NBER WORKING PAPER SERIES

JUDGING BANKS' RISK BY THE PROFITS THEY REPORT

Ben S. Meiselman
Stefan Nagel
Amiyatosh Purnanandam

Working Paper 31635
http://www.nber.org/papers/w31635

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2023

This research was conducted while Meiselman was an employee of the U.S. Department of the Treasury. The findings, opinions, and conclusions expressed here are entirely those of the authors and do not necessarily reflect the views or the official positions of the U.S. Department of the Treasury. We are grateful for comments from Viral Acharya, Matthew Baron, Murillo Campello, John Cochrane, Ken French, Robin Greenwood, Randy Krozsner, Daniel Paravisini, Philip Strahan, Raghuram Rajan, Uday Rajan, David Sraer, Jeremy Stein, Rene Stulz, Pietro Veronesi, Vikrant Vig, Vijay Yerramilli, and seminar and conference participants at the AFA meetings, Federal Reserve Bank, Imperial College, LBS Summer Finance Symposium, NBER Summer Institute (Corporate Finance), Office of the Comptroller of Currency, Securities and Exchange Commission, SITE Summer Workshop, SUNY Buffalo, University of California at San Diego, University College London, University of Iowa, Vanderbilt, and Wharton Liquidity Conference. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w31635

Judging Banks’ Risk by the Profits They Report
Ben S. Meiselman, Stefan Nagel, and Amiyatosh Purnanandam
NBER Working Paper No. 31635
August 2023
JEL No. G20,G30

ABSTRACT

In competitive capital markets, risky debt claims that offer high yields in good times have high systematic risk exposure in bad times. We apply this idea to bank risk measurement. We find that banks with high accounting return on equity (ROE) prior to a crisis have higher systematic tail risk exposure during the crisis. Proximate causes of crises differ, but the predictive power of ROE is pervasive, including during the financial crisis of 2007–2010 and the recent crisis triggered by the collapse of Silicon Valley Bank. ROE predicts systematic tail risk much better than conventional measures based on risk-weighted assets.

Ben S. Meiselman
U.S. Department of the Treasury
1500 Pennsylvania Avenue NW
Washington, DC 20220
benmeiselman@gmail.com

Stefan Nagel
University of Chicago
Booth School of Business
5807 South Woodlawn Avenue
Chicago, IL 60637
and NBER
stefan.nagel@chicagobooth.edu

Amiyatosh Purnanandam
University of Michigan
Ross School of Business
R5453, 701 Tappan Street
Ann Arbor, MI 48109
amiyatos@umich.edu

1 Introduction

Accurate and timely measurement of risk is a fundamental problem in bank regulation. Of particular concern are tail risk and systemic risk exposures of financial institutions, which can impose severe negative externalities on the rest of the economy. Equity capital requirements and deposit insurance premiums depend crucially on the regulator's assessment of the level of risk taken by a regulated bank. The Basel Committee on Banking Supervision and central banks around the world have devoted considerable resources to improving risk measurement over the years.

While details may vary, there is considerable commonality in the broad philosophy behind risk measurement across asset classes (such as trading book versus loan book) and across regulators (such as Federal Reserve Banks and the Federal Deposit Insurance Corporation)—they all rely on "models" of risk measurement. The process typically starts with a classification of different assets and activities into various risk categories based on a model approved by the regulator, followed by an aggregation exercise that again depends on a model. For example, a bank's trading book risk is measured with a Value-at-Risk model of different asset classes and the final aggregation allows for some model-implied diversification benefits across asset classes. Similarly, for the lending portfolio, risk-assessment is done based on external or internal credit rating models of loans and corporate bonds. The aggregated risk measure, in turn, dictates the level of equity capital or liquid assets a bank must keep in order to meet regulatory capital or liquidity requirements. We call such an approach to risk assessment and regulation the "model-based" approach.

Unfortunately, model-based regulation suffers from at least two problems. First, models can only capture risks that they are designed to capture. Models are necessarily imperfect and incomplete. Built to capture risks that were relevant according to historical experience, they may not be able to capture the risks relevant in future crises. Second, model-based regulation can be susceptible to manipulation by the regulated entities. Since it is prohibitively expensive to devise models that can capture all aspects of risk-taking behavior, model-based regulation ends up leaving substantial discretion in modeling choices with the regulated entities themselves. As a consequence, regulated entities have not only a private incentive, but also considerable ability to understate risk exposures.[1] Understatement of *systematic* risk is particularly worrisome, as this type of risk is closely related

[1] Empirical evidence in Behn, Haselmann, and Vig (2014) and Begley, Purnanandam, and Zheng (2017) suggests that banks make use of this ability to manipulate.

to *systemic* risk, which is of central relevance for optimal bank regulation (Acharya, 2009).[2] We therefore focus on the measurement of systematic rather than bank-specific risk in this paper.

We go back to first principles of risk and return analysis to propose an approach that is simpler, less vulnerable to manipulation, and hence a potentially useful complement to the established model-based approach. We start in the simplest possible setting in which banks operate in a competitive frictionless environment. The asset risk and return of a bank resembles the risk and return of a diversified portfolio of high-quality marketable risky debt such as, for example, investment-grade corporate bonds: In most periods ("good times"), default rates are low, while default losses are concentrated in occasional recessions and crises ("bad times"). The higher the portfolio's expected payoff in good times, the higher must be the portfolio's systematic risk. A similar logic should then apply to banks: High profits in good times should be indicative of a systematically risky asset portfolio that is likely to suffer in bad times.

To implement this idea, we would ideally like to measure the expected payoff of a bank's assets in good times. While this variable is not directly observable, accounting profits should be a useful proxy. In good times, the expected payoff of a risky bond portfolio is the promised yield less a small amount of expected default losses that are largely idiosyncratic. Similarly, the accounting profit on a bank's loan portfolio is roughly the promised yield on the loans less an adjustment for expected loan losses. In contrast, realized rates of return on the bank's stock at an annual or a quarterly frequency would not be good proxies because they are influenced by unexpected shocks to market values. For example, if the assets of a bank unexpectedly become less risky (e.g., because borrowers' collateral values improve), this generates a positive unexpected return, obscuring the positive relationship between risk and return. In analogy, the yield of a corporate bond portfolio in good times, possibly adjusted for the portfolio's average rates of default losses, would be a better indicator of its systematic risk than its realized return over a short time window.

A similar reasoning also applies to interest-rate risk. A bank that tilts towards long-duration assets in times of low interest rates and an upward-sloping yield curve will earn high rates of accounting profit as long as rates stay low, but with a risk of substantial losses in the event of a sharp rise in interest rates. Higher accounting profits are indicative of higher interest-rate risk

[2] Many commonly used empirical proxies of *systemic* risk are actually measures of co-movement with risk factors and hence measures of *systematic* risk rather than direct measures of systemic risk.

exposure.

Since any systematic risk exposure of a bank's asset portfolio is magnified by leverage, our preferred measure of bank profits is one that is also magnified by leverage: return on equity (ROE). We show in a simple model that ROE succinctly captures the combined effect of systematic asset risk and its magnification by leverage. A bank that earns high ROE in good times must have a combination of risky assets and high leverage.

We demonstrate the usefulness of our model-free approach using data from episodes of systemic stress for U.S. banks, namely the savings and loan crisis of the late 1980s (S&L crisis), the financial crisis of 2007–2010 (mortgage crisis), and the regional bank crisis of 2023 precipitated by the collapse of Silicon Valley Bank (SVB crisis). We added the SVB crisis after we completed the first draft of this paper, so the analysis of the SVB crisis is in some sense an out-of-sample test. To supplement this main analysis, we also examine the period around the Russian debt crisis of 1998 and a sample of European banks during the European sovereign debt crisis of 2008–2011. For each systemic stress episode, we relate banks' in-crisis systematic risk exposure to their ROE measured a year before the onset of the crisis. Our baseline measure for in-crisis risk exposure is the average of a bank's stock returns on "bad days" during the crisis, where bad days are days on which the return on a bank stock index is lower than the 5% quantile of its historical distribution. Banks with lower returns on bad days are banks with relatively larger systematic tail risk.[3]

We find that the pre-crisis ROE strongly predicts cross-sectional differences in banks' bad-day stock returns during crises. Pooled across the three crisis episodes in our main analysis, a one standard deviation (s.d.) higher pre-crisis ROE is associated with approximately 0.30 s.d. lower returns on bad days during the crisis. Part of the effect arises because ROE reflects higher leverage—consistent with Beltratti and Stulz (2012) who show that banks with higher leverage performed worse during the mortgage crisis—but a substantial part of it remains after controlling for leverage and other bank characteristics. We further find that ROE not only has predictive power for crisis risk exposure in a pooled analysis, but also separately in each of the individual crisis episodes. Even though very different types of risk materialized in these crises—e.g. credit risk in the mortgage crisis and interest-rate risk in the SVB crisis—the basic notion that generating high profits requires

[3]This measure of tail risk resembles the "expected shortfall" discussed by Acharya, Pedersen, Philippon, and Richardson (2017).

risk-taking applies in all of them.

In our framework, pre-crisis ROE reveals banks' exposure to systematic tail risk shocks. This suggests that banks' betas with respect to a stock market index could also be useful as a predictor of in-crisis performance. Whether this works empirically is not obvious, though. First, betas are not necessarily informative about risk exposures in the tails of the joint distributions of bank returns and the market index return. Second, investor sentiment fluctuations might distort the information in betas about banks' underlying risk exposures. These caveats notwithstanding, we find that pre-crisis beta is indeed a strong predictor of cross-sectional differences in banks' bad-day stock returns during crisis periods. This provides further support to the notion that banks' tail risk exposure is partially predictable using bank characteristics that are based on fundamental concepts of risk and return. However, even after accounting for the predictive power of bank betas, we find that ROE still retains substantial incremental power to predict bad-day stock returns during the S&L and mortgage crises. Thus, ROE has predictive power for publicly traded banks because ROE retains predictive power after adjusting for beta, and ROE also has predictive power for the many banks that are not publicly traded, for which beta is not available, because ROE is strongly predictive on its own.

We next evaluate the effectiveness of ROE compared to several crisis-specific variables for predicting tail risk. After each crisis, regulators and academics focus their attention on the proximate causes of the most recent crisis and they update the regulatory apparatus to better measure and control these sources of risk. In the wake of the S&L crisis, the focus was on brokered deposits. Following the mortgage crisis, regulators focused on banks' securitization business and the non-interest income received from these activities. Most recently, following the SVB crisis, long asset duration and uninsured deposit funding are under scrutiny. We show that in each episode, the pre-crisis ROE has substantial predictive power for in-crisis risk exposure even over and above these crisis-specific measures of bank fragility. Moreover, each crisis-specific measure has strong predictive power in the crisis that brought attention to it ex post, but not in the other crises. For example, high non-interest income is a strong predictor of poor performance during the mortgage crisis, consistent with Brunnermeier, Dong, and Palia (2020), but non-interest income is unrelated to risk exposure in the S&L crisis and predicts bank performance with the opposite sign during the SVB crisis. In contrast, pre-crisis ROE has consistent predictive power in all three of these crisis episodes.

We also evaluate the effectiveness of ROE compared to a widely used model-based risk measure for predicting tail risk. Banks are required to report risk-weighted assets as an aggregated statistic that summarizes their overall risk taking. We scale risk-weighted assets by the book value of total assets to create a measure of model-implied risk for the bank. We find that ROE performs significantly better than the model-implied risk measure in explaining cross-sectional differences in tail risk. The risk-weighted assets measure has little predictive power for tail risk once ROE is included as a predictor.

Finally, we look at how taking into account the incentives of managers and shareholders can help refine the profitability measures in their role as risk indicators. If managers and shareholders perceive risk-taking to be privately beneficial because of implicit government support that effectively provides underpriced insurance of downside risk, then managers and shareholders also have an incentive to pay out profits instead of retaining them as loss-absorbing capital (Acharya, Le, and Shin, 2017). We focus on two forms of payout: (1) dividends and share repurchase payouts to shareholders and (2) stock-based compensation to managers. Jointly, the two forms of pre-crisis payout predict systematic tail risk exposure roughly as well as ROE does. Hence, high rates of payouts to managers or shareholders in good times are a strong indication that the bank is engaged in activities that expose the bank to systematic tail risk in bad times.

Our approach is best suited for a competitive setting in which banks can achieve higher ROE in good times only through higher systematic risk exposure. If banks earn quasi-rents from market power in their deposit and lending franchises, or other lines of business, this distorts ROE as an indicator of risk exposure. The fact that ROE does well empirically as a predictor of risk exposure in crisis episodes suggests that this idealized competitive setting is a useful approximation. Our findings are also consistent with the analysis in Atkeson, d'Avernas, Eisfeldt, and Weill (2019) that attributes, based on a quantitative model, the high level of bank profitability prior to the mortgage crisis to tail risk exposure supported by government guarantees rather than high franchise value.

Our approach has antecedents in the banking literature. Morgan and Ashcraft (2003) show that interest rates charged by banks on commercial and industrial loans predict future loan performance and CAMEL rating downgrades by bank supervisors. They advocate using loan spreads as a measure of bank risk. Along similar lines, Calomiris (2011) proposes that capital requirements be based on loan spreads. Our profit-based approach applies the same logic that yield and risk are related, and it shares the incentive-robustness, but it is broader in that we do not focus only on loans, but also capture profits and risk resulting from capital market activities. This capital-markets component of profit and risk-taking is particularly relevant for the big systemically relevant banks that may be in the center of regulatory attention. Closest to our work, Moussu and Petit-Romec (2017) document a positive correlation between pre-crisis profitability for the 2008–09 crisis and in-crisis risk measures in a sample of large banks from 28 countries. The interpretation of this correlation is unclear, though, because pooling data across countries without country fixed effects can confound risk-related profitability with other country-level factors, such as, for example, differing levels of risk-free interest rates.[4] Our within-country analyses hold fixed such country-level factors. Moreover, we show that ROE also works as a predictor of bank crisis performance in the S&L and SVB crises.

Finally, our work is related to papers that uncover the drivers of specific crisis episodes such as the effect of non-interest income (Brunnermeier et al., 2020) or liability structure (Beltratti and Stulz, 2012) on performance of banks during the mortgage crisis. While these drivers may play an important role in a specific crisis episode, they may not be of equal importance in other crises. For example, while banks prior to the mortgage crisis often engaged in forms of risk-taking that produced non-interest income, risk-taking can also take place in the core lending business that generates interest income (Fahlenbrach, Prilmeier, and Stulz, 2017; Baron and Xiong, 2017). In contrast to crisis-specific predictors that are linked to the proximate cause of each crisis, ROE is a generic predictor of banks' systematic tail risk exposure in multiple crisis episodes.

The rest of the paper is organized as follows. Section 2 introduces our model-free measure of risk in the context of policy tools and model-based measures of risk. Section 3 articulates a stylized model of risky investment to build intuition for our measure of risk and empirical strategy. Section 4 describes the data, section 5 presents our results, and section 6 concludes.

[4] One specific concern is that their sample includes a large number of Japanese banks (75 out of a total of 273 that includes 46 U.S. banks). In the years leading up to the mortgage crisis, Japanese banks were still suffering from persistently low profitability that originated in the collapse of asset prices in Japan in the early 1990s. As the economic framework in our paper makes clear, the very low risk-free interest rates in Japan at the time are another likely contributor to low rates of return on equity. At the same time, Japanese banks were much less exposed to the shocks that hit U.S. banks during the mortgage crisis. This gives rise to positive relation between country-level average pre-crisis bank profitability and post-crisis risk realization, but this country-level correlation may have little to do with pre-crisis bank risk-taking.

2 Policy tools and measures of risk

Capital requirements are a key regulatory tool for managing systemic as well as bank-specific risk. Based on the recommendations from the international Basel Committee on Banking Supervision, national regulators require a particular fraction of bank liabilities to be equity (capital). Capital requirements are intended to keep banks solvent in times of stress and thus avoid the negative externalities of bank failure. Several regulatory measures of capital requirements, such as the risk-weighted Tier-1 capital ratio, are based on the assessed risk of bank assets. The assessment of risk, in turn, is based on some model of risk approved by the banking regulator.

Reliance on model-based regulation gained special attention in the modern era following the recommendation of Basel I in 1988. Basel I introduced a risk-weighting system under which banks were required to compute the "risk-weighted" assets of their entire portfolio by multiplying the dollar amount of assets within each risk category by a weight for that category (Getter, 2012). Capital adequacy regulations required banks to keep a minimum amount of capital (such as common equity) as a fraction of risk-weighted assets (RWA) thus computed. For example, safe assets like cash and Treasury bills received a weight of zero for their credit risk under Basel I, whereas corporate loans received a weight of one. Two key deficiencies of Basel I were soon obvious: it did not differentiate sufficiently across risk assets, and it did not explicitly address market risks. For example, all commercial loans received a risk-weight of one regardless of the underlying risk characteristics of the borrowers. Similarly, the regulation assigned a zero risk-weight on sovereign debt issued by all OECD countries regardless of differences in their inherent risk.[5] In addition, the initial Basel I rule focused on credit risk alone, making little or no distinction across banks that differ in terms of their exposure to market risk factors such as movements in interest rates or foreign exchange.

Recognizing some of these limitations, over the years the Basel Committee formulated and modified a set of rules for computing a bank's market risk such as its exposure to interest rates, exchange rate, equity, or commodity prices. The committee adopted a set of new models in 1996 under the Market Risk Amendment to Basel I, allowing banks to use models such as Value-at-Risk to compute their exposure to market losses. To address the deficiency with respect to credit risk, a new

[5] See "U.S. Implementation of the Basel Capital Regulatory Framework," Congressional Research Service, 2014, for an excellent summary of the evolution of these regulations.

set of regulations was adopted under the Basel II framework in 2004.[6] The key point of departure was to allow for more risk differentiation within the same asset class by increasing the number of risk categories. Basel II also allowed banks to base risk-weights according to the borrower's rating by nationally recognized credit rating agencies. For example, highly rated securities were now allowed to get a risk weight of 20%, significantly lower than the 100% weight that was applied to all commercial loans under Basel I.

In light of the financial crisis of 2007–2010, regulators around the world recognized some of the deficiencies of Basel II and market-risk regulations. It has been argued that banks under-reported their risk, engaged in regulatory arbitrage using complex off-balance sheet transactions, and ignored their exposure to liquidity risk. Basel III was motivated by a desire to fix these limitations by having better models of risk-detection and by having additional models for the computation of liquidity risk. Basel III included stress test standards to assess the level of capital a bank would have in a set of adverse economic scenarios. Unfortunately, stress test models are not necessarily informative about adverse scenarios that are not among the tested scenarios. For example, prior to the SVB crisis, banks were tested for a declining interest rate scenario but not for a rising interest rate scenario, leaving their exposure to rising interest rates undetected by the stress test models.

While countries differ in terms of their adoption of these regulations and their responses to the failure of the earlier generation of regulation, the core approach remains the same: design a new model to fix the shortcomings of the older models. Our key point in the paper is simple: any new model is subject to manipulation and susceptible to missing risk factors. In fact, a more complex model that tries to fix the shortcomings of previous models can be even more susceptible to manipulation. As model complexity increases and as markets become more sophisticated, the possibility of manipulation is likely to increase. Under model-based regulation, there are many opportunities for a bank to exercise judgment when assigning an asset to a risk category. For a bank with equity near the minimum threshold, it may be easier to misrepresent certain assets as less risky than they really are as a method of appearing to comply, rather than shedding assets or raising equity.

Our model-free approach is simple. While our measure of risk is also a ratio, namely some measure of accounting profits as a fraction of book equity, we call this a model-free measure because

[6] The precise date of adoption varies by country.

there is no judgment being made about the riskiness of particular assets.

3 Bank Profitability as a Measure of Risk

We set up a simple model to guide the empirical analysis and to clarify the key economic relationships we aim to uncover. Consider a discrete-time economy in which banks face a sequence of one-period independently and identically distributed investment opportunities. Investments made in period t pay off in period $t+1$. The market for these investment opportunities is competitive and arbitrage-free. As a consequence, we can price assets under risk-neutral probabilities. The per-period gross risk-free rate is R_F (where gross means one plus the interest rate). We omit time subscripts to reduce clutter, but an investment is undertaken at the beginning of a period and the payoff is determined by a realization at the end of the period.

At the end of each period, the economy is in one of two states: a good state u with risk-neutral probability of $1-\pi$ and a bad state d with risk-neutral probability π. We think of π as small so that u is the "usual" state and d is a "disaster" state. The available investment opportunities differ in their riskiness, which determines their state-dependent payoffs. Given the riskiness θ of a bank's portfolio of assets at the beginning of a period, the portfolio payoffs are $X^u(\theta) > R_F$ in the good state, with $\frac{\partial X^u}{\partial \theta} > 0$, and $X^d(\theta) < R_F$ in the bad state, with $\frac{\partial X^d}{\partial \theta} < 0$. We assume that θ can differ across banks, but an individual bank's θ is constant over time.

We normalize the asset payoffs such that the price of the assets at the time of the bank's beginning-of-period investment is always unity. Risk-neutral pricing therefore implies the following relationship between $X^u(\theta)$ and $X^d(\theta)$,

$$(1-\pi)X^u(\theta) + \pi X^d(\theta) = R_F. \tag{1}$$

which is also consistent with the opposite signs of $\frac{\partial X^u}{\partial \theta} > 0$ and $\frac{\partial X^d}{\partial \theta} < 0$.

This two-state set up captures the essential features of a bank's investment opportunities. The most straightforward way to interpret the risks in this model is to think of them as systematic credit risk shocks. The loans and debt securities that account for most of a typical bank's asset portfolio have highly non-linear payoffs: Relatively stable returns in most periods, but with the possibility of substantial losses in a deep recession or financial crisis. But one can also interpret the risks as interest-rate risks. In this interpretation, X_u and X_d are the values of a long-duration asset after holding it for one period. The good state in this case is one of stable long-term yields, while the bad state features a sharp increase in long-term yields and hence large losses on long-duration assets.

At the beginning of each period, the bank issues default-free one-period debt with face value equal to a fraction D of the value of the bank's assets at the time of issue. Including interest, the bank then must pay back DR_F at the end of the period. For now, we assume that the debt is default-free because θ is sufficiently low so that $X^d(\theta) \geqslant DR_F$ holds. We consider default and government insurance of the banks' liabilities in an extension below.

Our main interest centers on the relationship between the bank's profit in the good state and the systematic risk exposure in the bad state. With default-free debt, the value of equity as a fraction of bank liabilities is $1 - D$. Therefore, the bank's gross equity returns in the two states are

$$\begin{aligned} R^u(\theta) &= \frac{X^u(\theta) - DR_F}{1 - D}, \\ R^d(\theta) &= \frac{X^d(\theta) - DR_F}{1 - D}. \end{aligned} \tag{2}$$

Returns in the bad state then can be poor for two reasons. First, since $\frac{\partial X^d}{\partial \theta} < 0$, we have $\frac{\partial R^d}{\partial \theta} < 0$, and hence higher riskiness of assets (high θ) implies that the return in the bad state is poor. Second, this risk is magnified by high leverage (high D).

The standard regulatory approach to assessing this risk is to classify assets according to their riskiness based on ratings and risk models, and to assess the bank's leverage through regulatory capital ratios. In contrast to the standard approach, our approach exploits the connection between the riskiness of the bank's assets and the bank's payoff in the good state. In this frictionless model, a bank that is highly profitable in the good state must have a combination of risky assets and high leverage as these are the only ways to earn higher returns. Risk-neutral pricing in (1) implies $(1 - \pi)R^u + \pi R^d = R_F$, and hence

$$R^d - R_F = -\frac{1 - \pi}{\pi}(R^u - R_F). \tag{3}$$

Thus, high profitability in good times, as measured by the return on equity (ROE), and due to a combination of risky asset holdings and leverage, predicts higher downside equity risk in the next period. This is the key prediction that we examine empirically.

Insolvency and government support. Now suppose that $X^d < DR_F$ is possible. This means the bank can be insolvent in the bad state. In this case equity holders experience a total loss, but the loss absorption of equity is not sufficient to pay the debt back in full. If the government bails out the debt holders, the government bears the cost

$$L^d = \max\left[DR_F - X^d, 0\right]. \tag{4}$$

In risk-neutral expectation, the cost is $E^Q[L^d] = \pi L^d$. The government can eliminate this cost through capital regulation or by charging an insurance premium that requires banks to pay for the risk-neutral expected loss.

The capital regulation approach would be to assess the riskiness of assets, i.e., θ, and then require equity capital funding levels such that $D \leqslant X^d(\theta)/R_f$, which renders $L^d = 0$.

Alternatively, the government could charge an insurance premium that compensates the government in risk-adjusted terms for the cost of future bailouts. Using substitutions from Equations (1) and (2), the risk-neutral expected loss can be expressed as

$$E^Q[L^d] = \max\left[(1-\pi)(X^u(\theta) - R_F) - \pi(1-D)R_F, 0\right], \tag{5}$$

which is greater than zero if $X^d < DR_F$. As (5) shows, the insurance premium that compensates the government for bailout losses can be formulated as a tax on the bank's profitability in the good state. The first term inside the brackets is proportional to the excess return on assets in the good state, $X^u - R_F$, which in turn reflects the riskiness of assets. For any given level of leverage, a higher excess return on assets calls for a higher tax. The second term subtracts from the insurance premium and it reflects the loss absorption through shareholder equity. When $D < 1$, and hence shareholder equity absorbs part of the losses, the insurance premium can be reduced by the second term. The higher the equity level, the lower the tax. In the extreme case of zero equity, $D = 1$, the bank shareholders get a free call option paid for by the government. To fully charge for the cost of this option in this case, the government must tax away all return on assets above the risk-free rate. Received in the good state, i.e., with risk-neutral probability $(1-p)$, the risk-neutral expected value of this tax is then equal to the risk-neutral expected loss from bailouts.

Robustness to off-balance sheet exposures. This stylized model helps illustrate how using profits to measure risk can be more manipulation-proof than traditional risk measures. Consider the example of a bank that moves a fraction λ of its assets and liabilities off-balance sheet. Assume the portfolio of assets moved off the balance sheet has the same risk composition as the asset portfolio that stays on the balance sheet. Further assume that the liabilities moved off balance sheet are entirely debt—to conceal leverage from traditional risk assessment—and that the bank implicitly or explicitly guarantees these off-balance sheet liabilities. Profits and losses from the off-balance sheet investments flow back to the bank.

If the bank simply moves assets and liabilities off-balance sheet in this way, without changing the total leverage (i.e., combined on- and off-balance sheet), then the dollar level of profits stays the same and the dollar level of equity stays the same. Hence, the return on equity in both states of the world is unaffected by these accounting maneuvers. The ROE in good times still provides, as prescribed by (3), an accurate assessment of the magnitude of disaster risk exposure $R^d(\theta) - R_F$.

In contrast, traditional approaches to risk measurement can deliver misleading results when assets and liabilities are moved off-balance sheet. An observer comparing on-balance sheet assets to equity capital would conclude that the off-balance sheet construction had raised the equity capital ratio by a factor of $1/(1-\lambda)$, seemingly enhancing the safety of the bank. This downward bias in risk assessment is exacerbated if the assets that are moved off the balance sheet are riskier than those that remain on the balance sheet.

If the bank also raises total leverage when it moves assets and liabilities off the balance sheet—to keep on-balance sheet leverage constant, for example—this doesn't change the key relationship (3), because this relationship does not depend on the level of debt. More debt just makes the right-hand side and the left-hand side bigger. But high ROE in good times is still an indicator of high systematic tail risk.

Positive NPV assets. To highlight the relationship between risk and profitability in the most transparent way, our baseline model assumes that the bank acquires its assets in a competitive market. This competitiveness assumption is implicit in our use of risk-neutral probabilities to price the assets. For capital market transactions, this assumption should be non-controversial. For banks' traditional lending business, it may be less accurate as an approximation. Banks can have access to positive net present value (NPV) projects, sometimes as a result of market power in the local banking market or superior technology for screening and monitoring.

Market power from a deposit or lending franchise does not necessarily imply positive NPV, as operating costs of the franchise may drive rents to zero, as assumed, e.g., in Drechsler, Savov, and Schnabl (2021). But if there is a positive NPV after netting off these costs, this weakens the relationship between profitability and systematic risk exposure. Suppose the bank owns riskless positive NPV assets that earn the rate of return $R_F + s$ and account for a share $1 - \alpha$ of the bank's total assets. The bank then earns a return on equity in the two states of

$$R^u(\theta) = \frac{\alpha X^u(\theta) + (1-\alpha)(R_F + s) - DR_F}{1-D},$$
$$R^d(\theta) = \frac{\alpha X^d(\theta) + (1-\alpha)(R_F + s) - DR_F}{1-D}. \tag{6}$$

Following the same steps as above, we obtain a modified relationship between the bank's equity return in the bad state and the ROE in the good state:

$$R^d(\theta) - R_F = -\frac{1-\pi}{\pi}(R^u(\theta) - R_F) + \frac{1-\alpha}{\pi}s. \tag{7}$$

Compared with (3) we have an additional term that involves the abnormal return s the bank earns on its non-competitive assets.

For the purpose of using bank profitability as an indicator of risk, this additional term proportional to s introduces a measurement error. On one hand, high R^u could indicate high risk-taking and hence low equity returns in the bad state; on the other hand, high R^u could be a consequence of high s, which raises the equity return in both states. Moreover, this measurement error will likely be positively correlated with R^u as s is a component of R^u. This means that in a regression of $R^d(\theta)$ on $R^u(\theta)$ in a cross-section of banks, with the component related to s left in the residual as an unobservable, the OLS estimator of the negative slope coefficient on $R^u(\theta)$ in (7) will be biased towards zero. How big this bias is depends on the magnitude of cross-sectional variation in risk (θ) compared with cross-sectional variation in s and on the magnitude of the correlation of θ and s.

We address the positive NPV issue in two somewhat imperfect ways. First, we examine specifications with bank fixed effects. To the extent that s is constant over time, bank fixed effects absorb the component related to s in (7). This approach may also underestimate the strength of the relation between ROE and crisis risk, but for a different reason. To not drop out of the sample in the fixed-effects estimation, a bank must be present in at least two crisis episodes. This is therefore effectively conditioning on having survived an earlier crisis, which biases the coefficient on ROE towards zero.

Second, we exclude from our sample a small number of banks that derive much of their income from credit card business and fiduciary activities. Major credit card banks have long been known to earn surprisingly high rents. Ausubel (1991) uses credit card receivables pricing data to document high rents in the 1980s. Fleckenstein and Longstaff (2022) find similar levels of excess profits in more recent decades. Gallo, Apilado, and Kolari (1996) and Van Oordt and Zhou (2019) show that banks with high levels of fiduciary income have lower systematic risk and higher profitability than other banks. Removing these types of banks from the sample eliminates ones where ROE is most likely to be distorted by s.

Systematic risk and systemic risk. In our model, the bank's assets are subject to systematic tail risk, and profitability measures can be used to uncover this risk. Since we do not explicitly model the interdependence of banks in the economy, our model does not directly speak to the question of systemic risk contribution. However, the bad state in the model can be interpreted as a systemic event. To the extent that high risk premia can be earned for taking on exposures to rare systemic events, profitability measures should also be helpful for assessing an institution's likely exposure to these events. Banks with higher exposure to systemic events are, in turn, likely to make bigger contributions to systemic risk (Acharya et al., 2017).

3.1 Empirical Strategy

Our main tests cover three important banking crises in the United States in the modern era: the savings and loan crisis of the late 1980s (S&L crisis), the financial crisis of 2007–2010 (mortgage crisis), and the regional bank crisis of 2023 precipitated by the collapse of Silicon Valley Bank (SVB crisis). We focus on these episodes because of the severity of the crises as well as the availability of detailed accounting and regulatory data. We also examine a sample from the Russian crisis of 1998 that was a relatively milder crisis compared to the others we study in detail, and an out-of-country sample using the stress in the European banking sector during the 2008–2011 period.

For the empirical analysis, we need measures of equity returns in the good state, R^u, and the bad state, R^d. Stock returns, based on market valuations, and accounting profits are two obvious candidates. In the model above with one-period assets that have independent and identically distributed payoffs, there is no difference between the accounting ROE and stock returns. However, in a more realistic setting, accounting profitability should be a better indicator of risk exposures ex-ante in good times, while stock returns should be a better measure of the realized risk in a bad tail event.

An analogy with a levered portfolio of corporate bonds illustrates the logic. Similar to a portfolio of highly-rated corporate bonds, many bank assets are risky debt claims that pay close to their promised yield in good times, but with the risk of substantial losses in bad times. The promised yield of corporate bonds relative to a risk-free benchmark is a good indicator of their default risk. The accounting return on assets that a bank earns in good times resembles this promised yield. Similarly, with leverage, the accounting return on equity of a bank in good times is analogous to the levered promised yield of a corporate bond investment. Hence, we use the accounting return on equity relative to the risk-free rate in good times as a measure of bank risk.

In contrast, the realized stock market return at an annual or a quarterly frequency is not a good indicator of default risk. Asset prices are forward-looking and the realized return of a long-term asset is dominated by unexpected news about changes in the properties of payoffs and discount rates in future years. Recent returns on a corporate bond portfolio are therefore not a good measure of the portfolio's risk—in fact, they may be inversely related to the level of risk. The same logic applies to a bank's realized stock return. For this reason, we focus on accounting profits to measure profits in good times, $R^u(\theta)$.

However, during a crisis, when a bank's exposure to systematic tail event risk is revealed, the stock return captures this realization of risk better than the accounting profit. Losses are recognized in the financial accounts only with delay and only gradually. Stock prices, in contrast, immediately react to the unexpected news of the onset of a crisis and the bank's exposure to it. During a crisis, the tail event, and the bank's role in it, is the dominant piece of news affecting its stock return, which is exactly what we are aiming for. Thus, for measurement of profits in bad times, $R^d(\theta)$, stock returns are better suited than accounting profits. We use the average of a bank's stock returns on days when a bank stock index (or a market index) return is worse than the 5th percentile of its historical distribution to measure its exposure to a systematic tail event.

To take the relationship (3) between realized tail risk and pre-crisis ROE to the data, we need to keep in mind that, unlike in our model, the data is not generated by a two-state data generating process. Instead, crises may also differ in the strength of the crisis shock. Even if pre-crisis ROE was a perfect proxy for banks' exposure to the crisis shock, the magnitudes of realized returns that result from it may differ across crises depending on the magnitude of the shock. For our empirical analysis, we therefore generalize (3) to the following relationship

$$R_i^{\text{crisis}} = a + b(F \times ROE_i^{\text{prior}}), \tag{8}$$

where ROE_i^{prior} is bank i's accounting ROE in the year prior to the onset of the crisis, R_i^{crisis} is the average of bank i's stock market returns during the crisis period on days when tail risk shocks materialized, and $F < 0$ is the common factor realization that represents the crisis shock. Holding constant the level of systematic tail risk exposure captured by R^u, banks will experience lower returns in the crisis if F is more strongly negative. Hence, regressing R_i^{crisis} on ROE_i^{prior} should yield coefficients that vary across crises depending on the magnitude of F in each crisis.

For this reason, we work with standardized variables. After cross-sectionally demeaning and standardizing both sides of (8) in each crisis, we obtain

$$\frac{R_i^{\text{crisis}} - \bar{R}_i^{\text{crisis}}}{s.d.(R_i^{\text{crisis}})} = \frac{ROE_i^{\text{prior}} - \overline{ROE}^{\text{prior}}}{s.d.(ROE_i^{\text{prior}})}. \tag{9}$$

Hence, in this idealized case, regressing standardized bad-day stock returns on standardized ROE,

$$\frac{R_i^{\text{crisis}} - \bar{R}_i^{\text{crisis}}}{s.d.(R_i^{\text{crisis}})} = \gamma_0 + \gamma_1 \left(\frac{ROE_i^{\text{prior}} - \overline{ROE}^{\text{prior}}}{s.d.(ROE_i^{\text{prior}})} \right) + \varepsilon_i, \tag{10}$$

should yield a coefficient of unity.

Of course, in practice, the relationship between R_i^{crisis} and ROE_i^{prior} will not be as clean as in (8). While bad-day returns during a crisis should be heavily influenced by the crisis shock F, banks will also experience idiosyncratic shocks that generate dispersion in returns. As a consequence, the standard deviation of returns used in the standardization of the dependent variable also captures these idiosyncratic shocks, and hence the coefficient γ_1 in (9) will be attenuated away from unity towards zero and the R^2 will be less than 100%. But with standardized dependent and explanatory variables, we at least have a clear benchmark prediction of $\gamma_1 = 1$ in the idealized case without idiosyncratic noise in bad-day returns and ROE as a perfect measure of systematic tail risk exposure.

ROE and beta. The bad state in our model is meant to be a systematically bad state of the world in which not only an individual bank's asset values decline, but other banks' asset values and possibly the stock market overall declines as well. In this sense, having high asset risk, high leverage, and hence high ROE in good times is equivalent in our model to having high beta on a bank stock index, and possibly also high beta on an overall market index. For this reason, we also explore empirically whether beta measured in good times is a good predictor of exposure to tail risk events in bad times.

Whether beta works well, and whether it possibly subsumes the predictive role of ROE, is not obvious. Nagel and Purnanandam (2020) show that banks' risk exposures have option-like properties and they change dynamically as banks' assets experience valuation shocks. Consistent with this concern, Knaup and Wagner (2012) find empirically that banks' loadings on stock market index put options—a systematic risk measure that focuses on the tail of the distribution—are negatively related to banks' market betas in the years prior to the mortgage crisis. Relatedly, Sarin and Summers (2016) note that bank betas were unusually low prior to the mortgage crisis. In contrast, ROE would detect sales of out-of-the money puts because the proceeds from these sales (which may be implicit in various lending and investment strategies that load on credit and interest-rate risk) boost profitability in good times.

Even if the power of ROE to predict crisis risk exposure is entirely driven by the relationship between ROE and beta, it would still be valuable for regulators to know whether banks' crisis risk exposure can be predicted based on accounting measures alone because a large number of banks in the U.S. are not publicly traded. Moreover, for bank holding companies with multiple subsidiaries, beta may be available at the bank holding company level but not at the subsidiary level.

Crisis-specific predictors. After establishing our baseline results, we compare the predictive power of ROE to variables that are closely tied to the proximate causes of specific crises. The motivation for this analysis is that after every crisis, regulators focus on controlling the drivers of the previous crisis, often by designing more complex regulatory models that target these drivers.

For example, involvement in mortgage securitization and receipt of the resulting non-interest income was a key factor for exposure to the mortgage crisis. Several provisions in the post-mortgage crisis regulatory reform addressed weakness in the securitization market, for example, by requiring higher retention of equity tranches by sponsors or improved disclosure of off-balance sheet activities. Such reforms aim to correct the proximate cause of the past crisis. In contrast, ROE is potentially a generic predictor of bank risk that could work regardless of the specific nature of a particular crisis. To evaluate ROE as a generic predictor of systematic risk relative to crisis-specific predictors, we augment the regression in Equation (10) with these crisis-specific explanatory variables.

4 Data

For our main analysis, we construct distinct samples for the S&L crisis, the mortgage crisis, and the SVB crisis. Each sample comprises banks that met the following selection criteria: (1) income data and balance sheet data for the bank were present in the CRSP-COMPUSTAT merged database for the year prior to the crisis, (2) key accounting variables were present for the bank in the Call Report regulatory filings for the fourth quarter of the calendar year prior to the crisis, (3) the bank was present in a database maintained by the Federal Reserve Bank of New York that links CRSP-COMPUSTAT data to Call Report regulatory filing data, (4) daily stock market returns were present for the bank in the CRSP-COMPUSTAT merged database for the crisis period, (5) the bank's ratio of fiduciary income to interest income was not in the top 5% of banks that met the first four criteria in the same crisis period, (6) the bank's ratio of credit card loans to total assets was less than 19%, and (7) the bank's tangible common equity was nonnegative. We elaborate on each of these selection criteria below.

Income and balance sheet data, such as equity, assets, pretax income, and dividends, are from the CRSP-COMPUSTAT Fundamentals Annual database. Several additional accounting variables such as the level of uninsured deposits, the repricing maturity of securities, and risk-weighted assets are obtained from Call Report regulatory filings of banks. We link the CRSP-COMPUSTAT data to the Call Report data using a crosswalk maintained by the Federal Reserve Bank of New York. Daily stock market returns in the CRSP-COMPUSTAT merged database are from the University of Chicago's Center for Research in Security Prices (CRSP). Appendix A presents the details on the source and construction for all variables.

We exclude banks that derive a significant portion of their income from fiduciary activities. Data on fiduciary income comes from the Call Reports data for the fourth quarter of 1986, 2006, and 2021 for the S&L crisis, the mortgage crisis, and the SVB crisis, respectively. We construct the ratio of fiduciary income to interest income for each bank, and generate the empirical distribution of this ratio for each crisis separately. If a bank falls in the top 5% of the crisis-specific distribution then we exclude it from the sample. These banks specialize in activities such as tri-party repo clearing or trust business that are more utility-like and hence economically very different from the lending and securities investment activities that our conceptual framework assumes on banks' asset side.[7]

We also exclude banks that derive a significant portion of their income from credit cards. Data on credit card loans is available only for the mortgage crisis and the SVB crisis. Based on either the pooled or crisis-specific observations, we observe a large discontinuity in the empirical distribution of credit card loans to total assets at 19%. Therefore, we exclude banks with more than 19% of their assets in credit card loans from the mortgage and SVB crisis samples to ensure that our results are not contaminated by the well-documented rents earned by credit-card issuing banks.[8] Our key results remain similar if we do not impose these restrictions on fiduciary income or credit card activities in our sample selection criteria.

Our main explanatory variable, the return on equity, ROE_i^{prior}, is defined as the ratio of pre-tax income to the book value of tangible common equity. We exclude intangible assets from the equity calculation as their inclusion would introduce distortions in cross-bank comparisons. For example, inclusion of goodwill would mean that the assets of a recently acquired bank would be valued close to market value, while many assets of a bank that had no recent merger and acquisition history would not be marked-to-market. Further, we exclude banks with negative value of tangible common equity from the sample to ensure that our profitability measure is economically meaningful.

We measure accounting profitability about one year prior to the onset of the crisis. For the SVB

[7] Banks with high fiduciary income that get excluded from our sample include BNY Mellon, State Street Bank, and Northern Trust Corporation.

[8] Credit card loans as a fraction of assets exceeds 19% for four banks: American Express, Discover, Capital One, and Synchrony. The next bank according to this measure has a ratio of 7.3%. Since credit card loans data is not available in the Call Reports in 1986, we are unable to apply this filter for the S&L crisis. However, these four banks do not appear in the S&L sample due to other reasons: Discover Bank, Synchrony and Capital One became publicly traded banks at later dates, whereas American Express does not enter the sample in 1986 due to the unavailability of its Call Report for the year. Therefore, the unavailability of data on credit card loans does not matter for our sample selection procedure for the S&L crisis in any practical sense.

crisis, we take March and April of 2023 as the crisis period. The rise in the federal funds rate that caused banks' asset losses in this crisis began in March 2022. For this reason, we measure banks' profitability in fiscal year 2021, in the good times prior to the start of the interest rate hike. For the mortgage crisis, we define the crisis period as September 2007 to September 2010. The accounting measures of profitability are from fiscal year 2006. Again, our approach ensures that we measure profits in good times before the signs of stress in the mortgage market became visible. The S&L crisis was spread over multiple years in the late 1980s and early 1990s. Hence sharp identification of the crisis period is difficult. With that caveat in mind, we take accounting measures of profitability from banks' fiscal year 1986 statements, and the stock market returns are averaged across bad market (or bank) days from January 1988 through December 1990.

For our response variables, we construct measures of realized tail risk by computing average bank stock returns on "bad days."[9] Specifically, for each crisis event we compute the average return of a bank on all bad days during the crisis. The goal of this approach is to measure the tail risk of the bank during periods of extreme distress in the market.

We compute "bad days" using two methods. In the first approach, "bad bank days" are defined by poor returns on financial services firms identified by Fama and French industry portfolio index 44 from their 48-Industry-Portfolio data.[10] In the second approach, "bad market days" are defined by poor returns on the entire market portfolio. For both approaches we define bad days as days with returns lower than the 5th percentile of daily index returns from July 1, 1926 to December 31, 2014. The first draft of this paper was written before the SVB crisis and December 31, 2014 was the end of the sample period in our computation of the distribution of bad days in that first draft. To make the SVB crisis an out-of-sample test for our approach, we stick to this historical period for calculating the 5th percentile.[11]

In an extension of our main analysis, we also investigate the relation between profitability and tail risk in two additional crises: the Russian Crisis of 1998 and the European crisis of 2008–2011. For the Russian crisis, we measure tail risk using stock return data from June 1, 1998 to December 31, 1998. Profitability is measured based on fiscal year 1997 data. For the European crisis, we obtain

[9]Our measure resembles the concept of contribution to systemic risk developed by Acharya et al. (2017).

[10]We thank Ken French for providing the data on his website.

[11]That said, extending the sample all the way to 2023 does not change the definition of bad days in any material way.

financial and stock returns data for all banks in Western Europe that are covered in the Datastream database.[12] Profitability for the European crisis is measured based on fiscal year 2006 data, just before the onset of the global financial crisis. The crisis in the European banking sector was spread over a longer time period. To account for this feature of the crisis, we create two measures of tail risk for this sample. The first measure defines the stressful period as the calendar years 2008 and 2011. These two years capture the bulk of the losses experienced by European banks in the aftermath of both the U.S. mortgage crisis and the European sovereign debt crisis. The second measure defines the crisis period as the entire period from 2008-2012.

Descriptive Statistics. Table 1 presents the summary statistics of key variables used in our study. We winsorize the accounting variables that we use as tail risk predictors to ensure that our results are not driven by outliers.[13] We report the statistics for each of the three main crises separately in Panels A, B and C. During bad bank (market) days, banks' average return was -1.60% (-1.52%), -1.87% (-2.25%), and -3.79% (-3.77%) for the S&L, mortgage, and SVB crises, respectively. There is substantial cross-sectional variation in these returns, as indicated by both the standard deviation and the difference between the minimum and maximum values of these measures for each crisis. The median Return on Equity was similar prior to all three crises, in the range of 17–20%, with substantial dispersion across banks in the pre-crisis periods. Leverage, defined as the ratio of tangible assets to tangible equity, decreased from a median value of 16.85 prior to the S&L crisis to 13.36 prior to the mortgage crisis and further to 11.72 prior to the SVB crisis.

Table 1 also provides summary statistics for variables representing the proximate cause of each crisis. The extent of uninsured deposits in the bank's liability structure and the maturity profile of their securities holdings are two such factors for the SVB crisis (Jiang, Matvos, Piskorski, and Seru, 2023). We measure a bank's dependence on uninsured deposits by computing the ratio of deposits larger than $250,000 to the total assets of the bank for the SVB crisis. Since the FDIC insurance limit was $100,000 before the mortgage crisis, the variable is similarly constructed with deposits larger than $100,000 for the remaining two crises. The level of uninsured deposits for the average bank stood at the highest level at 45% for the SVB crisis, followed by 34% and 24% for the

[12] Publicly traded banks in the following countries are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Luxemburg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[13] The winsorization is done separately for each crisis at the 1% level.

Table 1: Summary Statistics

Table 1 presents the summary statistics of key variables used in the paper. The construction of these variables, along with an example, is provided in Appendix Tables A1 and A2. Accounting variables are measured prior to the onset of a crisis, and stock returns are measured during the crisis.

Panel A: S&L Crisis

	Mean	SD	Min	P50	Max	N
Return on Bad Market Days (%)	-1.519	0.976	-4.328	-1.440	1.190	144
Return on Bad Bank Days (%)	-1.603	1.164	-4.160	-1.558	2.679	144
Assets (USD billions)	12.194	23.466	0.088	4.453	196.124	144
Return on Equity (%)	14.048	14.382	-50.422	17.333	44.215	144
Dividends/Equity (%)	4.057	1.852	0.000	4.345	8.710	144
Asset/Equity	18.079	5.171	4.267	16.851	32.996	144
Asset Growth Rate (%)	15.719	15.144	-12.905	13.960	65.052	135
Brokered Deposits/Assets (%)	0.832	1.551	0.000	0.068	7.354	144
Uninsured Deposits/Assets (%)	24.163	9.510	6.444	23.265	50.849	144
Non-Interest Income/Assets (%)	1.229	0.595	0.229	1.145	4.858	144
Beta	0.532	0.354	-0.215	0.488	1.491	144

Panel B: Mortgage Crisis

	Mean	SD	Min	P50	Max	N
Return on Bad Market Days (%)	-2.252	2.056	-7.620	-1.694	5.277	407
Return on Bad Bank Days (%)	-1.873	1.783	-6.435	-1.272	2.675	407
Assets (USD billions)	20.821	144.443	0.086	1.207	1884.318	407
Return on Equity (%)	19.158	9.983	-11.019	19.932	45.186	407
Dividends/Equity (%)	4.633	3.746	0.000	4.150	17.754	407
Total Payout/Equity (%)	7.272	7.514	0.000	5.155	42.084	407
Asset/Equity	13.623	3.730	6.112	13.358	26.415	407
Asset Growth Rate (%)	10.817	12.456	-11.144	9.000	59.172	395
Long-Maturity Share (%)	16.305	19.944	0.000	9.317	100.000	403
Brokered Deposits/Assets (%)	4.769	7.547	0.000	2.153	41.031	407
Uninsured Deposits/Assets (%)	34.351	11.513	9.077	33.537	65.505	407
Non-Interest Income/Assets (%)	0.897	0.603	0.104	0.783	3.443	407
Beta	0.674	0.679	-0.229	0.485	2.185	407

Panel C: SVB Crisis

	Mean	SD	Min	P50	Max	N
Return on Bad Market Days (%)	-3.774	4.359	-61.640	-3.310	1.108	285
Return on Bad Bank Days (%)	-3.786	2.956	-32.968	-3.353	0.898	285
Assets (USD billions)	72.978	360.640	0.352	6.004	3743.567	285
Return on Equity (%)	18.157	6.311	1.163	18.414	37.911	285
Dividends/Equity (%)	3.520	2.127	0.000	3.519	9.592	285
Total Payout/Equity (%)	6.375	4.555	0.000	5.698	21.960	285
Asset/Equity	11.901	2.550	6.755	11.720	25.353	285
Asset Growth Rate (%)	11.976	12.105	-8.270	9.405	60.476	282
Long-Maturity Share (%)	37.626	24.816	0.000	36.272	99.865	285
Brokered Deposits/Assets (%)	2.154	3.865	0.000	0.435	19.108	285
Uninsured Deposits/Assets (%)	44.952	12.948	10.213	44.442	81.945	285
Non-Interest Income/Assets (%)	0.828	0.694	0.091	0.720	5.166	285
Beta	0.851	0.375	-0.035	0.895	1.792	285

mortgage and S&L crises, respectively. We construct an approximate measure of the duration of banks' securities portfolios by taking the ratio of holdings with greater than 15 years of maturity to the sum of all fixed-rate debt securities. We call this variable the long-maturity share of a bank. The data is not available for the S&L crisis since the Call Reports did not include these details at the time.[14] The average bank had 16.30% of its fixed-rate debt in securities with maturity longer than 15 years during the mortgage crisis, which increased to 37.63% for the SVB crisis.

Exposure to mortgage securitization is widely regarded as the key contributing factor to the mortgage crisis. Since securitization activities are often hidden in off-balance sheet vehicles, balance sheet variables are not informative about these activities. Instead, we exploit the fact that income from securitization business boosts non-interest income (Brunnermeier et al., 2020). Hence, we take the ratio of non-interest income to total assets. As shown in the table, this ratio was 1.23%, 0.90% and 0.83% for the S&L, mortgage, and SVB crises, respectively.

Finally, in the S&L crisis, dependence on brokered deposits played a prominent role. Banks obtain these deposits not directly from depositors, but through a broker who facilitates the transaction between the bank and the depositor. Banks competed aggressively to attract these deposits from areas in which they did not have bank branches, they often offered relatively higher rates on these deposits, and they used them to fund riskier investments. In the immediate aftermath of the S&L crisis, several commentators and regulators argued for decreasing the banking sector's reliance on these deposits.[15] Brokered deposits as a fraction of total assets for the average bank were 0.83%, 4.77%, and 2.15% for the S&L, mortgage, and SVB crises, respectively. While the average bank did not depend heavily on brokered deposits during the S&L crisis, the brokered deposits share of assets was as high as 7.4% for some banks.

5 Empirical Relation between Profits and Systematic Tail Risk

To evaluate the relationship between pre-crisis profitability and systematic tail risk exposure during a crisis, we first estimate equation (10) separately for each crisis and present the regression results in Columns (1) to (3) of Table 2. Both the dependent and explanatory variables are

[14] The prominent role of duration-mismatch in the S&L crisis may have been the very reason why regulators subsequently required disclosure of these numbers.

[15] For example, see https://www.congress.gov/bill/102nd-congress/senate-bill/543.

standardized to have mean equal to zero and standard deviation equal to one. The standardization is done for each crisis separately. Coefficient estimates in these regressions therefore represent the effect of a one standard deviation change in the profitability measure on the systematic risk measure, again in terms of its standard deviation (s.d.).

Panel A presents the estimation results for the "bad bank days" measure of tail risk. While the magnitudes differ across specifications, we find a consistently robust negative relation between pre-crisis ROE and bad-day crisis returns. Based on bad bank days, one s.d. higher ROE prior to the crisis is associated with -0.37, -0.53, and -0.18 s.d. lower returns during the S&L, mortgage and SVB crises, respectively. Panel B shows that results are similar for the "bad market days" measure of tail risk, which is not surprising because bad bank days and bad market days often coincide during a banking crisis. The estimates are statistically significant and economically meaningful.

As expected, the estimated coefficients on ROE and the R^2 are lower in the SVB and S&L samples than in the mortgage sample. Even if ROE is equally good as a predictor of systematic tail risk exposure in all three crises, we expect the coefficient estimates to be lower because the number of days with tail realizations is much smaller. In the SVB crisis, we observe a very small number of bad days in which the bank or market index experienced tail realizations: 7 bad bank days and 4 bad market days. In contrast, during the mortgage crisis period we observe 170 bad bank days and 115 bad market days. This means that the average bad-day returns during the SVB crisis are more vulnerable to idiosyncratic shocks than the average bad-day returns during the mortgage crisis, which are averaged over a much larger number of bad days. As we discussed in Section 3.1, contamination with idiosyncratic shocks attenuates the estimated coefficient on ROE in these regressions and lowers the R^2.

In the S&L crisis, too, the numbers of bad bank days (31) and bad market days (23) are lower than the corresponding numbers for the mortgage crisis. Moreover, the crisis and the pre-crisis periods in this case are not as sharply defined as in the mortgage crisis, which means that the pre-crisis ROE we measure may not be as cleanly attributable to good times as in the mortgage crisis.

Column (4) presents the pooled regression results with observations from all three crises. For the pooled regression estimate we standardize the variables (and winsorize the explanatory variable) based on pooled observations so that coefficient estimates still represent the effect of a one s.d.

Table 2: Profitability and Systematic Tail Risk

The dependent variable in these regressions is the average stock return of a bank during bad bank days of the crisis in Panel A, and bad market days in Panel B. The explanatory variable is the accounting return on equity prior to the crisis period. The dependent and explanatory variables are standardized. Standard errors are reported in parentheses below each coefficient estimate. Columns (1) to (3) are estimated with data for each crisis separately. Columns (4) and (5) pool observations for all three crises.

	(1)	(2)	(3)	(4)	(5)
Panel A: Bad Bank Days					
Return on Equity	-0.3635***	-0.5312***	-0.1781***	-0.3001***	-0.2059**
	(0.0877)	(0.0418)	(0.0594)	(0.0285)	(0.0827)
Nobs	144	407	285	836	344
Adjusted R-squared	0.1261	0.2804	0.0283	0.2436	0.4024
Crisis	S&L	Mortgage	SVB	All	All
Crisis Fixed Effects	NA	NA	NA	Yes	Yes
Bank Fixed Effects	NA	NA	NA	No	Yes
Panel B: Bad Market Days					
Return on Equity	-0.2248***	-0.5138***	-0.1718***	-0.2563***	-0.1928**
	(0.0815)	(0.0447)	(0.0602)	(0.0287)	(0.0839)
Nobs	144	407	285	836	344
Adjusted R-squared	0.0438	0.2621	0.0261	0.1384	0.1713
Crisis	S&L	Mortgage	SVB	All	All
Crisis Fixed Effects	NA	NA	NA	Yes	Yes
Bank Fixed Effects	NA	NA	NA	No	Yes

change in an explanatory variable on the outcome variable, again in terms of the s.d. of the dependent variable. We include a fixed effect for each crisis and cluster the standard errors at the bank level. One s.d. higher ROE during good time is associated with -0.30 s.d. lower average bad-day returns during the crises in Panel A and -0.26 s.d. in Panel B. Column (5) presents a strict specification with bank fixed effects, for the subset of banks that are present in at least two crises. Bank fixed effects could absorb persistent differences between banks in the extent of positive NPV business lines that may distort ROE as a risk measure. At the same time, though, this specification may understate the predictive power of ROE. Since a bank that fails or gets acquired by another one is not present in subsequent crises, the selected sample of surviving banks in this specification may systematically miss the banks that performed worst during the earlier crises. Nevertheless, we find a negative coefficient of -0.21 on the ROE variable in Panel A and -0.19 in Panel B. Overall we document a strong negative relation between ROE in good times and stock returns on days when crisis shocks materialized during bad times.

5.1 Profitability and Beta

Table 3 adds banks' pre-crisis market beta as an explanatory variable to the regressions from Table 2 Panel A. We use daily returns to estimate banks' market beta during the same year for which we compute the ROE measure in each crisis episode. We do not view this analysis as a horse race. In our model, banks with high pre-crisis ROE and high leverage also have high systematic risk. Therefore, pre-crisis ROE and pre-crisis beta both proxy for the same underlying systematic risk and leverage of the bank. In practice, neither one then is likely to be a perfect measure of this underlying risk, and hence it would be natural that both help empirically to predict exposure to systematic tail risk realizations. The purpose of this analysis is to see whether in cases when both measures are available, using them jointly can be useful.

Table 3 shows that pre-crisis beta is a strong predictor of exposure to systematic tail risk shocks. To save space, we now focus on bad bank days for our measure of tail risk. Our results remain similar for bad market days. As expected, the inclusion of beta lowers the coefficient on the ROE variable as the estimated beta and ROE are both imperfect proxies of the underlying systematic tail risk exposure of a bank. In the SVB crisis, beta absorbs the predictive power of ROE. Still, in the pooled sample, even after controlling for beta, banks with one s.d. higher ROE have 0.14 s.d.

lower returns on bad bank days.

Overall, when beta and ROE are both available, both are helpful for assessing bank risk. However, many U.S. banks are not publicly traded, so beta is not available. Whereas beta is valuable as a measure of risk only among publicly traded banks, ROE is valuable as a measure of risk in the entire banking sector.

5.2 Profitability vs. Proximate Drivers

After a banking crisis, it is typical for researchers, regulators, and policy-makers to investigate what led to the crisis. While such an analysis is useful for understanding the drivers of a particular crisis, the proximate drivers of a crisis only become obvious after the tail event has already been realized. In contrast, we posit that our proposed measure of risk, ROE, should be generalizable and predictive of performance during all crises based on fundamental economic reasoning: In sufficiently competitive markets, it is difficult for banks to earn high profits in good times without taking on substantial exposure to systematic risk. Therefore, pre-crisis ROE should have predictive power regardless of the causes of a particular crisis, while the variables that are identified ex post as proximate drivers of a particular crisis are more likely to be uninformative about performance during other crises. To provide evidence on this question, we now augment the regressions of Table 2 Panel A with proxies for the proximate causes of the S&L, mortgage, and SVB crises along with ROE.

5.2.1 S&L Crisis

We begin with the S&L crisis and proceed chronologically. Table 4 includes brokered deposits as a fraction of total assets prior to the crisis as an additional predictor variable. As discussed earlier, maturity mismatch and brokered deposits were two key drivers of the S&L crisis. Unfortunately, we do not have high-quality data on measures of duration risk for this crisis. Hence, we only consider the role of brokered deposits as a proximate cause in our regression analysis.

Column (1) of the table presents results for the S&L crisis. Banks with more brokered deposits as a fraction of total assets performed significantly worse during this crisis. One s.d. higher dependence on brokered deposits is associated with 0.15 s.d. lower return on bad bank days during the crisis. Columns (2) and (3) repeat this regression for the mortgage and SVB crises. The brokered deposits variable does explain some variation during the mortgage crisis, but it does not explain any meaningful variation in bad day returns during the SVB crisis. In contrast, the coefficient on ROE remains negative and significant across all three models, ranging between -0.19 and -0.54.

Column (4) pools all the observations across the three crises. We include an interaction term between brokered deposits and a dummy variable for each crisis. Brokered deposits is a strong predictor of performance during the S&L crisis, as indicated by a negative and significant coefficient on the interaction term "Brokered Deposit × S&L". It does not have a meaningful effect for the other two crises. As was the case for each individual crisis, ROE is a significant predictor of systematic tail risk in the pooled estimation.

5.2.2 Mortgage Crisis

The ratio of non-interest income to assets is our measure of the proximate driver of the mortgage crisis. Table 5 presents the results. Column (2) shows that banks with higher levels of non-interest income in good times performed poorly on bad bank days during the mortgage crisis. One s.d. higher non-interest income to asset ratio is associated with 0.11 s.d. lower returns during bad bank days of the mortgage crisis. The ratio of non-interest income to assets does not predict returns during bad bank days of the S&L crisis, and it has the "wrong" sign for the SVB crisis.

As shown in the pooled regression model of Column (4), banks with one s.d. higher non-interest income earned 0.10 s.d. lower returns on bad bank days during the mortgage crisis. During the SVB crisis, the role of this variable reverses: banks with one s.d. higher non-interest income earned 0.22 s.d. higher returns on bad bank days. The estimated coefficient on ROE is negative and significant in the regressions for each individual crisis and in the pooled regression.

5.2.3 SVB Crisis

We consider two drivers of the SVB crisis: the ratio of uninsured deposits to assets and the long-maturity share of fixed-rate securities. Results are provided in Table 6. Panel A uses the uninsured deposit ratio as the proxy for risk-taking, and Panel B uses the long-maturity share of fixed-rate securities as the proxy for risk-taking.

Column (3) of Panel A shows that banks with one s.d. higher uninsured deposit ratio had 0.43 s.d. lower returns on bad bank days during the SVB crisis. For the other two crises, the uninsured deposit ratio is not a significant predictor of systematic tail risk. In the pooled regression

Table 3: Beta and Systematic Tail Risk

The dependent variable in these regressions is the average stock return of a bank during bad bank days. The explanatory variables are the accounting return on equity prior to the crisis period and each bank's market beta estimated with daily returns during the same year in which we measure the accounting return on equity. The dependent and explanatory variables are standardized. Standard errors are reported in parentheses below each coefficient estimate. Columns (1) to (3) are estimated with data for each crisis separately. Column (4) pools observations for all three crises.

	(1)	(2)	(3)	(4)
Return on Equity	-0.3245***	-0.2798***	0.0200	-0.1363***
	(0.0978)	(0.0425)	(0.0487)	(0.0259)
Beta	-0.4850***	-0.6209***	-0.5140***	-0.4775***
	(0.0605)	(0.0328)	(0.0925)	(0.0334)
Nobs	144	407	285	836
Adjusted R-squared	0.3569	0.6025	0.2514	0.4358
Crisis	S&L	Mortgage	SVB	All
Crisis FE	NA	NA	NA	Yes

Table 4: Brokered Deposits as a Proxy for risk

The dependent variable in these regressions is the average stock return of a bank during bad bank days. The explanatory variables are the accounting return on equity prior to the crisis period and brokered deposits as a fraction of total assets. The dependent and explanatory variables are standardized. "S&L" is a dummy variable that equals one for the S&L crisis and zero otherwise. "Mortgage" and "SVB" are defined similarly. Standard errors are reported in parentheses below each coefficient estimate. Columns (1) to (3) are estimated with data for each crisis separately. Column (4) pools observations for all three crises.

	(1)	(2)	(3)	(4)
Return on Equity	-0.3667***	-0.5375***	-0.1923***	-0.3063***
	(0.0895)	(0.0409)	(0.0609)	(0.0281)
Brokered Deposits	-0.1511**	-0.0748*	0.0615	
	(0.0609)	(0.0413)	(0.0487)	
Brokered Deposits x S&L				-0.2465***
				(0.0920)
Brokered Deposits x Mortgage				-0.0385
				(0.0255)
Brokered Deposits x SVB				0.0946
				(0.0828)
Nobs	144	407	285	836
Adjusted R-squared	0.1430	0.2842	0.0285	0.2445
Crisis	S&L	Mortgage	SVB	All
Crisis FE	NA	NA	NA	Yes

Table 5: Non-interest Income as a Proxy for risk

The dependent variable in these regressions is the average stock return of a bank during bad bank days. The explanatory variables are the accounting return on equity prior to the crisis period and the ratio of non-interest income to total assets. The dependent and explanatory variables are standardized. "S&L" is a dummy variable that equals one for the S&L crisis and zero otherwise. "Mortgage" and "SVB" are defined similarly. Standard errors are reported in parentheses below each coefficient estimate. Columns (1) to (3) are estimated with data for each crisis separately. Column (4) pools observations for all three crises.

	(1)	(2)	(3)	(4)
Return on Equity	-0.3622***	-0.4904***	-0.2467***	-0.2996***
	(0.0883)	(0.0453)	(0.0650)	(0.0303)
Non-Interest Income	-0.0367	-0.1127**	0.2061***	
	(0.1256)	(0.0520)	(0.0523)	
Non-Interest Income x S&L				-0.0372
				(0.0703)
Non-Interest Income x Mortgage				-0.0959**
				(0.0398)
Non-Interest Income x SVB				0.2210***
				(0.0549)
Nobs	144	407	285	836
Adjusted R-squared	0.1212	0.2897	0.0629	0.2623
Crisis	S&L	Mortgage	SVB	All
Crisis FE	NA	NA	NA	Yes

model of Column (4), we confirm these findings. Whereas ROE remains a generic predictor of poor performance across all crises, uninsured deposits indicates high risk exposure only in the SVB crisis.

Panel B uses the long-maturity share of fixed-rate securities as a predictor. Column (1) shows that a one s.d. higher long-maturity share is associated with 0.27 s.d. lower bad bank day returns during the SVB crisis. The long-maturity share of fixed-rate securities was also a significant predictor of bad performance during the mortgage crisis.[16] ROE remains a strong predictor of tail risk exposure in both crises.

Taken together, our results show that drivers of bank tail risk exposure that were identified in the aftermath of a particular crisis are related to bank tail risk exposure during that particular crisis, but they generally do not have predictive power for tail risk exposure during other crises. The proximate cause of each crisis is different. In contrast, pre-crisis ROE is consistently predictive of bank tail risk exposure in all of the crises we examine, even when adjusting for the crisis-specific drivers identified ex post.

5.3 Comparison with Risk-Weighted Assets and Other Risk Proxies

Our basic approach that relates ROE to tail risk is rooted in one of the most fundamental ideas in finance: the trade-off between risk and return. Based on this trade-off, we infer risk from return. In contrast, established approaches in bank regulation focus on measuring risk directly. We now compare the two approaches in their ability to predict systematic tail risk exposure of banks during crises.

Specifically, we compare our ROE-based approach to the model-based measure of risk currently in use by bank regulators. We focus on risk-weighted assets (RWA), the measure recommended by the Basel Committee on Banking Supervision for determining capital requirements. The premise of most capital requirements is that banks with higher RWA are contributing more to systematic risk. To compare this measure of risk with our measure, we scale RWA by total assets for each bank. We include this variable—the ratio of RWA to total assets—as an additional regressor in our profitability-based regression specifications and report the results in Table 7. Since RWA data is only available for the mortgage and SVB crises, these regressions are estimated on the pooled observations from these two crises only.

[16] We do not have this data for the S&L crisis.

Table 6: Uninsured Deposits & Security Maturiy as a Proxy for risk

The dependent variable in these regressions is the average stock return of a bank during bad bank days. The explanatory variables are the accounting return on equity prior to the crisis period, the ratio of uninsured deposits to assets, and the long-maturity share of fixed-rate securities. The dependent and explanatory variables are standardized. "S&L" is a dummy variable that equals one for the S&L crisis and zero otherwise. "Mortgage" and "SVB" are defined similarly. Standard errors are reported in parentheses below each coefficient estimate. Columns (1) to (3) are estimated with data for each crisis separately. Column (4) pools observations for all three crises.

	(1)	(2)	(3)	(4)
Panel A: Uninsured Deposits as a Proxy for risk				
Return on Equity	-0.3867***	-0.5345***	-0.1521***	-0.3003***
	(0.0937)	(0.0419)	(0.0558)	(0.0291)
Uninsured Deposits	-0.0668	0.0149	-0.4254***	
	(0.0884)	(0.0436)	(0.1139)	
Uninsured Deposits x S&L				-0.1311*
				(0.0679)
Uninsured Deposits x Mortgage				-0.0083
				(0.0389)
Uninsured Deposits x SVB				-0.5284***
				(0.1315)
Nobs	144	407	285	836
Adjusted R-squared	0.1238	0.2789	0.2064	0.3235
Crisis	S&L	Mortgage	SVB	All
Crisis FE	NA	NA	NA	Yes
Panel B: Security Maturity as a Proxy for risk				
Return on Equity	-0.3635***	-0.5229***	-0.1694***	-0.3452***
	(0.0782)	(0.0413)	(0.0573)	(0.0337)
Long-Maturity Share		-0.1278***	-0.2657***	
		(0.0469)	(0.0780)	
Long-Maturity Share x Mortgage				-0.1222***
				(0.0437)
Long-Maturity Share x SVB				-0.3247***
				(0.0953)
Nobs	144	403	285	688
Adjusted R-squared	0.1261	0.2973	0.0959	0.2775
Crisis	S&L	Mortgage	SVB	All
Crisis FE	NA	NA	NA	Yes

In the regression reported in Column (1), the only regressors are ROE and the ratio of RWA to total assets. ROE remains a strong negative predictor of returns during crisis period. The coefficient on the RWA measure is positive and significant, indicating that, conditional on ROE, banks that are riskier according to the RWA measure performed better during the crisis. If ROE was a poor measure of risk and RWA was a good measure of risk, then we would expect the coefficient on RWA to have the opposite sign. Column (2) adds crisis fixed effects. The incremental explanatory power of RWA is small; the adjusted R^2 in Column (2) (24.08%) is only marginally higher than the adjusted R^2 for the same specification minus RWA as a regressor (23.61%). Furthermore, the magnitude of the coefficient on RWA is much smaller than the coefficient on ROE. RWA simply does not have much predictive power over and above ROE.

These results show that our simple profitability-based approach delivers significantly more predictive power than the model-based measures of risk. Risk-weighted assets are computed with a complex model involving a detailed analysis of different asset classes and their further categorization into various risk groups. Still, RWA-based risk measures perform worse than simple measures that can be easily obtained from publicly available financial reports of the firm.

Several other empirically-motivated measures have been proposed in the literature as predictors of tail risk. In Columns (3) and (4) we consider several of these measures along with ROE, all measured in the year prior to the onset of the crisis: (a) a dummy variable equal to one if a bank is in the top 2% of banks by total assets, (b) the logarithm of total assets, (c) leverage, and (d) the growth rate of total assets. We also include the crisis-specific drivers we analyzed in Section 5.2, i.e. non-interest income, brokered deposits, uninsured deposits, and the long-maturity share of fixed-rate securities. Interpretation of such a "kitchen-sink" regression is somewhat tricky. Whereas we have argued that there are fundamental economic reasons to expect ROE to be predictive of systematic risk exposure, the rationales connecting some of the other variables in this regression to bank risk are less clear. For example, the logarithm of total assets is not inherently connected to systematic risk exposure, but perhaps banks willing to take more risks become bigger in good times. We do not expect ROE to be a perfect measure of risk, so we expect the additional variables to absorb some of the predictive power of ROE. Columns (3) and (4) show that the magnitude of the coefficient on ROE drops, but there is still a consistent negative relation between ROE and tail risk even after including these other variables in the regression model. The coefficient on RWA is

Table 7: Profits vs. Regulatory Risk Weights

The dependent variable in these regressions is the average stock return of a bank during bad bank days. The explanatory variables are the accounting return on equity prior to the crisis period, the ratio of risk-weighted assets to total assets, and, in columns (3) and (4), a number of additional bank characteristics. Dependent and explanatory variables are all standardized. Standard errors are reported in parentheses below each coefficient estimate. The regressions pool observations for the mortgage and SVB crises episodes.

	(1)	(2)	(3)	(4)
Return on Equity	-0.3236***	-0.3485***	-0.0913**	-0.0824*
	(0.0342)	(0.0339)	(0.0384)	(0.0430)
Risk-Wt Assets/Assets	0.1388***	0.0821**	0.0055	0.0083
	(0.0306)	(0.0341)	(0.0237)	(0.0230)
Top 2% Banks			1.3877***	1.4447***
			(0.2961)	(0.3176)
Log(assets)			-0.7071***	-0.7343***
			(0.0611)	(0.0779)
Leverage			0.0132	0.0330
			(0.0394)	(0.0353)
Assets Growth			-0.1413**	-0.1430**
			(0.0615)	(0.0620)
Non-interest Income			0.0382*	0.0398*
			(0.0212)	(0.0217)
Brokered Deposits			0.0242	0.0309
			(0.0244)	(0.0277)
Uninsured Deposits			-0.1336***	-0.1436***
			(0.0381)	(0.0432)
Long-Maturity Share			-0.1054***	-0.1187***
			(0.0306)	(0.0374)
Nobs	692	692	675	675
Adjusted R-squared	0.1007	0.2408	0.5288	0.5294
Crisis	All	All	All	All
Crisis FE	No	Yes	No	Yes

insignificant in these regressions.

5.4 Payouts to Managers and Shareholders

So far our analysis focused on the predictive power of pre-crisis profitability for systematic tail risk exposure. A natural question arises: who gains from a business strategy that generates higher profits in good times at the expense of higher tail risk? From the private viewpoint of a manager or shareholder, a zero-NPV risky investment by the bank could be a positive-NPV opportunity if the downside risk is partly borne by society via implicit government guarantees or deposit insurance premia that are not properly risk-adjusted. If such a wedge between private and social valuations is an important driver of bank risk-taking, managers and shareholders also have an incentive to pay out realized profits in good times instead of retaining them to serve as loss-absorbing capital in bad times. From this perspective, high rates of payouts to shareholders in the form of dividends or share repurchases and high levels of managerial compensation can be the driving forces behind such a business strategy.

Hence, in our next set of analyses we ask whether large managerial compensation and payouts in good times predict the realization of tail risk in bad times. While detailed data on managerial compensation is not available for all banks, we are able to create a rough measure of managerial payout by looking at expenses on stock incentive plans prior to the mortgage and SVB crises. A change in accounting rules for managerial compensation in 2004 (SFAS 123R) required firms to expense the fair value of stock and option grants in their profit and loss statement. This amount provides a reasonable proxy for the stock-based component of managerial compensation in the year before the mortgage and SVB crises.[17] We scale the compensation variable by the equity value of the bank to construct the managerial payout measure.

Results are reported in Panel A of Table 8. We find that one s.d. increase in the compensation variable is related to about 0.29 s.d. lower returns on bad bank days during the mortgage crisis, and 0.21 s.d. lower returns on bad bank days during the SVB crisis. The slope coefficient in the pooled regression is 0.25. Thus when managers tend to benefit from profits in the form of higher

[17] An alternative approach would be to use compensation payout data from Compustat's executive compensation database. While this database provides more detailed information on various components of compensation, it covers less than 100 banks in our sample. In contrast, our approach allows us to obtain compensation information for almost all banks in our sample.

Table 8: Payouts

The dependent variable in these regressions is the average stock return of a bank during bad bank days. The explanatory variable is the pre-crisis expense on stock incentive plans in Panel A, the sum of cash dividends paid and shares repurchased during the pre-crisis period in Panel B, and both explanatory variables jointly in Panel C. Both explanatory variables are expressed as a fraction of book equity. Dependent and explanatory variables are standardized. Standard errors are reported in parentheses below each coefficient estimate.

	(1)	(2)	(3)
Panel A: Managerial Compensation			
Stock-Based Compensation	-0.2956***	-0.2093**	-0.2529***
	(0.0512)	(0.1033)	(0.0593)
Nobs	358	276	634
Adjusted R-squared	0.0829	0.0399	0.1790
Crisis	Mortgage	SVB	All
Crisis FE	NA	NA	Yes
Panel B: Shareholder Payout			
Shareholder Payout	-0.4113***	0.0139	-0.2079***
	(0.0531)	(0.0707)	(0.0364)
Nobs	407	285	692
Adjusted R-squared	0.1671	-0.0033	0.1758
Crisis	Mortgage	SVB	All
Crisis FE	NA	NA	Yes
Panel C: Managerial & Shareholder Payout			
Stock-Based Compensation	-0.2005***	-0.2236*	-0.2150***
	(0.0489)	(0.1161)	(0.0659)
Shareholder Payout	-0.4096***	0.0716	-0.1688***
	(0.0500)	(0.0892)	(0.0472)
Nobs	358	276	634
Adjusted R-squared	0.2376	0.0413	0.2013
Crisis	Mortgage	SVB	All
Crisis FE	NA	NA	Yes

stock-based compensation, their employers' balance sheets are more exposed to systematic tail risk.

In Panel B, we relate systematic tail risk in the mortgage and SVB crises to pre-crisis payouts to shareholders. We measure payout by the total amount of cash dividends paid and shares repurchased by the bank during the pre-crisis year as a fraction of book equity. Column (1) shows that banks with one s.d. higher payout earned 0.41 s.d. lower returns on bad bank days during the mortgage crisis. In contrast, during the SVB crisis we do not find that pre-crisis payouts have predictive power. We suspect that the failure to find predictive power in this instance is a consequence of policy. During the COVID-19 pandemic, the Federal Reserve Bank put restrictions on dividend payouts and share repurchases of bank holding companies. These restrictions were lifted only after June 30, 2021. Hence, for much of calendar year 2021, which we use as the year prior to the SVB crisis, payouts are restricted. We would expect the payout variable to be less informative in the SVB crisis than in other crises.

Panel C uses both payouts to managers and shareholders jointly as predictor variables. Both are strong predictors in the mortgage crisis. In the SVB crisis, consistent with Panel B, only managerial compensation has predictive power. Comparing the magnitudes of the slope coefficients and the R^2 in Panel C to those in Table 2, we see that pre-crisis payouts alone have roughly the same predictive power as total profits as measured by ROE. For the mortgage crisis, the R^2 in Table 2 is a little higher, and for the SVB crisis it's a little lower in Table 2. Hence, consistent with the private incentives view, when profits are paid out to managers or shareholders at high rates in good times, this is a strong indication that the bank is exposed to systematic tail risks.

5.5 Other Crises

We provide evidence from two other episodes of banking crises to further bolster our claim that profitability in good times is a useful measure of systematic tail risk. The first episode is the Russian and Long-Term Capital Management crisis in which several U.S. banks suffered significant losses in the second half of 1998. The second episode is the crisis in Europe during 2008–2012 when many European banks faced severe stress due to losses in mortgage-related assets and sovereign debt holdings. For both of these crises, we obtain data on profitability from the year prior to the crisis and measure tail risk using stock market returns during the crisis. We estimate the regression model linking profitability to tail risk using distinct samples for each crisis, following the approach in Table 2.

We report the estimated coefficient on the ROE measure along with the associated standard errors for all these crises in Table 9. For comparison, we also report the corresponding numbers of the S&L, mortgage, and SVB crises as well. Figure 1 plots the estimated coefficients along with 95% confidence intervals. Our analysis shows a clear pattern. In the Russian crisis analysis, one standard deviation increase in profitability is associated with 0.41 standard deviations lower returns during bad bank days.[18] In the European crisis analysis, the effect is comparable: one standard deviation increase in profitability is associated with 0.23–0.28 standard deviations lower returns depending on the precise definition of the crisis period.

Across the five crises that we consider in our paper—the S&L crisis, the mortgage crisis, the SVB crisis, the Russian Crisis, and the European crisis—higher profitability in good times predicts lower returns in bad times. While the underlying risk that triggered the crisis differs from one crisis to another—e.g. interest rate risk, mortgage losses, or exposure to sovereign debt—the link between profitability and systematic tail risk is always strong. These results highlight a key benefit of our approach. In the model-based approach, an analyst needs to figure out the source of risk for each crisis, which keeps changing from one crisis to the next. No such work is required for our profitability-based approach.

[18] We apply the same sample selection criteria for the Russian crisis as our main sample. For the European crisis sample, we do not have the Call Report data. Hence we are unable to impose restrictions based on credit card activities and fiduciary income of banks.

Figure 1: Results from other crises
This figure reports regression coefficients and 95% confidence intervals from a regression of systematic tail risk exposure (as measured by stock market returns on bad bank days) on pre-crisis ROE. The model is estimated separately for five different cross-sections: the S&L crisis, the mortgage crisis, the Russian crisis, the European crisis, and the SVB crisis. The regression for the European crisis includes country fixed effects.

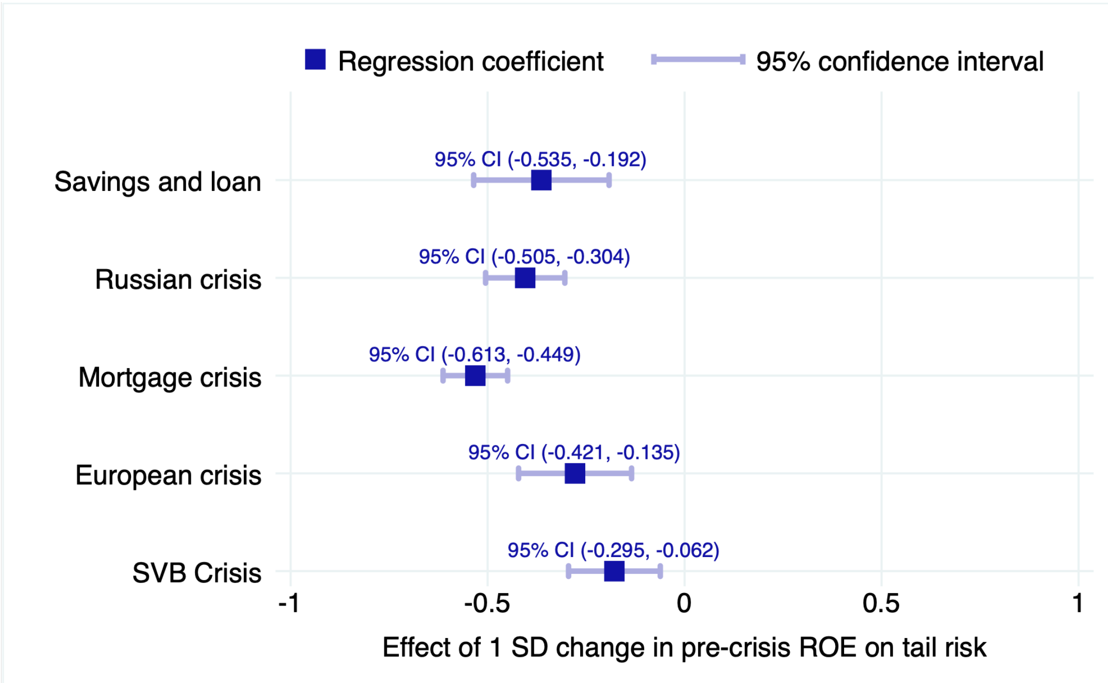

Table 9: Estimates from Other Crises

The dependent variable in these regressions is the average stock return of a bank on bad bank days during the crisis episode. The explanatory variable is the accounting return on equity prior to the crisis period. The year of measurement of the accounting return on equity is shown in the column "Profits in Year." The dependent and explanatory variables are standardized. Standard errors are reported in parentheses below each coefficient estimate. For the European Crisis sample, the regression model includes country fixed effects.

Crisis	ROE Coeff.	s.e.	Crisis Episode	Profits In Year
S&L Crisis	-0.363	0.088	1/1/1988 – 12/31/1990	1986
Russian Crisis	-0.405	0.051	6/1/1998 – 12/31/1998	1997
Mortgage Crisis	-0.531	0.042	9/1/2007 – 9/30/2010	2006
European Crisis	-0.278	0.073	1/1/2008 – 12/31/2008	2006
			1/1/2011 – 12/31/2011	
European Crisis	-0.235	0.070	1/1/2008 – 12/31/2012	2006
SVB Crisis	-0.178	0.059	3/1/2023 – 4/30/2023	2021

6 Conclusion

Assessing bank risk is a difficult and important problem. The standard, model-based approach of bank regulators is subject to manipulation by regulated entities. As a complement to the standard approach, we propose a model-free measure that uses profitability as an indicator of systematic tail risk exposure. This measure builds on the fundamental tradeoff between risk and return: it uses return in good times to estimate the underlying risk that is likely to materialize in bad times. Our measure is less likely to be manipulated than risk weights, and it seamlessly incorporates the contribution of leverage and off-balance sheet activity to systematic tail risk.

Using data surrounding recent episodes of systemic stress, we show that our measure is useful for predicting systematic tail risk. Accounting return on equity prior to the crisis predicts bank stock returns on the worst days of the crisis. Banks' pre-crisis market beta also has strong predictive power for systematic tail risk exposure during crises, but it's available only for publicly traded banks. Unlike various crisis-specific drivers of bank risks that have been discussed in the literature, return on equity is a powerful generic predictor of systematic tail risk exposure in each of the crises we examine.

The regime of model-based regulation puts banks and regulators in a perpetual game of cat-and-mouse. After one model fails, regulators construct a new model using lessons from the failure of the previous model. The newer model is typically more complex, which provides even more opportunity for manipulation. The underlying problem is a fundamental one: any quantitative model will be subject to manipulation as long as there are incentives to do so, an application of Goodhart's Law (Goodhart, 1984).

A profitability-based approach is more incentive compatible than model-based approaches that rely on asset risk classification. Underreporting risk could only be achieved by underreporting profits, which would inhibit the ability to distribute returns to shareholders and managers—a costly consequence from the viewpoint of managers. Profitability-based risk assessment further seamlessly incorporates the contribution to systematic risk of off-balance sheet activities. Model-based approaches typically focus on balance sheet inputs and therefore require special consideration for complex off-balance sheet transactions. In contrast, the profits earned from off-balance sheet activities flow through the income statement of the sponsoring bank and profit measures therefore reveal the off-balance sheet systematic risk contribution. Finally, the profitability-based approach is well-suited to capture risk from selling tail risk insurance that can be hard to detect with model-based approaches. To take a prototypical example, selling out-of-the-money put options embedded in financial products provides high profits in good times at the expense of very high systematic tail risk exposure.

Using reported profits to assess bank risk is a useful but not a perfect approach. The timing of risky activity might not coincide with the timing of profits, so there could be a delay with which risk is assessed. Basing the risk assessment on total profits might raise requirements unnecessarily on safe banks that earn rents in traditional deposit-taking and lending. Profits may also be subject to transitory shocks that could be unrelated to underlying systematic risk. But even with these limitations taken into account, the simplicity of our approach makes it an attractive complementary tool for risk-based regulation.

References

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability 5*(3), 224–255.

Acharya, V. V., H. T. Le, and H. S. Shin (2017). Bank capital and dividend externalities. *The Review of Financial Studies 30*(3), 988–1018.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2017). Measuring systemic risk. *The Review of Financial Studies 30*(1), 2–47.

Atkeson, A. G., A. d'Avernas, A. L. Eisfeldt, and P.-O. Weill (2019). Government guarantees and the valuation of american banks. *NBER Macroeconomics Annual 33*, 81–145.

Ausubel, L. M. (1991). The Failure of Competition in the Credit Card Market. *American Economic Review*, 50–81.

Baron, M. and W. Xiong (2017). Credit Expansion and Neglected Crash Risk. *Quarterly Journal of Economics 132*(2), 713–764.

Begley, T. A., A. K. Purnanandam, and K. C. Zheng (2017). The strategic under-reporting of bank risk. *Review of Financial Studies 30*(10), 3376–3415.

Behn, M., R. F. Haselmann, and V. Vig (2014). The limits of model-based regulation. Working Paper 75, SAFE.

Beltratti, A. and R. M. Stulz (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics 105*(1), 1–17.

Brunnermeier, M. K., G. N. Dong, and D. Palia (2020). Banks' non-interest income and systemic risk. *Review of Corporate Finance Studies*, forthcoming.

Calomiris, C. W. (2011). An Incentive-Robust Programme for Financial Reform. *The Manchester School 79*(s2), 39–72.

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on Deposits: Maturity Transformation Without Interest Rate Risk. *Journal of Finance 76*(3), 1091–1143.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz (2017). Why Does Fast Loan Growth Predict Poor Performance for Banks? *Review of Financial Studies 31*(3), 1014–1063.

Fleckenstein, M. and F. A. Longstaff (2022). The Market Risk Premium for Unsecured Consumer Credit Risk. *Review of Financial Studies 35*(10), 4756–4801.

Gallo, J. G., V. P. Apilado, and J. W. Kolari (1996). Commercial Bank Mutual Fund Activities: Implications for Bank Risk and Profitability. *Journal of Banking & Finance 20*(10), 1775–1791.

Getter, D. E. (2012). *US implementation of the Basel capital regulatory framework*, Volume 14. Congressional Research Service Library of Congress.

Goodhart, C. A. (1984). *Problems of Monetary Management: The UK Experience*. Springer.

Jiang, E. X., G. Matvos, T. Piskorski, and A. Seru (2023). Monetary Tightening and US Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs? Working Paper, National Bureau of Economic Research.

Knaup, M. and W. Wagner (2012). Forward-Looking Tail Risk Exposures at U.S Bank Holding Companies. *Journal of Financial Services Research 42*, 35–54.

Morgan, D. P. and A. B. Ashcraft (2003). Using loan rates to measure and regulate bank risk: Findings and an immodest proposal. *Journal of Financial Services Research 24*(2-3), 181–200.

Moussu, C. and A. Petit-Romec (2017). ROE in banks: Performance or risk measure? Evidence from financial crises. *Finance 38*(2), 95–133.

Nagel, S. and A. Purnanandam (2020). Banks' Risk Dynamics and Distance to Default. *Review of Financial Studies 33*(6), 2421–2467.

Sarin, N. and L. H. Summers (2016). Understanding Bank Risk Through Market Measures. *Brookings Papers on Economic Activity 2016*(2), 57–127.

Van Oordt, M. and C. Zhou (2019). Systemic Risk and Bank Business Models. *Journal of Applied Econometrics 34*(3), 365–384.

Appendices

A Data

Our samples are constructed by linking the CRSP-COMPUSTAT merged database maintained by Wharton Research Data Services (WRDS) with Call Report regulatory filings using a crosswalk maintained by the Federal Reserve Bank of New York (FRBNY). Daily stock market returns are from the Center for Research in Security Prices (CRSP). The merged CRSP-COMPUSTAT database has PERMCO, GVKEY, and stock market ticker identifiers. To merge information from the quarterly Call Reports, we use a mapping between PERMCO and the Call Report identifier created by FRBNY. Specifically, we begin with all banks in the quarterly Call Reports. For the S&L crisis, we obtain Call Report data from the Federal Reserve Bank of Chicago. For the mortgage and SVB crises, we obtain Call Report data from the Federal Financial Institutions Examination Council's central data repository (FFIEC).[19] We aggregate the quarterly Call Report data at the highest holder, i.e. at the bank holding company level, and match the aggregated Call Report variables with the corresponding financial data from CRSP-COMPUSTAT using the FRBNY link. Variable construction and data sources are provided in Appendix Tables A1 and A2.

[19] https://cdr.ffiec.gov/public/ManageFacsimiles.aspx

B Additional tables

Table A1: Construction of variables: CRSP-COMPUSTAT

Variable	**Data Source**	**Variable Name**	**Notes**
Common Equity	CCM Fundamentals Annual	ceq	The variable represents tangible common equity of a bank at the year end.
Tangible Common Equity	CCM Fundamentals Annual	ceqt	The variable represents tangible common equity of a bank at the year end.
Total Assets	CCM Fundamentals Annual	at	
Cash Dividends	CCM Fundamentals Annual	dvc	
Pre-tax Earnings	CCM Fundamentals Annual	pi	
Return on Equity	CCM Fundamentals Annual	pi/ceqt	The variable represents the ratio of pre-tax income to tangible equity.
Asset Growth	CCM Fundamentals Annual	$log(at)_t - log(at)_{t-1}$	Log difference in asset values over the year.
Share Repurchase	CCM Fundamentals Quarterly	cshopq $\times$ prcraq	Dollar value of shares repurchased every quarter, and then summed across quarters for the annual number.
Leverage	CCM Fundamentals Annual	(at-ceq+ceqt)/ceqt	Ratio of tangible asset value to tangible common equity.
Payout Ratio	CCM Fundamentals Annual & Quarterly	(Dividends+Share Repurchased)/Tangible Equity	Not available for the S&L crisis.
Stock-Based Compensation	CCM Fundamentals Annual	stkco	Not available for the S&L crisis.
Daily Stock Return	CRSP	ret	

Table A2: Construction of variables: Call Report

Variable	**Data Source**	**Variable Name**	**Notes**
Uninsured Deposit	Call Reports	RCONF051+RCONF047 for the SVB crisis RCON2710 for the mortgage and S&L crisis	Deposits above $250,000 for the SVB crisis, and deposits above $100,000 for the mortgage and S&L crisis. For the mortgage crisis the data was obtained from 2006Q1 since the reporting was not available for 2006Q2.
Total Deposits	Call Reports	RCON2200	
Brokered Deposits	Call Reports	RCON2365	
Securities with maturity 3 months-1 yr	Call Reports	RCFDA550+RCFDA556	Replaced with the RCON series if the RCFD series is missing.
Securities with maturity 1-3 yr	Call Reports	RCFDA551+RCFDA557	Replaced with the RCON series if the RCFD series is missing.
Securities with maturity 3-5 yr	Call Reports	RCFDA552+RCFDA558	Replaced with the RCON series if the RCFD series is missing.
Securities with maturity 5-15 yr	Call Reports	RCFDA553+RCFDA559	Replaced with the RCON series if the RCFD series is missing.
Securities with maturity gt 15 yr	Call Reports	RCFDA554+RCFDA560	Replaced with the RCON series if the RCFD series is missing.
Long-Maturity Share	Derived	Securities with greater than 15 years maturity as a ratio of all fixed rate debt security	Fixed rate debt security computed as the sum of all securities with maturity greater than 3 months.
Risk-Weighted Assets	Call Reports	RCONA223 for the mortgage crisis. RCFAA223 for the SVB crisis. NA for the S&L crisis.	For the SVB crisis, if the RCFA series is missing, then replaced with RCFDG641 or RCONG641 in that order.
Interest Income	Call Reports	RIAD4107	
Non-Interest Income	Call Reports	RIAD4079	
Credit Card Loans	Call Reports	RCONB561	NA for the S&L crisis.
Fiduciary Income	Call Reports	RIAD4070	
Assets	Call Reports	RCFD2170	

Note: Unless otherwise stated, all Call Report data is obtained from the Q4 report of the year for which we obtain information from the CRSP-COMPUSTAT database. Data for uninsured deposits are from Q2 of 1986 (for the S&L crisis) and Q1 of 2006 (for the mortgage crisis) because those are the only quarters in those calendar years for which uninsured deposits were available. All Call Report data items are first aggregated at the bank holding company level and then matched with the CRSP-COMPUSTAT databases using the PERMCO-entity link maintained by the Federal Reserve Bank of New York.