. This leads to potential interior optimal solutions for credit and interest rate risk management decisions for each bank that can vary over time. Thus, we can use the idiosyncratic component of a bank's *MB* ratio to measure the impact of a bank's hedging activity.

Using a sample of publicly traded U.S. commercial banks during 2001Q1-2024Q3, we find that a bank's usage of interest rate derivatives for hedging purposes is positively related to the bank-specific component of the firm's *MB* ratio after controlling for other factors related to macroeconomic conditions and bank's lending, trading, financing, and asset size. In terms of economic magnitude, a one-standard deviation increase in interest rate hedging can raise the median bank's *MB* ratio, which translates into a +0.743% gain in the market value of equity. This represents an economically significant improvement in annual stock returns of over 15% given that the total return on the equity of U.S. financial institutions, as proxied by the Financial Select Sector SPDR Fund (ticker XLF), was +4.766% per year during our sample period (i.e., +0.00743 / 0.04766 = +15.6%).

The impact of interest rate hedging can also be viewed in terms of its effect on the firm's *MB* ratio in relation to the overall variability in this metric. For example, a one-standard deviation increase in interest rate hedging can raise a bank's *Adjusted MB* ratio by +4.0% (relative to its full sample standard deviation of 0.2320).[6] This positive effect of interest rate hedging is significant both when monetary policy is tightening and when it is easing (proxied by changes in the Federal Funds rate). When interest rates are rising, this positive effect on *MB* is potentially even stronger when: a) the bank has a large amount of uninsured deposits (i.e., in the upper tercile), b) there is a great deal of unrealized losses on the bank's

[6] As we explain in a later section, the *Adjusted MB* ratio represents the residuals from a first-stage model to control for market-wide factors and isolate the bank-specific idiosyncratic component of a firm's *MB* ratio. This enables us to more clearly identify the impact of a bank's strategic and managerial choices on its valuation by removing systematic risk sources that may obfuscate the effect of the bank's internal decision-making process. We call this residual the "*Adjusted MB*" ratio throughout the rest of the paper. In addition, we express the economic magnitude of interest hedging as a percentage of the *Adjusted MB's* standard deviation rather than the mean of *Adjusted MB* because the full sample's average value is near-zero (-0.0029) and thus any estimated changes based on the mean *Adjusted MB* would be extremely large.

securities portfolio (both Held to Maturity, HTM, and Available for Sale, AFS, fixed income securities), or c) the bank creates a high amount of liquidity for its customers. In these sub-samples, the impact on *Adjusted MB* is +4.2%, +4.7%, and +3.7% of a standard deviation, respectively. This finding suggests that banks can add significant value by hedging interest rate risk, possibly by protecting the market value of longer-duration assets from interest rate increases. In particular, the benefits of interest rate hedging appear to be the greatest when the bank engages in more liquidity creation.

These results also hold after controlling for the statistically significant and positive effects of a bank's on-balance sheet interest rate risk exposure, as measured by *NIM Beta*. Overall, we find that both greater derivatives-based hedging activity and a positive *NIM Beta* exposure can increase a bank's market value during a rising rate environment. For example, the economic impact of hedging with derivatives on *Adjusted MB* is +4.6% when rates are rising and the bank has a positive *NIM Beta*, which is greater than the full sample estimate of +4.0%. Thus, our results are consistent with aspects of both the duration-based approach of DeMarzo et al. (2024) and the cash flow-focused model of Drechsler et al. (2021).

Our findings also expand upon Kim (2023), which previously demonstrated that banks selectively hedge interest rate risk when they face larger losses in their fixed income securities portfolio and rely more heavily on uninsured deposits. However, in contrast to the focus on a bank's fixed income portfolio losses, we directly examine the impact of a bank's selective hedging activity on its market value of equity. We also use the sudden tightening of the Federal Reserve's monetary policy during 2022Q1-2023Q1 as an event study to control for possible endogeneity. Using a triple difference-in-difference (DDD) test, we find that investors reacted more positively to banks that had greater interest rate risk exposure but also chose to use more derivatives to hedge this large rate shock, even after controlling for possible parallel trends and other potentially confounding effects.

In addition, we find weaker evidence that greater interest rate hedging during times of declining Federal Funds rates can have a positive and significant effect on a bank's *MB* ratio. This result, significant at the 5% level for the full sample, suggests that hedging when interest rates are falling can benefit shareholders, possibly due to locking in higher interest revenue while allowing interest expense to decline on lower-yielding insured deposits.

We contribute to the literature on bank valuation and risk management in five ways. First, we develop a two-stage estimation process to isolate bank-specific hedging activities and their impact on market value. Second, we show that derivatives-based interest rate hedging has been growing over our sample period and positively affects market value, especially when rates are rising and banks face greater liquidity risk (as measured by their heavy reliance on uninsured deposits and higher liquidity creation activity). Third, we find evidence that a bank's greater asset sensitivity to on-balance sheet interest rate risk exposure, as measured by a positive *NIM Beta*, is another important factor affecting market values during tighter monetary policy. Fourth, we find that interest rate hedging is also significantly and positively related to bank valuation when interest rates are declining, although this effect is more limited relative to a rising rate environment. Fifth, credit risk management (as measured by notional net amounts of credit derivatives usage) does not have a strong effect on a bank's *MB* ratio. Thus, by using a two-stage process that first filters out macro-level effects, our approach shows more clearly when interest rate risk management activity can enhance shareholder value while credit risk management does not appear to have a significant influence. These results are robust to tests for endogeneity, parallel trends, alternative asset pricing models, different sub-samples and scaling methods, as well as the use of a one-stage estimation process rather than our preferred two-stage method.

The paper is organized as follows. Section 2 motivates our approach. Section 3 describes our data while Section 4 presents our main results. Section 5 covers our robustness tests. Section 6 concludes.

2. Motivation for the Bank Valuation Model

Following Calomiris and Nissim (2014), Minton et al. (2019), Egan et al. (2022), and others, we use the market-to-book ratio of a bank's common equity because it facilitates cross-sectional comparison across firms that vary in size and business strategy as well as over time. For example, Calomiris and Nissim

(2014) and Bogdanova et al. (2018) report a large, secular decline in bank *MB* ratios after the 2008 Great Financial Crisis. They attribute this decline in part to increased information asymmetries associated with banks during the post-crisis period and find that the dividend-to-equity ratio is a consistently strong and positive influence on *MB* ratios and could serve as a signal of financial strength.[7]

Substantial new insights in recent years examine the sources of interest rate risk and how banks can manage this risk using on-balance sheet mechanisms. For example, Drechsler, Savov, and Schnabl (2021) develop a model of a bank's incentives to manage interest rate risk by adjusting the sensitivity of both asset and lending rates to changes in the overall level of interest rates, as proxied by the Federal Funds rate, which we will refer to here as "asset-sensitive" and "liability-sensitive" exposures. They find that a bank's traditional maturity transformation (borrowing short and lending long) does not materially expose banks to interest rate risk. Instead, they argue that when a bank has market power its "deposit franchise value" provides a natural hedge against any changes in the rates it earns on its loans and securities.

So, even though they estimate that banks might have a large duration mismatch (e.g., aggregate U.S. bank assets have a duration of 3.7 years versus 0.3 years for liabilities), the impact on bank equity is much smaller when compared to the expected drop based on conventional duration-based models of interest rate risk.[8] The net effect is a near-zero level of interest rate risk according to this approach and is offered as

[7] As noted in the Introduction, our valuation-based approach contrasts with prior work on bank risk management activities. For example, Sinkey and Carter (2000) find that banks that use derivatives tend to have riskier capital structures, larger maturity mismatches, and lower net interest margins. This suggests derivatives enable banks to take on more risk by possibly affecting equity value through increased leverage. Their study reveals that derivatives users tend to be larger banks and is consistent with scale economies in hedging. Purnanandam (2007) shows banks with high interest rate exposures hedge more during policy tightening, stabilizing lending, and indirectly supporting bank equity capital by reducing the impact of business cycle effects. This study is also consistent with hedging theories based on the cost of financial distress and costly external financing. Similarly, Kim (2023) focuses on interest rate risk exposures and finds that banks might selectively hedge such risks in an asymmetric way, with more hedging activity when interest rates rise, and fixed income portfolio losses grow larger.

[8] Related work in this research stream can be found in Drechsler, Savov, and Schnabl (2017), Drechsler, Savov, Schnabl, and Wang (2023), and McPhail, Schnabl, and Tuckman (2024). These papers extend the above model's insights to help explain, among other issues, how the interest rate-induced bank run on Silicon Valley Bank could occur despite this natural hedge due to the fragile nature of the bank's deposit franchise value, which was caused by a heavy reliance on uninsured deposits. According to this view, as rates rose and the bank's securities portfolio declined precipitously, uninsured depositors withdrew their funds, thus swiftly eroding the bank's ability to hedge its asset-based risk with offsetting adjustments in deposits.

an explanation as to why in the past many banks might not have had an incentive to extensively engage in derivatives-related interest rate hedging. Their results also suggest a "negative duration" associated with a bank's deposit franchise value (where this value increases when interest rates rise).

In contrast to the Drechsler et al. (2021) insights, DeMarzo, Krishnamurthy, and Nagel (2024) draw the opposite conclusion about deposit franchise value by developing an alternative model that suggests this value declines as interest rates rise due to reduced lending margins, thus challenging the idea that low deposit betas naturally hedge interest rate risk. They acknowledge that while operating costs could generate negative duration, this effect is more than offset by "positive duration" from fixed interest rate spreads via the bank's lending activity. Thus, consistent with conventional duration-based models of interest rate risk, franchise value has positive duration and declines as interest rates rise. In addition, other work such as Choi and Rocheteau (2023) show that bank market power would need to be quite strong to match the interest rate elasticity of aggregate deposits observed in U.S. data based on the Drechsler et al. (2021) model.[9] Consequently, it remains an open empirical question regarding the impact of derivatives-based hedging activity on firm value.

We define our study's key valuation metric, the bank's current market-to-book equity ratio (MB_0), as determined by the firm's return on its market value of equity (R_0), the growth in its book value of equity (g_0), as well as its lagged market-to-book ratio (MB_{-1}). To streamline the notation at this point in our discussion, we omit the bank-*i* subscript and use the time-*t* subscripts 0 and -1 to represent the current and lagged 1-period values of each variable via the following mathematical identity:

$$MB_0 \equiv \left(\frac{1+R_0}{1+g}\right) \cdot MB_{-1} \tag{1}$$

[9] Choi and Rocheteau (2023) take a different approach than Drechsler et al's central assumption of bank market power and instead show that another set of key drivers of bank behavior are the customer-specific differences in their liquidity needs (e.g., high- versus low-liquidity customers). In their model, less-liquid deposits exhibit a non-monotonic relationship with respect to changes in a monetary policy rate such as the Federal funds rate.

To estimate the empirical model outlined by Equation (1) in more detail, we need to first specify some observable variables for the right-hand side (RHS) factors, R_0, g, and the lagged *MB* ratio, MB_{-1}. Nearly all the variables can be obtained from a U.S. bank's Call Reports.

Following Froot and Stein (1998), we can include explanatory variables that control for both market-wide systematic factors and bank-specific idiosyncratic effects. This approach can help us pin down how bank-specific choices related to risk-taking and risk management affect the firm's equity returns after controlling for market-wide factors and can be summarized as simply:

$$R_0 = Systematic\ factors + Idiosyncratic\ factors \tag{2}$$

Substituting (2) into (1) yields:

$$MB_0 = \left(\frac{1 + R_0}{1 + g}\right) \cdot MB_{-1} = \left(\frac{1 + Systematic\ factors + Idiosyncratic\ factors}{1 + g}\right) \cdot MB_{-1} \tag{3}$$

Equation (3) shows that a bank's market-to-book ratio is related to these two main sources of stock returns as well as the firm's growth rate of the book value of equity (*g*) and the lagged market-to-book ratio (MB_{-1}).[10] Note that the *MB* ratio-based model outlined above is usually a more empirically tractable model than estimating a stock return-based model such as Equation (2) due to the more stable, stationary nature of *MB* ratios. Thus, we use (3) as a baseline model in our empirical tests described later.

In addition, we can show how our method relates to the DeMarzo et al. (2024) model by equating their Equation (5) to our Equation (3) presented above. To make the two approaches comparable in terms of our *MB* framework, we scale their model of a bank's market value of equity by its book value. They show that the bank's market value of equity can be decomposed into two parts: 1) a "portfolio value" based on the book value of equity (*BVE*) and the marked-to-market gains on the bank's portfolio of tradeable

[10] We can modify the above relationship further to account for the fact that the growth rate of the book value equity (*g*) is also influenced by systematic and idiosyncratic factors and so it can be subsumed within Equation (3)'s numerator.

securities (net of any non-deposit financing), denoted as $MTM_{T\text{-}B}$, and 2) the bank's "franchise value" which is derived from both its asset- and deposit-related return spreads, *S*, its operating costs, *C*, and denoted as *PV(S-C)*. They show that to prevent insolvency, the bank's net securities position, $MTM_{T\text{-}B}$, should hedge any potential losses to franchise value. Accordingly, our Equation (4) shown below demonstrates the linkage between DeMarzo et al's (2024) structural relationship (in the first equality) and our empirical model (the second equality):

$$MB_0 = 1 + \left(\frac{MTM_{T-B}}{BVE}\right) + \left(\frac{PV(S-C)}{BVE}\right) = \left(\frac{1 + Systematic\ factors + Idiosyncratic\ factors}{1+g}\right) \cdot MB_{-1} \quad (4)$$

From Equation (4) we can see that both the portfolio and franchise values of DeMarzo et al. (2024) can be affected by both systematic and idiosyncratic factors, as well as the bank's growth rate and lagged *MB* ratio.

To make these ideas more concrete, we use prior research to identify specific systematic factors for testing purposes. As noted earlier, Froot and Stein (1998) demonstrate that it is usually not optimal to hedge 100% of the bank's risk in a world where there is a convex relationship between financing costs and the bank's chosen level of external financing. Thus, a bank will select an interior optimum level of exposure to these systematic and idiosyncratic risks that correspond to the costs and benefits of hedging these risks. In their setup, Froot and Stein (1998) assume one systematic factor that is related to the bank's tradable risks and a second bank-specific factor which considers how the non-tradable risk of a new asset added to the bank's portfolio correlates with its existing assets' non-tradable risk. Equations (2) - (4) neatly summarize this concept in a stylized fashion and many researchers have attempted to estimate the specific components of the systematic factor. For example, among many others, the multi-factor models of Flannery and James (1984), Chen, Roll, and Ross (1986), Fama and French (1993, 2015), have been used to describe the key factors affecting a firm's equity returns.

In the case of bank returns, special consideration has been given to factors that relate to two major risks facing these financial institutions, namely, interest rate and credit risks. For example, Begenau, Piazzesi, and Schneider (2015) extend Flannery and James (1984) and identifies two significant factors related to interest rate and credit risk via the use of swap rates as well as high- and low-rated corporate bond yields. In contrast, Chen, Roll, and Ross (1986) develop a more generalized asset pricing model that tests five factors and finds that the two most significant factors relate to an interest rate risk measure (the term structure premium) and credit risk (a bond default premium).

Given the above discussion, we expand upon Chen, Roll, and Ross (1986) to include not only systematic factors but also two bank-specific variables. First, we include the *MB* ratio lagged one quarter because call report data is made available on a lagged basis and thus the prior quarter's *MB* ratio might contain information that is not fully reflected in stock prices until the current quarter. In addition, including this lagged *MB* ratio is consistent with Equations (1) and (3), which shows that the current *MB* ratio is a function of the bank's equity return (R_0), book value of equity growth rate (g), and the lagged market-to-book ratio (MB_{-1}). Following Minton et al. (2019), we also include size-based piecewise linear functions defined in the Appendix (*Assetbelow50b* and *Assetabove50b*) to account for possible "TBTF" effects.[11]

$$MB_{i,t} = f(\Omega_t) + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{5}$$

where,

Ω_t= a vector of time-*t* risk factors typically employed in asset pricing models (including *MKT, SMB, HML, RMW, CMA, TERM,* and *DEF).* as well as bank-specific variables related to the lagged *MB* ratio, $MB_{i,t-1}$, and firm size (*Assetbelow50b* and *Assetabove50b*);

γ_i = time-invariant bank-specific factor to capture bank-level cross-sectional differences;

δ_t = time-varying factor to capture other market-wide effects beyond those specified in Ω_t; and

$\varepsilon_{i,t}$ = idiosyncratic component due to random shocks and time-varying bank-specific factors.

[11] We now include subscripts *i* and *t* to specify firm-level and time-related variables.

Note that Equation (5) is our first-stage panel regression and shows the factors that affect a bank's $MB_{i,t}$ ratio are due to risks related to systematic, market-wide factors like stock returns and economic activity (*MKT; SMB; HML; RMW; CMA*), interest rates (*TERM*), lending (*DEF*), and other time-varying fixed effects (δ_t) not captured by these "macro" factors. In addition, as Equation (3) showed, *bank-specific* measures are also relevant, such as its past relative valuation ($MB_{i,t-1}$), bank-level fixed effects (γ_i), firm size ($Assetbelow50b_{i,t}$ and $Assetabove50b_{i,t}$), and time-varying idiosyncratic risk ($\varepsilon_{i,t}$).[12]

The time-varying idiosyncratic factor from Equation (5), $\varepsilon_{i,t}$, can then be used in a second-stage regression because this component of the *MB* ratio represents our best estimate of the impact on firm value that is due to time-varying, bank-specific choices that are not attributable to market-wide factors, past prior valuations, or time-invariant firm-level factors (e.g., the bank's current geographic region). In theory, $\varepsilon_{i,t}$, should capture any effects of a bank's interest rate and credit risk management decisions (among other choices related to lending, investing, and financing). This approach is similar in spirit to Egan et al. (2022), where a bank's market-to-book ratio is regressed on bank characteristics as well as common, industry-wide sensitivities to identify bank-specific effects on firm value. In Egan et al. (2022), their emphasis is on the valuation effects due to lending and deposit-taking. In our case, we focus on bank-specific hedging decisions and specify this second-stage panel regression as follows: [13]

$$Adjusted\ MB_{\ i,t} = f(Lending_{i,t-1}; Investing_{i,t-1}; Trading_{i,t-1}; Financing_{i,t-1};$$

[12] In robustness tests presented later in Tables 8-9, we replace the three Chen et al (1986) systematic factors of *MKT (i.e., $R_m - R_f$), DEF* and *TERM* in Equation (5) with the Fama-French five factors and show how the results based on those factors are consistent with the model based on Chen et al (1986).

[13] Note that we denote bank-specific explanatory variables with the *i,t-1* subscript and these are lagged 1 quarter because Call Report data is usually publicly available during the quarter following the reporting period. By lagging these variables at *t-1*, it permits the explanatory variables to most closely correspond to the *MB* ratio publicly observed at time-*t*. Also, technically speaking, the RHS variables of (6) should all be multiplied by $MB_{i,t-1}$ to conform with (3), although we abstract from this point because we have already explicitly accounted for $MB_{i,t-1}$ in the first-stage panel regression described by Equation (5).

$$IR\ hedging_{i,t-1};\ MGAP_{i,t-1};\ NIM\ Beta_{i,t-1};\ Credit\ deriv_{i,t-1};\ X_{i,t-1}) + \nu_{i,t} \quad (6)$$

where,

$Adjusted\ MB_{i,t} =$ the time-varying residual, $\varepsilon_{i,t}$, from the first-stage panel regression shown in Equation (5).

In addition to the Drechsler et al. (2021) *NIM Beta* variable, we follow Minton et al. (2019) and include additional control variables for a bank's main activities (scaled by Total Assets, or "TA") such as:[14]

$Lending_{t-1}$ = credit risk-taking proxy: (Risk-Weighted Assets / TA); credit quality proxy: (Net charge-offs loans / TA),

$Investing_{t-1}$ = the bank's investment securities portfolio as a percentage of Total Assets (Securities / TA);

$Trading_{t-1}$ = net trading assets / TA;

$Financing_{t-1}$ = financial capital (Book Value of Equity / TA) and uninsured deposit financing (Uninsured deposits / TA);

$IR\ hedging_{i,t-1}$ = derivatives-based interest rate risk management proxy: (Gross notional amount of interest rate derivatives used for risk management purposes / TA); and

$MGAP_{i,t-1}$ = on-balance sheet short-term interest rate risk exposure: 1-year maturity gap (the dollar difference between assets and liabilities repricing in 1 year / TA);

$NIM\ Beta_{i,t-1}$ = Drechsler et al. (2021) measure of net interest rate sensitivity of a bank's total on-balance sheet assets and liabilities;

[14] Note that Calomiris and Nissim (2014) and Minton et al. (2019) scale their independent variables by the firm's book value of equity rather than total assets. However, other papers in this literature like Delis and Karavias (2015) scale these types of variables by total assets. As a robustness test in the Appendix, we scale the independent variables by the firm's book value of equity and obtain qualitatively similar results to those reported in the main text.

$Credit\ deriv_{i,t-1}$ = credit risk management proxy: (Net notional position in credit derivatives used for risk management purposes / TA);

$X_{i,t-1}$ = proxies for firm-specific operating conditions: efficiency ratio and growth in assets; and

$\nu_{i,t}$ = time-varying, bank-specific random error.

Note that the $CreditRisk_{i,t}$, $IR\ Hedging_{i,t}$, and $NIM\ Beta_{i,t-1}$ variables, which proxy for the bank's credit and interest rate risk choices, represent our main variables of interest. We expect a significant and *positive* sign on the regression coefficients for these variables if the bank's risk management decisions improve the bank's market value, after controlling for market-wide factors and other bank-level effects such as the firm's financial leverage and lending activity. Conversely, significantly negative signs on these variables would suggest the banks are, on average, making suboptimal risk management choices. In this way, we can use risk management models like Froot and Stein (1998) and market valuation models from Egan et al. (2022) and Minton et al. (2019) to evaluate the effects of risk management decisions on a bank's market value.

3. Data

3.1. Sample Selection

We collect quarterly financial data for all U.S. publicly listed bank holding companies (BHCs) identified using the CRSP-FRB link of the Federal Reserve Bank of New York. Our sample period covers 2001Q1 to 2024Q3. We obtain the banks' stock prices from the CRSP dataset. We collect the Call Report data for the BHC's member banks and consolidate it at the BHC level. Our dataset is restricted to publicly traded BHCs because we need a bank's stock price to calculate its market-to-book value of equity. All variables are defined in detail, with relevant call report codes, in Table A1 of the Appendix.

We also collect several market-wide systematic factors that are shown to affect equity returns. These factors include *MKT*, the Fama-French market risk factor ($R_m - R_f$); *SMB*, the Fama-French size factor; *HML*, the Fama-French value factor; *RMW*, the Fama-French profitability factor; *CMA*, the Fama-French investment factor; *TERM*, the spread between 10-year and 2-year treasury yield; and *DEF*, the spread between BAA corporate bond yield and the yield on 10-year Treasury note. We download *MKT*, *SMB, HML, CMA, and RMW* from Kenneth French's website, and collect *TERM* and *DEF* from the Federal Reserve Bank of St. Louis. We include these factors in our first-stage regressions to reflect conditions related to the stock market, economic growth, and interest rates.

As with Minton et al. (2019), we exclude banks with a deposits-to-assets ratio below 10% to ensure that our sample only includes deposit-taking banks. Further, we winsorize all variables at the 99% level to adjust for outliers. The resulting dataset is an unbalanced panel comprising 957 banks and 36,367 bank-quarter observations over the period 2001Q1-2024Q3.

3.2. Variables Description

In the first-stage regression, the dependent variable is the BHC's Market-to-Book ratio (*MB*), calculated as the bank's market capitalization divided by the bank's total equity. The control variables include the systematic factors described above, the BHC's lagged *MB*, and two size-related linear functions to indicate the BHC's size to account for potential bank-specific size anomalies (e.g., Gandhi and Lustig, 2015). The piece-wise size-based variables account for how much of a BHC's total assets are above and below $50 billion.

In our second-stage analysis, we use the time-varying bank-specific residual from the first-stage regression as the dependent variable and regress it on bank-specific variables. As noted earlier, our key variables related to interest rate risk are the bank's on- and off-balance sheet measures, *NIM Beta* and *IR Hedging*. *IR Hedging* reflects the bank's notional values of interest rate derivatives for hedging purposes, calculated as the bank's total gross notional amount of interest rate derivatives for purposes other than trading, scaled by the book value of assets[15]. As noted in the Introduction, recent studies by Drechsler et al. (2021) and DeMarzo et al. (2024) highlight the role of a bank's sensitivity (or "beta") of interest income and interest expense to changes in interest rates and can be summarized by their difference, *NIM Beta*. This variable captures the overall sensitivity of a bank's Net Interest Margin (NIM) where a positive *NIM Beta* indicates the bank adjusts the rates earned on its assets more aggressively than the rates paid on its liabilities (i.e., its "income beta" is larger than its "expense beta"). In this case, we can describe the bank's exposure to changing interest rates as "asset sensitive" because the rate the firm charges on its assets moves more than its liabilities. Conversely, a bank's interest rate risk is "liability sensitive" when the rate it charges on its liabilities respond more robustly than its assets.

From a cash flow perspective, a *positive NIM Beta* increases a bank's profits when overall interest rates *rise* because interest income would expand more than interest expense. Conversely, a *negative NIM Beta* can enhance a bank's profits when rates *fall* because the decline in interest expense will outweigh the decline in interest income. Drechsler et al. (2021) showed that this *NIM Beta* was nearly zero in aggregate for the U.S. banking industry and concluded that these banks naturally hedge their NIM and thus are not significantly exposed to interest rate risk from a cash flow perspective. However, as DeMarzo et al. (2024) and others have pointed out, from a duration-based valuation perspective, a bank's market value can still be exposed to interest rate risk, especially in cases like Silicon Valley Bank in March 2023, which held a large amount of unhedged long-term securities that were financed with short-term (and mostly uninsured) deposits. In this case, using off-balance sheet hedging via the *IR Hedging* metric might enhance a bank's market value above and beyond the bank's ability to hedge via its on-balance sheet *NIM Beta* exposure. Thus, our model described by Equation (6) provides a mechanism to test under what conditions *IR Hedging*

[15] Our *IR Hedging* variable, drawn from publicly available Call Report data, captures gross notional amounts of interest rate derivatives used for hedging. Unlike McPhail, Schnabl, and Tuckman (2024), who leverage non-public CFTC data on individual swap positions, our measure does not distinguish net long versus short positions.

and/or *NIM Beta* affect a bank's *MB* ratio, after controlling for other macroeconomic and firm-specific factors.

In terms of credit risk management, *Credit Deriv* reflects the net dollar amount of the bank's credit protection purchased and sold from credit default swaps, total return swaps, credit options, and other credit derivatives (scaled by total assets). This is a somewhat noisy measure because, unlike interest rate derivatives, the usage of credit derivatives is not reported in the call reports separately for hedging or trading purposes. In terms of an on-balance sheet-based measure of risk, we also include *Net Chargeoffs*, loan charge-offs and write-downs minus loan recoveries, scaled by the book value of assets.

As described by Equation (6), we control for several other bank financial characteristics that can affect equity returns, including *RWA*, risk-weighted assets (net of allowances and other deductions), scaled by the book value of assets; *MGAP*, 1-year maturity repricing gap ratio, scaled by the book value of assets; *Asset Growth*, the quarterly growth rate in the book value of assets; *Equity-to-assets ratio,* the total book value of equity, divided by total assets; *Uninsured Deposits*, total deposits that exceed FDIC insurance coverage, scaled by the book value of assets; *Securities*, the sum of securities held to maturity and securities available for sale in the bank's investment portfolio, scaled by the book value of assets; and *Net Trading Assets*, the difference between trading assets and trading liabilities, scaled by the book value of assets.

3.3. Summary statistics

Table 1 reports the summary statistics for the main variables used in our analysis for the full sample. Our main variable of interest, the market-to-book ratio, has an average of 1.50 over our sample. Moreover, interest rate hedging, *IR Hedging*, has an average value of 0.047 over the course of our sample. We show the graph of quarterly average market-to-book and *IR Hedging* during 2001Q1-2024Q3 in Figure 1. Here, there is a clear decline in average market-to-book around and during the Global Financial Crisis of 2007-09. Moreover, *IR Hedging* increases over the sample period to nearly 10% of a bank's total assets, likely due to both increased accessibility of derivatives markets to banks and the potential for rising interest rates as the Federal Funds rate was near-zero for most of the quarters in the sample. *IR Hedging* increases markedly starting around 2019, and again in the post-COVID period of 2022 onward. This is consistent with the Federal Reserve's rate hikes to fight inflation following the heart of the COVID crisis.

As shown in Table 1, the value of *IR Hedging* is 0 at the 25th percentile, and the value of *Credit Deriv* is 0 at the 75th percentile, meaning that at least 25% of bank-quarter observations correspond to banks that are not hedging interest rate risk with derivatives, and that at least 75% of bank-quarter observations relate to banks that are not hedging credit risk with off-balance sheet items.[16] In addition, the average on-balance sheet measure of interest rate risk (*NIM Beta*) is near-zero (-0.039) although its standard deviation is relatively high at 0.620. In part, the relatively small amount of interest rate hedging may be related to the low-interest rate environment that banks operated in for the majority of our sample period. However, as noted above related to Figure 1, the usage of derivatives for interest rate risk management has more than doubled in the last 6 years of our sample. Other control variables are generally in line with expectations.

Figure 2 further plots the quarterly average *IR Hedging* ratio alongside the percentage of banks in our sample with positive *IR Hedging* from 2001Q1 to 2024Q3. The figure reveals two notable patterns. First, the extensive margin of hedging participation has expanded substantially over the sample period: the share of banks using interest rate derivatives for hedging purposes has risen from roughly 30-40% in the early 2000s to approximately 80% by the end of the sample. Second, this expansion in participation has been accompanied by an increase in hedging intensity, as the average *IR Hedging* ratio has grown considerably, particularly from 2019 onward. Taken together with Figure 1, these trends suggest that the growth in aggregate *IR Hedging* documented earlier is driven by both a greater percentage of banks entering the derivatives market and existing hedgers scaling up their positions. The acceleration in both measures around 2019-2024 is consistent with banks anticipating or responding to the prospect of rising interest rates

[16] Most of the sample has a zero value for *Credit Deriv*. There are fewer than two thousand observations where this variable is negative and a 1,000+ observations where it is positive and these non-zero values are distributed evenly across time.

following the prolonged near-zero rate environment and underscores the increasing importance of derivatives-based interest rate risk management in the most recent portion of our sample.

4. Results

As a "baseline" model, we first estimate the impact of systematic factors on equity returns and conduct a panel regression specified earlier by Equation (5). Table 2 shows the first-stage regression results. Here, we regress the bank's market-to-book (*MB*) on a variety of market-wide risk factors, the size variables, and $Assetbelow50b_t$ and $Assetabove50b_t$, which capture how much the bank has in terms of assets above and below \$50 billion, as well as the bank's lagged *MB*, and bank and time fixed effects. Column (1) shows results including *MKT, TERM* and *DEF* but omitting *SMB, HML, RMW,* and *CMA* while column (2) includes these factors but omits *TERM* and *DEF*.

Both columns show that *MKT* and lagged *MB* are positively and significantly related to a bank's current *MB* level. Moreover, we find that *Assetbelow50b* is negatively and significantly related to *MB*. In addition, we find that the coefficient on *Assetabove50b* is negative but not significant. Taken together, it is important to recall that both size variables are continuous, linear functions and not binary dummy variables. Thus, these variables' parameters are not showing that small banks have lower relative valuations, but rather that *MB* ratios are decreasing in asset size. Our result is consistent with Minton et al. (2019) that finds an overall negative relationship between bank size and *MB* ratios while the biggest banks do not appear to benefit from a "TBTF" subsidy.[17] The results further show that the coefficients on risk factors like *TERM, DEF, SMB, HML, RMW,* and *CMA* are, in some cases, marginally significant, but seemingly not as important to bank *MB* as lagged *MB*, *MKT*, and the size variables.

[17] This result contrasts with Gandhi and Lustig (2015), who find that large banks have lower risk-adjusted returns that are likely due to size-dependent exposure to bank-specific "tail risk" and the potential of government guarantees that protect against this risk, but not for small and medium banks.

As noted in the Introduction, after estimating the first-stage model, we extract the residuals from regression (1) in Table 2 to isolate the idiosyncratic component of a bank's *MB* ratio. Using this residual, we can more clearly identify the impact of a bank's strategic and managerial choices on its valuation by removing systematic risk sources that may cloud the effect of the bank's internal decision-making process. As noted earlier, we call this residual the "*Adjusted MB*" ratio.

We present the results from a baseline second-stage panel regression in Table 3. In this table, we rely on the model described by Equation (6).[18] Column (1) reports the results, while Columns (2) and (3) show the results from regressions when we split the sample into periods in which the Federal funds rate is increasing or decreasing, respectively, to assess the impact of differing interest rate environments on bank valuation and decision making. All regressions in Table 3 include bank and time fixed effects. Moreover, the dependent variable in our second-stage regressions is an estimated residual from the first stage, and so standard clustered standard errors might understate the true sampling uncertainty by ignoring estimation error from the first stage (Pagan, 1984). To address this concern, we report bootstrapped standard errors clustered by bank and time, which provide more reliable finite-sample inference in the presence of generated regressors.[19]

In our main results for the full sample shown in Column (1), the coefficient of *IR Hedging* is positive and statistically significant. This result suggests that bank valuation increases with interest rate hedging activities. Moreover, the coefficient for *Credit Deriv* is positive but not statistically meaningful, suggesting that the usage of credit derivatives, while positively associated with *Adjusted MB*, does not have a significant impact on the bank's value. Our finding for *IR Hedging* is also economically significant. Using

---

[18] Given that Froot and Stein (1998) suggests a potential interior optimum solution to the bank's risk management problem, we test our model by also including a squared term for *IR Hedging* but find (in unreported results) that this nonlinear term is not significant and so we focus on the linear form of *IR Hedging* in the results reported here.

[19] We used Stata's built-in bootstrap prefix function with 1,000 replications. In each replication, the data are resampled and the full *reghdfe* specification is re-estimated. The reported bootstrap standard errors are the standard deviations of the coefficient estimates across the full set of replications.

the coefficient on *IR Hedging* from Regression (1), 0.101, we show that a one-standard deviation increase in *IR Hedging* (0.0912) is associated with a change in *Adjusted MB* of +0.00921, which is an increase in *Adjusted MB* of approximately 4.0% relative to its own standard deviation of 0.2320.

The coefficients on control variables in Regression (1) of Table 3 are generally as expected. *Net Chargeoff* is negative and significantly related to *Adjusted MB*. This finding is related to increasing realized credit risk from bad loans and is consistent with prior studies such as Calomiris and Nissim (2014) and Minton et al. (2019). Alternatively, the coefficients on *Securities* and *Net Trading Assets* are positively and significantly related to the bank's *Adjusted MB*. Here, this result can potentially represent the bank's preparation for an anticipated liquidity need. For a typical commercial bank, both *Securities* and *Net Trading Assets* can potentially include the bank's holdings of Treasury securities, which can be quickly exchanged for cash at stable prices. Although we do not focus on liquidity risk management in this paper, we can potentially interpret this particular result related to a bank's securities holdings as an example of investors' attention to this type of risk. In addition, a bank's asset growth also has a positive effect on its *Adjusted MB.*

The weak results for credit derivatives usage are consistent with a literature that documents the limitations of CDS as a credit risk management tool. Das, Kalimipalli, and Nayak (2014) show that CDS trading was largely detrimental to corporate bond markets, with no improvement in pricing efficiency or liquidity. Bolton and Oehmke (2011) highlight the 'empty creditor' problem, whereby banks that purchase credit protection may over-insure in equilibrium, leading to reduced monitoring incentives and an inefficiently high incidence of costly bankruptcy. This practice effectively transforms CDS from a risk management tool into a source of moral hazard. These findings suggest that CDS instruments may be inherently limited in their ability to enhance bank market values, even when used for hedging purposes. In addition, Acharya, Schnabl, and Suarez (2013) document that banks have historically used credit-related securitization vehicles primarily for regulatory arbitrage rather than genuine risk transfer, further suggesting that off-balance sheet credit risk management tools may not create shareholder value in the same manner as interest rate derivatives. As noted earlier, our *Credit Deriv* variable from the Call Reports also does not distinguish between client-driven trading activity and the bank's own risk management needs, which likely adds noise to our estimates.

Regressions (2) and (3) of Table 3 split our sample between quarters when the Federal Funds rate is increasing or decreasing. To capture the interest rate environment a bank has been operating in over the past year, the "Federal Funds Rates up (down)" period includes only quarters when the Federal Fund Rate is higher (lower) than its level from four quarters ago. We again find the same results as in regression (1). During rising rate environments, Column 2 shows the coefficient for *IR Hedging* is positively and significantly related to *Adjusted MB*, while the coefficient on *Credit Deriv* is positive but not statistically significant. In addition, the *NIM Beta* is positive and significant, which suggests that a bank's market value is enhanced during rising rate conditions when: a) the bank's on-balance sheet position is "asset sensitive" from a cash flow perspective *and* b) it chooses to use more interest rate derivatives (possibly to hedge any duration-based negative effects on the firm's market value).

We also find in Table 3 that our control variables follow a generally similar pattern to those in the full sample results although *Securities* holdings are no longer significant and *Asset Growth* is now positively related to the bank's *Adjusted MB.* This latter finding and the positive coefficient for *NIM Beta* suggest that investors reward banks that grow faster when rates are rising because they are better positioned to increase their lending rates relative to their deposit rates. Also, we find the *Efficiency Ratio* to be negatively related to market value. This is consistent with DeMarzo et al's (2024) observation that a bank's operating costs can be viewed as a short position in a fixed rate bond.

Column 2 provides evidence that market values are larger due to interest rate hedging activity and greater asset sensitivity in rising interest rate environments. In terms of economic magnitude, the coefficient on *IR Hedging* is 0.086 during rising rate environments, and a one-standard deviation increase represents a +0.0079 increase in *Adjusted MB* (i.e., +3.5% of the *Adjusted MB's* standard deviation). Notably, the results in Column 3 show that the coefficient on *IR Hedging* (0.130) is also positively and significantly related to *Adjusted MB* when rates are falling and has an economic impact on *Adjusted MB* of +4.7%. In addition, *Net Chargeoff, MGAP,* and *Securities* are also significant in this subsample.

Taken together, the results in Table 3 suggest that the market values interest rate hedging in both rising and falling rate environments. In rising rate markets, banks generally face refinancing risk as they rely on very short-term liabilities (like deposits), which are potentially more susceptible to rate increases compared to their relatively longer-lived assets (resulting in a positive asset-liability duration gap). In falling rate environments, hedging may help lock in higher interest revenue while allowing interest expense to decline. As we show below, the benefits of hedging when rates fall are further supported in specific subsamples related to bank financing and investment holdings.

Our findings are also consistent with the broader corporate finance literature on selective hedging. Knill, Minnick, and Nejadmalayeri (2006) show that non-financial firms selectively increase their hedging activity when they anticipate adverse market conditions rather than maintaining constant hedge ratios. We observe an analogous pattern in the banking sector: the positive valuation effect of interest rate hedging is most pronounced when banks face adverse conditions like rising rates combined with large uninsured deposit exposures, significant unrealized securities losses, or higher liquidity creation. This suggests that, as in the corporate hedging literature, the market rewards firms that strategically increase hedging when their risk exposures are greatest.

Table 4 investigates the link between hedging and a bank's uninsured deposits. Following the 2023 regional banking crisis in the U.S., the importance of uninsured deposits became very clear, given their heightened risk of a run due to increased interest rate risk and a bank's unrealized securities losses. In this set of tests, we sort our data in two ways: first, by increasing and decreasing interest rate environments, as noted above, and second, into top and bottom terciles of bank uninsured deposits.

Regression (2) of Table 4 reveals that the coefficient on *IR Hedging* remains positive and statistically significant as it relates to *Adjusted MB* for banks with high uninsured deposits when rates are rising. Results for banks in the top tercile of uninsured deposits are shown in columns (2) and (4) under the heading of ">67%" and for the lowest tercile in columns (1) and (3). In contrast to regression (2), we find that the coefficient on *IR Hedging* remains positive but is not statistically different from zero in columns (1), (3), and (4). This result suggests that interest rate hedging at banks is not valued by the market as much during falling interest rate environments or when banks do not take on a large amount of uninsured deposits in rising rate environments. The former finding could occur because it is more beneficial in this case for a bank to avoid hedging during falling rates by allowing for greater funding flexibility in setting deposit rates for large, uninsured depositors. The latter result may be related to a greater probability of FDIC action to protect the depositors during a time of stress, should the bank have meaningful exposure to rising interest rates.

The results in Table 4 also continue to suggest that our credit risk hedging variable, *Credit Deriv*, is not highly valued by the market. Throughout the four regressions here, the coefficient on *Credit Deriv,* has mixed signs, and is not statistically different from zero in any regression.

In Table 5, we further examine the idea of how interest rate hedging specifically interacts with bank valuation. As we have noted, the 2023 U.S. regional banking crisis revealed that investors can become highly aware of the unrealized losses that a bank may have on its securities portfolio. To this end, we collect data regarding banks' unrealized losses on their available-for-sale (AFS) and held-to-maturity (HTM) portfolios. In both cases, unrealized losses are normalized by total assets. We once again sort banks into terciles of unrealized losses for each portfolio and split our sample between rising and falling rate environments. Panel A of Table 5 examines unrealized losses on the AFS portfolio while Panel B examines unrealized losses on the HTM portfolio.

The results in Panel A show that *IR Hedging* is positively but not significantly related to *Adjusted MB* for banks with high unrealized losses during times of rising interest rates (i.e., AFS losses in the top tercile). Regression (2) in Panel B shows that for the HTM portfolio, only banks with high unrealized losses that hedge during rising rate environments are rewarded by investors. For other subsamples based on HTM losses, we observe that *IR Hedging* is not valued by investors. These results draw a clear distinction between HTM and AFS losses, showing that bank *MB* may be more sensitive to the former rather than the latter.

Panel C of Table 5 examines sample sorts based on the total of both AFS and HTM unrealized losses. Again, we find that *IR Hedging* has a positive and significant coefficient during rising rate environments for banks with high unrealized losses on their total investment portfolios. The *IR Hedging* coefficient is large (+0.140) for the subsample of banks in the top tercile of unrealized losses and appears to be driven by the positive relationship shown earlier in Panel B between *Adjusted MB* and the HTM portfolio. Assuming a one-standard deviation increase in *IR Hedging*, this model's parameter estimate yields an estimated economic impact that represents a +4.7% increase in the *Adjusted MB* (relative to its subsample standard deviation 0.2334). This observation indicates that investors value more highly banks that hedge when they hold larger unrealized losses in their securities portfolios and rates are rising. Given that fixed income securities typically decline as interest rates climb, investors appear to reward banks that hedge because such firms might be able to mitigate potentially larger losses in the future. In contrast, the results in Regressions (3) and (4) show that the coefficient for *IR Hedging* is positive but not significant when interest rates are falling. Taken together, these results reinforce our findings in Panel B, that investors value interest rate hedging in rising rate environments, and particularly for banks with higher unrealized losses on their HTM securities portfolios.

We also study the differential impact of interest rate hedging for banks that are more actively creating liquidity. Banks that are liquidity creators should be more likely to use low duration funding sources (e.g., deposits) and invest in high duration assets (e.g., mortgages), thus exposing them to a wider duration gap and greater interest rate risk exposure. To investigate this, we lean on Berger and Bouwman's (2009) measure of liquidity creation activity and sort our sample accordingly. We follow their approach and develop our LC variables using specific Call Report codes as defined in Table A7 of the Appendix.

Table 6 shows our results related to liquidity creation (LC). In Panel A, we sort banks by Berger and Bouwman's (2009) *CATFAT* and *CATNONFAT* measures. The former captures a bank's total liquidity creation, while the latter removes any off-balance sheet (OBS) liquidity creation from the estimation. We find that high LC banks are rewarded more from investors for hedging interest rate risk for certain types of liquidity creation activity. In Panel A, regressions (1) and (3) correspond to above-median *CATFAT* and the *IR Hedging* coefficients are both positive and significant. Panel B focuses on on-balance sheet asset-side LC and liability-side LC and reports positive and statistically significant *IR Hedging* coefficients across all four subsamples. Finally, Panel C examines above- and below-median off-balance sheet LC. Here, we find strong results as the coefficient on *IR Hedging* is positive and significantly related to *Adjusted MB* for the above-median subsample. When off-balance sheet liquidity creation is above the median, we report one of our largest positive coefficients within this table at +0.114 and it is significant at the 5% level. This observation suggests that banks with a large amount of OBS activity related to issuing loan commitments, lines of credit, and letters of credit, etc. might be more exposed to interest rate fluctuations and therefore have a greater incentive to hedge this risk. Altogether, the results for both on-balance sheet and off-balance sheet liquidity provision are in line with our expectation that high LC banks should benefit the most from hedging interest rate risk, likely because their business model choice is inherently more exposed to this risk.

In Table 7, we split the sample into positive and negative *NIM Beta* banks and within rising and falling interest rate environments. We find that, like in other tests, *IR Hedging* seems to matter most when interest rates are rising and when the bank's balance sheet is in a positive *NIM Beta* position (as reported in the first row of Column 2). As noted in the Introduction, the economic magnitude of a one-standard deviation increase in *IR Hedging* corresponds to a +4.6% improvement in a bank's *Adjusted MB* when rates are rising and the bank has a positive *NIM Beta* position. Although the effect of *IR Hedging* is positive but insignificant, banks with a negative *NIM Beta* benefit when rates rise due to their on-balance sheet interest rate sensitivity, as shown by the last row of Table 7 for Columns 1 and 2.

In the rising rate subsample, we also observe that *Asset Growth* enhances market value for positive *NIM Beta* banks while higher operating costs, as measured by the *Efficiency Ratio*, decrease *Adjusted MB* for negative *NIM Beta* banks. Like we saw earlier in Table 3, these effects are consistent with the notion that a positive *NIM Beta* represents an "asset-sensitive" firm and thus greater asset growth is more likely to strengthen a firm's asset position and consequently enhance the *MB* ratio. In addition, the positive and significant parameters for both *IR Hedging* and *NIM Beta* in column 2 of Table 7 show that banks can benefit from this asset-sensitivity by simultaneously managing both duration-based valuation losses and cash flow sensitivity, respectively. Conversely, a negative *NIM Beta* corresponds to a "liability-sensitive" bank and thus greater operating costs (as measured by the *Efficiency Ratio*) can worsen the firm's liability position and therefore is likely to reduce market value.

The most significant variables when rates are decreasing are *MGAP, Securities* and *Net Trading Assets* for positive *NIM Beta* banks, as shown in Column (4) of Table 7. In this case, neither *IR Hedging* nor *NIM Beta* variables are significant and suggests that interest rate hedging is not, on average, beneficial in a falling rate environment. However, when a bank is "asset-sensitive" within this interest rate scenario, it seems that market value can be enhanced by increasing its 1-year maturity repricing gap, and via adding assets that are especially rate-sensitive such as *Securities* and *Net Trading Assets*. So, rather than reducing risk in this situation, "asset-sensitive" banks could be taking on interest rate risk in the hope that falling rates will increase the profitability and value of these assets. Overall, the results reported here show that there are statistically and economically significant benefits to hedging interest rate risk and, at times, taking on additional interest rate risk when rates are declining.

5. Robustness

5.1 Fama-French 5-Factor model results

To test the robustness of our analysis, we use the Fama-French five factors as the systematic variables that affect equity returns and *MB* ratios in our first-stage regressions and use the corresponding residuals as the dependent variable in our second-stage regressions. The results are reported in Tables 8 and 9. We find that the results from using the Fama-French five factor model are generally consistent with those from our main specifications.

Table 8 presents our baseline results, along with results related to splitting our sample by rising and falling rates, and high / low uninsured deposits. As we have shown before, *IR Hedging* is positively and significantly related to the regression residual, *Adjusted MB,* across all specifications except for regressions (4), (6), and (7), which correspond to low uninsured deposits in rising rate environments and falling rate environments when uninsured deposits are either relatively low or high, respectively. Table 9 splits the sample between rising and falling rates, along with using high / low terciles of the banks' total AFS and HTM unrealized losses. Like the results from Table 5 based on our original first-stage model, *IR Hedging* is positively and significantly related to the *Adjusted MB* in rising rate environments for banks with high unrealized losses in their securities portfolios.

5.2 Additional robustness tests

In the Appendix we report two additional time series graphs as Figures A1 and A2 to compare our average *IR Hedging* variable with the *Adjusted MB* ratio and the Federal Funds rate. We also perform several additional tests and report them in Tables A2-A6. Table A2 repeats our second-stage panel regressions for rising and falling rate conditions but splits the sample by the median (rather than terciles) for uninsured deposits. These results are qualitatively similar to our findings in Table 4. In addition, we examine the impact of different levels of lending activity in Table A3 using median values and find results like Table 3 that show *IR Hedging* is significant in rising rate environments for banks that are above-median lenders. This finding is largely consistent with our LC findings in Table 6.

We also follow some of the prior literature such as Calomiris and Nissim (2014) that found that a firm's dividend ratio (normalized by common equity) can be a signal of financial strength and positively impact *MB*. In Table A4, we include an additional control variable for a bank's dividend ratio in our second-stage regression as in Calomiris and Nissim (2014) and find a significant and positive effect of dividends on *MB* when rates are falling. Most importantly, our *IR Hedging* parameters remain robust to the inclusion of dividends. In addition, in Table A5, we follow Minton et al. (2019) and scale all our independent variables by the book value of common equity (in contrast to our scaling these variables by the book value of total assets). This table confirms that our *IR Hedging* variable is robust to this alternative scaling method in rising rate environments, as in most of our prior tests.

Lastly, we confirm in Table A6 that our two-stage panel regression process and the choice of asset pricing factors in the first stage are not obscuring the true relationship between *IR Hedging* and *MB*. In this table, we collapse the two-stage model of Equations (5) and (6) into a one-stage panel regression by removing all the asset pricing factors and using the unadjusted *level* of the *MB ratio* (rather than a residual) as the dependent variable. As Table A6 shows, *IR Hedging* remains positive and significant for the full sample while *Credit Deriv* is still insignificant. Overall, the test results of Tables A2-A6 show that our findings are robust to alternative methods of splitting the sample, scaling our explanatory variables differently, including additional control variables, as well as using an alternative one-stage estimation process.

5.3 Triple Difference-in-Differences (DDD) Test

A potential concern with our baseline results is that the positive relationship between *IR Hedging* and *Adjusted MB* may reflect reverse causality or omitted variables rather than a causal effect of hedging on market value. For instance, banks that hedge more may also differ systematically in other dimensions that drive higher equity valuations. To strengthen the causal interpretation of our findings, we rely on the Federal Reserve's aggressive monetary tightening cycle that began in 2022Q1 as a plausibly exogenous shock to the value of interest rate risk management.

Between 2022Q1 and mid-2023, the Federal Funds rate rose from near zero to over 5%, representing one of the most rapid tightening episodes in recent U.S. history. This shock was largely exogenous to individual bank valuation decisions, as it was driven by the Federal Reserve's response to economy-wide inflationary pressures rather than by conditions specific to any single bank. Crucially, this sharp and largely unanticipated increase in rates dramatically raised the importance of interest rate hedging by imposing substantial mark-to-market losses on unhedged fixed income portfolios and increasing the funding costs associated with rate-sensitive liabilities. This setting provides a natural experiment in which the value of pre-existing hedging positions should be revealed differentially across banks with varying degrees of interest rate risk exposure. In addition, as shown in Figure 3, the estimates of a triple interaction term (described below in Equation 7) show that the valuation effect of interest rate hedging strengthens notably at the start of the rate shock in 2022Q1 as well as in 2022Q3, providing visual and statistical support for a structural change in how the market valued hedging activity following the onset of the tightening cycle. In addition, the lack of significance for the pre-shock coefficients during the -4 to -2 quarters in Figure 3 confirms that there are no pre-shock parallel trends.

To compute the parameter estimates displayed in Figure 3, we implement a triple difference-in-differences (DDD) specification that exploits three independent sources of variation. The first dimension is temporal: we compare outcomes before the shock (2021Q1-2021Q4) to those after the shock (2022Q1-2023Q1). The second dimension captures pre-existing hedging intensity: we classify banks as "Treated" if their average *IR Hedging* over the *pre-shock* period exceeds the sample median, and as non-treated otherwise. By measuring hedging intensity over a window that precedes the shock, we mitigate concerns that contemporaneous hedging decisions responded endogenously to changing market valuations. The third dimension captures a bank's vulnerability to interest rate risk through its liquidity creation activity. As documented in Table 6, banks that create more liquidity tend to fund long-duration assets (e.g., mortgages, lines of credit, and commercial loans) with short-duration liabilities (e.g., deposits), thus exposing them to a wider duration gap and making them inherently more vulnerable to rising interest rates. We classify banks as "High LC" if their pre-shock liquidity creation exceeds the sample median, again measured over 2021Q1-2021Q4, to avoid contamination from the post-shock period.

The DDD specification takes the following form:

$$Adjusted\ MB_{i,t} = \beta_1(Post_t \times Treated_i \times High\ LC_i) + \beta_2(Post_t \times Treated_i)$$

$$+ \beta_3(Post_t \times High\ LC_i) + Controls_{i,\,t-1} + \gamma_i + \delta_t + \epsilon_{i,t} \qquad (7)$$

where $Post_t$ are event-time dummies and equal one for each specific quarter during the post-shock period of 2022Q1 to 2023Q1 as well as for the pre-shock period of 2021Q1-2021Q3 (and zero for the pre-event reference period of 2021Q4). $Treated_i$ equals one for banks with above-median pre-shock *IR Hedging*, and $High\ LC_i$ equals one for banks with above-median pre-shock liquidity creation. Bank fixed effects (γ_i) absorb all time-invariant bank characteristics, including the main effects of $Treated_i$ and $High\ LC_i$ and their cross-sectional interaction, while quarter fixed effects (δ_t) absorb all aggregate time-series variation, including the main effect of $Post_t$. The full set of time-varying bank-level controls from our baseline specification (Equation 6) is also included. The coefficient of interest is on the triple interaction term's coefficient, β_1, which captures whether, among banks with greater liquidity creation and thus higher inherent interest rate risk exposure, those that had pre-committed to hedging experienced differentially higher $Adjusted\ MB$ following the exogenous rate shock.

Table 10 reports the results. The triple interaction term, $Post \times\ Treated \times\ High\ LC$, is positive and statistically significant at the 1% level, with a coefficient of 0.058.[20] This finding provides direct evidence that interest rate hedging created shareholder value precisely where it was most needed: among banks whose liquidity creation activities left them most exposed to the consequences of rising rates. The magnitude of the coefficient is economically meaningful. Table 10 indicates that, within the subset of high-LC banks, those with above-median pre-shock hedging positions experienced an $Adjusted\ MB$ that was approximately 5.8 percentage points higher during the post-shock period relative to their less-hedged, equally exposed peers.

[20] We performed a placebo test and confirmed its insignificance relative to our Table 10 findings.

Notably, both two-way interaction terms are negative and statistically significant: $Post \times Treated$ carries a coefficient of -0.032 (t = -2.707) and $Post \times High\ LC$ a coefficient of -0.041 (t = -2.982). While these negative effects might be surprising at first glance, these coefficients make sense when considered alongside the positive triple difference parameter estimate. The negative coefficient on $Post \times High\ LC$ is intuitive: banks with greater liquidity creation inherently maintain wider duration gaps and thus suffered larger valuation declines when the rate shock materialized. This is consistent with our earlier findings that interest rate exposure erodes market value during tightening cycles (Tables 4 and 5) and aligns with the broader literature on the risks of maturity transformation (Drechsler et al., 2023; Jiang et al., 2024). The negative coefficient on $Post \times Treated$ indicates that, unconditionally, banks classified as hedgers experienced lower $Adjusted\ MB$ in the post-shock period. This finding likely reflects a combination of factors. First, hedging is costly: maintaining derivatives positions involves direct expenses such as bid-ask spreads as well as margin requirements and monitoring costs, as well as opportunity costs from forgoing potential gains on unhedged positions. When a bank hedges but does not face significant interest rate risk exposure, these costs may outweigh the benefits, resulting in a lower valuation. Second, this pattern may reflect a selection effect: banks that hedge more intensively may tend to be those with more complex balance sheets or greater underlying risk exposures, characteristics that the market might have penalized broadly during a period of heightened uncertainty about bank solvency following the collapse of Silicon Valley Bank and other regional banks in early 2023.

The critical insight from the triple difference is that these unconditional penalties reverse for banks when hedging matters most. The positive and significant β_1 shows that, conditional on high liquidity creation, pre-committed hedging generated a valuation premium that more than offset the costs captured by the two-way interactions. In net terms, high-LC banks that hedged experienced a post-shock change in Adjusted MB of approximately -0.032 - 0.041 + 0.058 = -0.015, which is economically small. By contrast, treated banks with low LC experienced a decline of -0.032, and high-LC banks that did not hedge experienced an even larger decline of -0.041. The market thus did not reward hedging indiscriminately;

rather, it recognized and rewarded hedging specifically at banks where the protection was most material to the firm's risk profile.

Overall, the DDD results strengthen the causal interpretation of our baseline findings by demonstrating that the valuation benefits of interest rate hedging emerge differentially in response to an exogenous shock and are concentrated precisely among the banks with the greatest ex ante vulnerability. The pattern of coefficients also helps rule out several alternative explanations. If the positive association between hedging and valuation were driven entirely by omitted bank quality (i.e., hedgers are simply "better" banks), then we would expect the unconditional *Post x Treated* coefficient to be positive rather than negative. Instead, the results point to a mechanism in which the protective value of hedging is activated by adverse interest rate movements and amplified by the bank's underlying interest rate risk exposure, consistent with a genuine risk management channel.

6. Conclusion

This paper evaluates the market's perception of the value of hedging for banks. We investigate how banks' market-to-book ratios change relative to interest rate and credit risk hedging. Our findings indicate that the market clearly values interest rate risk hedging by commercial banks and has the potential to raise the median bank's stock returns by about 0.7% per year (a +15.6% improvement over an industry average return of 4.766%). In contrast, investors do not appear to value as highly a bank's attempts to hedge credit risk. These results are consistent across various sample sorts, different control variables, and alternative estimation methods that control for endogeneity, parallel trends, and different asset pricing models.

In contrast to prior literature, we isolate the firm's risk management choices by estimating a two-stage model that identifies the time-varying, bank-specific idiosyncratic nature of a bank's market-to-book ratios. We do this by regressing market-to-book ratios on a battery of systematic risk factors and recovering the residual, which we presume proxies for the firm-specific portion of market-to-book ratio, and better reflects how the firm's strategic choices and management style impact the market-to-book ratio. Our findings build upon earlier work on bank market-to-book ratios by Calomiris and Nissim (2014) and Minton et al. (2019). In contrast to these studies, we focus on the impact of bank risk management decisions and provide new insights into how banks can create value for their equity investors. We also contribute to the recent debate on the impact of bank interest rate exposure on firm value, as described by the focus on cash flow hedging in Drechsler et al. (2021) and the emphasis on duration-based valuation effects in DeMarzo et al. (2024). We find empirical support for both viewpoints, but which vary depending on monetary conditions and the specific interest rate sensitivities of the bank's assets and liabilities. In addition, by isolating when and how hedging can improve a bank's market value, policymakers and bank examiners can also benefit when analyzing a bank's risk management activities.

Our results carry important implications for bank supervisors and policymakers. The 2023 regional banking crisis exposed how unhedged interest rate risk can rapidly erode depositor and investor confidence, yet supervisory frameworks have historically focused on credit risk and capital adequacy rather than on how banks manage interest rate exposures through derivatives. Our finding that interest rate hedging is most valuable precisely when it is most needed (e.g., during monetary tightening, for banks with large uninsured deposit bases and significant unrealized securities losses) suggests that regulatory stress tests should more explicitly incorporate the role of derivatives-based hedging in assessing bank resilience. Moreover, the concentration of hedging activity among larger institutions, combined with the negligible derivatives usage at the 25th percentile of our sample, indicates that many smaller banks remain exposed to the same interest rate dynamics that contributed to the failures of Silicon Valley Bank and Signature Bank. Policymakers may wish to consider whether supervisory guidance or incentive structures could encourage broader adoption of prudent hedging practices, particularly among community and regional banks whose deposit franchises may provide less natural insulation from rate shocks than previously assumed.

References:

Acharya, V.V., Schnabl, P., and G. Suarez, 2013, Securitization without risk transfer, *Journal of Financial Economics* 107, 515-536.

Begenau, J., M. Piazzesi, and M. Schneider, 2015, Banks' risk exposures, NBER working paper.

Berger, A.N., and C.H.S. Bouwman, 2009, Bank liquidity creation, *Review of Financial Studies* 22, 3779–3837.

Berger, A.N. and J. Sedunov, 2024, The life-cycle of systemic risk and crises, *Journal of Money, Credit, and Banking* 56, 1923-1961.

Bogdanova, B., Fender I., and E. Takáts, 2018, The ABCs of Bank PBRs, *BIS Quarterly Review*, Bank for International Settlements, March, 81-95.

Bolton, P., and M. Oehmke, 2011, Credit default swaps and the empty creditor problem, *Review of Financial Studies* 24, 2617-2655.

Calomiris, C.W., and D. Nissim, 2014, Crisis-related shifts in the market valuation of banking activities, *Journal of Financial Intermediation* 23, 400-435.

Chen, N.F., R. Roll, and S.A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.

Choi, M., and G. Rocheteau, 2023, A model of retail banking and the deposits channel of monetary policy, *Journal of Monetary Economics* 139, 127-147.

Choi, W.W., Kim, J., and M. Kim, 2016, Derivatives holdings and market values of U.S. bank holding companies, *Applied Economics* 48, 1-11.

Das, S.R., Kalimipalli, M., and S. Nayak, 2014, Did CDS trading improve the market for corporate bonds? *Journal of Financial Economics* 111, 495-525.

Delis, M.D., and Y. Karavias, 2015, Optimal versus realized bank credit risk and monetary policy, *Journal of Financial Stability* 16, 13-30.

DeMarzo, P.M., Krishnamurthy, A., and S. Nagel, 2024, Interest rate risk in banking, NBER Working Paper No. 33308.

Dermine, J., 2015, *Bank Valuation and Value Based Management: Deposit and Loan Pricing, Performance Evaluation, and Risk*, 2nd edition, McGraw- Hill Education.

Diamond, D.W., 1984, Financial intermediation and delegated monitoring, *Review of Economic Studies* 51, 393-414.

Drechsler, I., A. Savov, and P. Schnabl, 2017, The deposits channel of monetary policy, *Quarterly Journal of Economics* 132, 1819-1876. (doi:10.1093/qje/qjx019)

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

Drechsler, I., A. Savov, P. Schnabl, and O. Wang, 2023, Deposit Franchise Runs, forthcoming, *Journal of Finance*, DOI: 10.1111/jofi.70034 .

Egan, M., Lewellen, S. and A. Sunderam, 2022, The Cross-Section of Bank Value, *Review of Financial Studies*, 35, 2101–2143.

Flannery, M.J., and C.M. James, 1984, The effect of interest rate changes on the common stock returns of financial institutions, *Journal of Finance* 39, 1141-1153.

Froot, K. A. and J. C. Stein, 1998, Risk management, capital budgeting, and capital structure policy for financial institutions: An integrated approach. *Journal of Financial Economics* 47, 55–82.

Gandhi, P. and H. Lustig, 2015, Size anomalies in U.S. bank stock returns, *Journal of Finance*, 70, 733-768.

Jiang, E.X., Matvos, G., Piskorski, T., and A. Seru, 2024, Monetary tightening and U.S. bank fragility in 2023: Mark-to-market losses and uninsured deposit runs? *Journal of Financial Economics* 159, 103899.

Kim, R., 2023, Do banks hedge the risk of fixed-income security holdings? Working paper.

Knill, A.M., Minnick, K., and A. Nejadmalayeri, 2006, Selective hedging, information asymmetry, and futures prices, *Journal of Business* 79, 1475-1501.

McPhail, L., Schnabl, P., and B. Tuckman, 2024, Do banks hedge using interest rate swaps? NBER Working Paper No. 31166.

Miloș, M.C., and L.R. Miloș, 2022, Use of derivatives and market valuation of the banking sector: Evidence from the European Union. *Journal of Risk and Financial Management* 15, 501.

Minton, B.A., Stulz, R.M., and A.G. Taboada, 2019, Are the largest banks valued more highly? *Review of Financial Studies* 32, 4604-4652.

Pagan, A., 1984, Econometric issues in the analysis of regressions with generated regressors, *International Economic Review* 25, 221-247.

Pagano, M.S., and J. Sedunov, 2025, *Managing Financial Institutions: An Integrated Valuation Approach*, World Scientific Series in Modern Finance: Advanced Topics in Finance for the Academician and Practitioner, Vol. 3.

Purnanandam, A., 2007, Interest rate derivatives at commercial banks: An empirical investigation, *Journal of Monetary Economics* 54, 1769-1808.

Saunders, A., Cornett, M.M. and O. Erhemjamts, 2024, *Financial Institutions Management: A Risk Management Approach,* McGraw-Hill, New York.

Sinkey, J.F., and D.A. Carter, 2000, Evidence on the financial characteristics of banks that do and do not use derivatives. *Quarterly Review of Economics and Finance* 40, 431–449.

Sopranzetti, B., and B. Kiess, 2024, *Valuation and Financial Forecasting: A Handbook for Academics and Practitioners*, World Scientific Series in Modern Finance: Advanced Topics in Finance for the Academician and Practitioner, Vol. 2.

Stulz, R., 2013, How companies can use hedging to create shareholder value, *Journal of Applied Corporate Finance* 25, 21-29.

Figure 1: Quarterly mean Market-to-Book Ratio and Interest Rate Hedging (2001Q1–2024Q3)

This graph presents the quarterly average market-to-book (MB) ratio and interest rate (IR) hedging for U.S. banks from 2001Q1 to 2024Q3. The left axis corresponds to the market-to-book ratio, while the right axis corresponds to the interest rate hedging ratio.

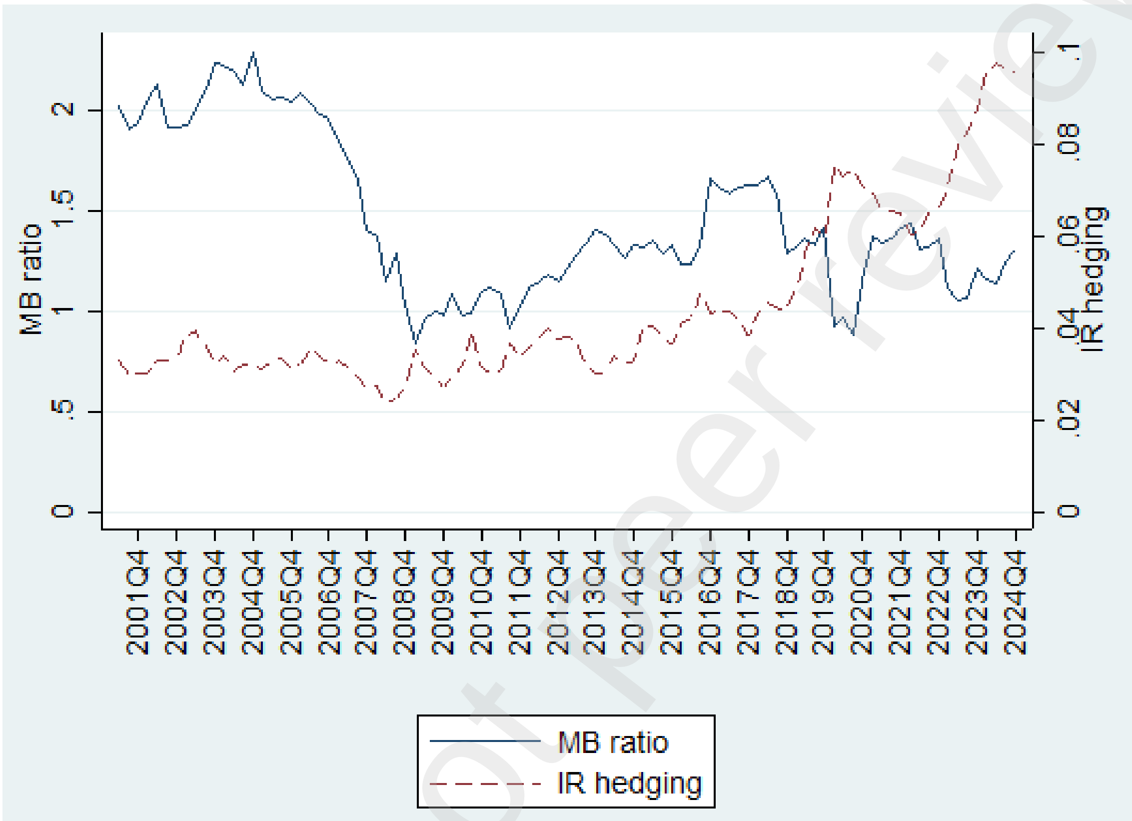

Figure 2: Quarterly mean Interest Rate Hedging and percentage of banks with positive IR hedging (2001Q1–2024Q3)

This graph presents the quarterly average interest rate (IR) hedging and the percentage of banks with positive IR hedging for U.S. banks from 2001Q1 to 2024Q3. The left axis corresponds to the percentage of banks with positive *IR Hedging*, while the right axis corresponds to the mean *IR Hedging* measure.

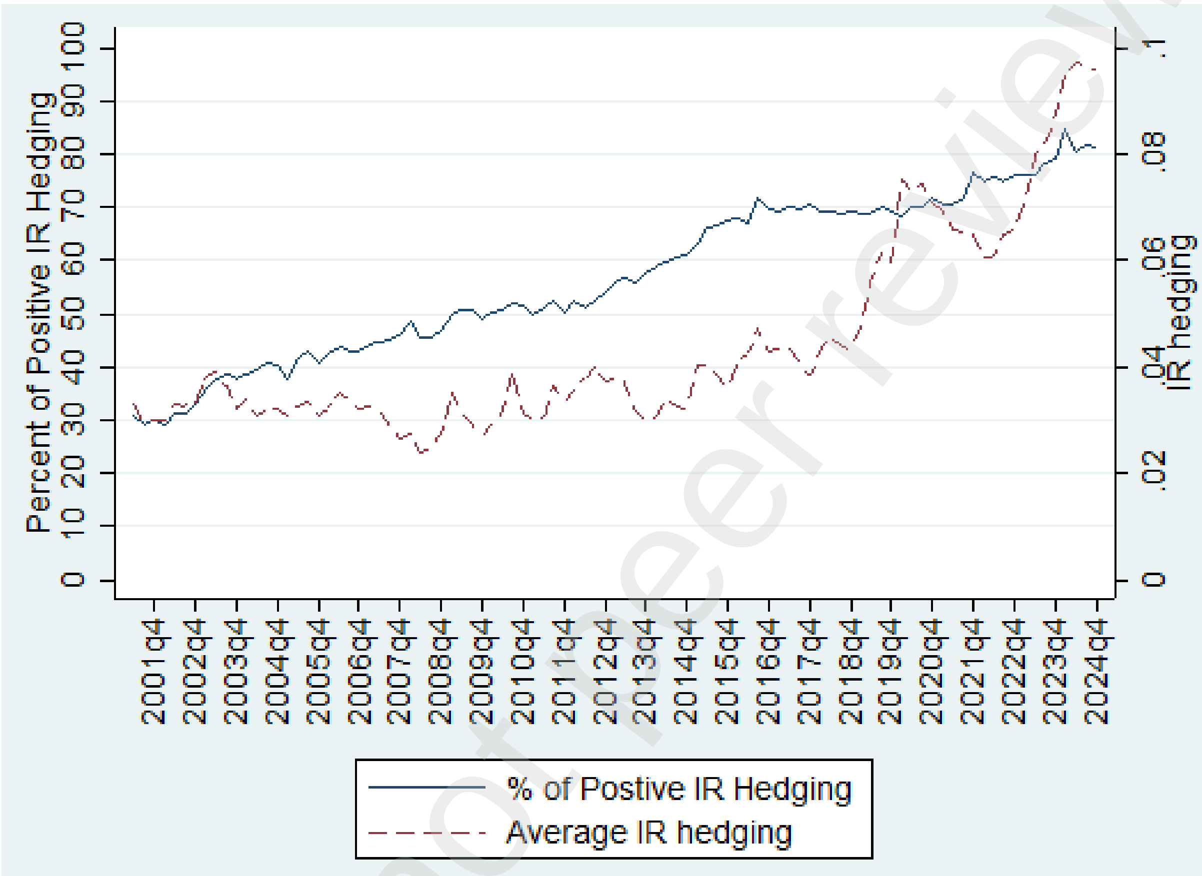

Figure 3: Rolling-Sample Estimates of the Effect of Interest Rate Derivatives Hedging

This figure plots the estimated coefficients for the interaction term, *Post x Treated x High LC,* based on the triple difference-in-difference (DDD) test described in Equation (7), which regresses adjusted market-to-book ratio, *Adj. MB*, on bank-level control variables, interaction terms, and fixed effects. Each point represents the coefficient estimates for the triple interaction term starting with 2021Q1 (denoted as -4 on the horizontal axis) and continuing through the event window (from the initial shock in 2022Q1, denoted as 0 on the timeline, through 2023Q1, shown at time +4). The vertical bars denote 95% confidence intervals based on two-way clustered standard errors at the bank and quarter levels.

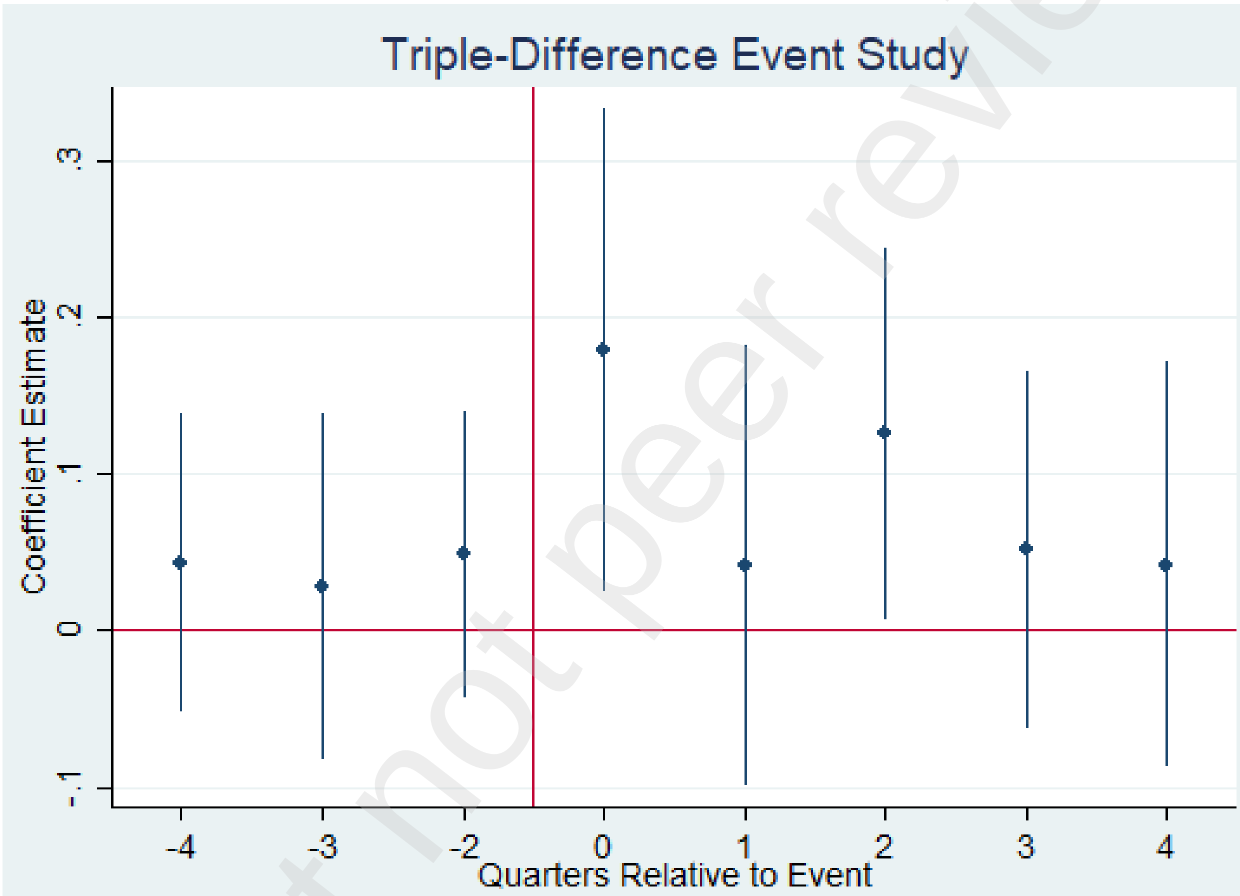

Table 1: Summary Statistics
This table presents summary statistics of factor variables, bank-specific variables, and other variables used in our analyses during 2001Q1-2024Q3. All variables are measured at a quarterly frequency. Table A1 defines all variables. Panel A presents summary statistics for the entire sample, while Panels B and C present summary statistics for the sample split by rising versus falling Federal funds rate (over the past four quarters). All variables are winsorized at the 1% and 99% levels except for *NIM Beta*, where we follow Drechsler et al. (2021) and winsorize this variable at the 5% and 95% levels.

Panel A: Full Sample

	N	Mean	S.D.	Min	25%	Median	75%	Max
1st Stage Variables								
MB	36367	1.50	1.20	0.17	0.91	1.24	1.74	9.62
MKT (%)	36367	0.65	2.88	-7.78	-0.66	1.06	2.24	7.23
TERM (%)	36367	1.21	0.94	-0.93	0.31	1.26	2.03	2.80
DEF (%)	36367	2.52	0.74	1.46	1.96	2.43	2.92	5.58
SMB (%)	36367	0.22	1.60	-4.20	-0.93	0.14	1.15	5.43
HML (%)	36367	0.05	2.06	-7.98	-1.16	0.11	0.97	5.74
RMW (%)	36367	0.38	1.48	-3.73	-0.57	0.19	1.10	5.49
CMA (%)	36367	0.15	1.36	-2.72	-0.73	-0.09	1.10	4.69
2nd Stage Variables								
Adjusted MB (Macro)	27724	-0.0029	0.2320	-7.6321	-0.0980	-0.0102	0.0871	8.8269
Adjusted MB (FF5)	27724	-0.0023	0.2246	-7.6407	-0.0915	-0.0064	0.0817	8.6586
IR Hedging	27724	0.0472	0.0912	0.0000	0.0000	0.0067	0.0520	0.5338
NIM Beta	27724	-0.0385	0.6196	-1.7885	-0.1702	0.0288	0.2296	1.1109
Net Chargeoff	27724	0.0011	0.0022	0.0000	0.0001	0.0004	0.0011	0.0141
Credit Deriv	27724	-0.0001	0.0018	-0.0091	0.0000	0.0000	0.0000	0.0089
RWA	27724	0.6998	0.2040	0.0000	0.6574	0.7409	0.8114	1.0359
MGAP	27724	0.0118	0.1033	-0.1638	-0.0305	-0.0054	0.0014	0.4598
Asset Growth	27724	0.0227	0.0562	-0.0820	-0.0042	0.0130	0.0343	0.3511
Equity-to-assets Ratio	27724	0.1049	0.0239	0.0554	0.0883	0.1022	0.1190	0.1868
Efficiency Ratio	27724	3.9619	3.9433	-2.9075	2.1353	2.9319	4.3862	31.1987
Uninsured Deposits	27724	0.2505	0.1293	0.0267	0.1594	0.2315	0.3158	0.7193
Securities	27724	0.1938	0.1110	0.0057	0.1165	0.1755	0.2517	0.6106
Net Trading	27724	0.0022	0.0096	0.0000	0.0000	0.0000	0.0000	0.0701
Market Equity (log)	27724	13.0793	1.8637	6.9237	11.8051	12.8116	14.1467	20.1732
Book Equity (log)	27716	12.8798	1.6921	8.2414	11.6607	12.5626	13.7711	19.9330
Total Assets (log)	27724	15.1605	1.6438	10.5747	13.9804	14.8305	15.9831	22.0552
Catfat LC	27624	0.2337	0.1419	-0.3112	0.1560	0.2504	0.3328	0.4877

Panel B: Subsample when Federal funds rate rises

2nd Stage Variables	N	Mean	S.D.	Min	25%	Median	75%	Max
Adjusted MB (Macro)	15856	0.0012	0.2206	-7.9912	-0.0897	-0.0036	0.0892	2.4117
Adjusted MB (FF5)	15856	-0.0012	0.2143	-7.9859	-0.0828	-0.0043	0.0792	2.4062
IR Hedging	15856	0.0496	0.0910	0.0000	0.0000	0.0094	0.0575	0.5338
NIM Beta	15856	-0.0163	0.6332	-1.7885	-0.1569	0.0486	0.2737	1.1109
Net Chargeoff	15856	0.0009	0.0019	0.0000	0.0001	0.0003	0.0009	0.0141
Credit Deriv	15856	-0.0001	0.0018	-0.0091	0.0000	0.0000	0.0000	0.0089
RWA	15856	0.6895	0.2265	0.0000	0.6578	0.7446	0.8141	1.0359
MGAP	15856	0.0333	0.1238	-0.1638	-0.0245	-0.0019	0.0098	0.4598
Asset Growth	15856	0.0213	0.0538	-0.0820	-0.0036	0.0123	0.0321	0.3511
Equity-to-assets Ratio	15856	0.1064	0.0235	0.0554	0.0908	0.1042	0.1203	0.1868
Efficiency Ratio	15856	3.9868	3.7676	-2.9075	2.1919	3.0136	4.4532	31.1987
Uninsured Deposits	15856	0.2587	0.1300	0.0267	0.1673	0.2414	0.3260	0.7193
Securities	15856	0.1903	0.1093	0.0057	0.1155	0.1728	0.2441	0.6106
Net Trading	15856	0.0020	0.0091	0.0000	0.0000	0.0000	0.0000	0.0701
Market Equity (log)	15856	13.2713	1.8339	7.2410	12.0015	13.0068	14.3187	20.1800
Book Equity (log)	15856	13.0244	1.6980	8.4334	11.7734	12.7347	13.9197	19.9330
Total Assets (log)	15856	15.2888	1.6567	11.0918	14.0776	14.9766	16.1089	21.9791
Catfat LC	15856	0.2479	0.1409	-0.3112	0.1745	0.2674	0.3445	0.4877

Panel C: Subsample when Federal funds rate decreases

2nd Stage Variables	N	Mean	S.D.	Min	25%	Median	75%	Max
Adjusted MB (Macro)	10860	-0.0090	0.2594	-7.6321	-0.1136	-0.0198	0.0850	8.8269
Adjusted MB (FF5)	10860	-0.0049	0.2508	-7.6407	-0.1063	-0.0096	0.0863	8.6586
IR Hedging	10860	0.0462	0.0937	0.0000	0.0000	0.0039	0.0476	0.5338
NIM Beta	10860	-0.0150	0.4821	-1.7885	-0.1350	0.0192	0.1737	1.1109
Net Chargeoff	10860	0.0015	0.0026	0.0000	0.0001	0.0005	0.0016	0.0141
Credit Deriv	10860	-0.0001	0.0017	-0.0091	0.0000	0.0000	0.0000	0.0089
RWA	10860	0.7059	0.1869	0.0000	0.6565	0.7368	0.8068	1.0359
MGAP	10860	-0.0080	0.0789	-0.1638	-0.0397	-0.0101	0.0000	0.4598
Asset Growth	10860	0.0239	0.0583	-0.0820	-0.0050	0.0138	0.0371	0.3511
Equity-to-assets Ratio	10860	0.1023	0.0242	0.0554	0.0854	0.0989	0.1162	0.1868
Efficiency Ratio	10860	3.8941	4.1089	-2.9075	2.0530	2.8005	4.2473	31.1987
Uninsured Deposits	10860	0.2448	0.1280	0.0267	0.1552	0.2247	0.3071	0.7193
Securities	10860	0.1967	0.1124	0.0057	0.1170	0.1774	0.2601	0.6106
Net Trading	10860	0.0027	0.0103	0.0000	0.0000	0.0000	0.0000	0.0701
Market Equity (log)	10860	12.8870	1.8910	6.9237	11.6215	12.5972	13.9807	20.0081
Book Equity (log)	10860	12.7705	1.6801	8.2414	11.5855	12.4131	13.6329	19.7439
Total Assets (log)	10860	15.0771	1.6275	10.6856	13.9343	14.7229	15.9029	22.0552
Catfat LC	10860	0.2199	0.1404	-0.3112	0.1411	0.2355	0.3183	0.4000

Table 2: Market-to-book ratio and systematic variables: 1st stage regression

This table presents quarterly regression estimates and associated *t*-statistics analyzing the effect of macroeconomic factors on the market-to-book ratio. The dependent variable is MB, defined as the market value of equity divided by the book value of equity. The independent variables include macroeconomic factors in Column (1) and the Fama-French five-factors in Column (2). Both specifications include indicators for whether the bank's total assets exceed \$50 billion. All models include bank and year time fixed effects. All variables are defined in Appendix Table A1. Standard errors are clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)
Dependent variable	MB	MB
MB_{t-1}	0.855***	0.860***
	(38.818)	(39.455)
MKT_t	0.025***	0.015***
	(6.675)	(6.139)
$TERM_t$	0.049	
	(1.242)	
DEF_t	-0.042	
	(-0.905)	
SMB_t		0.028***
		(6.288)
HML_t		0.024***
		(2.997)
RMW_t		-0.002
		(-0.315)
CMA_t		-0.004
		(-0.508)
$Assetbelow50b_t$	-0.761***	-0.746***
	(-3.207)	(-3.171)
$Assetabove50b_t$	-0.005	-0.005
	(-0.693)	(-0.684)
Bank and time FE	Yes	Yes
Observations	35,389	35,389
R-squared	0.950	0.952

Table 3: Second-Stage Residual analyses: Market-to-book ratio and bank risk management
This table reports quarterly regression estimates examining the relationship between *Adjusted MB*, the residual from the first-stage regression (Table 2, Column 1), and bank risk management variables. Column (1) shows results for the full sample. Columns (2) and (3) correspond to the periods when the federal funds rate increased and decreased, respectively. The associated *t*-statistics are reported in the brackets. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. All models include bank and quarter time fixed effects. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent variable	(1) Adjusted MB	(2) Adjusted MB Federal Funds Rate up	(3) Adjusted MB Federal Funds Rate down
IR Hedging$_{t-1}$	0.101***	0.086**	0.130**
	(2.920)	(2.196)	(2.237)
Net Chargeoff$_{t-1}$	-0.037***	-0.019	-0.037**
	(-2.902)	(-0.922)	(-2.368)
Credit Deriv$_{t-1}$	1.153	0.754	0.301
	(1.221)	(0.779)	(0.180)
RWA$_{t-1}$	0.008	0.026	-0.008
	(0.623)	(1.542)	(-0.339)
MGAP$_{t-1}$	-0.007	-0.088	0.175**
	(-0.122)	(-1.165)	(2.423)
Asset Growth$_{t-1}$	0.054	0.120***	-0.015
	(1.603)	(2.925)	(-0.260)
Equity-to-Assets $_{t-1}$	0.051	0.105	-0.041
	(0.309)	(0.585)	(-0.128)
Efficiency Ratio$_{t-1}$	-0.001**	-0.002**	-0.001
	(-2.095)	(-2.463)	(-0.687)
Uninsured Deposits$_{t-1}$	-0.008	-0.052	0.027
	(-0.141)	(-0.705)	(0.346)
Securities$_{t-1}$	0.100***	0.075	0.156**
	(2.621)	(1.466)	(2.418)
Net trading Assets$_{t-1}$	0.731*	0.873**	0.729
	(1.935)	(2.217)	(1.214)
NIM Beta $_{t-1}$	0.006**	0.009***	-0.005
	(2.495)	(2.731)	(-0.855)
Bank and Time FE	Yes	Yes	Yes
Observations	27,397	15,856	10,860
R-squared	0.128	0.159	0.172

Table 4: Alternative specification: subsample analysis by tercile of uninsured deposits

This table reports regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the first-stage regression (Table 2, Column 1). Results are shown separately for periods when the federal funds rate increased (Columns 1-2) and decreased (Columns 3-4), and within each, for banks in the bottom (<33%) and top (>67%) terciles of uninsured deposits. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All control and independent variables are lagged one quarter and defined in Appendix Table A1. All models include bank and time fixed effects. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<33% Uninsured deposits	>67% Uninsured deposits	<33% Uninsured deposits	>67% Uninsured deposits
IR Hedging$_{t-1}$	0.088	0.085*	0.104	0.154
	(1.102)	(1.928)	(0.838)	(1.562)
Net Chargeoff$_{t-1}$	0.002	-0.035	-0.027	-0.060**
	(0.036)	(-1.456)	(-1.124)	(-2.310)
Credit Deriv$_{t-1}$	0.881	1.632	-2.885	1.591
	(0.248)	(1.143)	(-0.646)	(0.714)
RWA$_{t-1}$	0.025	0.024	-0.001	-0.002
	(0.366)	(1.592)	(-0.019)	(-0.058)
MGAP$_{t-1}$	-0.461	0.066	0.018	0.239**
	(-1.239)	(1.312)	(0.110)	(2.349)
Asset Growth$_{t-1}$	0.130	0.099	0.006	-0.070
	(1.486)	(1.514)	(0.077)	(-0.536)
Equity-to-Assets $_{t-1}$	0.231	0.129	-0.044	0.240
	(0.519)	(0.447)	(-0.116)	(0.301)
Efficiency Ratio$_{t-1}$	-0.001	-0.002*	0.002	-0.002
	(-0.658)	(-1.919)	(1.537)	(-1.157)
Uninsured Deposits$_{t-1}$	-0.276	0.031	0.131	0.052
	(-1.269)	(0.443)	(0.710)	(0.501)
Securities$_{t-1}$	0.111	0.100*	0.207**	0.096
	(0.666)	(1.693)	(2.157)	(0.649)
Net trading Assets$_{t-1}$	0.440	-0.099	-1.053	0.292
	(0.283)	(-0.196)	(-0.902)	(0.426)
NIM Beta $_{t-1}$	0.009	0.006	0.015	-0.011
	(1.458)	(1.214)	(1.308)	(-0.962)
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	4,742	5,326	3,161	3,760
R-squared	0.164	0.253	0.266	0.201

Table 5: Alternative specification: subsample analysis by tercile of unrealized losses on AFS and HTM securities

This table reports quarterly regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the first stage regression (Table 2, Column 1). The table is divided into three panels based on different types of unrealized losses. In each panel, results are presented separately for periods when the federal funds rate increased (Columns 1-2) and decreased (Columns 3-4). Within each section, subsamples represent banks in the bottom (<33%) and top (>67%) terciles of the unrealized losses. Panel A corresponds to subsamples based on unrealized losses from *Available-for-Sale (AFS)* securities, Panel B to *Held-to-Maturity (HTM)*, and Panel C to combined unrealized losses from both *AFS* and *HTM*. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All models include bank and time fixed effects. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Subsamples based on unrealized losses from AFS

	(1)	(2)	(3)	(4)
VARIABLES	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<33%	>67%	<33%	>67%
IR Hedging$_{t-1}$	0.033	0.104	0.064	0.319
	(0.493)	(1.002)	(1.118)	(1.494)
Net Chargeoff$_{t-1}$	-0.044	-0.012	-0.035	-0.044
	(-0.943)	(-0.225)	(-1.589)	(-1.494)
NIM Beta $_{t-1}$	0.009	-0.001	-0.010	0.001
	(1.405)	(-0.069)	(-0.962)	(0.085)
Bank Controls	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	5,359	5,100	3,667	3,490
R-squared	0.214	0.208	0.267	0.198

Panel B: Subsamples based on unrealized losses from HTM

	(1)	(2)	(3)	(4)
VARIABLES	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<33%	>67%	<33%	>67%
IR Hedging$_{t-1}$	-0.116	0.137***	0.029	0.033
	(-0.695)	(2.690)	(0.212)	(0.364)
Net Chargeoff$_{t-1}$	-0.080*	-0.013	-0.014	-0.028
	(-1.834)	(-0.421)	(-0.452)	(-0.898)
NIM Beta $_{t-1}$	-0.004	0.006	-0.011	-0.024
	(-0.342)	(0.989)	(-0.971)	(-1.379)
Bank Controls	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	3,826	3,938	3,277	1,667
R-squared	0.244	0.266	0.154	0.344

Panel C: Subsamples based on unrealized losses from both AFS and HTM

	(1)	(2)	(3)	(4)
VARIABLES	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<33%	>67%	<33%	>67%
IR Hedging$_{t-1}$	-0.074	0.140*	0.032	0.308
	(-0.973)	(1.892)	(0.532)	(1.555)
Net Chargeoff$_{t-1}$	-0.035	-0.004	-0.028	-0.045
	(-0.727)	(-0.076)	(-1.271)	(-1.597)
NIM Beta $_{t-1}$	0.006	0.008	-0.013	0.003
	(0.659)	(1.547)	(-1.136)	(0.227)
Bank Controls	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	5,343	5,150	3,668	3,515
R-squared	0.206	0.216	0.271	0.197

Table 6: Alternative specification: subsample analysis by median liquidity creation (LC) measures (2001Q1-2024Q3)

This table reports regression estimates and associated t-statistics where the dependent variable is *Adjusted MB*, the residual from the first-stage regression (Table 2, Column 1). Results are shown for subsamples split by whether banks are above or below the median of various LC measures. *Catfat* is the comprehensive liquidity creation measure, while *Catnonfat, LCA, LCL, and LCOBS* represent its sub-components based on assets, liabilities, and off-balance sheet items. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. We construct the *LC* measures for the entire sample period (2001Q1-2024Q3) following the method outlined in Berger and Bouwman (2009) and detailed in our Appendix. All control and independent variables are lagged one quarter and defined in Appendix Table A1. All models include bank and time fixed effects. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Subsamples based on median LC measures Catfat and Catnonfat:

	(1)	(2)	(3)	(4)
VARIABLES	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	LC>Median Catfat	LC<Median Catfat	LC>Median Catnonfat	LC<Median Catnonfat
IR Hedging$_{t-1}$	0.084**	0.080	0.065**	0.081
	(2.512)	(1.381)	(2.414)	(1.451)
Net Chargeoff$_{t-1}$	-0.048***	-0.021	-0.052***	-0.022
	(-3.733)	(-0.959)	(-4.054)	(-0.976)
NIM Beta $_{t-1}$	0.004	0.009**	0.004	0.009**
	(1.189)	(2.224)	(1.197)	(2.044)
Controls	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	14,458	12,787	14,405	12,860
R-squared	0.224	0.123	0.201	0.122

Panel B: Subsamples based on median LC measures on Assets and Liabilities:

	(1)	(2)	(3)	(4)
VARIABLES	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	LC>Median LCA	LC<Median LCA	LC>Median LCL	LC<Median LCL
IR Hedging$_{t-1}$	0.090**	0.116*	0.095**	0.076*
	(2.267)	(1.927)	(2.053)	(1.752)
Net Chargeoff$_{t-1}$	-0.046***	-0.011	-0.051**	-0.026
	(-3.509)	(-0.509)	(-2.387)	(-1.567)
NIM Beta $_{t-1}$	-0.000	0.013***	0.007*	0.005
	(-0.030)	(3.030)	(1.715)	(1.296)
Controls	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	14,108	13,167	14,360	12,894
R-squared	0.193	0.136	0.190	0.154

Panel C: Subsamples based on median LC measures on Off-Balance-Sheet activities:

VARIABLES	(1) Adjusted MB LC>Median LCOBS	(2) Adjusted MB LC<Median LCOBS
IR $Hedging_{t-1}$	0.114**	0.077
	(2.329)	(1.546)
Net $Chargeoff_{t-1}$	-0.051***	-0.021
	(-3.351)	(-1.008)
NIM Beta $_{t-1}$	-0.000	0.010***
	(-0.035)	(2.710)
Controls	Yes	Yes
Bank and Time FE	Yes	Yes
Observations	14,250	12,997
R-squared	0.189	0.118

Table 7: Residual analysis split by Drechsler et al. (2021) Net Interest Margin (NIM) Betas and monetary policy regimes

This table reports regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the first-stage regression (Table 2, Column 1). Results are shown separately for periods when the federal funds rate increased (Columns 1-2) and decreased (Columns 3-4), and within each, for banks with interest rate risk measures based on positive and negative NIM betas, as defined in Drechsler et al. (2021). The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All control and independent variables are lagged one quarter and defined in Appendix Table A1. All models include bank and time fixed effects. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	NIM Beta<0	NIM Beta>0	NIM Beta<0	NIM Beta>0
IR $Hedging_{t-1}$	0.079	0.112**	0.158	0.091
	(1.130)	(2.469)	(1.227)	(1.156)
Net $Chargeoff_{t-1}$	-0.072**	0.031	-0.031	-0.027
	(-2.312)	(1.068)	(-1.091)	(-1.336)
Credit $Deriv_{t-1}$	1.787	-1.142	-1.674	1.839
	(1.237)	(-0.789)	(-0.578)	(0.678)
RWA_{t-1}	0.005	0.034	0.099	-0.030
	(0.162)	(1.463)	(1.295)	(-1.217)
$MGAP_{t-1}$	0.053	-0.103	-0.033	0.237***
	(0.780)	(-1.057)	(-0.195)	(2.720)
Asset $Growth_{t-1}$	0.113*	0.126**	-0.060	0.043
	(1.740)	(2.193)	(-0.495)	(0.760)
Equity-to-Assets $_{t-1}$	-0.161	0.443*	0.820	-0.089
	(-0.591)	(1.715)	(0.895)	(-0.355)
Efficiency $Ratio_{t-1}$	-0.003***	-0.001	0.000	-0.001
	(-3.591)	(-0.769)	(0.253)	(-0.611)
Uninsured $Deposits_{t-1}$	-0.100	-0.065	0.064	0.011
	(-0.933)	(-0.562)	(0.371)	(0.118)
$Securities_{t-1}$	-0.002	0.151**	0.129	0.213***
	(-0.027)	(2.507)	(0.909)	(2.590)
Net trading $Assets_{t-1}$	1.034	0.744	-0.910	2.166**
	(1.310)	(1.464)	(-1.011)	(2.493)
NIM $Beta_{t-1}$	0.012*	0.030**	-0.014	-0.002
	(1.700)	(2.177)	(-1.140)	(-0.164)
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	6,881	8,914	4,988	5,755
R-squared	0.198	0.195	0.199	0.244

Table 8: Second-Stage Residual analysis: using Fama-French five-factor 1st stage regression

This table reports quarterly regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the Fama-French five-factor first-stage regression (Table 2, Column 2). Column (1) shows results for the full sample; Columns (2) and (3) correspond to periods when the federal funds rate increased and decreased, respectively. Columns (4) to (7) show the results for the subsamples of banks bottom (<33%) and top (>67%) terciles of uninsured deposits. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All models include bank and time fixed effects. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) Adjusted MB	(2) Adjusted MB	(3) Adjusted MB	(4) Adjusted MB	(5) Adjusted MB	(6) Adjusted MB	(7) Adjusted MB
		Federal Funds Rate up	Federal Funds Rate down	Federal Funds Rate up		Federal Funds Rate down	
				<33% Uninsured deposits	>67% Uninsured deposits	<33% Uninsured deposits	>67% Uninsured deposits
IR Hedging$_{t-1}$	0.097***	0.082**	0.126**	0.083	0.083*	0.096	0.154
	(2.804)	(2.019)	(2.145)	(1.038)	(1.879)	(0.775)	(1.558)
Net Chargeoff$_{t-1}$	-0.036***	-0.017	-0.035**	0.003	-0.034	-0.025	-0.058**
	(-2.696)	(-0.832)	(-2.242)	(0.069)	(-1.426)	(-1.040)	(-2.247)
NIM Beta$_{t-1}$	0.006**	0.009***	-0.005	0.008	0.006	0.014	-0.011
	(2.523)	(2.811)	(-0.849)	(1.429)	(1.205)	(1.304)	(-0.965)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,397	15,856	10,860	4,742	5,326	4,938	4,911
R-squared	0.071	0.107	0.114	0.133	0.198	0.101	0.139

Table 9: Second-Stage Residual analysis: using Fama-French five-factor 1st stage regression

This table reports quarterly regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the Fama-French five-factor first stage regression (Table 2, Column 2). Columns (1) –(4) show results split by periods when the federal funds rate increased and decreased, and by banks' unrealized losses from Available-for-sale and Held-to-maturity securities (bottom and top 33%). The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All models include bank and time fixed effects. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) Adjusted MB	(2) Adjusted MB	(3) Adjusted MB	(4) Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<33% Unrealized AFS+HTM	>67% Unrealized AFS+HTM	<33% Unrealized AFS+HTM	>67% Unrealized AFS+HTM
IR Hedging$_{t-1}$	-0.081	0.137*	0.031	0.307
	(-1.054)	(1.848)	(0.516)	(1.547)
Net Chargeoff$_{t-1}$	-0.034	-0.002	-0.026	-0.044
	(-0.710)	(-0.040)	(-1.176)	(-1.536)
NIM Beta$_{t-1}$	0.006	0.007	-0.013	0.003
	(0.632)	(1.519)	(-1.124)	(0.215)
Controls	Yes	Yes	Yes	Yes
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	5,343	5,150	3,668	3,515
R-squared	0.165	0.171	0.185	0.160

Table 10: Triple Difference-in-Difference analysis around the rate-hiking event of 2022Q1

This table reports regression estimates from a triple difference-in-differences specification where the dependent variable is *Adjusted MB*, the residual from the first-stage regression shown in Table 2. The identifying shock is the Federal Reserve's rate-tightening cycle beginning in 2022Q1. *Post* are event-time dummies and equal one for each specific quarter for the post-shock period of 2022Q1 to 2023Q1 as well as during the pre-shock period of 2021Q1-2021Q3 (and zero for the pre-event reference period of 2021Q4). *Treated* equals one if the bank's average *IR Hedging* during the pre-shock period exceeds the sample median. *High LC* equals one if the bank's pre-shock average liquidity creation exceeds the sample median, measured over the same pre-shock window. The regression includes three interaction terms: *Post x Treated, Post x High LC,* and the triple interaction *Post x Treated x High LC.* The main effects of *Treated, High LC,* and *Treated x High LC* are absorbed by bank fixed effects. All control variables from the baseline second-stage specification (Equation 7) are included, lagged one quarter, and defined in Appendix Table A1. The Net Charge-off variable is multiplied by 100 for scaling purposes. All models include bank and quarter time fixed effects. Standard errors are bootstrapped and clustered by bank and time. The associated t-statistics are reported in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)
Dependent variable	Adjusted MB
Post * Treated	-0.032***
	(-2.707)
Post * High LC	-0.041***
	(-2.982)
Post * Treated * High LC	0.058***
	(3.521)
IR Hedging$_{t-1}$	0.102***
	(3.107)
Net Chargeoff$_{t-1}$	-0.037***
	(-2.793)
Credit Deriv$_{t-1}$	1.090
	(1.119)
RWA$_{t-1}$	0.007
	(0.574)
MGAP$_{t-1}$	-0.008
	(-0.132)
Asset Growth$_{t-1}$	0.055*
	(1.697)
Equity-to-Assets $_{t-1}$	0.058
	(0.363)
Efficiency Ratio$_{t-1}$	-0.001**
	(-2.094)
Uninsured Deposits$_{t-1}$	-0.009
	(-0.182)
Securities$_{t-1}$	0.096***

	(2.612)
Net trading Assets$_{t-1}$	0.709*
	(1.826)
NIM Beta $_{t-1}$	0.006**
	(2.476)
Constant	-0.028
	(-0.928)
Bank and Time FE	Yes
Observations	27,397
R-squared	0.128

Appendix

Table A1: Variable definition

Variable name	Definition
MB	Market value of equity divided by the book value of equity. Market value is calculated as PRC*SHROUT from CRSP. Book value of equity is RCFD3210 from: FDIC CALL reports.
MKT	The excess return on the market, Rm-Rf, where Rm is the value-weighted return on all CRSP firms incorporated in the United States, and Rf is the 1-month Treasury-bill rate.
TERM	The difference between the 10-year and 2-year treasury yield. Source: The Federal Reserve Bank of St. Louis.
DEF	Default rate. It is the difference between the BAA corporate bond yield and the yield on the 10-year Treasury. Source: The Federal Reserve Bank of St. Louis.
SMB	The average return on the three smallest portfolios minus the average return on the three biggest portfolios. Source: Fama French Library.
HML	The average return on the two highest value portfolios minus the average return on the two growth portfolios. Source: Fama French Library.
RMW	The difference between the returns on diverse portfolios of stocks with robust and weak profitability. Source: Fama French Library.
CMA	The difference between the returns on diverse portfolios of stocks of low and high investment firms. Source: Fama French Library.
Adjusted MB (Macro)	The residuals from the first stage regression as specified in Table 2, Column (1).
Adjusted MB (FF5)	The residuals from the first stage regression as specified in Table 2, Column (2).
Credit Deriv	The difference between the net notional amounts of protection purchased and protection sold from credit default swaps, total return swaps, credit options, and other credit derivatives. Source: FDIC CALL reports:(RCFDC969+RCFDC971+RCFDC973+RCFDC975)-(RCFDC968+RCFDC970+RCFDC972+RCFDC974)
IR Hedging	Total gross notional amount of interest rate derivatives for purposes other than trading, scaled by the book value of assets. Source: CALL reports: RCFD8725+RCFD8729.
NIM Beta	The difference between the "interest income beta" and "interest expense beta" as described in Drechsler, Savov, and Schnabl (2021). Rolling 20-quarter regressions are estimated at the bank level to estimate these betas for each bank-quarter in the sample.
RWA	Risk-weighted assets (net of allowances and other deductions), scaled by the book value of assets. Source: CALL reports: RCFDA223.

MGAP	Maturity Gap Ratio, scaled by the book value of assets.: Source: CALL reports: (RCONA570 + RCONA571 + RCONA564 + RCONA565) +(RCONA549 + RCONA550 + RCONA555 + RCONA556)-(RCONA579 + RCONA580+ RCONA584 + RCONA585) + RCONB987-RCONB993
Net Chargeoff	Loan charge-offs and write-downs minus loan recoveries, scaled by the book value of assets
Asset Growth	Quarterly growth rate in the book value of assets
Equity-to-Asset ratio	Total book value of equity, divided by total assets
Efficiency ratio	The ratio of total noninterest expense to total noninterest income, defined following Minton, Stulz, and Taboada (2019).
Uninsured Deposits	CALL reports: RCON5597
Securities	Sum of securities held to maturity and securities available for sale, scaled by the book value of assets. Source: CALL reports: sum(RCFD1754, RCFD1773).
Net trading	The difference between trading assets and trading liabilities, scaled by the book value of assets.
Assetbelow50b; Assetabove50b	Piecewise linear specification breaking up asset size into two variables, following Erel, Nadauld, and Stulz (2013). "Asset below 50 b" captures the first \$50 billion in assets and takes the value: min (asset size, \$50 billion). The "Assetabove50b" captures the asset size in excess of \$50 billion, taking the value: max (asset size- \$50 billion, 0)
Unrealized losses on AFS securities	CALL reports: RCON1773-RCON1772
Unrealized losses on HTM securities	CALL reports: RCON1754-RCON1771
Liquidity Creation (LC)	A measure of a bank's liquidity creation activity, as described in Berger and Bouwman (2009). Data for 2001-2016 is obtained from Christa Bouwman's website and we have followed their general description of various forms of the LC variable to update the sample through 2024Q3 based on Call Report data.
Post	Event-time dummies and equal one for each specific quarter during the post-shock period of 2022Q1 to 2023Q1, as well as for the pre-shock period of 2021Q1-2021Q3 (and zero for the reference period of 2021Q4).
Treated	Equals one if the bank's average *IR Hedging* during the pre-shock period exceeds the sample median.
High LC	*High LC* equals one if the bank's pre-shock average liquidity creation (LC) exceeds the sample median, measured over the same pre-shock window.

Table A2: Second-Stage Residual analysis: subsample analysis by median uninsured deposits

This table reports quarterly regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the first-stage regression (Table 2, Column 1). Results are shown separately by the periods when the federal funds rate increased (Columns 1-2) and decreased (Columns 3-4), and within each, for banks below and above the median level of uninsured deposits. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All models include bank and time fixed effects. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<Median Uninsured deposits	>Median Uninsured deposits	<Median Uninsured deposits	>Median Uninsured deposits
IR Hedging$_{t-1}$	-0.012	0.082**	-0.021	0.131*
	(-0.124)	(2.165)	(-0.182)	(1.752)
Net Chargeoff$_{t-1}$	-0.021	-0.017	-0.038**	-0.029
	(-0.543)	(-0.921)	(-1.960)	(-1.162)
Credit Deriv$_{t-1}$	1.270	1.351	-0.999	0.704
	(0.573)	(1.167)	(-0.348)	(0.345)
RWA$_{t-1}$	-0.018	0.038***	-0.012	-0.007
	(-0.352)	(2.653)	(-0.332)	(-0.256)
MGAP$_{t-1}$	-0.355	0.036	0.155	0.242***
	(-1.463)	(0.836)	(1.348)	(2.631)
Asset Growth$_{t-1}$	0.096	0.084*	-0.040	-0.022
	(1.625)	(1.763)	(-0.700)	(-0.232)
Equity-to-Assets $_{t-1}$	0.216	0.060	0.208	-0.185
	(0.674)	(0.287)	(0.729)	(-0.340)
Efficiency Ratio$_{t-1}$	-0.001	-0.003***	0.001	-0.002
	(-0.630)	(-3.359)	(0.550)	(-1.336)
Uninsured Deposits$_{t-1}$	-0.199	0.031	0.179	0.041
	(-1.219)	(0.503)	(1.462)	(0.472)
Securities$_{t-1}$	0.054	0.069	0.242***	0.005
	(0.564)	(1.454)	(3.315)	(0.043)
Net trading Assets$_{t-1}$	0.172	0.467	0.807	0.252
	(0.227)	(1.047)	(1.024)	(0.381)
NIM Beta $_{t-1}$	0.010**	0.009**	0.002	-0.009
	(2.389)	(2.355)	(0.198)	(-0.987)
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	7,407	8,098	5,059	5,693
R-squared	0.156	0.237	0.245	0.199

Table A3: Alternative specification: subsample analysis by median loans

This table reports regression estimates and associated *t*-statistics where the dependent variable is *Adjusted MB*, the residual from the first stage regression (Table 2, Column 1). Results are shown separately for periods when the federal funds rate increased (Columns 1-2) and decreased (Columns 3-4), and within each, for banks below or above the median level of net loans. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All models include bank and time fixed effects. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Adjusted MB	Adjusted MB	Adjusted MB	Adjusted MB
	Federal Funds Rate up		Federal Funds Rate down	
	<Median Loans	>Median Loans	<Median Loans	>Median Loans
IR Hedging$_{t-1}$	0.024	0.120***	0.132*	0.038
	(0.318)	(3.019)	(1.685)	(0.608)
Net Chargeoff$_{t-1}$	-0.008	-0.022	-0.009	-0.047***
	(-0.216)	(-1.116)	(-0.339)	(-2.785)
Credit Deriv$_{t-1}$	1.084	1.948	0.163	-3.146
	(0.807)	(1.053)	(0.077)	(-1.032)
RWA$_{t-1}$	0.042	-0.013	0.002	0.017
	(1.565)	(-0.473)	(0.058)	(0.402)
MGAP$_{t-1}$	-0.133	-0.077	0.242**	0.021
	(-1.003)	(-0.990)	(2.219)	(0.204)
Asset Growth$_{t-1}$	0.198***	0.024	-0.026	0.089
	(3.269)	(0.459)	(-0.318)	(1.465)
Equity-to-Assets $_{t-1}$	0.722***	-0.194	0.233	0.073
	(3.090)	(-0.722)	(0.360)	(0.264)
Efficiency Ratio$_{t-1}$	-0.003**	-0.002**	0.001	-0.001
	(-2.178)	(-2.390)	(0.406)	(-1.579)
Uninsured Deposits$_{t-1}$	-0.140	0.046	0.012	0.031
	(-1.010)	(0.668)	(0.088)	(0.458)
Securities$_{t-1}$	0.084	0.262**	0.218**	0.048
	(1.082)	(2.326)	(1.964)	(0.402)
Net trading Assets$_{t-1}$	1.395**	-0.048	1.075	-0.563
	(2.128)	(-0.089)	(1.569)	(-0.716)
NIM Beta $_{t-1}$	0.010**	0.007	-0.003	-0.011
	(1.970)	(1.594)	(-0.308)	(-1.349)
Bank and Time FE	Yes	Yes	Yes	Yes
Observations	8,120	7,654	5,520	5,252
R-squared	0.179	0.191	0.160	0.245

Table A4: Second-Stage Residual analyses: control for dividends

This table reports quarterly regression estimates examining the relationship between the residual from the first-stage regression (Table 2, Column 1) and bank risk management variables. Column (1) shows results for the full sample. Columns (2) and (3) correspond to the periods when the federal funds rate increased and decreased, respectively. The *Net Charge-off* variable and *Dividends* are multiplied by 100 for scaling purposes. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. All models include bank and quarter time fixed effects. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent variable	Adjusted MB	Adjusted MB Federal Funds Rate up	Adjusted MB Federal Funds Rate down
IR Hedging$_{t-1}$	0.101***	0.090**	0.124**
	(2.924)	(2.226)	(2.102)
Net Chargeoff$_{t-1}$	-0.037***	-0.023	-0.032**
	(-3.000)	(-1.214)	(-2.043)
Credit Deriv$_{t-1}$	1.154	0.964	0.307
	(1.207)	(1.047)	(0.193)
RWA$_{t-1}$	0.008	0.028	-0.009
	(0.619)	(1.571)	(-0.408)
MGAP$_{t-1}$	-0.007	-0.089	0.176**
	(-0.125)	(-1.148)	(2.548)
Dividends$_{t-1}$	-0.035	-15.162	16.872***
	(-0.004)	(-0.974)	(2.592)
Asset Growth$_{t-1}$	0.054	0.119***	-0.014
	(1.637)	(2.807)	(-0.244)
Equity-to-Assets $_{t-1}$	0.051	0.131	-0.070
	(0.329)	(0.740)	(-0.223)
Efficiency Ratio$_{t-1}$	-0.001**	-0.002**	-0.001
	(-2.060)	(-2.466)	(-0.622)
Uninsured Deposits$_{t-1}$	-0.008	-0.048	0.019
	(-0.147)	(-0.695)	(0.247)
Securities$_{t-1}$	0.100***	0.075	0.150**
	(2.592)	(1.501)	(2.394)
Net trading Assets$_{t-1}$	0.731*	0.890**	0.695
	(1.927)	(2.152)	(1.206)
NIM Beta $_{t-1}$	0.006**	0.009***	-0.005
	(2.551)	(2.763)	(-0.805)
Bank and Time FE	Yes	Yes	Yes
Observations	27,397	15,856	10,860
R-squared	0.128	0.159	0.173

Table A5: Second-Stage Residual analyses: control variables normalized by book value of equity

This table reports quarterly regression estimates examining the relationship between the residual from the first-stage regression (Table 2, Column 1) and bank risk management variables. Column (1) shows results for the full sample. Columns (2) and (3) correspond to the periods when the federal funds rate increased and decreased, respectively. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. All models include bank and quarter time fixed effects. Standard errors are bootstrapped and clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Dependent variable	Adjusted MB	Adjusted MB Federal Funds Rate up	Adjusted MB Federal Funds Rate down
IR Hedging$_{t-1}$	0.006	0.007*	0.003
	(1.064)	(1.728)	(0.279)
Net Chargeoff$_{t-1}$	-0.471***	-0.246	-0.524***
	(-3.099)	(-1.114)	(-2.811)
Credit Deriv$_{t-1}$	0.067	0.016	-0.030
	(0.638)	(0.125)	(-0.162)
RWA$_{t-1}$	-0.001	-0.001	-0.001
	(-0.393)	(-0.175)	(-0.322)
MGAP$_{t-1}$	-0.001	-0.010	0.022**
	(-0.139)	(-1.034)	(2.437)
Asset Growth$_{t-1}$	0.037	0.082*	-0.010
	(1.034)	(1.697)	(-0.169)
Equity-to-Assets $_{t-1}$	-0.109	-0.034	-0.284
	(-0.409)	(-0.095)	(-0.725)
Efficiency Ratio$_{t-1}$	-0.002*	-0.003*	-0.001
	(-1.956)	(-1.689)	(-1.278)
Uninsured Deposits$_{t-1}$	-0.008	-0.012	-0.006
	(-1.203)	(-1.260)	(-0.632)
Securities$_{t-1}$	0.004	0.003	0.005
	(0.871)	(0.496)	(0.717)
Net trading Assets$_{t-1}$	0.073*	0.103**	0.061
	(1.913)	(2.434)	(1.032)
NIM Beta $_{t-1}$	0.007**	0.009***	-0.005
	(2.562)	(2.755)	(-0.852)
Bank and Time FE	Yes	Yes	Yes
Observations	27,439	15,889	10,870
R-squared	0.124	0.153	0.172

Table A6: One-Stage Regression of Market-to-book ratio and bank risk management

This table reports quarterly regression estimates examining the relationship between Market-to-Book ratio and bank risk management variables and includes lagged *MB* ratio as an additional explanatory variable. Column (1) shows results for the full sample. Columns (2) and (3) correspond to the periods when the Federal funds rate increased and decreased, respectively. The *Net Charge-off* variable is multiplied by 100 for scaling purposes. All control and independent variables are lagged by one quarter and defined in Appendix Table A1. All models include bank and quarter time fixed effects. Standard errors are clustered by bank and time. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Dependent variable	MB	MB Federal Funds Rate up	MB Federal Funds Rate down
MB_{t-1}	0.854***	0.833***	0.853***
	(35.022)	(21.347)	(22.347)
IR $Hedging_{t-1}$	0.084*	0.063	0.130
	(1.969)	(1.155)	(1.596)
Net $Chargeoff_{t-1}$	-0.035**	-0.025	-0.034
	(-2.526)	(-1.279)	(-1.592)
Credit $Deriv_{t-1}$	1.561	1.805	0.428
	(1.420)	(1.390)	(0.214)
RWA_{t-1}	0.010	0.031	-0.006
	(0.541)	(1.155)	(-0.155)
$MGAP_{t-1}$	-0.033	-0.124	0.155
	(-0.430)	(-1.180)	(1.648)
Asset $Growth_{t-1}$	0.052	0.119**	-0.010
	(1.565)	(2.442)	(-0.175)
Equity-to-Assets $_{t-1}$	0.038	-0.043	-0.029
	(0.179)	(-0.121)	(-0.088)
Efficiency $Ratio_{t-1}$	-0.001**	-0.002**	-0.001
	(-2.277)	(-2.134)	(-0.921)
Uninsured $Deposits_{t-1}$	-0.030	-0.067	0.009
	(-0.352)	(-0.853)	(0.079)
$Securities_{t-1}$	0.088	0.062	0.152
	(1.583)	(0.875)	(1.671)
Net trading $Assets_{t-1}$	0.491	0.496	0.456
	(1.021)	(0.939)	(0.614)
$Astbelow50b_{t-1}$	-0.306***	-0.208**	-0.250
	(-3.323)	(-2.638)	(-1.358)
$Astabv50b_{t-1}$	-0.000	-0.003	0.001
	(-0.035)	(-0.425)	(0.219)
NIM Beta $_{t-1}$	0.007**	0.009**	-0.003
	(2.329)	(2.144)	(-0.542)

Bank and Time FE	Yes	Yes	Yes
Observations	27,397	15,856	10,860
R-squared	0.959	0.961	0.960

Table A7: Construction of Liquidity Creation (LC) Measures

This appendix describes the construction of the liquidity creation (LC) measures used in the paper. We create our liquidity creation measures through 2024Q3 generally following the method outlined in Berger and Bouwman (2009), who classify bank activities into liquid, semi-liquid, and illiquid categories across assets, liabilities, and off-balance-sheet activities. Liquidity creation measures are first constructed at the bank level using U.S. bank Call Report data and then aggregated to the BHC level. All LC measures are scaled by gross total assets (GTA).

The primary liquidity creation measure is the category-based "fat" measure (CATFAT), which incorporates both on-balance-sheet and off-balance-sheet activities. We also construct the category-based "nonfat" measure (CATNONFAT), which excludes off-balance-sheet liquidity creation. In addition, we separately analyze asset-side (LC_A), liability-side (LC_L), and off-balance-sheet (LC_OBS) liquidity creation. The formulas to compute the liquidity creation measures are the following.

- *LC_A = 0.5 × Illiquid Assets − 0.5 × Liquid Assets*
- *LC_L = 0.5 × Liquid Liabilities − 0.5 × Illiquid Liabilities and Equity*
- *LC_OBS = 0.5 × Illiquid Guarantees − 0.5 × Liquid OBS Positions*
- *CATFAT = LC_A + LC_L + LC_OBS*
- *CATNONFAT = LC_A + LC_L*

The table below reports the liquidity creation categories and the corresponding Call Report variables used in constructing the LC measures.

Liquidity Creation Component	Call Report Variable(s)
Liquid Assets	
Cash	RSSD0010
Securities	RCFD1754 + RCFD1773
TradingAssets	RCFD3545
Fedfundssold	RCONB987
allow_lll (Allowance for loan and lease losses)	RCFD3123
Illiquid Assets	
CommercialRealEstate	RCFDF158 + RCFDF159 + RCFDF160 + RCFDF161 + RCFD1460
CommercialandIndustrialLoans	RCON1766
AgricultureLoans	RCFD1590
Loans_statelclgov	RCFD2107
loan_lease_fin	RCON2165
PremisesandFixedAssets	RCFD2145
OtherREowned	RCFD2150
UnconsolidatedInvestments	RCFD2130
Goodwill	RCFD3163
IntangibleAssets	RCFD0426
OtherAssets	RCFD2160
Liquid Liabilities	
TransactionsDeposits	RCON2210
SavingsDeposits	RCON2385
FedFundsPurchased	RCFD2800
Trading_liability	RCFD3548

Illiquid Liabilities	
SubordinatedDebt	RCFD3200
TotalOtherLiabilities	RCFD2930 + RCFD2938
Equity	RCFD3210
Illiquid OBS guarantees	
UnusedLoanCommitments_14Fam	RCFD3814
UnusedLoanCommitments_cc	RCFD3815
UnusedLoanCommitments_re	RCFD3816
UnusedLoanCommitments_underwrite	RCFD3817
UnusedLoanCommitments_other	RCFD6550
NetFinancialperfStandbyLOCs	RCFD3819
Performancestandby	RCFD3821
Commandothletters	RCFD3411
Liquid OBS	
Interest rate derivatives (gross fair value)_neg	RCFD8745
Foreign exchange derivatives (gross fair value)_neg	RCFD8738
Equity derivatives (gross fair value)_neg	RCFD8739
Commodity derivatives (gross fair value)_neg	RCFD8740

* Additional Note: If an RCFD value is not reported for a given Call Report variable, then the corresponding RCON value for the same Call Report item is used instead.

Figure A1: Quarterly mean Adjusted MB and Interest Rate Hedging (2001Q1–2024Q3)

This graph presents the quarterly average market-to-book (MB) ratio residual from the first-stage regression (Table 2, Column 1) and Interest Rate (IR) hedging for U.S. banks from 2001Q1 to 2024Q3. The left axis corresponds to the MB residual, while the right axis corresponds to the interest rate hedging ratio.

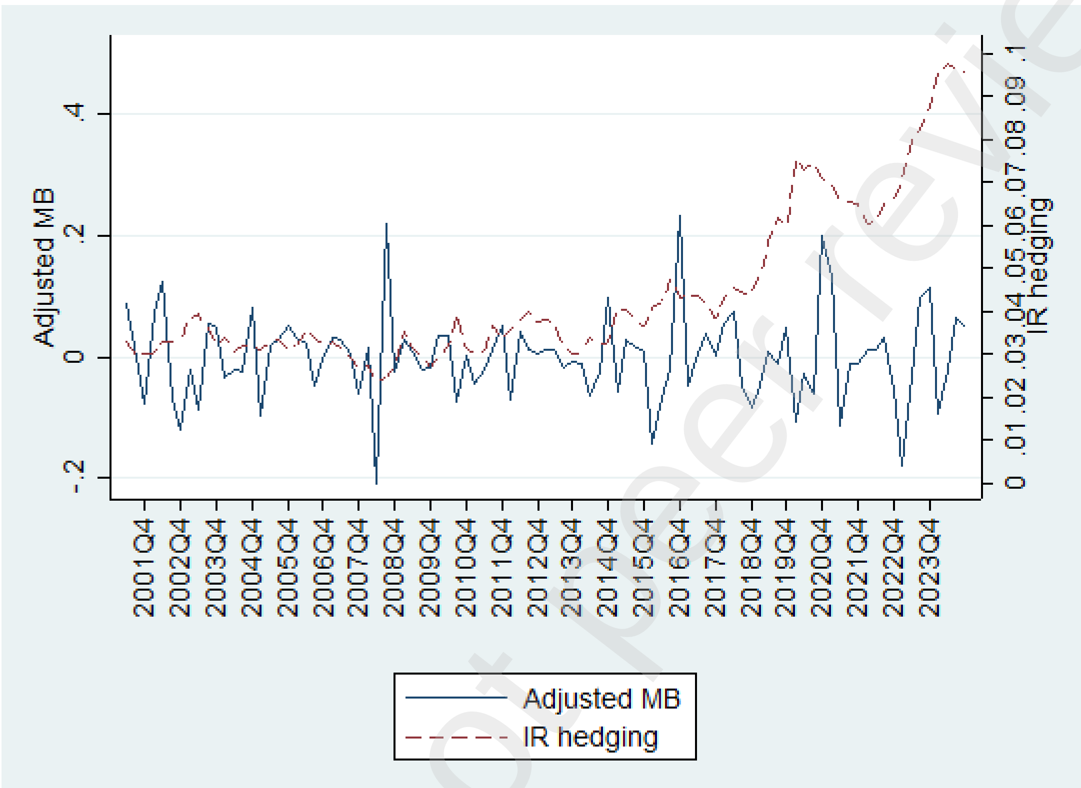

Figure A2: Quarterly mean Interest Rate Hedging and the Federal Funds Rate (2001Q1–2024Q3)

This graph plots the quarterly average Interest Rate (IR) hedging ratio for U.S. banks and the Federal Funds rate from 2001Q1 to 2024Q3. The left axis represents the Federal Funds rate, while the right axis represents the interest rate hedging ratio.