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SYSTEMIC RISK MEASURES:
TAKING STOCK FROM 1927 TO 2023

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ABSTRACT

We assess the efficacy of systemic risk measures that rely on U.S. financial firms' stock return co-movements with market- or sector-wide returns under stress from 1927 to 2023. We ascertain stress episodes based on widening of corporate bond spreads and narrative dating. Systemic risk measures exhibit substantial and robust predictive power in explaining the cross-section of market realized outcomes, viz., volatility and returns, during stress episodes. The measures also help predict bank failures and balance-sheet outcomes, confirming their relevance for understanding risks to the real economy emanating from banking sector fragility. Overall, market-based systemic risk measures offer a promising complement to macro-prudential and supervisory assessments of the financial sector.

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1 Introduction

More than 15 years after the 2007/8 global financial crisis (GFC) when banks and non-bank financial intermediaries failed *en masse*, it is time to evaluate the key systemic risk measures that emerged in its wake. Financial regulation underwent a fundamental shift since the GFC. Instead of focusing solely on *microprudential* regulation, which emphasizes the stress of individual institutions in isolation, *macroprudential* regulation, which addresses systemic risk, i.e., the risk that the entire financial system is under stress, became paramount.[1] General equilibrium channels, such as fire sales and liquidity spirals and their real-sector consequences such as credit crunch and lack of market intermediation, gained primary importance. Researchers, therefore, looked for empirical measures of financial vulnerability that had explanatory power for where such channels might be the most powerful at work.

Systemic risk measures that emerged have both a cross-sectional and a time dimension. Cross-sectionally, systemic risk measures are directional. Some capture how much the risk of a specific financial institution spills over to the rest of the financial sector, while others measure how much an individual institution is exposed to a system-wide financial crisis. Some others combine such information with that on non-equity liabilities to estimate under-capitalization of financial firms under stress. The time-series component of systemic risk measures arises from their ability to serve as early warning indicators of a potential financial crisis. Ideally, these measures should also determine whether a financial crisis is a temporary phenomenon, indicating economic resilience, or a more prolonged, permanent, issue (Brunnermeier, 2024). In practice, resilience is shaped ex post by the choice of specific public policies which systemic risk measures may reflect ex ante (at least to some extent).

This article evaluates the efficacy of systemic risk measures that rely on U.S. financial firms' stock return co-movements with market- or sector-wide returns under stress over the period from 1927 to 2023. Specifically, it examines the contribution and exposure versions of CoVaR (Adrian & Brunnermeier, 2016), the Marginal Expected Shortfall or the MES (Acharya et al., 2017), and SRISK (Acharya, Engle & Richardson, 2012). All four measures are depicted in Figure 1. The paper identifies stress episodes shown as gray bars in Figure 1, using a two-step procedure. First, episodes are identified based on narrative analysis and previous studies that date financial crises or stress periods. Second, the start and end points of each episode are specified based on the elevation of the Gilchrist & Zakrajšek (2012) credit spread, for the period from 1959 to 2023, and for the earlier period from 1927 to 1958, alternative credit spread measures are used due to sparser data availability.

Our empirical analysis shows that these systemic risk measures exhibit substantial and robust predictive power in explaining future cross-section of market outcomes. Financial institutions with higher systemic risk measures are projected to experience higher volatility and lower returns during subsequent stress episodes. This is especially the case for banks. In addition, the systemic risk measures also help predict bank failures beyond the predictions based solely on Call Reports and balance-sheet accounting measures. Moreover, the systemic risk measures also improve the predictability of banking sector outcomes affecting the real economy such as loan growth, commercial and industrial (C&I) loan growth, real estate loan growth, return on assets, and growth in the ratio of uninsured deposits to total deposits.

[1]Note that Acharya (2009) and Crockett (2000); Borio (2003) were important precursors of this shift.

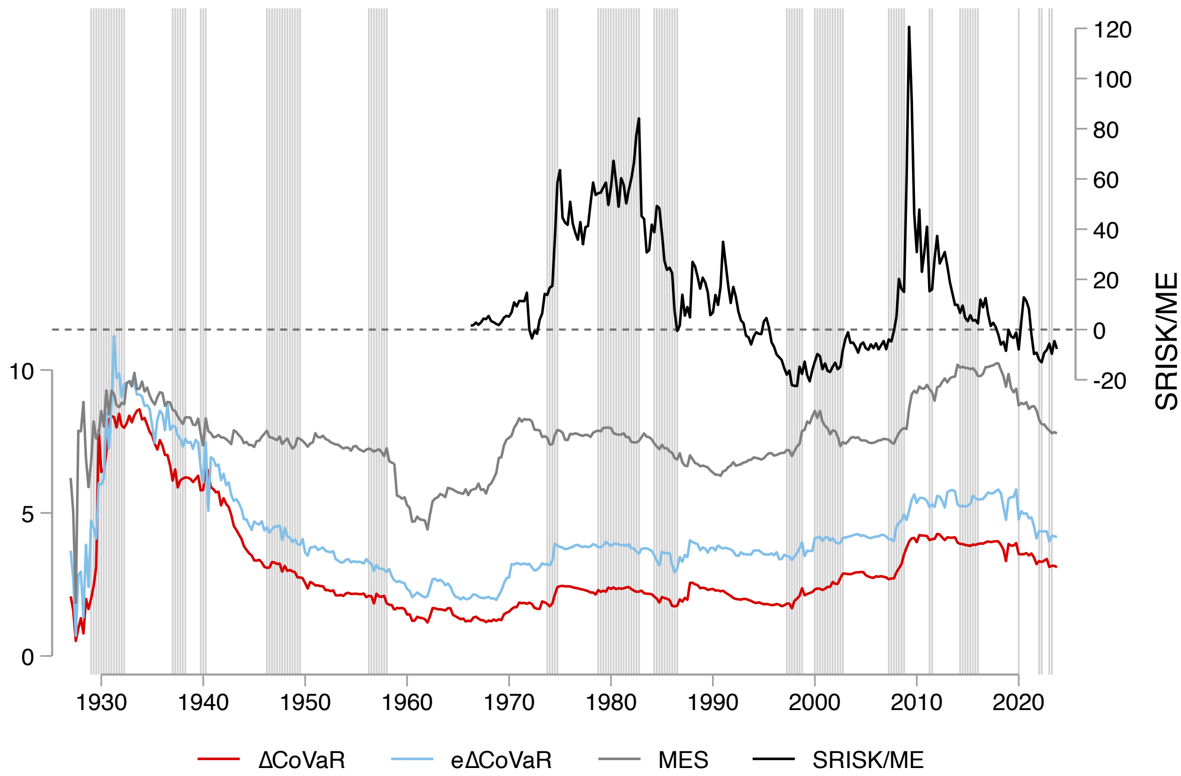

Figure 1: Market-capitalization weighted average ΔCoVaR, eΔCoVaR, MES and SRISK divided by the market capitalization (ME) from 1927 until 2023. The grey vertical bars represent the Moody's spread peak-to-trough quarters until 1973, and the GZ spread peak-to-trough quarters after 1973.

In summary, market-based systemic risk measures appear over a long period of time to pass the efficacy test of predicting the cross-section, the time-series, and the real-sector transmission of financial stress. Our findings highlight, therefore, that market-based systemic risk measures should be a crucial part of the toolbox for macroprudential and supervisory assessments of the financial sector. Unlike traditional regulatory accounting measures, our systemic risk measures do not suffer from the backward-looking bias, since these measures are based on stock market prices. For example, prior to the GFC, accounting and regulatory ratios (such as the Basel risk-weight based capitalization ratios) created the misleading illusion that banks had sufficiently large equity cushions. While regulatory stress tests adopted since the GFC are also useful remedies, they continue to rely on regulatory risk weights (Acharya, Engle & Pierret, 2014), depend on specific stress scenarios that do not necessarily evolve with the evolving nature of financial risks, and are therefore less robust. At a minimum, market-based systemic risk measures analyzed in this article offer substantial promise as valuable complementary tools to regulatory stress tests.

The structure of this article is as follows: Section 2 describes the data sources and definition of stress episodes, as well as the systemic risk measures. Section 3 documents the predictive power of systemic risk measures in predicting subsequent stress volatility and returns, bank failures, and real variables. Section 4 focuses on the earlier episodes before 1959 for which data sources are scarce. Section 5 concludes with some directions for further research.

2 Data and Methodology

2.1 Data and Sample

We use daily stock prices from the Center for Research in Security Prices (CRSP) Database from December 1925 to December 2023, for all (5,417) financial institutions in the United States (U.S.), where "financial institutions" are defined based on the same SIC codes used in Adrian & Brunnermeier (2016). The CRSP dataset is merged with Compustat to retrieve total bank liabilities that are available starting in 1965.

The balance sheet and income statement variables are from the Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income ("Call Reports"), available for the sample of commercial banks and collected from 1959 onwards by Correia, Luck & Verner (2024). We use the CRSP-FRB linking table of the Federal Reserve of New York to match the CRSP database to Call Reports from 1986 to 2023. The rest of the sample (1959-1986) is matched manually based on the name and location of the bank. Call Reports are aggregated at the parent bank level using the FFIEC relationship table, where the parent is the bank with publicly listed stocks in the CRSP database.

We also use the list of bank failures and assistance transactions from the Federal Deposit Insurance Corporation (FDIC) from 1934 to the present (similarly to Correia, Luck & Verner, 2024). Finally, the macroeconomic variables and financial indices we use in this paper are detailed in the next section.

2.2 Definition of Stress Episodes

Our methodology for dating stress episodes uses several sources, including data on corporate bond spreads, previous banking studies, and a narrative analysis of stress events. We first identify broad event "windows" from multiple sources. For the "early" sample spanning 1927 to 1958, the years of the event window are selected from stock market crashes and banking crisis years identified for the U.S. in Reinhart & Rogoff (2009, 2011) ("RR years" hereafter). For the "modern" sample spanning 1959 to 2023, we rely on a narrative analysis of the most recent stress episodes to identify window years in addition to RR years. The narrative of stress episodes as well as a detailed description of our methodology are provided in the Appendix. Although our methodology differs from Reinhart & Rogoff (2009),[2] the selection of event windows based on the narrative complements their database, which ends in 2010.

Second, we search for the trough and peak values of a credit spread for each window to determine the start and end months of the episode, respectively. As the credit spread, we use the Gilchrist & Zakrajšek (2012) corporate bond spread index, commonly referred to as the GZ spread, which is available monthly starting in 1973. The GZ spread is constructed as an unweighted average of credit spreads from senior unsecured bonds issued by U.S. non-financial firms. It reflects the average credit risk premium demanded by investors for holding corporate bonds over risk-free securities. Prior to 1973, we use the difference between Moody's Seasoned Baa and Aaa Corporate Bond Yield indices. Moody's corporate bond yields are available monthly starting in January 1919 from the Federal Reserve Bank of St. Louis database FRED.

The modern stress episodes identified with our methodology are listed in Panel A of Table 1, together with the start date, end date, length in months of the episode, the corresponding

[2] The identification of stock market crashes in Reinhart & Rogoff (2009) is based on real equity prices following the methodology of Barro & Ursúa (2017), while our methodology relies on nominal corporate bond spreads.

percentage point change in the GZ spread, and the returns on the S&P500 index and a CRSP financial index we build as a market-capitalization weighted average of stock prices of financial institutions in the CRSP database. We additionally report the maximum drawdown ("dd") on the S&P500 and CRSP financial indices. The maximum drawdown is the percentage difference between the minimum index value and its prior maximum value within an episode. All reported estimates are from nominal spreads and indices, constrasting with the RR approach based on real equity prices.[3] Among modern stress episodes, the GFC was the most severe with a 6.4 percentage points (p.p.) increase in the GZ spread and negative corrections to the S&P500 and CRSP financial stock indices of 41 and 52 percent, respectively, over 18 months from May 2007 to November 2008. The largest increase in the GZ spread during the GFC is followed by the Covid19 Pandemic (2.37 p.p. increase over 3 months), and the Dot.com Bubble (2.36 p.p. increase over 33 months).

The five early stress episodes are listed in Panel B of Table 1. Since the S&P500 index is not available for the full sample, we instead report the returns and maximum drawdowns on the Dow Jones Industrial Average (DJI) index. We note that the Great Depression was the most severe among early episodes, with a credit spread increase of almost 5 p.p., and negative corrections to the DJI and CRSP financial stock indices of 86 and 96 percent, respectively, over 39 months from February 1929 to May 1932.

Our methodology yields more episodes than those identified in the literature on crises (Bordo et al., 2001; Reinhart & Rogoff, 2011; Laeven & Valencia, 2013, 2020; Jordà, Schularick & Taylor, 2015). For example, the Jordà-Schularick-Taylor Macrohistory Database lists 1930, 1984, and 2007 as the first years of a systemic banking crisis. In contrast, the episodes in Table 1 also include periods that could be described as episodes of stressed conditions in credit and stock markets.

Finally, to validate the identification of stress episodes in Table 1, we use eight alternative definitions of stress episodes that we detail in the Appendix. The alternative definitions are independent from the narrative analysis and RR years. We instead use the worst quarters of credit risk indices, stock indices, realized stock volatility, and other macroeconomic variables as stress episode dates. We analyze the convergence of the different definitions for the modern sample, and find that the dates classified as stress episodes by most definitions are included in the episodes presented in Table 1.

2.3 Systemic Risk Measures

While a range of systemic risk measures have been proposed in the literature (for example, Billio et al., 2012; Huang, Zhou & Zhu, 2009; Huang, Zhou & Haibin, 2012),[4] we focus on two sets that rely on the co-movement of a financial firm's market return with that on aggregate market indices under stress. In particular, we focus on $\triangle$CoVaR and the exposure $\triangle$CoVaR (e$\triangle$CoVaR) of Adrian & Brunnermeier (2016), and MES and SRISK of Acharya, Engle & Richardson (2012), Acharya et al. (2017), and Brownlees & Engle (2017).

[3]For example, during the 1977–82 stock market crash episode, the S&P500 index and the CRSP financial index showed positive nominal returns of 44 p.p. and 43 p.p., respectively, over the episode, since the indices are not inflation-adjusted. However, the episode also features maximum drawdowns in nominal terms of -24 p.p. and -34 p.p. on the S&P500 index and the CRSP financial index, respectively.

[4]See Bisias et al. (2012) for a comprehensive survey of systemic risk analytics.

2.3.1 Definitions

△CoVaR. △CoVaR is the change in the value-at-risk (VaR) of the financial system portfolio conditional on a firm being under "distress" relative to its median "state":

$$\Delta CoVaR^{system|i} = CoVaR^{system|X^i=VaR^i_q} - CoVaR^{system|X^i=VaR^i_{50}}, \quad (1)$$

where $\Pr(X^{system}|X^i = VaR^i_q \leq CoVaR^{system|X^i=VaR^i_q}_q) = q$, X^i is a "return loss" for firm i, $X^{system} = -r^{system}$ is the net return loss for a financial index, and q=95% in the distress state as opposed to q=50% in the median state.

e△CoVaR. e△CoVaR is the exposure △CoVaR, defined as the change in the VaR of the firm conditional on the financial index being under distress (q=95%) relative to its median state:

$$e\Delta CoVaR^{i|system} = eCoVaR^{i|X^{syst}=VaR^{syst}_q} - eCoVaR^{i|X^{syst}=VaR^{syst}_{50}}. \quad (2)$$

The estimation of △CoVaR of firm i at time t, $\Delta CoVaR^i_{q,t}$ (with q=95%), requires the estimation of $\beta^i_{q,t}$ from quantile regressions, and the estimation of the median and 95% quantile of the firm's return loss distribution: $\Delta CoVaR^i_{q,t} = \hat{\beta}^i_{q,t}(VaR^i_{q,t} - VaR^i_{50,t})$. Similarly, $e\Delta CoVaR^i_{q,t}$ (with q=95%) requires the estimation of $\beta^{i,e}_{q,t}$ from quantile regressions, and the estimation of the median and 95% quantile of the system return loss distribution: $e\Delta CoVaR^i_{q,t} = \hat{\beta}^{i,e}_{q,t}(VaR^{syst}_{q,t} - VaR^{syst}_{50,t})$.

LRMES and MES. The Long-Run Marginal Expected Shortfall (LRMES) is the six-month return loss of a firm conditional on a 40% loss ($C = -0.4$) on the market index:

$$LRMES_{it} = -\mathrm{E}_t(R_{it+1:t+h}|R_{mt+1:t+h} < C). \quad (3)$$

In contrast, the Marginal Expected Shortfall (MES) is the weekly return loss of the firm conditional on a $-c$ loss on the market index during a week:

$$MES_{it} = -\mathrm{E}_t(R_{it+1}|R_{mt+1} < c). \quad (4)$$

The LRMES can be approximated by $LRMES^{stat}_{it} = -\sqrt{h}\beta_i \mathrm{E}\left(r_{mt+1}|r_{mt+1} < c\right)$ (Brownlees & Engle, 2017), where $r_{mt} = \log(1 + R_{mt})$ is the market logarithmic return, β_i is the market beta of firm i, h is the forecast horizon, and $c = \log(1 + C)/\sqrt{h}$. In addition, $\mathrm{E}\left(r_{mt+1}|r_{mt+1} < c\right)$ is a function of market volatility σ_m, as described in the Appendix. Using this approximation, LRMES is a simple function of the MES: $LRMES_{it} = \sqrt{h}MES_{it}$.

SRISK. SRISK is the expected capital shortfall (in U.S. dollars) of the firm in the aggregate stress scenario described in eq. (3):

$$SRISK_{it} = k * (ME_{it}(1 - LRMES_{it}) + D_{it}) - ME_{it}(1 - LRMES_{it}), \quad (5)$$

where ME_{it} is the market value of equity of institution i, D_{it} are its total non-equity liabilities. We also use a measure of market leverage $Lvg_{it} = A_{it}/ME_{it}$, where quasi-market assets $A_{it} = ME_{it} + D_{it}$, and $k \leq ME_{it}/A_{it}$.

2.3.2 Estimation

Measures are derived at the end of each month based on a rolling window of ten years of weekly return data available up to that month. We derive $\triangle$CoVaR, e$\triangle$CoVaR, LRMES, and MES from January 1927 until December 2023. SRISK is derived for a shorter time period starting in the 1960s due to the limited availability of liabilities from Compustat. We additionally require at least three years of available returns for the estimation of systemic risk measures for the modern sample.

The system return for $\triangle$CoVaR and e$\triangle$CoVaR is the return on the CRSP financial index. The market index for (LR)MES is the S&P500 index for the modern sample, and the CRSP financial index for the early sample, due to the unavailability of the S&P500 index for early dates. We employ $C = -0.4$ (-40%), $k = 0.08$ (8%), and $h = 24$ weeks (six months), consistent with the choices made at NYU Stern VLAB (vlab.stern.nyu.edu/srisk).

2.3.3 Systemic risk from 1927 to 2023

We show the market-capitalization weighted averages of $\triangle$CoVaR, e$\triangle$CoVaR, MES, and the ratio of SRISK divided by the firm's market capitalization (ME) in Figure 1 for the entire sample period. $\triangle$CoVaR and e$\triangle$CoVaR reached their maximum values during the Great Depression, while the average MES level was the highest between the European sovereign debt crisis and the pandemic. SRISK/ME is only available starting in the 1960s, and reached a maximum value of 120% of the financial sector market capitalization during the GFC.[5] SRISK can also take negative values when a financial institution has a capital surplus. This is notably the case in the late 1990s and early 2000s, when the average SRISK/ME was negative as a result of low market leverage. In the Appendix, we decompose SRISK/ME as a linear function of (LR)MES and market leverage. We therefore also report the results for MES and market leverage separately throughout the paper.

In Table 2, we report unweighted average systemic risk measures separately for the early sample and the modern sample in Panel A, and for banks and non-banks in Panel B. We compare the measures three years and one year before the stress episode, as well as during the episode. We additionally report SRISK/ME for the modern sample. The average SRISK/ME ratio is negative during stress episodes due to non-bank financial institutions having capital surpluses. While all systemic risk measures are high before a crisis and then decrease during the episode in the modern sample, this pattern is not always confirmed in the early sample. This is mainly due to systemic risk measures increasing only during the three years of the Great Depression but not before.

We compare banks and non-bank financial institutions (non-banks) in Panel B for the modern sample, where banks correspond to institutions for which we could identify a unique identifier (RSSD ID) assigned by the Federal Reserve in its National Information Center (NIC) database. We find that measures capturing a co-movement with the market index ($\triangle$CoVaR, e$\triangle$CoVaR, and MES) are all larger for non-banks. In contrast, measures that integrate leverage like SRISK/ME are larger for banks. We also report the ratio of SRISK scaled by the quasi-market assets (SRISK/A), and the ratio SRISKp/ME which is equal to SRISK/ME for undercapitalized financial institutions (i.e., for institutions with positive SRISK), and zero otherwise. All SRISK ratios show a similar pattern of larger capital shortfalls (or smaller surpluses) at banks relative to non-banks, and in

[5] During the GFC, some large financial institutions had capital shortfalls according to SRISK that amounted to several times their market capitalizations, explaining the SRISK/ME peak above 100% of the sector market capitalization during that episode. Starting in the mid-1970s and into the 1980s, large values of the SRISK/ME ratio came from high market leverage as many institutions' market capitalization fell while their total liabilities continued to increase. This period was challenging for financial institutions due to unfavorable economic conditions, and in particular the ongoing effects of the 1973 oil crisis, coupled with stagflation, and high interest rates.

particular, before the stress episodes. Similarly, capitalization measures point to the undercapitalization of banks, compared to non-banks: market leverage (Lvg) is larger, and the ratio of book equity to assets (book_eq) is smaller for banks.

3 Predictive Regressions

For the modern sample, we assess the ability of systemic risk measures to predict the cross-section of (i) financial firm outcomes, viz., realized volatility and market returns of banks and non-banks (Section 3.1); (ii) bank failures (Section 3.2); and, (iii) bank balance-sheet outcomes (Section 3.3). Given the limited nature of the exercise for the early sample due to data availability constraints, we present the analysis for the early period separately in Section 4.

3.1 Market Outcomes

We estimate the following specification to predict market outcomes of banks and non-banks during a stress episode:

$$\begin{aligned} y_{ie} &= \beta_1 Measure_{ie} \times bank_i + \beta_2 Measure_{ie} \times (1 - bank_i) \\ &\quad + (\beta_3 bank_i + \beta_4 (1 - bank_i)) \times book\_eq_{ie} \\ &\quad + (\delta_1 bank_i + \delta_2 (1 - bank_i)) \times control_{ie} + \alpha\, bank_i + \alpha_e + \epsilon_{ie} \end{aligned} \tag{6}$$

where y_{ie} is the average market outcome of firm i during stress episode e (9 episodes), $bank_i$ is an indicator variable taking the value of one for banks and zero for non-banks, and α_e are episode fixed effects. The systemic risk measure, $Measure_{ie}$, the ratio of book equity to total assets $book\_eq_{ie}$, and the variable $control_{ie}$ controlling for firm size are all measured the quarter before the episode starts. The size of a financial institution is a clear confounding variable of systemic risk measures in this regression, given its correlation with both the measures and the market outcomes. We use the logarithm of the firm market capitalization as a measure of firm size. We could alternatively use the logarithm of total assets but this variable is available only for a limited sample.

The market outcomes we consider are the quarterly realized volatility in Table 3, Panel A, and the quarterly realized returns in Table 3, Panel B. The quarterly realized market outcomes are averaged during each episode, such that we have a cross-section of banks per episode. We report in Columns (1) and (2) the results of a baseline regression excluding systemic risk measures from the regression (i.e., imposing $H_0 : \beta_1 = \beta_2 = 0$). The other columns report the estimates when including respective systemic risk measures.

From the two panels of Table 3, we make the following observations. First, systemic risk measures predict increased volatility and lower returns realized during a stress episode. There are few exceptions that occur for non-banks or when episode fixed effects are included.[6] In general, the effect of systemic risk measures is larger for banks than non-banks, with the exception of e$\triangle$CoVaR and MES predicting higher realized volatility for non-banks in Table 3. The adjusted R-squared also shows improvement in the regressions with systemic measures compared to the baseline results in Column (1). For realized volatility regressions, the largest improvements come from MES and leverage in Column (11), followed by e$\triangle$CoVaR in Column (5). For predicting

[6]We also note that there is no substantial improvement in the adjusted R-squared from adding systemic risk measures when the regressions already include episode fixed effects. Despite the estimates associated with the systemic risk measures being statistically significant, part of their variation that predicts episode realized outcomes is absorbed by the episode fixed effects.

realized returns, the largest improvement comes from adding $\triangle$CoVaR in Column (3). We also note that the regression fit systematically improves when we decompose SRISK/ME and estimate separate parameters for its components MES and Lvg.

3.2 Bank Failures

Correia, Luck & Verner (2024) show that bank failures are surprisingly predictable using simple accounting metrics from banks' financial statements. In this section, we replicate their results at the consolidated parent bank level, and add systemic risk measures to the predictive model. The parent bank is the bank with publicly listed stocks, and we define a failure at the parent bank level if the parent or any of its offspring banks, identified from the FFIEC relationship table, failed or received assistance from the FDIC. We count 51 bank failures out of 1,131 institutions in the modern sample. The last three bank failures in our sample are Silicon Valley Bank, Signature Bank, and First Republic Bank, which respectively failed on March 7, 2023; March 12, 2023; and May 1, 2023. While these bank failures correspond to a stress episode according to our definition in Table 1, bank failure dates do not always coincide with a stress episode and are in fact often delayed (notably, following the GFC). To retain a maximum number of bank failures in the analysis, we do not condition our sample on stress episodes in this section.

3.2.1 Systemic risk trends before failure

The date of a bank failure is defined in our sample as the date of the last available Call Report for the bank that failed or received assistance according to the FDIC. Correia, Luck & Verner (2024) show gradually deteriorating trends in solvency indicators during the ten years before a bank's failure. We study the dynamics in systemic risk indicators of failing banks using the same methodology. Specifically, we estimate: $y_{it} = \alpha_i + \sum_{j=-40}^{-1} \beta_j \times \mathbf{1}_{j=t} + \epsilon_{it}$, where y_{it} is a systemic risk indicator or a capitalization measure of a failing bank, j measures the number of quarters before failure, and α_i are bank fixed effects. The sample is restricted to banks that failed from 1959 through 2023, and the ten years before they failed. The trends in systemic risk indicators before failure are captured by the sequence $\{\beta_j\}$, which is presented in Figure 2.

From Figure 2, we note that all systemic risk indicators increase in the year before failure. $\triangle$CoVaR, e$\triangle$CoVaR and MES respectively increase six, seven, and eight quarters before the last Call Report is filed by the failing bank. In the three quarters before the bank files its last Call report, SRISK/ME and market leverage are significantly larger and the book equity ratio is significantly smaller than ten years before failure. For example, SRISK/ME increases by almost two standard deviations the quarter before the last Call Report relative to ten years before failure. Measures that capture co-movements with a market index increase by less than a standard deviation, but start increasing earlier.

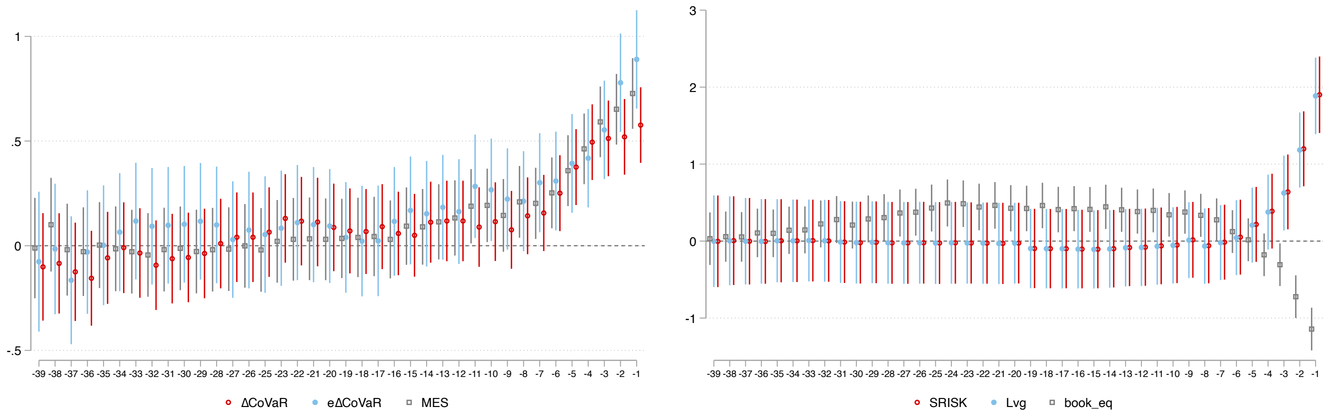

Figure 2: The figure presents the sequence of coefficients from estimating $y_{it} = \alpha_i + \sum_{j=-40}^{-1} \beta_j \times \mathbf{1}_{j=t} + \epsilon_{it}$ (see Correia, Luck & Verner, 2024), where the dependent variable is a quarterly systemic risk or capitalization measure indicated in the figure legend. The sample is restricted to banks that failed from 1959 through 2023, and the ten years before they fail. All measures are scaled by their standard deviations.

3.2.2 Predicting bank failures

Next, we compare failing banks with their non-failing counterparts. We estimate the following specification to predict a bank failure in the next year:

$$Failure_{i,t+1\to t+h} = \alpha + \beta Measure_{it} + \epsilon_{i,t+1\to t+h} \tag{7}$$

where $Failure_{i,t+1\to t+h} = 1$ if a bank fails in the next h quarters and is equal to zero otherwise, and $h = 4$ (one year). We show the OLS estimates of this regression in Table 4, where $Measure_{it}$ is $\triangle$CoVaR in Column (1), e$\triangle$CoVaR in Column (2), MES in Column (3), SRISK/ME in Column (4), MES controlling for market leverage in Column (5), market leverage in Column (6), and the ratio of book equity to total assets in Column (7). We report the adjusted R-squared of each linear probability model, and the Pseudo R-squared from a corresponding logit regression. Finally, to quantify the predictive power of each measure, we construct receiver operating characteristic curves (ROC) and compare the area under the curve (AUC) of each logit model. The ROC curve shows the true positive rate as a function of the false positive rate for any classification threshold. We display the ROC curves in Figure 3 (left panel), and report the AUC of each model in Table 4. A model with an AUC of 0.5 is uninformative and corresponds to the green reference line in Figure 3. Models with AUC above 0.5 are more likely to predict true failures than false ones.

Table 4 shows that all systemic risk measures predict a higher probability of bank failure in the next year. In addition, banks with lower market leverage or which are better capitalized according to the book equity ratio are less likely to fail. The capital structure of the bank appears to be a strong predictor of bank failure. The AUC is the largest for SRISK/ME (0.911) that includes both MES and market leverage, followed by market leverage (0.887), MES combined with market leverage (0.880), and the book equity ratio (0.815). From the left panel of Figure 3, we observe a similar pattern where measures that are a function of the capital structure of the bank (SRISK/ME, market leverage, book equity ratio) are better predictors of bank failures than the systemic risk measures capturing co-movements with the market index under stress conditions ($\triangle$CoVaR, e$\triangle$CoVaR, and MES).

To compare the predictive performance of the systemic risk measures with the results of Correia, Luck & Verner (2024), we estimate the following specification, which is closer to their model for predicting a bank failure in the next year:

$$\begin{aligned} Failure_{i,t+1\to t+h} \quad = \quad & \alpha + \beta_1 Solvency_{it} + \beta_2 Funding_{it} + \beta_3 Solvency_{it} \times Funding_{it} \\ & + \beta_4 Growth_{it} + \beta_5 AggregateConditions_t + \beta_6 Measure_{it} + \epsilon_{i,t+1\to t+h} \end{aligned} \tag{8}$$

where $Solvency_{it}$, $Funding_{it}$, $Growth_{it}$, and $AggregateConditions_t$ are taken from Correia, Luck & Verner (2024) and respectively capture the risk of insolvency, the reliance on non-core funding, the asset growth of the bank, and the aggregate economic conditions. $Solvency_{it}$ is the ratio of net income to total assets, $Funding_{it}$ is the ratio of time deposits to total deposits, and $Growth_{it}$ is the asset growth of the bank over the past three years. As an indicator of aggregate economic conditions, we deviate from Correia, Luck & Verner (2024), who use GDP growth, and instead use the GZ spread, which better aligns with our definition of stress episodes. The estimates of this regression are reported in Table 5, together with the AUC of corresponding ROC curves that are displayed in the right panel of Figure 3.

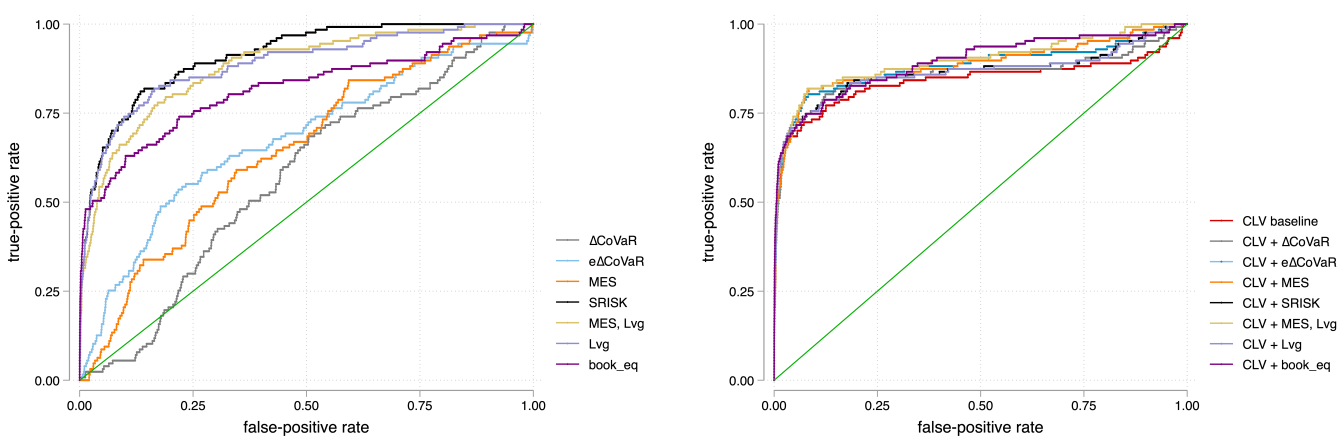

Figure 3: Receiver operating characteristic curves (ROC) from predicting bank failures next year using systemic risk or capitalization measures. The left panel displays the ROC curves relative to the classification models based on eq. (7). The right panel displays the ROC curves relative to the classification models based on eq. (8), controlling for variables used in Correia, Luck & Verner (2024) (referred to as "CLV"). The red ROC in the left panel refers to the baseline classification model using CLV variables only, the other ROC curves are obtained from models also including systemic risk or capitalization measures described in the legend.

The first observation from Table 5 and the right panel of Figure 3 is that systemic risk measures are complementary to the indicators in the model of Correia, Luck & Verner (2024). We use the latter as our reference model (denoted "CLV"), and report the associated estimates in Column (1).[7] We find that all measures capturing the performance of the predictive models —adjusted R-squared, Pseudo R-squared, and AUC— improve compared to the baseline CLV model. The second observation is that the measures that summarize the predictive performance of each model do not improve to a large extent when we add additional measures to the baseline CLV model,

[7] We note that the estimates we obtain for this baseline model have the same signs as the estimates in Correia, Luck & Verner (2024) (Table B9), despite the different sample used in our analysis. In contrast to their methodology, we estimate the probability of failure at the parent bank level, and our sample is limited to publicly traded banks.

indicating that this model is already performing well in predicting bank failures. The AUC of the baseline CLV model in Column (1) is 0.841, and the largest AUC of 0.898 is obtained for the model that features both MES and market leverage in Column (6), followed by the AUC of 0.892 for the book equity ratio in Column (8), and 0.885 for MES in Column (4).[8] Similarly, the ROC curves displayed in the right panel of Figure 3, where the red curve stands for the baseline CLV model, are also closer to each other reflecting fewer discrepancies in the predictive performance of the models analyzed in this figure.

Finally, while for understanding how stress conditions impact the estimates of the predictive model, we use the GZ spread as our indicator of aggregate economic conditions and estimate the following specification that interacts it with bank-level measures to predict a bank failure in the next year:

$$\begin{aligned} Failure_{i,t+1\to t+h} \;=\;& \alpha + \beta_1 Solvency_{it} + \beta_2 Funding_{it} + \beta_3 Solvency_{it} \times Funding_{it} \\ & + \beta_4 Growth_{it} + \beta_5 Measure_{it} + \gamma gz_t + [\delta_1 Solvency_{it} + \delta_2 Funding_{it} \\ & + \delta_3 Solvency_{it} \times Funding_{it} + \delta_4 Growth_{it} + \delta_5 Measure_{it}] \times gz_t + \epsilon_{i,t+1\to t+h} \end{aligned} \tag{9}$$

where gz_t is the GZ spread (Gilchrist & Zakrajšek, 2012) in quarter t. The β parameters capture the marginal effect of each indicator under a counterfactual GZ spread of zero. In contrast, the δ parameters capture the differential effect of each indicator in predicting bank failure when the GZ spread is wider by one percentage point. For example, to gauge the differential effect of the indicators during the GFC where the GZ spread reached a peak of almost 8 percentage points, the δ estimates should be multiplied by a factor of 8.[9] The marginal effect of an indicator in the linear probability model is therefore $\beta + 8\delta$ during the worst months of the GFC. The OLS estimates of all δ parameters and β_5 of this regression are reported in Table 6, together with the corresponding AUC of ROC curves for each model.

Comparing Column (1) of Table 5 and Column (1) of Table 6, we note an improvement in the predictive accuracy of the baseline CLV model that is simply due to adding the interaction terms with our indicator for aggregate stress. The AUC increases from 0.841 to 0.852 for the same sample of observations. The estimates of CLV variables interacted with the GZ spread are all statistically significant at the 5% level at least, suggesting that these variables strongly predict failure probability in stressed economic conditions. We find a similar result for systemic risk measures and capitalization measures, except for SRISK/ME and market leverage in Columns (5) and (7), respectively. For these two indicators, the ability to predict bank failure does not depend on the level of the GZ spread, and banks with a larger SRISK/ME or market leverage are always more likely to fail. For other systemic risk measures —△CoVaR, e△CoVaR, and MES— the predictive power depends on economic conditions. For the lowest value of the GZ spread of 0.6 percentage points observed in 1978, the marginal effects of a one percentage point increase in △CoVaR, e△CoVaR, and MES, are respectively 12, 9, and 7 percent increase in the failure rate. They compare to marginal effects during the GFC of 170, 124, and 101 percent increase in the failure rate, respectively. Comparing the predictive performance of the models presented in Table 6, the largest AUC is obtained for the model featuring MES and market leverage (0.919), followed by book equity (0.907), and e△CoVaR (0.901). Consistent with previous results, all systemic risk

[8]The AUC we obtain in our analyses should not to be compared to the AUC reported in Correia, Luck & Verner (2024) since the sample is different. Similarly, the AUC of Tables 5 and 6 should not to be compared to the AUC in Table 4, since the number of observations differs. The same applies to the adjusted R-squared and the Pseudo R-squared.

[9]See Figure 1 (Panel A) in Favara et al. (2016).

and capitalization measures seem to add value to predicting bank failures as they all exhibit larger AUCs compared to the baseline model of Column (1).

3.3 Balance Sheet Outcomes

To assess how financial fragility proxied by our systemic risk measures might affect the real economy, we analyze their impact on bank balance sheets in a stress episode. We follow a methodology similar to the one adopted in Section 3.1. We focus on outcomes reported by banks in Call Reports during stress episodes, and measure systemic risk the quarter before the starting date of the episode as identified in Table 1 (Panel A). We estimate the following specification to predict bank balance sheet outcomes during a stress episode:

$$y_{ie} \quad = \quad \beta Measure_{ie} + \delta controls_{ie} + \alpha_e + \epsilon_{ie} \tag{10}$$

where y_{ie} is the average balance sheet outcome of bank i during episode e, and α_e are episode fixed effects. The variables $controls_{ie}$ include the size of the bank and its book equity ratio measured the quarter before the episode starts, and as a pre-trend, the average balance sheet outcome during the year prior to the episode.

The estimates of this regression are presented in Table 7, where the dependent variable is, successively, the loan growth, the commercial and industrial (C&I) loan growth, the real estate loan growth, the return on assets, and the growth in the ratio of uninsured deposits to total deposits. Growth variables are quarterly percentage growth rates, and the return on assets is the quarterly net income divided by lagged total assets. Dependent variables are then averaged over the quarters of an episode for each bank to construct y_{ie}. $Measure_{ie}$ corresponds to $\triangle$CoVaR in Columns (1) and (2), e$\triangle$CoVaR in Columns (3) and (4), MES in Columns (5) and (6), SRISK/ME in Columns (7) and (8), and MES (controlling for market leverage) in Columns (9) and (10).

Table 7 shows that systemic risk measures predict reduced loan growth, lower bank profitability, and less reliance on uninsured deposits during stress episodes. For example, a one p.p. increase in $\triangle$CoVaR is associated with a -1.43 p.p. average loan growth rate in a stress episode. Interestingly, when we decompose loans in the two main categories of C&I and real estate loans, we find that $\triangle$CoVaR and e$\triangle$CoVaR significantly predict real estate loan growth, while MES and SRISK/ME better predict C&I loan growth. Systemic risk indicators also predict lower bank profitability in a stress episode. For example, a one p.p. increase in MES is associated with a -0.02 percent return on assets which corresponds to 2.5 times its standard deviation. Finally, not all systemic risk measures have statistically significant estimates for predicting uninsured deposits dynamics, but $\triangle$CoVaR and MES estimates are statistically significant at the 1% level. Both measures predict a loss of uninsured deposits as opposed to insured ones in a stress episode, which coincides with the interpretation of runs by uninsured depositors from banks with poor fundamentals.

Overall, these results are consistent with banking fragility leaving the economy less resilient in terms of bank credit and funding outcomes; crucially, the fragility can be predicted by market-based measures of bank systemic risk.

4 Predictive Regressions for the Early Period: 1927-1958

In this section, we aim to predict outcomes of financial institutions during the early stress episodes that occurred between 1927 and 1958. This exercise is significantly more challenging due to data limitations. The early sample corresponds to the period before banks were required to file Call Reports. The Compustat dataset also begins reporting accounting data starting only in the 1960s. We therefore lack the accounting data required to construct SRISK. In addition, the coverage of stock prices for banks in CRSP is limited during that period. The sample includes 85 financial institutions; among them, only 29 are banks according to SIC codes, and 13 of these banks were delisted and disappeared from the CRSP sample before 1930. We will therefore focus on the systemic risk measures (△CoVaR, e△CoVaR, and MES) that do not require accounting data, and on a sample that is mostly composed of non-bank financial institutions.

Specifically, we count 17 banks and 42 non-banks that satisfy the data requirements for the estimation of the following specification to predict market outcomes during the early episodes:

$$y_{ie} \quad = \quad \beta Measure_{ie} + \delta control_{ie} + \alpha_e + \epsilon_{ie} \tag{11}$$

where y_{ie} is the average market outcome of financial institution i during stress episode e (i.e., one of the five episodes defined in Panel B of Table 1). The systemic risk measure $Measure_{ie}$ and the control variable for firm size $control_{ie}$ are measured the quarter before the episode starts. The estimates of this regression are presented in Table 8. The dependent variable is the average realized volatility in Panel A, and the average realized returns in Panel B. Compared to eq. (6), we do not estimate parameters for banks and non-banks separately, given the small number of banks. We also do not control for the book equity ratio that is not available for this sample.

Table 8 shows that the results of Section 3.1 for the modern sample are confirmed in early episodes of stress. △CoVaR, e△CoVaR, and MES predict increased volatility and lower returns realized during a stress episode. The largest adjusted R-squared in both realized volatility and realized returns regressions is obtained with △CoVaR when controlling for the financial institution's size but excluding episode fixed effects (Column (2)), and is followed by MES (Column (8)).

Although we faced significant data constraints, we were able to compute SRISK for the eight national banks in our sample during the period from 1928 to 1936, using data collected by Correia, Luck & Verner (2024). Due to the limited size of this sample and the fact that seven of these banks were delisted and disappeared from the CRSP dataset by 1928, it was not feasible to replicate the regression specification of eq. (11). However we could derive simple Spearman rank correlations on this limited sample for the ratio of SRISK to market capitalization. Our analysis reveals a positive correlation of 0.48 with realized volatility, and a negative correlation of -0.1 with realized returns, suggesting that SRISK would also predict increased realized volatility and lower realized returns in the early sample.

Overall, despite the data limitations inherent in the early sample, our results indicate that systemic risk measures such as △CoVaR, e△CoVaR, MES, and SRISK/ME retain their predictive power for market outcomes during stress episodes. This underscores the robustness of these measures across different time periods and economic conditions, though clearly more research is warranted to put together stock market data on a larger sample of banks and combine it with their balance sheets for important historical episodes such as the Great Depression.

5 Conclusion

In this paper, we documented robust cross-sectional predictive power in stock market based systemic risk measures for financial fragility —adverse stock market returns for financial firms, bank failures, and deterioration in the growth of bank deposits, credit and profitability— witnessed over the period 1927 to 2023. One, significant data challenges preclude an analysis of a more substantive sample of banks in the pre-FDIC era when banking panics were significantly more commonplace. Expanding datasets and systemic risk measurement remains an important gap to fill. Secondly, both non-bank financial intermediaries (NBFIs) and deposit-like wholesale finance claims have evolved significantly over the sample period we studied. How has the systemic risk of NBFIs evolved over time and what role has reliance on wholesale liabilities played in this evolution? Thirdly, banks and NBFIs have become significantly interconnected over time via both term lending and provision of credit lines by banks. How does this interconnection show up in systemic risk measures? Finally, an advantage of using stock prices of financial firms in systemic risk measurement is that they are least vulnerable to a bias arising from public backstops. Nevertheless, the role of these backstops has continued to rise, for banks as well as NBFIs. Has this affected the efficacy of systemic risk measures over time? Clearly, there is much scope for further research.

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Panel A: Modern Sample (1959-2023)								
episode	start	end	months	GZ	SP500		fin. index	
				sprd (%)	ret (%)	dd (%)	ret (%)	dd (%)
High inflation in the U.S.	9-1973	12-1974	15	1.75	-36.77	-41.40	-35.73	-46.82
1977-82 stock market crash	10-1978	10-1982	48	1.21	43.54	-23.79	43.44	-34.12
S&L Crisis	5-1984	8-1986	27	1.58	68.00	0	54.24	-11.14
LTCM hedge fund failure	8-1997	10-1998	14	1.12	22.15	-15.57	-10.08	-36.40
Dot.com Bubble	1-2000	10-2002	33	2.36	-36.48	-46.28	-24.11	-36.84
Global Financial Crisis	5-2007	11-2008	18	6.44	-41.45	-42.16	-52.09	-52.09
European Sovereign Debt Crisis	3-2011	9-2011	6	1.16	-14.66	-17.03	-18.99	-20.15
2014-16 oil price shock	6-2014	2-2016	20	1.52	-1.43	-8.89	0.90	-9.81
Covid19 Pandemic	12-2019	3-2020	3	2.37	-20.00	-20.00	-18.47	-18.47
Ukraine war/energy crisis	12-2021	6-2022	6	0.70	-20.58	-20.58	-8.77	-8.77
Bank Failures in 2023	1-2023	5-2023	4	0.15	2.53	0	-2.96	-5.97

Panel B: Early Sample (1927-1958)								
episode	start	end	months	Moody's	DJI		fin. index	
				sprd (%)	ret (%)	dd (%)	ret (%)	dd (%)
The Great Depression	2-1929	5-1932	39	4.64	-85.90	-88.24	-95.59	-95.59
Recession of 1937–38	2-1937	4-1938	14	1.86	-40.34	-47.13	-49.50	-60.00
1939-41 stock market crash	10-1939	6-1940	8	0.42	-19.63	-23.48	-19.42	-31.00
Post-World War II Recession	3-1946	7-1949	40	0.32	-11.85	-21.42	5.22	-15.25
Recession of 1958	4-1956	1-1958	21	0.79	-12.81	-15.86	-16.21	-23.39

Table 1: Stress episodes description. Panel A describes the eleven modern stress episodes (1959-2023), while Panel B describes the five early stress episodes (1927-1958). "start" and "end" respectively indicate the start date and the end date of the episode, and "months" is the length in months of the episode. "GZ sprd" is the change in the GZ spread (Gilchrist & Zakrajšek, 2012) in percentage points. "Moody's sprd" is the change in the spread between Moody's Baa and Aaa Corporate Bond Yields in percentage points. "SP500" is the S&P500 index, "DJI" is the Dow Jones Industrial Average index, "fin. index" is the CRSP financial index. "ret" denotes the index return in percentage points over the episode. "dd" is the maximum drawdown on an index, defined as the percentage difference between its minimum and the prior maximum value within an episode. There is no drawdown when the minimum index value is reached at the beginning of the episode.

Panel A: early vs. modern sample

	early sample			modern sample		
	3y before	1y before	stress	3y before	1y before	stress
ΔCoVaR	3.55	3.44	3.82	1.80	1.76	1.54
eΔCoVaR	6.23	6.16	6.09	2.67	2.68	2.42
MES	8.85	8.75	8.42	5.06	5.01	4.67
SRISK/ME				11.18	2.04	-2.70

Panel B: banks vs. non-banks (modern sample)

	banks			non-banks		
	3y before	1y before	stress	3y before	1y before	stress
ΔCoVaR	1.76	1.74	1.51	1.82	1.77	1.54
eΔCoVaR	2.55	2.61	2.24	2.72	2.70	2.48
MES	4.35	4.37	3.85	5.34	5.26	4.98
SRISK/ME	19.45	10.95	5.85	6.08	-3.26	-7.70
SRISK/A	-2.10	-2.41	-2.63	-14.29	-15.19	-14.39
SRISKp/ME	37.60	29.65	25.50	37.64	29.59	24.98
Lvg	12.48	11.38	11.06	9.75	8.63	8.29
book_eq	9.76	9.79	9.24	27.43	27.82	25.27

Table 2: Descriptive statistics. The table presents unweighted average systemic risk measures for quarters respectively three years and one year before the start date of a stress episode (resp. "3y before" and "1y before"), and during the stress episode ("stress"). Panel A presents descriptive statistics separately for the early sample (1927-1958) and for the modern sample (1959-2023). Panel B presents descriptive statistics for banks and non-banks separately, over the modern sample period (1959-2023). SRISK/ME is SRISK scaled by the market capitalization, SRISK/A is SRISK scaled by quasi-market assets, SRISKp is the positive truncated SRISK, Lvg is the market leverage, and book_eq is the ratio of book equity to total assets.

	Panel A: Realized volatility during stress episodes					
Measure:	baseline		ΔCoVaR		eΔCoVaR	
	(1)	(2)	(3)	(4)	(5)	(6)
Measure×bank			0.32	0.63**	0.78***	0.72***
			(1.01)	(2.04)	(3.66)	(3.54)
Measure×nonbank			-0.64***	-0.56**	1.29***	1.11***
			(-2.78)	(-2.10)	(7.77)	(6.77)
book_eq×bank	-0.03	-0.26**	-0.03	-0.28**	-0.05	-0.27**
	(-0.40)	(-2.51)	(-0.48)	(-2.56)	(-0.69)	(-2.54)
book_eq×nonbank	-0.01*	-0.01**	-0.01*	-0.01**	-0.00*	-0.01**
	(-1.68)	(-2.34)	(-1.67)	(-2.33)	(-1.71)	(-2.22)
Observations	6,436	6,436	6,436	6,436	6,436	6,436
Adj. R-squared	0.032	0.262	0.033	0.264	0.058	0.280
Episode FE	N	Y	N	Y	N	Y
Measure:	MES		SRISK/ME		MES (+Lvg)	
	(7)	(8)	(9)	(10)	(11)	(12)
Measure×bank	0.37***	0.75***	2.65***	3.18***	0.09	0.46***
	(2.59)	(5.40)	(6.47)	(6.64)	(0.70)	(3.69)
Measure×nonbank	0.68***	0.94***	0.34***	0.26	0.68***	0.96***
	(7.82)	(9.33)	(2.70)	(1.35)	(7.71)	(9.54)
Lvg×bank					0.21***	0.26***
					(6.38)	(6.33)
Lvg×nonbank					0.02*	0.01
					(1.94)	(0.59)
book_eq×bank	-0.03	-0.28***	0.15**	-0.04	0.16**	-0.05
	(-0.50)	(-2.65)	(2.06)	(-0.66)	(2.06)	(-0.85)
book_eq×nonbank	-0.01**	-0.01***	-0.00	-0.01*	-0.00*	-0.01***
	(-2.34)	(-3.27)	(-1.30)	(-1.86)	(-1.95)	(-2.99)
Observations	6,436	6,436	6,436	6,436	6,436	6,436
Adj. R-squared	0.050	0.295	0.047	0.280	0.062	0.310
Episode FE	N	Y	N	Y	N	Y

Panel B: Realized returns during stress episodes						
Measure:	baseline		ΔCoVaR		eΔCoVaR	
	(1)	(2)	(3)	(4)	(5)	(6)
Measure×bank			-7.83***	-4.22***	-2.31***	-1.57***
			(-7.86)	(-4.41)	(-3.99)	(-3.40)
Measure×nonbank			-2.72***	-0.40	-0.06	-0.06
			(-2.92)	(-0.45)	(-0.12)	(-0.12)
book_eq×bank	-1.82***	-0.18	-1.68***	-0.14	-1.77***	-0.15
	(-5.58)	(-0.96)	(-5.35)	(-0.72)	(-5.60)	(-0.82)
book_eq×nonbank	-0.01	0.01	-0.01	0.01	-0.01	0.01
	(-0.45)	(0.77)	(-0.46)	(0.71)	(-0.45)	(0.75)
Observations	6,436	6,436	6,436	6,436	6,436	6,436
Adj. R-squared	0.006	0.245	0.011	0.246	0.007	0.246
Episode FE	N	Y	N	Y	N	Y
Measure:	MES		SRISK/ME		MES (+Lvg)	
	(7)	(8)	(9)	(10)	(11)	(12)
Measure×bank	-1.36***	-1.13***	-5.21***	-4.84***	-0.87**	-0.72**
	(-3.25)	(-3.24)	(-5.77)	(-5.27)	(-2.07)	(-2.06)
Measure×nonbank	0.60	-0.14	-0.08	0.58**	0.61	-0.21
	(1.29)	(-0.38)	(-0.40)	(2.54)	(1.30)	(-0.57)
Lvg×bank					-0.37***	-0.36***
					(-5.01)	(-5.06)
Lvg×nonbank					-0.02	0.05**
					(-1.04)	(2.51)
book_eq×bank	-1.80***	-0.17	-2.18***	-0.51***	-2.13***	-0.48**
	(-5.50)	(-0.91)	(-5.54)	(-2.72)	(-5.47)	(-2.57)
book_eq×nonbank	-0.01	0.01	-0.01	0.01	-0.01	0.01
	(-0.44)	(0.76)	(-0.46)	(0.91)	(-0.45)	(0.94)
Observations	6,436	6,436	6,436	6,436	6,436	6,436
Adj. R-squared	0.007	0.246	0.008	0.247	0.009	0.247
Episode FE	N	Y	N	Y	N	Y

Table 3: Predictive regression of realized volatility (Panel A) and realized returns (Panel B) during stress episodes (1959-2023). The dependent variable is the average market outcome of a financial institution during stress episodes. The systemic risk measure (Measure), the ratio of book equity to total assets (book_eq), and the control variable for the firm size are all measured the quarter before the episode starts. Stress episodes are defined in Table 1. Measure is △CoVaR in Columns (3) and (4), e△CoVaR in Columns (5) and (6), MES in Columns (7) and (8), SRISK as a fraction of the firm's market capitalization (ME) in Columns (9) and (10), and MES (controlling for market leverage, Lvg) in Columns (11) and (12). Coefficient estimates on SRISK/ME and Lvg are multiplied by 100. The even Columns (2) to (12) include episode fixed effects. t-statistics based on standard errors clustered at the firm level are reported in parentheses. Sample: 2,241 financial institutions, including 777 banks.

	Failure probability (fail in next year)						
Measure:	ΔCoVaR (1)	eΔCoVaR (2)	MES (3)	SRISK/ME (4)	MES (+Lvg) (5)	Lvg (6)	book_eq (7)
Measure	0.06**	0.11***	0.06***	0.87***	0.05***	0.07***	-0.15***
	(2.06)	(6.80)	(5.45)	(43.49)	(4.94)	(43.21)	(-13.99)
Lvg					0.07***		
					(43.15)		
Observations	33,250	33,250	33,250	33,250	33,250	33,250	33,250
Adj. R-squared	0.000	0.001	0.001	0.054	0.054	0.053	0.006
Pseudo R2 (logit)	0.002	0.025	0.017	0.117	0.127	0.115	0.195
AUC	0.571	0.676	0.647	0.911	0.880	0.887	0.815

Table 4: Predicting bank failures: systemic risk and capitalization measures. The dependent variable is equal to one if the bank fails in the next year, and zero otherwise. Measure is $\triangle$CoVaR in Column (1), e$\triangle$CoVaR in Column (2), MES in Column (3), SRISK/ME in Column (4), MES controlling for market leverage in Column (5), market leverage in Column (6), and the ratio of book equity to total assets in Column (7). OLS estimates and adjusted R-squared refer to the linear probability model described in eq. (7). Coefficient estimates on SRISK/ME and Lvg are multiplied by 100. Pseudo R-squared are obtained from corresponding logit regressions. AUC is the area under the receiver operating characteristic (ROC) curve.

	Failure probability (fail in next year)							
Measure:	CLV	ΔCoVaR	eΔCoVaR	MES	SRISK/ME	MES(+Lvg)	Lvg	book_eq
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
solvency	0.48***	0.49***	0.49***	0.49***	0.49***	0.50***	0.49***	0.46***
	(8.39)	(8.43)	(8.58)	(8.54)	(8.68)	(8.76)	(8.65)	(7.96)
funding	0.04***	0.05***	0.05***	0.05***	0.03***	0.04***	0.03***	0.04***
	(20.95)	(21.90)	(23.35)	(23.51)	(15.62)	(16.85)	(14.64)	(19.45)
solvency×funding	-4.93***	-4.93***	-4.91***	-4.93***	-4.07***	-4.10***	-4.08***	-4.85***
	(-36.18)	(-36.18)	(-36.10)	(-36.19)	(-29.50)	(-29.70)	(-29.56)	(-34.46)
asset_growth	0.02	0.03	0.03	0.04	0.23***	0.23***	0.22***	-0.01
	(0.33)	(0.47)	(0.48)	(0.58)	(3.26)	(3.30)	(3.17)	(-0.12)
aggregate_cond	0.16***	0.14***	0.17***	0.17***	0.20***	0.20***	0.20***	0.17***
	(4.92)	(4.30)	(5.16)	(5.18)	(6.19)	(6.30)	(6.12)	(5.19)
Measure		0.20***	0.18***	0.12***	0.61***	0.10***	0.05***	-0.03**
		(6.74)	(10.75)	(10.87)	(28.75)	(8.72)	(28.10)	(-2.36)
Lvg						0.05***		
						(27.32)		
Observations	33,208	33,208	33,208	33,208	33,208	33,208	33,208	33,208
Adj. R-squared	0.072	0.073	0.075	0.075	0.094	0.095	0.093	0.072
Pseudo R2 (logit)	0.280	0.291	0.312	0.309	0.314	0.335	0.313	0.357
AUC	0.841	0.859	0.882	0.885	0.865	0.898	0.863	0.892

Table 5: Predicting bank failures: systemic risk and capitalization measures, controlling for variables used in Correia, Luck & Verner (2024) (denoted "CLV"). The first column refers to the baseline CLV model without additional measure of systemic risk or capitalization. Measure is △CoVaR in Column (2), e△CoVaR in Column (3), MES in Column (4), SRISK/ME in Column (5), MES controlling for market leverage in Column (6), market leverage in Column (7), and the ratio of book equity to total assets in Column (8). OLS estimates and adjusted R-squared refer to the linear probability model described in eq. (8). Coefficient estimates on asset growth, aggregate conditions (proxied by the GZ spread in percentage points), SRISK/ME, and Lvg are multiplied by 100. Pseudo R-squared are obtained from corresponding logit regressions. AUC is the area under the receiver operating characteristic (ROC) curve.

	Failure probability (fail in next year)							
Measure:	CLV	ΔCoVaR	eΔCoVaR	MES	SRISK/ME	MES(+Lvg)	Lvg	book_eq
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
solvency×gz	0.30***	0.32***	0.34***	0.34***	0.33***	0.36***	0.33***	0.34***
	(7.04)	(7.51)	(7.99)	(7.95)	(7.88)	(8.69)	(7.82)	(7.64)
funding×gz	2.32***	2.77***	2.69***	2.87***	2.13***	2.84***	2.18***	2.45***
	(11.73)	(13.41)	(13.28)	(14.05)	(10.68)	(13.62)	(10.89)	(12.20)
solvency×funding×gz	-1.37***	-1.35***	-1.34***	-1.33***	-1.58***	-1.57***	-1.59***	-1.49***
	(-14.30)	(-14.14)	(-13.99)	(-13.92)	(-16.56)	(-16.45)	(-16.67)	(-14.70)
asset_growth×gz	-17.04**	-17.46**	-18.69**	-17.47**	-15.11**	-17.12**	-15.68**	-16.47**
	(-2.28)	(-2.34)	(-2.51)	(-2.35)	(-2.04)	(-2.32)	(-2.12)	(-2.18)
Measure		-0.28***	-0.17***	-0.16***	0.65***	-0.20***	0.05***	-0.12***
		(-4.05)	(-4.10)	(-5.98)	(13.73)	(-7.41)	(14.24)	(-4.53)
Measure×gz		21.29***	15.52***	12.63***	-0.30	13.10***	-0.16	3.73***
		(7.34)	(9.16)	(11.10)	(-0.16)	(11.56)	(-1.04)	(3.39)
Lvg						0.06***		
						(15.21)		
Lvg×gz						-0.39**		
						(-2.49)		
Observations	33,208	33,208	33,208	33,208	33,208	33,208	33,208	33,208
Adj. R-squared	0.083	0.086	0.088	0.089	0.108	0.112	0.107	0.084
Pseudo R2 (logit)	0.285	0.298	0.318	0.314	0.319	0.340	0.317	0.366
AUC	0.852	0.875	0.901	0.898	0.890	0.919	0.887	0.907

Table 6: Predicting bank failures: systemic risk and capitalization measures interacted with the GZ spread (denoted "gz") in percentage points. Systemic risk and capitalization measures are varied across columns as in Table 5. OLS estimates and adjusted R-squared refer to the linear probability model described in eq. (9). Coefficient estimates on asset growth, gz, SRISK/ME, and Lvg are multiplied by 100, and on solvency are divided by 100. Pseudo R-squared are obtained from corresponding logit regressions. AUC is the area under the receiver operating characteristic (ROC) curve.

Measure:	ΔCoVaR		eΔCoVaR		MES		SRISK/ME		MES (+Lvg)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
loan growth										
Measure	-1.43***	-1.19**	-0.46***	-0.31**	-0.39***	-0.28**	-0.77***	-0.44	-0.33**	-0.26**
	(-2.92)	(-2.11)	(-2.81)	(-2.00)	(-3.17)	(-2.14)	(-4.30)	(-1.60)	(-2.48)	(-1.99)
Lvg									-0.05***	-0.03
									(-3.00)	(-1.08)
Observations	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Adj. R-squared	0.006	0.005	0.003	0.004	0.004	0.004	0.003	0.004	0.004	0.004
C&I loan growth										
Measure	-1.25**	-1.09	-0.61**	-0.49*	-0.71***	-0.59***	-1.40***	-0.90**	-0.59***	-0.55***
	(-2.08)	(-1.22)	(-2.03)	(-1.65)	(-3.72)	(-2.75)	(-4.16)	(-2.47)	(-2.94)	(-2.60)
Lvg									-0.09***	-0.06
									(-3.18)	(-1.64)
Observations	2,202	2,202	2,202	2,202	2,202	2,202	2,202	2,202	2,202	2,202
Adj. R-squared	0.007	0.156	0.006	0.156	0.010	0.159	0.009	0.157	0.012	0.159
real estate loan growth										
Measure	-1.85***	-1.38**	-0.57***	-0.44***	-0.33	-0.00	-1.25***	-0.46	-0.18	0.03
	(-2.58)	(-1.98)	(-3.35)	(-2.96)	(-1.44)	(-0.01)	(-3.58)	(-1.54)	(-0.74)	(0.08)
Lvg									-0.11***	-0.05**
									(-3.61)	(-2.23)
Observations	2,210	2,210	2,210	2,210	2,210	2,210	2,210	2,210	2,210	2,210
Adj. R-squared	0.010	0.159	0.005	0.158	0.005	0.157	0.007	0.157	0.008	0.157
return on assets										
Measure	-0.03*	0.01	-0.03***	-0.02***	-0.02***	-0.01**	-0.07**	-0.07**	-0.01*	-0.01*
	(-1.82)	(0.46)	(-3.20)	(-2.84)	(-2.60)	(-2.58)	(-2.27)	(-1.98)	(-1.71)	(-1.96)
Lvg									-0.01***	-0.01***
									(-3.13)	(-3.07)
Observations	2,227	2,227	2,227	2,227	2,227	2,227	2,227	2,227	2,227	2,227
Adj. R-squared	0.184	0.297	0.188	0.301	0.185	0.299	0.192	0.307	0.198	0.312
uninsured deposit growth										
Measure	-1.17***	-0.31	-0.55**	-0.31	-0.44**	-0.31*	-1.64	-1.23	-0.34**	-0.27
	(-2.90)	(-0.68)	(-2.03)	(-1.10)	(-2.35)	(-1.67)	(-1.27)	(-0.83)	(-2.02)	(-1.56)
Lvg									-0.10	-0.08
									(-0.94)	(-0.69)
Observations	1,726	1,726	1,726	1,726	1,726	1,726	1,726	1,726	1,726	1,726
Adj. R-squared	0.013	0.030	0.012	0.030	0.013	0.031	0.014	0.032	0.015	0.032
Episode FE	N	Y	N	Y	N	Y	N	Y	N	Y

Table 7: Predictive regression of balance sheet outcomes during stress episodes (1959-2023). The dependent variable is an average balance sheet outcome of a bank during a stress episode. The systemic risk measure (Measure) and the control variables are all measured the quarter before the episode starts. Control variables include the firm size, book equity ratio, and the average bank outcome the year before the episode starts. Stress episodes are defined in Table 1. Measure is indicated in the first line of the table. Coefficient estimates on SRISK/ME and Lvg are multiplied by 100. The even Columns (2) to (10) include episode fixed effects. t-statistics based on standard errors clustered at the bank level are reported in parentheses.

Panel A: realized volatility (during stress episodes)									
Measure:		ΔCoVaR			eΔCoVaR			MES	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Measure	2.22***	2.12***	2.21***	1.62***	0.95**	0.64	2.16***	1.45***	1.41***
	(4.25)	(4.83)	(3.35)	(3.02)	(2.21)	(1.26)	(5.94)	(4.54)	(4.09)
Observations	171	171	171	171	171	171	171	171	171
Adj. R-squared	0.103	0.379	0.447	0.178	0.332	0.418	0.227	0.368	0.479
Size control	N	Y	Y	N	Y	Y	N	Y	Y
Episode FE	N	N	Y	N	N	Y	N	N	Y

Panel B: realized returns (during stress episodes)									
Measure:		ΔCoVaR			eΔCoVaR			MES	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Measure	-4.89***	-4.72***	-2.56*	-2.49**	-1.31	0.13	-3.18***	-1.89	-1.60
	(-3.38)	(-3.31)	(-1.81)	(-2.21)	(-1.21)	(0.18)	(-2.94)	(-1.47)	(-1.58)
Observations	171	171	171	171	171	171	171	171	171
Adj. R-squared	0.046	0.117	0.173	0.037	0.079	0.167	0.043	0.084	0.177
Size control	N	Y	Y	N	Y	Y	N	Y	Y
Episode FE	N	N	Y	N	N	Y	N	N	Y

Table 8: Predictive regression of realized volatility (Panel A) and realized returns (Panel B) during stress episodes (1927-1958). The dependent variable is the average market outcome of a financial institution during stress episodes. The systemic risk measure (Measure), and the control variable for the firm size are all measured the quarter before the episode starts. Stress episodes are defined in Table 1 (Panel B). Measure is △CoVaR in Columns (1) to (3), e△CoVaR in Columns (4) to (6), and MES in Columns (7) and (9). Columns (3), (6) and (9) include episode fixed effects. t-statistics based on standard errors clustered at the firm level are reported in parentheses. Sample: 59 financial institutions, including 17 banks.

Systemic Risk Measures:
Taking Stock from 1927 to 2023
Online Appendix

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This appendix provides additional details about the sample construction in Section 1, the definition of stress episodes in Section 2, and the definition and estimation of systemic risk measures in Section 3.

1 Data and Sample Description

1.1 CRSP/Compustat Sample

Our initial sample comprises daily equity data from the Center for Research in Security Prices (CRSP) Database for all financial institutions with two-digit Compustat SIC codes between 60 and 67, as in Adrian & Brunnermeier (2016). Following their methodology, we retain only ordinary common shares and exclude daily equity observations with missing or negative prices. This yields a sample of 5,417 financial institutions with unique identifying PERMCO codes in CRSP, covering the period from December 31, 1925, to December 29, 2023. Market capitalization is calculated by multiplying the number of shares outstanding by the stock price. We derive logarithmic returns and aggregate the data at the weekly frequency to estimate systemic risk measures, and at the quarterly frequency to derive realized returns and realized volatility.

We detail the estimation procedure for monthly systemic risk measures that capture co-movements of financial firms' returns with the returns on an index ($\triangle$CoVaR, e$\triangle$CoVaR, MES, LRMES) in Section 3. Additionally, the systemic risk measure SRISK is a function of LRMES, firm market capitalization, and total non-equity liabilities, as defined in eq. (4) of the paper. We obtain the total liabilities of financial institutions from Compustat, merging the Compustat dataset with our stock returns and systemic risk measures aggregated at the quarterly frequency, resulting in a sample of 4,452 financial firms with unique identifying PERMCO codes. While total asset data are available starting in the first quarter of 1962, total liabilities data are only available for a sample of 3,762 financial firms beginning in the first quarter of 1965 and continuing until the last quarter of 2023.

1.2 Call Reports and FDIC Bank Failures & Assistance Data

In addition to Compustat data, we use balance sheet and income statement variables from the Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income ("Call Reports"). Call Report data are available for the sample of commercial banks, collected from 1959 onwards by Correia, Luck & Verner (2024). Merging Call Reports with the CRSP dataset of stock data and systemic risk measures involves two steps: (1) assigning regulatory identification numbers (RSSD ID) to banks reporting in CRSP, and (2) reconstructing the structure of bank ownership to aggregate the Call Reports at the parent bank level corresponding to the institution reporting in CRSP.

In the first step, we use the NY Fed CRSP-FRB Linking Table.[1] This table dynamically links the permanent company number (PERMCO) used in CRSP to the unique regulatory identification numbers used in Call Reports (RSSD ID), including 1,471 PERMCO-RSSD links from June 30, 1986, to September 29, 2023. For the period from the first quarter of 1959 to the first quarter of 1986, we extend the links of banks present in the CRSP dataset (after June 1986) backward in time for our list of PERMCOs. For the 384 PERMCOs that appear only before June 1986 in the CRSP

[1] NY Fed CRSP-FRB Linking Table available at: https://www.newyorkfed.org/research/banking_research/crsp-frb

dataset, we manually matched 159 of them with RSSD identifiers based on the bank's name and location (when available from Compustat), using the National Information Center (NIC) website (https://www.ffiec.gov/NPW).

In the second step, we identify the parent bank as the entity in CRSP with an identifying PERMCO, and reconstruct the structure of bank ownership using the FFIEC Relationships Table.[2] We link subsidiary banks to their parents after applying the following filters: we exclude non-controlled relationships; retain only relationships identified after an "initial relationship record" or a "reestablishment of a relationship"; keep only direct relationships; exclude non-equity-based relationships; exclude investments in non-banking companies; exclude unregulated relationships; and exclude relationships if the ownership or control pertains to a non-banking company. The resulting sample includes 9,109 subsidiary banks linked to 1,619 parent banks, ensuring that each subsidiary is linked to only one parent. For the 505 subsidiaries linked to more than one parent, we select the parent bank with the largest percentage of ownership or control in the subsidiary (PCT_EQUITY). However, some of the Call Reports data are not available for the full sample period. This is notably the case of the classification of deposits into (un)insured deposits, which is only available starting in the second quarter of 1982.

Finally, we merge the sample of 9,109 banks with the list of bank failure and assistance transactions from the Federal Deposit Insurance Corporation (FDIC) using the FDIC certificate number (also available to identify institutions in the dataset of Correia, Luck & Verner, 2024).[3] We identify 177 bank failures or assistance transactions in our sample, starting in 1959. The FDIC data are lagged by one quarter to ensure they match the last Call Report data available for the bank before its failure. All data are then aggregated at the parent bank-quarter level for a sample of 1,344 consolidated banks with stock prices available in CRSP.

2 Stress Episodes

We describe our methodology for dating stress episodes in Section 2.1. The narrative analysis of recent stress episodes is presented in Section 2.2. We then analyze the convergence of several stress episode definitions in Section 2.

2.1 Methodology

Our procedure for dating stress episodes involves two steps. First, we identify broad event "windows" from multiple sources, including previous studies and a narrative analysis of stress events. We present the event windows in Figure 1 and Table 1. Second, we search for the trough and peak values of a credit spread relative to each window to define the start and end months of the episode. For the credit spread, we use the Gilchrist & Zakrajšek (2012) corporate bond spread index, commonly referred to as the GZ spread and available monthly starting in 1973.[4] Prior to 1973, we use the difference between Moody's Seasoned Baa and Aaa Corporate Bond Yield indices. Moody's corporate bond yields are available monthly starting in January 1919 from the Federal Reserve Bank of St. Louis database FRED.

[2]FFIEC Relationships Table available at: https://www.ffiec.gov/npw/FinancialReport/DataDownload

[3]Bank failures and assistance data available at: https://banks.data.fdic.gov/bankfind-suite/failures

[4]The GZ spread data can be accessed at: https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html

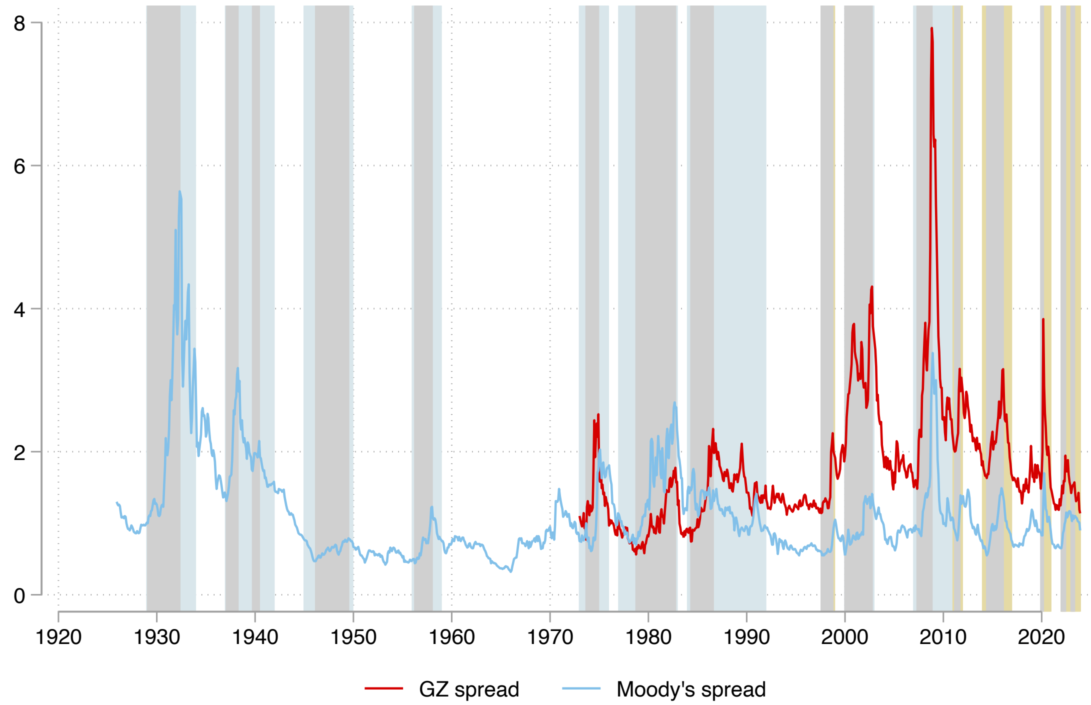

Figure 1: Stress episode dating methodology. "GZ spread" is the GZ spread (Gilchrist & Zakrajšek, 2012) in percentage points. "Moody's spread" is the spread between Moody's Baa and Aaa Corporate Bond Yields in percentage points. Blue vertical bars are the event windows based on Reinhart & Rogoff (2009) (RR) years, yellow vertical bars are the event windows based on the narrative years provided in Section 2.2 when RR years are not available, and grey vertical bars are the stress episode dates starting with the month of the trough value and ending with the month of the peak value of a credit spread (i.e., GZ spread after 1973, Moody's spread before 1973).

For the "early" sample spanning 1927 to 1958, the years of the event window are selected from stock market crashes and banking crisis years identified for the U.S. by Reinhart & Rogoff (2009, 2011) ("RR years" hereafter). Whenever NBER recession years are consecutive to RR years, we consider the largest window by taking the union of events.[5] For example, our Post-World War II Recession episode starts with an NBER recession in 1945, is followed by RR stock market crashes from 1946-1948, and ends with another NBER recession in 1949. For each episode, we identify the start and end dates as the dates corresponding to the lowest and highest values of the Moody's spread within the window. If there is no trough before the peak (i.e., the peak date is the first date of the window), there is no increase in the spread within the window, and the episode is dropped. This occurs only for the NBER recession of 1927.

For the "modern" sample spanning 1959 to 2023, we rely on a narrative analysis of the most recent stress episodes to identify window years in addition to RR years, since Reinhart & Rogoff (2009) database ends in 2010. The narrative of stress episodes is provided in Section 2.2, and

[5]However, we drop isolated NBER recessions that are not directly preceded or followed by RR years. This includes the 1953-54 NBER recession for the early period, and NBER recessions in 1960 and 1970 for the modern sample.

identifies the episode of the LTCM hedge fund failure as well as four episodes after the Global Financial Crisis (GFC), in addition to five episodes based on RR years. The post-GFC narrative episodes include the European sovereign debt crisis in 2011, the 2014-16 oil price shock, the Covid19 pandemic in 2020, the Russian-Ukrainian conflict in 2022, and the failure of regional U.S. banks in 2023. The identification of "windows" based on the narrative comes from the years mentioned in the narrative. We search for a peak value of the GZ spread within the narrative window, and a trough value before the peak date, allowing the trough date to be located slightly (i.e., a maximum of six months) before the start of the narrative window to remain conservative in our predictive regressions. Some narrative windows may overlap with the other windows. For example, the European Sovereign Debt Crisis episode starts when the GFC episode is not over yet. In this case, we start the window after the GFC years in Reinhart & Rogoff (2009).

Panel A: Modern Sample (1959-2023) Event Windows

	episode	start	end	event type
1	High inflation in the U.S.	1973	1975	1973-75 NBER recession; 1973-74 RR stock market crash
2	1977-82 stock market crash	1977	1982	1977-82 RR stock market crash; 1980 NBER recession; 1981-82 NBER recession.
3	S&L crisis	1984	1991	1984-91 RR banking crisis; 1989-91 RR stock market crash; 1990-91 NBER recession.
4	LTCM hedge fund failure	1997	1998	1998 Narrative.
5	Dot.com Bubble	2000	2002	2000-02 RR stock market crash; 2001 NBER recession
6	Global Financial Crisis	2007	2010	2007-10 RR banking crisis; 2008 RR stock market crash; 2008-09 NBER recession.
7	European Sovereign Debt Crisis	2011	2011	2009-11 Narrative.
8	2014-16 oil price shock	2014	2016	2014-16 Narrative.
9	Covid19 Pandemic	2020	2020	2020 Narrative; 2020 NBER recession.
10	Ukraine war/energy crisis	2022	2022	2022 Narrative.
11	Bank Failures in 2023	2023	2023	2023 Narrative.

Panel B: Early Sample (1927-1958) Event Windows

	episode	start	end	description
1	The Great Depression	1929	1933	1929-33 NBER recession; 1929-33 RR banking crisis; 1929-32 RR stock market crash.
2	Recession of 1937–38	1937	1938	1937-38 NBER recession; 1937 RR stock market crash
3	1939-41 stock market crash	1939	1941	1939-41 RR stock market crash.
4	Post-World War II Recession	1945	1949	1945 NBER recession; 1946-48 RR stock market crash; 1948-49 NBER recession.
5	Recession of 1958	1956	1958	1957-58 NBER recession; 1956-58 RR stock market crash.

Table 1: Description of event windows. The table presents the event windows used to search for trough and peak values of a credit spread for the identification of start and end months of stress episodes. RR stock market crash and banking crises years are from Reinhart & Rogoff (2009). The narrative of stress episode events is available in Section 2.2.

2.2 Narrative of Stress Episodes

The narrative dating of stress episodes for the modern sample is based on a variety of formal and informal sources and is reproduced in this section.

1970s: High inflation in the U.S.

- Aug 15, 1971: President Nixon announced the suspension of the convertibility of the U.S. dollar into gold, effectively ending the Bretton Woods system.
- 1971-1973: U.S. dollar experienced devaluation.
- Aug 15 - Nov 13, 1971: Nixon imposed a 90-day freeze on wages and prices.
- Nov 14, 1971: Nixon introduced second phase of the economic stabilization program.
- Dec 18, 1971: Smithsonian Agreement introduced limited flexibility in currency exchange rates without fully reinstating the prior fixed system.
- Apr 30, 1973: Nixon formally ended the second phase of wage and price control.
- Oct 17, 1973: OPEC imposed an oil embargo on countries supporting Israel in the Yom Kippur War.
- Jan 1974: Oil production cuts quadrupled the oil price from $2.9 a barrel to $11.65.
- Mar 18, 1974: Most OPEC nations end a 5-month oil embargo against the U.S.
- Aug 8, 1974: President Nixon announces his resignation.
- Dec 6, 1974: The U.S. experienced a severe market crash, with DJIA reaching its lowest point.
- Apr 1, 1979: The reformed Iranian government nationalized its oil industry.
- Jul 25 1979: Paul Volcker became the Chairman of the Fed, adopting tight monetary policies.
- Nov 4, 1979: Iranian militants stormed the U.S. embassy, initiating Iran Hostage Crisis.
- Late 1979: Oil prices surged during this period, reaching historically high levels.
- Jan 1980: Inflation (CPI) reached the peak of around 14%.

1980s: Savings and Loan Crisis, Real Estate Crash & Stock Market Crash in 1987

- 1982: Existing home sales fell nearly 50% from the peak in 1978.
- July 5, 1982: Collapse of Penn Square Bank.
- Oct 15, 1982: The Garn-St.Germain Depository Institutions Act was signed into law, relaxing regulations on savings and loans.
- Sep 19, 1984: Bailout of Continental Illinois National Bank.
- Oct 22, 1986: The Tax Reform Act was signed into law, eliminating tax incentives for real estate.
- Aug 25, 1987: The Dow Jones Industrial Average (DJIA) reached its peak at 2,722.42 points.

- Oct 16, 1987: The stock market experienced a notable decline on Friday.
- Oct 19, 1987: The U.S. stock market experiences a historic crash, with the DJIA dropping 22.6%.
- Oct 20, 1987: Global stock markets experienced significant declines in the wake of Black Monday.
- Aug 2, 1988: First Republic Bank Corporation, based in Texas, collapsed.
- Sep 1988: American Savings and Loan, a major S&L based in California, failed.
- Dec 1988: Gibraltar Savings failed.
- Apr 14, 1989: Lincoln Savings and Loan collapsed in 1989 due to risky and fraudulent activities.
- Feb 2, 1990: CenTrust Bank, an S&L association based in Miami, Florida failed.
- Sep 1, 1990: Citi's stock dropped to below $20.
- Oct 1, 1990: Citi's stock price reached its bottom, around $15.
- Nov 9, 1990: Chase's stock was traded at single-digit of around $3, with rumors that they might fail.

Sep 1998: LTCM hedge fund failure

- Aug 17, 1998: Russia defaulted on its debt obligations. LTCM experienced a huge loss as it had substantial exposure to Russian government bond.
- Sep 23, 1998: LTCM sought a bailout from major Wall Street investment banks to prevent its collapse.
- Sep 23, 1998: On the same day, Alan Greenspan, Chair of the Fed, facilitated a meeting among the banks to arrange a rescue package.
- Late Sep, 1998: A consortium of major financial institutions, including Goldman Sachs, Merrill Lynch, and J.P. Morgan, agrees to inject capital into LTCM to stabilize its positions.
- Oct 1998: LTCM's operations winded down as the fund sells off its remaining positions. o Early 2000: LTCM officially closed.

2000-2002: Dot.com Bubble

- 1995-2000: There was a surge in investments in internet-related companies.
- Mar 20, 2000: NASDAQ reached its all-time high.
- Mar 24, 2000: Dot.com bubble started to burst.
- Mar 2000 - Oct 2002: Stock prices of many internet companies continued to decline.
- Oct 9, 2002: NASDAQ hit bottom.

Global Financial Crisis

- Feb 7, 2007: HSBC announced significant losses in its subprime mortgage division.
- Aug 9, 2007: European Central Bank injected €95bn into the banking system.
- Aug 14, 2007: Fed injected $38bn into the banking system.
- Mar 16, 2008: Bear Stearns was sold to JP Morgan Chase for a fraction of its previous value.
- Jul 11, 2008: IndyMac Bancorp was seized by regulators.
- Sep 7, 2008: U.S. Government seized control of Fannie Mae and Freddie Mac.
- Sep 15, 2008: Lehman Brothers filed for bankruptcy.
- Sep 16, 2008: AIG was bailed out by the U.S. government.
- Oct 29, 2008: The DJIA experienced its largest single-day drop.
- Mar 6, 2009: The DJ hit its lowest point, closing at around 6547 points.

European Sovereign Debt Crisis

- Apr 27, 2009: Greece revealed that its budget deficit is much higher than previously reported.
- Feb 11, 2010: Greece announced austerity measures to address its debt crisis, triggering social unrest.
- Apr 23, 2010: Greece formally requested financial assistance from EU and IMF.
- May 2, 2010: EU and IMF agreed on a €110bn bailout package for Greece.
- May 6, 2010: The DJIA plunged nearly 1000 points in a matter of minutes (flash crash).
- Nov 28, 2010: Ireland requested a €67.5bn bailout package from EU and IMF.
- Aug 4, 2011: S&P downgraded the credit rating of the U.S. from AAA to AA+.
- Aug 8, 2011: European markets experienced significant losses.

Oil Price Shock in 2014-2016

- Mid-2014: Oil prices began declining from $100+ per barrel.
- Nov 27, 2014: OPEC decided not to cut oil production.
- Jun 5, 2015: U.S. crude oil inventories hit their highest level in over 80 years.
- Dec 4, 2015: OPEC maintained its decision to keep production levels unchanged.
- Jan 20, 2016: Oil prices briefly dropped below $30 per barrel.
- Feb 16, 2016: Saudi Arabia, Qatar, and Russia agreed to freeze oil production.

- Apr 17, 2016: OPEC and non-OPEC producers failed to reach an agreement on production freeze.
- Nov 30, 2016: OPEC finalized a deal to cut production by 1.2mn barrels per day.
- Dec 2016: Oil prices began to recover, with crude rising above $50 per barrel.

Repo Market Spike during COVID

- Mar 9, 2020: Stock market plunged worldwide.
- Mar 11, 2020: Repo spread in overnight market spiked.
- Mar 12, 2020: Fed announced plans to inject $1.5tn into the financial system.
- Mar 16, 2020: Fed announced relaunch of QE with $700bn in asset purchases.

Russia-Ukraine Conflict

- Feb 24, 2022: Russia invades Ukraine, leading to sharp declines in global stock markets due to increased risk aversion. Oil prices surge past $100 per barrel for the first time since 2014.
- Late February 2022: Western nations impose severe economic sanctions on Russia, including removing select Russian banks from the SWIFT payment system. The Russian ruble plummets to a record low, and the Moscow Stock Exchange suspends trading.
- Mar 8, 2022: The U.S. bans imports of Russian oil and gas; Brent crude oil prices spike to nearly $130 per barrel, exacerbating global inflation concerns.
- Mar 2022: Prices of wheat, corn, and other commodities surge as Ukraine and Russia account for a significant share of global grain exports, impacting food prices worldwide.
- Jun 15, 2022: In response to soaring inflation partly driven by the conflict, central banks including the U.S. Federal Reserve implement significant interest rate increases. The Fed raises its benchmark rate by 75 basis points, the largest hike since 1994.
- Sep 5, 2022: Russia suspends gas deliveries through the Nord Stream 1 pipeline indefinitely, citing maintenance issues. European natural gas prices hit record highs, deepening the energy crisis and impacting European economies and currencies.

Bank Failures in 2023

- Mar 10, 2023: Silicon Valley Bank closed.
- Mar 12, 2023: Signature Bank closed.
- May 1, 2023: First Republic Bank was acquired by JP Morgan Chase Bank.
- Jul 28, 2023: Heartland Tri-State Bank closed.
- Nov 3, 2023: Citizens Bank at Sac City, IA, failed.

2.3 Alternative Definitions of Modern Stress Episodes

We use several alternative definitions of stress episodes in the modern sample that are not related to the narrative of stress events in Section 2.2. Specifically, we use: (1) NBER recession dates, (2) stress episode dates corresponding to the 10% largest GZ spread, the 10% largest excess bond premium, and the 10% largest estimated probability of a recession from Gilchrist & Zakrajšek (2012), (3) stress episode dates corresponding to the 10% largest credit-to-GDP gap as defined by the Bank for International Settlement (BIS), (4) stress episode dates corresponding to the 10% worst performance quarters of an index (S&P500, CRSP financial, and CRSP bank indices), and (5) stress episode dates corresponding to the 10% largest realized volatility of the S&P500 index. In total, the definitions yield 8 additional stress episode indicators. We build an index of convergence of these indicators by simply summing the indicator variables. Figure 2 presents the convergence indicator together with the GZ spread, and our stress episode dates from the methodology outlined in Section 2.1.

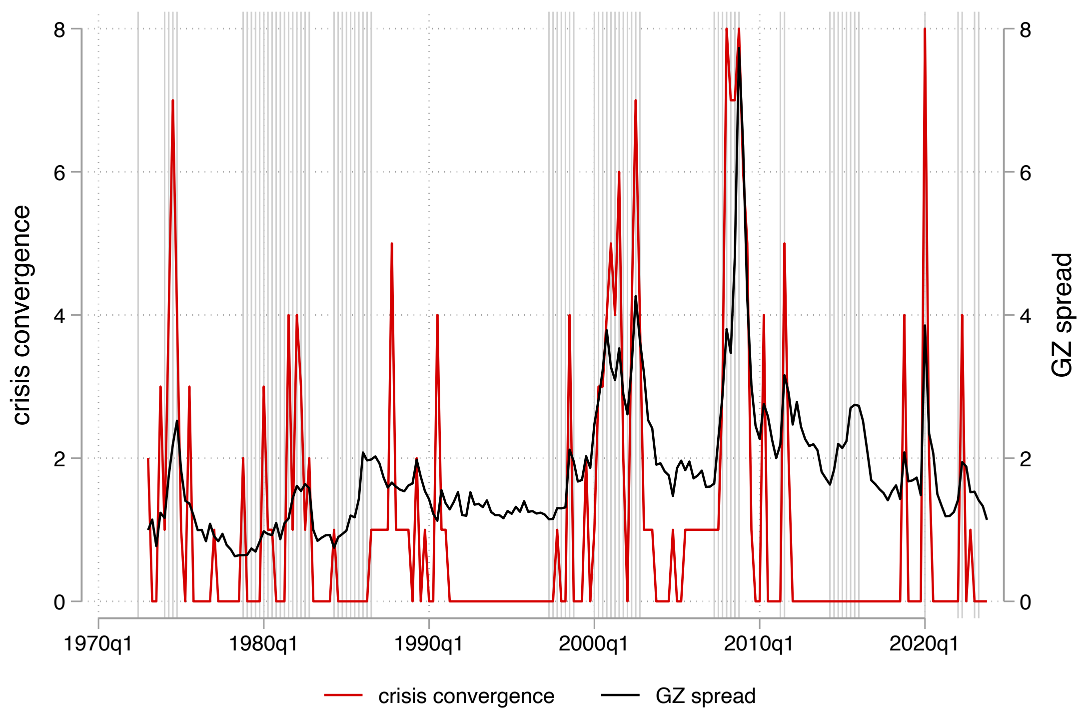

Figure 2: Stress episode convergence indicator and GZ spread. The convergence indicator takes a maximum value of 8 if all 8 alternative stress episode definitions (independent from the narrative of stress episodes in Section 2.2) indicate the date as a stress episode quarter. Vertical lines indicate stress episode quarters from the methodology outlined in Section 2.1.

3 Systemic Risk Measures: Definitions and Estimation

In this section, we provide additional details on the derivation and estimation of the △CoVaR, the exposure △CoVaR (e△CoVaR), the Marginal Expected Shortfall (MES), and the Long-Run Marginal Expected Shortfall (LRMES). We also decompose the ratio of SRISK to the firm market capitalization into a linear function of LRMES and market leverage. All systemic risk measures are defined in Section 2.3 of the paper.

3.1 △CoVaR and e△CoVaR

The "return loss" for firm i and the return loss for a financial index are respectively denoted by X^i and X^{system}. The predicted value from the quantile regression of financial system portfolio return losses on the losses of firm i gives the value-at-risk (VaR) of the financial system conditional on X^i:

$$CoVaR_q^{system|X^i} = \hat{X}_q^{system|X^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i, \tag{1}$$

where $\hat{X}^{system|X^i}$ denotes the predicted value for a q%-quantile of the financial system conditional on a return realization X^i of institution i.

Using the predicted value of $X^i = VaR_q^i$ yields the $CoVaR_q^i$ measure (precisely, $CoVaR_q^{system|X^i=VaR_q^i}$)

$$CoVaR_q^i = VaR^{system|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{2}$$

and

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{system|VaR_{50}^i} = \hat{\beta}_q^i (VaR_q^i - VaR_{50}^i). \tag{3}$$

Similarly, the $eCoVaR_q^i$ measure is obtained from:

$$eCoVaR_q^i = VaR^{i|X^{syst}=VaR_q^{syst}} = \hat{\alpha}_q^{i,e} + \hat{\beta}_q^{i,e} VaR_q^{syst} \tag{4}$$

and

$$e\Delta CoVaR_q^i = eCoVaR_q^i - eCoVaR_q^{i|VaR_{50}^{syst}} = \hat{\beta}_q^{i,e} (VaR_q^{syst} - VaR_{50}^{syst}). \tag{5}$$

The estimation of $\Delta CoVaR_q^i$ requires the estimation of $\hat{\beta}_q^i$ from quantile regressions of a financial index return losses on the firm return losses, and the estimation of the VaR at q% (VaR_q^i) and the median (VaR_{50}^i) of the firm return loss. The estimation of $e\Delta CoVaR_q^i$ requires the estimation of $\hat{\beta}_q^{i,e}$ from quantile regressions of a firm return losses on the financial index return losses, and the estimation of the VaR at q% (VaR_q^{syst}) and the median (VaR_{50}^{syst}) of the financial index return loss. We estimate $\hat{\beta}_q^i$, $\hat{\beta}_q^{i,e}$, VaR_q^i, VaR_q^{syst}, VaR_{50}^i, and VaR_{50}^{syst} at the end of each month based using a sample of ten years of weekly logarithmic return losses on firm stock price and a financial index available up to that month. We use $q = 95\%$ and, and for the financial index, we use the CRSP financial index, which is defined as the market-capitalization weighted average of stock prices of financial institutions in the CRSP database.

3.2 LRMES and MES

The firm and market logarithmic returns are respectively denoted by $r_{it} = -X^i$ and r_{mt}, and are assumed to be i.i.d. from a bivariate normal distribution with zero mean. The market volatility, firm volatility, and correlation parameters are denoted respectively as σ_m, σ_i, and ρ_i. The forecast horizon is h. LRMES can be approximated (Brownlees & Engle, 2017, p. 55) by

$$LRMES_{it} = -\sqrt{h}\beta_i \mathrm{E}\left(r_{mt+1} | r_{mt+1} < c\right) \tag{6}$$

where $\beta_i = \rho_i \frac{\sigma_i}{\sigma_m}$ (market beta of institution i), and

$$\mathrm{E}\left(r_{mt+1} | r_{mt+1} < c\right) = -\sigma_m \frac{\phi(c/\sigma_m)}{\Phi(c/\sigma_m)}, \tag{7}$$

with $\phi(.)$ and $\Phi(.)$ denoting, respectively, the pdf and cdf of a standard normal distribution, and $c = \log(1+C)/\sqrt{h}$. From that definition, MES is obtained from $MES_{it} = LRMES_{it}/\sqrt{h}$.

The estimation of MES and LRMES requires the estimation of the firm's market beta β_i and the market volatility σ_m. The firm's market beta β_i and the market volatility σ_m are estimated at the end of each month using a sample of ten years of weekly logarithmic returns for the firm stock price and the market index available up to that month. We use the S&P500 index as the market index for the modern sample, and the CRSP financial index for the early sample due to the unavailability of the S&P500 index for that period. In addition, we set $C = -0.4$ (-40%), and $h = 24$ weeks (6 months) in accordance with the choices made at NYU Stern VLAB (vlab.stern.nyu.edu/srisk).

3.3 SRISK Decomposition

SRISK is the expected capital shortfall (in U.S. dollars) of the firm in the scenario of a 40% loss on the market index over six months. It is a function of LRMES, the market capitalization of the firm (ME_{it}) and its total non-equity liabilities (D_{it}):

$$SRISK_{it} = (k-1) * ME_{it}(1 - LRMES_{it}) + kD_{it} \tag{8}$$

where k is a prudential capital ratio such that $k \leq ME_{it}/\left(ME_{it} + D_{it}\right)$.

In the paper, we use the ratio of SRISK scaled by the market capitalization of the firm (ME_{it}):

$$\frac{SRISK_{it}}{ME_{it}} = (k-1) * (1 - LRMES_{it}) + k\frac{D_{it}}{ME_{it}} \tag{9}$$

which can be decomposed into

$$\frac{SRISK_{it}}{ME_{it}} = (k-1) * (1 - LRMES_{it}) + k\left(Lvg_{it} - 1\right) \tag{10}$$

where $Lvg_{it} = \left(ME_{it} + D_{it}\right)/ME_{it}$. From eq. (10), the ratio of SRISK to market capitalization is a linear function of LRMES and market leverage (Lvg_{it}). In addition, LRMES is a function of MES, given by $LRMES_{it} = \sqrt{h}MES_{it}$. Regression specifications that include (LR)MES and market leverage as independent variables instead of SRISK alone allow for more flexibility in the weighting of the two components in eq. (10).

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