

Securities Valuation Disclosures and Bank Earnings Resilience after Monetary Tightening

Hamoud Yassine

University of Algiers 3, Algeria

Email: hamoud.yacine@yahoo.fr

Received: 18.03.2026

Accepted: 06.10.2026

Published: 07.10.2026

Abstract

Do securities fair value disclosures identify persistent earnings pressure after monetary tightening? Using FDIC bank regulatory filings, this study relates December 2022 held-to-maturity (HTM) and available-for-sale (AFS) valuation shortfalls to annual net interest margin (NIM) and return on assets through 2025. The eligible baseline contains 3,927 deposit-taking institutions; the annual NIM samples contain 3,835, 3,753, and 3,637 banks. Specifications include separate HTM and AFS portfolio shares, baseline earnings and prior earnings changes, capital, liquidity, asset mix, uninsured funding, and geographic fixed effects. A shortfall equal to one percentage point of baseline assets is associated with 15.40 basis points lower NIM in 2024 for HTM and 13.74 basis points for AFS. Both associations remain negative in 2025 and extend to profitability. An exact accounting decomposition attributes most of the 2024 NIM association to weaker interest-income growth, with a smaller interest-expense component. Adding valuation gaps reduces repeated same-year cross-validation RMSE by 1.89–3.22%, but worsens time-ordered one-year-ahead prediction by 2.36% and 0.51%. HTM and AFS NIM slopes are not statistically distinguishable after portfolio composition is controlled. The evidence supports the relevance of valuation disclosures for assessing subsequent earnings resilience, while documenting limits to temporal forecast transfer. It does not identify a causal effect of accounting designation or correct selection arising from failures and acquisitions.

Keywords: bank earnings resilience; fair value disclosures; held-to-maturity securities; available-for-sale securities; net interest margin; interest rate risk

JEL classification: G21; G28; M41; E43

1 Introduction

The decline in a fixed-rate security's market value and the pressure on a bank's reported earnings need not occur at the same time. A higher discount rate changes fair value immediately. Interest income on a retained security continues to reflect its contractual return, while deposits, wholesale liabilities, loans, and replacement investments reprice at different speeds. A bank can therefore avoid realizing a securities loss and still experience a weaker interest margin. This paper examines whether the securities valuation shortfalls disclosed at the end of 2022 identify differences in subsequent earnings resilience through 2025.

The distinction between held-to-maturity (HTM) and available-for-sale (AFS) securities makes this question particularly relevant to financial reporting. Both portfolios disclose amortized cost and fair value, although their valuation changes enter financial statements differently. These disclosures may contain information beyond the amount invested in securities and the bank's current margin. Yet a large valuation gap can also reflect portfolio duration, asset selection, liability structure, or hedging choices. An assessment of its information content must therefore control separately for the size of each securities portfolio and distinguish a conditional association from the consequences of choosing an accounting designation.

The idea that fair values contain information about future bank income is established. Evans, Hodder, and Hopkins (2014) connect accumulated securities fair value adjustments to subsequent bank financial performance. Earlier studies examine the value relevance of bank fair value disclosures and the risk information in fair value income measures (Barth, Beaver, and Landsman, 1996; Hodder, Hopkins, and Wahlen, 2006). The present study extends this line of inquiry to the earnings adjustment following the 2022 tightening episode. It follows a broad population of regulatory filers across three annual horizons, separates interest-income and interest-expense associations, and contrasts prediction for other banks in the same outcome year with transfer to a later calendar year.

This focus complements research on the interaction of asset valuation losses and uninsured deposits during the 2023 banking turmoil. Jiang et al. (2024), Glancy et al. (2024), and Cipriani, Eisenbach, and Kovner (2024, revised 2026) study fragility, funding facilities, and deposit runs. Dursun-de Neef, Ongena, and Schandlbauer (2026) examine monetary policy, HTM securities, and uninsured withdrawals. The outcome here is the annual earnings change of institutions that remain observable under the same certificate number. Earnings resilience concerns the capacity to sustain margins and profitability after funding and asset yields adjust; it is distinct from the occurrence of a run or the probability of failure.

The data come from the FDIC BankFind financials API. Positive portfolio-level shortfalls between amortized cost and fair value in December 2022 are scaled by that date's total assets. Annual December NIM and return on assets (ROA) in 2023, 2024, and 2025 are compared with their 2022 values. The primary models include separate HTM and AFS portfolio shares; capital, cash, loans, and size; the estimated uninsured deposit share; baseline earnings; the preceding annual earnings change; and geographic fixed effects. All computations use archived public extracts and are accompanied by executable replication code.

Three findings define the paper's contribution. First, both valuation gaps are associated with lower later NIM and ROA conditional on these observables. In 2024, an additional gap equal to one percentage point of baseline assets corresponds to 15.40 basis points lower NIM for HTM and 13.74 basis points for AFS. The associations remain negative in 2025. Second, an accounting

decomposition shows that weaker interest-income growth accounts for most of the 2024 margin association, while greater interest expense relative to earning assets also contributes. Third, the incremental prediction result depends on the validation setting: gains of 1.89–3.22% in same-year held-out RMSE do not transfer to the two later-year exercises.

The comparison across accounting categories is informative because it disciplines an interpretation based on recognition alone. When only total securities share is controlled, the HTM NIM slope appears substantially more negative than the AFS slope. Once the two portfolio shares enter separately, the 2024 difference is only -1.66 basis points and is not statistically distinguishable from zero ($p = 0.548$). The evidence supports reading both sets of disclosures when assessing earnings exposure. It does not show that HTM classification causes a larger earnings penalty.

For financial stability monitoring, the results suggest a practical use of information already present in regulatory filings. Book capital and current earnings summarize different aspects of a bank's position from the fair value discount on its securities stock. The discount can help identify institutions whose earnings adjustment warrants closer attention, but the negative temporal validation results caution against transporting fixed coefficients across rate-cycle conditions. The paper makes this boundary observable rather than treating statistical significance as proof of a deployable forecasting tool.

Section 2 develops the accounting and economic setting. Section 3 describes the data, selection rules, inference, and validation protocols. Section 4 reports earnings associations, component results, sensitivity checks, and prediction performance. Section 5 discusses their implications and limits. Section 6 concludes. Supplementary materials document field definitions, preprocessing, attrition, and additional estimates.

2 Accounting setting and economic predictions

2.1 Valuation information and securities classification

Call Report Schedule RC-B provides amortized cost and fair value for HTM and AFS securities. HTM securities generally remain at amortized cost on the balance sheet, subject to the applicable accounting adjustments. AFS securities are generally carried at fair value, with unrealized valuation changes recognized in other comprehensive income rather than current net income. These distinctions are described in the contemporaneous reporting instructions (FFIEC, 2022). Regulatory capital treatment of accumulated other comprehensive income differs across institutions, so accounting recognition and regulatory capital recognition cannot be treated as identical (Federal Reserve Board, 2023).

A net fair value shortfall is a valuation measure, not an immediate interest expense or an inevitable realized loss. For a retained fixed-rate instrument, it can summarize the present value of earning a contractual return below prevailing market yields. Changes in credit risk and other pricing factors can also affect fair value. Moreover, the portfolio-level measure nets unrealized gains against losses and does not disclose the maturity of each cash flow. It is consequently a summary of an observed securities position rather than a direct measure of effective duration.

Accounting research provides two reasons to study this summary. Fair value disclosures can convey information absent from book values, and accumulated valuation adjustments may be related to subsequent recognized income. Barth, Beaver, and Landsman (1996) study incremental information in bank fair value disclosures; Evans, Hodder, and Hopkins (2014) analyze their relation to future financial performance. Hodder, Hopkins, and Wahlen (2006) show that fair

value income volatility captures risk beyond narrower income measures. The present design tests whether a securities discount retains a later earnings association after separately conditioning on the size of its accounting portfolio.

Portfolio designation is itself a decision. Kim, Kim, and Ryan (2025) document incentives associated with designating securities as HTM. Granja et al. (2024) examine book-value risk management and limited hedging, while Greenwald, Krainer, and Paul (2024) study monetary transmission through bank securities portfolios. These findings motivate the separate portfolio-share controls: an HTM valuation gap should not be allowed to stand in for holding a large HTM book. They also rule out interpreting the coefficient difference as an experiment in recognition rules. AFS and HTM holdings can differ in duration, credit composition, management intent, and accompanying risk management.

2.2 Asset repricing and funding adjustment

Banks combine assets with different repricing schedules and liabilities whose effective duration depends partly on depositor behavior. Hanson et al. (2015) discuss banks as patient fixed-income investors. Drechsler, Savov, and Schnabl (2017, 2021) emphasize deposit pricing and the value of the deposit franchise. A bank with sticky funding can maintain earnings even when fixed-rate asset values decline. Conversely, an institution that must raise deposit rates or replace low-cost funding can face pressure while its securities income adjusts slowly.

The strength of this offset varies across banks and over time. Emin, James, and Li (2025) examine variable deposit betas, and English, Van den Heuvel, and Zakrajšek (2018) study interest rate risk and equity valuations. Abdymomunov, Gerlach, and Sakurai (2026) analyze interest rate risk in the U.S. banking sector. Together, these studies motivate examining both valuation and earnings exposure. A securities discount can coincide with a valuable liability franchise; its gross size alone does not identify the change in a bank's net economic value.

The first empirical prediction is a negative conditional association between the December 2022 securities discount and subsequent NIM change. A low-yielding securities stock can slow the rise in asset income, and funding adjustment can increase the interest expense burden. Either force can contribute to a weaker margin relative to otherwise similar banks. A second prediction is that the association can persist beyond 2023 because the existing asset stock does not immediately mature or reprice. The annual comparisons test persistence in an observable earnings relationship, not the structural timing of a monetary policy treatment effect.

An accounting decomposition supplies a further diagnostic. FDIC NIM equals interest income divided by average earning assets less interest expense divided by the same denominator. If the valuation gap mainly reflects low-return assets, it should be associated with weaker growth in the income ratio. If funding adjustment matters, it may also be associated with a higher expense ratio. These are associations with reported components. The expense ratio includes interest on nondeposit liabilities, and changes in the common denominator affect both components; neither coefficient is a direct estimate of a deposit rate or a deposit beta.

2.3 Funding composition and liquidity risk

Uninsured funding provides a reason for sensitivity to deposit competition and a possible source of liquidity vulnerability. Diamond and Dybvig (1983) and Goldstein and Pauzner (2005) analyze coordination risk in demandable claims. Iyer and Puri (2012) examine depositor relationships and networks, and Egan, Hortaçsu, and Matvos (2017) connect competition and fragility. Recent

evidence on the 2023 episode uses transaction or market information that is much richer than quarterly balance-sheet totals (Jiang et al., 2024; Cipriani, Eisenbach, and Kovner, 2024, revised 2026).

A surviving bank's total deposits can remain stable even while their reported insurance composition changes. This matters for assessing subsequent funding conditions, but quarterly balances cannot reveal individual withdrawals, intraperiod liquidity stress, or account-level transfers. The paper therefore includes uninsured funding as a baseline control and tests whether it modifies the gap association. A separate December 2022–June 2023 composition exercise is descriptive. It is not a mediation analysis and does not identify the timing or incidence of bank runs. Public assistance and deposit insurance arrangements are additional relevant influences on funding outcomes (Glancy et al., 2024; Huberdeau-Reid and Pennacchi, 2025).

3 Data and empirical design

3.1 Public sources and sample construction

The financial data were downloaded from FDIC BankFind on 30 September 2026. The archive includes six date-specific financial extracts: December 2021 through December 2025 and June 2023. Failure, institution, and history extracts provide public event information for 2023–2025. The query manifest records request URLs, dates, row counts, database indices, and SHA-256 checksums. Financial observations are uniquely identified by certificate number and report date. All monetary balance-sheet entries are in thousands of dollars; FDIC income ratios are percentages (FDIC, 2026).

December 2022 contains 4,773 financial observations. Requiring positive deposits leaves 4,720, and an asset threshold of \$100 million leaves 3,961. We additionally require positive book equity, an observed geographic code, and an estimated uninsured-to-total-deposit ratio between zero and one. The resulting baseline has 3,927 eligible institutions. Two lack complete primary baseline predictors. Complete matching to later annual NIM produces samples of 3,835 in 2023, 3,753 in 2024, and 3,637 in 2025. These are counts of regulatory filers satisfying the specified screens, rather than a reconstruction of FDIC industry aggregates.

The exposure date precedes the March 2023 failures but follows the interest rate changes of 2022. It is therefore fixed before the earnings outcomes without being predetermined relative to monetary tightening. Matching follows the same certificate number and does not consolidate acquired banks into an acquiring institution's historical accounts. Failed banks and some merger targets cannot supply a comparable future outcome. The estimand is a conditional association among later-observed filers, not average earnings pressure for every bank exposed at the baseline.

We make this selection visible. Relative to the eligible baseline, 92 observations are unmatched or incomplete in 2023, 174 in 2024, and 290 in 2025. Public failure records flag 5 of the 2025 exclusions; merger or absorption histories flag a further 169, and voluntary-closing histories flag 33. The remaining 83 are unresolved by this screen. The history records also identify surviving participants, so they are useful for excluding event-affected observations but do not provide complete bank lineage.

3.2 Exposure measures and earnings outcomes

For each institution, the HTM valuation gap is the positive part of amortized cost less fair value, divided by December 2022 assets. The AFS measure uses the corresponding AFS fields. Both are multiplied by 100, so a unit is a shortfall equal to one percentage point of assets. Equations (1) and

(2) use **FDIC** field names to make the construction auditable. A net gain is assigned zero in the primary measures; an alternative retains signed differences. These measures do not incorporate the fair value of loans, deposit franchise value, or comprehensive off-balance-sheet hedges.

$$H_i = 100 \times \max(SCHA_{i, 2022} - SCHF_{i, 2022}, 0) / ASSET_{i, 2022} \quad (1)$$

$$A_i = 100 \times \max(SCAA_{i, 2022} - SCAF_{i, 2022}, 0) / ASSET_{i, 2022} \quad (2)$$

The eligible baseline has a pronounced mass at zero in the **HTM** measure: 65.6% of institutions have no positive net **HTM** shortfall. The **HTM** median is zero and its 90th percentile is 1.02% of assets. The **AFS** median is 1.83% and its 90th percentile is 5.00%. Consequently, comparing the two slopes per unit does not compare their aggregate importance. The **AFS** measure spans a much larger typical exposure range. Table 1 reports unmodified baseline means, standard deviations, and quantiles.

Table 1 Baseline sample and descriptive statistics**Panel A Sample construction**

Screen	Institutions
December 2022 financial observations	4,773
Positive deposits	4,720
Positive deposits and assets of at least \$100 million	3,961
Eligible baseline after all screens	3,927
Complete primary baseline predictors	3,925
NIM outcome samples in 2023 / 2024 / 2025	3,835 / 3,753 / 3,637

Panel B Raw baseline variables

Variable	Mean	SD	P10	Median	P90
HTM valuation gap	0.32	0.92	0.00	0.00	1.02
AFS valuation gap	2.29	2.03	0.10	1.83	5.00
Log total assets	13.24	1.36	11.86	12.96	14.91
Equity / assets	9.50	5.11	5.49	8.84	13.34
Cash / assets	7.50	8.65	1.64	4.66	15.94
Net loans / assets	62.69	16.45	41.06	64.91	81.75
HTM amortized cost / assets	3.56	8.60	0.00	0.00	12.57
AFS fair value / assets	20.20	14.88	2.17	17.78	40.41
Baseline ROA	1.29	9.10	0.48	1.08	1.72
Baseline NIM	3.49	1.13	2.66	3.41	4.24
Prior annual NIM change	0.14	0.49	-0.28	0.13	0.56
Prior annual ROA change	-0.05	1.39	-0.52	-0.03	0.35
Uninsured / total deposits (%)	29.08	14.21	13.23	27.10	47.40

Notes: Baseline is December 2022. All shares and income ratios are percentages; changes are percentage points. Log assets uses amounts in \$000. Raw statistics precede winsorization. $N = 3,927$ except prior NIM and ROA changes ($N = 3,925$). The large raw ROA standard deviation reflects extreme observations; estimation applies documented predictor cutoffs. HTM and AFS gaps are positive portfolio shortfalls divided by total assets. SD denotes sample standard deviation.

NIM is annualized net interest income divided by average earning assets. ROA is the FDIC annualized return-on-assets ratio. December observations represent full-year ratios; the annual outcome is the December ratio in year t minus the December 2022 ratio. Each comparison thus measures a difference between annual rates, not cumulative earnings lost over the intervening years. The raw baseline ratio is used when forming the change. Winsorizing a baseline earnings regressor does not change the baseline value subtracted from the outcome.

The NIM control set contains log total assets; equity, cash, and net loans relative to assets; HTM amortized cost and AFS fair value relative to assets; estimated uninsured funding; baseline NIM and ROA; and NIM in 2022 less NIM in 2021. The separate portfolio shares are measured on their respective balance-sheet carrying bases. They control portfolio quantity without claiming to identify identical economic portfolios. The ROA specification omits baseline NIM and the NIM trend and instead includes the 2021–2022 ROA change alongside baseline ROA. Both specifications include fixed effects for the baseline STALP geographic code.

3.3 Uninsured deposits and reporting coverage

DEPUNINS is an estimate whose construction is not uniform across all filers. Larger banks report estimated uninsured deposits in Call Report Schedule RC-O. For institutions not reporting this item, FDIC uses balances and counts of deposit and retirement accounts above the standard insurance limit to calculate an estimate (FDIC, 2024). The distinction is relevant around the \$1 billion reporting threshold. The uninsured ratio in this study divides the published estimate by consolidated total deposits and is a funding exposure proxy, not an account-level insurance determination.

Insurance estimates and consolidated deposits also have different reporting bases. DEPINS plus DEPUNINS need not equal DEP, which can include foreign-office deposits and differs from the assessment-liability base. At December 2022, the 95th percentile of the absolute difference between DEP and these two estimates is 0.76% of DEP. Replacing DEP with deposit liabilities before assessment exclusions less allowed exclusions gives a 95th-percentile discrepancy of 0.00%. This diagnostic shows why adding the estimated insured and uninsured components mechanically to infer total deposit flows would be inappropriate.

The FDIC's July 2023 reporting letter identified errors, including inappropriate deductions for collateralized deposits and intercompany balances (FDIC, 2023). The archived extracts may incorporate subsequent amendments; the study is not based on immutable real-time reporting vintages. We center the baseline uninsured share at its median, 27.10%, and scale it in ten-percentage-point units. Size subsamples and an uninsured-share interaction provide sensitivity checks, but they cannot make differently constructed estimates identical.

3.4 Estimation and statistical inference

For each outcome year, we estimate a separate ordinary least squares cross section with both gaps included simultaneously. Equation (3) gives the NIM specification; the ROA model follows the same structure with the control changes described above. The gap coefficients measure percentage

points of annual NIM change per percentage point of baseline assets in the valuation gap. The fixed effects absorb average differences across baseline geographic codes; the design is not a within-bank treatment comparison.

$$\Delta NIM_{i,t} = \alpha_t + \beta_{H,t} H_i + \beta_{A,t} A_i + \gamma_t X_{i,2022} + \delta_{s(i),t} + \varepsilon_{i,t} \quad (3)$$

Primary continuous predictors are winsorized at their eligible December 2022 baseline 1st and 99th percentiles. Each annual outcome is winsorized at the corresponding complete estimation sample's 1st and 99th percentiles. This rule retains banks with unusually large changes while limiting their influence. Raw descriptive statistics remain available, including the substantial dispersion of baseline ROA. We report untrimmed outcomes and a 5th/95th-percentile alternative rather than assuming that a single outlier rule is innocuous.

Standard errors are clustered by baseline geography, allowing arbitrary residual dependence within each of the 55 state and jurisdiction codes represented in the primary samples. We apply the conventional finite-sample covariance correction $G/(G-1)$ times $(n-1)/(n-k)$, where k counts all design columns. Tests and confidence intervals use a Student t reference with $G-1$ degrees of freedom (Cameron and Miller, 2015; MacKinnon, Nielsen, and Webb, 2023). Geographic clustering does not necessarily capture dependence among affiliates operating across states or national common shocks. HC3 inference is included as a sensitivity comparison.

Robustness exercises change portfolio controls, the prior earnings trend, HTM participation, gap sign coding, outcome trimming, and sample composition. We screen large asset changes and very large banks, exclude institutions appearing in relevant public event histories, restrict to the common three-year cohort, and split baseline assets at \$1 billion. Additional specifications replace baseline NIM with its income and expense components and add the noncurrent-loan ratio. Inverse-observability weighting uses a regularized logistic model of later observation from baseline covariates and geography. It evaluates sensitivity to observed selection; it does not recover outcomes missing because of unobserved distress.

3.5 Interest components and predictive validation

For the 2024 component exercise, we regress changes in the interest-income ratio, interest-expense ratio, and NIM on identical regressors and identical observations. All three outcomes are untrimmed. Because NIM equals the income ratio less the expense ratio, linearity implies the same identity for each estimated slope. Independent outcome winsorization would destroy that identity. The replication code checks it numerically, and the exercise is presented as an accounting decomposition rather than a causal mediation model.

Prediction is evaluated separately from coefficient inference (Shmueli, 2010). The same-year exercise compares the full NIM control model with a model adding both gaps. Each annual matched sample is randomly divided into five folds, with 20 reproducible repetitions. All predictor cutoffs and the training-outcome cutoffs are estimated inside the training fold. Held-out outcomes remain untrimmed. Fixed effects use training-sample categories; an unseen held-out geographic category receives no additional estimated category effect. RMSE and mean absolute error (MAE) aggregate the held-out errors across banks and repetitions.

The time-ordered exercise asks a different question and maintains a fixed one-year target. It uses rolling December 2022, 2023, and 2024 baseline cohorts, with the same eligibility rules and covariate definitions, to predict NIM in the next December less NIM in that cohort's baseline December. The 2024 target is predicted using the 2022→2023 training cohort. The 2025 target is

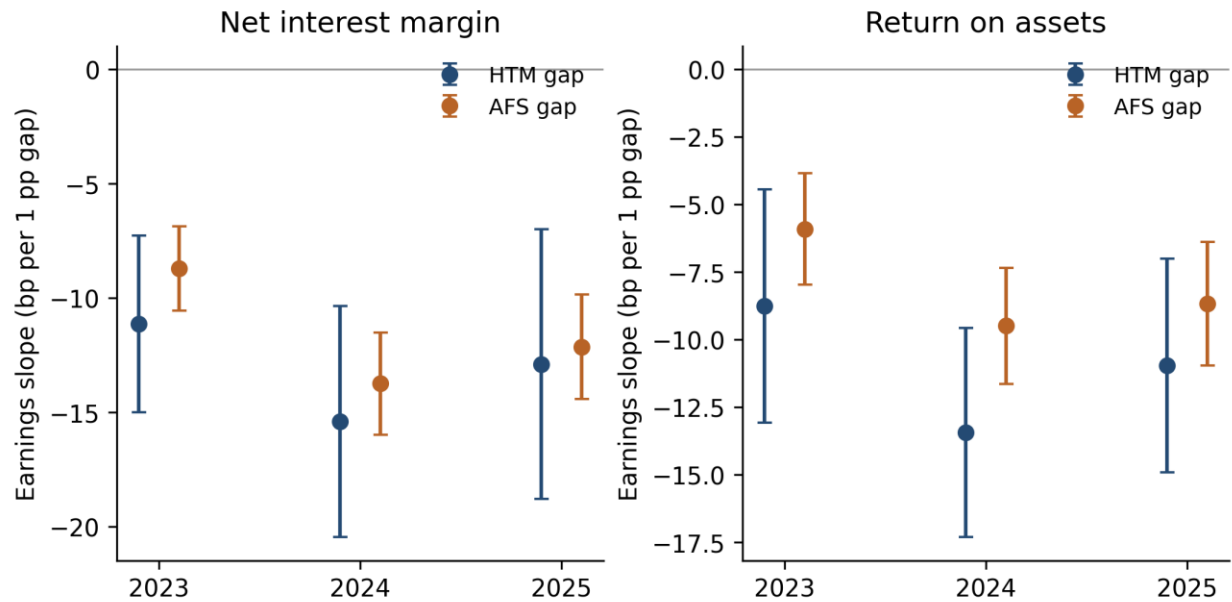
predicted using pooled 2022→2023 and 2023→2024 training cohorts. Training-only preprocessing is again enforced, and test outcomes remain raw. No future cohort contributes outcomes to estimation.

These exercises use the September 2026 revised data extracts and are therefore pseudo out-of-time tests rather than demonstrations of real-time vintage performance. The rolling one-year target also differs from the primary 2022-to-2024 and 2022-to-2025 comparisons. Confidence intervals for relative RMSE gains resample 2,000 geographic clusters from stored test losses. They quantify uncertainty in the loss comparison conditional on fitted models and fold assignments; they do not refit the entire estimation procedure in every bootstrap draw. Supplementary Section S6 records the protocol and sample sizes.

4 Empirical results

4.1 Persistent margin associations

Table 2 reports every nongeographic coefficient in the primary NIM models, together with sample sizes, fit, and the HTM-AFS equality test. Both gaps have negative coefficients in all three years. For 2023, a one-percentage-point larger HTM gap is associated with 11.13 basis points lower NIM change; the AFS association is 8.70 basis points. The estimates are 15.40 and 13.74 basis points in 2024 and 12.89 and 12.13 in 2025. All six gap p values are below 0.001 under the stated cluster inference. Figure 1 presents the corresponding 95% intervals.

Figure 1 Earnings associations across the three annual horizons

Notes: Coefficients and 95% geographic-cluster t intervals are from Tables 2 and 3. One gap unit is one percentage point of December 2022 assets. All outcomes are changes from the annual 2022 baseline. Separate HTM and AFS portfolio shares are controlled.

Table 2 Valuation gaps and annual net interest margin changes

Regressor / statistic	2023	2024	2025
HTM valuation gap	−0.111 ^{***} (0.019)	−0.154 ^{***} (0.025)	−0.129 ^{***} (0.029)
AFS valuation gap	−0.087 ^{***} (0.009)	−0.137 ^{***} (0.011)	−0.121 ^{***} (0.011)
Log total assets	−0.023 ^{**} (0.010)	−0.027 ^{**} (0.011)	−0.031 ^{***} (0.011)
Equity / assets	−0.002 (0.004)	−0.008 [*] (0.005)	−0.013 ^{***} (0.005)
Cash / assets	0.012 ^{***} (0.003)	0.012 ^{***} (0.004)	0.007 [*] (0.004)
Net loans / assets	−0.019 ^{***} (0.002)	−0.024 ^{***} (0.003)	−0.017 ^{***} (0.002)
HTM amortized cost / assets	−0.003 (0.003)	−0.002 (0.004)	−0.000 (0.004)
AFS fair value / assets	−0.001 (0.003)	0.002 (0.003)	0.004 (0.003)
Uninsured share (10 pp units)	−0.019 [*] (0.011)	−0.023 [*] (0.012)	−0.027 ^{***} (0.009)
Baseline ROA	0.074 ^{***} (0.022)	0.082 ^{***} (0.025)	0.056 ^{**} (0.022)
Baseline NIM	0.071 ^{**} (0.029)	0.016 (0.035)	−0.065 [*] (0.034)
Prior annual NIM change	0.320 ^{***} (0.028)	0.209 ^{***} (0.037)	0.093 ^{**} (0.042)
Intercept	1.541 ^{***} (0.295)	2.282 ^{***} (0.415)	2.743 ^{***} (0.437)
Institutions	3,835	3,753	3,637
Geographic fixed effects	Yes	Yes	Yes

Regressor / statistic	2023	2024	2025
Geographic clusters	55	55	55
R ²	0.406	0.380	0.295
HTM-AFS equality test p	0.206	0.548	0.819

Notes: Dependent variable is December outcome-year ratio less its raw December 2022 value, in percentage points. Both gaps are percentage points of baseline assets. Other shares are percentages. Uninsured share is centered and scaled by 10 percentage points. Predictors and outcomes are winsorized at 1/99 under Section 3. Cluster standard errors are in parentheses; t inference uses G–1 degrees of freedom. ***, **, * denote $p < 0.01, 0.05, 0.10$. State and jurisdiction coefficients are included in the replication CSV. The equality test uses the covariance between the two gap slopes.

The 2024 HTM confidence interval ranges from -20.47 to -10.34 basis points, while the AFS interval ranges from -15.98 to -11.51. These slopes are economically noticeable relative to the distribution of exposures. Moving from zero to the baseline HTM 90th percentile corresponds to approximately 15.69 basis points lower fitted 2024 NIM change. Moving from the AFS median to its 90th percentile corresponds to approximately 43.57 basis points. These are contrasts within the conditional linear model, holding controls fixed; they are neither realized accounting losses nor feasible portfolio interventions.

The larger absolute coefficients in 2024 than in 2023 are consistent with earnings adjustment extending beyond the acute stress year. The 2025 estimates remain negative even though their absolute magnitudes decline. Comparing annual coefficients is descriptive because both the macroeconomic setting and the observed sample change. Restricting the 2024 analysis to the common 2023–2025 cohort produces HTM and AFS slopes of -15.20 and -13.89 basis points, close to the primary estimates. This reduces concern that the 2024 result is created solely by the inclusion of banks that disappear before 2025, while leaving broader selection concerns intact.

The equality tests qualify the category comparison. In the separate-portfolio specification, the HTM-AFS NIM difference has p values of 0.206, 0.548, and 0.819 across 2023–2025. None rejects equality at the 5% level. By comparison, controlling only total securities share produces 2024 slopes of -17.66 and -12.90 basis points and a larger statistically significant difference. The accounting-category ranking is sensitive to how portfolio quantity is held constant. The negative association for each gap is more stable than a claim that HTM carries a uniquely greater per-unit earnings effect.

The additional coefficients help interpret the conditioning set. In the 2024 model, the cash share has a positive association with NIM change, the loan share a negative association, and the prior NIM change a positive association. These controls are not separately identified causal channels. Their presence demonstrates that the securities-gap result is not merely a comparison between banks with different initial margins or broad asset shares. The separate HTM and AFS quantity coefficients themselves are imprecisely estimated in 2024, while the gaps retain negative associations.

4.2 Profitability beyond the interest margin

Table 3 reports the full primary ROA specification. HTM and AFS gaps are associated with lower profitability changes in every year. The 2024 slopes are -13.44 and -9.49 basis points of ROA per one-percentage-point gap. The corresponding 2025 estimates are -10.95 and -8.67 basis points. The ROA models have lower explanatory fit than the NIM models, with 2024 R^2 of 0.234 compared with 0.380 for NIM.

Table 3 Valuation gaps and annual return on assets changes

Regressor / statistic	2023	2024	2025
HTM valuation gap	−0.088 ^{***} (0.022)	−0.134 ^{***} (0.019)	−0.110 ^{***} (0.020)
AFS valuation gap	−0.059 ^{***} (0.010)	−0.095 ^{***} (0.011)	−0.087 ^{***} (0.011)
Log total assets	−0.031 ^{**} (0.014)	−0.018 (0.011)	−0.011 (0.009)
Equity / assets	−0.002 (0.005)	0.003 (0.005)	0.001 (0.005)
Cash / assets	0.012 ^{***} (0.003)	0.003 (0.003)	0.004 (0.004)
Net loans / assets	−0.008 ^{***} (0.003)	−0.016 ^{***} (0.002)	−0.008 ^{**} (0.004)
HTM amortized cost / assets	0.001 (0.003)	−0.002 (0.003)	0.003 (0.004)
AFS fair value / assets	−0.001 (0.003)	−0.003 (0.002)	0.004 (0.003)
Uninsured share (10 pp units)	−0.007 (0.011)	0.009 (0.008)	−0.004 (0.008)
Baseline ROA	−0.089 ^{**} (0.037)	−0.155 ^{***} (0.033)	−0.205 ^{***} (0.032)
Prior annual ROA change	−0.016 (0.036)	−0.118 ^{***} (0.031)	−0.132 ^{***} (0.036)
Intercept	1.139 ^{***} (0.311)	1.680 ^{***} (0.280)	1.233 ^{***} (0.353)
Institutions	3,835	3,753	3,637
Geographic fixed effects	Yes	Yes	Yes
Geographic clusters	55	55	55
R ²	0.189	0.234	0.188

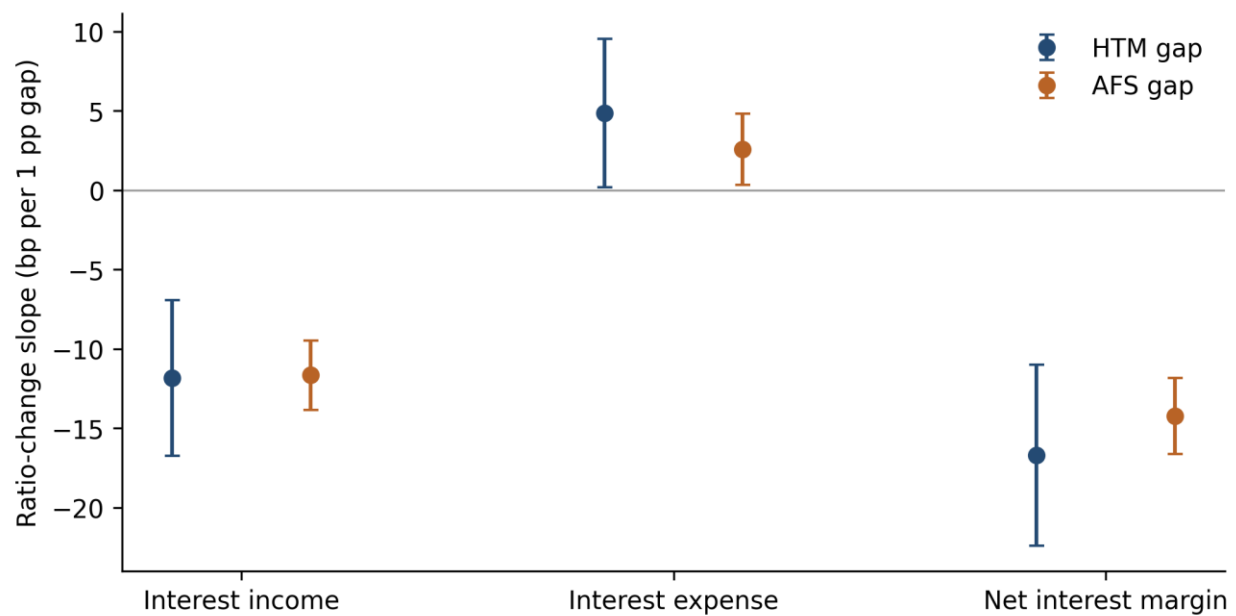
Regressor / statistic	2023	2024	2025
HTM-AFS equality test p	0.240	0.080	0.349

Notes: Dependent variable is December outcome-year ratio less its raw December 2022 value, in percentage points. Both gaps are percentage points of baseline assets. Other shares are percentages. Uninsured share is centered and scaled by 10 percentage points. Predictors and outcomes are winsorized at 1/99 under Section 3. Cluster standard errors are in parentheses; t inference uses $G-1$ degrees of freedom. ***, **, * denote $p < 0.01, 0.05, 0.10$. State and jurisdiction coefficients are included in the replication CSV. The equality test uses the covariance between the two gap slopes.

ROA includes credit provisions, noninterest income and expense, taxes, and other reported items. Its negative association provides evidence that the signal is relevant to a broader profitability outcome, but it does not prove that NIM mediates the relationship. Subsequent regulatory assessments and restructuring can also affect reported profits. The HTM-AFS ROA equality test in 2024 has $p = 0.080$; it does not reject equality at 5%. Accordingly, neither earnings outcome supplies a stable causal ranking of accounting categories.

4.3 Interest income and interest expense

Table 4 and Figure 2 decompose the untrimmed 2022–2024 NIM association on the identical 3,753-bank sample. The HTM gap is associated with 11.85 basis points less growth in interest income relative to average earning assets and 4.84 basis points more growth in the expense ratio. Their difference is a 16.70-basis-point lower NIM change. For AFS, the income association is 11.66 basis points lower and the expense association 2.57 basis points higher, implying 14.23 basis points lower NIM.

Figure 2 Associations with interest income and expense components

Notes: Points and 95% t intervals correspond to Table 4. Each component is an annual ratio in percent. A coefficient unit is basis points per one percentage point of assets in the baseline valuation gap.

Table 4 Accounting decomposition of 2022 to 2024 interest margin changes

Exposure	Interest income ratio change	Interest expense ratio change	NIM change
HTM valuation gap	-11.85*** (2.45)	4.84** (2.34)	-16.70*** (2.84)
AFS valuation gap	-11.66*** (1.10)	2.57** (1.12)	-14.23*** (1.19)
Institutions	3,753	3,753	3,753
R ²	0.298	0.368	0.357

Notes: Gap coefficients and standard errors are basis points per one-percentage-point gap. All models use identical observations and the full primary NIM regressor set. All three outcomes are untrimmed. Both component ratios use average earning assets as the denominator, and NIM equals income ratio less expense ratio. The maximum coefficient-identity discrepancy is below 10^{-9} percentage points. Standard errors are clustered by geography; significance notation follows Table 2. Interest expense includes nondeposit funding. The decomposition does not identify causal mediation.

The weaker income-ratio growth accounts arithmetically for approximately 71.0% of the absolute HTM NIM coefficient and 82.0% of the AFS coefficient. These proportions describe a linear accounting identity, with no claim that the components are statistically independent or causal shares. The interest-expense associations are smaller but positive, with p values of 0.043 and 0.025. The untrimmed NIM coefficients are somewhat more negative than the primary winsorized estimates, which is why the component results are displayed separately.

This pattern is consistent with a securities discount summarizing a stock of assets that benefits less from higher market rates, accompanied by some adjustment in funding costs. The income measure covers all interest-earning assets, so it cannot assign the association exclusively to securities coupons. The expense measure covers deposits and other interest-bearing liabilities, so it cannot establish a deposit-pricing mechanism. Loan repricing, liability substitution, derivatives, and changes in the earning-asset denominator remain possible contributors. The decomposition narrows the accounting interpretation without replacing a mechanism identification design.

4.4 Sensitivity to specification and sample selection

Table 5 summarizes the main 2024 sensitivities. Adding a positive-HTM-holdings indicator leaves the HTM gap association at -15.08 basis points. Restricting to positive HTM holders gives -15.24 for HTM and -14.48 for AFS. Retaining signed gaps with only upper-tail winsorization also preserves both negative signs. These checks reduce concern that the HTM result consists only of the extensive-margin difference between holding no HTM securities and holding some.

Table 5 Selected sensitivity tests for 2024 NIM change

Specification	HTM bp (SE)	AFS bp (SE)	Banks	Equality test p
Primary: separate portfolio shares	−15.40*** (2.53)	−13.74*** (1.12)	3,753	0.548
Total-securities share only	−17.66*** (1.76)	−12.90*** (1.01)	3,753	<0.001
HTM holder indicator added	−15.08*** (2.54)	−13.75*** (1.11)	3,753	0.635
Positive HTM holdings only	−15.24*** (2.56)	−14.48*** (1.53)	1,554	0.810
Signed gaps; upper tail winsorized	−14.63*** (2.60)	−13.75*** (1.12)	3,753	0.758
Untrimmed outcome	−16.70*** (2.84)	−14.23*** (1.19)	3,753	0.409
Outcome winsorized at 5/95	−12.88*** (2.35)	−12.51*** (0.87)	3,753	0.886
Stable assets; below \$100bn	−14.95*** (2.52)	−13.64*** (1.07)	3,698	0.638
Public merger/failure flags excluded	−16.36*** (2.38)	−13.80*** (1.12)	3,577	0.325
Common 2023–2025 cohort	−15.20*** (2.57)	−13.89*** (1.07)	3,637	0.640
Baseline assets at least \$1bn	−10.54* (5.58)	−8.31*** (2.26)	936	0.721
Baseline assets below \$1bn	−20.49*** (3.79)	−14.72*** (1.23)	2,817	0.156
Inverse observability weighted	−15.49*** (2.56)	−13.77*** (1.11)	3,753	0.537

Notes: Coefficients and standard errors are basis points of NIM change per one-percentage-point baseline gap. All rows use geographic clustering and the primary controls except the stated change. The stable-assets screen requires outcome assets between 0.5 and 2 times baseline assets and assets below \$100 billion in both years. Public-event exclusion screens merger, absorption, consolidation, and failure records through 2024, including surviving participants; it does not consolidate lineages. Signed gaps retain negative values and are winsorized only above their baseline 99th percentile. Common cohort requires all three annual primary NIM outcomes. Weighting is a sensitivity to observation conditional on recorded covariates.

The outlier and restructuring checks show similar directional results. The untrimmed outcome gives gap slopes of -16.70 and -14.23 basis points. Winsorizing the outcome at the 5th and 95th percentiles attenuates the magnitudes to -12.88 and -12.51. The stable-asset screen, combined with assets below \$100 billion in both baseline and outcome years, retains 3,698 banks and gives -14.95 and -13.64. Excluding institutions flagged in merger, absorption, or failure histories through 2024 retains 3,577 banks and yields -16.36 and -13.80.

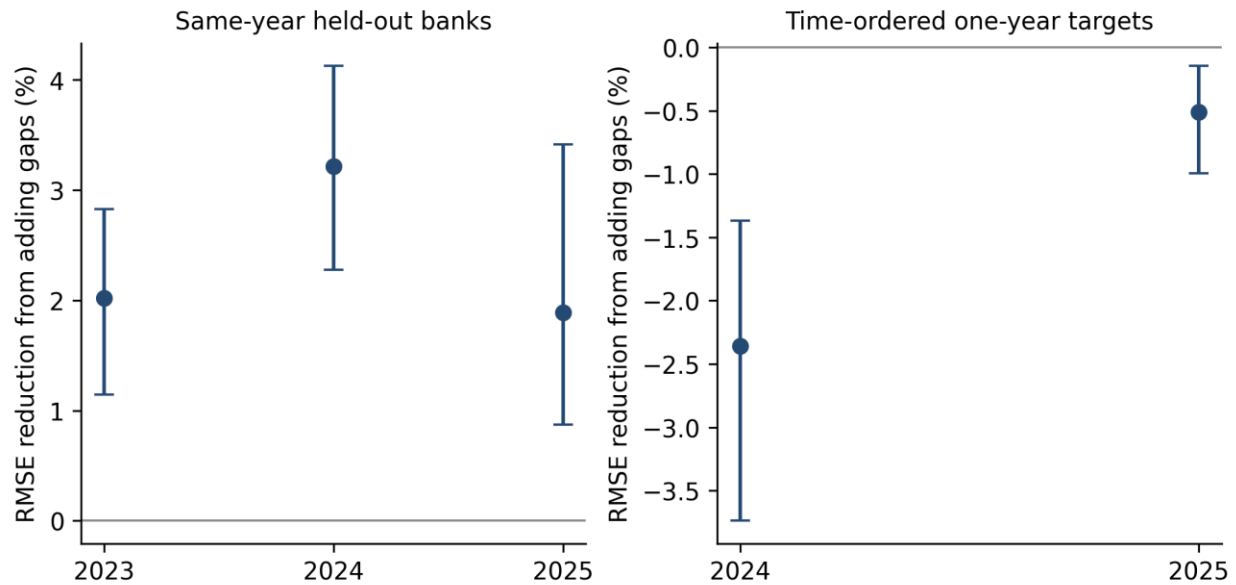
The size split indicates heterogeneity rather than a uniform response. Among banks with at least \$1 billion in baseline assets, the HTM coefficient is -10.54 basis points with a standard error of 5.58; among smaller eligible banks it is -20.49 with a standard error of 3.79. The larger-bank HTM estimate is less precise and does not reject zero at 5%. The AFS slope is negative in both groups. Size also corresponds to differences in uninsured-deposit reporting, so this split should not be read as identifying which single economic characteristic explains the different magnitudes.

Replacing baseline NIM with its interest-income and interest-expense components and adding the noncurrent-loan ratio leave the gap signs unchanged. The inverse-observability-weighted estimates are -15.49 and -13.77 basis points, close to the primary slopes. This weighting relies on a model of selection from observed baseline characteristics. It does not repair nonrandom loss of future earnings for failed banks or unrecorded merger histories. The attrition results therefore remain a boundary on the population interpretation, even when sensitivity estimates are numerically similar.

The uninsured-funding interaction provides little evidence for a simple amplification claim. The HTM interaction coefficient is 1.10 basis points per ten-percentage-point higher uninsured share ($p = 0.138$); the AFS interaction is -0.09 basis points ($p = 0.810$). The joint test has $p = 0.297$. An uninsured funding exposure can matter for bank fragility without producing a detectable interaction in these annual earnings regressions. Measurement differences, funding replacement, and the selection of observable survivors all limit what this null result can resolve.

4.5 Same-year prediction and temporal transfer

Table 6 separates the two validation settings, and Figure 3 plots their relative RMSE gains. In repeated same-year validation, adding the gaps reduces RMSE from 0.508 to 0.498 percentage points for 2023, from 0.611 to 0.592 for 2024, and from 0.673 to 0.660 for 2025. The reductions are 2.02%, 3.22%, and 1.89%. MAE also decreases in each year. For 2024, the cluster-resampled 95% interval for the relative RMSE gain is 2.28–4.13%.

Figure 3 RMSE gains under the two validation settings

Notes: Positive values favor adding gaps; negative values favor the control model. Whiskers show the conditional cluster-resampled intervals in Table 6. The panels use different exposure cohorts and horizons as explained in Section 3.5.

Table 6 Incremental prediction information and temporal transfer**Panel A Repeated same-year five-fold validation**

Outcome year	Test banks	Controls RMSE	Plus RMSE	gaps	Gain %	95% interval	gain
2023	3,835	0.508	0.498		2.02	[1.15, 2.83]	
2024	3,753	0.611	0.592		3.22	[2.28, 4.13]	
2025	3,637	0.673	0.660		1.89	[0.87, 3.42]	

Panel B Time-ordered one-year-ahead validation

Outcome year	Test banks	Controls RMSE	Plus RMSE	gaps	Gain %	95% interval	gain
2024	3,791	0.604	0.618		-2.36	[-3.74, -1.37]	
2025	3,715	0.595	0.598		-0.51	[-0.99, -0.15]	

Notes: RMSE is in percentage points of NIM change. Gain = $100 \times (1 - \text{gap-model RMSE} / \text{control-model RMSE})$; negative values mean worse prediction. Panel A uses the fixed 2022 baseline and 20 five-fold repetitions, with training-only preprocessing and raw test outcomes. Panel B uses rolling eligible cohorts and next-year changes. Training is 2022→2023 for the 2024 target (N = 3,835), and pooled 2022→2023 plus 2023→2024 for the 2025 target (N = 7,626). The 2026 revised vintage makes Panel B pseudo out-of-time rather than real-time. Intervals resample 2,000 geographic clusters of stored losses, conditional on fitted models. MAE and complete protocol appear in Supplementary Section S6.

These improvements concern prediction for held-out banks under the same realized outcome-year environment. They show incremental cross-sectional information relative to a control model that already includes portfolio quantities and prior earnings. They do not mean that the coefficients were known before that year's outcomes. The test losses use raw outcomes, making the errors larger than they would be under evaluation against a winsorized outcome. Training-only preprocessing prevents information from held-out banks from entering the estimated cutoffs.

The time-ordered results are materially different. A model trained on the 2022→2023 cohort predicts the 2023→2024 one-year change with RMSE of 0.604 percentage points using controls and 0.618 after adding the gaps. The relative change is a 2.36% worsening. For the 2024→2025 test cohort, expanding training to the two preceding cohorts produces RMSE of 0.595 and 0.598, a 0.51% worsening. MAE also rises in both temporal tests. The cluster-resampled RMSE-gain intervals lie below zero, conditional on these fitted models.

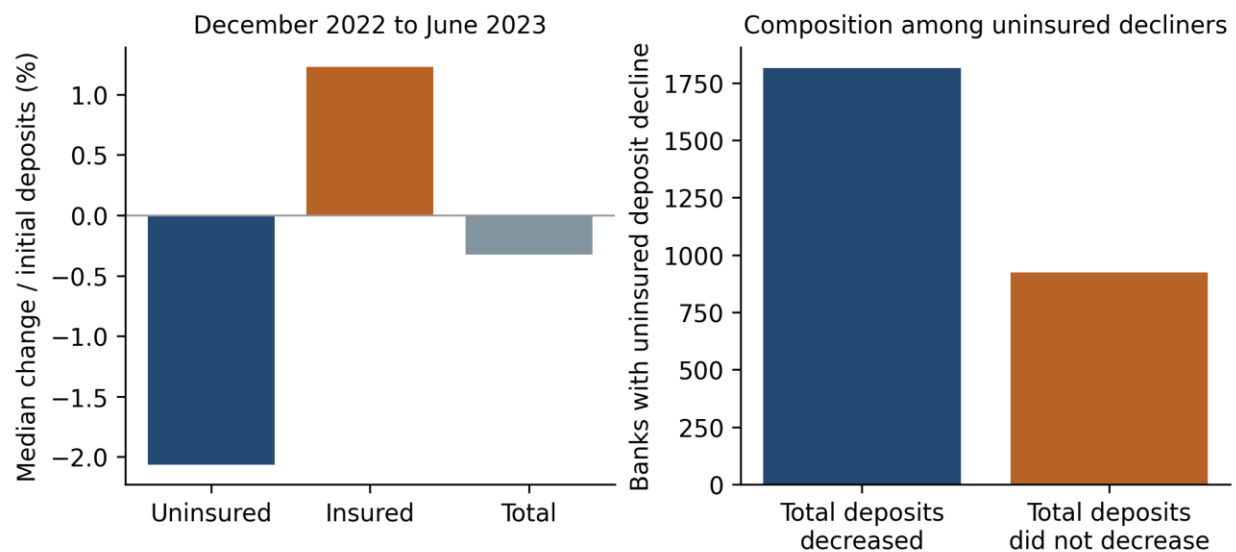
The temporal tests do not contradict the fixed-2022 association because they change the exposure cohort and keep a one-year horizon. Instead, they show that the incremental cross-sectional relationship does not automatically provide a stable mapping from a current gap to next year's change as the cycle evolves. A bank's valuation discount, its stock of securities, funding repricing, and investment opportunities can move together over successive years. The design does not

identify which change causes the failure to transfer. It supplies a directly observable limit to presenting this linear specification as a stand-alone operational forecasting model.

4.6 Reported deposit composition after the stress episode

Figure 4 reports December 2022–June 2023 deposit changes for 3,880 matched eligible banks. Median bank-level changes divided by initial total deposits are -2.06% for estimated uninsured deposits, +1.23% for estimated insured deposits, and -0.33% for total deposits. Among 2,737 institutions with a reported uninsured decline, 923, or 33.7%, have nonnegative total deposit change. Stable totals can therefore coexist with a material change in reported insurance composition.

Figure 4 Reported deposit composition after the 2023 stress



Notes: December 2022 to June 2023 changes use 3,880 matched baseline institutions. Left panel shows medians of bank-level changes divided by initial total deposits. Component medians need not add. Right panel classifies the 2,737 uninsured-deposit decliners by their total-deposit change; 923 have nonnegative total change. Insurance estimates and consolidated deposits have different coverage. These are balance changes, not direct measures of withdrawals.

The three medians need not add even if the underlying bank-level components share a consistent reporting base, because a median is not a linear aggregation operator. Here the estimated components also differ from consolidated total-deposit coverage. Revisions to reporting, intercompany balances, foreign-office deposits, or liability reclassification can contribute to measured changes. The result describes reported stocks at two quarter ends. It does not demonstrate depositor-level switching, identify a run, or establish that the valuation gap induced the composition change.

5 Discussion and limitations

5.1 Information content for earnings resilience

The earnings results connect the valuation of a securities stock to the later adjustment of reported flows. A bank can carry an HTM portfolio at amortized cost and maintain positive book capital while its existing assets earn less than newly available alternatives. Reading the disclosed discount

alongside the amount invested and the bank's funding profile gives a fuller picture of this exposure. The AFS result indicates that information already recognized outside current income also remains relevant to later operating performance. The separate-portfolio models support attention to both categories.

The component exercise strengthens this interpretation by showing that the main 2024 association appears in weaker interest-income growth as well as a smaller rise in the expense burden. This is an observable bridge between securities values and earnings resilience. It stops short of attributing the income coefficient to specific securities or the expense coefficient to individual deposit contracts. A more direct mechanism study would require security-level cash flows, effective duration, loan repricing schedules, derivative positions, and liability-specific rates.

The portfolio-control comparison also informs how the accounting evidence should be presented. A finding that the HTM slope exceeds the AFS slope when only total securities are controlled can confound recognition with the allocation of the securities book. The disappearance of a significant NIM difference after the two shares enter separately is a substantive result. It weakens a designation-specific interpretation while preserving the evidence that both disclosed gaps identify later earnings differences. This distinction is relevant to debates about fair value information and recognition (Laux and Leuz, 2009; Beatty and Liao, 2014).

For supervisors and analysts, the evidence supports a diagnostic use: examine valuation gaps when evaluating a bank's earnings adjustment, and assess the income and expense components alongside balance-sheet quantities. It does not support an automatic failure flag or a universal capital deduction inferred from these slopes. The Office of Financial Research (2025a, 2025b) emphasizes that asset losses and liability offsets must be considered together. A negative relative earnings association can coexist with positive profitability, stable deposits, and a valuable deposit franchise.

5.2 Why validation changes the practical interpretation

Same-year held-out improvement is useful evidence of incremental information, but the temporal losses restrict how that evidence can be used. Random folds expose a model to other banks under the realized outcome-year environment. A later-year forecast asks the same mapping to survive changes in that environment. The paper's negative transfer results make the second requirement explicit. They encourage periodic validation across vintages, exposure cohorts, and monetary conditions before using the specification for decisions.

A model designed for deployment might incorporate rate-path variables, interactions between asset maturity and liability repricing, or a rolling estimation window. Such extensions would need genuinely later test data and a specification chosen without inspecting those outcomes. This study does not tune a more flexible model to overturn the unfavorable temporal result. Its documented linear exercise provides a reproducible benchmark and a constraint on the strength of the forecasting claim.

5.3 Selection measurement and identification

Three limitations matter directly for interpretation. First, the sample conditions on a comparable later filing. Public histories explain many exclusions but not all, and no annual earnings counterfactual is observed for failed institutions. Common-cohort restrictions and weighting based on observables are sensitivity checks rather than corrections for distress-related missing outcomes.

The associations characterize retained regulatory filers and should not be extrapolated to the full distribution of losses among institutions at risk in 2022.

Second, the valuation measures are net portfolio discounts scaled by total assets. They omit security-level duration, the economic value of deposits and loans, and comprehensive hedges. The uninsured-deposit estimate mixes direct reporting and FDIC calculations and uses a denominator with different coverage from assessment liabilities. Raw earnings ratios can also reflect unusual transactions, which makes the reported trimming choices relevant. The archived data and alternative specifications allow readers to inspect these choices, but transparency does not eliminate measurement error.

Third, designation and risk management are jointly chosen. No instrument, policy discontinuity, or comparable-security assignment isolates an accounting-rule effect. The geographic fixed effects and broad controls do not remove unobserved managerial preferences, customer relationships, loan quality, or derivatives. National policy interventions and common shocks also fall outside a simple interpretation of state-clustered uncertainty. Thus the paper provides conditional earnings evidence and validation diagnostics, not an estimate of how forced reclassification would alter bank performance.

6 Conclusion

December 2022 HTM and AFS securities valuation shortfalls are associated with weaker subsequent annual margins and profitability among matched bank regulatory filers through 2025. The results persist when separate portfolio shares, initial earnings, preceding earnings changes, balance-sheet composition, uninsured funding, and geography are controlled. The 2024 component decomposition shows a larger association with weaker interest-income growth and a smaller positive interest-expense association. Sensitivity to sample and trimming choices changes magnitude more than direction.

The evidence also establishes two boundaries. HTM and AFS NIM slopes are not statistically distinguishable once their portfolio quantities enter separately, and positive same-year held-out prediction gains do not transfer to the later-year one-year targets. These findings favor using securities valuation disclosures as part of an assessment of earnings resilience while validating any forecasting rule across changing conditions. They do not justify a causal claim about accounting designation or a prediction of bank failure. The accompanying extracts, manifest, code, and complete coefficient files make the reported results reproducible.

References

- Abdymomunov, A., Gerlach, J. R., and Sakurai, Y. (2026). Interest rate risk in the U.S. banking sector. *Journal of International Money and Finance*, 165, 103587. <https://doi.org/10.1016/j.jimonfin.2026.103587>
- Barth, M. E., Beaver, W. H., and Landsman, W. R. (1996). Value-relevance of banks' fair value disclosures under SFAS No. 107. *The Accounting Review*, 71(4), 513–537. <https://www.gsb.stanford.edu/faculty-research/publications/value-relevance-banks-fair-value-disclosures-under-sfas-107>
- Beatty, A., and Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, 58(2–3), 339–383. <https://doi.org/10.1016/j.jacceco.2014.08.009>
- Cameron, A. C., and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50(2), 317–372. <https://doi.org/10.3368/jhr.50.2.317>
- Cipriani, M., Eisenbach, T. M., and Kovner, A. (2024; revised 2026). Tracing bank runs in real time. Federal Reserve Bank of New York Staff Report 1104. <https://doi.org/10.59576/sr.1104>
- Diamond, D. W., and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3), 401–419. <https://doi.org/10.1086/261155>
- Drechsler, I., Savov, A., and Schnabl, P. (2017). The deposits channel of monetary policy. *Quarterly Journal of Economics*, 132(4), 1819–1876. <https://doi.org/10.1093/qje/qjx019>
- Drechsler, I., Savov, A., and Schnabl, P. (2021). Banking on deposits: Maturity transformation without interest rate risk. *Journal of Finance*, 76(3), 1091–1143. <https://doi.org/10.1111/jofi.13013>
- Dursun-de Neef, H. Ö., Ongena, S., and Schandlbauer, A. (2026). Monetary policy, held-to-maturity securities, and uninsured deposit withdrawals. *European Accounting Review*, 35(2), 503–528. <https://doi.org/10.1080/09638180.2025.2478164>
- Egan, M., Hortaçsu, A., and Matvos, G. (2017). Deposit competition and financial fragility: Evidence from the US banking sector. *American Economic Review*, 107(1), 169–216. <https://doi.org/10.1257/aer.20150342>
- Emin, M., James, C., and Li, T. (2025). Variable deposit betas and bank exposure to interest rate risk. *Journal of Financial Intermediation*, 62, 101147. <https://doi.org/10.1016/j.jfi.2025.101147>
- English, W. B., Van den Heuvel, S. J., and Zakrajšek, E. (2018). Interest rate risk and bank equity valuations. *Journal of Monetary Economics*, 98, 80–97. <https://doi.org/10.1016/j.jmoneco.2018.04.010>
- Evans, M. E., Hodder, L., and Hopkins, P. E. (2014). The predictive ability of fair values for future financial performance of commercial banks and the relation of predictive ability to banks' share prices. *Contemporary Accounting Research*, 31(1), 13–44. <https://doi.org/10.1111/1911-3846.12028>
- Federal Deposit Insurance Corporation (FDIC). (2023). Estimated uninsured deposits reporting expectations. <https://www.fdic.gov/news/financial-institution-letters/2023/estimated-uninsured-deposits-reporting-expectations>

- Federal Deposit Insurance Corporation (FDIC). (2024). Quarterly Banking Profile, fourth quarter 2023. FDIC Quarterly, 18(1). Definitions of estimated insured and uninsured deposits. <https://www.fdic.gov/system/files/2024-07/fdic-v18n1-4q2023.pdf>
- Federal Deposit Insurance Corporation (FDIC). (2026). BankFind Suite API documentation. <https://api.fdic.gov/banks/docs>
- Federal Financial Institutions Examination Council (FFIEC). (2022). Instructions for preparation of Consolidated Reports of Condition and Income, FFIEC 031 and FFIEC 041. Updated December 2022. Schedule RC-B and Schedule RC-O. https://www.ffiec.gov/sites/default/files/data/reporting-forms/hv-031/FFIEC031_FFIEC041_202212_i.pdf
- Federal Reserve Board. (2023). Supervision and Regulation Report: Banking system conditions, November. <https://www.federalreserve.gov/publications/2023-november-supervision-and-regulation-report-banking-system-conditions.htm>
- Glancy, D., Ionescu, F., Klee, E., Kotidis, A., Siemer, M., and Zlate, A. (2024). The 2023 banking turmoil and the Bank Term Funding Program. Finance and Economics Discussion Series 2024-045. <https://doi.org/10.17016/FEDS.2024.045>
- Goldstein, I., and Pauzner, A. (2005). Demand-deposit contracts and the probability of bank runs. *Journal of Finance*, 60(3), 1293–1327. <https://doi.org/10.1111/j.1540-6261.2005.00762.x>
- Granja, J., Jiang, E. X., Matvos, G., Piskorski, T., and Seru, A. (2024). Book value risk management of banks: Limited hedging, HTM accounting, and rising interest rates. NBER Working Paper 32293. <https://doi.org/10.3386/w32293>
- Greenwald, D., Krainer, J., and Paul, P. (2024). Monetary transmission through bank securities portfolios. NBER Working Paper 32449. <https://doi.org/10.3386/w32449>
- Hanson, S. G., Shleifer, A., Stein, J. C., and Vishny, R. W. (2015). Banks as patient fixed-income investors. *Journal of Financial Economics*, 117(3), 449–469. <https://doi.org/10.1016/j.jfineco.2015.06.015>
- Hodder, L. D., Hopkins, P. E., and Wahlen, J. M. (2006). Risk-relevance of fair-value income measures for commercial banks. *The Accounting Review*, 81(2), 337–375. <https://doi.org/10.2308/accr.2006.81.2.337>
- Huberdeau-Reid, A., and Pennacchi, G. (2025). Adverse selection in deposit insurance and government funding following the 2023 banking crisis. *Journal of Financial Intermediation*, 63, 101165. <https://doi.org/10.1016/j.jfi.2025.101165>
- Iyer, R., and Puri, M. (2012). Understanding bank runs: The importance of depositor-bank relationships and networks. *American Economic Review*, 102(4), 1414–1445. <https://doi.org/10.1257/aer.102.4.1414>
- Jiang, E. X., Matvos, G., Piskorski, T., and Seru, A. (2024). Monetary tightening and U.S. bank fragility in 2023: Mark-to-market losses and uninsured depositor runs? *Journal of Financial Economics*, 159, 103899. <https://doi.org/10.1016/j.jfineco.2024.103899>
- Kim, S., Kim, S., and Ryan, S. G. (2025). Banks' motivations for designating securities as held to maturity. *The Accounting Review*, 100(4), 303–330. <https://doi.org/10.2308/TAR-2023-0615>

- Laux, C., and Leuz, C. (2009). The crisis of fair-value accounting: Making sense of the recent debate. *Accounting, Organizations and Society*, 34(6-7), 826-834. <https://doi.org/10.1016/j.aos.2009.04.003>
- MacKinnon, J. G., Nielsen, M. Ø., and Webb, M. D. (2023). Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics*, 232(2), 272-299. <https://doi.org/10.1016/j.jeconom.2022.04.001>
- Office of Financial Research. (2025a). The state of banks' unrealized securities losses. 15 May. <https://www.financialresearch.gov/the-ofr-blog/2025/05/15/the-state-of-banks-unrealized-securities-losses/>
- Office of Financial Research. (2025b). 2025 annual report to Congress, section on interest rate risk. <https://www.financialresearch.gov/annual-reports/files/OFR-AR-2025.pdf>
- Shmueli, G. (2010). To explain or to predict? *Statistical Science*, 25(3), 289-310. <https://doi.org/10.1214/10-STS330>