

WHEN DEPOSITS RUN

**AN EVENT STUDY ON THE COLLAPSE OF SILICON VALLEY
BANK**

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Bachelor Thesis
Stockholm School of Economics
2026



When Deposits Run: An Event Study on the Collapse of Silicon Valley Bank

Abstract:

We find that equity markets penalized banks for fragile uninsured deposit funding, rather than their duration exposure, during the collapse of Silicon Valley Bank. In our study of 185 publicly traded U.S. banks, a one-standard-deviation increase in the uninsured deposit ratio yields a 1.85 percentage point more negative cumulative abnormal return in the $[0, +3]$ trading day window (coefficient -0.117 , $p < 0.01$), while duration exposure and its interaction with uninsured deposits are statistically insignificant. The return penalty is concentrated in banks above the sample-median uninsured deposit ratio of 0.40 (coefficient -0.287 , $p < 0.01$), indicating a threshold beyond which markets price run-prone funding. Daily panel regressions on excess returns provide no evidence on market pricing of either fragility measure pre-collapse in 2022, and the ex-post coefficient on uninsured deposits is essentially zero. The event thus reveals a three-stage pattern: no market pricing pre-collapse, instant repricing of uninsured deposits during the collapse, and ex-post resolution by regulatory intervention. In this episode, market discipline operated only until policy intervened.

Keywords:

Bank Runs, Uninsured Deposits, Abnormal Returns, Duration Exposure, Threshold Equilibrium

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Bachelor Thesis

Bachelor Program in Business and Economics

Stockholm School of Economics

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1. Introduction

The U.S. banking industry faced its worst banking stress since the global financial crisis in March 2023, following coordinated withdrawals that led to the collapse of Silicon Valley Bank (SVB). On March 9, withdrawals reached USD 42 billion, with around another USD 100 billion expected the following day¹, largely due to SVB's fragile funding structure. Roughly 92.5% of SVB's deposits were uninsured, and they were mostly held by technology companies funded by venture capitalists (Jiang, Matvos, Piskorski, and Seru, 2024). Uninsured deposits, along with unrealized losses on long-term bonds were the mechanisms underlying the collapse and made the bank highly susceptible to runs. Jiang et al. (2024) illustrate this process as they develop their model of self-fulfilling solvency runs that would have threatened the U.S. banking sector had regulators not intervened. Furthermore, Silicon Valley Bank's collapse led to a sharp decline in the value of bank stocks. The KBW Nasdaq Regional Banking Index, an index of publicly traded U.S. regional banks and thrifts, dropped more than 20%² during the period of SVB's collapse. In contrast, the S&P 500 index declined by only 5%³.

Thus, an important question emerges concerning the relationship between market discipline and banking research, namely whether the stock market already factored in ex-ante bank balance-sheet vulnerabilities, or whether the event revealed systematic mispricing of these weaknesses. Such a question is relevant not only for regulatory requirements and stakeholder monitoring, but also for research on the performance of banks during systemic crises.

We contribute to the literature in four primary ways. First, our study extends the closest comparable empirical papers. The first is Martins (2024), who studies the joint SVB-Credit Suisse collapse on a sample of the 100 largest publicly traded U.S. banks. He finds that uninsured deposits amplified negative cumulative abnormal returns (CARs). The second is Choi, Goldsmith-Pinkham, and Yorulmazer (2023), who study a sample of 224 U.S. banks using cumulative excess returns relative to the S&P 500 from February 1 over two windows ending on March 17 and May 25, 2023. They document that uninsured deposit funding and unrealized losses in held-to-maturity securities scaled by tier 1 capital are significantly priced during this period, while held-to-maturity securities over assets is not. We extend these prior works in several aspects. We define the event date on March 8, which is the date of the first public announcement regarding SVB's unrealized losses. This lets us avoid the contamination Martins (2024) himself warns about in his joint study and separates the run dynamics from the depositor guarantee and Bank Term Funding

¹ See Appendix E for the timeline of the event

² See Nasdaq, "KBW Nasdaq Regional Banking Index (KRX)," available at <https://indexes.nasdaqomx.com/Index/Overview/KRX> (accessed May 9, 2026).

³ See S&P Dow Jones Indices, "S&P 500," available at <https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview> (accessed May 9, 2026).

Program announced on March 12, both of which are included in the windows constructed by Choi et al. (2023).

In addition to Martins (2024), we add a duration exposure proxy and its interaction with uninsured deposits, following Jiang et al. (2024), which provides a direct cross-sectional test of the mechanisms their model identifies. We estimate these effects using the Fama-French five-factor model augmented with momentum (Carhart, 1997), rather than the three-factor model used by Martins (2024). This provides a richer benchmark for expected bank returns during a period of substantial cross-sectional variation in profitability, investment behavior, and return momentum. Moreover, we estimate panel regressions of daily excess returns over balanced pre- and post-event windows with formal *Post* and *Post-interaction* terms, examining whether markets priced these fragilities before and after the collapse of Silicon Valley Bank. Finally, we provide evidence on a non-linear pricing effect through a sample-median split that the linear specifications used by Choi et al. (2023) and Martins (2024) cannot detect. Throughout, our analysis primarily builds upon the theoretical literature of bank runs (Diamond and Dybvig, 1983; Demirgüç-Kunt and Detragiache, 2002; Egan, Hortaçsu, and Matvos, 2017), and the mechanisms analyzed in Jiang et al. (2024).

Second, we examine the market pricing of uninsured deposit funding and duration exposure over the immediate event window of the collapse of Silicon Valley Bank. The analysis uses CARs estimated with the Fama-French five-factor model with momentum. We find that uninsured deposits were significantly priced at the 1% level, with a coefficient of -0.117 in the $[0, +3]$ window. In contrast, duration exposure is statistically insignificant, suggesting that banks were penalized for their vulnerability to bank runs stemming from depositor composition rather than from interest-rate risk arising from their bond portfolios.

Third, we investigate whether uninsured deposit exposure was priced prior to SVB's collapse. Running panel regressions of daily excess returns over a pre-event window spanning 213 to 50 days before the collapse, we find no statistically significant relationship between uninsured deposits and stock returns, robust to both pooled OLS and firm fixed effects. This result is consistent with the idea that certain kinds of risk can remain latent, unappreciated by investors, until a relevant shock reveals them, as is evident from the literature on the 2007-2009 financial crisis (Beltratti and Stulz, 2012).

Fourth, we analyze whether SVB's failure caused any systematic repricing of banks based on their funding characteristics. We observe a positive and marginally significant (10% level) *Post x Uninsured Deposits* interaction term in the firm fixed effects panel regression, while it remains insignificant in the standard OLS panel. Combined with the severe penalty in the event-study CARs, we find no evidence of a systematic repricing. Instead, it is consistent with a flattening of the pricing schedule, presumably due to the joint guarantee provided for SVB and Signature Bank depositors, as well as the initiation of the Bank Term Funding Program.

Overall, these findings contribute to the literature on bank crisis performance in modern-day banking systems characterized by digitization and rapid information diffusion. Beltratti and Stulz (2012) find that, during the 2007-2009 crisis, large banks with less short-term capital-market funding fragility, more deposits, more Tier 1 capital, and less exposure to U.S. real estate performed better. Our results extend this to the collapse of Silicon Valley Bank and test the market pricing of the mechanisms examined by Jiang et al. (2024). We complement Choi et al. (2023) by isolating a short event-window response, using cumulative abnormal returns based on the Fama-French framework, formal pre- and post-event tests, and by detecting a threshold for the return penalty of uninsured deposit funding. The 2023 episode differs from the 2007-2009 crisis in that liability-side composition, particularly the share of uninsured deposits, was the dominant market-priced risk characteristic. This is relevant for bank supervision and for investor behavior in a setting where deposit outflows can happen within hours.

Our study is conducted on a sample of 185 publicly listed U.S. banks. Balance sheet data is obtained from Capital IQ, and uninsured deposit data is sourced from regulatory call reports available in Wharton Research Data Services (WRDS). Stock returns are collected from the Center for Research in Security Prices (CRSP).

2. Theoretical Framework

2.1. Uninsured Deposits and Run-Prone Funding Structures

Diamond and Dybvig (1983) provide the canonical model in which short-term demandable liabilities are used to finance long-term illiquid assets. In these instances, even fully solvent banks risk bankruptcy due to coordinated withdrawals arising from depositors anticipating that other depositors will withdraw their funds. Furthermore, Egan, Hortaçsu, and Matvos (2017) find that incentives for withdrawal diverge between uninsured and insured depositors during financial distress. Depositors without insurance are more likely to withdraw their funds, while those with insurance tend to keep their deposits unchanged.

Jiang, Matvos, Piskorski, and Seru (2024) build on these findings in their model of self-fulfilling solvency runs in the context of the collapse of Silicon Valley Bank. Specifically, they illustrate that even banks with fully liquid assets are vulnerable to self-fulfilling solvency runs if they suffer from large asset losses while uninsured deposits constitute a large proportion of their financing. Moreover, they also highlight that these self-fulfilling solvency runs would have threatened several U.S. banks after the collapse of Silicon Valley Bank, if the Federal Deposit Insurance Corporation (FDIC), Federal Reserve, and the U.S. Treasury would not have intervened.

The theory remains ambiguous about the impact of deposit insurance on these aspects. Demirgüç-Kunt and Detragiache (2002) point out that insurance reduces the likelihood of bank runs due to panic, however, it simultaneously weakens monitoring of bank risk-taking by equity holders, creditors, and depositors. Therefore, a higher ratio of uninsured deposits reveals banks with high vulnerability to bank runs, which in theory are also most heavily monitored by its depositors and equity holders. Essentially, it suggests that equity markets should already have reflected this mechanism in bank stock prices prior to the crisis. If the effect is absent, it highlights a core aspect of the run channel and reveals whether market scrutiny was weakened due to deposit insurance.

2.2. Duration Exposure and Monetary Tightening

Banks invest a significant share of funds into fixed-income securities recorded as held-to-maturity (HTM) or available-for-sale (AFS). AFS securities are recognized at fair value, while HTM securities are measured at amortized cost. Hanson, Shleifer, Stein, and Vishny (2015) show that holdings of these long-duration securities rely on a funding structure characterized by stable deposits, as it enables the owning institution to withstand early liquidation due to security price volatility. The relationship between a bank's interest rate sensitive assets and its liability composition therefore becomes a risk if they face withdrawals from their depositors.

This relationship became evident when interest rates were rapidly raised during 2022. Jiang et al. (2024) observe that the entire U.S. banking sector experienced significant unrealized losses stemming from their holdings of long-duration fixed-income securities. However, they also underline that the funding structure was pivotal to the crisis that occurred. Banks with mainly insured retail deposits could withstand considerable

mark-to-market losses without being threatened by bank runs. Conversely, banks funded with mainly uninsured deposits instead become vulnerable to large withdrawals as it forces them to sell their securities at the current market value. Thus, as the market value is below book value, it means that to fulfill one dollar of withdrawals, they need to liquidate assets with a book value above one dollar. Eventually the bank turns insolvent and unable to meet remaining claims.

Beltratti and Stulz (2012) establish a useful benchmark with their findings that the stock market performance of large banks with less funding fragility, more deposits, more Tier 1 capital, and less exposure to U.S. real estate performed markedly better during the period July 2007-December 2008 of the global financial crisis. Therefore, a highly relevant context for our study is whether similar aspects or bank liability structures were the deciding factors in the collapse of Silicon Valley Bank, which was characterized by a combination of duration exposure and fragile funding structures.

2.3. Market Pricing of Latent Risks and Identification of an Unfolding Event

The market pricing of balance sheet vulnerability prior to exposure to an exogenous shock is a different aspect than its actual presence. In accordance with the efficient market hypothesis (Fama, 1970), such vulnerabilities should always be reflected in expected equity returns and valuations. Following Armitage (1995) and MacKinlay (1997), an event-study enables examination of this conjecture by measuring actual returns compared to theoretical returns during a systematic event. Methodological details are presented in Section 3. Through the event-study we are able to observe the market's reaction at the point in time when the variables become salient. In contrast, the panel regression examines if the variables are systematically priced by investors.

Despite public access to financial statements, pre-event market pricing may still be absent. For instance, the moral hazard issue introduced by insured deposits may result in weak investor monitoring prior to the shock (Demirgüç-Kunt and Detragiache, 2002). Consequently, there are two possible outcomes. Either fragility is not reflected systematically in returns and becomes significantly priced because of the collapse, or equity valuations already incorporated these balance sheet vulnerabilities beforehand.

There are also implications regarding the sequential arrival of information during the collapse of Silicon Valley Bank. It started with announcements of large unrealized losses and subsequent equity offering, followed by depositor withdrawals and regulatory intervention (see the timeline in Appendix E). Thus, we construct multiple short event windows based on the initial public disclosure for the purpose of our event study. We also ensure that the panel regressions remain close enough to the event window to absorb the market's valuation adjustments while simultaneously minimizing the impact of event-induced variance and cross-sectional dependence by excluding the surrounding trading days.

2.4. Hypotheses

Building on the literature reviewed above, we formulate three hypotheses. These are stated below.

2.4.1. Hypothesis 1 (H1): The Fragility Pricing Hypothesis

Banks with higher ratios of uninsured deposits and greater duration exposure experienced significantly more negative cumulative abnormal returns during the collapse of Silicon Valley Bank.

2.4.2. Hypothesis 2 (H2): The Ex-Ante Underpricing Hypothesis

Before the event, neither the uninsured deposit ratio nor the duration-exposure ratio was systematically priced in daily bank stock returns.

2.4.3. Hypothesis 3 (H3): The Ex-Post Pricing Hypothesis

The collapse of Silicon Valley Bank produced a discrete change in the cross-sectional pricing of uninsured deposit funding and duration exposure.

3. Data and Methodology

3.1. Sample Construction and Summary Statistics

The initial sample comprises all publicly traded U.S. commercial and investment banks, totaling approximately 650 institutions. Estimated uninsured deposits are obtained from regulatory call reports accessed through WRDS, while the other balance sheet variables are obtained from Capital IQ⁴. We remove banks with missing data on uninsured deposits and control variables, as well as those with unreliable data⁵. Removal also applies to banks traded exclusively on the over-the-counter market. Finally, banks that became insolvent during the event have been excluded to avoid survivorship bias and maintain a balanced panel. The final sample consists of 185 entities.⁶

Table 1: Summary Statistics 2022Q4

Statistic	N	Mean	St. Dev.	Min	Median	Max
Uninsured Deposit Ratio	185	0.384	0.158	0.036	0.400	0.888
Liquidity	185	0.048	0.053	0.007	0.027	0.312
Log (Total Assets)	185	23.223	1.618	20.747	22.854	28.930
Duration Exposure Ratio	185	0.055	0.066	0.000	0.036	0.372
Tier 1 Capital Ratio	185	0.127	0.030	0.082	0.122	0.325
Profitability (ROA)	185	0.013	0.005	-0.016	0.013	0.028

Note: Summary statistics as of 2022Q4 for the final sample of 185 publicly traded U.S. banks. All variables are unitless ratios except Log(Total Assets). Uninsured deposit data are sourced from regulatory call reports via WRDS; remaining variables from Capital IQ. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Liquidity is defined as cash and cash equivalents divided by total assets; Duration exposure ratio is held-to-maturity securities divided by total assets.

⁴ For GS and SCHW, held-to-maturity security numbers are obtained from LSEG Workspace, as it was not available alongside the rest of the data from Capital IQ.

⁵ Due to inconsistent data for a few parent companies and their subsidiaries, some traded entities ended up with an uninsured deposit ratio exceeding 1, i.e., values exceeding the theoretical maximum of 1.

⁶ See Appendix B for size of the excluded institutions measured as the logarithm of assets.

Table 2: Correlation Between the Uninsured Deposit Ratio and the Duration Exposure Ratio

Quarter	Correlation
2022Q1	0.1153
2022Q2	0.1454
2022Q3	0.1405
2022Q4	0.0955

Note: Pairwise correlation between the uninsured deposit ratio and the duration exposure ratio across the 185 sample banks, computed at each fiscal quarter-end of 2022.

Table 2 presents the correlation between the duration-exposure ratio and the deposit ratio for each quarter in 2022. Since the correlation remains low throughout, multicollinearity is unlikely to inflate standard errors when these variables are jointly included in our regressions.

3.2. Fragility Measures

3.2.1. The Uninsured Deposit Ratio

Funding fragility and bank-run risk arising from banks' reliance on uninsured funding is captured by the uninsured deposit ratio. Uninsured deposits are those exceeding the Federal Deposit Insurance Corporation (FDIC) insurance limit. Egan, Hortaçsu, and Matvos (2017) show that demand for uninsured deposits falls sharply as bank distress increases. This encourages depositors to withdraw funds from banks with perceived default risk during financial distress.

The uninsured deposit ratio for bank i is defined as:

$$\text{Uninsured Deposit Ratio}_i = \frac{\text{Estimated Uninsured Deposits}_i}{\text{Total Deposits}_i}$$

Total deposits are retrieved from Capital IQ, while estimated uninsured deposits are obtained from call reports via WRDS. For publicly traded bank holding companies with multiple subsidiaries, each filing separate call reports, uninsured deposits are first summed across all subsidiaries. The aggregate amount is then attributed to the publicly traded parent company, to ensure consistency between the observed unit in the return data and the balance sheet variables.

The uninsured deposit ratio is based on the study by Jiang et al. (2024), who analyzed the Silicon Valley Bank event. They show that banks with larger shares of uninsured deposits are especially prone to withdrawals. Approximately 92.5% of deposits at Silicon Valley Bank were uninsured at the end of 2022, which rendered the institution

highly susceptible to significant simultaneous withdrawals in response to solvency concerns.

During the year leading up to the event, the cross-sectional distribution of the uninsured deposit ratio exhibits no major shift among most sample institutions. Table 1 reports a median of 40% and a maximum of 88.8%. Across Q1-Q3, the median remained in the interval 39.4% to 40.2%, while the maximum ranges from 79.4% to 80.7%, as seen in Tables 1.A-1.C in Appendix C. Across all quarters, the minimum value remains between 3.6% and 4%. The significant increase of the maximum value in the quarter preceding the collapse is noteworthy, however since the standard deviation remains at around 16% in all quarters, it rather reflects idiosyncratic movement at the most exposed bank instead of a distributional shift. Thus, we argue that the uninsured deposit ratio is pre-determined and not an endogenous response to the stress that materialized in March 2023.

3.2.2. Duration Exposure Ratio

Banks allocate significant resources to fixed-income securities because stable deposit funding allows them to withstand price fluctuations without being forced into early liquidation (Hanson, Shleifer, Stein, and Vishny, 2015). In the case of Silicon Valley Bank, their deposits were primarily invested in securities classified as HTM (Board of Governors of the Federal Reserve System, 2023). By year-end 2022, 78% of their securities holdings were in HTM securities, while the average large banking organization only had 42%. This was driven by their portfolio shift to HTM securities in January 2021. Additionally, their HTM holdings had a weighted-average duration of 6.2 years.

The market value of debt securities is inversely related to interest rates, which exposes banks with large portfolios of these instruments to significant unrealized losses during periods of rising interest rates, such as in 2022. Jiang et al. (2024) document that the 2022-2023 monetary tightening cycle reduced the mark-to-market value of U.S. bank assets by an average of 10%, implying aggregate unrealized losses of approximately USD 2 trillion. The distribution was skewed, with the median unrealized losses of a bank amounting to roughly 9% of assets, while the worst-affected 5% of banks experienced declines exceeding 20%. Accordingly, HTM securities are used to construct a proxy for these exposures, which led to forced security sales that precipitated the Silicon Valley Bank run. To facilitate comparisons across banks and to illustrate balance sheet structure, we divide HTM securities by total assets.

The duration exposure ratio for bank i is constructed as:

$$Duration\ Exposure\ Ratio_i = \frac{HTM\ Securities_i}{Total\ Assets_i}$$

All data used to construct this ratio is sourced from Capital IQ⁷. The underlying distribution of this metric for our sample remains stable during the entire monetary tightening episode during 2022. Table 1 reports a median of 3.6% and a maximum of 37.2%. While there is some variation in the median, which ranges from 0.9% to 3.1%

⁷ Except GS and SCHW; see Footnote 4

across Q1-Q3, the maximum remains stable at 37.5% to 38.5%, as shown by Tables 1.A-1.C in Appendix C. In all quarters, the minimum value was 0%. Hence, the distributional stability supports treating the variable as pre-determined measure of exposure to interest rate risk in the analysis.

3.3. Event Study Design

This study investigates the impact of the collapse of Silicon Valley Bank on the equity performance of U.S. banks. In accordance with Armitage (1995), returns are analyzed across three short event windows, which are selected based on the event date to minimize estimation distortion from confounding events and to isolate the immediate market response. The first public news regarding the collapse of Silicon Valley Bank emerged on March 8, 2023, when significant unrealized losses in its bond portfolio were reported. Therefore, this date is defined as $t=0$, and all days within the constructed event windows are treated as trading days.

The three event windows analyzed are $[0, +2]$, $[0, +3]$, and $[0, +4]$. The shortest window captures the immediate stock market reaction to the initial announcements (see Appendix E for the event timeline) and concludes on March 10 ($t=2$). The second window extends to March 13, the next trading day, to incorporate news of regulatory intervention in Silicon Valley Bank, including the subsequent deposit guarantee communicated by the FDIC, Treasury, and Federal Reserve. The longest window accounts for the possibility of delayed market valuation adjustments and ends on March 14.

Expected returns are estimated by the Fama and French (2015) five-factor model, which extends the three-factor model of Fama and French (1992) by adding profitability and investment factors. To improve the performance of the model, it is augmented with the momentum factor (Carhart, 1997). Relative to the three-factor specification used in Martins (2024), the five-factor model with momentum provides a broader control for systematic return variation, particularly relevant during the 2022–2023 tightening cycle when profitability, investment intensity, and momentum effects varied substantially across banks. The estimation window for factor loadings follows recommendations by Armitage (1995), spanning 250 to 50 trading days before March 8 ($t=-250$ to $t=-50$). This ensures that anticipation effects or information leakage do not bias the parameter estimates (MacKinlay, 1997). We obtain the Fama-French factors with momentum and the market portfolio at a daily frequency from the Fama-French Data Library in WRDS (Fama and French, 2023). Daily stock returns are downloaded from CRSP.

The following formulas, where R denotes excess returns, E represents the theoretical expected return, i indexes the firm, and t denotes time in days, are used to calculate abnormal returns and cumulative abnormal returns following MacKinlay (1997):

$$AR_{i,t} = R_{i,t} - (\alpha_{i,t} + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \beta_{i,MOM}MOM_t) = R_{i,t} - E(R_{i,t})$$

$$CAR_i(t_0, t_j) = \sum_{t=t_0}^{t_j} AR_{i,t}$$

The use of daily returns introduces concerns regarding non-synchronous trading and non-normality in returns. Brown and Warner (1985) demonstrate that OLS-based event study methods remain robust, with minimal impact on test statistics as sample size increases. To assess the statistical significance of cumulative abnormal returns, the adjusted BMP test (Boehmer, Musumeci, and Poulsen, 1991) and the non-parametric Corrado (1989) rank test are employed. Conventional tests are avoided due to cross-sectional correlation, which, as Kolari and Pynnönen (2010) note, often leads to downward-biased standard errors and overstated significance levels.

3.4. Cross-Sectional Regression: H1

This study conducts cross-sectional regressions of cumulative abnormal returns on balance-sheet characteristics reported in Q4 2022 to estimate the effects of uninsured deposits and duration exposure on banks' returns during the crisis. The choice of using pre-event characteristics follows Beltratti and Stulz (2012) and Ongena, Smith, and Michalsen (2003), as it addresses reverse causality concerns and ensures that the results reflect ex-ante exposures.

The regression of CAR for bank i over event window $w \in \{[0,+2], [0,+3], [0,+4]\}$, where the uninsured deposit to deposit ratio is denoted as $Unins$, and Dur represents the duration exposure ratio, is:

$$CAR_{i,w} = \alpha_e + \beta_1 Unins_i + \beta_2 Dur_i + \beta_3 (Unins_i \times Dur_i) + \gamma' Controls_i + \varepsilon_{i,w}$$

To ensure robustness to the timing of different market reactions, multiple event windows are constructed as market adjustments may occur over several trading days (MacKinlay, 1997; Armitage, 1995; Fama, 1970). The inclusion of an interaction term between uninsured deposits and duration exposure is motivated by Jiang et al. (2024), who demonstrate that bank vulnerability increases when a fragile deposit composition coincides with asset-side losses. Variables included in the interaction term are mean-centered to reduce multicollinearity. This procedure is done by subtracting the sample-mean from each observation. HC3 heteroskedasticity-robust standard errors are used to enhance inference reliability (MacKinnon and White, 1985).

3.5. Panel Regressions: H2 and H3

Panel regressions of daily excess stock returns on balance sheet variables are conducted to examine whether the market priced duration exposure and uninsured deposits before and after the collapse of Silicon Valley Bank. We also impose a post-crisis dummy. All balance sheet variables are reported quarterly for fiscal year 2022 and enter the regressions with a 30-day lag after the end of the relevant quarter to avoid look-ahead bias.

The regression is estimated over two non-overlapping windows. A pre-event window of $[-213, -50]$ and a post-event window of $[+50, +200]$ trading days relative to $t=0$. This provides sufficient observations for estimation and limits each window to approximately one trading year on either side of the event. Days $[-49, +49]$ are excluded to avoid contamination from anticipatory investor behavior and idiosyncratic volatility

related to the event. The exclusion of the event window and the surrounding trading days is to avoid biased betas and distorted inference due to event-induced variance (Boehmer et al., 1991; Kolari and Pynnönen, 2010).

The panel regression, where $R_{i,t}$ is the daily excess return of bank i on day t , $Post$ is a dummy for the post-crisis window, and F denotes the Fama-French five-factor model with momentum, is:

$$R_{i,t} = \alpha + \beta_1 Unins_i + \beta_2 Dur_i + \beta_3 (Unins_i \times Dur_i) + \beta_4 Post + \beta_5 (Post \times Unins_i) + \beta_6 (Post \times Dur_i) + \beta_7 (Post \times Unins_i \times Dur_i) + \delta' F_t + \gamma' Controls_i + \varepsilon_{i,t}.$$

All specifications cluster standard errors by both firm and time to account for residual serial correlation within firms and cross-sectional dependence across firms within trading days, following Petersen (2009); see also Wooldridge (2010) for a textbook treatment of clustered standard errors in panel data. To validate our results in the presence of potential omitted variable bias, we run robustness checks with firm fixed effects to account for persistent differences in, for instance, culture, reputation, and business model. Variables entering interaction terms are mean-centered by demeaning them at the sample average. We will also run the regressions with the interaction term between uninsured deposits and duration exposure excluded.

3.6. Overlap of Factor Estimation Window and Panel Regressions

The overlap between the factor estimation window and the pre-event pricing panel regression window is intentional and has no implications for the validity of our results. The event study uses this time period to estimate the betas of the respective banks with respect to the Fama-French factors and momentum, while the panel regression analyzes the systemic pricing of balance sheet characteristics.

The choice is also conservative, as the pre-event window coincides with the period of rapidly rising interest rates in 2022. Therefore, banks' exposure to maturity mismatches and uninsured deposit structures was highly economically relevant, yet is not reflected in equity returns, as revealed by our results. If anything, this strengthens our finding that the abnormal returns around March 8 reflect the market's reaction to the collapse of Silicon Valley Bank, as it was not a continuation of an already priced market trend.

3.7. Control Variables

In addition to the Fama-French five-factor model with momentum, the following control variables, with data obtained from Capital IQ, are used for the purpose of this study:

Total Assets: Bank size is measured as the logarithm of total assets. Size proxies for “too-big-to-fail” expectations and perceived government support, both of which may influence equity valuation (Beltratti and Stulz, 2012; O'Hara and Shaw, 1990).

Liquidity: Liquidity is measured as cash and cash equivalents scaled by total assets. Banks with stronger liquidity buffers are better positioned to meet sudden short-term obligations (Carré and Klossner, 2024; Acharya, Shin, and Yorulmazer, 2010).

Tier 1 Capital Ratio: The tier 1 capital ratio, defined as tier 1 capital over risk-weighted assets, controls for regulatory capital strength. Well-capitalized banks are more capable of absorbing losses, which reduces vulnerability during crises (Cecchetti, Kress, and Schoenholtz, 2025).

Profitability: Return on assets is used as the measure of profitability. Higher profitability is associated with stronger cash flows and, an improved ability to respond to adverse shocks. Profitability is commonly included as a control variable in empirical banking literature (e.g., Beltratti and Stulz, 2012; Ongena, Smith, and Michalsen, 2003).

Post-event Dummy: A binary variable equal to one for observations subsequent to the collapse of Silicon Valley Bank. It captures shifts in investor sentiment regarding the banking sector.

4. Results and Analysis

4.1. Aggregate Abnormal Returns

Table 3: Event-Study Results (CAR)

Window	Mean	Min	Median	Max	St. Dev	Corrado	ADJ BMP
0,+2	-3.65%	-26.35%	-3.21%	2.09%	3.55%	-15.32***	-2.50**
0,+3	-8.33%	-69.11%	-6.60%	4.50%	8.87%	-20.67***	-2.26**
0,+4	-7.33%	-56.83%	-5.73%	6.28%	7.43%	-16.96***	-2.22**

*Note: Cumulative abnormal returns (CAR) across the 185 sample banks for three event windows, with $t=0$ = March 8, 2023. Abnormal returns are estimated using the Fama-French five-factor model augmented with momentum, with an estimation window $[-250, -50]$ trading days before $t=0$. The Corrado (1989) rank test and adjusted BMP test (Boehmer et al., 1991) are used for significance testing. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.*

Table 3 reports the negative and large cumulative abnormal returns for all three event windows. Mean cumulative abnormal returns are -3.65%, -8.33%, and -7.33% for the $[0, +2]$, $[0, +3]$, and $[0, +4]$ windows, respectively. The adjusted BMP test is significant at the 5% level, while the non-parametric Corrado rank test shows significance at the 1% level. Hence, the result is robust to cross-sectional dependence and event-induced variance.

Surprisingly, the largest drawdown did not occur in the $[0, +2]$ window, when news of deposit withdrawals and the shutdown of Silicon Valley Bank was publicly disclosed. The substantial developments over the weekend following March 10, when government support was communicated, caused banks to suffer significant losses in the equity market. In the $[0, +4]$ window, the recovery of 1% compared to the $[0, +3]$ window indicates that investors reassessed the impact of Silicon Valley Bank's collapse on bank valuations.

4.2. Cross-Sectional Pricing of Fragility: H1

Table 4 below shows cross-sectional regressions of cumulative abnormal returns on both the duration exposure ratio and the uninsured deposit ratio. Regressions 4-6 include the interaction term between duration exposure and uninsured deposits and serve as our main specifications. All regressions use the balance sheet control variables.

Table 4: Cross-Sectional Pricing of Fragility

	<i>Dependent variable:</i>					
	CAR					
	0,+2 (1)	0,+3 (2)	0,+4 (3)	0,+2 (4)	0,+3 (5)	0,+4 (6)
Duration Exposure Ratio	-0.062 (0.048)	-0.122 (0.114)	-0.122 (0.108)			
Uninsured Deposit Ratio	-0.013 (0.017)	-0.120*** (0.039)	-0.083** (0.036)			
Duration Exposure (centered)				-0.070 (0.053)	-0.135 (0.116)	-0.133 (0.109)
Uninsured Deposits (centered)				-0.011 (0.018)	-0.117*** (0.039)	-0.079** (0.037)
Interaction				0.335 (0.429)	0.558 (0.824)	0.504 (0.764)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interaction	No	No	No	Yes	Yes	Yes
Outlier banks excluded	No	No	No	No	No	No
Observations	185	185	185	185	185	185
R ²	0.038	0.082	0.080	0.046	0.085	0.084

*Note: OLS cross-sectional regressions of CAR on fragility measures and controls, N = 185. HC3 heteroskedasticity-robust standard errors in parentheses. All explanatory variables are measured as of 2022Q4. Columns (4)-(6) include an interaction between uninsured deposits and duration exposure. Both centered at the sample mean. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets. *p<0.1; **p<0.05; ***p<0.01.*

The explanatory power of our model is low, as the R² values in Table 4 range from 0.038 to 0.085 across all regressions. In the unfolding of this sudden panic run, variation in the cross-section of returns is mainly driven by investor coordination and communication, such as attention on social media, depositor composition, and correlated beliefs (Cookson, Fox, Gil-Bazo, Imbet, and Schiller, 2026). These aspects are not reflected in balance sheet variables. Cookson et al. (2026) illustrate that a one-standard-deviation increase in pre-existing Twitter exposure resulted in a 4.3 percentage point larger stock market loss during the run period. Moreover, they find that pre-exposure did not displace classical bank-run channels; rather it was the interaction with uninsured deposit funding and mark-to-market losses that was the main factor. The balance sheet variables account only for the component of return variation that the market priced, not the risk channels per se. This study aims to examine whether markets priced these mechanics rather than their explanatory power for returns, hence the low explanatory power is not a major concern.

4.2.1. Uninsured Deposit Ratio

The uninsured deposit ratio negatively affects cumulative abnormal returns in all three windows across all specifications. It is only statistically significant in the $[0, +3]$ and $[0, +4]$ windows. In columns 5 and 6, the coefficient on uninsured deposits is -0.117 (significant at the 1% level) and -0.079 (significant at the 5% level), respectively. All else equal, a 10-percentage point increase in the uninsured deposit ratio hence yields a 1.17 percentage point and 0.79 percentage point more negative cumulative abnormal return. A one standard deviation⁸ increase in the uninsured deposit ratio results in about a 1.85 percentage point more negative cumulative abnormal return in the $[0, +3]$ window, which corresponds to approximately 21% of the cross-sectional standard deviation of CARs of 8.87%. This result remains robust for regressions 2 and 3 without the interaction term, with coefficients of -0.120 and -0.083. Significance levels remain at 1% and 5%. The negative and significant pricing of uninsured deposits is also consistent with the findings of Martins (2024), despite differences in expected-return specification (our Fama-French five-factor model with momentum versus Martins' three-factor model), event-window construction, and sample composition, suggesting that the result is robust to alternative methodological choices.

This result validates H1, as investors penalized banks with run-prone funding structures. Uninsured depositors have strong incentives to withdraw funds during financial distress, leading to a high proportion of uninsured deposits becoming an amplified run risk, a finding consistent with both Egan et al. (2017) and Diamond and Dybvig (1983). It indicates that investors reassessed pre-existing vulnerabilities that were ignored prior to the collapse of Silicon Valley Bank. The result is also compatible with Choi et al. (2023) who document a coefficient of -0.035 on the standardized uninsured deposit share in their multivariate specification. The larger magnitude in our short-window estimate is consistent with the interpretation that the immediate investor panic on March 8-14 was partially attenuated in their longer window due to the regulatory intervention on March 12.

Another explanation is that uninsured deposits serve as a proxy for bank vulnerability to runs and as measure of ex-ante depositor monitoring (Demirgüç-Kunt and Detragiache, 2002). Larger shares of uninsured deposits should attract more monitoring, which suggests that stock prices should already have reflected this factor. However, our results indicate that pre-collapse monitoring was weak. This discussion is covered in detail in Section 5 with panel regression insights.

4.2.2. Duration Exposure Ratio

The duration exposure ratio is not statistically significant in any specification, and the coefficient ranges from -0.062 to -0.135. Despite the collapse being partly triggered by unrealized losses on long-term bonds, banks were not penalized for exposure to this risk. The result is consistent with Jiang et al. (2024), who underline that the asset-side alone could not have driven the collapse. A bank with large holdings of HTM securities and primarily insured retail depositors is faced with weaker withdrawal incentives than a bank funded through concentrated, large deposits by major companies and institutions.

⁸ As reported in Table 1, the standard deviation for the uninsured deposit ratio is 15.8%.

Therefore, it is the funding structure that is the vulnerability, which was penalized by investors.

The absence of significance for the duration exposure ratio is unlikely to be caused by multicollinearity. In Table 2, the reported correlation between the duration exposure ratio and uninsured deposit ratio ranges from approximately 0.10 to 0.15. Hence, the relationship is either truly insignificant, or it arises from elsewhere.

A major concern is that our study's duration exposure proxy may be subject to attenuation bias, introducing measurement error. Jiang et al. (2024) state that discrepancies in estimated losses can arise from assumptions about asset characteristics that are not directly observable in call reports. Furthermore, the measure neglects the bonds' maturity structure and banks' hedging strategies for interest rate risk. A bank that primarily holds 20% of assets in short-term treasury bills ends up with the same ratio as a bank with 20% of assets in 10-year mortgage-backed securities, with the latter having significantly higher exposure to interest-rate risk. Thus, the absence of a statistically significant relationship could be the result of an imperfect proxy. This outcome is consistent with Choi et al. (2023), who also report this measure as insignificant when jointly included with unrealized HTM losses divided by tier 1 capital. The pattern reinforces our concerns of a coarse proxy. With access to unrealized-loss data and security-level maturity structures as in Jiang et al. (2024), we thus argue that this problem can be mitigated.

4.2.3. Interaction Between Uninsured Deposits and Duration Exposure

As reported across regressions 4 to 6 in Table 4 above, the interaction term between uninsured deposits and duration exposure is between 0.335 and 0.558 in every event window, however statistically insignificant throughout. This result is inconsistent with Jiang et al. (2024) whose model predicts that large duration exposure should amplify the impact of uninsured deposit funding, and vice versa. We develop two possible interpretations of this result.

The first is based on the contamination from the potential measurement error in our duration proxy, as mentioned in Section 4.2.2 above. Thus, the insignificance could merely be a consequence of this shortcoming. Choi et al. (2023) also document an insignificant interaction between uninsured deposits and the proportion of HTM holdings, while the interaction term between the share of uninsured deposits and unrealized HTM losses over tier 1 capital appears significant. Hence, the interacting effect emphasized by Jiang et al. (2024) appears to be detectable only when realized economic loss exposure is reflected directly in the proxy.

The second explanation, however, suggests that investors evaluated fragility more broadly than Jiang et al. (2024) predict in their model. Banks were penalized for investors' perception of run-prone funding structures, irrespective of their unrealized losses in their security portfolios. Investors had limited time to analyse bank balance sheet characteristics during the window spanning from Wednesday, March 8, to the markets' close on Friday evening. The uninsured deposit figures are easily identified and computed from publicly available information, while the exposure to mark-to-market losses highlighted by Jiang et al. (2024) requires combining approximated estimations of unrealized losses with deposit characteristics. Table 4 above discloses that the coefficient on the uninsured deposit ratio is barely affected by the interaction term. For instance, in

column 2, the coefficient is -0.120, while the measure's corresponding coefficient in the regression in column 5 is -0.117, which is consistent with this view.

Overall, we find evidence in support of H1 for fragile funding with uninsured deposits as it is significantly priced by investors. We also find a qualified null for duration exposure and the interaction between the two variables. The discussion is developed further in Section 5.2.

4.3. Panel Regressions: Pre-event Pricing and Structural Repricing (H2 and H3)

Table 5 below reports pooled OLS panel regressions of banks' daily excess stock returns over a pre-event period [-213, -50] and a post-event period [+50, +200] trading days relative to March 8. Our main specification is displayed in column 2, which includes the interaction between uninsured deposits and duration exposure.

Table 5: Panel Regressions of Market Pricing Pre- and Post Collapse

	<i>Dependent variable:</i>	
	Daily excess stock return	
	(1)	(2)
Post	0.0006 (0.0007)	0.0006 (0.0007)
Duration Exposure (centered)	0.0005 (0.0012)	0.0002 (0.0013)
Uninsured Deposits (centered)	-0.0004 (0.0005)	-0.0003 (0.0005)
Duration Exposure x Uninsured Deposits		0.0090 (0.0075)
Post x Duration Exposure	-0.0004 (0.0020)	-0.00003 (0.0021)
Post x Uninsured Deposits	0.0019 (0.0012)	0.0018 (0.0012)
Post x Duration Exposure x Uninsured Deposits		-0.0113 (0.0071)
Controls	Yes	Yes
Interaction	No	Yes
Firm fixed effects	No	No
Two-way clustered SE	Yes	Yes
Observations	58,275	58,275
R ²	0.4518	0.4518

*Note: Pooled OLS estimates with firm x time clustered standard errors in parentheses; N = 58,275 bank-days across 185 banks. The pre-event window is [-213, -50] and the post-event window is [+50, +200] trading days relative to t=0 = March 8, 2023. All accounting variables are measured prior to the event. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets; Post is a post-event dummy. Centering is done at the sample mean. *p<0.1; **p<0.05; ***p<0.01.*

4.3.1. H2: Was Fragility Priced Before the Collapse?

As reported in Table 5, the main specification coefficient on uninsured deposits in column 2 is -0.0003, with the corresponding no-interaction estimate at -0.0004. Neither is statistically significant. The same applies to the duration exposure measure, which in the interaction model has a coefficient of 0.0002 and in the no-interaction model has a coefficient of 0.0005. Finally, the interaction term is also insignificant with a coefficient estimate of 0.0090. Thus, we fail to reject H2 as neither fragility measure was priced by the equity markets prior to the collapse of Silicon Valley Bank.

This outcome is highly informative, as the pre-event window spans one of the most aggressive monetary-tightening cycles in history. Investors had access to financial statements and quarterly reports at all times, from which exposure to long-duration assets and fragile funding is observable. Hence, investors should be aware of the implications. However, as our results show, returns show no significant pricing of either factor. This aligns with the empirical findings of Demirgüç-Kunt and Detragiache (2002), who state that monitoring by equity investors and depositors may weaken if deposits are insured. We also acknowledge that the absence of significant pricing of fragility in excess returns does not imply that market prices were not adjusted to these risks. For instance, banks may have different price-to-book ratios due to their exposure to fragility, which is not necessarily reflected in daily stock returns. Therefore, our null result concludes that fragility delivered no abnormal returns during this period and should not be treated as evidence that stock prices did not reflect these vulnerabilities.

4.3.2. H3: Did the Collapse Trigger a Structural Repricing?

To evaluate H3, we focus on the interaction of our fragility variables with the post-event dummy. From column 2 in Table 5 above we show that all fragility measures remain statistically insignificant in the post-period, i.e., the event did not result in a structural repricing of these risk channels. In column 2, *Post x Uninsured Deposits* has a coefficient of 0.0018 and in column 1 it is 0.0019. *Post x Duration Exposure* shows an estimate of -0.00003 in column 2 and -0.0004 in column 1. Finally, *Post x Duration Exposure x Uninsured Deposits* has a coefficient of -0.0113. Thus, we do not find consistent evidence in support of H3. In Table 8 under Section 4.4.3 we report a firm fixed effects specification, which shows significance at the 10% level for both *Post x Uninsured Deposits* and *Post x Uninsured Deposits x Duration Exposure*.

Analyzing the coefficients closer and disregarding the significance contributes further to the findings. For instance, the pre-event slope on uninsured deposits in column 2 of Table 5 is -0.0003 at the mean of duration exposure. Post-event the slope instead becomes $-0.0003 + 0.0018 = 0.0015$. In the firm fixed effects model (Table 8, column 2), the slope pre-event is -0.0030 and the post-event slope is $-0.0030 + 0.0023 = -0.0007$. For the interaction term, the post-event slopes are -0.0023 and -0.0050, respectively. This means that the coefficient is basically zero and that the fragile banks did not outperform following the collapse. Combining this result with the pre-collapse and event-window findings illustrates the different stages of the event, where fragility was not systematically reflected in stock returns before the collapse, however it resulted in lower cumulative abnormal returns during the event, and then regulatory intervention mitigated the panic. The discussion is developed further in Section 5.3. Hence, based on the marginal significance in only one model, our rejection of H3 remains.

4.4. Robustness Checks

4.4.1. Excluding Outlier Banks

Table 6: CAR Regressions Excluding Outlier Banks

	<i>Dependent variable:</i>					
	CAR					
	0,+2 (1)	0,+3 (2)	0,+4 (3)	0,+2 (4)	0,+3 (5)	0,+4 (6)
Duration Exposure Ratio	-0.057 (0.036)	-0.137 (0.088)	-0.130 (0.093)			
Uninsured Deposit Ratio	-0.009 (0.015)	-0.098*** (0.031)	-0.075** (0.034)			
Duration Exposure (centered)				-0.052 (0.036)	-0.125 (0.090)	-0.121 (0.093)
Uninsured Deposits (centered)				-0.011 (0.015)	-0.101*** (0.032)	-0.077** (0.035)
Interaction				-0.152 (0.244)	-0.377 (0.559)	-0.266 (0.622)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interaction	No	No	No	Yes	Yes	Yes
Outlier banks excluded	Yes	Yes	Yes	Yes	Yes	Yes
Observations	182	182	182	182	182	182
R ²	0.044	0.092	0.114	0.046	0.094	0.115

*Note: Three banks with extreme return movements during the event window (SCHW, WAL, MCB) are excluded, yielding N = 182. Interaction is Duration Exposure Ratio x Uninsured Deposit Ratio (both are mean-centered). HC3 standard errors in parentheses. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets. *p<0.1; **p<0.05; ***p<0.01.*

In our original sample, Charles Schwab (SCHW), Western Alliance Bancorporation (WAL), and Metropolitan Commercial Bank (MCB) are determined to be influential observations based on their Cook's distance. Across regressions 1-6 in Table 4, SCHW's distance is in the interval [0.29, 0.77], MCB's is in [0.06, 0.26], and WAL's is in [0.21, 0.25]. The threshold is $4/n = 0.022$ for our original sample. The cumulative abnormal returns for these banks across the three event windows range from -69.11% to -13.53%. Therefore, we remove these institutions from our original sample and re-estimate the CAR regressions to determine whether the results are robust to exclusion of these extreme cases.⁹

As reported in Table 6, the results remain robust after the removal of these outliers. The uninsured deposit ratio is still negative in all regressions and remains statistically significant at the 1% level in the [0, +3] window and at the 5% level in the [0, +4] window. The coefficients are -0.101 and -0.077 respectively for our main regressions 5 and 6. For the full sample the corresponding coefficients are -0.117 and -0.079. Similarly to before, duration exposure remains positive and insignificant. The interaction term switches sign to positive, however likewise insignificant.

⁹ See Table F1 in Appendix F for these banks' CARs and fragility variables

4.4.2. Sample Split at the Median Uninsured Deposit Ratio

In our original setting in Table 4 we assume linearity across the sample, so that the stock return of a bank with an uninsured deposit ratio in the 10th percentile and one in the 90th percentile is equally affected by a one percentage point increase in the ratio. For instance, Silicon Valley Bank itself was a severe case with an uninsured deposit ratio of 92.5% (Jiang et al., 2024). The linearity assumption cannot reveal whether the priced effect is concentrated in extreme cases like Silicon Valley Bank or is homogeneous across the distribution. Therefore, we split the sample at the median uninsured deposit ratio of 40% and re-run our regressions of cumulative abnormal returns during the event window. Variables are mean-centered at the sub-sample mean. The results are revealed in Table 7 below.

Table 7: CAR Regressions - Sample Split at Median Uninsured Deposit Ratio

	<i>Dependent variable:</i>					
	CAR					
	Below Median			Above Median		
	(1)	(2)	(3)	(4)	(5)	(6)
Duration Exposure (centered)	-0.027 (0.097)	-0.134 (0.154)	-0.095 (0.150)	-0.065 (0.059)	-0.089 (0.150)	-0.112 (0.151)
Uninsured Deposits (centered)	0.045 (0.032)	0.054 (0.062)	0.125** (0.054)	-0.064* (0.039)	-0.287*** (0.090)	-0.287*** (0.092)
Interaction	1.354* (0.775)	2.815** (1.316)	2.178 (1.386)	0.309 (0.503)	-0.203 (1.257)	0.502 (1.363)
Event window	0,+2	0,+3	0,+4	0,+2	0,+3	0,+4
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interaction	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92	92	92	93	93	93
R ²	0.131	0.147	0.181	0.091	0.126	0.167

Note: OLS cross-sectional regressions estimated separately for banks below ($N = 92$) and above ($N = 93$) the sample median uninsured deposit ratio of 40.0% as of 2022Q4. Interaction is Duration Exposure Ratio $\times$ Uninsured Deposit Ratio (both are sub-sample mean-centered). HC3 standard errors in parentheses. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Comparing the results in Table 7 to those in Table 4 delivers four meaningful insights. Starting off, the negative pricing of the uninsured deposit ratio is exclusively in the above-median group. The coefficient in column 5 is -0.287 and significant at the 1% level. Relative to the coefficient for the full sample in column 5 of Table 4 at -0.117. The below-median subsample in column 2 of Table 7 has an insignificant coefficient of 0.054, however in column 3 it turns significant at the 5% level in the [0, +4] window with a coefficient of 0.125. Therefore, investors did not penalize uninsured deposit funding equally across the sample.

Secondly, the concentration of the pricing effect in the above-median group aligns with Goldstein and Pauzner (2005) who extend Diamond and Dybvig (1983). They show a unique threshold equilibrium in which runs occur once fundamentals fall below a critical level. Specifically, when the run incentive connected to the depositors' contract increases, this threshold shifts outward. Unlike insured depositors, uninsured depositors become threatened by these run incentives. Therefore, market returns should in turn be more negative for banks who are close or above this level, which the results in Table 7 also imply.

Thirdly, the interaction term is significant at the 10% level in the $[0, +2]$ window in the below-median subsample and at the 5% level in the $[0, +3]$ window. The coefficients are 1.354 and 2.815, respectively. However, within the $[0, +4]$ window, it becomes insignificant again. In the above-median group, it is insignificant in all event windows. Hence, we interpret this cautiously. Because the interaction term is significant only in this setting, there is no consistent pattern in the amplification channel when uninsured deposits interact with interest rate risk exposure. The below-median subsample consists mainly of retail-funded banks, thus with lower uninsured deposit ratios. In turn, the residual variation may be a proxy for e.g., commercial banking activities, rather than solely a fragility funding channel. Particularly since the effect is insignificant in the above-median group where the run channel is present.

The fourth insight, as before, is that duration exposure remains insignificant across all specifications. However, the concerns described in 4.2.2 regarding potential measurement error remain.

In conclusion, the findings reported in Table 7 strengthen the original insights from Table 4. The uninsured funding structure is a risk channel priced by investors; however, it is contingent on the institutions' level of uninsured deposits. Banks with higher shares of uninsured deposits experienced lower returns during the event and vice versa.

4.4.3. Panel Regressions with Firm Fixed Effects

Table 8: Panel Regressions of Market Pricing with Firm Fixed Effects

	<i>Dependent variable:</i>	
	Daily excess stock return	
	(1)	(2)
Post	0.0007 (0.0008)	0.0007 (0.0008)
Duration Exposure (centered)	0.0012 (0.0049)	0.0003 (0.0051)
Uninsured Deposits (centered)	-0.0030* (0.0017)	-0.0030 (0.0021)
Duration Exposure x Uninsured Deposits		0.0081 (0.0257)
Post x Duration Exposure	-0.0005 (0.0019)	-0.0001 (0.0022)
Post x Uninsured Deposits	0.0023* (0.0012)	0.0023* (0.0012)
Post x Duration Exposure x Uninsured Deposits		-0.0131* (0.0078)
Controls	Yes	Yes
Interaction	No	Yes
Firm fixed effects	Yes	Yes
Two-way clustered SE	Yes	Yes
Observations	58,275	58,275
R ²	0.4528	0.4529

*Note: Firm fixed-effects specifications absorb all time-invariant unobserved heterogeneity across banks. Firm × time clustered standard errors in parentheses. N = 58,275 bank-days across 185 banks. The pre-event window is [-213, -50] and the post-event window is [+50, +200] trading days relative to t=0 = March 8, 2023. All accounting variables are measured prior to the event. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets; Post is a post-event dummy. Centering has been done at the sample mean. *p<0.1; **p<0.05; ***p<0.01.*

The final robustness check concerns the OLS regressions in Table 5 on the market pricing of the fragility measures pre- and post-collapse. We address time-invariant heterogeneity not captured by our original control variables, such as business model, reputation, and regional concentration, that could correlate with the variables in our model. Therefore, the panel regressions of Table 5 are re-estimated with firm fixed effects. Two-way clustered standard errors are kept.

As reported in Table 8 column 2 above in the main specification with the interaction term, mean-centered uninsured deposits pre-event have a coefficient of -0.0030. The

estimate is identical in the other regression displayed in column 1, and it is marginally significant at the 10% level. However, despite this significance, we still fail to reject H2 (no pre-event pricing) because it is significant at only the 10% level in one of our specifications. It is not enough to reject the hypothesis.

The *Post x Uninsured Deposits* coefficient is 0.0023 and is significant at the 10% level in columns 1 and 2 of Table 8. Therefore, the implied slope post-collapse becomes $-0.0030 + 0.0023 = -0.0007$, which is basically zero. This is consistent with our interpretation from Section 4.3.2. The interaction term in column 2 of Table 8 has an insignificant coefficient of 0.0081, while the coefficient on *Post x Duration Exposure x Uninsured Deposits* is -0.0131 and significant at the 10% level. Hence, it suggests a modest shift in the pricing relationship after the collapse of Silicon Valley Bank, at least on a within firm level. This is consistent with the fragility mechanism described by Jiang et al. (2024), which becomes salient to the equity market only after the event revealed the vulnerability in practice. However, given the minimal significance in this firm fixed effects specification, we see the result as suggestive rather than conclusive.

To conclude, the firm fixed effects specification confirms the decision to fail to reject H2 and provides no convincing evidence to validate H3. Moreover, it reveals the first instance in which the interaction between uninsured deposits and duration exposure may be priced following the Silicon Valley Bank episode. However, the joint-exposure variable is only marginally significant at the 10% level.

5. Discussion

5.1. Uninsured Deposit Fragility as the Primary Pricing Channel

Our findings that the cross-sectional negative pricing of exposure to uninsured deposits in the event window is robust, statistically significant, and concentrated among banks with above-median uninsured deposit ratios align with Diamond and Dybvig (1983). When a bank is funded by short-term demandable deposits and invests those funds in long-term, illiquid assets, it enables multiple equilibria. The first is a no-bank-run equilibrium in which only depositors who need liquidity withdraw, resulting in optimal risk sharing. There is also an equilibrium for bank runs, where depositors withdraw their funds because they anticipate others will do the same. This occurs even for fully solvent banks. However, the asymmetrical pricing effect between the above- and below-median groups introduces considerations beyond panic-driven coordination. Egan et al. (2017) show that demand for uninsured deposits falls sharply when a bank is perceived to be in financial distress, whereas demand for insured deposits remains largely unaffected. This insurance status asymmetry reveals the connection between solvency and news regarding withdrawal pressure through a depositor channel. A bank's exposure to runs is dependent on the uninsured proportion of its funding, as insured depositors do not react. All the potential equilibria are generated by the strength of this depositor response. Therefore, the uninsured deposit ratio is a proxy for this identified run risk, where the likelihood increases with weak bank fundamentals. It is not solely a panic-driven coordination equilibrium independent of a bank's financial position.

The resulting pattern aligns with both the Diamond-Dybvig framework and the non-linear market pricing. Markets penalized above-median institutions through more negative cumulative abnormal returns during the event window, while the effect on below-median banks was either not statistically significant or resulted in less negative returns, as reported in column 3 of Table 7. This non-linearity was revealed by the median split of the sample. Thus, we can conclude that there is a critical level, after which investors begin to penalize banks for their exposure to uninsured deposits and self-fulfilling bank runs.

Conversely, it reveals another aspect of the discussion. A high ratio of uninsured deposits should accordingly increase stakeholder monitoring to control firm risk-taking (Demirgüç-Kunt and Detragiache, 2002). Ex ante effective monitoring should therefore already be reflected in pre-event stock prices, resulting in lower abnormal return penalties during the event. The observed negative cumulative abnormal returns during the event, as well as the failure to reject H2, therefore indicate that the dominant mechanism during this episode was bank-run vulnerability and not depositor monitoring. Consequently, depositor insurance thus results in weaker monitoring, and fragility is only priced in response to an exogenous shock, as illustrated by the collapse of Silicon Valley Bank.

The non-linear pattern also provides insights relative to Martins (2024), who reports a significantly negative pooled linear coefficient on uninsured deposits similar to our coefficient of -0.117 in the $[0, +3]$ window in both magnitude and sign. Our results from the median-split in Table 7 indicate that such a pooled linear estimate is best interpreted as a sample-weighted average, with the negative effect concentrated in the upper half of the distribution and a positive or insignificant effect in the lower half.

5.2. Why Funding Fragility Was Priced and Duration Exposure Was Not

The most interesting asymmetry throughout our results is that uninsured deposits are significantly and negatively priced, while duration exposure remains insignificant in all settings. Based on this, we develop three possible reasons discussed below.

Measurement error in our duration exposure proxy constitutes the first reason. While it captures the balance-sheet composition of HTM securities relative to total assets, it fails to reflect the actual maturity structure of the underlying securities and other interest-rate hedging activities. Jiang et al. (2024) note that estimates of unrealized losses are highly sensitive to assumptions about asset characteristics that are not directly observable in call reports. The outcome is attenuation bias in the variable that affects the final coefficient. Moreover, as reported in Table 2, the correlation between our fragility variables ranges from 0.10 to 0.15. Thus, we eliminate multicollinearity as the reason for the consistent insignificance of our duration exposure variable. It is therefore fully possible that the market prices duration exposure, and our imperfect proxy fail to capture the effect.

The second possibility arises from the conditional pricing evidence from Jiang et al. (2024), who show that losses on the asset side of the balance sheet are contingent on a run-prone funding structure. A bank with a high allocation to HTM securities and funded mainly by insured retail depositors does not face the threat of coordinated withdrawals that a bank funded by uninsured depositors does. Consequently, the banks' mark-to-market losses do not result in a high probability of forced liquidation. This essentially means that the insignificance of our duration exposure ratio is the expected result. However, it also suggests that the interaction between duration exposure and uninsured deposits should be significant, which is not the case, as shown in Section 4.2.3. This remains ambiguous, although we refer to the potential measurement error for an alternative explanation.

The most developed interpretation is the time pressure investors faced upon receiving information about Silicon Valley Bank. From the March 8 announcement covering large losses on securities and a planned equity offering to the March 10 resolution, investors had only 48 hours to identify balance sheet vulnerabilities across the banking sector. The uninsured deposit ratio is easily observable from call reports, while unrealized losses are more difficult to estimate by combining multiple noisy estimates, as highlighted by Jiang et al. (2024). Therefore, these aspects are consistent with the view that markets price banks based on their vulnerability to bank runs rather than their duration exposure in their security holdings. The coefficient on uninsured deposits in the $[0, +3]$ window of Table 4 reflects this as well. With the interaction term, the coefficient is -0.117; without it, it is -0.120. It is essentially unaffected by the interaction term's presence.

5.3. Interpretation of the Post-Event Flattening

Now we provide an interpretation of the results reported in Section 4.3.2 and the firm fixed effects analogue in Section 4.4.3. In both cases, the implied post-collapse slope on uninsured deposits is almost flat (+0.0015 in pooled OLS and -0.0007 with firm fixed effects). Together with the inability to reject H2 during the pre-collapse period, this provides a coherent three-stage dynamic in which the fragile-deposit pricing does not

exist ex ante, becomes heavily priced during the acute period (see Table 4), and stops being priced following the re-calibration of tail risk via policy intervention. The *Post x Uninsured Deposits* coefficient should therefore be seen as the return to a regime of no pricing rather than a re-pricing toward greater fragility of banks. We maintain our interpretation, as the flat slope precludes any alternative interpretation in terms of rewarding fragile banks post-event, as a positive sign on the *Post x Uninsured Deposits* interaction would superficially suggest.

The most plausible rationale behind the flatness of the schedule is, unsurprisingly, policy intervention. On Sunday, March 12, 2023, the U.S. Treasury Department, the Federal Reserve, and the FDIC jointly announced guarantees of all deposits at SVB and Signature Bank, including those above the FDIC insurance limits. On the same day, the Federal Reserve also introduced the Bank Term Funding Program, whereby depository institutions could borrow at par value against eligible securities, removing the forced sale of assets channel (Arseneau, Klee, Kotidis, and Siemer, 2025). Both policies altered the equilibrium considerations of uninsured depositors at other fragile banks: the signal that the regulators were prepared to offer depositor protection above the statutory limit for these specific banks implied that the costs of holding uninsured deposits were lower at other fragile banks, while the BTFP meant that a deposit run would not translate into a solvency event anymore. In equilibrium, these changes reduce the price discount on stocks of banks with large amounts of uninsured deposits, resulting in a precise prediction of our empirical finding. The interpretation is in line with the classic government-guarantee literature on bank fragility (Diamond and Dybvig, 1983), which shows that a credible government guarantee can solve the coordination problem among depositors and eliminate the run equilibrium without changing the fundamentals of the bank.

Another interpretation is that the flat schedule is due to fundamental improvements in bank balance sheets due to deposit inflows, capital injections, or effective balance sheet management post-crisis. While this cannot be entirely excluded, there are two observations in our dataset that are not consistent with such an interpretation. First, the speed of adjustment, with the uninsured deposit schedule already flattened in the window $[+50, +200]$, is too fast to be consistent with the usual balance sheet adjustment timeline. Second, the flattening happens precisely in the uninsured deposits dimension while capital levels, liquidity positions, and profits remain unaffected and are not loaded by any relevant interactions. This makes an expectations-based explanation driven by the government backstop more appealing.

The only marginally significant interaction coefficient *Post x Duration x Uninsured* with an estimate of -0.0131 and significant at the 10% level (Table 8 column 2), implies the existence of a residual structural pricing channel. The incomplete nature of post-event flattening among doubly fragile banks suggests that the stock market applied a run-risk discount for such banks even following the government guarantee policy. We interpret this result as a signal that, despite flattening of the deposit pricing channel, the joint asset-liability pricing channel formalized by Jiang et al. (2024) remained in place.

5.4. Identification, Endogeneity, and Limitations

The study's methodology is based on ex ante balance-sheet characteristics of U.S. banks. Therefore, differences in bank returns reflect investors' evaluations of the vulnerabilities that these structures entail. However, there are some methodological concerns and limitations that we must discuss.

The first potential issue is omitted variable bias in the CAR regressions across the defined event windows. Banks with high uninsured deposit ratios may also have differences in depositor industry, depositor concentration, and business model. These factors may all be associated with their perceived fragility and returns. We control for size, liquidity, profitability, and capitalization, which partially mitigates the omitted variable bias concern. Another relief follows from our findings in Table 7, the sample median split, which reveals that the negative market pricing of uninsured deposits is concentrated among banks with high uninsured deposit ratios. The pricing effect being the strongest in this location of the distribution is more consistent with the mechanism of the event and the literature than an omitted variable.

Another concern is our sample selection. The initial sample comprises around 650 U.S. banks, which is reduced to 185 after filtering the data. Many of the removed banks were smaller and traded over the counter. Consequently, our sample becomes biased toward larger institutions, which, by definition, are more transparent and receive greater investor coverage. Therefore, this has implications for the null result on H2 and makes the failure to reject conservative, as the banks that are less scrutinized by the market are excluded from the study. The CAR regressions examining H1 do not suffer the same weakness, as they focus on within-sample variation.

The third concern is potential measurement error in the duration exposure proxy, which has been mentioned in Sections 4.2.2 and 5.2. It fails to capture the actual heterogeneity in banks' true interest-rate exposure because the maturity structure is not reflected in it. A bond that matures in 30 years and a treasury bill would yield the same duration exposure, according to our proxy. However, their true exposure to interest rates is very different. It also fails to capture hedging methods that banks may use. Therefore, the insignificance of duration exposure throughout this study may arise from measurement error, in addition to the conditional pricing finding discussed by Jiang et al. (2024). The validity of the results can be substantially improved by having access to detailed data on the actual security holdings of all banks, and by reducing reliance on individual assumptions when combining multiple noisy estimates to calculate unrealized losses.

Finally, the ex-post panel regression fails to cleanly distinguish the impact of the policy response from other contemporaneous potential adjustments. These include changes in deposit flows and changes in funding costs, both of which may affect bank valuations. With access to data on deposit flows and unrealized losses at the bank level, e.g., as in Jiang et al. (2024), the analysis can cover the mechanisms underlying the collapse with even greater confidence.

We additionally note that Choi et al. (2023) examine aspects of the SVB collapse that we do not, particularly bank-size and too-big-to-fail effects, anticipation measured through daily coefficients on 2022 balance-sheet vulnerabilities, and the role of cash holdings separate from broader liquidity measures. We treat these as natural extensions to our study, given that we primarily analyze the market pricing of the main fragility mechanisms around the event itself.

6. Conclusion

The collapse of Silicon Valley Bank provides a natural setting to examine whether equity markets priced the mechanism underlying the event across U.S. bank stocks. We use the event to examine whether investors systematically priced uninsured deposit funding and duration exposure on a sample of 185 publicly traded U.S. banks before, during, and after the collapse.

Focusing on the $[0, +3]$ window during the event, we find partial support for H1, as equity markets penalized banks funded by uninsured deposits. The coefficient on the uninsured deposit ratio is -0.117 and significant at the 1% level. A ten-percentage-point increase in the uninsured deposit ratio thus implies a 1.17 percentage point more negative cumulative abnormal return (CAR), and a one-standard-deviation increase implies a 1.85 percentage point more negative CAR, equivalent to roughly 21% of the cross-sectional standard deviation of CARs during the window. The result is robust to the removal of outliers, although the coefficient attenuates to -0.101 , still significant at the 1% level. To test whether the pricing effect is linear, we also split the sample at the median uninsured deposit ratio of 0.40 and find that the negative effect exists only in the upper part of the sample: the coefficient in the $[0, +3]$ window is -0.287 and significant at the 1% level. Conversely, the lower part of the distribution has a positive coefficient of 0.125 in the $[0, +4]$ window, significant at the 5% level. There is therefore a critical level beyond which investors penalize banks for their uninsured deposit exposure.

Duration exposure, measured as HTM securities divided by total assets, is statistically insignificant across all specifications. The interaction term between duration exposure and uninsured deposits is also insignificant, except for the below-median estimates in the $[0, +2]$ and $[0, +3]$ windows when the sample is split at the median uninsured deposit ratio of 0.40, although we remain cautious regarding this result. The stand-alone insignificance is consistent with Jiang et al. (2024), who find that asset-side losses alone could not have caused the collapse of Silicon Valley Bank without the fragile funding structure. By the same logic, however, their model would predict a significant interaction term, which we do not observe. The most likely explanation is measurement error in our duration-exposure proxy, which also applies to its stand-alone insignificance throughout the study.

We run panel regressions of daily excess returns over the pre-event window $[-213, -50]$ trading days relative to the event date and find no statistically significant relationship with either fragility measure. We therefore fail to reject H2, the ex-ante underpricing of these vulnerabilities. After the event, we run similar panel regressions over the $[+50, +200]$ window. The coefficient on uninsured deposits is 0.0015 in our pooled OLS specification and -0.0007 with firm fixed effects. Both are essentially zero. The corresponding interaction coefficient ($Post \times Uninsured\ Deposits$) is significant at the 10% level only in the firm fixed effects specification (Table 8). This is most plausibly

explained by the depositor guarantee and Bank Term Funding Program issued by the Treasury, the Fed, and the FDIC on March 12, which relieved systemic stress and brought back the ex-ante investor sentiment. Hence, we do not find consistent evidence in support of H3.

These results contribute to the existing literature on the empirical phenomenon of bank runs. Diamond and Dybvig (1983) provide the theoretical foundations and define the conditions under which runs emerge, and Goldstein and Pauzner (2005) extend the framework to obtain a unique threshold equilibrium. Egan, Hortaçsu, and Matvos (2017) document how uninsured depositors respond to distress through withdrawals while insured depositors do not. Choi et al. (2023) provide the closest comparable empirical evidence. They find cross-sectional pricing of uninsured deposits and unrealized HTM losses on a different sample using long-horizon cumulative excess returns from February 1 through March 17 and May 25, 2023. Our findings establish similar results to theirs on uninsured deposits using a short-event window design that isolates the market reaction from the March 12 regulatory intervention. We provide additional results on how equity markets price the mechanisms underlying the collapse empirically. Fragility is priced in a non-linear pattern above the threshold but not below, consistent with the threshold equilibrium of Goldstein and Pauzner (2005). Compared with Jiang et al. (2024), whose model has duration exposure and depositor fragility interactively producing risk, our evidence shows that markets aggressively priced the latter without pricing the former or the joint interaction. This is consistent with the findings of Choi et al. (2023) who also document an insignificant HTM divided by assets variable as well as its interaction with the uninsured deposit share.

Several limitations require attention. Our duration-exposure proxy does not control for the maturity structure or for hedging strategies banks may have employed to manage interest-rate risk, introducing potential attenuation bias of uncertain size that could explain the consistently insignificant results for duration exposure and the interaction term. The 185 banks in our final sample represent approximately one quarter of the initial sample, and the excluded banks have a median log-asset value of 20.7 versus 23 in the final sample. Our results are therefore biased toward larger institutions with higher stakeholder monitoring pressures, which makes the failure to reject ex-ante underpricing conservative. Finally, the post-event panel regressions cannot fully separate the effect of regulatory intervention from contemporaneous changes in deposit flows and bank funding costs.

Three main extensions follow from our study. First, incorporating security-level maturity, unrealized losses, and derivative-position data would allow testing whether the conditional pricing hypothesis of Jiang et al. (2024) holds once the threat of attenuation bias is removed. Second, including depositor-concentration measures, depositor characteristics, and the social-media exposure measures developed by Cookson et al. (2026) would help discipline the unobservable coordination channel. Finally, extending the analysis to European banks following the emergency takeover of Credit Suisse by

UBS would test whether the same pricing mechanisms operate under different regulatory and depositor-protection regimes.

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7. Appendices

Appendix A: Definitions

Bank fragility: The proportion of uninsured deposits of total deposits, duration exposure ratio as well as the interaction between the two.

Fragile funding: A bank with a high ratio of deposits being uninsured, which leaves the bank more vulnerable to runs.

Uninsured deposits: Deposits exceeding the FDIC coverage limit of USD 250,000 per bank, per depositor.

Duration exposure: A banks exposure to interest-rate risk based on the share of held-to-maturity securities to total assets.

Bank run: A coordinated withdrawal of deposits by a bank's depositors that renders solvency concerns self-fulfilling.

Appendix B: Size of Excluded Banks

Table B1: Size of Excluded Banks

Size 2022Q1						
Statistic	N	Mean	St. Dev.	Min	Median	Max
Log(Total Assets)	425	20.927	1.417	17.952	20.680	26.884
Size 2022Q2						
Statistic	N	Mean	St. Dev.	Min	Median	Max
Log(Total Assets)	453	20.869	1.408	17.953	20.627	26.838
Size 2022Q3						
Statistic	N	Mean	St. Dev.	Min	Median	Max
Log(Total Assets)	420	20.960	1.423	17.916	20.701	26.820
Size 2022Q4						
Statistic	N	Mean	St. Dev.	Min	Median	Max
Log(Total Assets)	469	20.882	1.415	17.483	20.658	26.844

Note: Distribution of Log(Total Assets) for banks excluded from the 185-bank sample, at each fiscal quarter-end of 2022. Observation counts vary across quarters due to missing values. Data from Capital IQ.

Appendix C: Summary Statistics (Q1-Q3 2022)

Table 1.A: Summary Statistics 2022Q1

Statistic	N	Mean	St. Dev.	Min	Median	Max
Uninsured Deposit Ratio	185	0.390	0.158	0.038	0.402	0.794
Liquidity	185	0.096	0.071	0.008	0.082	0.344
Log(Total Assets)	185	23.190	1.634	20.827	22.789	29.006
Duration Exposure Ratio	185	0.039	0.056	0.000	0.009	0.375
Tier 1 Capital Ratio	185	0.132	0.029	0.091	0.125	0.270
Profitability (ROA)	185	0.011	0.004	-0.016	0.011	0.027

Table 1.B: Summary Statistics 2022Q2

Statistic	N	Mean	St. Dev.	Min	Median	Max
Uninsured Deposit Ratio	185	0.390	0.159	0.040	0.394	0.802
Liquidity	185	0.069	0.061	0.008	0.048	0.313
Log(Total Assets)	185	23.199	1.633	20.804	22.806	28.977
Duration Exposure Ratio	185	0.049	0.060	0.000	0.030	0.385
Tier 1 Capital Ratio	185	0.130	0.033	0.093	0.123	0.387
Profitability (ROA)	185	0.012	0.004	0.002	0.012	0.044

Table 1.C: Summary Statistics 2022Q3

Statistic	N	Mean	St. Dev.	Min	Median	Max
Uninsured Deposit Ratio	185	0.388	0.160	0.037	0.395	0.807
Liquidity	185	0.056	0.055	0.007	0.036	0.302
Log(Total Assets)	185	23.208	1.625	20.765	22.815	28.959
Duration Exposure Ratio	185	0.052	0.064	0.000	0.031	0.378
Tier 1 Capital Ratio	185	0.128	0.031	0.092	0.121	0.357
Profitability (ROA)	185	0.013	0.005	-0.029	0.013	0.028

Note: Summary statistics for the 185 sample banks at each fiscal quarter-end Q-Q3 2022 (Table 1.A = Q1; Table 1.B = Q2; Table 1.C = Q3). Uninsured deposits from regulatory call reports via WRDS; remaining variables from Capital IQ. Liquidity is defined as cash and cash equivalents divided by total assets; Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets.

Appendix D: Event-Study Diagnostics

Table D1: Event-Study Diagnostics

Window	Correlation (Normal)	Correlation (Event)	Var (AR)	Var (SAR)	Pesaran	BPLM
0,+2	0.188	0.325	2.695	2.814	73.45***	26358.57***
0,+3	0.188	0.323	9.578	9.568	84.40***	28159.59***
0,+4	0.188	0.310	11.211	10.482	90.53***	29642.19***

*Note: Cross-sectional dependence diagnostics for abnormal-return residuals across the 185 sample banks over the three event windows ($t=0$ = March 8, 2023). Correlation (Normal) is the average pairwise residual correlation over $[-250, -50]$; Correlation (Event) is the pairwise correlation over the event window; Var(AR) and Var(SAR) are cross-sectional variances of abnormal and standardized abnormal returns; Pesaran is the Pesaran (2021) CD test; BPLM is the Breusch-Pagan LM test. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.*

Appendix E: Event Timeline

March 8: Silicon Valley Bank announce balance-sheet restructuring with their sale of 21 billion USD of AFS securities at a 1.8 billion after-tax loss and a planned 2.5 billion equity offering (Board of Governors of the Federal Reserve System, 2023).

March 9: Depositors withdraw over USD 40 billion from the bank. Management expects USD 100 billion more the following day (Board of Governors of the Federal Reserve System, 2023).

March 10: California Department of Financial Protection and Innovation close the bank and appoint the FDIC as receiver (Board of Governors of the Federal Reserve System, 2023).

March 12: Signature Bank is closed (Federal Deposit Insurance Corporation, 2023b). The FDIC, Federal Reserve, and Department of Treasury issue a joint statement that all depositors will have access to all of their funds, starting on March 13 (Department of the Treasury, Board of Governors of the Federal Reserve System and Federal Deposit Insurance Corporation, 2023). The Bank Term Funding Program is also announced (Arseneau et al., 2025).

March 13: Silicon Valley Bank opens and resumes operations as a bridge bank (Federal Deposit Insurance Corporation, 2023a).

Appendix F: Cumulative Abnormal Returns and Bank Characteristics

Table F1: Cumulative Abnormal Returns and Bank Characteristics for Outlier Banks

Ticker	CAR [Window]			Bank Characteristics	
	[0, +2]	[0, +3]	[0, +4]	Duration Exposure	Uninsured Deposits
SCHW	-17.01%	-26.75%	-19.68%	0.318	0.183
WAL	-26.35%	-69.11%	-56.83%	0.019	0.580
MCB	-13.53%	-53.15%	-15.95%	0.081	0.410

Notes: Cumulative abnormal returns (CARs) for Charles Schwab (SCHW), Western Alliance Bancorporation (WAL), and Metropolitan Bank Holding Corp. (MCB) over the event windows [0, +2], [0, +3], and [0, +4] trading days relative to $t=0$ (March 8, 2023). Abnormal returns are computed as the residual from the Fama-French five-factor model augmented with momentum, with factor loadings estimated over the [-250, -50] trading-day window. Duration Exposure Ratio and Uninsured Deposit Ratio are reported as of 2022Q4. Uninsured deposit ratio equals uninsured deposits divided by total deposits; Duration exposure ratio is held-to-maturity securities divided by total assets.

Appendix G: AI Disclaimer

ChatGPT and Claude were used to assist with the production of code in R, and to improve language, grammar, clarity, and quality of the written text. Additionally, Grammarly was used to improve language.