A Framework for Evaluating Banks' Resilience to Runs[⋆]

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Abstract

The failure of Silicon Valley Bank (SVB) brought renewed attention to the risk to financial institutions of runs on their deposits. In this paper, we propose a framework to determine whether conditions exist for banks to experience runs. We compare the performance of our method with several alternative measures of bank fragility. Our measure is able to identify weak banks earlier and as accurately as any of the alternatives, and at much lower cost in terms of falsely identifying banks as weak. The results indicate that this metric could be used to help banks effectively manage their balance sheets to avoid creating conditions where depositors have an incentive to run.

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1. Introduction

The failure of Silicon Valley Bank (SVB) on March 10, 2023 highlighted the risks to financial institutions of runs on their deposits. The run on SVB was triggered by the March 8 announcement of a \$1.75bn capital raise to offset a \$1.8bn loss caused by the sale of \$21bn of securities.[1] Just two days after that announcement, the Federal Deposit Insurance Corporation (FDIC) placed SVB into receivership following the withdrawal by depositors of \$40bn on March 9 and the expected withdrawal of \$100bn on March 10.[2]

SVB's regulatory capital ratios based on Call Report data from December 31, 2022 indicated the bank was in a strong financial positions with a Tier 1 Leverage Ratio of 7.96% and a 15.26% CET1 Capital Ratio, both well above required minimums. However, a combination of high levels of unrealized losses and unstable funding (86.44% of deposits were uninsured) created the conditions for a bank run. The current regulatory framework, including stress testing,[3] does not have tools that fully incorporate either of those factors, which impeded the ability of banking supervisors to recognize and address the problems at SVB.

In this paper, we develop a framework for identifying banks that are susceptible to runs that incorporates both the fair value of banks' assets *and* the structure of their liabilities. Our modeling strategy is to use the information about assets and liabilities to determine whether conditions exist for banks to experience runs on their deposits. First, we assume that all runnable funding, which we define as uninsured deposits and short-term wholesale

[1] The full press announcement can be viewed at: https://ir.svb.com/news-and-research/news/news-details/2023/SVB-Financial-Group-Announces-Proposed-Offerings-of-Common-Stock-and-Mandatory-Convertible-Preferred-Stock/default.aspx

[2] The Federal Reserve Board review of the supervision and regulation of SVB (2023) can be viewed at: https://www.federalreserve.gov/newsevents/pressreleases/bcreg20230428a.htm

[3] The Federal Reserve, for example, assumes in its stress testing program that banks maintain the level of assets they hold at the beginning of the stress period. Although hypothetical interest expenses can change because of the macroeconomic stress scenarios, the level of funding remains the same across the stress period. See 2022 Supervisory Stress Test Methodology, Board of Governors of the Federal Reserve System, March 2022, p.15 for further information.

deposits, is withdrawn. To meet those requests for withdrawals, banks start by selling cash and short-term liquid assets, and if necessary, selling AFS securities, HTM securities, and loans until all withdrawal requests are paid. Second, we value each bank after it has paid everyone who withdraws money. We account for fair value gains and losses on each bank's assets and calculate its new leverage ratio based on the value of the remaining assets and liabilities after the run on deposits.

In our framework, depositors at a bank with a post-funding shock leverage ratio that is less than or equal to zero have an incentive to withdraw uninsured deposits immediately. The reason is that if the bank were to liquidate all of its assets, it would not have enough money to repay all of its deposits so those who do not have deposit insurance should withdraw their money, leading to a run on the bank. However, we would not expect depositors to wait until the bank's leverage ratio fell to zero to withdraw their deposits, but rather to shift their deposits to a stronger bank at a critical level above zero. For the purposes of our empirical tests, we define that critical level as banks' post-funding shock leverage ratio falling below 4%, the FDIC's threshold for undercapitalized banks.

Using Call Report data through September 30, 2023, our model shows that a significant number of banks would be undercapitalized if they experienced a funding shock. Furthermore, our model identifies a significant number of fragile banks, including SVB, as early as 2022:Q1, the quarter when the Federal Reserve started to rise interest rates. Thus, the results of the model can be used to provide an early warning signal to banks' management, market participants, and regulators. If the susceptibility of SVB to deposit runs had been identified as early as 2022:Q1, it is possible that management actions and/or intervention from banking supervisors could have limited (or even avoided) the failure of the bank and the subsequent losses to the financial system.

We compare our framework to other fragility measures, including the regulatory leverage ratio (*Leverage Ratio*) and two derived measures that include unrealized gains and losses on securities (*LR – UGL Securities*) and unrealized gains and losses on securities and loans (*LR – UGL Securities & Loans*). We also consider two measures that are derived from Jiang et al. (2023): *JMPS Replica* and *JMPS (F&S UL)*. We find that our measure is able to identify at least as many true positives - defined as the number of banks identified as fragile that eventually become distressed - as the other alternatives with a significantly lower number of false positives - defined as the number of banks identified as fragile that did not become distressed. Thus, our proposed measure is as accurate as any of the alternatives while producing far fewer false positives.

The cost of false positives for the banking system is potentially high, something of particular importance as supervisors consider enacting new policies to implement the final components of the Basel III agreement and respond to the failure of SVB.[4] We estimate the cost if banks identified as weak by each measure were required to increase their capital to meet the 4% leverage requirement. Our measure generally estimates lower costs of increasing capital industry-wide than the alternatives, and our required capital increases are concentrated among large banks.[5]

We employ Complementary Log-Log, Logistic, and Ordinary Least Squares regression methods to investigate how our proposed fragility metric is related to bank failures and other indicators of financial distress. First, we show that our measure provides additional information after controlling for a set of bank level time-varying controls, including leverage ratios and quarter fixed effects. Second, we show that the measure is significant in predicting

[4]On July 27, 2023 the Office of the Comptroller of the Currency, the Board of Governors of the Federal Reserve System, and the Federal Deposit Insurance Corporation released the *"Interagency Overview of the Notice of Proposed Rulemaking for Amendments to the Regulatory Capital Rule"* (2023) where, among other things, they propose to include gains and losses from certain securities in banks' capital ratios.

[5]We only estimate the cost for weak banks of adding capital to meet the 4% leverage ratio, but falsely identifying banks as weak has additional costs. First, there is the cost to banks and banking agencies of heightened supervisory scrutiny (more bank exams, supervisory restrictions on banking activities, etc.) of weak banks. Second, there is the potential for financial instability if incorrectly identifying banks as weak leads to runs on healthy banks.

defaults at different horizons. Third, we show that the measure is robust to alternative choices of the threshold to identify a fragile bank, from 3% to 7%. Fourth, we show that our measure is particularly useful in predicting defaults during periods of rising interest rates and for large banks. Finally, we check the robustness of our results by substituting bank defaults with banks' Z-Scores and probabilities of default, and our proposed measure is significant in predicting those response variables.

Our empirical tests focus on the 2022-2023 time period, when sharp increases in interest rates in the U.S. generated large unrealized losses at many banks. However, the framework does not apply only to interest rate risk, but more generally to any kind of shock that affects a bank's fair value. Losses related to credit and operational risk could be incorporated into the model, thus increasing the accuracy of the fair value estimates. To the extent that those types of losses are either not included in regulatory metrics or only included with a lag, they will provide valuable information about the risk of banks experiencing runs.[6]

Our results indicate that this framework would be useful for bank management and banking supervisors to avoid creating conditions that could lead to runs. The framework could be integrated into the current regulatory system by adding the difference between a minimum leverage ratio, like the FDIC's undercapitalized threshold, and the post-shock model-implied leverage ratio to the current capital requirements. This policy would incentivize bank managers to avoid the combination of unrealized losses and runnable funding that makes bank runs more likely.

The rest of the paper proceeds as follows: Section 2 surveys related work and explains how our paper contributes to the literature. We outline our run risk framework in Section 3, describe the data in Section 4, and present the alternative fragility measures in Section 5. We compare our proposed fragility measure with alternatives in Section 6 and present

[6]It is worth noting, too, that in some environments banks will experience fair value gains, indicating that *ceteris paribus* they are less susceptible to runs than book values would imply in our framework.

the analysis of future defaults, controlling for confounding factors, in Section 7. Section 8 discusses the policy implications of our proposal, and Section 9 summarizes and concludes.

2. Related Literature

Our work combines and contributes to two strands of the literature. First, we contribute to the literature focusing on the debate between fair value vs. book value accounting for banks as our results highlight some unintended consequences of book value accounting. Early work on this topic includes Morris and Sellon (1991), which discusses the pros and the cons of market value accounting, Berger et al. (1991), which outlines some potential problems with market value accounting, and Barth (1994), which shows that errors in fair value estimations may have driven previous results and provides evidence that fair value estimates of investment securities provide significant explanatory power beyond that provided by historical cost. More recent work includes Bleck and Liu (2006), which shows that marking to market can provide investors with an early warning mechanism while historical cost gives management a veil under which they can potentially mask a firm's true economic performance. Blankespoor et al. (2013) find that leverage measured using the fair values of financial instruments explains significantly more variation in bond yield spreads and bank failure than other less fair-value-based leverage ratios. Heaton et al. (2010) focus instead on the potential destabilizing effect of market value accounting. Beatty and Liao (2014) provide a comprehensive survey of empirical research.

The currently high level of unrealized losses in the banking system, caused by sharp increases in interest rates, explains the renewed focus on this topic, as evidenced by the recent works of Jiang et al. (2023) and Flannery and Sorescu (2023). Marsh and Laliberte (2023) discuss the ways in which declining securities mark-to-market valuations may influence bank behavior. Our work contributes to this literature by developing a framework to identify banks that are particularly susceptible to runs when there is a large gap between fair value and book value of assets. Our results thus generally support the view that fair value accounting is more informative than book value accounting, highlighting the subset of banks for which the difference in accounting standards makes a sensible difference when evaluating the solidity of the institutions.

The gap between the two standards is generally large for those banks that are more exposed to interest rate risk. Alternative views have emerged in the literature regarding the exposure of banks to interest risk. The early work of Flannery and James (1984) provides evidence of significant interest rate risk due to the mismatch of effective maturities of banks' assets and liabilities. Abdymomunov et al. (2023) reaffirm its relevance in recent years, although the literature has generally treated interest rate risk as negligible since the Great Financial Crisis. For example, Drechsler et al. (2021), show how banks closely match the interest rate sensitivities of their interest income and expenses, insulating their equity from interest rate shocks. Our work contributes to this literature by highlighting a channel through which interest rate risk can lead to bank runs, especially in the presence of high levels uninsured deposits.

In our framework interest rate risk plays a key role in identifying fragile banks along with bank funding which is the second literature to which we contribute. Starting from the seminal model of Diamond and Dybvig (1983), researchers have investigated the value of deposit contracts, the role of deposit insurance, and bank runs. Our framework broadly fits the Goldstein and Pauzner (2005) extension of Diamond and Dybvig (1983) as we assume a bank run occurs if and only if the fundamentals are below some critical value, and when that happens, uninsured depositors run. In our setting the critical value is determined by the combination of a bank's capital, unrealized losses, and funding structure. From the Egan et al. (2017) model extension we borrow the concept of focusing on uninsured depositors as their elasticity to bank default is likely large enough to potentially trigger a run. Our critical value - below which a run occurs - is directly related to the amount of uninsured deposits.

Next we present our framework in details.

*** Need to discuss other types of shocks - add references to credit risk and ops risk. ***

3. Run Risk Framework

In this section we outline our framework for identifying banks that are at serious risk of default in a rising interest rate environment. The key element that differentiates our metrics from other fragility measures is that we combine banks' funding weakness with the effect of rising rates on banks' assets. According to our measure, a bank with very high unrealized losses but very stable funding will not be considered as risky as a bank with significantly lower unrealized losses but with less stable funding. To our knowledge, most measures of banks' fragility, including (enhanced) regulatory ratios and the fragility measure derived from Jiang et al. (2023), do not differentiate banks with respect to their funding structure but focus on evaluating the effect of unrealized losses on banks' balance sheets and their solvency.

In our framework, we first shock banks through the withdrawal of all liabilities that are at risk of runs. We label such liabilities *runnable liabilities* and define them as the sum of uninsured deposits and all other liabilities with maturity less than one year. Although our framework currently focuses on uninsured deposits and wholesale deposits with remaining maturity of one year or less, it could incorporate any definition of "runnable" funding.

Next, we assume that banks follow a standard order of preference in generating funds to respond to the withdrawal shock. First, banks draw from cash and short term liquid assets, then, if they have not yet met the withdrawal shock requirement, banks start selling other assets.If they have to sell other assets, banks may have to realize previously unrealized losses, which will impact their capital and leverage ratios. When cash and short-term liquid assets are not sufficient, banks sell available for sale (AFS) securities first, then held to maturity (HTM) securities, and lastly loans. For each type of asset (AFS, HTM, and Loans), we assume that securities or loans with maturities less than three months carry no unrealized losses and are sold before the other assets of the same type but with longer maturities. Then banks sell the next "maturity bucket" within the same asset type, incurring unrealized losses, until reaching the next asset type, if necessary, to meet the withdrawal shock. Given the data reported by the banks in the Call Report Form 031, we create six maturity buckets: less than three months, three months to one year, one to three years, three to five years, five to fifteen years, and more than fifteen years.[7] Figure 1 presents a flowchart summarizing the framework.

[Insert Figure 1 about here]

Those banks whose leverage ratio falls below 4%, the FDIC undercapitalized threshold, after meeting the liability withdrawal through asset sales, are considered fragile.[8]

Our choice of identifying fragile banks in the proposed framework is based on two assumptions: a) we focus on the leverage ratio as measure of solvency, and b) we select the undercapitalized definition as the identifying threshold. Both assumptions can be easily modified based on the intended use of the metric. Regarding the first assumption, we select the leverage ratio, instead of other measures like the total risk-based capital ratio, the risk-based capital ratio, or the common equity Tier 1 capital ratio, for two reasons. First, we would like our measure to be as simple and objective as possible. As such, we prefer to use a measure that does not depend on estimating risk-based capital. Second, we would like to be able to test our measure over a reasonably long time horizon, spanning several rising rate environments.

Regarding the second assumption, the threshold level, we select the undercapitalized threshold as it is the threshold below which the FDIC Prompt Corrective Action (PCA) im-

[7] The FDIC Form 031 can be found at: https://www.ffiec.gov/pdf/FFIEC_forms/FFIEC031_202312_f.pdf

[8] The FDIC Prompt Corrective Action directive can be viewed at: https://www.fdic.gov/regulations/examinations/enforcement-actions/ch-05.pdf

poses supervisory actions that can include restrictions on capital distributions, management fees, asset growth, and mergers and acquisitions. In selecting the undercapitalized threshold as an identifier of fragile banks, we assume that uninsured depositors and other short-term lenders withdraw their funding if a bank reached that threshold. The choice of the threshold is a flexible assumption that impacts how "severe" the identification is: the higher the threshold (more severe), the more banks will be identified as fragile, the lower the threshold (less severe) the fewer banks will be identified as fragile. Depending on how the measure is utilized - e.g., in a market, supervisory, or policy setting - we acknowledge that different thresholds may be preferable as changing the severity affects both true positives and false positives. Different settings likely weight differently the occurrence of true positives vs. false positives.

4. Data

In this paper, we rely on the data reported by FDIC-insured financial institutions in the Consolidated Reports of Condition and Income (commonly referred to as the Call Report). In particular, we source data from the FFIEC forms 031, 041, or 051 depending on the institutions' size and whether they have foreign offices. Filing is required by law for all state member banks, state nonmember banks, national banks, and savings associations.

We select 1996:Q1 as the start date of our study given the availability of several key metrics and 2023:Q3 as the end date since it is the last available quarterly report at the time of writing. The sample comprises 799,101 bank-quarter observations from 13,108 unique institutions. The institutions captured in our sample are mostly institutions with total assets of less than 1$ Bn (11,011). There are 2,097 banks with more than 1$ Bn in assets, of which 331 have more than 10$ Bn in assets. Table 1 reports the definitions of the variables used in the study, and Table 2 reports descriptive statistics.

[Insert Table 1 and Table 2 about here]

The average asset size of the institutions in our study is relatively small at 1.723$ Bn. Institutions in our sample, on average, also have low trading assets to assets (*Trading-to-Assets*), high loans to assets (*Loans-to-Assets*), and low non-interest income to gross income (*NII-to-GI*). These figures are not surprising since the sample is mostly composed of relatively small institutions with simple business models.

The average *Z-Score*, the number of standard deviations by which returns would have to fall from the mean in order to wipe out the bank equity (following, among many others, Boyd and Graham (1986), Hannan and Hanweck (1988), and Boyd et al. (1993)), is relatively high. This indicates that most of the institutions in our sample are safe, or far from default, which is also captured in the average probability of default (*Merton PD*). To estimate probabilities of default, we follow Bharath and Shumway (2008), but our results are qualitatively unchanged throughout the paper if we estimate them following Nagel and Purnanandam (2020) instead.

In the next two sections, we focus on how we define and construct two key variables in our framework: runnable liabilities and unrealized losses.

4.1. Runnable Liabilities

We define runnable liabilities as the sum of uninsured deposits and other liabilities with maturity less than one year. To measure uninsured deposits, we leverage both the estimated amount of uninsured deposits reported by banks and the value and number of deposit accounts of more than $250,000.[9]

Short-term liabilities are defined as the sum of federal funds purchased in domestic offices under agreement to repurchase (RCONB993), securities sold under agreements to repurchase (RCFDB995), and two items from the other borrowed money (Schedule RC-M) with remaining maturity, or repricing, of one year or less: Federal Home Loan Bank advances (RCFDF055) and other unspecified borrowing (RCFDB571).

[9] Please see Appendix A for details on estimating uninsured deposits.

Figure 2 presents the time series of runnable liabilities, uninsured deposits, and short term liabilities as a fraction of assets at the aggregate level.

[Insert Figure 2 about here]

Figure 2 shows that runnable liabilities have steadily grown from 1996:Q1, where they represented around 25% of total assets, to 2023:Q3, where they represent a little less than 40%. The increase is mostly due to the increase in uninsured deposits while the short-term liabilities have remained relatively stable or even decreased. There are two visible exceptions in the time series: a) the period around the Great Recession when the Emergency Economic Stabilization Act (ESSA) passed and temporarily raised the FDIC coverage limit to $250,000 (which was made permanent by the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010) and b) the period starting from the default of SVB in 2023Q1. In both cases, we can see a significant decrease in uninsured deposit as a fraction of total assets. In the first case, the reason is "mechanical"; suddenly increasing the insurance limit decreases the amount of uninsured deposits.[10] In the second case, depositors with amounts over the insurance limit likely withdrew funds to reduce their exposure to possible bank defaults.

4.2. Unrealized Gains & Losses

The second key variable in our study is the estimation of unrealized gains & losses. Unrealized gains & losses capture the difference between the banks' mark-to-market and book assets. In periods of rising interest rates, like the one that started in 2022:Q1, it is likely that the mark-to-market value of assets are significantly lower than the book value of assets, reflecting unrealized losses in the balance sheet. To compute total unrealized gains & losses, we separately estimate unrealized gains & losses from securities and loans, the two

[10] Note however that the FFIEC reports changed, reflecting the new limit, in 2009:Q3, almost a year after the ESSA which was passed in October 2008

most substantial assets types that are sensitive to interest rates.[11]

Regarding loans, banks are required to report allowances for loan and leases losses in the Call Report and account for such losses in their Tier 1 Capital. However, changes in mark-to-market values of loans due to rate changes are not reported. To estimate loan losses, we follow the methodology and calculations outlined in Flannery and Sorescu (2023).[12]

A key assumption in this procedure to estimate interest risk related loan losses is that the loans are "fairly priced" at the onset of the increase in interest rates. We believe that assumption is reasonable, on average, and thus we estimate loan losses using as benchmark quarters those quarters prior to increases in interest rates. In our sample, starting from 1996:Q1, we observed four periods of interest rates increases: starting in 1999:Q3, 2004:Q2, 2016:Q4, and 2022:Q1. The quarters prior to those dates are used as benchmark quarters, and unrealized losses on loans are estimated until interest rates start decreasing.[13]

In order to replicate the fragility measure proposed by Jiang et al. (2023), we also estimate loan losses following their methodology.[14] We are confident that we successfully replicated Flannery and Sorescu (2023) as our estimates of total unrealized losses are identical to the ones reported in their paper (around 1.1$ trillion) once we select the same sample of banks and quarters. However, it is worth noticing that the total unrealized losses estimated following the methodology of Jiang et al. (2023) are lower than the ones they report (1.8$ trillion Vs. 2.2$ trillion). This is likely due to our selection of ETFs and indices in the different maturity buckets as we could not find all matching maturities and had to make some assumption. Figure 3 presents the time series of unrealized losses from securities and loans scaled by aggregate Tier 1 Capital over the period [1996:Q1-2023:Q3].

[11]For a detailed description of how we estimate gains and losses on banks' securities portfolios, please see Appendix B

[12]For details on how Flannery and Sorescu (2023) value banks' loan portfolios, please see Appendix C.

[13]To identify the benchmark quarters we used the Federal Funds Effective Rate available at: https://fred.stlouisfed.org/series/FEDFUNDS

[14]For details on the Jiang et al. (2023) methodology for valuing banks' loans, please see Appendix D.

[Insert Figure 3 about here]

Figure 3 shows that unrealized losses, in terms of % of Tier 1 Capital, from the last period of rising interest rates are significantly larger than the losses from the three preceding periods. This is likely due to the speed at which interest rates have risen in the most recent period. It can also be seen that Jiang et al. (2023)'s estimates of unrealized losses are almost double the estimates from Flannery and Sorescu (2023) (peak at 115% of Tier 1 Capital vs. 55%). For the reminder of the paper, we employ Flannery and Sorescu (2023)'s estimates of unrealized losses, unless otherwise specified, because we agree with the authors' argument that such estimates make optimal use of Call Report data in accepting banks' securities loss estimates and, for loan losses, leverage the "representative loan" approach instead of using changing ETF values which introduces estimation error and could also reflect changes in default risk in addition to interest rate risk.[15]

5. Fragility Measures

In this section we outline the fragility measures we compare to our proposed measure from Section 3. The first set of measures are the regulatory leverage ratio (*Leverage Ratio*) and two derived measures that include unrealized losses on securities (*LR – UGL Securities*) and unrealized losses on loans (*LR – UGL Securities & Loans*). The second set of measures are derived from Jiang et al. (2023): *JMPS Replica* and *JMPS (F&S UL)*.

5.1. Leverage Ratios

The first measure of bank fragility we consider is the regulatory leverage ratio (*Leverage Ratio*) which is the ratio of banks' Tier 1 capital over total assets. We select the leverage ratio as our baseline measure over other regulatory measures like the total risk-based capital

[15]See Section IV.D, starting at page 23, of Flannery and Sorescu (2023) for a detailed discussion of the difference in the two methodologies.

ratio, the risk-based capital ratio, and the common equity Tier 1 capital ratio for the same two reasons outlined in Section 3.

The second and third measures considered in our study are closely related to the leverage ratio: (*LR – UGL Securities*) and (*LR – UGL Securities & Loans*). The former accounts in Tier 1 capital for unrealized gains and losses on securities (leveraging the banks' reported number) while the latter accounts also for the gains and losses on loans (following Flannery and Sorescu (2023)).

To identify fragile banks using the proposed leverage ratios, we have to select a threshold under which banks are identified as fragile. To be consistent with our proposed measure, we select 4%, the threshold below which the FDIC's Prompt Corrective Action (PCA) applies.

Under all the leverage measures, banks with lower Tier 1 capital with respect to total assets will be considered more fragile. In the two enhanced measures, banks with higher unrealized losses from securities andor loans will be considered more fragile. How banks fund the assets plays no role in determining whether a bank is considered fragile. Table 2 Panel A, presents summary statistics of the measures as well as the indicators reflecting whether banks are below the fragility threshold: *Leverage Ratio* $I^{<4\%}$, *LR – UGL Securities* $I^{<4\%}$, and *LR – UGL Securities & Loans* $I^{<4\%}$. The regulatory leverage ratio is on average 11.56% with 0.38% of bank-quarters being below the 4% threshold. The two measures that consider unrealized gains & losses are relatively similar on average, but the percent of bank-quarters below the fragility threshold is higher at 0.67% and 1.49%, respectively. This is expected since adding unrealized losses to Tier 1 capital forces several banks' to cross the threshold.

5.2. Insured Deposit Coverage Ratios

The insured deposit coverage ratio is a measure proposed by Jiang et al. (2023) to capture risks to bank solvency that allows the share of uninsured depositors withdrawing their money to vary. The measure is defined as:

$$Insured\,Deposit\,Coverage\,Ratio_{i,q} = \frac{Mark{-}to{-}Market\,Assets_{i,q} - s * Uninsured\,Deposits_{i,q} - Insured\,Deposits_{i,q}}{Insured\,Deposits_{i,q}}$$

Where i represents the bank, q the quarter, and s is the share of uninsured depositors withdrawing. A negative value of insured deposit coverage ratio means that the remaining mark-to-market assets value, after paying uninsured depositors who withdrew their deposits, is not sufficient to repay all insured deposits.[16]

We construct two measures based on Jiang et al. (2023): *JMPS Replica*, and *JMPS FS UGL*. The first measure is based on our replication of the authors' procedure to value mark-to-market assets while the second measure uses Flannery and Sorescu (2023)'s procedure to value mark-to-market assets.[17] From the two continuous measures we create two indicator variables to identify fragile banks when the measure is negative: *JMPS Replica I* $^{<0}$ and *JMPS FS UGL I* $^{<0}$.

Under the insured deposit coverage measure, banks with lower mark-to-market assets will be considered more fragile. How banks fund their assets plays a role only to the extent that banks use deposits versus wholesale loans or equity. Insured deposits are treated in the same manner as uninsured deposits. Furthermore, equity and wholesale liabilities (of all maturities) enter the formula in the same, indirect, way creating no distinction between the two sources of funding for determining the fragility of a bank. Table 2 Panel A, presents summary statistics of the measures. The difference in both mean and share of banks that

[16] Jiang et al. (2023) discuss two scenarios: one when s is equal to 1 and one where s equal to 0.5. In our study, we assume the former scenario, where s is equal to 1, because we believe that once a single uninsured depositor has an incentive to run then all of the remaining depositors will too. Furthermore, the assumption of s equal to 1 is consistent with our proposed framework and thus makes the comparison of the measures more consistent.

[17] Section 4.2 of this paper provides a summary on how unrealized gains & losses are estimated under the two methodologies and thus mark-to-market assets

are identified as fragile is very noticeable. This is due two main reasons. First, we could only replicate Jiang et al. (2023)'s measure for the last period, when there was a rapid increase in interest rates. Thus, we have fewer observations and in a more severe, in terms of interest risk, period with respect to the same measure but using Flannery and Sorescu (2023)'s estimate of mark-to-market assets for which we are able to cover the entire sample period. Second, Flannery and Sorescu (2023) estimate around half of the unrealized losses, conditioning on the same period, thus yielding much higher mark-to-market assets increasing the insured deposit coverage ratio and reducing the number of banks identified as fragile, *ceteris paribus.*

6. Comparative Analyses

In this section, we compare the performance of our proposed run risk measure and the fragility measures outlined in Section 5. We first analyze the ability of the measures to identify defaults tracking the true positive ratio, the false positive ratio, and the area under the curve (AUC), a metric that evaluates the accuracy of a binary predictor. Second, we show the behaviour of the fragility measures during the recent period on six notable cases. Third, we compare the gap in equity - the amount of capital needed to avoid a bank being identified as fragile - in both dollar aggregate and as a percentage of total assets.

6.1. Fragility Measures and Defaults

In Table 3, we report the analyses aimed at comparing the performance of the fragility measures in identifying bank failures. To determine whether a bank defaults we leverage the FDIC's Failed Bank List.[18] While there are certainly instances of banks in distress that do not default because, for example, they are acquired, we believe that including them

[18]The list can be found at: https://www.fdic.gov/resources/resolutions/bank-failures/failed-bank-list/

does not change the interpretation of the results.[19] However it would reduce consistency and increase the difficulty for other researchers to replicate results. We subsequently check whether the fragility measures identify the defaulted bank as fragile two quarters ahead of the failure.[20] To compare fragility measures, we then identify the true positives, when the fragility measures correctly identify the bank as fragile, and the false positives, when the fragility measure identifies the bank as fragile, but it did not default in two quarters. In addition, we also report the asset-weighted true positive and false positive ratios, which are the ratio of true positives over total positives and the ratio of false positives over total negatives, respectively. The reasoning behind reporting asset-weighted measures is that we believe that policymakers, market participants, supervisors, and researchers are generally more interested in evaluating the measures' ability to forecast failure for banks that can pose a serious treat to the overall financial system. In our analyses we focus on false positives, in addition to true positives because, in our view, they represents a significant cost. We believe policymakers and supervisors should carefully consider the trade-offs between true positives and false positive when implementing new rules. A new rule that "saves" few additional institutions from failure (true positives) at the expenses of imposing costs - like raising capital, extra examinations, etc... - to banks that ultimately do not fail (false positives) may not be desirable from a social welfare perspective. Because of such a trade-off, we compute an accuracy statistic, the area under the curve (AUC). AUC combines the information from both true positives and false positives in one statistic and can be employed using asset-weighed metrics. AUC measures the area under the curve in the receiver operating characteristics

[19] We are not able to identify a scenario where any of the measures is systematically better or worse in identifying those "shadow" defaults. Nevertheless, we recognize that creating a broader definition of defaults that includes cases not identified in the FDIC default list is likely a worthy endeavour for future works.

[20] In unreported analyses we extended the horizon to three and four quarters ahead of the default without any significant relative difference between the performance measures. All metrics perform worse as the number of quarters between the default and when the measure is evaluated increases, but the relative ranking remain unchanged. Analyses are available upon request

space (ROC), which is the space defined by the true positive ratio in the y axis and the false positive ratio in the x axis. The higher the value the better. An AUC of 0.5 indicates that the predictor is not different than a random guess and an AUC of 1 indicates perfect performance. Although it depends on the setting, in general, an AUC between 0.7 and 0.8 is considered acceptable while above 0.8 is considered good.

Since few of the measures considered in the study are specifically designed to identify fragile banks in rising interest rate periods, we evaluate the performance over four different data samples. *All Banks* considers all banks and all types of default over the full period [1996:Q1-2023:Q3]. This sample is meant to capture the ability of the fragility measures to identify all defaults without focusing on any particular environment. *Large Banks* considers only banks whose maximum assets reached at least $10 billion over the full period [1996:Q1-2023:Q3]. This sample evaluates the ability of the measures to identify defaults particularly for large institutions that would be a threat to the financial system if they were to default. *IR-only* considers only banks that are identified as having defaulted due to interest risk or deposit runs and whose maximum assets reached at least $1 billion over the full period [1996:Q1-2023:Q3].[21] This sample evaluates the ability of the measures to identify interest rate risk and deposit run driven defaults. *Recent IR* considers only banks whose maximum assets reached at least $1 billion over the period [2022:Q1-2023:Q3]. This sample evaluates the ability of the measures to identify defaults in the recent post-pandemic interest rates lift off period. Table 3 presents the results.

[Insert Table 3 about here]

The relative performance of the measures is broadly consistent across the different samples. *LR - UGL - Securities & Loans* and *Run Risk Ratio* have the highest asset-weighted

[21] The reasoning behind selecting the $1 billion threshold is that for institutions above that threshold we were able to consistently identify the reasoning behind the failure. That was not the case in investigating smaller institution failures.

true positive ratios and are able to identify, two quarters ahead, more than 70% of the defaulted assets. Among those two measures, *LR - UGL - Securities & Loans* has a slight higher true positive in the sample with all banks and the full period. However, *LR - UGL - Securities & Loans* has also the highest false positive ratios across all samples, followed by *LR - UGL - Securities*. In terms of asset-weighted AUC, the *Run Risk Ratio* fragility measures outperform all the other measures with values above 80 in all samples. While not having the highest true positive ratio in any of the samples, it outperforms the measures with similar true positive ratios because it does so at a much lower cost in terms of false positives. This is particularly evident when *Run Risk Ratio* is compared with *LR - UGL - Securities & Loans*, the second-best fragility measure according to the AUC metrics: in all samples the true positives of the two measures are very similar, but *LR - UGL - Securities & Loans* has a false positive ratios in the range of 40% - 50% versus *Run Risk Ratio* which identifies as fragile one-forth of the banks with a false positive ratio of around 10% across samples.

To better understand the behaviour of the measures in the recent period, we also plot in Figure 4 the number of banks identified as fragile over the period [2022:Q1-2023:Q3]. The figure shows that at the onset of the increasing interest rate period very few banks were identified as fragile across all measures. The pattern of the measures is quite similar, as expected since they all have unrealized losses as a common driver. Fragile-identified banks spiked in 2022Q3 and are again on the rise at the end of the sample in 2023Q3. *LR - UGL - Securities & Loans* and *JMPS Replica* are the two measures that identify the most banks. It is worth noticing that our *JMPS Replica* identifies around 1,500 fragile banks in 2023:Q1 compared to the 1,600 that are reported in Jiang et al. (2023). The difference is expected as in our JMPS replica measure the estimate of unrealized losses is slightly lower than the one reported by the authors. This has a positive effect on mark-to-market assets and thus increases the banks' insured deposit coverage ratio, lowering the number of banks identified as fragile.

[Insert Figure 4 about here]

The last analyses we perform examining the ability of fragility measures to predict defaults is investigating their performance across default horizons. Using the full sample of banks, we show in Figure 5 how the measures perform across different default horizons: from one quarter (1Q) to eight quarters (8Q) to default. Measures that are able to detect true positives earlier should be preferred as they give banks' management and supervisors more time to react and thus more easily make changes to improve the banks' conditions before it is too late.

The true positive ratios panel shows that *Run Risk Ratio* and *LR - UGL on Securities & Loans* are the two measures that are able to detect true positives earlier, reaching a ratio above 50% as early as 4 quarters in advance and increasing up to 80% one quarter ahead. *JMPS Replica* shows an interesting behavior as it is able to detect a large bank default three quarters in advance - First Republic Bank - but is not able to two quarters in advance as the bank's condition improved. In Section 6.1.1, we discuss this case in detail along with other notable examples. The false positive ratios panel does not show any particular path. The ratio at which measures wrongly identify fragile banks does not significantly change with the horizon.

[Insert Figure 5 about here]

To summarize the results in this section, we believe that our proposed measure, *Run Risk Ratio*, is statistically more accurate in predicting defaults, particularly for large banks and in periods of rising interest rates. It has to be noted that the AUC metrics, on which we are basing our conclusion, equally weights true positives and false positives. We are aware that the objective function of policymakers and supervisors may not be to be as accurate as possible in an equal-weighted setting. For example, we can see good reasons to weight true positives more than false positives as the ability of a measure to identify banks that are in distress is likely more valuable to a policymaker or supervisor than the ability to wrongly identify as fragile a bank that does not default. The AUC measure can be modified to take higher weights for true positives in order to align the results with the objective function of policymakers and supervisors. However, unless a weight close to 1 for true positives is selected, *Run Risk Ratio* performs better as it is already almost maximizing the true positive ratios with a lower false positive ratio.

6.1.1. Notable Cases

In this section, we focus on the behaviour of the fragility measures during the recent period on six notable cases. First, we investigate two banks that failed: Silicon Valley Bank and First Republic Bank. Then we analyse two large banks with a substantial gap among the measures: Charles Schwab and State Street Corporation. Last, we show how the measures perform on the two largest banks in the sample: JP Morgan Chase and Bank of America.

Figure 6 Panel A, presents the two defaulted banks. For the case of Silicon Valley Bank, both *Run Risk Ratio* and *LR - UGL on Securities & Loans* fragility indicators would have detected SVB as fragile bank as early as 2022:Q2 as their measures fall below the 4% threshold. This is due the very large amount of unrealized losses, which impacts both measures, combined with a very large proportion of runnable funding, which is only considered in our proposed measure. The two JMPS measures get closer to turning negative, and, as such, identify the bank as fragile in 2022:Q2 and 2022:Q3, but the unrealized losses (computed with either methodology) are simply not large enough to trigger it. In order for SVB to be identified as fragile by the JMPS measures in 2022:Q4, SVB's last reporting date, its unrealized losses would need to be at least \$33.648 billion. The amount is equal to its reported assets (\$209.026 billion) minus total deposits (\$175.378 billion). SVB's sum of HTM securities (91.321$ billion), AFS securities ($25.976 billion), and loans ($73.613 billion), across all maturities, amounts to $191.546 billion. Furthermore, $61.416 billion of SVB's loans (83.43%) are reported as having a maturity, or repricing date, less than a year with the vast majority ($59.430 billion) being under three months. Thus, given the remaining maturity of the loans, it is not surprising that Flannery and Sorescu (2023)'s estimation of loan losses are $1.031 billion, an 8.45% average loss on loans with maturity longer than one year. Bank reported loss on securities, which have a much higher duration - only $1.114 billion, or 1.21%, have a maturity less than one year - are $17.685 billion. Thus, the total unrealized losses using Flannery and Sorescu (2023)'s methodology are $18.716 billion, 55.62% of what is needed for the JMPS fragility measure to identify SVB as weak. Our replica of unrealized losses, following Jiang et al. (2023), estimates them at $22.637 billion, which is also relatively far from the required $33.648 billion needed to identify SVB as fragile. As discussed in Section 5.2, funding plays a limited role in the JMPS measures. The fact that SVB had an extraordinary amount of uninsured deposits with respect to insured deposits does not impact the formula. The overall amount of funding coming from all deposits as a fraction of assets does, and it is not extraordinarily high. For example, in 2022:Q4, SVB funded 83.90% of assets with deposits, which is close to the unconditional mean for the entire sample, 82.17%. In contrast, Charles Schwab funded a much higher percent of assets with deposits (93.48%) which were mostly insured (76.24%). The high deposit-to-asset share identifies Charles Schwab as fragile in the JMPS measures even if it does not have such high unrealized losses in relative terms.

First Republic Bank shows a similar pattern to SVB as both *Run Risk Ratio* and *LR - UGL on Securities & Loans* fragility indicators would have detected the bank as fragile four quarters ahead. In this case, the *JMPS Replica* measure does identify the bank as fragile three quarters ahead but then depositors run - in 2023:Q1 deposits drop from 176.436 to 104.473, a 40.78% decrease - and the JMPS measure significantly improves as total deposits decrease significantly more than the assets.

The regulatory *Leverage Ratio* does not pick either of the defaulted banks as fragile and it is actually quite far from doing so as it does not incorporate in its computation the large amount of unrealized losses.

Next, in Figure 6 Panel B, we analyze the two banks with the largest gaps among the measures. For Charles Schwab it can be seen that the *LR - UGL on Securities & Loans* and both the JMPS measures identify the bank as fragile. This is because of the high unrealized losses for all three measures, and because, as discussed above, Charles Schwab funds a significant amount of assets with deposits, 93.48%, for the JMPS measures. The reason why *Run Risk Ratio* does not identify Charles Schwab as a fragile bank even though it has high unrealized losses is because of the funding: 76.24% of its deposits are insured and thus it does not have a high amount of runnable funding, which makes the funding shock in our proposed framework relatively small. Given the small shock, Charles Schwab is not "forced" to sell a large portion of assets and thus it does not have to fully recognize in Tier 1 capital all the estimated unrealized losses.

State Street Corporation shows a slightly different pattern than Charles Schwab as only the *LR - UGL on Securities & Loans* measure identifies it as fragile even though its unrealized losses are comparable to Charles Schwab. The difference with Charles Schwab is that State Street Corporation funds its assets with a low portion of deposits (81.15%). This is considered favorably in the JMPS measures which remains far from identifying the bank as fragile.

Last, in Figure 6 Panel C, we show the two largest banks in the sample. None of the fragility measures identify JP Morgan Chase as fragile while for Bank of America *LR - UGL on Securities & Loans* does. This happens because Bank of America has sizeable unrealized losses which impact negatively all measures except the regulatory one. But the high unrealized losses are not combined with an exceptionally high portion of assets being funded by deposits (JMPS measures) nor with a high amount of runnable funding (our proposed measure). Thus, while getting closer to the threshold with many measures it does not cross it.

6.2. Fragility Measures Costs

In this section we analyze the costs associated with the fragility measures under the hypothetical scenario that banks would be required to re-capitalize or transform liabilities whenever their fragility measure drops below the threshold. Specifically, we select four quarters during the last rising rate period - 2021:Q4, 2022:Q2, 2022:Q4, and 2023:Q2 - and evaluate the equity gap, defined as the amount of capital a bank needs to avoid being considered fragile under the measures. We report the aggregate equity gap, in $ billions, for the entire banking industry as well as the average gap in terms of leverage ratio, both equally and asset-weighted. For our proposed measure, *Run Risk Ratio*, banks can avoid being identified as fragile by transforming their liabilities. Thus, we report the amount of liabilities that have to be transformed from runnable to more stable as a share of total liabilities.

An alternative or additional cost of identifying banks as fragile is the time spent by supervisors in understanding the condition of the those banks. In order to provide a proxy for such costs, we report the number of banks that are identified as fragile. The level of scrutiny required in checking the conditions of a bank is not equal across bank sizes. Larger banks, which pose a higher threat to the financial system, are usually given more attention. Thus, we also report the number of fragile banks within three size portfolios: small banks (maximum assets below $1 billion), medium banks (maximum assets between $1 and $10 billion), and large banks (maximum assets above $10 billion). Table 4 present results.

[Insert Table 4 about here]

Table 4 shows that in 2021:Q4, before interest rates started rising, only two small banks were identified as fragile. In both cases, the bank had a regulatory ratio below 4% before adding the impact of unrealized losses. Thus, they are identified as fragile by all the measures that use the leverage ratio as the threshold for identification. Only a few months after interest rates started rising in 2022:Q2, there were already a significant number of banks identified as fragile. The number increased through 2022:Q4 and decreased in 2023:Q2.

In 2022:Q4, the regulatory leverage ratio was still identifying the same two banks that were defined as fragile even before the increase in interest rates. This is not surprising as unrealized losses are not considered in the measure. The two derived measures, which include unrealized losses, identify 367 and 1,866 banks as fragile, respectively. The addition of the estimate of unrealized losses on loans thus seems to play an important role, multiplying by five the number of banks identified as fragile. We believe this to be an important finding from a regulatory perspective as, currently, banks are only required to report fair value estimates on securities and not on loans. The relation does not materially change when the other two quarters after the interest rates started increasing are examined.

Our proposed measure identifies a substantially lower number of banks as fragile, except when compared to the regulatory leverage ratio. This result is consistent with the findings in Section 6.1 where our measure was shown to have a comparatively low false positive ratio. Interestingly, even with a lower overall number of banks identified as weak, our proposed measure identifies more large banks as fragile than all methods except for the *LR - UGL Securities & Loans*. The difference is striking when compared with the JMPS measures which identify a significantly higher number of banks as fragile, but the vast majority of them are small. This is likely because small banks' funding is primarily derived from deposits - insured and uninsured - which is a risk factor for the JMPS measures.

The equity gap, in aggregate, loosely follows the number of identified banks, particularly large ones, reaching \$207 billion for the *LR - UGL Securities & Loans* measure. It is worth noticing that the mean leverage gap (either equal or asset weighted) of our proposed measure is significantly lower than all the other alternative measures, although the aggregate gap is not. This is because of the composition of the identified banks. Our proposed method identifies a higher share of larger banks as fragile. Thus, even with a significantly smaller mean equity gap, the aggregate equity gap is not as far apart. Conversely, one may interpret this result as the alternative measures imposing significantly higher capital costs on small and medium banks.

Last, considering the most severe quarter in our sample, 2022Q4, banks that are identified as fragile in our sample would need to "transform", on average, 1.65% of their liabilities from runnable to more stable sources of funding. For the less severe quarters, such figure drops to 1.28% and 0.92%, respectively. We believe this to be a key feature of our proposed framework as the addition of capital is not required to avoid being identified as fragile.

To summarize this section, we believe that the considered measures have potentially different costs in the hypothetical scenario where regulators will require banks to stay above the minimum threshold and/or will have increased scrutiny for such institutions. The difference is both in the number of banks that are identified as fragile and in in the amount of capital they will have to raise. Our proposed measure stands out as the measure that selects a relatively smaller number of small banks and that, on average, would require a lower increase in equity as share of assets.

7. Runs Risk Ratio Analyses

In this section we more rigorously investigate whether our proposed *Run Risk Ratio* fragility indicator is related to bank defaults. To do so, we employ a Complementary Log-Log regression (cloglog) which is a statistical modelling technique used to analyze binary response variables similar to the better known logistic regression (logit). The cloglog regression is an extension of the logistic regression model and is particularly useful when the probability of an event is very small or very large since its function, contrary to the logit, is asymmetrical and skewed to one side. As our variable of interest is defaults, which are fortunately rare, we believe it is the appropriate modeling choice. In our main regression table we present results also employing the logit regression for robustness purposes.

First, we show that our fragility measure provides additional information after controlling for a set of bank level controls, including the leverage ratio and quarter fixed effects. Second, we show that the measure is significant in predicting defaults at different default horizons. Third, we show that the measure is robust to alternative choices of the threshold for identifying a fragile bank, from 3% to 7%. Fourth, we show that our measure is particularly useful in predicting defaults during periods of rising interest rates and for large banks. Last, to check the robustness of our measure to alternative dependent variables, we substitute default with banks' Z-Score and probabilities of default measured several quarters after the independent variables employing an OLS regression. Even when bank fixed effects are considered in the specification, our proposed measure is still significant in predicting the response variables.

The cloglog, logit, and OLS regressions presented in this section follow the below specification:

$$Distress\,Measure_{i,q+n} = \beta_1 Run\,Risk\,I_{i,q} + \beta_2 \Sigma Controls_{i,q} + \beta_i + \beta_q + \epsilon_{i,q}$$

Where i represents the bank and q the quarter. *Distress Measure* is the default for the cloglog and logit regression specifications, and the Z-Score or probabilities of default for the OLS regression. n is the number of quarters ahead the distress measure is evaluated, which is four unless otherwise specified. *Run Risk I* is an indicator variable that takes the value of one if the *Run Risk Ratio* is below 4% (unless otherwise specified), or else takes the value of zero. *Controls* is a set of bank level control variables (Leverage Ratio, Ln(Assets), RWA-to-Assets, Trading-to-Assets, Loans-to-Assets, RoA, and NII-to-GI). β_i and β_q represents bank and quarter fixed effects when employed.

7.1. Run Risk Ratio and Defaults

In the first regression analysis, we investigate whether our proposed measure of fragility *Run Risk I* is significant in explaining defaults two quarters ahead after controlling for a set of bank-level time-varying controls and quarter fixed effects. Specifically, we control for potentially confounding effects coming from banks' size (natural logarithm of assets), banks' types (RWA-to-Assets, Trading-to-Assets, Loans-to-Assets, NII-to-GI), and banks' profitably (RoA). We also control for the leverage ratio, as a measure of bank riskiness, because our intent is to understand whether our proposed measure brings additional information once leverage is accounted for. Understanding if our proposed fragility measure adds extra information is particularly important for policymakers or supervisors who want to implement any action, like increased capital or scrutiny, based on this metric. Table 5 presents the results:

[Insert Table 5 about here]

Columns (1)-(3) present the cloglog regression results and show that our proposed measure is statistically significant at the 1% level in predicting future defaults. This is robust to the introduction of bank-level time-varying controls in column (2) and quarter fixed effects in column (3). In column (4), we report the estimate of a logistic regression using the same specification as column (3), and our proposed measure is still statistically significant at the 1% level. The impact of our proposed measure is not only statistically significant but also economically meaningful. Leveraging the coefficient estimates from the logit specification, the odds of defaulting in two quarters, for a bank identified as fragile, are a little less than eleven times higher $((exp(2.475) - 1) = 10.881)$.[22]

[22] The unconditional probability of default for a bank in our sample is 0.07%, thus we believe such additional impact, while being very large economically, should not be particularly surprising, as it is targeting firms that are in distress

7.2. Run Risk Ratio and Default Horizons

From a supervisory and bank management perspective, a measure that identifies fragility earlier is preferable as it allows more time to react and potentially improve a bank's situation. Thus, we investigate the ability of the measure to predict defaults at different horizons. In particular, in Table 6, we show the measure performance over the 1-2, 3-4, 5-12, and 13-20 quarter horizons.

[Insert Table 6 about here]

Table 6 shows that the measure remains statistically significant at the 1% level even at longer default horizons, suggesting that it does provide useful information about banks' probability of default as far as five years ahead. Nevertheless, the coefficient magnitude decreases from the 1-2 quarter default horizons to the 5-12 quarter default horizon, suggesting a reduced impact of our measure on the odds of default.

7.3. Run Risk Ratio and Fragility Thresholds

In our proposed framework, we identify the threshold level below which a firm is considered fragile at 4%. This is an assumption based on the FDIC prompt corrective action rule that allows supervisors to step in and restrict the ability of bank's management to perform certain actions. While we believe this is a reasonable threshold that will trigger depositors to run, it is also possible that attentive depositors may run earlier (i.e. before reaching that level), or distracted depositors may run later (i.e. at a lower threshold). In Table 7, we analyze the performance of our measure changing such assumption.

[Insert Table 7 about here]

Table 7 shows that in changing the fragility threshold, the statistical significance of our proposed measure does not change. In terms of economic magnitude, it is relatively similar across different thresholds and seems to decrease from the 5% level, where it peaks, as threshold values increase.

7.4. Run Risk Ratio, Size, and Interest Rates

We design our proposed framework to capture the risk of deposit runs. To test that our measure fulfills its intended purpose, we interact an indicator variable for rising rates with our fragility indicator. The indicator for rising interest rates matches the timing of the default (four quarters ahead), and it is equal to one during the following four interest rising periods: [1999:Q3-2000:Q2], [2004:Q2-2003:Q3], [2016:Q4-2019:Q1], and [2022:Q1-2023:Q3]. Given the results presented in Section 6, where we show that larger banks seem to be more likely to suffer from interest rate risk driven defaults, we interact our fragility measure with an indicator of bank size that takes the value of one if the maximum assets are higher than $10 billion, or else zero. Table 8 presents the results.

[Insert Table 8 about here]

Table 8 Column (1), shows that the interaction term of our measure of fragility and period of rising interest rates is positive and statistically significant at the 1% level. This suggests that our proposed metric provides incremental information for those banks that defaulted during a period of rising interest rates. Column (2) shows that our measure is particularly able to predict defaults of large institutions, regardless of time, as its interaction with the size indicator is positive and statistically significant at the 1% level.

7.5. Run Risk Ratio, Z-Scores, and Probabilities of Default

Last, in order to test the robustness of our findings, we replicate our main specification substituting the response variable. We consider both banks' Z-Score and probabilities of default. Z-Score is the number of standard deviations by which returns would have to fall from the mean in order to wipe out a bank's equity, and we evaluate it following, among others, Boyd and Graham (1986), Hannan and Hanweck (1988), and Boyd et al. (1993). To estimate Merton's probabilities of default, we follow Bharath and Shumway (2008). Both measures are computed at three future horizons - four, eight, and twelve quarters - with respect to when the independent variables are measured. As both response variables are continuous, we are able to employ an OLS regression to estimate its coefficients. Table 9 presents the results.

[Insert Table 9 about here]

Table 9 Columns (1)-(3), shows that the coefficient estimates of our proposed measure are negative and statistically significant at the 1% level across all three horizons. Banks identified as fragile are thus correlated with lower Z-Scores, indicating worse future conditions. Columns (4)-(6) show that our measure is statistically significantly correlated at the 1% level with banks' future probabilities of default for up to eight quarters. Consistent with the Z-Score specifications, this indicates that banks identified as fragile will be in weaker financial condition (higher probability of default) in future quarters.

8. Policy Implications

We believe that our proposed framework is well placed to be used by market participants and supervisors as a monitoring tool. The highly flexible nature of the model - the level of the funding shock, the targeted capital measure, and the level of the capital measure can all be tuned - allows the user to set the "severity" level and thus effectively control the trade off between true positives and false positives. As market participants and supervisors may have different preferences, such flexibility allows users to set their own parameters based on their specific goals.

In addition to being used as a monitoring tool, our model can be integrated into the current regulatory system. Specifically, the difference between a minimum leverage ratio, like the FDIC's undercapitalized threshold, and the post-shock model-implied leverage ratio could be added to the current capital requirements. This policy would incentivize bank managers to avoid the combination of unrealized losses and runnable funding that makes bank runs more likely. An appealing feature of the model is that banks would not necessarily have to raise capital to meet the requirement. They could decide to transform some of their runnable liabilities to more stable ones to satisfy this requirement.

9. Conclusion

In this paper, we develop a framework for identifying banks that are susceptible to runs that incorporates both the fair value of banks' assets and the structure of their liabilities. Focusing on the recent period of rising interest rates, our model shows that a significant number of banks would be undercapitalized if they experienced a funding shock. Furthermore, our measure identifies a significant number of fragile banks, including SVB, as early as 2022:Q1. Thus, the results of the model can be used to provide an early warning signal to banks' management, market participants, and regulators.

We compare our framework to several other fragility measures and find that our proposed measure is as accurate as any of the alternatives in predicting bank distress while producing far fewer false positives. The cost of false positives for the banking system is potentially high, and our measure generally results in lower costs of industry-wide bank re-capitalization than the alternatives, and our required capital increases are concentrated among large banks.

This framework could be integrated into the current regulatory system by adding the difference between a minimum leverage ratio, like the FDIC's undercapitalized threshold, and the post-shock model-implied leverage ratio to the current capital requirements. This policy would incentivize bank managers to avoid the combination of unrealized losses and runnable funding that makes bank runs more likely.

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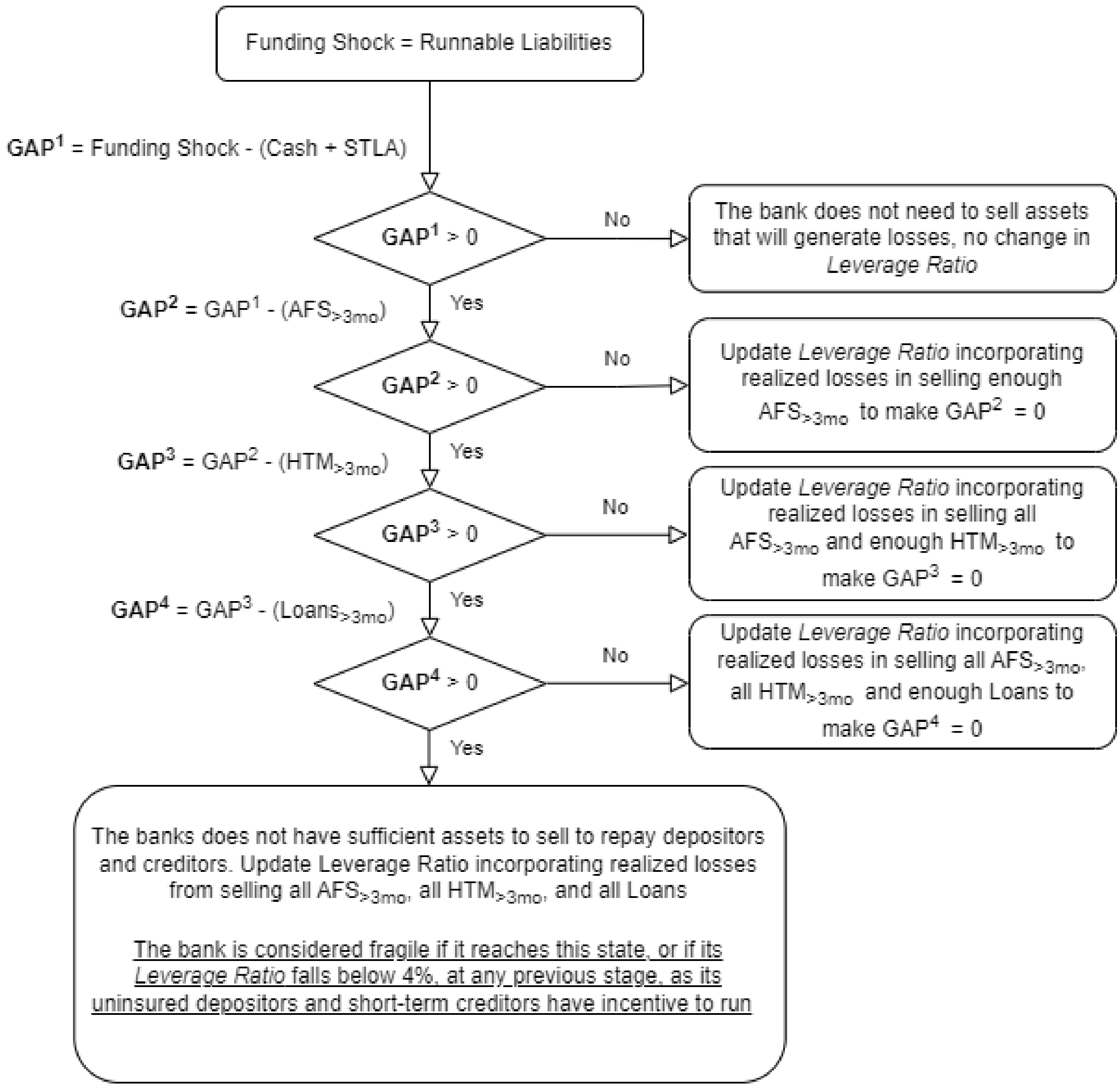


Figure 1: **Run Risk Framework**
This figure presents the flowchart of our run risk framework. Runnable liabilities are defined as the sum of banks' uninsured deposits and other liabilities with maturity or repricing date of one year or less.

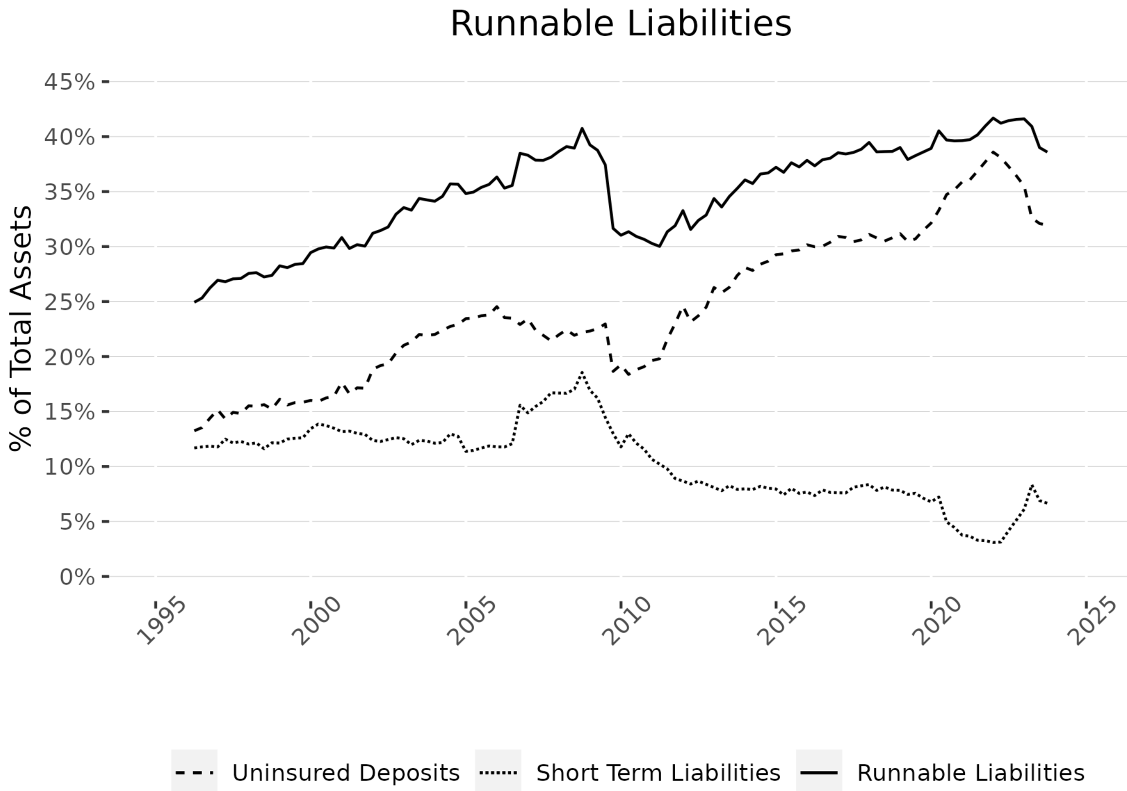


Figure 2: **Runnable Liabilities**
This figure presents the time series of uninsured deposits, short term liabilities, and runnable liabilities as a fraction of total assets at the aggregate level over the period [1996:Q1-2023:Q3].

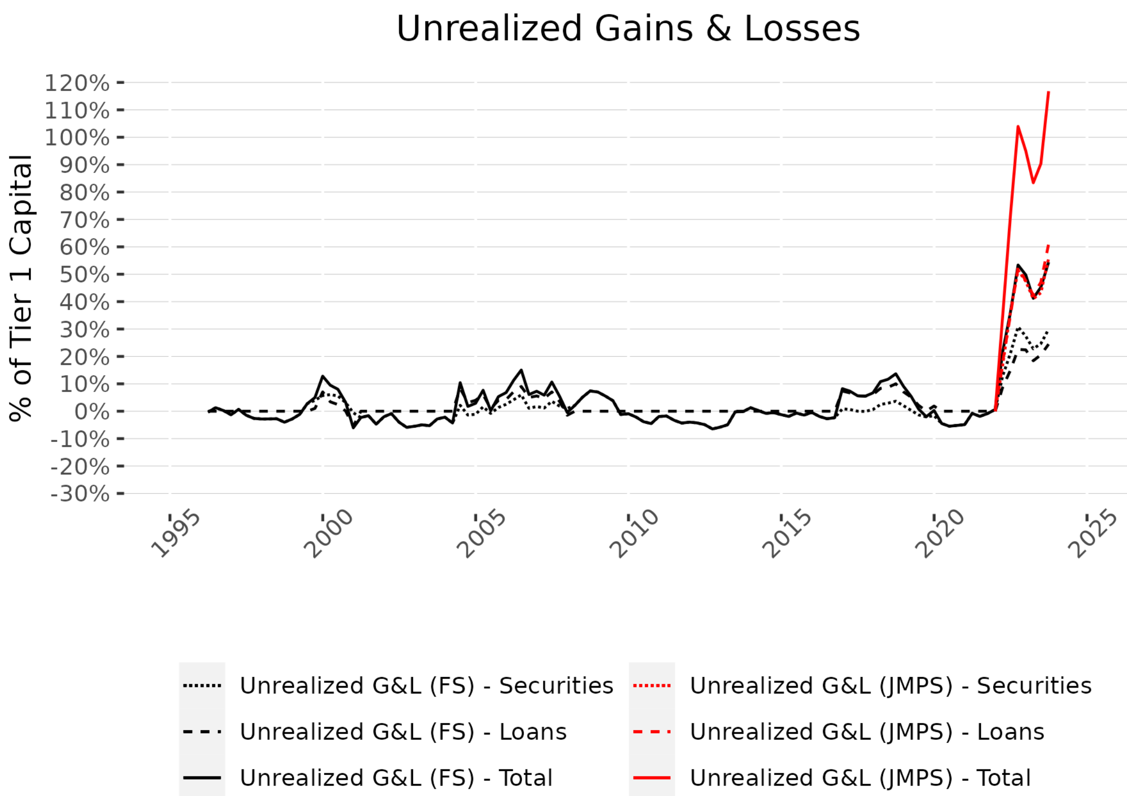


Figure 3: **Unrealized Gains & Losses**
This figure presents the time series of unrealized gains & losses from securities (AFS & HTM) and loans scaled by aggregate Tier 1 Capital over the period [1996:Q1-2023:Q3] following the methodologies of Flannery and Sorescu (2023) and Jiang et al. (2023).

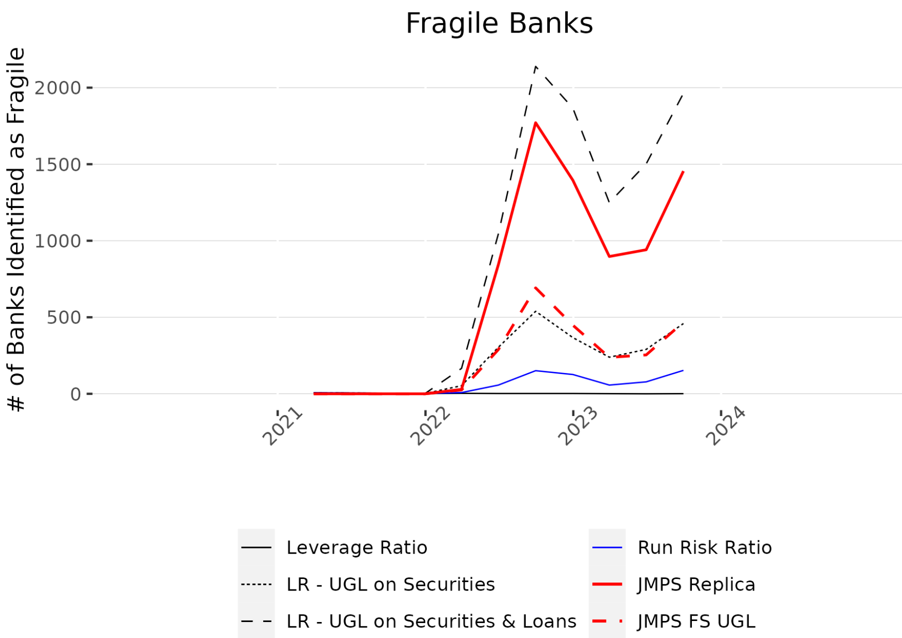
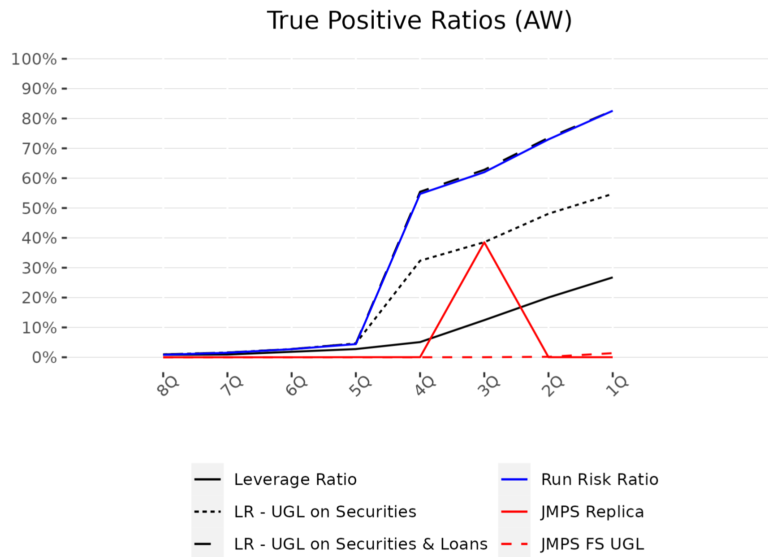


Figure 4: **Fragile Banks**

This figure presents the time series of banks identified as fragile according to the fragility measures considered in the study over the period [2022:Q1-2023:Q3]. Fragility measures' definitions are reported in Table 1.



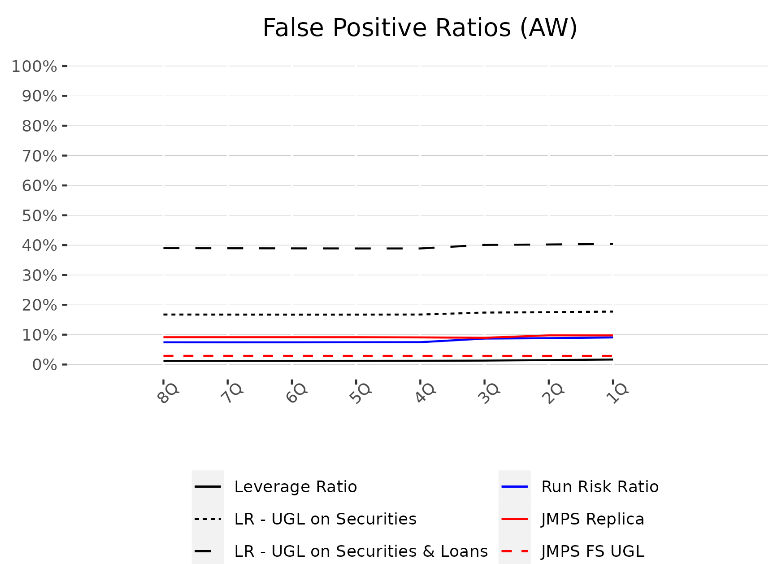
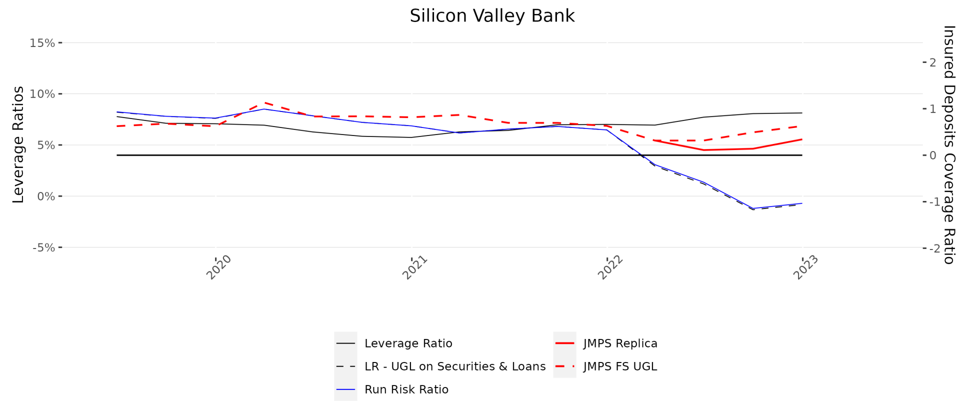


Figure 5: **True and False Positive Ratios Across Default Horizons**
This figures presents the asset-weighted true positive ratios and false positive ratios for the full sample and fragility measures from the one quarter default horizon to the eight quarter default horizon. Fragility measures' definitions are reported in Table 1.

Panel A: Defaulted Banks



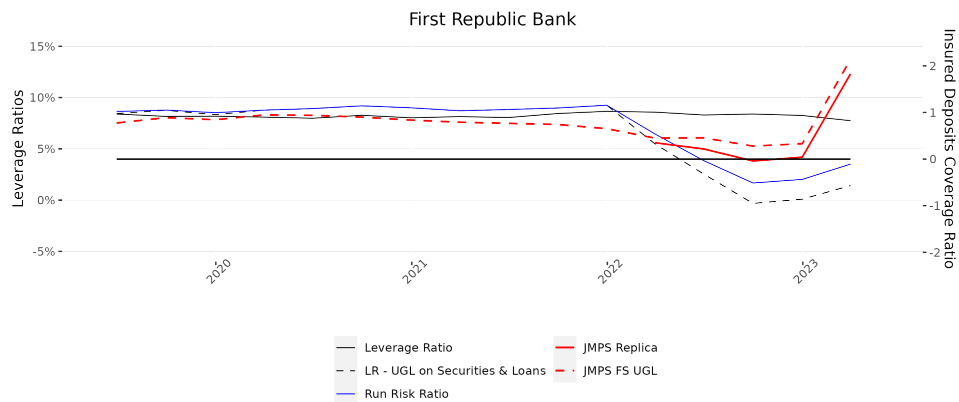
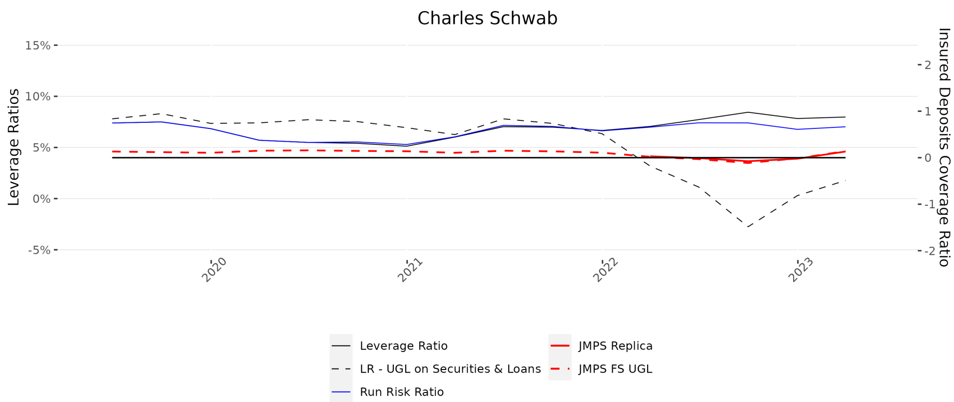
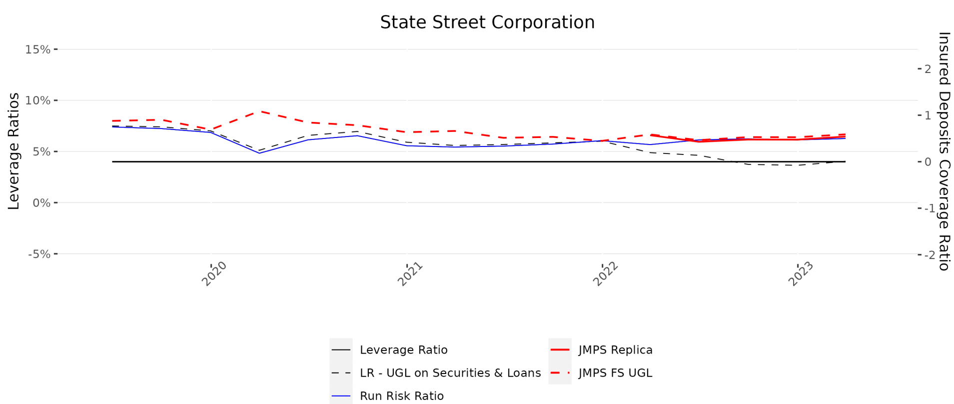


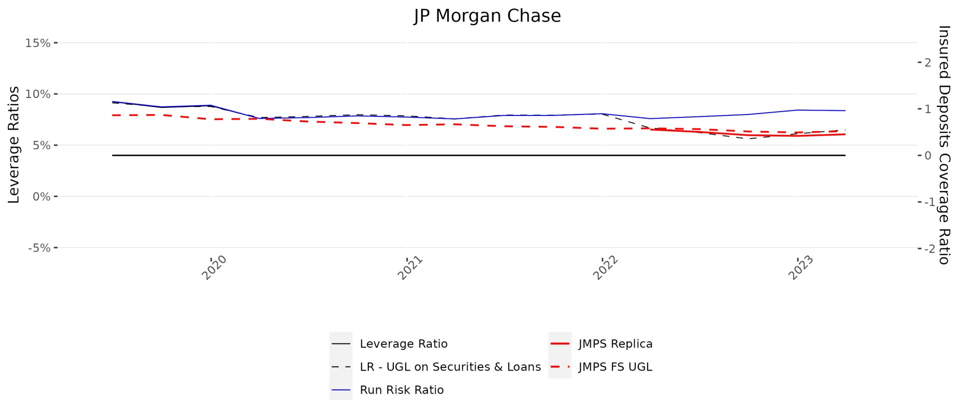
Figure 6: **Notable Cases**
This figure presents the time series of fragility measures for two defaulted banks, Silicon Valley Bank and First Republic Bank, in Panel A. The two banks with the largest gap among fragility measures, Charles Schwab and State Street Corporation, in Panel B. And the two largest bank in the sample, JP Morgan Chase and Bank of America, in Panel C. All time series are over the period [2019:Q1-2023:Q3].

Panel B: Large Differences' Banks





Panel C: Largest Banks



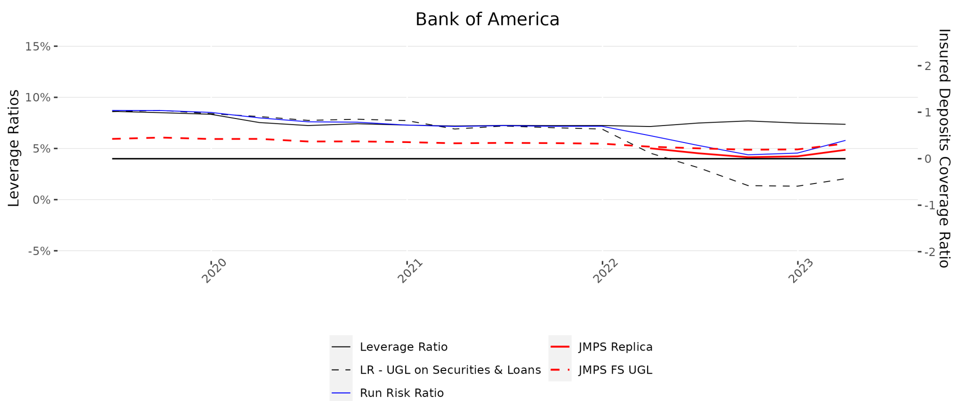


Table 1: **Definitions**

This table presents fragility measure definitions in Panel A and bank variable definitions in Panel B.

Panel A: Fragility Measures

Leverage Ratio	Bank Tier 1 Capital divided by total assets
Leverage Ratio I $^{<4\%}$	An indicator variable that takes the value of 1 if the *Leverage Ratio* is below 4%, otherwise 0. It identifies banks that are considered fragile under the *Leverage Ratio* measure.
LR - UGL Securities	Bank Tier 1 Capital, minus unrealized losses on securities, divided by total assets
LR - UGL Securities I $^{<4\%}$	An indicator variable that takes the value of 1 if the *LR - UGL on Securities* is below 4%, otherwise 0. It identifies banks that are considered fragile under the *LR - UGL on Securities* measure.
LR - UGL Securities & Loans	Bank Tier 1 Capital, minus unrealized losses on securities and on loans, divided by total assets
LR - UGL Securities & Loans I $^{<4\%}$	An indicator variable that takes the value of 1 if the *LR - UGL on Securities & Loans* is below 4%, otherwise 0. It identifies banks that are considered fragile under the *LR - UGL on Securities & Loans* measure.
Run Risk Ratio	Bank Tier 1 Capital, minus unrealized losses on securities and on loans that were sold due to the funding shock, divided by total assets. The funding shock is defined as the sum of banks' uninsured deposits and other liabilities with maturity or repricing date of one year of less.
Run Risk Ratio I $^{<4\%}$	An indicator variable that takes the value of 1 if the *Run Risk Ratio* is below 4%, otherwise 0. It identifies banks that are considered fragile under the *Run Risk Ratio* measure.
JMPS Replica	The Insured Deposit Coverage Ratio as presented in Jiang et al. (2023). It is the mark-to-market value of assets minus the sum of insured and uninsured deposits, divided by insured deposits. Mark-to-Market assets are estimated using the methodology presented in Jiang et al. (2023)
JMPS Replica I $^{<0}$	An indicator variable that takes the value of 1 if the *JMPS Replica* is below 0, otherwise 0. It identifies banks that are considered fragile under the *JMPS Replica* measure.
JMPS FS UGL	The Insured Deposit Coverage Ratio as presented in Jiang et al. (2023). It is the mark-to-market value of assets minus the sum of insured and uninsured deposits, divided by insured deposits. Mark-to-Market assets are estimated using the methodology presented in Flannery and Sorescu (2023)
JMPS FS UGL I $^{<0}$	An indicator variable that takes the value of 1 if the *JMPS FS UGL* is below 0, otherwise 0. It identifies banks that are considered fragile under the *JMPS FS UGL* measure.

Panel B: Bank Variables

Assets	Bank total assets (in billions of U.S. dollars).
Uninsured Deposits-to-Assets	Bank uninsured deposits divided by total assets.
Runnable Liabilities-to-Assets	Bank runnable liabilities divided by total assets. Bank runnable liabilities are defined as the sum of banks' uninsured deposits and other liabilities with maturity or repricing date of one year or less.
Unrealized Losses-to-Assets	Bank unrealized losses divided by total assets. Unrealized losses are estimated following Flannery and Sorescu (2023).
RWA-to-Assets	Bank Risk-Weighted Assets divided by total assets.
Trading-to-Assets	Bank trading assets divided by total assets.
Loans-to-Assets	Bank loans divided by total assets.
RoA	Bank yearly net income divided by total assets.
NII-to-GI	Bank net interest income divided by gross income
Z-Score	The number of standard deviations by which returns would have to fall from the mean in order to wipe out the bank equity. We follow the measure originally presented in Boyd and Graham (1986).
Merton PD	Bank probability of default estimated following Bharath and Shumway (2008)

Table 2: **Descriptive Statistics**
This table presents descriptive statistics of fragility measures in Panel A and other bank variables in Panel B. The sample includes 799,101 quarterly observations from 13,101 unique reporting institutions over the period [1996:Q1-2023:Q3]. Variable definitions are reported in Table 1.

Panel A: Fragility Measures

	N	Mean	Std	P25	P50	P75
Leverage Ratio	799,101	11.56%	9.32	8.26	9.65	11.79
Leverage Ratio I $^{<4\%}$	799,101	0.38%	6.17	0.00	0.00	0.00
LR - UGL Securities	799,101	11.57%	9.39	8.22	9.68	11.89
LR - UGL Securities I $^{<4\%}$	799,101	0.67%	8.14	0.00	0.00	0.00
LR - UGL Securities & Loans	799,101	11.35%	9.45	8.01	9.51	11.75
LR - UGL Securities & Loans I $^{<4\%}$	799,101	1.49%	12.10	0.00	0.00	0.00
Run Risk Ratio	799,101	11.52%	9.34	8.22	9.62	11.79
Run Risk Ratio I $^{<4\%}$	799,101	0.46%	6.75	0.00	0.00	0.00
JMPS Replica	28,430	0.14%	0.25	0.02	0.09	0.17
JMPS Replica I $^{<0}$	28,430	20.56%	40.41	0.00	0.00	0.00
JMPS FS UGL)	799,101	0.30%	0.29	0.15	0.21	0.31
JMPS FS UGL I $^{<0}$	799,101	0.25%	5.01	0.00	0.00	0.00

Panel B: Bank Variables

	N	Mean	Std	P25	P50	P75
Assets (in $Bn)	799,101	1.723	34.176	0.057	0.126	0.309
Uninsured Deposits-to-Assets	799,101	0.158	0.111	0.080	0.135	0.210
Runnable Liabilities-to-Assets	799,101	0.191	0.131	0.099	0.165	0.254
Unrealized Losses-to-Assets	799,101	0.002	0.013	-0.003	0.000	0.004
RWA-to-Assets	774,457	0.662	0.151	0.573	0.671	0.761
Trading-to-Assets	799,101	0.000	0.010	0.000	0.000	0.000
Loans-to-Assets	799,101	0.616	0.175	0.525	0.643	0.739
RoA	761,234	0.880	0.805	0.579	0.955	1.307
NII-to-GI	799,013	0.136	2.690	0.061	0.098	0.153
Z-Score	761,234	180.309	173.001	62.037	124.776	234.529
Merton PD	761,233	0.001	0.026	0.000	0.000	0.000

Table 3: **Fragility Measures and Defaults**

This table presents the number of unique banks, the number of defaults, the number of true positives, the asset-weighted true positive ratio, the false positives, the asset-weighted false positive ratio, and the area under the curve (AUC) for all fragility measures and four samples. The *All Banks* sample considers all banks and all types of default over the full period [1996:Q1-2023:Q3]. The *Large Banks* sample considers only banks whose maximum assets reached at least $10 billion over the full period [1996:Q1-2023:Q3]. The *IR-only* sample considers only banks that are identified as defaulted due to interest risk or deposit runs, whose maximum assets reached at least $1 billion, and over the full period [1996:Q1-2023:Q3]. The *Recent IR* sample considers only banks whose maximum assets reached at least $1 billion over the period [2022:Q1-2023:Q3]. Variable definitions are reported in Table 1.

Sample	Fragility Measure Indicator	Banks - Unique	Defaults	True Positives	True Positive Ratio	False Positives	False Positive Ratio	Area Under Curve
	Regulatory LR	13,108	528	377	20.04%	577	1.49%	59.28
	LR - UGL Securities	13,108	528	390	48.10%	1,252	16.98%	65.56
	LR - UGL Securities & Loans	13,108	528	391	73.54%	2,935	39.66%	66.94
All Banks	Run Risk Ratio	13,108	528	385	73.00%	809	8.83%	82.08
	JMPS Replica	4,825	5	1	0.03%	1,830	9.77%	45.13
	JMPS FS UGL	13,108	528	7	0.16%	744	2.90%	48.63
	Regulatory LR	331	7	2	3.23%	6	1.12%	51.06
	LR - UGL Securities	331	7	4	40.53%	44	18.85%	60.84
	LR - UGL Securities & Loans	331	7	5	76.31%	134	42.33%	66.99
Large Banks	Run Risk Ratio	331	7	5	76.31%	47	9.16%	83.57
	JMPS Replica	180	3	0	0.00%	24	6.14%	46.93
	JMPS FS UGL	331	7	0	0.00%	9	2.43%	48.78
	Regulatory LR	2,097	6	2	0.37%	100	1.44%	49.47
	LR - UGL Securities	2,097	6	3	39.24%	267	17.74%	60.75
	LR - UGL Securities & Loans	2,097	6	4	78.54%	759	40.94%	68.80
IR-only	Run Risk Ratio	2,097	6	4	78.54%	241	9.30%	84.62
	JMPS Replica	1,091	3	0	0.00%	334	8.29%	45.85
	JMPS FS UGL	2,097	6	0	0.00%	94	2.59%	48.71
	Regulatory LR	1,091	3	0	0.00%	0	0.00%	50.00
	LR - UGL Securities	1,091	3	1	39.13%	123	21.48%	58.83
	LR - UGL Securities & Loans	1,091	3	2	78.70%	588	52.61%	63.04
Recent IR	Run Risk Ratio	1,091	3	2	78.70%	111	8.90%	84.90
	JMPS Replica	1,091	3	0	0.00%	334	8.29%	45.85
	JMPS FS UGL	1,091	3	0	0.00%	89	3.56%	48.22

Table 4: **Fragility Measures Costs**
This table presents the number of banks identified as fragile, the aggregate equity gap, the mean leverage ratio equity gap, and the mean stable liabilities gap for the 2021:Q4, 2022:Q2, 2022:Q4, and 2023:Q2 quarters and across all fragility measures. Small banks are defined as banks with maximum assets below $1 billion. Medium banks are defined as banks with maximum assets between $1 and $10 billion. Large banks are defined as banks with maximum assets above $10 billion. Equity gap is defined as the amount of capital a bank needs to avoid being considered fragile under the measure. The stable liabilities gap is defined as the share of liabilities that a bank needs to transform from runnable to stable to not be considered fragile. Variable definitions are reported in Table 1.

Quarter	Fragility Measure Indicator	Positives	Small Banks	Medium Banks	Large Banks	Equity Gap ($Bn)	Mean Lev R Gap	Mean Stable Liabilities Gap
	Regulatory LR	2	2	0	0	0.005	1.72%	
	LR - UGL Securities	2	2	0	0	0.006	1.84%	
2021:Q4	LR - UGL Securities & Loans	2	2	0	0	0.006	1.84%	
	Run Risk Ratio	2	2	0	0	0.005	1.72%	1.76%
	JMPS Replica	0	0	0	0			
	JMPS FS UGL	0	0	0	0			
	Regulatory LR	2	2	0	0	0.004	1.65%	
	LR - UGL Securities	304	239	55	10	22.325	1.91%	
2022:Q2	LR - UGL Securities & Loans	1,045	780	229	36	74.596	1.16%	
	Run Risk Ratio	57	20	30	7	8.216	1.20%	1.28%
	JMPS Replica	844	723	113	8	24.370	1.80%	
	JMPS FS UGL	289	268	17	4	13.446	2.22%	
	Regulatory LR	2	2	0	0	0.000	0.08%	
	LR - UGL Securities	367	297	57	13	53.394	1.39%	
2022:Q4	LR - UGL Securities & Loans	1,866	1,349	432	85	207.943	1.93%	
	Run Risk Ratio	126	47	60	19	25.364	1.52%	1.65%
	JMPS Replica	1,395	1,163	219	13	61.720	3.63%	
	JMPS FS UGL	448	397	46	5	11.771	1.78%	
	Regulatory LR	0	0	0	0			
	LR - UGL Securities	290	237	43	10	30.060	0.86%	
2023:Q2	LR - UGL Securities & Loans	1,502	1,077	355	70	133.518	1.66%	
	Run Risk Ratio	78	34	35	9	3.493	0.86%	0.92%
	JMPS Replica	941	812	122	7	37.682	3.99%	
	JMPS FS UGL	254	231	21	2	4.747	3.35%	

Table 5: **Run Risk Ratio and Defaults**

This table reports coefficients from cloglog and logit regressions of bank defaults on the fragility measure proposed in our framework and control variables. The estimation sample comprises an unbalanced panel of 799,101 quarterly observation from 13,108 unique financial institutions over the period [1996:Q1-2023:Q3]. *Run Risk I* is our proposed fragility measure, an indicator variable that takes the value of one if the leverage ratio, after accounting for the funding shock, is below 4%, zero otherwise. *Leverage Ratio* is the regulatory leverage ratio measured as Tier 1 capital over total assets. *Ln(Assets)* is a natural log transformation of total assets. *RWA-to-Assets* is the share of risk-weighted assets to total assets. *Trading-to-Assets* is the share of trading assets to total assets. *Loans-to-Assets* is the share of loans to total assets. *RoA* is the share of yearly net income to total assets. *NII-to-GI* is the ratio of net interest income to gross income. Columns (1)-(3) report coefficients from a cloglog regression methodology while column (4) presents coefficients from a logit methodology. Columns (3)-(4) include quarter fixed effects. The error terms are heteroskedasticity-consistent (HC) following Huber-White methodology. p-values are presented in parentheses.

	Bank Default			
	Complementary Log-Log			Logit
	(1)	(2)	(3)	(4)
Run Risk I	5.942***	3.003***	2.924***	2.475***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage Ratio		−9.965**	−13.562***	−32.784***
		(0.040)	(0.000)	(0.000)
Ln(Assets)		0.215***	0.147***	0.121***
		(0.000)	(0.000)	(0.000)
RWA-to-Assets		2.412***	2.458***	3.207***
		(0.000)	(0.000)	(0.000)
Trading-to-Assets		2.937**	1.945	0.669
		(0.048)	(0.229)	(0.768)
Loans-to-Assets		3.406***	1.847***	1.740***
		(0.000)	(0.000)	(0.000)
RoA		−116.717***	−109.241***	−112.171***
		(0.000)	(0.000)	(0.000)
NII-to-GI		0.001**	0.001***	0.001**
		(0.019)	(0.007)	(0.035)
Quarter FE	No	No	Yes	Yes
N	799,101	736,572	736,572	736,572
Pseudo R^2_{McF}	0.376	0.500	0.553	0.568
Pseudo R^2_{Nag}	0.381	0.505	0.558	0.573

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: **Run Risk Ratio and Default Horizons**
This table reports coefficients from cloglog regressions of bank defaults on the fragility measure proposed in our framework and control variables. The estimation sample comprises an unbalanced panel of 736,572 quarterly observation from 13,108 unique financial institutions over the period [1996:Q1-2023:Q3]. In column (1), the response variable, default, takes the value of one if the bank fails within two quarters. In column (2), the response variable takes the value of one if the bank fails between three and four quarters. In column (3), the response variable takes the value of one if the bank fails between five and four twelve quarters. In column (4), the response variable takes the value of one if the bank fails between twelve and twenty quarters. *Run Risk I* is our proposed fragility measure, an indicator variable that takes the value of one if the leverage ratio, after accounting for the funding shock, is below 4%, zero otherwise. *Leverage Ratio* is the regulatory leverage ratio measured as Tier 1 capital over total assets. *Ln(Assets)* is a natural log transformation of total assets. *RWA-to-Assets* is the share of risk-weighted assets to total assets. *Trading-to-Assets* is the share of trading assets to total assets. *Loans-to-Assets* is the share of loans to total assets. *RoA* is the share of yearly net income to total assets. *NII-to-GI* is the ratio of net interest income to gross income. All specifications include quarter fixed effects. The error terms are heteroskedasticity-consistent (HC) following Huber-White methodology. p-values are presented in parentheses.

	Bank Default			
	Complementary Log-Log			
	(1) 1-2 Q	(2) 3-4 Q	(3) 5-12 Q	(4) 13-20 Q
Run Risk I	3.795***	2.323***	1.373***	1.461***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage Ratio	−12.960***	−14.808***	−12.822***	−3.229***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	0.108***	0.192***	0.164***	0.161***
	(0.000)	(0.000)	(0.000)	(0.000)
RWA-to-Assets	2.439***	2.525***	2.422***	1.967***
	(0.000)	(0.000)	(0.000)	(0.000)
Trading-to-Assets	6.186***	−48.868*	−19.100***	−43.962***
	(0.000)	(0.074)	(0.000)	(0.002)
Loans-to-Assets	1.326***	2.128***	3.629***	3.993***
	(0.001)	(0.000)	(0.000)	(0.000)
RoA	−109.269***	−107.653***	−74.470***	−50.485***
	(0.000)	(0.000)	(0.000)	(0.000)
NII-to-GI	0.002***	−0.006	−0.042***	−0.055***
	(0.000)	(0.834)	(0.000)	(0.000)
Quarter FE	Yes	Yes	Yes	Yes
N	736,572	735,516	734,464	730,352
Pseudo R^2_{McF}	0.626	0.410	0.283	0.216
Pseudo R^2_{Nag}	0.628	0.412	0.290	0.221

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: **Run Risk Ratio and Fragility Thresholds**

This table reports coefficients from cloglog regressions of bank defaults on the fragility measure proposed in our framework and control variables. The estimation sample comprises an unbalanced panel of 736,572 quarterly observation from 13,108 unique financial institutions over the period [1996:Q1-2023:Q3]. *Run Risk* $I^{<n\%}$ is an indicator variable that takes the value of one if the leverage ratio, after accounting for the funding shock, is below n%, zero otherwise. *Run Risk I* is an indicator variable that takes the value of one if the leverage ratio, after accounting for the funding shock, is below 4%, zero otherwise. *Leverage Ratio* is the regulatory leverage ratio measured as Tier 1 capital over total assets. *Ln(Assets)* is a natural log transformation of total assets. *RWA-to-Assets* is the share of risk-weighted assets to total assets. *Trading-to-Assets* is the share of trading assets to total assets. *Loans-to-Assets* is the share of loans to total assets. *RoA* is the share of yearly net income to total assets. *NII-to-GI* is the ratio of net interest income to gross income. All specifications include quarter fixed effects. The error terms are heteroskedasticity-consistent (HC) following Huber-White methodology. p-values are presented in parentheses.

	Bank Default				
	Complementary Log-Log				
	(1)	(2)	(3)	(4)	(5)
Run Risk I $^{<3\%}$	2.543***				
	(0.000)				
Run Risk I		2.924***			
		(0.000)			
Run Risk I $^{<5\%}$			3.017***		
			(0.000)		
Run Risk I $^{<6\%}$				2.848***	
				(0.000)	
Run Risk I $^{<7\%}$					2.278***
					(0.000)
Leverage Ratio	−15.588***	−13.562***	−13.359***	−14.791***	−22.636***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	0.171***	0.147***	0.100***	0.067***	0.090**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.010)
RWA-to-Assets	2.597***	2.458***	2.460***	2.640***	3.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading-to-Assets	0.302	1.945	3.316**	0.361	−0.659
	(0.882)	(0.229)	(0.031)	(0.870)	(0.825)
Loans-to-Assets	1.775***	1.847***	2.022***	2.125***	1.822***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
RoA	−122.686***	−109.241***	−96.317***	−95.856***	−109.315***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NII-to-GI	0.001**	0.001***	0.000	0.000	0.001
	(0.025)	(0.007)	(0.585)	(0.501)	(0.329)
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	736,572	736,572	736,572	736,572	736,572
Pseudo R^2_{McF}	0.534	0.553	0.558	0.554	0.533
Pseudo R^2_{Nag}	0.539	0.558	0.563	0.559	0.538

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8: **Run Risk Ratio, Size, and Interest Rates**

This table reports coefficients from cloglog regressions of bank defaults on the fragility measure proposed in our framework and control variables. The estimation sample comprises an unbalanced panel of 736,572 quarterly observation from 13,108 unique financial institutions over the period [1996:Q1-2023:Q3]. *Run Risk I* is an indicator variable that takes the value of one if the leverage ratio, after accounting for the funding shock, is below 4%, zero otherwise. *Rising Interest Rates* is an indicator equal to one if the response variable, default is measured in the periods:[1999:Q3-2000:Q2], [2004:Q2-2003:Q3], [2016:Q4-2019:Q1], and [2022:Q1-2023:Q3]. *Large Bank I* is a indicator variable equal to one if the bank maximum assets ever exceeded $10 billion. *Leverage Ratio* is the regulatory leverage ratio measured as Tier 1 capital over total assets. *Ln(Assets)* is a natural log transformation of total assets. *RWA-to-Assets* is the share of risk-weighted assets to total assets. *Trading-to-Assets* is the share of trading assets to total assets. *Loans-to-Assets* is the share of loans to total assets. *RoA* is the share of yearly net income to total assets. *NII-to-GI* is the ratio of net interest income to gross income. All specifications include quarter fixed effects. The error terms are heteroskedasticity-consistent (HC) following Huber-White methodology. p-values are presented in parentheses.

	Bank Default	
	Complementary Log-Log	
	(1)	(2)
Run Risk I	2.840***	2.854***
	(0.000)	(0.000)
Run Risk I * Rising Interest Rates	0.947***	
	(0.000)	
Large Bank I		−1.596***
		(0.000)
Run Risk I * Large Bank I		2.036***
		(0.000)
Leverage Ratio	−13.581***	−13.692***
	(0.000)	(0.000)
Ln(Assets)	0.134***	0.193***
	(0.000)	(0.000)
RWA-to-Assets	2.457***	2.455***
	(0.000)	(0.000)
Trading-to-Assets	2.590*	4.026**
	(0.084)	(0.012)
Loans-to-Assets	1.986***	1.826***
	(0.000)	(0.000)
RoA	−107.377***	−110.378***
	(0.000)	(0.000)
NII-to-GI	0.001***	0.001***
	(0.009)	(0.009)
Quarter FE	Yes	Yes
N	699,530	736,572
Pseudo R^2_{McF}	0.558	0.555
Pseudo R^2_{Nag}	0.562	0.560

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9: **Run Risk Ratio, Z-Scores, and Probabilities of Default**

This table reports coefficients from OLS regressions of banks' Z-Score and probability of default on the fragility measure proposed in our framework and control variables. The estimation sample comprises an unbalanced panel of 703,210 quarterly observation from 13,108 unique financial institutions over the period [1996:Q1-2023:Q3]. *Run Risk I* is an indicator variable that takes the value of one if the leverage ratio, after accounting for the funding shock, is below 4%, zero otherwise. *Leverage Ratio* is the regulatory leverage ratio measured as Tier 1 capital over total assets. *Ln(Assets)* is a natural log transformation of total assets. *RWA-to-Assets* is the share of risk-weighted assets to total assets. *Trading-to-Assets* is the share of trading assets to total assets. *Loans-to-Assets* is the share of loans to total assets. *RoA* is the share of yearly net income to total assets. *NII-to-GI* is the ratio of net interest income to gross income. All specifications include quarter fixed effects. The error terms are heteroskedasticity-consistent (HC) following Huber-White methodology. p-values are presented in parentheses.

	Ordinary Least Squares					
	Z-Score			Merton PD		
	(1) 4Q	(2) 8Q	(3) 12Q	(4) 4Q	(5) 8Q	(6) 12Q
Run Risk I	−21.595***	−10.572***	−9.502***	0.090***	0.028***	−0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.351)
Leverage Ratio	258.155***	125.429***	79.743***	−0.026***	−0.024***	−0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	14.899***	8.755***	6.370***	0.002***	0.003***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RWA-to-Assets	−39.896***	−27.411***	−23.045***	0.002***	0.005***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading-to-Assets	−124.454***	−71.975***	−35.692***	0.017	0.031*	0.042**
	(0.000)	(0.000)	(0.001)	(0.292)	(0.086)	(0.024)
Loans-to-Assets	2.780	−1.497	−1.891*	−0.002***	−0.002***	−0.002***
	(0.311)	(0.295)	(0.082)	(0.001)	(0.001)	(0.002)
RoA	2659.820***	1484.973***	1097.465***	−0.254***	−0.160***	−0.059***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NII-to-GI	−0.062	−0.028**	−0.019***	0.000***	0.000	0.000**
	(0.173)	(0.045)	(0.002)	(0.000)	(0.380)	(0.047)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	703,210	661,710	623,197	703,209	661,709	623,196
Adj R^2	0.283	0.394	0.452	0.142	0.150	0.168

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix A. Measuring Uninsured Deposits

We estimate uninsured deposits as follows: amount of deposits more than \$250,000 (RCONF051) - number of accounts of more than \$250,000 (RCONF052) times \$250,000. We then take the maximum between our estimated uninsured deposits and the figure reported by the banks. We decided to measure uninsured deposits with the above procedure because we found several cases of inconsistent uninsured deposits reporting from quarter to quarter, particularly the more we go back in time. The amounts and number of accounts above the FDIC deposit insurance limit, as reported in the memoranda of schedule RC-O, seems to be more consistent although they are likely a lower bound - as per discussion with supervisors and bankers - which is why we took the maximum between the two numbers. Note that the FDIC deposit insurance limit changed in our sample from \$100,000 to \$250,000 during the Great Recession. In the time periods before the change, we estimate uninsured deposit using the same procedure but using the \$100,000 threshold.

Appendix B. Valuing Securities Portfolios

Regarding securities, an important distinction has to be noted. Banks, at the time of purchase, have to classify their securities as either held-to-maturity (HTM) or available-for-sale (AFS). This classification determines how, and if, unrealized changes, gains or losses, in the security's market value are already incorporated into the bank's Tier 1 Capital. For both securities' classifications, banks have to report the dollar amount of their securities at the amortized cost and at fair value. The latter indicates what the bank believes the security can be sold for under the current conditions. For HTM securities the difference between the amortized cost and fair value allows for an estimate of unrealized losses. For AFS securities the estimation of unrealized losses is more complicated as securities are carried at fair value on the balance sheet. Unrealized gains and losses on AFS securities do not affect the net income but are accounted into the Other Comprehensive Income (OCI), that accumulates over time into the Accumulated Other comprehensive Income (AOCI) which measures cumulative unrealized AFS losses (among other things). While all banks account for AOCI gains and losses in their GAAP measure of equity, after November 2019 only 49 banks (at 2022:Q4) include it in their Tier 1 Capital. Remaining banks took the opportunity, given by regulators, to opt-out of the requirement that AOCI be included in Tier 1 Capital. We thus assume AFS gains and losses to be zero for banks that are already including AOCI in their Tier 1 Capital while treating them as HTM securities for banks that opted-out. In our framework, as per Flannery and Sorescu (2023), we accept banks' own estimate of unrealized gains and losses on securities as legitimate.

For a more detailed description of the exact mechanism through which unrealized AFS losses are accounted in banks balance sheet we refer the reader to Section II of Flannery and Sorescu (2023). Furthermore, Marsh and Laliberte (2023) presents an excellent visualization of the mechanism in Figure 1 of their work.

Appendix C. Flannery and Sorescu (2023) Loan Portfolios Evaluation

We replicate Flannery and Sorescu (2023) banks' loan portfolios value as follows:

1. All loans classified in the "three months or less" maturity bracket are assumed to have no significant interest risk related losses.

2. For each of the five remaining maturity brackets, we estimate the amount of loans that is not already reported at fair value, reducing the face values by the allowance for loans and lease losses.

3. For each of the remaining five maturity brackets, we assume that all loans can be reduced to a single "representative loan" with a maturity or repricing interval generally equal to the bracket's midpoint. We then compute the percentage change, resulting from interest rate increases, in the fair value of that loan between the last quarter before the interest rates started rising and the targeted quarter. This percentage is defined as the "haircut" factor.

4. We multiply, within each maturity bracket, the haircut factor in item 3. by the volume of loans in item 2. and sum this product across maturity brackets to provide a estimate of interest-rate losses incurred by a bank's loan portfolio at the targeted quarter.

A key assumption in this procedure to estimate interest risk related loan losses is that the loans are "fairly priced" at the onset of the increase in interest rates. We believe such assumption is reasonable, on average, and thus we estimate loan losses using as benchmark quarters those quarter prior to increase in interest rates. In our sample, starting from 1996:Q1, we observed four periods of interest rates increases: starting in 1999:Q3, 2004:Q2, 2016:Q4, and 2022:Q1. The quarters prior to those dates are thus used as benchmark quarters and unrealized losses on loans are estimated until interest rates start decreasing

Appendix D. Jiang et al. (2023) Mark-to-Market Valuation Methodology

First, the authors do not accept banks' own estimate of unrealized gains and losses on securities and thus mark-to-market all interest sensitive assets - securities and loans - with the same procedure. Second, they account for the maturity of the assets applying a price decline, per each of the available maturity brackets, based on the change in the iShares U.S. Treasury Bond ETFs and the S%P Treasury Bond indices of matching maturities. Their choice of the benchmark quarter to evaluate change in prices is slightly different than Flannery and Sorescu (2023) as they use the quarter when interest rates started increasing (2022:Q1) instead of the quarter prior to the increase (2021:Q4). Third, they identify assets that are linked to real estate (RMBS and residential mortgages) and apply a multiplier - RMBS multiplier - to account for the additional risk coming from prepayment. The multiplier is defined as the change in iShares MBS ETF over the change in S&P Treasury Bond Index of matching maturities.

Appendix E. Fragility Measures and Bank Characteristics

In this appendix, we compare the characteristics of the banks that default with the ones that do not default and the ones that are identified as fragile by the measures. Specifically, we present the sample averages across multiple variables of interest and test the difference between means. For presentation purposes, since we have seven fragility measure samples in addition to the two states (defaulted and not defaulted), we report the difference in means using the two states as benchmarks against which all the other samples are compared to.

We select total assets, leverage ratio, return on assets, unrealized losses over total assets, runnable liabilities over total assets, Z-Score, and probability of default as variables of interest. While the list is by no mean exhaustive in representing all relevant bank characteristics, we believe it broadly captures size, profitability, riskiness, and the two main drivers of the fragility measures: unrealized losses and runnable liabilities.

Each sample is composed of bank-quarter observations that match the sample requirement. For the defaulted banks, we select the bank characteristics two quarters ahead. For each of the measures, we select the bank-quarters that are identified as fragile by said measure. The no default sample is composed of all bank quarters for institutions that do not default in two quarters. We focus on the *IR-only* subset given the stated purposes - identifying banks particularly prone to interest risk - of most of the measures considered in the study. Table E.10 presents the results.

[Insert Table E.10 about here]

Table E.10 shows that, unsurprisingly, defaulted banks have a significantly lower leverage ratio, RoA, and a significantly higher probability of default and share of both unrealized losses and runanble liabilities to assets than non defaulted banks. Interestingly, the assets of defaulted banks are also significantly higher than the non defaulted ones potentially indicating that larger banks are more prone to default due to interest rate risk.

The three leverage ratio based measures - *Leverage Ratio*, *LR - UGL on Securities*, and *LR - UGL - Securities & Loans* - progressively select more and more banks (from 32 to 2,903) as the measures add (more) unrealized losses in the Tier 1 capital. The regulatory ratio is the stricter measure as it does not account for unrealized losses, and thus it requires a bank to be in a worse condition, *ceteris paribus*, to be below the 4% fragility threshold. As such, the characteristics of the banks selected in the samples are less and less weak as (more) unrealized losses are added to the ratio. Nevertheless, banks identified even by the less strict measure, *LR - UGL - Securities & Loans*, are significantly weaker than the non defaulted ones but stronger than the defaulted ones.

Our proposed measure and the JMPS measures behave similarly as they are intended to identify banks exposed to interest rate risk. In general, the measures select banks weaker than the non-defaulted but stronger than the defaulted. But there are some noticeable differences. First, our proposed measure identifies banks that are larger, on average, than the ones identified by the JMPS measures, although not as large as the defaulted banks. Second, our proposed measure select banks with lower regulatory leverage ratios (7.7% versus 9.7% and 9.5%) and lower probabilities of default. This difference is clearly expected when compared to the *JMPS Replica* measure, as our proposed measure is stricter (447 observations versus 1,189) and thus selects banks that are closer to distress. The reason why *JMPS FS UGL* selects fewer banks as fragile but with higher leverage ratios, on average, with respect to our proposed measure is because the level of Tier 1 capital does not enter the JMPS measure directly. In their measure, capital is treated exactly as all other liabilities of all maturities. Total equity capital, not only Tier 1 capital, and all non-deposits liabilities, even the those that are short-term , act as a"buffer" against a decrease in the mark-to-market value of assets. Thus, it is the composition of the liabilities and equity that makes the difference between the two measures. Last, our proposed measure identifies banks that have significantly higher runnable liabilities with respect to the JMPS measures. In fact, there is no statistically significant difference between our sample and the sample of defaulted banks. This is expected as our measure directly uses runnable liabilities in the computation while the JMPS measures do not take that aspect into account.

To summarize, we believe that the considered measures identify banks with different characteristics as fragile. For the leverage based measures, unrealized losses, and the starting leverage ratio are the drivers. High runnable liabilities and high unrealized losses are the main drivers for our proposed measure. JMPS measures are mainly driven by unrealized losses but also by the composition of the liabilities in a significantly different way than in our method. Insured and uninsured deposits are treated equally, and the higher their sum the more at risk a bank is. Equity capital and all non-deposit liabilities of all maturities are also treated equally and reduce the risk to the bank.

Table E.10: **Fragility Measures and Bank Characteristics**

This table presents averages and difference in means for total assets, leverage ratio, return on assets (RoA), unrealized losses over total assets (UL Over TA), runnable liabilities over total assets (RL Over TA), Z-Score, and probability of default (Merton PD). The *Default* sample includes banks identified as defaulted due to interest risk or deposit runs, whose maximum assets reached at least $1 billion, the banks' characteristics are gathered two quarters prior to default. The *No Default* sample includes all bank-quarters for non-defaulted institutions whose maximum assets reached at least $1 billion. *Leverage Ratio*, *LR - UGL on Securities*, *LR - UGL - Securities & Loans*, *Run Risk Ratio*, *JMPS Replica*, *JMPS FS UGL* samples include all bank-quarters observations identified as fragile by the respective fragility measure. All samples span the full time period [1996:Q1-2023:Q3]. Variable definitions are reported in Table 1.

Sample	Bank-Quarters		Total Assets	Leverage Ratio	RoA	UL Over TA	RL Over TA	Z-Score	Merton PD
Default	6	Mean	90.653	5.369	0.077	0.041	0.535	106.964	13.150
		Mean	10.118	10.503	1.092	0.014	0.317	195.965	0.047
No default	37822	Diff Vs Default	-80.535^{**}	5.134^{*}	1.015^{***}	-0.026^{***}	-0.218^{***}	89.001	-13.103^{***}
		t-stat	(-2.197)	(1.649)	(3.961)	(-3.323)	(-3.372)	(1.235)	(-17.252)
		Mean	1.954	1.831	-0.308	0.008	0.152	64.508	9.464
		Diff Vs Default	-88.699^{***}	-3.538^{***}	-0.385	-0.033^{***}	-0.383^{***}	-42.457	-3.686
Leverage Ratio	32	t-stat	(-5.176)	(-3.191)	(-0.981)	(-3.983)	(-3.807)	(-0.500)	(-0.325)
		Diff Vs No default	-8.164	-8.672^{***}	-1.400^{***}	-0.006^{*}	-0.165^{***}	-131.457^{***}	9.416^{***}
		t-stat	(-0.514)	(-6.432)	(-12.609)	(-1.830)	(-5.897)	(-4.212)	(27.304)
		Mean	38.680	7.971	0.910	0.076	0.394	105.648	2.816
		Diff Vs Default	-51.972	2.602^{***}	0.833^{***}	0.035^{**}	-0.141^{*}	-1.317	-10.335
LR - UGL Securities	547	t-stat	(-0.531)	(2.715)	(3.346)	(2.306)	(-1.712)	(-0.027)	(-1.591)
		Diff Vs No default	28.562^{***}	-2.532^{***}	-0.182^{***}	0.062^{***}	0.077^{***}	-90.317^{***}	2.768^{***}
		t-stat	(7.086)	(-7.760)	(-6.733)	(71.961)	(11.280)	(-11.931)	(24.764)
		Mean	19.510	8.874	1.002	0.068	0.374	145.180	0.530
		Diff Vs Default	-71.142	3.505^{***}	0.925^{***}	0.027^{***}	-0.161^{***}	38.215	-12.620^{***}
LR - UGL Securities & Loans	2903	t-stat	(-1.306)	(5.189)	(5.106)	(2.795)	(-2.629)	(0.674)	(-4.430)
		Diff Vs No default	9.392^{***}	-1.629^{***}	-0.089^{***}	0.054^{***}	0.057^{***}	-50.785^{***}	0.483^{***}
		t-stat	(5.213)	(-11.488)	(-7.527)	(140.847)	(18.864)	(-15.151)	(9.883)
		Mean	15.039	7.713	0.890	0.075	0.489	122.085	0.868
		Diff Vs Default	-75.614^{***}	2.344^{***}	0.813^{***}	0.034^{***}	-0.046	15.121	-12.282^{***}
Run Risk Ratio	447	t-stat	(-3.397)	(2.683)	(3.512)	(2.767)	(-0.585)	(0.259)	(-3.665)
		Diff Vs No default	4.921	-2.790^{***}	-0.201^{***}	0.060^{***}	0.172^{***}	-73.880^{***}	0.821^{***}
		t-stat	(1.156)	(-7.731)	(-6.755)	(64.549)	(22.832)	(-8.818)	(8.697)
		Mean	5.932	9.730	1.035	0.080	0.332	142.565	1.039
		Diff Vs Default	-84.721^{***}	4.361^{***}	0.958^{***}	0.040^{***}	-0.203^{***}	35.601	-12.111^{***}
JMPS Replica	1189	t-stat	(-7.672)	(5.286)	(5.624)	(4.236)	(-3.610)	(0.648)	(-2.947)
		Diff Vs No default	-4.187	-0.773^{***}	-0.057^{***}	0.066^{***}	0.015^{***}	-53.400^{***}	0.992^{***}
		t-stat	(-1.606)	(-3.491)	(-3.104)	(114.430)	(3.249)	(-10.341)	(13.551)
		Mean	8.972	9.490	1.079	0.098	0.348	94.960	5.259
		Diff Vs Default	-81.680^{***}	4.121^{***}	1.002^{***}	0.057^{***}	-0.187^{**}	-12.004	-7.891
JMPS FS UGL	252	t-stat	(-4.548)	(5.222)	(5.064)	(4.329)	(-2.508)	(-0.293)	(-0.873)
		Diff Vs No default	-1.146	-1.013^{**}	-0.013	0.084^{***}	0.031^{***}	-101.005^{***}	5.212^{***}
		t-stat	(-0.202)	(-2.108)	(-0.319)	(67.492)	(3.059)	(-9.077)	(32.625)