Back to Basics: Bank *beta* and Systemic Risk*

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Abstract
Prior work documents several accounting and market-based predictors of banks' systemic risk with roots in capital markets theory, model-based regulation, or risk culture. We ask which of these measures are dominant predictors of bank value during systemic crisis episodes in the 1972-2022 period. Within and across crises and for various robustness tests, we find that market-based risk measures – beta and marginal expected shortfall – are consistently the strongest cross-sectional forecasting variables in statistical significance and explanatory power, and particularly so for banks with assets exceeding $2 billion. Our findings illustrate some shortcomings of episode-specific or narrative-based metrics in conditional forecasting exercises.

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Keywords: systemic risk; beta; marginal expected shortfall

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1 Introduction

For centuries, banking crises have been met with policy interventions and regulations meant to address the specific precipitating cause of each crisis (Metrick and Schmelzing, 2021). Post-crisis interventions are typically justified by the systemic nature of bank failures, which can disrupt financial intermediation and impose severely negative effects on the real economy.[1] In the wake of the 2007-2009 global financial crisis (GFC), economists have proposed various measures to capture banks' exposures to systemic risk[2], which is often defined by the bank's stock returns on days during a crisis episode when banking sector stock returns are stressed (Fahlenbrach, Prilmeier, and Stulz, 2012; Sedunov, 2016; Meiselman, Nagel, and Purnanandam, 2020). These measures, including asset illiquidity, leverage, short-term funding, asset and loan growth, and noninterest income, reflect various narrative-based risk-taking channels motivated by the GFC experience.[3] The recent failures of Silicon Valley Bank, Signature Bank, and First Republic Bank in 2023 in which the U.S. regulators implemented systemic risk exceptions to fully protect depositors were associated with a different risk-taking channel related to uninsured deposits.[4] These events illustrate that banks' risk-taking activities differ across crises, and that it is important to identify banks with high systemic risk exposures in the cross-section.

Whether these measures or others motivated by individual crisis narratives explain systemic risk during the typical or average crisis is an empirical question (Goetzmann, Kim,

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[1] See, for example, Cerra and Saxena, 2008; Reinhart and Rogoff, 2009; Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013; Acharya, Pedersen, Philippon, and Richardson, 2017; Krishnamurthy and Muir, 2017; Baron, Verner, and Xiong, 2021; Baron and Dieckelmann 2021; Ivanov and Karolyi, 2021)

[2] Some may refer to our measure of systemic risk as systematic tail risk exposure.

[3] See Beltratti, and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012) on asset illiquidity, leverage, and short-term funding, Fahlenbrach, Prilmeier, and Stulz (2018) on asset and loan growth, Brunnermeier, Dong, and Palia (2020) on noninterest income, Meiselman, Nagel, and Purnanandam (2020) on bank profits, and Acharya, Pedersen, Philippon, and Richardson (2017) on MES.

[4] See the March 12, 2023 press release here: https://home.treasury.gov/news/press-releases/jy1337

and Shiller, 2022). Moreover, narrative explanations of risk-taking channels associated with specific crises may themselves lead to policies that, if successful, reduce the likelihood of subsequent crises and bank failures following the same narrative. For example, Basel III capital and liquidity regulations were designed to address the risk-taking channels of banks that led to the GFC, but the problems these regulations were intended to address may not have explained the recent failures of Silicon Valley Bank, Signature Bank, and First Republic Bank (Choi, Goldsmith-Pinkham, and Yorulmazer 2023; Cookson, Fox, Gil-Bazo, Imbet, and Schiller 2023).

In this paper, we ask whether a representative set of candidate measures consistently predict banks' systemic risk exposure across crisis episodes in the 1972 to 2022 sample period. Consistent with prior work (Fahlenbrach, Prilmeier, and Stulz, 2012; Sedunov, 2016; Meiselman, Nagel, and Purnanandam, 2020), we use a bank's stock performance on days during a crisis episode when banking sector stock returns are stressed as a measure of its exposure to systemic risk. Notably, this measure cannot distinguish among alternative characterizations of systemic risk. That is, our analysis cannot distinguish between definitions of systemic risk based on contagion or systematic tail risk exposure as we would expect banks generating contagion and banks more exposed to tail risk factors to experience especially negative returns on adverse days during crisis episodes).

Our prediction exercise yields four key findings. First, both accounting (or narrative-based) and market-based measures proposed in prior work predict banks' systemic risk. Second, we find that market-based measures – market beta, market capitalization, and marginal expected shortfall (MES) – dominate narrative-based accounting measures in both statistical and economic significance, explaining about 60% of the cross-sectional variation in our stock price-based measure of systemic risk across crisis episodes. Furthermore, whereas the cross-sectional predictive power of accounting measures varies across crisis episodes, market-based measures are consistent predictors within and across crisis episodes. These findings suggest that the crisis narratives represented by each accounting measure predict systemic risk for individual crisis episodes ex post, but do not generalize across crises. And they are consistent with a model in which efficient markets reflect the available and relevant information derived from the accounting measures.

Third, among banks that experience multiple crisis episodes in our sample period, we find that these market-based measures are highly persistent, consistent with a risk culture (Fahlenbrach, Prilmeier, and Stulz, 2012), and the accounting measures individually explain an almost trivially small amount of the within-bank variation across crises. Fourth, after controlling for lagged crisis performance, these market-based measures continue to explain an economically significant amount of the variation in banks' systemic risk, suggesting that within-bank changes in these measures capture risk culture dynamics. We conclude from these findings that market-based measures are the strongest predictors of crisis performance in the cross-section and may therefore provide valuable information for identifying a given bank's systemic risk outside of our sample period. To illustrate that point, we find in Figure 1 that the 2022 estimated market beta of three recently resolved banks in 2023, Silicon Valley Bank, Signature Bank, and First Republic Bank, all ranked in the top 5% of the distribution of estimated betas.

To evaluate whether various market-based and accounting measures predict systemic risk, we follow Meiselman, Nagel, and Purnanandam (2020) (MNP, hereafter) by using a proxy for systemic risk defined as the average of a bank's stock returns on "bad days" during a banking crisis, where bad days are defined as the 5% worst days for the banking sector index based on its historical return distribution from 1926 to 2022. As MNP point out, this measure resembles the systemic expected shortfall measure defined in Acharya, Pedersen, Philippon, and Richardson (2017). Therefore, in our setting, asking whether a measure predicts the systemic risk of banks is reduced to asking whether pre-crisis cross-sectional variation in that measure (e.g., market beta) explains cross-sectional variation in equity returns of banks on bad days during the crisis.

To identify banking crises in our sample, we rely on the banking crisis chronology of Baron, Verner, and Xiong (2021), which accounts for banking crises with and without panics and is defined using banking sector equity returns, consistent with our measure of systemic risk. This chronology includes three banking crises in the US after 1970 that start in 1984, 1990, and 2007. Because the end of a crisis episode is not defined using this approach, we explore alternative crisis windows for robustness. We also find quantitatively similar results using the alternative crisis dates employed by MNP and Fahlenbrach, Prilmeier, and Stulz (2012) as well as coincident NBER recession dates.

We consider a wide range of potential measures to predict cross-sectional differences in banks' stock returns on adverse days within the crisis episode (i.e., a bank's systemic risk). Aside from the various accounting measures proposed in prior research following the GFC, we also include market beta, MES, market capitalization, risk-weighted assets, and uninsured deposits. Analytically, MES and market beta are closely related (Benoit et al., 2017; Löffler and Raupach, 2018), and both are designed to capture elements of systematic risk. While MES is motivated by extreme value theory and linked to tail risk exposure, market beta is derived from an economic model and carries an intuitive economic interpretation of systematic risk exposure. From an implementation standpoint, both MES and equity beta are computationally simple and leverage publicly available data. We include market capitalization to capture differences between large and small banks in light of evidence concerning large and small bank behaviors (e.g., Gandhi and Lustig, 2015; Minton, Stulz, and Taboada, 2019; Baron, Schularick, and Zimmerman, 2022). Finally, we include risk-weighted assets given its use in capital regulation as a measure of risk on the asset side of banks' balance sheets and uninsured deposits given its role in the recent bank failures.

To examine the predictive power of various measures over our three banking crises, we consider three types of statistical models. Given the high correlation between MES and beta, we estimate models that separately include MES and beta. We also include a model that includes a decomposition of MES into systematic and idiosyncratic parts to evaluate which component – the one associated with beta or the one orthogonal to beta – is a more important predictor of systemic risk. Our baseline econometric approach is a panel regression with time fixed effects to focus on cross-sectional predictions. To evaluate the economic significance of alternative candidate predictors we follow Lemmon et al. (2008) and report a variance decomposition for each specification. This variance decomposition is informative about the economic relevance of candidate predictors because it illustrates the fraction of the model's sum of squares attributable to each predictor.

Our estimates reveal that beta and MES have very similar predictive power for systemic risk. In our baseline specifications, the average R^2 for both models is 0.505. These specifications also reveal that beta, MES, and market capitalization remain statistically and economically significant after including the various accounting measures. In our baseline specification, we find that a one standard deviation increase in beta is associated with a 0.41 standard deviation decrease in equity returns on bad days and explains 51% of the total Type III partial sum of squares. None of the candidate accounting measures are consistently significant after including these market-based measures. However, the accounting measures explain beta and MES in years prior to crisis episodes, consistent with market-based measures incorporating information from the accounting system. Both pre-crisis MES and pre-crisis beta are useful cross-sectional predictors of bank stock performance on bad days during crisis periods. MES has a small amount of incremental predictive power relative to beta, but beta has an intuitive economic interpretation and is a stronger predictor of average bank stock returns.

Our results imply that market-based measures, such as beta, MES, and market capitalization, can parsimoniously reflect various risk-taking channels of banks. But why might these market-based measures be particularly informative about the systemic risk of individual banks? Our interpretation is that market-based measures capture persistent features of bank risk culture or business models, consistent with Fahlenbrach, Prilmeier, and Stulz (2012). Consistent with this interpretation, we find that past-crisis performance predicts crisis performance across banks, but loses predictive power in the presence of beta and MES. Additionally, market-based measures are correlated with the accounting measures that reflect risk-taking channels across crisis episodes, even though these accounting measures themselves do not consistently predict crisis performance across crisis episodes. Finally, variation in each of the market-based measures is almost entirely explained by bank fixed effects, consistent with persistent risk exposures. Together, these findings suggest that banks have persistent differences in risk exposures even though their risk-taking activities vary across crisis episodes.

We contribute to two strands of literature on financial crises, one of which concerns measures of bank risk-taking. For example, Beltratti, and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012) proposed asset illiquidity, leverage, and short-term funding, Fahlenbrach, Prilmeier, and Stulz (2018) proposed asset and loan growth, Brunnermeier, Dong, and Palia (2020) proposed noninterest income, Meiselman, Nagel, and Purnanandam (2020) proposed bank profits, and Acharya, Pedersen, Philippon, and Richardson (2017) proposed MES and leverage as candidate bank-level predictors of systemic risk. To this literature, we contribute evidence that discriminates amongst measures based on their predictive power for systemic risk, and we find that market-based measures dominate in statistical and economic significance and, unlike narrative-based accounting measures, maintain predictive power across crisis episodes. These measures have attractive features of being available at a high frequency and for de novo and consolidated institutions for which prior accounting data or crisis experience is unobserved. We also contribute to the literature on the causes and macroeconomic consequences of banking crises (e.g., Baron and Xiong, 2017; Lopez-Salido, Stein, and Zakrajsek 2017). Our paper evaluates a set of measures that may predict banks' systemic risk during U.S. banking crises after 1972 for which data is available. These findings complement the extant crisis literature on the stock market's neglect of crash risk (e.g., Baron and Xiong, 2017) because they show that while the market may not estimate aggregate risk in the system, it does assess the relative systemic risk of individual banks in the cross section.

2 Data and empirical strategy

2.1 Data

Bank sample - Following MNP, our bank sample consists of bank holding companies and commercial banks (hereafter banks) in the mapping file maintained by the Federal Reserve Bank of New York (FRB).[5] We use the 2021-3 version, which includes 1,426 unique PERMCO's. With the mapping, we merge daily stock returns from the University of Chicago's Center for Research in Security Prices (CRSP) with annual accounting data from Compustat - Fundamentals.[6] We supplement Compustat – Fundamentals with net charge-offs from Compustat – Bank and risk weighted assets as well as uninsured deposits from Call Reports

[5] https://www.newyorkfed.org/research/banking_research/datasets.html.
[6] We do not use Compustat - Bank as our main accounting data source, because 76 banks in the FRB mapping, including Citigroup, Goldman Sacks, and Morgan Stanley, are not included in Compustat - Bank. We also do not use FR Y9-C and Call Reports as the primary data source, due to that they cover a shorter sample period.

(Consolidated Reports of Condition and Income).[7] The number of banks in Compustat is small before 1972 and increases substantially after 1993. Therefore, we use the sample period from 1972 to 2022. Following Fahlenbrach, Prilmeier, and Stulz (2018), we create one unified record for Citigroup, using Citicorp data before the merger and Citigroup data after the merger. We focus on banks with fiscal year ending in December to eliminate timing mismatch between accounting and equity-market variables. Our final sample includes 657 unique banks over the three banking crises with required data for empirical analyses.

Systemic risk– We do not use average equity returns on all days during a crisis to measure systemic risk of banks, as average returns on all days even during a crisis may capture not only systemic but also positive shocks (Fahlenbrach, Prilmeier, and Stulz, 2012; Sedunov, 2016; Meiselman, Nagel, and Purnanandam, 2020). For instance, while the bankruptcy of Lehman Brothers filed on September 15, 2008 was a system-wide negative shock, Federal Reserve's $900 billion provision in short-term cash loans for banks announced on October 6 2008 was a large positive shock, which partly offset the Lehman Brothers shock. As such, positive and negative returns on all days during a crisis can be clustered, making it difficult to differentiate banks' exposures to systemic risk based on average returns. Therefore, we follow MNP and use average equity returns on a sample of bad days during a banking crisis as our baseline systemic risk measure. More specifically, "bad days" are defined as the worst 5% of trading days from 1926 to 2022 for the banking industry portfolio

[7] For bank holding companies (BHCs), FR Y9-C (Consolidated Financial Statements for Holding Companies) does not report uninsured deposits. Therefore, we follow prior research (e.g., Kashyap et al., 2002) to aggregate uninsured deposits reported in Call Reports to the BHC level. We use the same process to aggregate risk weighted assets and total assets to the BHC level, to circumvent the asset-size threshold for filing the FR Y-9C and to scale uninsured deposits and risk-weighted assets in a consistent fashion.

index constructed and provided by Kenneth French (industry 44 of 48).[8,9] To compute equity returns on bad days, we aggregate CRSP daily stock returns on a value-weighted basis to the level of PERMCO. Since crisis end years are not identified by Baron, Verner, and Xiong (2021), we compute the simple average of daily returns on bad days by PERMCO over three alternative crisis windows, namely one year, two years, and three years. Our baseline crisis window is one year.

To visualize the distributional differences between average returns on all days and those on bad days, we plot the cross-sectional distributions of mean returns of banks on all days and those on bad days during three banking crises, indicated by crisis start years in Figure 2. We use the three-year crisis window. For instance, for the banking crisis starting in 2007, the left box plot shows the cross-sectional distribution of mean returns on all days in each year between 2007 and 2009, and the right box plot depicts the cross-sectional distribution of mean returns on bad days in each year during the same crisis. As can be seen, mean returns on all days are highly clustered compared to those on bad days, due to partly positive shocks, which are irrelevant for measuring systemic risk of banks in crises.

Importantly, we note that the MNP measure of systemic risk is just one of many possible systemic risk measures. We have selected it based on its interpretability and appropriateness for our research question and empirical design, which concerns discriminating amongst banks based on the likelihood that they experience a significant capital shortfall (i.e., fail to remain a going concern) on the worst days of a crisis episode. As Kaserer and Klein (2018) write, "Systemic risk is in a way an elusive concept as illustrated by the lack of a universal definition in the empirical literature to date. Financial crises have

[8] Fig. A1 in Appendix depicts the number of bad days in each year over our sample period from 1972 to 2022.

[9] These data are available at Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html

been defined, and systemic risk has been measured, in terms of financial returns, capital shortfall, and default losses. Contributions concerned with the individual systemic importance of financial institutions have taken different perspectives and have measured systemic importance in terms of institutions' contribution to financial instability, and in terms of institutions' exposure to turmoil in the broader financial system." Consequently, an important caveat to our analysis is that we are not able to draw inferences about the various important concepts of systemic risk, only the one for which our analysis has been designed.

Market-based measures – Acharya, Pedersen, Philippon, and Richardson (2017) define MES as the average of a bank's daily equity returns during the 5% worst days in any given year for the banking industry index (multiplied by -1). Since MES is estimated within one-year windows, we also estimate each bank's market betas using weekly data over the same one-year horizons to facilitate the comparison between beta and MES. More specifically, we estimate beta with weekly data in the pre-crisis year:

$$r_{i,w} - rf_w = a_i + b_i \times MKT_w + e_{i,w} \tag{1}$$

where $r_{i,w}$ is the return of bank i in week w, rf_w is the risk-free rate, and MKT_w is the market excess return. We use the estimate of b_i in equation 1 later in equations 2 and 3.

Accounting measures – We follow prior research to construct accounting measures. ROE is defined as the ratio of pre-tax income to book value of equity, and RWA is computed as the ratio of risk weighted assets to total assets (see MNP). Three-year asset and loan growth (ΔAsset and ΔLoan) are a bank's total assets and loan growth from year $t-3$ to year t, respectively (see Fahlenbrach, Prilmeier, and Stulz, 2018). Short-term funding (Funding) is defined as debt with maturities of less than one year divided by total liabilities, and liquidity beta (Liquidity) is estimated as the loading on the market-wide liquidity innovations of Pástor and Stambaugh (2003)[10] controlling for the market excess return (see Fahlenbrach, Prilmeier, and Stulz, 2012). Noninterest income (Noninterest) is scaled by total assets (see Brunnermeier, Dong, and Palia, 2020). Leverage (LVG) is defined as book value of assets divided by book value of equity (see Beltratti and Stulz, 2012). For robustness, we also explore market leverage, which is computed as (book value of assets – book value of equity + market value of equity)/market value of equity. Given the recent bank failures, we also account for uninsured deposits scaled by total assets (Uninsured). Table A1 in Appendix summarizes variable definitions and data sources. To mitigate the effects of outliers in accounting variables, we winsorize the accounting variables at the 1% and 99% levels.

Panel A of Table 1 reports the summary statistics for the variables used in the empirical analysis over the three banking crises identified by Baron, Verner, and Xiong (2021). While stock returns on bad days are measured over the baseline one-year crisis window (i.e., t), accounting and market-based measures are from the pre-crisis year (i.e., $t - 1$). First, given that equity returns on bad days are daily, its mean of -1.93% implies an average daily equity loss of 1.93% when the system is experiencing returns in the negative tail of the sectoral return distribution. Second, Uninsured (uninsured deposits by total assets) and RWA (risk weighted assets by total assets) have fewer observations, as they are from Call Reports (which started in 1986) and RWA is only available after 1995. Therefore, we cannot examine their predictive power for at least one banking crisis. Third, various measures differ substantially in terms of their means and standard deviations. Therefore, to facilitate comparison among these measures, we standardize all variables to have mean equal to zero and standard deviation equal to one in empirical tests.

[10] https://finance.wharton.upenn.edu/~stambaug/.

Panel B of Table 1 reports the correlations matrix. First, beta and MES have a correlation coefficient of 0.80, consistent with prior research (Sedunov, 2016). Second, asset and loan growth are strongly correlated with a correlation coefficient of 0.90. Similarly, book and market leverage are highly correlated. Third, beta and MES are correlated with various accounting measures (e.g., Liquidity, Funding, Noninterest, LVG, and Uninsured), suggesting that beta and MES may capture various risk-taking channels.

2.2 Empirical strategy

We focus on three banking crises after 1970 identified by Baron, Verner, and Xiong (2021). Our goal is to test whether any of our candidate measures have predictive power for systemic risk outside of the global financial crisis. We start with univariate regressions of the following form:

$$r_{i,c}^{Crisis} = \delta \times Exposure_{i,c}^{Prior} + \nu_c + \varepsilon_{i,c} \tag{2}$$

where $r_{i,c}^{Crisis}$ is the average of bank i' s equity returns on bad days during crisis c, and $Exposure_{i,c}^{Prior}$ is an exposure measure of bank i in the year prior to the onset of crisis c. Again, "bad days" are defined as the worst 5% of trading days from 1926 to 2022 for the banking industry portfolio index. The specification also includes time fixed effects, ν_c, which makes identification rely on cross-sectional variation.

Since MES and beta are strongly related to each other analytically and empirically (Sedunov, 2016; Löffler and Raupach, 2018), we consider two alternative multivariate models to evaluate the incremental predictive power of these exposure measures: one model accounts for beta, and the other includes MES.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c} \tag{3a}$$

$$r_{i,c}^{Crisis} = \rho \times MES_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c} \tag{3b}$$

where $beta_{i,c}^{Prior}$/$MES_{i,c}^{Prior}$ is *beta*/MES of bank i in the year prior to the onset of crisis c, and $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i. The estimation of *beta* and MES as well as other accounting and market-based measures are discussed in Section 2.1.

To inform the marginal predictive power of MES, we decompose MES into the components associated and unassociated with equity beta. Recall that we use Eq. (1) to estimate beta with weekly data in the pre-crisis year. With the estimated beta, we can decompose daily equity returns in the pre-crisis year into two components, and their averages on the 5% worst days for the year define the two components of MES. For instance, the MES component associated with beta is $MES_{i,beta} = \frac{\sum_{d=1}^{n} \hat{b}_i MKT_d}{n} = \hat{b}_i \overline{MKT}$, where $\hat{b}_i$ is the estimated beta in the pre-crisis year from Eq. (1), MKT_d is the market excess return on day d (a 5% worst day in the year for the banking industry index), n is the number of the 5% worst days in the year, and $\overline{MKT}$ thus is the average market excess return on the 5% worst days in the year. Since in a cross section, $\overline{MKT}$ is the same across banks, the variation in $MES_{i,beta}$ is entirely driven by the variation in beta. Similarly, $MES_{i,non-beta} = \frac{\sum_{d=1}^{n} (r_{i,d} - \hat{b}_i MKT_d)}{n}$. In most MES regressions, we use $MES_{i,beta}$ and $MES_{i,non-beta}$ instead of MES, as $MES_{i,non-beta}$ captures incremental predictive power of MES relative to beta.

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c} \quad (3c)$$

where $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES of bank i in the year prior to the onset of crisis c.

Since higher risk exposure in the cross section of banks should predict lower equity returns in systemic events, we expect coefficients on exposure measures to be negative. Given that we standardize all variables to have mean equal to zero and standard deviation equal to one, coefficient estimates in these regressions represent the marginal effect of a one standard deviation increase in an exposure measure on realized systemic risk in terms of its standard deviation. Our baseline crisis window is one year, although we explore two other alternative crisis windows for robustness. In all regression, we use heteroscedasticity-consistent standard errors (Huber/White/sandwich estimators).

To shed light on economic significance of alternative exposure measures, following Lemmon et al. (2008), we report the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model (excluding time fixed effects), which provides a normalization that forces the fractions associated with alternative exposure measures to sum to one. Intuitively, the variance decomposition informs the fractions of the model sum of squares attributable to particular exposure measures. We exclude time fixed effects, as we are interested in the cross-sectional predictive power of alternative exposure measures.

3 Empirical results

3.1 Main results

In Table 2, we regress the baseline systemic risk measure (i.e., equity returns on bad days over the one-year crisis window) on each exposure measure in isolation (with time fixed effects). The idea is to test if these exposure measures have predictive power beyond the global financial crisis. First, the coefficients on all exposure measures have expected negative signs, and they are all statistically significant, except for loan and asset growth.[11] Second, statistically and economically, market exposure measures (i.e., MES, beta, and log MV) have higher predictive power relative to accounting measures. For instance, Column (2) shows that the coefficient on beta is -0.60 (implying that a one standard deviation increase in beta

[11] Loan and asset growth do not have significant predictive power in the US. This is consistent with Lopez-Salido, Stein, and Zakrajsek (2017).

predicts a 0.60 standard deviation decrease in equity returns on bad days over the three banking crises), and that the associated adjusted-R^2 is 0.40. In contrast, Column (8) reports that the coefficient on short-term funding is -0.19 (suggesting that a one standard deviation increase in short-term funding is associated with a 0.19 standard deviation decrease in equity returns on bad days), and that the associated adjusted-R^2 is 0.03. Third, the predictive power of Uninsured (uninsured deposits by total assets) and RWA (risk weighted assets by total assets) is also economically weak. As can be seen from Columns (12) and (13), the associated adjusted R^2s are 0.02 and 0.03, respectively. Given that Uninsured and RWA are not available for all crises, we report multivariate regression results with Uninsured and RWA in the Appendix. In general, our results are robust to including Uninsured and RWA. Fourth, strongly correlated variables exhibit similar predictive power. For instance, while Columns (10) and (11) show similar predictive power between book and market leverage, Columns (5) and (6) reveal comparable predictive power between asset and loan growth. To avoid multicollinearity in multivariate regressions, we only include loan growth, as it is more emphasized in the literature (e.g., Fahlenbrach, Prilmeier, and Stulz, 2018), and book leverage, as it is more comparable to other accounting measures.

Since analytically and empirically, MES and beta are strongly correlated, we consider two alternative multivariate models to evaluate the incremental predictive power of these exposure measures: one model accounts for beta, and the other includes MES. Table 3 presents the results. In Panel A, Columns (1), (3), and (5) report results for the pooled OLS regressions, and Columns (2), (4), and (6) show results with time fixed effects. In Panel B, we present the corresponding variance decomposition. First, the two models based on MES and beta have very similar predictive power. For instance, across the two alternative specifications, the average R^2 for the model based on beta in Columns (1) and (2) is 0.505, and that for the MES regressions in Columns (3) and (4) is also 0.505. Second, with the presence of accounting measures, market-based exposure measures (i.e., beta, MES, and log MV) remain statistically and economically significant. For instance, with time fixed effects, Column (2) in Panel A shows that the coefficient on beta is -0.41, implying that a one standard deviation increase in beta, *ceteris paribus*, predicts a 0.41 standard deviation decrease in equity returns on bad days during crises, and Column (2) in Panel B reports that the fraction of the total Type III partial sum of squares explained by beta is about 51%. Third, accounting measures become either statistically and/or economically insignificant after controlling for market-based exposure measures. For instance, although short-term funding has significant predictive power in isolation in Table 2, it becomes statistically insignificant with the presence of market-based exposure measures in Panel A of Table 3. Although Noninterest is still statistically significant in Panel A, its economic significance in Panel B is generally weak (i.e., the fraction of the total Type III partial sum of squares explained by Noninterest is no more than 4%).

To inform marginal predictive power of MES relative to beta, we repeat the same analysis in Columns (5) and (6), except that we use the two components of MES instead of MES. Although the coefficient on the component of MES that is not associated with beta, $MES_{non\text{-}beta}$, is statistically significant with or without time fixed effects in Panel A, its economic significance in Panel B is much weaker. For instance, Column (6) shows that while the fraction of the total Type III partial sum of squares explained by the MES component associated with beta, MES_{beta}, is around 58%, that explained by $MES_{non\text{-}beta}$ is about 11%. The evidence thus suggests that marginal predictive power of MES relative to beta may be limited.

In summary, our results in Tables 2 and 3 suggest that the market-based measures (i.e., beta, MES, and log MV) have statistically and economically significant predictive power over all three banking crises. Note that while MES and beta contain similar information, beta carries a more intuitive economic interpretation.

3.2 Robustness checks

We conduct a battery of robustness checks and report the results in this section. Overall, our results are robust to alternative crisis windows, alternative regression specifications, and alternative crisis definitions.

Alternative crisis windows – As MNP point out, some crises may spread over multiple years (e.g., the S&L crisis). We therefore explore alternative crisis windows in Table 4. In Columns (1) and (2), the dependent variable is average equity returns on bad days over the two-year crisis window. For instance, for the S&L crisis, we compute average returns on bad days during 1984 and 1985. In Columns (3) and (4), we use the three-year crisis window to compute average equity returns on bad days (e.g., 1984-1986 for the S&L crisis). We report regression results with time fixed effects in Panel A and the corresponding variance decomposition in Panel B. To inform marginal predictive power of MES relative to beta, we use the two components of MES instead of MES in Columns (2) and (4). As can be seen, the results based on the alternative crisis windows are qualitatively similar to those based on the one-year baseline crisis window in Table 3. First, the models based on MES and beta have similar predictive power. For instance, across the two alternative crisis windows, the average R^2 for the model based on beta in Columns (1) and (3) is 0.615, and that for the MES regressions in Columns (2) and (4) is 0.635. Furthermore, although the coefficient on the component of MES that is not associated with beta, $MES_{non\text{-}beta}$, is statistically significant in Panel A, its economic significance in Panel B is weaker. Second, with the presence of accounting measures, market exposure measurers remain statistically and economically significant. For instance, with the two-year crisis window, Column (1) in Panel A shows that the coefficient on beta is -0.37, and Column (1) in Panel B reports that the fraction of the total Type III partial sum of squares explained by beta is about 32%. Third, accounting measures, in general, are not statistically or economically significant after controlling for market exposure measures. For instance, although liquidity has statistically significant predictive power in Panel A, its economic significance based on the variance decomposition in Panel B is immaterial, about 2%.

Cross-sectional regressions – To increase statistical power, we employ panel regressions on the pooled sample. However, such results could be disproportionately impacted by the global financial crisis, as the number of banks in our sample during the GFC is much larger (i.e., 384 out of 657 banks in the pooled sample). We therefore explore predictive power of various exposure measures in each crisis-specific cross section with the baseline systemic risk measure (i.e., equity returns on bad days within the one-year crisis window). In Table A2 of the Appendix, we regress the baseline systemic risk measure on each exposure measure in isolation. Interestingly, whereas the cross-sectional predictive power of accounting measures varies across individual crisis episodes, market-based measures are consistent predictors within each crisis episode. Table A2 suggests that the crisis narratives represented by each accounting measure predict systemic risk for individual crises ex post, but do not necessarily generalize across crises. The multivariate regression results are reported in Table 5 and are consistent with those based on the pooled sample in Table 3. First, the models based on MES and beta have similar predictive power. For instance, across the three crises, the average R^2 for the models based on beta in Columns (1), (3), and (5) is 0.42, and that for the MES regressions in Columns (2), (4), and (6) is 0.45. Furthermore, MES_{beta} has more explanatory power relative to $MES_{non\text{-}beta}$. Second, with the presence of the accounting measures, the market exposure measures, in general, are still statistically and economically significant. Third, the accounting measures are not consistently significant, statistically and economically, after controlling for the market-based exposure measures.

Bank size – There may be important heterogeneity between large and small banks (e.g., Gandhi and Lustig, 2015; Minton, Stulz, and Taboada, 2019). We therefore repeat our tests by bank size. More specifically, following Fahlenbrach, Prilmeier, and Stulz (2018), we use $2 billion in total assets (measured in 2013 US dollars) as the cutoff point: large banks are defined as banks with total assets exceeding $2 billion, and small banks are those with total assets below $2 billion. The results are presented in Table 6 and are not materially different from those based on all banks in Table 3. First, the models based on MES and beta have similar predictive power, and MES_{beta} has more predictive power than $MES_{non\text{-}beta}$. Second, after accounting for the accounting measures, the market-based exposure measures are still statistically and economically significant. Third, the accounting measures are not consistently significant with the presence of market-based exposure measures. Interestingly, the results suggest that the market-based measures seem to be more informative about large banks (i.e., banks with asset sizes exceeding $2 billion).

Alternative crisis definitions – In this paper we use the banking crises identified by Baron, Verner, and Xiong (2021). For robustness, we explore alternative crisis definitions. First, following MNP, the global financial crisis is defined over the period from September 2007 through September 2010, and the S&L crisis is from July 1988 through June 1990. Second, we focus on two crises defined by Fahlenbrach, Prilmeier, and Stulz (2012), the global financial crisis from July 1, 2007 to December 31, 2008 and the 1998 crisis between August 3 and December 31, 1998. Third, we consider each recession in the US as a crisis and use NBER dates to define each crisis. For instance, the recession from December 2007 to June 2009 is considered as a crisis. The systemic risk measure is average equity returns on bad days during each crisis. The results are reported in Table 7 and are generally consistent with those based on the three crises identified by Baron, Verner, and Xiong (2021) in Table 3. First, the models based on MES and beta have similar predictive power, and MES_{beta} has more explanatory power compared to $MES_{non\text{-}beta}$. Second, with the presence of the accounting measures, the market-based exposure measures remain statistically and economically significant. Third, the accounting measures are generally insignificant after controlling for the market-based exposure measures.

Uninsured deposits – The bank failures in 2023 suggest that uninsured deposits are an important indicator of risk-taking. We collect uninsured deposits from Call Reports starting in 1986. Due to this data constraint, we can only test the predictive power of uninsured deposits for the recent two crises staring in 1990 and 2007. The results are reported in Table A3 of Appendix. Our results are not materially changed with the inclusion of the uninsured deposits ratio. For instance, while the market-based measures remain statistically and economically significant, none of the accounting measures are statistically or economically significant. In fact, the coefficient on noninterest income has the opposite sign to what would be predicted. Furthermore, with the presence of the market-based measures, the uninsured deposits ratio is both statistically and economically insignificant (e.g., the fraction of the total Type III partial sum of squares explained by the uninsured deposits ratio is less than 0.5%).

Risk weighted assets - Risk-weighted assets are used by banks and regulators to inform banks' risk. Since such data is only available for the global financial crisis, we estimate a cross-sectional variant of Eqs. (3a) and (3c) (without time fixed effects) and report the results in Table A4 of Appendix. First, our results are robust to including RWA. For instance, while the market-based exposure measures are still statistically and economically significant, none of the accounting measures are consistently significant. Noninterest income again has the opposite sign to what would be predicted. Second, although RWA is statistically significant, the fraction of the total Type III partial sum of squares explained by RWA is small, less than 3%.

3.3 Interpretation

Tables 2 to 7 (as well as A2 to A4) show that market-based exposure measures have significant predictive power for our measure of systemic risk. Our interpretation is that market-based measures capture the persistence in a bank's risk culture and/or its business model suggested by Fahlenbrach, Prilmeier, and Stulz (2012). We provide supporting evidence in this section.

As Fahlenbrach, Prilmeier, and Stulz (2012) imply, if there is persistence in a bank's risk culture and/or its business model, its performance in a prior crisis should have predictive power over its performance during a subsequent crisis. We therefore estimate the following model:

$$r_{i,c}^{Crisis} = \alpha \times r_{i,c-1}^{Crisis} + \nu_c + \varepsilon_{i,c} \tag{4}$$

where $r_{i,c-1}^{Crisis}$ is the average equity return of bank i on bad days during the prior crisis. If there is persistence in performance, we expect α to be positive. If market-based exposure measures capture such persistence in a bank's risk culture and/or its business model, we expect $r_{i,c-1}^{Crisis}$ to lose its predictive power as soon as market-based measures are included. The results are reported in Table 8 and are consistent with our expectations. Column (1) includes only $r_{i,c-1}^{Crisis}$ (as well as time fixed effects), and the coefficient on $r_{i,c-1}^{Crisis}$ is indeed significantly positive. In Columns (2) and (3), we include the market-based exposure measures (as well as the accounting measures). As can be seen, $r_{i,c-1}^{Crisis}$ loses its predictive power. Furthermore, while the market-based exposure measures are all statistically and economically significant, the accounting measures are either statistically or economically insignificant.

If the market-based exposure measures capture risk culture or business model, they should be significantly correlated with accounting measures pertinent to risk-taking of banks (e.g., noninterest income activities). The correlation matrix in Table 1 provides initial evidence. In this section, we provide formal evidence by regressing each market-based measure on various accounting measures in the years prior to the three banking crises (i.e., 1983, 1989, and 2006). The results are reported in Table 9. First, consistent with our conjecture, the market-based measures, such as beta, MES_{beta}, and (log) market capitalization, are significantly correlated with various accounting measures pertinent to risk-taking. For instance, Columns (1) and (2) show that banks with higher beta in the years prior to the banking crises are more profitable and also have more illiquid assets, higher short-term funding, greater noninterest income, and higher leverage. Column (4) suggests that larger banks in the years prior to the banking crises have higher profitability, faster loan growth, more short-term funding, higher noninterest income, and greater leverage, consistent with Baron, Schularick, and Zimmerman (2022). Second, interestingly, $MES_{non\text{-}beta}$ is not significantly correlated with any accounting measures pertinent to banks' risk-taking.

If the market-based measures capture the persistence in a bank's risk culture and/or its business model, we expect the market-based measures to be persistent too. We therefore regress each market-based measure on various accounting measures with not only time but also bank fixed effects over the entire sample period from 1975 to 2022. Note that we lose the first three years to compute the three-year loan growth. The results are presented in Table 10. Panel A shows regression results, and Panel B reports corresponding variance decomposition. First, with bank fixed effects, Panel A shows that the correlations between the accounting and market-based measures, in general, become much weaker. Second, Panel B shows that the cross-sectional variation in the market-based measures is almost entirely explained by bank fixed effects.

That market-based measures capture the persistence in risk culture and/or business model is important. First, this suggests that banks without prior-crisis performance data (e.g., a newly merged bank) can be assessed based on currently available market-based measures. In particular, market-based measures, compared to accounting measures, not only parsimoniously capture various risk-taking activities but also are available at higher frequencies without reporting lags. Furthermore, the persistence suggests that market-based measures from earlier years could also have predictive power over banks' systemic risk. That is, market-based measures could be informative predictors of cross-sectional differences in our measure of banks' systemic risk two or three years prior to a crisis. To illustrate, we repeat our baseline regressions, except that we use market (as well as accounting) measures from two or three years prior to the three banking crises (i.e., $t-2$ or t - 3). The results are reported in Table 11 and suggest that lagged market-based measures from $t-2$ or $t-3$ still have statistically and economically significant predictive power over the tail of the distribution of equity returns identified on bad days during the three banking crises.

3.4 Additional results

Fahlenbrach, Prilmeier, and Stulz (2018) show that high loan growth predicts poor average stock returns over the next three years. In contrast, we find that loan growth generally does not have significant predictive power over equity returns on bad days during crises. It is important to point out that our results are not inconsistent with Fahlenbrach, Prilmeier, and Stulz (2018), as we focus on stock returns on bad days during crises, as opposed to average stock returns over both crisis and benign periods. To illustrate, we regress average three-year equity returns on lagged exposure measures. The results are reported in Table A5 in Appendix, Columns (1) and (2) include all banks. First, loan growth is a significant predictor of future three-year average returns, consistent with Fahlenbrach, Prilmeier, and Stulz (2018). Second, *beta* has a positive coefficient, consistent with the notion in standard asset-pricing models that higher beta means higher required returns. Third, log MV (i.e., size) is negatively correlated with mean returns, consistent with Fama and French (1993, 2015) and Gandhi and Lustig (2015). In Columns (3) and (4), we exclude small banks and obtain qualitatively similar results.

We follow MNP and focus on equity returns on bad days during crises as our bank-specific systemic risk measure, as accounting measures may recognize losses with delay and only gradually. It is still interesting to examine if market exposure measures can predict accounting losses. To account for the possibility that accounting losses may be recognized with a delay and only gradually, we regress the cumulative three-year charge-off rates on lagged exposure measures for the three banking crises. The results are reported in Table A6 in the Appendix and suggest that market-based measures also have significant predictive power over charge-offs even in the presence of accounting exposure measures.

4 Conclusion

Building on previous studies, we examine the incremental predictive power of both accounting and market-based measures for a measure of banks' exposure to systemic risk (Fahlenbrach, Prilmeier, and Stulz (2012), Sedunov (2016), Meiselman, Nagel, and Purnanandam (2020)). Our results suggest that pre-crisis market-based measures – beta and marginal expected shortfall – are persistent and economically significant predictors of bank stock performance on down days during a subsequent crisis episode. In contrast to accounting measures, market-based measures have key advantages due to their computational simplicity, availability in real time, and for de novo and recently consolidated banks. Our interpretation is that market-based measures capture the persistence in a bank's risk culture and/or its business model suggested by Fahlenbrach, Prilmeier, and Stulz (2012). In particular, even though crisis narratives – and the associated risk-taking channels reflected in accounting measures – vary across crisis episodes, the persistence of banks' risk cultures suggests that high-risk banks will dynamically pursue different risk-taking channels that expose them to different risks. Our findings suggest that market-based measures reflect the likely performance of a bank's stock on "bad days" during a crisis episode regardless of the particular risk-taking channels that the bank selects.

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Figure 1 Distribution of beta in 2022

Figure 1 plots the kernel density of bank beta in 2022. The solid vertical line indicates the 95 percentile, and three dashed vertical lines indicate the beta estimates for Silicon Valley Bank (SIVB), Signature Bank (SBNY), and First Republic Bank (FRC).

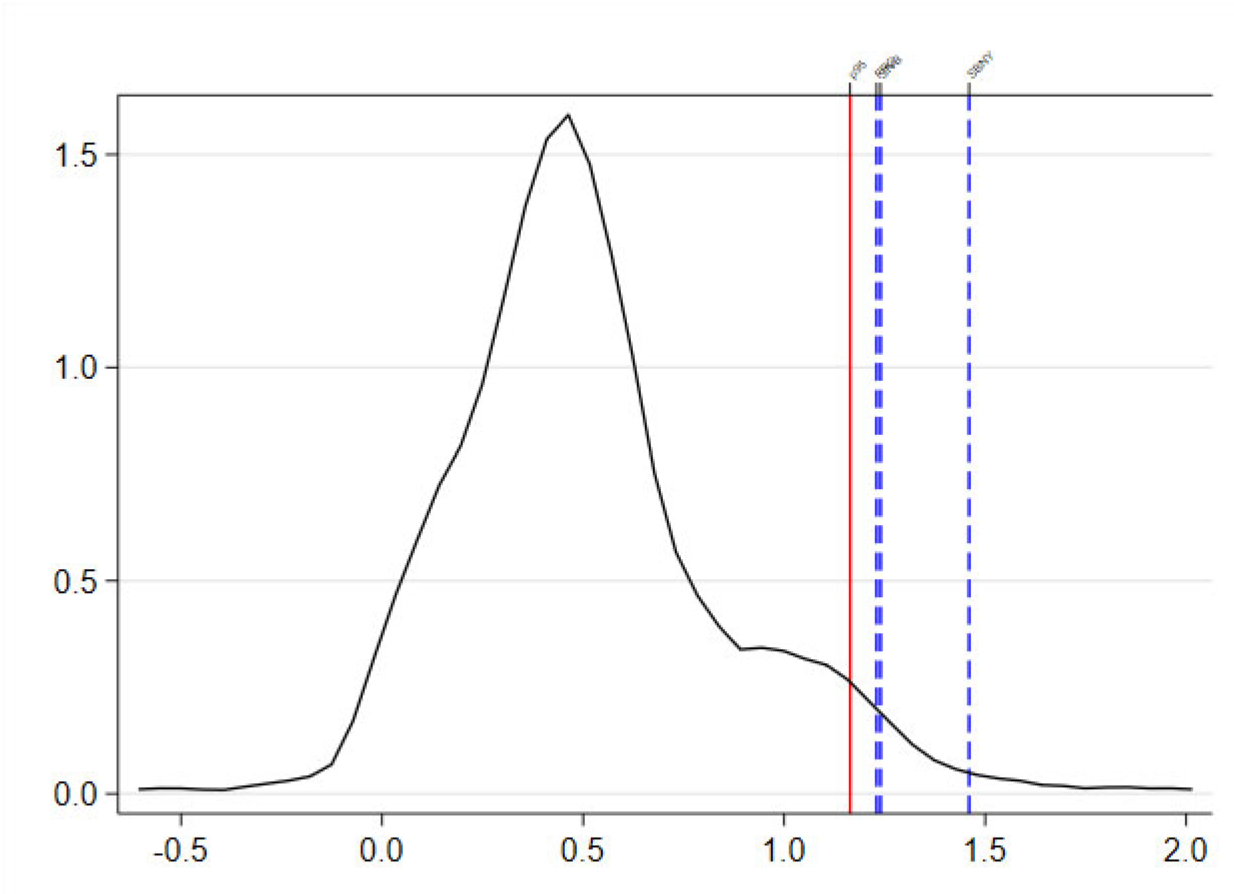

Figure 2 Cross-sectional distributions of mean returns

We plot the cross-sectional distributions of mean returns of banks on all days and those on bad days in each year during three banking crises, indicated by crisis start years. We use the three-year crisis window. For instance, for the banking crisis starting in 2007, the left box plot shows the cross-sectional distribution of mean returns on all days in each year between 2007 and 2009, and the right box plot depicts the cross-sectional distribution of mean returns on bad days in each year during the same crisis.

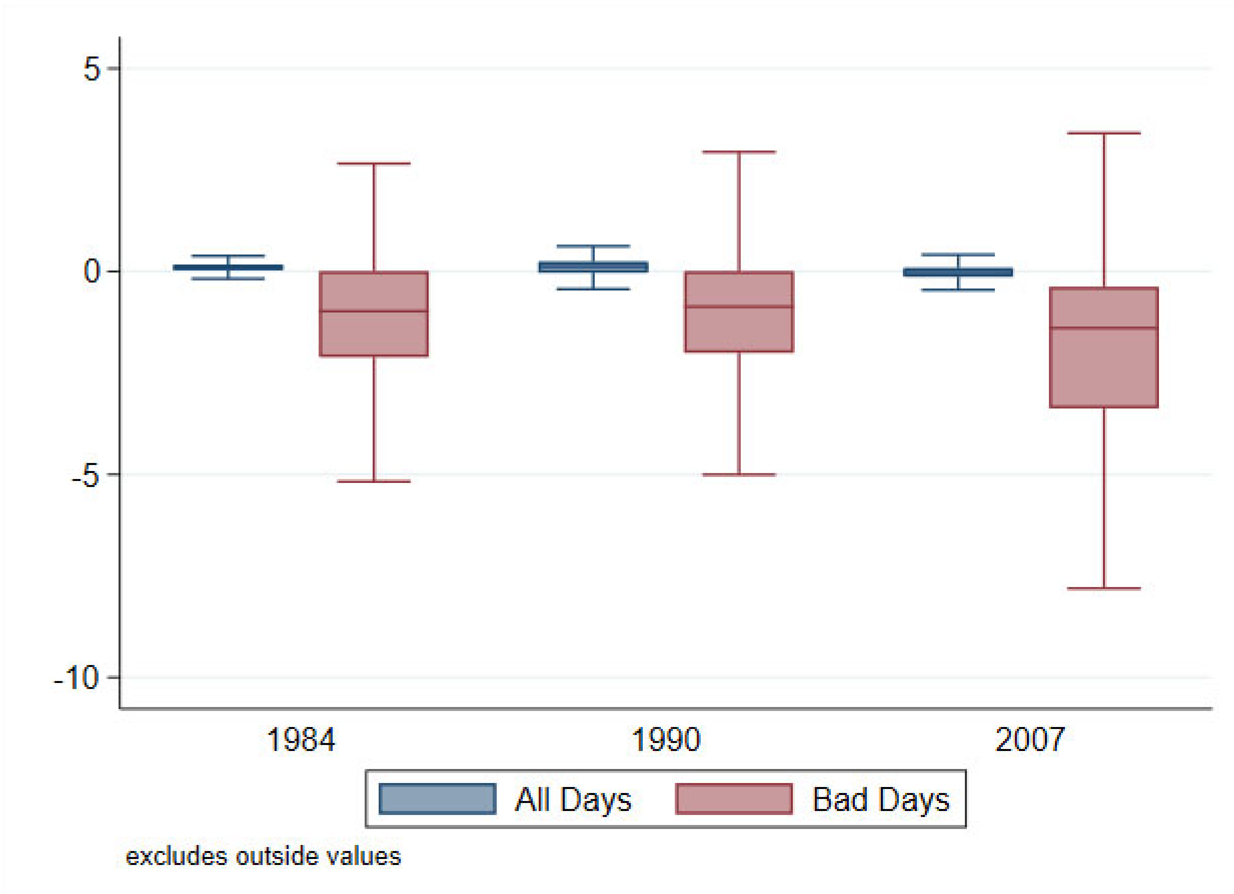

Table 1 Summary statistics and correlation matrix

Panel A of the table reports the summary statistics for the three banking crises. While equity returns on bad days are computed over the baseline one-year crisis window (i.e., t), exposure measures are from the pre-crisis year (i.e., $t-1$). Panel B reports the correlations matrix.

Panel A: Summary Statistics

	(1) N	(2) Mean	(3) SD	(4) Min	(5) P25	(6) P50	(7) P75	(8) Max
r^{bad}	657	-1.93	1.66	-10.89	-3.36	-1.66	-.58	4.05
beta	657	.63	.56	-.54	.2	.53	1.03	2.34
MES	657	.86	.83	-1.45	.22	.78	1.45	3.76
MV ($Billion)	657	2.2	13.64	.01	.13	.29	.79	239.76
ROE	657	15.14	10.95	-73.69	11.39	16.35	20.42	39.14
ΔLoan	657	13.64	9.67	-16.8	7.62	12.6	18.88	44.64
ΔAssets	657	11.64	8.92	-11.81	5.68	10.56	16.56	41.33
Liquidity	657	.03	.24	-.72	-.11	.03	.19	.72
Funding	657	9.49	7.03	0	4.16	8.35	13.47	34.67
Noninterest	657	1.17	.74	0	.72	1.03	1.39	5.14
LVG (Book)	657	13.79	4.64	3.02	10.45	13.13	16.13	32.44
LVG (MKT)	657	11.67	8.93	2.57	6.12	8.61	14.53	81.09
Uninsured	513	22.91	11.54	1.24	14.36	21.09	29.83	56.06
RWA	374	76.01	11.45	35.75	69.53	76.86	83.26	99.86

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) r^{bad}	1.00													
(2) beta	-0.63	1.00												
(3) MES	-0.64	0.80	1.00											
(4) MV	-0.12	0.06	0.10	1.00										
(5) ROE	-0.09	0.04	0.03	0.07	1.00									
(6) ΔLoan	-0.04	0.00	-0.02	0.06	0.13	1.00								
(7) ΔAsset	-0.01	-0.02	-0.07	0.05	0.11	0.90	1.00							
(8) liquidity	-0.14	0.18	0.21	-0.06	-0.04	0.00	-0.02	1.00						
(9) Funding	-0.17	0.21	0.15	0.11	-0.09	-0.08	-0.05	-0.08	1.00					
(10) Noninterest	-0.10	0.13	0.14	0.27	0.13	-0.18	-0.16	-0.08	0.14	1.00				
(11) LVG (Book)	-0.08	0.09	0.11	-0.07	-0.24	-0.14	-0.08	-0.03	0.38	0.03	1.00			
(12) LVG (MKT)	-0.08	0.00	0.04	-0.07	-0.29	-0.26	-0.19	-0.11	0.31	0.00	0.69	1.00		
(13) Uninsured	-0.14	0.15	0.06	0.00	0.17	0.18	0.19	0.02	-0.17	0.05	-0.11	-0.20	1.00	
(13) RWA	-0.17	0.01	0.04	0.02	0.32	0.26	0.29	-0.04	-0.26	-0.02	-0.15	-0.29	0.34	1.00

Table 2 Individual Exposure Measure Regressions

Our univariate specification is

$$r_{i,c}^{Crisis} = \delta \times Exposure_{i,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank *i*'s equity returns on bad days during crisis *c*, and $\text{Exposure}_{i,c}^{\text{Prior}}$ is an exposure measure of bank *i* in the year prior to the onset of crisis *c*. The specification also includes time fixed effects, ν_c, Our baseline crisis window is one year, and we use heteroscedasticity-consistent standard errors. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
MES	-1.44***												
	(0.06)												
beta		-0.60***											
		(0.03)											
Log MV			-0.71***										
			(0.05)										
ROE				-0.11*									
				(0.05)									
ΔLoan					-0.04								
					(0.04)								
ΔAssets						-0.00							
						(0.04)							
Liquidity							-0.21***						
							(0.05)						
Funding								-0.19***					
								(0.04)					
Noninterest									-0.12**				
									(0.05)				
LVG^{Book}										-0.16***			
										(0.05)			
LVG^{MKT}											-0.17**		
											(0.08)		
Uninsured												-0.12***	
												(0.04)	
RWA													-0.17***
													(0.05)
Obs.	657	657	657	657	657	657	657	657	657	657	657	513	374
Adj. R^2	0.44	0.40	0.34	0.01	-0.00	-0.00	0.02	0.03	0.01	0.01	0.01	0.02	0.03

Table 3 Baseline Regressions

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$
$$r_{i,c}^{Crisis} = \rho \times MES_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$
$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i' s equity returns on bad days during crisis c, $beta_{i,c}^{Prior}/MES_{i,c}^{Prior}$ is *beta*/MES of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. The specification also includes time fixed effects, ν_c. Our baseline crisis window is one year. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Regression Results

	(1)	(2)	(3)	(4)	)5)	(6)
beta	-0.42***	-0.41***				
	(0.03)	(0.03)				
MES			-0.96***	-1.00***		
			(0.07)	(0.07)		
MES_{beta}					-0.94***	-0.93***
					(0.07)	(0.06)
$MES_{non\text{-}beta}$					-0.27***	-0.33***
					(0.06)	(0.06)
Log MV	-0.48***	-0.51***	-0.43***	-0.44***	-0.41***	-0.43***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
ROE	-0.03	-0.02	-0.03	-0.02	-0.03	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
ΔLoan	0.01	0.02	-0.01	0.00	-0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Liquidity	-0.07	-0.10**	-0.05	-0.10**	-0.04	-0.09**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Funding	0.03	0.05	-0.01	0.01	0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Noninterest	0.11***	0.10**	0.10***	0.07***	0.10***	0.08***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
LVG	-0.05	-0.03	-0.03	-0.01	-0.03	-0.01
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Obs.	657	657	657	657	657	657
Adj. R^2	0.50	0.51	0.49	0.52	0.52	0.53
Year FE	N	Y	N	Y	N	Y

Panel B: Variance Decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
beta	55.29	51.33				
MES			62.65	62.40		
MES_{beta}					62.46	58.25
$MES_{non\text{-}beta}$					8.11	11.18
Log MV	38.69	42.37	32.22	32.89	25.15	26.62
ROE	0.18	0.07	0.33	0.12	0.26	0.09
ΔLoan	0.02	0.08	0.05	0.00	0.01	0.00
Liquidity	1.03	2.21	0.73	2.65	0.38	1.54
Funding	0.37	0.82	0.05	0.08	0.06	0.34
Noninterest	3.66	2.96	3.61	1.83	3.19	1.98
LVG	0.75	0.16	0.36	0.04	0.37	0.01

Table 4 Alternative Crisis Windows

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i's equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one and explore alternative crisis windows. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	2yr		3yr	
	(1)	(2)	(3)	(4)
beta	-0.37***		-0.37***	
	(0.03)		(0.03)	
MES_{beta}		-0.85***		-0.87***
		(0.06)		(0.06)
$MES_{non-beta}$		-0.32***		-0.36***
		(0.06)		(0.05)
Log MV	-0.71***	-0.63***	-0.78***	-0.69***
	(0.05)	(0.05)	(0.05)	(0.05)
ROE	0.01	0.01	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.03)
ΔLoan	-0.01	-0.02	-0.08**	-0.09***
	(0.03)	(0.03)	(0.03)	(0.03)
Liquidity	-0.10**	-0.09**	-0.13***	-0.11***
	(0.04)	(0.04)	(0.04)	(0.04)
Funding	0.04	0.03	0.04	0.02
	(0.04)	(0.04)	(0.03)	(0.03)
Noninterest	0.06**	0.05*	0.02	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)
LVG	-0.07	-0.05	-0.03	-0.00
	(0.06)	(0.05)	(0.04)	(0.04)
Obs.	657	657	657	657
Adj. R^2	0.56	0.58	0.67	0.69
Year FE	Y	Y	Y	Y

Panel B: Variance Decomposition

	2yr		3yr	
	(1)	(2)	(3)	(4)
beta	32.45		28.44	
MES_{beta}		40.26		36.07
$MES_{non-beta}$		8.61		9.56
Log MV	63.41	48.38	67.07	50.23
ROE	0.01	0.01	0.04	0.03
ΔLoan	0.02	0.12	1.46	2.05
Liquidity	1.84	1.44	2.49	1.97
Funding	0.52	0.21	0.34	0.10
Noninterest	0.92	0.54	0.05	0.00
LVG	0.82	0.43	0.11	0.00

Table 5 Cross Sectional Regressions by Crisis

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i's equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one and explore alternative crisis windows. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Cross-sectional Regressions

	1984		1990		2007	
	(1)	(2)	(3)	(4)	(5)	(6)
beta	-0.47***		-0.33***		-0.40***	
	(0.13)		(0.07)		(0.04)	
MES_{beta}		-1.03***		-0.75***		-0.92***
		(0.33)		(0.13)		(0.07)
$MES_{non\text{-}beta}$		-0.06		-0.30***		-0.34***
		(0.23)		(0.08)		(0.06)
Log MV	-0.35	-0.33	-0.17**	-0.16*	-0.56***	-0.48***
	(0.25)	(0.28)	(0.09)	(0.08)	(0.05)	(0.05)
ROE	0.11	0.10	-0.05	-0.04	-0.05	-0.04
	(0.17)	(0.18)	(0.05)	(0.04)	(0.05)	(0.04)
ΔLoan	0.08	0.08	-0.01	-0.01	-0.03	-0.04
	(0.09)	(0.09)	(0.06)	(0.05)	(0.03)	(0.03)
Liquidity	-0.08	-0.09	-0.13*	-0.10	-0.10**	-0.06
	(0.13)	(0.13)	(0.07)	(0.07)	(0.05)	(0.04)
Funding	0.03	0.02	-0.02	-0.02	0.03	0.02
	(0.12)	(0.12)	(0.05)	(0.05)	(0.04)	(0.04)
Noninterest	0.16	0.16	0.01	-0.00	0.12***	0.10***
	(0.16)	(0.16)	(0.05)	(0.05)	(0.04)	(0.03)
LVG	-0.22	-0.20	-0.11*	-0.07	0.08	0.06
	(0.13)	(0.14)	(0.06)	(0.06)	(0.06)	(0.05)
Obs.	131	131	142	142	384	384
Adj. R^2	0.20	0.19	0.39	0.45	0.68	0.71

Panel B: Variable Decomposition

	1984		1990		2007	
	(1)	(2)	(3)	(4)	(5)	(6)
beta	54.71		61.95		48.12	
MES_{beta}		55.95		53.94		56.06
$MES_{non\text{-}beta}$		0.55		30.12		8.98
Log MV	10.03	9.67	11.57	6.67	45.52	30.52
ROE	3.02	2.83	3.96	1.45	0.27	0.19
ΔLoan	3.59	4.01	0.04	0.07	0.21	0.49
Liquidity	3.10	3.94	11.89	4.83	1.26	0.54
Funding	0.40	0.36	0.53	0.37	0.15	0.07
Noninterest	5.12	6.04	0.06	0.01	3.73	2.77
LVG	20.04	16.65	9.99	2.55	0.73	0.38

Table 6 Regressions by Bank Size

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i' s equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one and explore alternative crisis windows. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	Small		Large	
	(1)	(2)	(3)	(4)
beta	-0.19***		-0.36***	
	(0.05)		(0.05)	
MES_{beta}		-0.47***		-0.84***
		(0.09)		(0.10)
$MES_{non\text{-}beta}$		-0.17***		-0.27***
		(0.06)		(0.07)
Log MV	-0.38**	-0.37***	-0.31***	-0.26***
	(0.15)	(0.14)	(0.06)	(0.06)
ROE	-0.17**	-0.15**	-0.03	-0.03
	(0.08)	(0.07)	(0.05)	(0.04)
ΔLoan	-0.02	-0.03	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
Liquidity	-0.06	-0.05	-0.04	-0.04
	(0.06)	(0.06)	(0.05)	(0.05)
Funding	0.07	0.07	0.05	0.03
	(0.05)	(0.05)	(0.04)	(0.04)
Noninterest	0.09*	0.08*	0.08**	0.07*
	(0.05)	(0.05)	(0.04)	(0.04)
LVG	0.26***	0.24***	-0.13**	-0.09*
	(0.07)	(0.07)	(0.06)	(0.06)
Obs.	213	213	442	442
Adj. R^2	0.34	0.35	0.39	0.41
Year FE	Y	Y	Y	Y

Panel B: Variance Decomposition

	Small		Large	
	(1)	(2)	(3)	(4)
beta	30.80		59.09	
MES_{beta}		35.22		63.76
$MES_{non\text{-}beta}$		9.86		12.70
Log MV	18.09	16.00	25.35	15.46
ROE	10.11	7.49	0.58	0.51
ΔLoan	0.52	0.91	0.41	0.23
Liquidity	1.63	1.34	0.90	0.53
Funding	3.23	3.01	1.91	0.59
Noninterest	7.05	4.80	3.84	2.62
LVG	28.57	21.37	7.92	3.60

Table 7 Alternative Crisis Definitions

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i's equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one and explore alternative crisis windows. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	MNP		FPS		NBER	
	(1)	(2)	(3)	(4)	(5)	(6)
beta	-0.37***		-0.36***		-0.38***	
	(0.03)		(0.03)		(0.03)	
MES_{beta}		-0.60***		-0.58***		-0.70***
		(0.07)		(0.05)		(0.04)
$MES_{non\text{-}beta}$		-0.25***		-0.22***		-0.16***
		(0.04)		(0.04)		(0.03)
Log MV	-0.73***	-0.71***	-0.54***	-0.52***	-0.37***	-0.31***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
ROE	0.07*	0.01	-0.00	0.00	-0.07	-0.07
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
ΔLoan	-0.04	-0.04	-0.08***	-0.09***	-0.03*	-0.03*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Liquidity	-0.05	-0.08	-0.02	-0.04	-0.10***	-0.09***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Funding	0.02	0.02	-0.01	0.00	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Noninterest	0.01	0.00	0.04	0.05**	0.05	0.07*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)
LVG	-0.01	-0.01	-0.05	-0.05	0.03	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)
Obs.	521	521	709	709	1,319	1,319
Adj. R^2	0.70	0.69	0.63	0.61	0.73	0.73

Panel B: Variance Decomposition

	MNP		FPS		NBER	
	(1)	(2)	(3)	(4)	(5)	(6)
beta	29.87		39.50		52.50	
MES_{beta}		27.41		32.56		57.96
$MES_{non\text{-}beta}$		7.39		10.07		8.38
Log MV	68.44	63.84	56.72	51.61	40.79	26.09
ROE	0.88	0.02	0.00	0.00	1.35	1.62
ΔLoan	0.38	0.42	2.39	3.59	0.45	0.51
Liquidity	0.31	0.79	0.06	0.40	2.94	2.15
Funding	0.07	0.12	0.01	0.00	0.06	0.09
Noninterest	0.04	0.00	0.87	1.27	1.59	2.70
LVG	0.01	0.01	0.44	0.51	0.30	0.51

Table 8 Persistence in Risk Culture and/or Business Model

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \alpha \times r_{i,c-1}^{Crisis} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i's equity returns on bad days during crisis c, and $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i in the year prior to the onset of crisis c. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	(1)	(2)	(3)
r_{c-1}^{Crisis}	0.13***	-0.03	-0.03
	(0.04)	(0.04)	(0.04)
beta		-0.35***	
		(0.05)	
MES_{beta}			-0.82***
			(0.08)
$MES_{non\text{-}beta}$			-0.38***
			(0.07)
Log MV		-0.49***	-0.37***
		(0.08)	(0.06)
ROE		-0.04	-0.03
		(0.05)	(0.04)
ΔLoan		0.07	0.04
		(0.05)	(0.04)
Liquidity		-0.16**	-0.11*
		(0.06)	(0.06)
Funding		0.02	0.00
		(0.04)	(0.04)
Noninterest		0.11*	0.08*
		(0.06)	(0.04)
LVG		0.04	0.04
		(0.07)	(0.06)
Obs.	251	251	251
Adj. R^2	0.15	0.55	0.61

Panel B: Variance Decomposition

	(1)	(2)	(3)
r_{c-1}^{Crisis}	100.00	0.46	0.42
beta		39.68	
MES_{beta}			51.07
$MES_{non\text{-}beta}$			18.18
Log MV		47.36	24.67
ROE		0.39	0.31
ΔLoan		1.78	0.59
Liquidity		4.55	1.96
Funding		0.21	0.00
Noninterest		5.27	2.45
LVG		0.29	0.35

Table 9 Market and Accounting Exposure Measures

Panel A reports the regression results.

$$Exposure_{i,c}^{Market} = \sum_k \beta_k \times Exposure_{i,k,c}^{Accounting} + \nu_c + \varepsilon_{i,c}$$

where $Exposure_{i,c}^{Market}$ is a market exposure of bank i in the year prior to the onset of crisis c, and $Exposure_{i,k,c}^{Accounting}$ is an accounting exposure of bank i in the same year. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	beta	MES_{beta}	$MES_{non\text{-}beta}$	Log MV
	(1)	(2)	(3)	(4)
ROE	0.10*	0.05*	0.02	0.17***
	(0.06)	(0.03)	(0.05)	(0.04)
ΔLoan	0.04	0.02	-0.01	0.12***
	(0.04)	(0.02)	(0.03)	(0.04)
Liquidity	0.28***	0.14***	0.01	0.03
	(0.05)	(0.03)	(0.03)	(0.04)
Funding	0.23***	0.12***	-0.03	0.25***
	(0.04)	(0.02)	(0.03)	(0.03)
Noninterest	0.16***	0.08***	-0.00	0.29***
	(0.04)	(0.02)	(0.04)	(0.05)
LVG	0.23***	0.12***	0.04	0.07*
	(0.05)	(0.03)	(0.04)	(0.04)
Obs.	657	657	657	657
Adj. R^2	0.15	0.15	0.07	0.27

Panel B: Variance Decomposition

	beta	MES_{beta}	$MES_{non\text{-}beta}$	Log MV
	(1)	(2)	(3)	(4)
ROE	3.99	3.83	16.41	7.73
ΔLoan	0.15	0.12	2.68	8.93
Liquidity	30.91	30.37	10.77	0.85
Funding	34.34	34.97	16.47	32.19
Noninterest	17.55	17.40	2.42	47.80
LVG	13.07	13.31	51.24	2.50

Table 10 Persistence in Market-based Measures

Panel A reports the regression results.

$$Exposure_{i,c}^{Market} = \sum_k \beta_k \times Exposure_{i,k,c}^{Accounting} + \nu_c + \mu_i + \varepsilon_{i,c}$$

where $Exposure_{i,c}^{Market}$ is a market exposure of bank i in the year prior to the onset of crisis *c,* and $Exposure_{i,k,c}^{Accounting}$ is an accounting exposure of bank i in the same year. The specification also includes time fixed effects, ν_c, and bank fixed effects, μ_i. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	beta (1)	MES_{beta} (2)	$MES_{non\text{-}beta}$ (3)	Log MV (4)
ROE	-0.10***	-0.12***	-0.03	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)
ΔLoan	-0.00	-0.01	0.01	0.09***
	(0.01)	(0.01)	(0.01)	(0.00)
Liquidity	0.00	-0.05***	-0.05***	0.00
	(0.01)	(0.01)	(0.01)	(0.00)
Funding	0.03***	0.01	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.00)
Noninterest	0.00	-0.00	0.04**	-0.01
	(0.01)	(0.01)	(0.02)	(0.00)
LVG	-0.04**	-0.04***	-0.04*	-0.13***
	(0.02)	(0.02)	(0.02)	(0.01)
Obs.	11,776	11,776	11,776	11,776
Adj. R^2	0.58	0.71	0.16	0.94

Panel B: Variance Decomposition

	beta (1)	MES_{beta} (2)	$MES_{non\text{-}beta}$ (3)	Log MV (4)
ROE	1.36	2.58	0.24	0.28
ΔLoan	0.00	0.02	0.01	0.71
Liquidity	0.00	0.59	0.78	0.00
Funding	0.10	0.01	0.36	0.14
Noninterest	0.00	0.00	0.23	0.00
LVG	0.11	0.20	0.31	0.84
Bank FE	98.44	96.60	98.08	98.02

Table 11 Alternative Lags

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i' s equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Panel Regressions

	t-2		t-3	
	(1)	(2)	(3)	(4)
beta	-0.36***		-0.40***	
	(0.04)		(0.05)	
MES_{beta}		-0.73***		-0.56***
		(0.10)		(0.08)
$MES_{non\text{-}beta}$		-0.11*		-0.16***
		(0.06)		(0.04)
Log MV	-0.51***	-0.53***	-0.57***	-0.56***
	(0.05)	(0.06)	(0.05)	(0.05)
ROE	-0.03	-0.03	0.08	0.04
	(0.06)	(0.06)	(0.06)	(0.05)
ΔLoan	0.01	0.01	-0.01	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Liquidity	-0.05	-0.09**	-0.14***	-0.17***
	(0.04)	(0.04)	(0.04)	(0.04)
Funding	0.03	0.03	0.04	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
Noninterest	0.07**	0.07**	0.09**	0.08**
	(0.03)	(0.03)	(0.04)	(0.04)
LVG	-0.07	-0.05	-0.06	-0.05
	(0.06)	(0.06)	(0.05)	(0.05)
Obs.	622	622	593	593
Adj. R^2	0.44	0.42	0.42	0.41
Year FE	Y	Y	Y	Y

Panel B: Variance Decomposition

	t-2		t-3	
	(1)	(2)	(3)	(4)
beta	41.50		30.23	
MES_{beta}		32.18		26.11
$MES_{non\text{-}beta}$		2.13		5.77
Log MV	53.41	58.50	58.80	55.83
ROE	0.20	0.23	1.79	0.37
ΔLoan	0.05	0.03	0.05	0.14
Liquidity	0.83	3.13	4.95	7.41
Funding	0.49	0.64	0.73	1.44
Noninterest	1.92	2.38	2.62	2.32
LVG	1.61	0.79	0.82	0.61

Appendix

Figure A1 Number of Bad Days

Fig. A1 depicts the number of bad days in each year over our sample period from 1972 to 2022. Bad days are defined as the 5% worst days for the banking sector index based on its historical return distribution from 1926 to 2022, which is -1.99%.

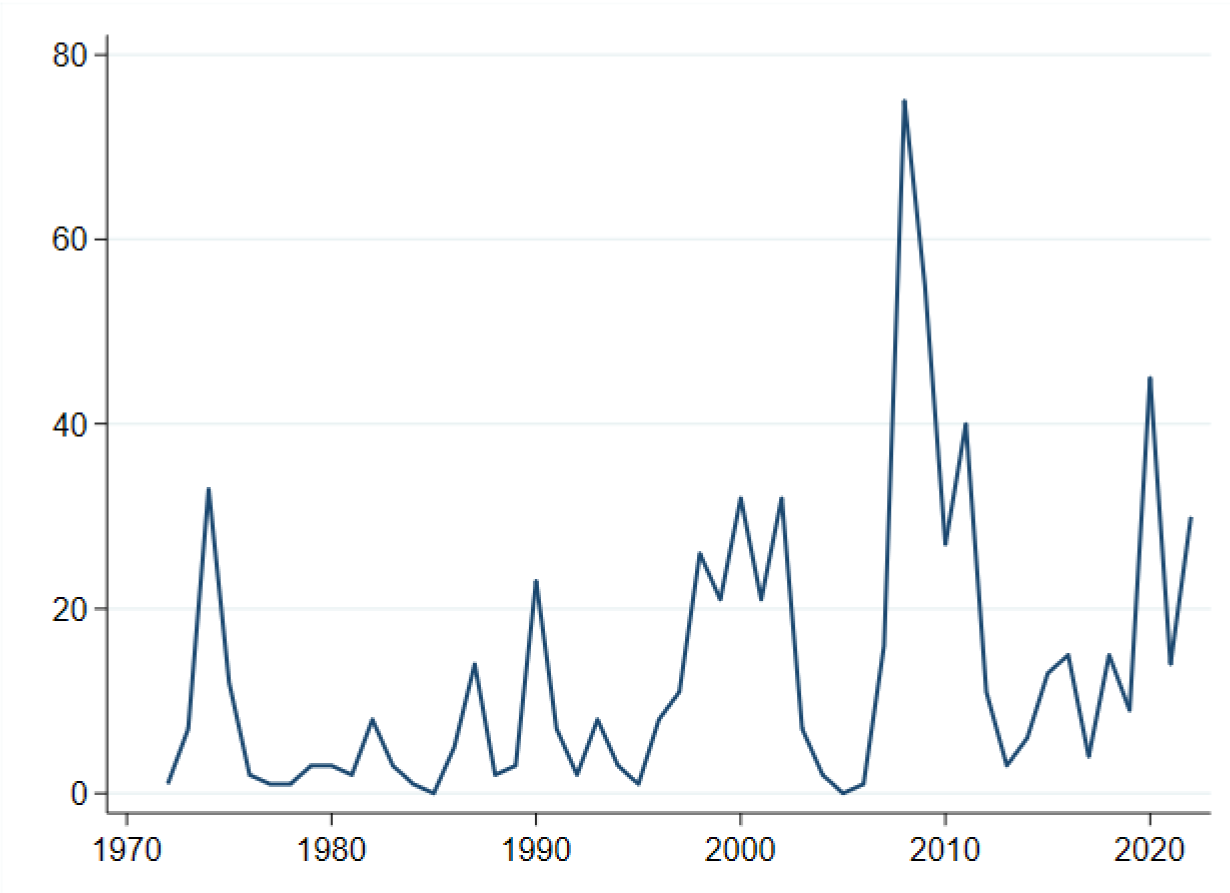

Table A1: Variable Definitions and Sources

Variable	Description	Calculation	Source
r^{Crisis}	Equity returns on bad days during a banking crisis	r^{bad} is defined as the simple average of daily returns on bad days over alternative measurement windows. “Bad days” are the worst 5% of trading days from 1926 to 2021 for the banking industry portfolio index from Kenneth French (industry 44 of 48).	CRSP
MES	Marginal expected shortfall	MES is defined as the average of a bank’s daily equity returns during the 5% worst days in any given year for the banking industry index.	CRSP
beta	Equity beta	beta is estimated with weekly data over a one-year horizon.	CRSP
Log MV	Logarithm of market Capitalization	Log MV = log (Price × Shares Outstanding)	CRSP
ROE	Return on equity	ROE is defined as the ratio of pre-tax income to book equity.	Compustat
Log Assets	Logarithm of total assets	Log Assets = log (Total Assists)	Compustat
RWA	Ratio of Risk weighted assets to total assets	RWA is computed as the ratio of risk weighted assets to total assets.	Call Reports
Uninsured	Ratio of uninsured deposits to total assets	Uninsured is uninsured deposits by total assets.	Call Reports
ΔLoan	Three-year loan growth	ΔLoan is the loan growth from year $t-3$ to year t	Compustat
ΔAssets	Three-year asset growth	ΔAssets is the assets growth from year $t-3$ to year t	Compustat
Funding	Short-term funding	Funding is defined as debt with maturities of less than one year divided by total liabilities.	Compustat
LVG (Market)	Financial Leverage (Market)	Leverage (Market) is computed as (book value of assets - book value of equity + market value of equity)/market value of equity	Compustat & CRSP
LVG (Book)	Financial Leverage (Book)	Leverage (Book) is computed as book value of assets/book value of equity	Compustat
Liquidity	Liquidity beta	Liquidity is estimated as the loading on the market-wide liquidity innovations of Pástor and Stambaugh (2003), controlling for the market’s excess return.	CRSP
Noninterest	Ratio of noninterest income to total assets	Noninterest is noninterest income by total assets.	Compustat
CO	Cumulative three-year charge-off rate	$CO_{i,t} = \frac{\sum_{k=0}^{2} NCO_{i,t+k}}{Loan_{i,t-1}}$, where $NCO_{i,t+k}$ is the net charge-off amount of bank i in year $t+k$, and $Loan_{i,t-1}$ is the total loan amount in year t - 1.	Compustat

Table A2 Cross-sectional Regressions with Individual Measures

Our univariate specification is

$$r_{i,c}^{Crisis} = \delta \times Exposure_{i,c}^{Prior} + \varepsilon_{i,c}$$

where $\mathrm{r}_{i,c}^{\mathrm{Crisis}}$ is the average of bank *i's* equity returns on bad days during crisis *c*, and $\mathrm{Exposure}_{i,c}^{\mathrm{Prior}}$ is an exposure measure of bank *i* in the year prior to the onset of crisis *c*. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In each row, we report the cross-sectional regressions with a measure over three crises, respectively. To save space, we only report the parameter estimates. In all regression, we use heteroscedasticity-consistent standard errors. *** p<0.01, ** p<0.05, * p<0.1

	(1) 1984	(2) 1990	(3) 2007
MES	-1.33***	-1.01***	-1.57***
	(0.33)	(0.10)	(0.07)
Beta	-0.65***	-0.47***	-0.62***
	(0.15)	(0.05)	(0.03)
Log MV	-0.73***	-0.45***	-0.76***
	(0.26)	(0.07)	(0.05)
ROE	0.10	0.07	-0.41***
	(0.23)	(0.04)	(0.14)
ΔLoan	0.09	0.01	-0.10*
	(0.09)	(0.05)	(0.06)
Liquidity	0.09	-0.11	-0.40***
	(0.11)	(0.08)	(0.07)
Funding	-0.13	-0.19***	-0.22***
	(0.11)	(0.04)	(0.05)
Noninterest	0.25*	-0.11	-0.15**
	(0.14)	(0.07)	(0.06)
LVG	-0.43***	-0.28***	0.13
	(0.14)	(0.05)	(0.09)

Table A3 Regressions with Uninsured Deposits

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i's equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In all regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Cross-sectional Regressions

	(1)	(2)
Uninsured	-0.02	-0.03
	(0.03)	(0.03)
beta	-0.40***	
	(0.03)	
MES_{beta}		-0.92***
		(0.06)
$MES_{non\text{-}beta}$		-0.36***
		(0.05)
Log MV	-0.51***	-0.43***
	(0.05)	(0.04)
ROE	-0.02	-0.02
	(0.04)	(0.03)
ΔLoan	-0.00	-0.02
	(0.03)	(0.03)
Liquidity	-0.12***	-0.08**
	(0.04)	(0.04)
Funding	0.04	0.02
	(0.03)	(0.03)
Noninterest	0.08**	0.07**
	(0.04)	(0.03)
LVG	0.05	0.05
	(0.05)	(0.04)
Obs.	513	513
Adj. R^2	0.63	0.66

Panel B: Variance Decomposition

	(1)	(2)
Uninsured	0.21	0.44
beta	50.21	
MES_{beta}		56.46
$MES_{non\text{-}beta}$		12.85
Log MV	44.10	27.09
ROE	0.12	0.09
ΔLoan	0.01	0.08
Liquidity	2.46	1.05
Funding	0.42	0.14
Noninterest	2.05	1.36
LVG	0.42	0.44

Table A4 Regressions with RWA

Panel A reports the regression results.

$$r_{i,c}^{Crisis} = \gamma \times beta_{i,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

$$r_{i,c}^{Crisis} = \rho_1 \times MES_{i,beta,c}^{Prior} + \rho_2 \times MES_{i,non-beta,c}^{Prior} + \sum_k \delta_k \times Exposure_{i,k,c}^{Prior} + \nu_c + \varepsilon_{i,c}$$

where $r_{i,c}^{Crisis}$ is the average of bank i's equity returns on bad days during crisis c, $beta_{i,c}^{Prior}$ is $beta$ of bank i in the year prior to the onset of crisis c, $Exposure_{i,k,c}^{Prior}$ is exposure measure k of bank i, and $MES_{i,beta,c}^{Prior}$ and $MES_{i,non-beta,c}^{Prior}$ are the two components of MES. We standardize all variables to have mean equal to zero and standard deviation equal to one. Our baseline crisis window is one year. In all regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1). Panel B presents the variance decomposition, the fraction of the total Type III partial sum of squares for a particular model. That is, we divide the partial sum of squares for each exposure measure by the aggregate partial sum across all exposure measures in the model.

Panel A: Cross-sectional Regressions	(1)	(2)
RWA	-0.10***	-0.10***
	(0.04)	(0.03)
beta	-0.41***	
	(0.04)	
MES_{beta}		-0.94***
		(0.07)
$MES_{non-beta}$		-0.34***
		(0.06)
Log MV	-0.56***	-0.48***
	(0.05)	(0.05)
ROE	-0.00	0.01
	(0.05)	(0.04)
ΔLoan	-0.00	-0.02
	(0.03)	(0.03)
Liquidity	-0.10**	-0.07
	(0.05)	(0.05)
Funding	0.01	-0.00
	(0.04)	(0.04)
Noninterest	0.11**	0.10***
	(0.04)	(0.03)
LVG	0.08	0.05
	(0.06)	(0.05)
Obs.	374	374
Adj. R^2	0.69	0.71

Panel B: Variance Decomposition	(1)	(2)
RWA	2.56	2.37
beta	49.49	
MES_{beta}		56.86
$MES_{non-beta}$		8.81
Log MV	42.59	28.54
ROE	0.00	0.00
ΔLoan	0.00	0.06
Liquidity	1.28	0.59
Funding	0.01	0.00
Noninterest	3.37	2.43
LVG	0.70	0.33

Table A5 Regressions with Average Three-year Returns

The regression model is:

$$r_{i,t} = \sum_k \beta^k Exposure_{i,t-1}^k + \nu_t + \varepsilon_{i,t}$$

where $r_{i,t}$ is the three-year average return of bank i, and $Exposure_{i,t-1}^k$ is lagged exposure measure k of bank i. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1).

	(1)	(2)	(3)	(4)
beta	0.02***		0.02***	
	(0.01)		(0.00)	
MES		-0.00		0.01
		(0.01)		(0.01)
Log MV	-0.07***	-0.06***	-0.05***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
ROE	0.01	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
ΔLoan	-0.02***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Liquidity	0.01**	0.01**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Funding	-0.01**	-0.01**	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Noninterest	0.03***	0.03***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
LVG	0.02***	0.03***	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Obs.	10,846	10,846	6,726	6,726
Adj. R^2	0.28	0.28	0.33	0.33
Year FE	Y	Y	Y	Y

Table A6 Regressions with Three-year Cumulative Charge Offs

The regression model is:

$$CO_{i,c} = \sum_k \beta^k Exposure_{i,c}^k + \nu_c + \varepsilon_{i,c}$$

where $CO_{i,t}$ is the three-year cumulative charge-off rate of bank i during crisis c, and $Exposure_{i,c}^k$ is exposure measure k of bank i in the year prior to the onset of crisis c. The specification also includes time fixed effects, ν_c. We standardize all variables to have mean equal to zero and standard deviation equal to one. In all panel regression, we use heteroscedasticity-consistent standard errors (*** p<0.01, ** p<0.05, * p<0.1).

	(1)	(2)	(3)	(4)
beta	0.12**	0.11*		
	(0.06)	(0.06)		
MES			0.41***	0.41***
			(0.14)	(0.15)
Log MV	0.39***	0.38***	0.34***	0.32***
	(0.09)	(0.09)	(0.09)	(0.10)
ROE		-0.19***		-0.19***
		(0.07)		(0.07)
ΔLoan		0.27***		0.28***
		(0.06)		(0.06)
Liquidity		0.07		0.06
		(0.07)		(0.07)
Funding		-0.02		-0.01
		(0.06)		(0.06)
Noninterest		0.07		0.08
		(0.07)		(0.07)
LVG		0.06		0.04
		(0.06)		(0.07)
Obs.	653	653	653	653
Adj. R^2	0.09	0.13	0.10	0.13
Year FE	Y	Y	Y	Y