Judging Banks' Risk by the Profits They Report *

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Abstract

In competitive capital markets, portfolios of risky debt claims have high systematic risk exposure in bad times if they offer a high yield in good times. We apply this idea to measurement of bank risk. We show empirically that high rates of profit in good times are an indicator of systematic tail risk exposure in a subsequent crisis. Profit components arising from non-interest income or that are paid out as dividends and managerial compensation are particularly strongly predictive of risk. Pre-crisis profit measures do a better job in predicting systematic tail risk than conventional measures based on risk-weighted assets.

Keywords: Risk of financial institutions, systemic risk, risk measurement
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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 can be highly 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. Empirical evidence in Behn, Haselmann, and Vig (2014) and Begley, Purnanandam, and Zheng (2017) suggests that banks make use of this ability to manipulate. Understatement of *systematic* risk is particularly worrisome, as this type of risk is closely related to *systemic* risk, which is of central relevance for optimal bank regulation (Acharya 2009).[1] We therefore focus on the measurement of systematic rather than bank-specific risk in this paper.

We 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 resemble 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, say, annual or quarterly frequency would not be good proxies because they are distorted 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.

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: the return on equity (ROE). We show in a simple model that the ROE succinctly captures the combined effect of systematic asset risk and its magnification by leverage. A bank that earns high ROE in good times

[1] 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.

must have a combination of risky assets and high leverage.

We demonstrate the usefulness of our model-free approach using data from three recent periods of systemic stress for the U.S. banks, namely the financial crisis of 2007-2010, the savings and loan (S&L) crisis of the late 1980s, and Russian debt crisis of 1998. In addition, we also investigate the relationship between profitability and systematic tail risk for a sample of European banks during the European sovereign debt crisis of 2008-2011. For each period of systemic stress, we relate pre-crisis profit-based measures of risk to a measure of in-crisis systematic risk exposure. Our main measure of pre-crisis profits is ROE, the before-tax profit of a bank scaled by the book value of equity, a year before the onset of the crisis. As baseline risk measure, we use 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. This measure of tail risk resembles the "expected shortfall" discussed by Acharya, Pedersen, Philippon, and Richardson (2017), as banks with lower returns during bad days are banks with relatively larger tail risk. We show that the pre-crisis ROE helps explain the cross-sectional variation in banks' stock returns on "bad days" during the crisis period.

Our empirical analyses are mostly focused on the subprime mortgage crisis sample, simply due to better data coverage and a very well defined period of stress. Bad days are defined based on the Fama/French banking industry portfolio. We find that banks with a higher pre-crisis ROE measured in 2006 perform significantly worse on bad days of the mortgage crisis: a one standard deviation (s.d.) higher ROE is associated with approximately 0.5 s.d. lower returns on bad days. 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 crisis—but a substantial part of it comes from a strong relationship between ROA and tail risk.

Our baseline approach presumes a competitive setting in which higher ROE in good times can be achieved only through higher systematic risk exposure. This approach may work better for capital market activities of banks (such as trading or securitization) than for relationship-based activities that may be a source of rents and positive net present value. Supporting this explanation, Atkeson, d'Avernas, Eisfeldt, and Weill (2019) show, based on a quantitative model, that the high level of bank profitability prior to the financial crisis is better explained by tail risk exposure supported by government guarantees than high franchise value. We further pursue this line of reasoning by breaking accounting profits into profits from the core lending business and all remaining profits. Profits in the core lending business, i.e. interest income, can also come from risk-taking—Fahlenbrach, Prilmeier, and Stulz (2017) find that banks with high loan growth subsequently performed poorly. But in general, profits from the core lending business are more likely to be sources of relationship-based positive net present value than profits outside the core lending business (Martynova, Ratnovski, and Vlahu 2015). We show that the relationship between pre-crisis profits and tail risk is considerably stronger for non-interest income, the portion of profits attributable to market activities outside the core lending business. This result is related to the finding in Brunnermeier, Dong, and Palia (2020) that a higher share of non-interest income is associated with higher systemic risk contributions, but our focus here is on variation in the level, not only the share of income.[2]

What could be the underlying incentive behind a bank's decision to earn higher profits in good times at the expense of higher tail risk? We focus on two forms of payout that banks make from their short-term profits: dividends and share repurchase payouts to the shareholders and compensation to their managers. We first analyze whether the relationship between profits and tail risk becomes stronger when profits are paid out to bank shareholders. Risk-shifting incentives can manifest not only in a riskier asset portfolio composition and higher leverage, but also in higher payouts (Acharya, Le, and Shin 2017). Thus, profits that are paid out as dividends should be a particularly informative indicator of tail risk exposure. This is what we find. There is a strong empirical link between dividend payout and tail risk.

In our next set of tests, we explore the relationship between CEO compensation and tail risk. We construct a comprehensive dataset of CEO compensation for all banks in our sample, and thus provide one of the first detailed evaluations of this relationship in the literature.[3] We show that

[2] Saunders, Schmid, and Walter (2015) argue that non-interest income in normal times does not contribute to insolvency in periods of systemic stress, but insolvency measures systematic tail risk exposure imperfectly, especially when a number of banks are rescued by regulators either explicitly or implicitly.

[3] Earlier work is often limited to the sample of banks covered only in the Standard & Poor's Executive Compensation database.

higher payout to CEOs is associated with significantly higher tail risk exposure; the relationship is especially strong for payouts in the form of cash bonuses. Further, we show that our profitability measures are especially informative of tail risk exposure when the CEOs earn a significantly higher portion of their compensation in bonus payments. These results suggest that when the managers and shareholders of a bank stand to gain from short term earnings, the bank is more likely to engage in riskier activities to earn profits.

We also compare the effectiveness of our simple measure in detecting tail risk with a widely used model-based risk measure. Banks are required to report risk-weighted assets as an aggregated proxy for 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 our profit-based measure performs significantly better than the model-implied risk measure in explaining cross-sectional differences in tail risk. The risk-weighted assets measure has no marginal predictive power for tail risk once profitability is included in the regression.

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.[4] 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.

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

[4]The Basel Committee on Banking Supervision issued its first recommendations for model-based regulation in 1988 (Basel I). The committee refined those recommendations in 2004 (Basel II), and then again in 2010 (Basel III). Each round of recommendations addressed weaknesses revealed in the prior years with a refined model.

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 with high profits due to market power in traditional deposit-taking and lending, but using finer measures focused on non-interest income could be more vulnerable to manipulation. 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.

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 bank risk measure. 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 should be in the center of regulatory attention. Closest to our work, Moussu and Petit-Romec (2017) document a positive correlation between pre-crisis profitability 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.[5] Our within-country analyses hold fixed such country-level factors. Moreover, we provide a simple economic framework to analyze the risk-return effects for banks, and we analyze the differential predictive role for risk exposure played by non-interest income and by income components paid out to shareholders and executives.

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.

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 (BCBS), 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. 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

[5] 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 financial 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 and assets. At the same time, Japanese banks were much less exposed to the shocks that hit U.S. banks during the financial 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.

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 does not differentiate sufficiently across risk assets and it does 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.[6] 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. 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 set of regulations was adopted under the Basel II framework in 2004.[7] 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. Recent proposals in Basel III are 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. 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.

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

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

Our key point in the paper is simple: any new model is subject to manipulation. 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. Many assets require judgment on the part of the bank to determine into which category they belong. 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 there is no judgment being made about the riskiness of particular assets.

3 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 an economy with discrete time in which banks face a sequence of one-period 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 them under risk-neutral probabilities. The per-period risk-free interest rate is R_F.

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 "normal" 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, the portfolio payoffs are $X^u(\theta) > 1+R_F$ in the good state and $X^d(\theta) < 1+R_F$ in the bad state. 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 is always one. Risk-neutral pricing therefore implies the following relationship between $X^u(\theta)$ and $X^d(\theta)$:

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

This two-state set up captures the essential features of a bank's investment opportunities. 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.

Now suppose that at each date t the bank issues default-free one-period debt with face value equal to a fraction D of the time-t value of the bank's assets. To be default-free, the debt's promised payoff $D(1+R_F)$ in $t+1$ must be less than the value of the bank's assets in the bad state at $t+1$, so $D \leq X^d/(1+R_F)$.

Our main interest centers on the relationship between the bank's profit in the good state and the systematic risk exposure of its asset portfolio. The bank's equity excess return in the bad state,

$$R_E^d(\theta) - R_F = \frac{X^d(\theta) - 1 - R_F}{1 - D}, \tag{2}$$

represents the realization of this risk exposure. A bank with low X^d is a bank with assets that will do poorly in the bad state and this risk is magnified by 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. Conditional on the good state realized at t, the bank's gross return on assets is $R_A^u(\theta) = X^u(\theta) - 1$ (i.e., gross of interest expense). Combining (2) and (1), we get

$$R_E^d(\theta) - R_F = -\frac{1-\pi}{(1-D)\pi}(R_A^u(\theta) - R_F) \tag{3}$$

Thus, high profitability in good times as measured by $R_A^u(\theta)$ predicts higher downside equity risk in the next period. However, to the extent that leverage varies across banks, there will be heterogeneity in the coefficient on $R_A^u(\theta)$ depending on the level of D. In this sense, $R_A^u(\theta)$ is an imperfect measure of a bank's systematic risk exposure.

The leverage effect is captured by the return on equity,

$$R_E^u(\theta) = \frac{X^u(\theta) - D(1 + R_F)}{1 - D} - 1, \tag{4}$$

as a measure of profitability. Substituting into (3) we obtain

$$R_E^d(\theta) - R_F = -\frac{1 - \pi}{\pi}(R_E^u(\theta) - R_F) \tag{5}$$

Thus, the bank's equity return in the bad state is negatively related to the return on equity in the good state. The bank's return on equity in good times provides an estimate of the combined effects of asset risk and leverage. For this reason, $R_E^u(\theta)$ is our preferred measure of a bank's systematic risk exposure.

Robustness to off-balance sheet exposures. This stylized model demonstrates one way that using profits to measure risk is 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—a method of concealing leverage from traditional risk assessment—and that the bank implicitly or explicitly guarantees these 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 (5), an accurate assessment of the magnitude of disaster risk exposure $R_E^d(\theta) - R_F$.

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. The error introduced into the standard risk assessment by moving assets off the balance sheet is exacerbated if the assets that are moved off the balance sheet are riskier than those that remain on the balance sheet. In this case, the traditional risk measures would suffer from an even more severe downward bias.

If the bank raises total leverage along with the accounting maneuvers to move assets and liabilities off the balance sheet—to keep on-balance sheet leverage constant, for example—this doesn't change the key relationship (5), 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 lending market or superior technology for screening and monitoring. Indeed, canonical models of banking often rely on these advantages as a key reason for banks' existence in the first place. In these models, bank profits in normal times reflect access to positive NPV projects and may be unrelated to risk-taking.

The existence of positive NPV assets on the banks' books can weaken 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. Conditional on the good state at $t = 1$, the bank earns a gross return on its assets of

$$R_A^u(\theta) = \alpha(X^u(\theta) - 1) + (1 - \alpha)(R_F + s) \tag{6}$$

on its assets. 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:

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

Compared with (5) we have an additional term involving abnormal return s the bank earns on its non-competitive assets. For the purposes of using bank profitability as an indicator of risk, this additional term introduces a measurement error. High $R_E^u(\theta)$ could indicate high risk-taking and hence predict low equity returns in the bad state, or it could represent high levels of positive NPV assets, which implies high equity return in the bad state.

For this reason, the relationship between higher profits and tail risk is expected to be especially strong for banks that make most of their profits through market-related activities—activities in which they are unlikely to have any superior skills or advantage. The core lending and deposit taking business of a bank is relatively more likely to generate profits from positive NPV projects, and other banking activities are relatively more likely to generate profits by risk-taking. Based on this intuition, we break banks' overall profitability into two parts: one that comes from interest income and the other from non-interest income. We expect the relationship between returns and risk to be especially concentrated in non-interest income, which is often derived from market-related activities such as trading operations and securitization business. On the other hand, interest-based income is more likely to arise from access to positive NPV projects. Division of profitability across interest and non-interest income to separate positive NPV projects and riskier activities is consistent with Egan, Lewellen, and Sunderam (2017), who study the sources of value creation in banks. They find that "high asset productivity is associated with high interest income, even after including a battery of controls for bank risk taking."

In addition, we expect the relationship between accounting profits and tail risk to be stronger as the banking market becomes more competitive. Increased competition is likely to push the fraction of business that comes from competitive business, α, closer to one. As the importance of the positive NPV term in equation (7) decreases, the relationship between accounting profits in good times and tail risk should strengthen. Similarly we expect the relationship to be stronger as the banking activities become more dependent on market-based activities such as securitization and trading income. Compared to the S&L crisis, during the subprime mortgage crisis both these forces strengthened: banking markets became more competitive after a series of inter- and intra-state branching deregulation in the 1980s and 1990s, and after the Glass-Steagall Act banks increased their reliance on market-related activities. Based on this intuition, we investigate the difference in the relationship between profitability and tail risk across the mortgage crisis and the S&L crisis to shed further light on this issue.

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 the 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, Pedersen, Philippon, and Richardson 2017).

3.1 Empirical strategy

Our main test is based on the financial crisis of 2007-2010, called the mortgage crisis sample in the rest of the paper. We focus on this episode because of the severity of the crisis and the availability of detailed data on bank profitability. We also examine a sample from the S&L crisis, the Russian crisis of 1998 (that was a relatively milder crisis compared to the S&L and subprime mortgage crisis) and an out-of-country sample using the stress in the European banking sector. For each sample, we relate bank profitability before the crisis to performance during the period of systemic stress. As we present the results, we discuss the relative advantages and disadvantages of each sample.

For the empirical analysis, we need measures of equity returns in the good state, $R_E^u(\theta)$, and the bad state, $R_E^d(\theta)$. Stock returns, based on market valuations, and accounting profits are two obvious candidates. In the model, there is not really a difference between 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 corporate bond portfolio 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 profit that a bank derives from its assets in good times resembles this promised yield. Since most bank assets are not marked-to-market, the reported profit gross of interest expenses is roughly the assets' yield minus possibly a small adjustment for expected defaults.[8]

In contrast, the realized return over, say, the recent year, is not a good indicator of default risk. Asset prices are forward-looking and the realized return is dominated by unexpected news. Recent returns on a corporate bond portfolio may be a good indicator of recent unexpected changes in the portfolio's risk, but not of the level of the portfolio's risk. The same logic applies to a bank's realized stock return. Thus, we focus on accounting profits to measure profits in good times, $R_E^u(\theta)$.

However, during a crisis, when a bank's exposure to systematic tail event risk is revealed, the stock return captures this risk exposure 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, $R_E^d(\theta)$, 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.

Motivated by the relationship developed in equations (3) and (5), we estimate the following cross-sectional model that relates stock market returns in bad times to accounting profits in good times:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \epsilon_i \tag{8}$$

where P_i^{prior} is an accounting measure of bank i's profitability in the year prior to the onset of the crisis, and R_i^{crisis} is the average of bank i's stock market returns on bad days during the crisis

[8] To a good approximation, this would still be true even with marking-to-market because mark-to-market adjustments in good times are typically small.

period. We estimate this model using several accounting measures of profitability, including return on equity. The risk-free rate on the right-hand side of (5) is absorbed by the intercept in (8). In analyses with multiple crisis periods, we use time dummies to absorb different risk-free rates in each time period.

For the mortgage crisis sample, the accounting measures of profitability are from the bank's fiscal year 2006, and the stock market returns are averaged across bad market days (or bad bank days) from September 2007 through September 2010. For the S&L sample, the period of crisis is not as well defined as the mortgage crisis sample. The S&L crisis was spread over multiple years in the late 1980s and early 1990s. Hence sharp identification of P_i^{prior} in our equation is a bit challenging for this test. With that caveat in mind, we take accounting measures of profitability from the bank's fiscal year 1986, and the stock market returns are averaged across bad market (or bank) days from July 1988 through June 1990.

4 Data

The data consist of annual income and balance sheet reports and daily stock market returns for commercial banks. Daily stock market returns are from the University of Chicago's Center for Research in Security Prices (CRSP). Income and balance sheet data—equity, assets, pretax income, net interest income, and dividends—are from the CRSP-Compustat Banks Fundamentals Annual database. Risk-weighted assets for commercial banks and bank holding companies are from Call Reports. Call Report data items are linked with CRSP-COMPUSTAT databases using the link file maintained by the Federal Reserve Bank of New York to map bank identifiers from the Call Reports to firm identifiers in the CRSP-Compustat database.

For our explanatory variables, we construct two key measures of profitability. The return on assets, $R_A^u(\theta)$, is measured as gross profits scaled by the book value of assets in the pre-crisis year, where gross profit is simply the sum of pre-tax income and interest expense. The return on equity, $R_E^u(\theta)$, is defined as the ratio of pre-tax income to the book value of equity. Using the bond portfolio analogy, the return on assets (ROA) measure in good times approximates the yield on the asset portfolio of the bank. The return on equity (ROE) corresponds to the leveraged yield, net of interest expense.

We further break down the gross profit measure into two components: interest income and non-interest income. Interest income captures income from the core lending operations of the business. We construct it as the gross interest income of the bank adjusted for provisions for losses and a proportional adjustment for all other costs such as salaries and administrative expenses. Non-interest income is constructed as the sum of non-interest income reported by the bank and gains and losses on securities trading with a proportional adjustment for all other costs such as salaries and administrative expenses.[9] The proportional adjustment of these other costs across interest and non-interest income is done simply based on their relative proportion in the firm's gross profit. Thus, the breakdown of profits into these components is only an approximation. Appendix Table A1 provides an example of the precise construction of these variables using the fiscal year 2006 data of Bank of America.

For our response variables, we construct measures of tail risk by computing bank stock returns on "bad days."[10] 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.[11] 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. A bank's tail risk is simply its average return across all bad days during the crisis.

From these data sources we create three samples. The mortgage crisis sample matches income and balance sheet data from fiscal 2006 with stock market returns from September 2007 through September 2010, the most stressful time period associated with the crisis. The S&L crisis sample matches income and balance sheet data from fiscal 1986 with stock market returns from July 1988

[9] Banks report gains or losses on securities as a separate item from non-interest income.

[10] Our measure resembles the concept of contribution to systemic risk developed by Acharya, Pedersen, Philippon, and Richardson (2017).

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

through June 1990. The pooled crisis sample is a union of the mortgage crisis sample and the S&L crisis sample. We match 11,325 bank-year observations from 1986 to 2012, out of which we use 450 cross-sectional observations for the mortgage crisis sample.

For the Russian crisis, we obtain data on all U.S. banks meeting the same sample selection criteria as applied to the mortgage and S&L crisis samples. 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 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, compared to the subprime mortgage crisis in the U.S. 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.

5 Empirical relation between profits and systematic risk

To evaluate the extent to which pre-crisis profitability predicts tail risk, we first estimate equation (8) for the mortgage crisis sample. All variables are standardized to have mean equal to zero and standard deviation equal to one. 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. With this standardization, we can directly compare the economic importance of different profitability measures across specifications.

[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.

5.1 Mortgage crisis sample

The mortgage crisis sample is ideal for testing the relationship between our model-free measures of risk and performance during a period of stress. First, the mortgage crisis was one of the worst economic crises since the Great Depression, which gives a meaningful measure of tail risk. Second, the beginning of the mortgage crisis period is fairly well defined, and the crisis is concentrated within a few years. The clear time frame of the mortgage crisis is good for measuring the incidence of tail risk and relating tail risk to measures of pre-crisis profitability. Third, stronger reporting standards over the years have improved the availability and precision of variables used in our analysis. As we discuss later, these features will be missing from the S&L crisis sample.

Table 1 reports summary statistics for the mortgage crisis sample. The average (median) ROA for fiscal year 2006 of banks in the sample is 4.044% (4.058%), with a standard deviation of 0.826%. The average (median) ROE is considerably higher at 19.436% (19.858%), reflecting the high leverage ratios of banks in the sample. As expected, a large fraction of bank profits are generated through interest income. Average interest income scaled by the book value of assets (ROA: Interest Income) is 3.455%, whereas average non-interest income scaled by the book value of assets (ROA: Non-interest Income) is 0.589%. Average stock market returns for banks in the sample are –1.9% on bad bank days and –2.2% on bad market days. There is considerable cross-sectional heterogeneity in both returns on bad bank days and returns on bad market days, which is helpful for estimating the relationship between profitability measures and tail risk. The histogram of average return on bad bank days and pre-crisis ROA shown in Figure 1 further illustrates the rich heterogeenity in these key measures.

Table 2 shows that higher accounting profitability during good times is associated with larger incidence of tail risk realizations during the crisis. Each row of the table presents results from a single cross-sectional regression using one accounting profitability measure and one measure of tail risk. Estimates for ROA are grouped in Panel A, and estimates for ROE are grouped in Panel B. As shown in the first (fourth) row of Panel A, a one standard deviation increase in ROA is associated with a 0.335 (0.339) standard deviation decrease in stock returns during bad bank (market) days. Similarly, as shown in the first (fourth) row of Panel B, a one standard deviation increase in

ROE is associated with a 0.544 (0.530) standard deviation decrease in stock returns during bad bank (market) days. These estimates are statistically significant at the 1% level. The results are economically important: for example, banks with one s.d. higher ROE in 2006 earned about 0.92% lower return on an average bad day of the mortgage crisis. Further, we plot the average return during bad days across the deciles of ROE in Figure 2. The relationship between profitability and tail risk is almost monotonic.

The estimated relationship between accounting profitability and tail risk is especially strong for the non-interest portion of profits. As shown in Table 2, a one standard deviation increase in the ratio of the non-interest portion of profits to assets (ROA-NonInterest) is associated with a 0.413 (0.390) standard deviation decrease in stock market returns on bad bank (market) days. Similar results hold for the ratio of the non-interest portion of profits to equity (ROE-NonInterest). Further, the non-interest income ratios explain more of the variation in tail risk than the interest income ratios, with R^2 in the range of 13-15%. Like non-interest income, interest income is positively associated with tail risk, but the relationship is much weaker. Interest income explains 2-8% variation in tail risk compared to the corresponding range of 13-15% for non-interest income.

As an alternative method of measuring the relative importance of interest and non-interest income, we regress stock market returns on interest income and non-interest income in the same regression model. Reinforcing the message from univariate regressions, Table 3 shows that the coefficients are much larger for profitability measures based on non-interest income than for measures based on interest income. Panel A of Table 3 shows that a one standard deviation increase in ROA-NonInterest is associated with a 0.466 (0.446) standard deviation decrease in returns on bad bank (market) days, and these coefficients are highly significant. On the other hand, the corresponding coefficients for ROA-Interest are almost halved at 0.233 and 0.246 for bad bank and bad market days, respectively. Further, Table 3 shows the partial R^2 for each of the two variables, and the explanatory power of non-interest income is much stronger. Overall these results show that accounting profits can be a meaningful tool to detect systematic tail risk. Both interest and non-interest income are strong predictors of tail risk. In line with our intuition, results are especially strong for profits that are closer to market-based activities, namely the non-interest portion of profits.

Payouts to shareholders. So far our results have focused on the explanatory power of profits and their source (interest or non-interest income) on tail risk. A natural question arises: why are banks assuming more tail risk for boosting short-term profits? If banks are hiding their true risk with model-based regulation, then they must be imposing negative social externalities. So what is the underlying private motivation to engage in such behavior? Said differently, who gains from a business strategy that generates higher profits in good times at the expense of higher tail risk? In our next set of analyses we focus on these incentives by looking at payouts to the shareholders of the firm. Specifically, we ask whether large dividend payouts in good times explain the realization of tail risk in bad times.

In Table 4, we relate tail risk to dividends paid out to shareholders in 2006. The regression models presented in Panel A of Table 4 replace the earlier measures of profitability with measures of dividend payouts. The first row of Table 4 shows that banks with one standard deviation higher dividend-to-equity payout have 0.445 standard deviation lower returns during bad bank days. The coefficient estimate is highly significant and has high explanatory power with R^2 of over 20%. Other rows of the Table show that the results are fairly robust to alternative measures of dividend and tail risk. Banks that were paying out more of their profits as dividends were also banks that experienced larger negative returns during the crisis on the worst days for the banking industry and the market as a whole. In Panel B, we add the payout from share repurchases to dividend payouts. Our results are similar.

In Table 5 we estimate a model that includes both total payouts (i.e., dividends plus repurchases) and remaining profits (i.e. profits minus the payouts) as two explanatory variables in the model. These estimates allow us to directly compare the relative predictive strength of profits that are paid out to shareholders with profits that are retained by the bank. Our results show that banks with higher payouts have significantly higher tail risk exposure.

Payouts to CEOs. Building on our results on payouts to shareholders, we now analyze the explanatory power of payouts to CEOs during 2006 on tail risk measures during the crisis. Existing literature is often constrained by data availability on CEO compensation for the entire cross-section of banks, and therefore relies on the subset of banks that are covered by the Executive Compensation database of Standard & Poors. While this database provides useful information on the largest banks, it misses out variations contained in a large cross-section of banking industry. It is well known that medium and small banks were also among the stressed banks during the financial crisis. Hence analyzing the behavior of the entire cross-section of banks is important for furthering our understanding of the drivers of tail risk. We supplement the Executive Compensation database with hand-collected data for CEO compensation on other banks in the sample through their SEC filings under form DEF 14a. These filings provide us with a detailed account of CEO total compensation as well as the breakdown of compensation into salary, bonus, stock awards, and option awards. Stock and option awards are accounted for as per the stock and option expensing rule of Financial Accounting Standard Boards rule 123R. In total, we obtain data for 421 banks: 97 banks from the Executive Compensation Database and an additional 324 firms through SEC filings.

Since our paper provides one of the first looks at the comprehensive sample of CEO compensation prior to the financial crisis, we first provide detailed descriptive statistics on variables of interest in Table 6. The average total compensation is about $1.6 million, broken down into approximately $387,000 in salary, $342,000 in cash bonus, $240,000 in stock awards, and $331,000 in option awards, with the remaining component of compensation belonging to other forms of payout such as retirement and insurance benefits. Cash bonus includes payments made to CEOs for achieving or beating performance goals that are often linked to accounting earnings such as net interest margin or return on equity. Compensation is cross-sectionally dispersed and skewed: total compensation ranges from a minimum of $120,000 to a maximum of $39 million in our sample. We also report summary statistics on the proportion of total compensation paid out in different forms. The median firm pays 53% of its compensation in the form of salary, and it ranges from almost 0% to almost 100% for the sample. Similarly, the bonus compensation ranges from almost 0% to 67% for the sample, with a median of 17%. Stock and option-based compensation rages from 0% to 94%, with a median of 6%. Thus there is wide variation in compensation policy across the sample of firms.

Table 7 provides regression results linking tail risk to CEO compensation. For brevity, we only report results based on the measure of tail risk on bad bank days. The results remain similar for tail risk measured by bad market days. We regress the tail risk measure on the ratio of total compensation to assets, as well as on the components of compensation, namely salary, bonus, stock awards, and option awards. In these regressions we flexibly control for the well-documented size effect in CEO compensation by including fixed effects for bank size using twenty size groups based on total assets. As shown in Column (I) of the table, one standard deviation higher CEO compensation (as scaled by the total assets of the bank) is associated with -0.10 standard deviation lower returns during the crisis, which is statistically significant at the 1% level. Columns (II) - (IV) investigate the predictive power of different components of compensation on tail risk: the largest impact comes from compensation that is paid out in the form of short-term incentives. Stock and option grants are also negatively associated with returns on bad bank days. However, when we include the components (salary, bonus, stock awards, and option awards) together in the regression model, the bonus payout dominates all other forms of payout. This is an important finding: a simple measure of short-term payout during 2006 is able to explain considerable variation in bank tail risk.

To more directly relate our earlier results to CEO payout, we estimate the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \beta_2 \times HighBonus_i + \beta_3 \times P_i^{\text{prior}} \times HighBonus_i + \epsilon_i$$

In the above model, *High Bonus* is an indicator variable that equals one for a bank with a ratio of bonus to total compensation above the median. These are the banks where CEO compensation likely has higher "slope" for short-term earnings, and hence a stronger incentive to produce earnings that can be paid out as compensation. The interaction term provides the effect of the profitability measure for such firms. The key results are contained in Columns (IV) and (V) of Table 8. The effect of ROA (Column IV) and ROE (Column V) on tail risk is concentrated within banks with higher bonus payouts. This result is consistent with the findings of Bhattacharyya and Purnanandam (2011) who show that banks with higher sensitivity of managerial compensation to short term earnings had higher defaults in their mortgage portfolio during the crisis.

These results show that when bank managers and shareholders reap higher profits in good times, profits become an even stronger measure of tail risk in bad times. In sum, our results show that simple measures of profitability, and simple measures of payouts, can be helpful tools to regulators in detecting the buildup of tail risk and designing banking policies. Next we investigate how useful these profitability measures are relative to existing model-based regulatory measures.

Comparison with risk-weighted assets. We now compare our model-free measure of risk to the model-based measure of risk currently in use by bank regulators. As described earlier, we focus on risk-weighted assets recommended by the Basel Committee on Banking Supervision. The premise of most capital requirements is that banks with higher risk-weighted assets are contributing more to systematic risk. To compare this measure of risk with our measure, we scale risk-weighted assets by total assets for each bank. We include this variable as an additional regressor in our profitability-based regression specifications to estimate the following cross-sectional regression:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \beta_2 \times \left(\frac{RWA}{Assets}\right)_i^{\text{prior}} + \epsilon_i \tag{9}$$

Table 9 presents the results. Each row corresponds to one specific regression model using a pair of accounting profitability and tail risk measure. We report the estimated coefficient β_1 under the heading "Profit" and β_2 under "Model". Table 9 also reports the R^2 obtained in the model using both profitability and model-based risk measures, as well as the R^2 obtained with just one of these variables included in the regression at a time.

The first row of Table 9 uses ROA as the measure of profitability and return on bad bank days as the measure of tail risk. A one standard deviation increase in this profitability measure is associated with a 0.321 standard deviation decrease in returns during bad bank days. The RWA based measure, in comparison, has an insignificant coefficient of just 0.005. The difference in explanatory power is even more stark: while the profitability based measure provides an R^2 of over 11%, the model-based risk measure produces an R^2 of less than 1% by itself. When we use ROE as the measure of profitability, the gap is even bigger.

These results show that our simple measures of risk have significantly more explanatory power than the model based measure. 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.

5.2 Savings and loan crisis sample

The S&L crisis of the late 1980s and early 1990s provides another setting to test the usefulness of our profitability measure in detecting risk. However, it is not quite as well-suited to this investigation as the mortgage crisis for a number of reasons. First, the sample is smaller. Second, we do not have high quality data on net interest income for years prior to 1986, so we use 1986 as our pre-crisis year. While most banks were not yet in distress in 1986, some already were. Thus, unlike the mortgage crisis sample, we do not have a clean identification of pre-crisis and crisis years for this sample. Third, and related to this point, the onset of the S&L crisis was in general much more spread out over time than the mortgage crisis. Some banks did not experience distress for several years after 1986. Our crisis period definition July 1988 through June 1990 should allow us to capture most of the distress revelation, but probably not to the same extent as in the mortgage crisis sample. With these limitations in mind, we proceed with the same set of analyses that we conducted for the mortgage crisis.

Table 10 provides the descriptive statistics for the S&L crisis sample. During this crisis, banks experienced an average return of -1.6% on bad bank days and -1.4% on bad market days. These returns are slightly better than the corresponding returns for the mortgage crisis period, as expected. During the pre-crisis year, on average banks had ROA of 5.417% and ROE of 15.360%. For the S&L crisis sample, we do not have sufficient data to break down these profits into interest and non-interest income, as we did for the mortgage crisis period.

Table 11 presents the results relating profitability to tail risk for this sample. Across both measures of profitability, ROA and ROE, and for both measures of tail risk, our coefficient estimates remain negative and significant. A one standard deviation increase in the profitability measure was associated with a 0.15–0.20 higher tail risk measure, depending on the model specification. The R^2

ranges between 5–11%. Overall, our key results are similar to the mortgage crisis.

5.3 Pooled Results

Now we pool the cross-sectional observations from both crises and reproduce these results in Table 12. For this purpose we estimate the following model that allows us to evaluate the relative difference in the predictability of tail risk exposures with predictability across the two crises:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \beta_2 \times mortgage_i + \beta_3 \times P_i^{\text{prior}} \times mortgage_i + \epsilon_i$$

P_i is a measure of accounting profit for bank i in 1986 or 2006; $mortgage_i$ equals one for all observations belonging to the mortgage crisis subsample and zero for the S&L crisis. This mortgage crisis fixed effect allows us to absorb, for example, the different levels of risk-free interest rates in the two pre-crisis samples and their effects on bank profitability levels.

As expected, the effect of ROA and ROE remain strong. A one standard deviation increase in profitability ratios corresponds to a reduction in returns on bad days of $-.128$ to $-.275$ standard deviations depending on the model specification. Interestingly, the effect is much stronger for the mortgage crisis as shown by economically large (-0.15 to 0.45) and significant coefficients on the interaction term. We expect our measure to work better in predicting tail risk when banking market becomes more competitive and when banks move their business mix more in favor of market-driven activities such as securitization and trading activities. Both these conditions are present for the mortgage crisis period following a series of banking deregulations in the 1980s and 1990s. In addition, banks moved their business mix in favor of market related activities in the aftermath of the Glass-Steagall Act repeal. Therefore, profitability in 2006 is likely to to reflect a higher proportion of income from competitive market risk-taking than in the S&L period. These results are suggestive that the link between profitability and systematic tail risk exposure depends on industry competitiveness, although with the caveat that measurement in the S&L period is more challenging, which could also affect the magnitude of the estimates.

5.4 Other Crises

We provide evidence from two other episodes of banking crises to further bolster our claim that profitability in good times is a reasonable 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 a year before the crisis and measure tail risk using returns data from the crisis period. We estimate the regression model linking profitability to tail risk using the same cross-sectional approach that we used in the earlier analysis.

We report the estimated coefficient on the ROE measure along with the associated t-statistics for all these crises in Table 13. Figure 3 plots the estimated coefficients along with 95% confidence intervals. For completeness, we report the corresponding numbers of the mortgage crisis and the S&L crisis as well. Our analysis shows a clear pattern. In the Russian crisis analysis, one standard deviation increase in profitability is associated with 0.25 standard deviations lower returns during bad bank days. 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 stressful period.

Across the four crises that we consider in our paper—the mortgage crisis, the S&L crisis, the Russian Crisis, and the European crisis—higher profitability predicts lower returns in bad times. While the underlying risk that triggered the crisis differs from one crisis to another—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 in our simple approach.

5.5 Alternative Specification and Robustness Tests

We report several robustness checks in the appendix. Table A2 provides regression results for the mortgage crisis sample where we control for the CAPM beta of banks estimated with the yearly data from 2006. As shown there, across model specifications, profitability measures predict tail risk even after controlling for market beta. Interestingly, market beta by itself has a strong predictive power for systematic tail risk. It can serve as an additional useful risk measure for banking regulation.

Table A3 produces regression results for the ROE variable after adding a number of control variables that may be related to tail risk. We control for the size of the bank, both in a linear fashion by including log of total assets as an additional regressor as well as by including fixed effects for bank size quantiles. Growth rates measure the year-over-year log change in total assets, and they are computed using data from 2005 and 2006. We also control for dependence on deposit financing by including the deposit-to-asset ratio. The loans to assets ratio controls for the asset mix of the bank, and the loan loss provisions to asset ratio in 2006 accounts for the quality of the lending portfolio that was observable in 2006. These measures are included to rule out the concern that our results are either explained away or dominated by proxies such as asset growth and firm size. That is not the case. Across a series of specifications, ROE is a strong predictor of tail risk.

In our base model for the mortgage crisis, we use profitability from 2006 as the measure of prior period profits. We choose 2006 as the year immediately preceding the crisis. To understand the evolution of profit-risk relationship over time, Table A4 uses profitability numbers from earlier years and shows that the relationship between profitability and tail risk is present even for earlier years (2001-2005). Sensibly, the predictive power of profitability for crisis tail risk realizations becomes stronger as we approach the onset of the crisis. For example, banks with one s.d. higher ROA in 2002 have 0.083 s.d. lower returns in the crisis. This coefficient steadily increased to -0. 221 for year 2004 and eventually reached -0.335 for the base year 2006.

Finally, we restrict our sample to banks in the top half of size distribution only and present the results of this sub-sample in Table A5. Our main results linking ROA and ROE to tail risk remain similar. However, for this subsample, non-interest income completely drives the results. The findings are consistent with the idea that largest banks increased their profitability by engaging in business outside of core lending activities, such as trading and securitization.

Overall our robustness tests show that our main result is not driven by the choice of a specific year for measuring profits in "good" times, the omission of control variables such as lagged growth rates of the bank, or a subset of only very small banks.

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 systemic risk.

Using data surrounding recent episodes of systemic stress, we show that our measure is useful for predicting tail risk. Reported profits prior to the crisis predict bank stock returns on the worst days of the crisis. We show that our results are stronger for non-interest income, which we attribute to high-risk banking activity outside the core lending business. The predictive power of profits is further concentrated in components that are paid out to shareholders or, in the form of compensation, to bank executives.

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Table 1: Summary statistics: Mortgage crisis

This table presents the summary statistics of key variables used in the paper for the mortgage crisis. "Bad bank days" are days when the Fama/French banking industry portfolio return is lower than its 5th percentile during July 1926 to December 2014. "Bad market days" are defined similarly, but based on the CRSP value-weighted market index return (NYSE, AMEX, NASDAQ & ARCA). Average bad-day returns are calculated from bad days between September 1, 2007, and September 30, 2010. Accounting profitability measures are from the firm's fiscal year ending in 2006. *ROA* measures accounting return on asset without deducting interest expenses. *ROE* is pre-tax income scaled by book value of equity. *ROA: Interest Income* and *ROE: Interest Income* measures profitability from the interest based income of the bank. To compute this measure, we attribute non-interest expenses to interest and non-interest income based on the proportion of revenue that comes from each source. The construction of these variables, along with an example, is provided in Appendix Table A1.

	Obs	Mean	Std Dev	Median	Min	Max
Return on Bad Bank Days (%)	450	-1.9	1.7	-1.4	-6.4	2.7
Return on Bad Market Days (%)	449	-2.2	2.0	-1.7	-7.6	5.3
Equity ($ billions)	450	0.7	4.1	0.1	0.0	55.8
Assets ($ billions)	450	15.3	103.4	1.2	0.1	1,459.7
Return on Asset (%)	450	4.044	0.826	4.058	-0.668	7.930
Return on Asset: Interest Income (%)	450	3.455	0.802	3.403	-0.804	7.625
Return on Asset: Non-Interest Income (%)	450	0.589	0.426	0.513	-0.079	3.690
Return on Equity (%)	450	19.436	11.434	19.858	-47.973	78.301
Return on Equity: Interest Income (%)	450	10.599	9.357	11.004	-49.684	41.021
Return on Equity: Non-Interest Income (%)	450	8.837	9.140	6.651	-0.646	99.474
Dividends / Equity	450	4.753	4.196	4.266	0.000	38.164
Dividends / Assets	450	0.337	0.274	0.318	0.000	2.252
Repurchase / Equity	450	2.778	5.661	0.131	0.000	55.342
Repurchase / Assest	450	0.193	0.402	0.009	0.000	5.027
Total Payout / Equity	450	7.531	8.413	5.411	0.000	65.047
Total Payout / Assest	450	0.530	0.547	0.394	0.000	5.559

Table 2: Profits and risk: Mortgage crisis

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and prior accounting returns using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \epsilon_i.$$

P_i is a measure of accounting profit for bank i in 2006. The dependent variable R_i^{crisis} measures the average return of bank i on days with low bank index or market index returns during the crisis period between September 1, 2007, and September 30, 2010. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the income measure. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses.

Income Measure	Tail Risk Measure	Coefficient	R^2	Obs
	Panel A: Accounting Return on Asset			
ROA	Bad Bank Days	-0.335	0.115	450
		(-8.669)		
ROA-Interest	Bad Bank Days	-0.143	0.021	450
		(-3.013)		
ROA-NonInterest	Bad Bank Days	-0.413	0.147	450
		(-7.875)		
ROA	Bad Market Days	-0.339	0.119	449
		(-7.877)		
ROA-Interest	Bad Market Days	-0.160	0.026	449
		(-2.996)		
ROA-NonInterest	Bad Market Days	-0.390	0.131	449
		(-7.428)		
	Panel B: Accounting Return on Equity			
ROE	Bad Bank Days	-0.544	0.300	450
		(-15.750)		
ROE-Interest	Bad Bank Days	-0.283	0.080	450
		(-5.065)		
ROE-NonInterest	Bad Bank Days	-0.425	0.156	450
		(-5.968)		
ROE	Bad Market Days	-0.530	0.286	449
		(-14.320)		
ROE-Interest	Bad Market Days	-0.290	0.085	449
		(-4.789)		
ROE-NonInterest	Bad Market Days	-0.397	0.137	449
		(-5.914)		

Table 3: Components of profit measures

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and prior accounting returns, broken down by interest and non-interest sources of income, using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times int_i^{\text{prior}} + \beta_1 \times nonint_i^{\text{prior}} + \epsilon_i.$$

The explanatory variable int_i is a measure of interest income for bank i in 2006; $nonint_i$ is a measure of non-interest income. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the income measure. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses.

		Interest	Non-Interest	R^2			
Profit Measure	Tail Measure	Coefficient	Coefficient	Joint	Interest	Non-Interest	Obs
		Panel A: Accounting Return on Asset					
ROA	Bad Bank Days	-0.233	-0.466	0.200	0.021	0.147	450
		(-5.758)	(-8.930)				
ROA	Bad Market Days	-0.246	-0.446	0.191	0.026	0.131	449
		(-5.405)	(-8.343)				
		Panel B: Accounting Return on Equity					
ROE	Bad Bank Days	-0.398	-0.526	0.306	0.080	0.156	450
		(-10.880)	(-11.100)				
ROE	Bad Market Days	-0.400	-0.499	0.289	0.085	0.137	449
		(-10.370)	(-10.520)				

Table 4: Payouts to shareholders

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and shareholder payouts. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the payout measure. In Panel A, shareholder payout is measured with cash dividends. Panel B looks at total payout including share repurchases. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses.

Income Measure	Tail Risk Measure	Coefficient	R^2	Obs
	Panel A: Cash Dividends			
Dividends / Equity	Bad Bank Days	-0.445	0.202	450
		(-8.579)		
Dividends / Assets	Bad Bank Days	-0.334	0.115	450
		(-7.301)		
Dividends / Equity	Bad Market Days	-0.408	0.171	449
		(-8.104)		
Dividends / Assets	Bad Market Days	-0.312	0.101	449
		(-6.942)		
	Panel B: Total Payout			
Payout / Equity	Bad Bank Days	-0.392	0.150	450
		(-6.124)		
Payout / Assets	Bad Bank Days	-0.291	0.084	450
		(-3.530)		
Payout / Equity	Bad Market Days	-0.358	0.126	449
		(-5.897)		
Payout / Assets	Bad Market Days	-0.270	0.073	449
		(-3.445)		

Table 5: Payout versus other components of profit measures

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and prior accounting returns, broken down by profits paid out as dividends or repurchase and the rest of profits, using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times payout_i^{\text{prior}} + \beta_1 \times rest_i^{\text{prior}} + \epsilon_i.$$

The explanatory variable $payout_i$ is a measure of payout for bank i in 2006 (scaled by assets or equity); $rest_i$ is a measure of bank's overall profit minus payout. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the dividend measure. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics in parentheses.

		Payout	Rest	R^2			
Profit Measure	Tail Measure	Coefficient	Coefficient	Joint	Payout	Rest	Obs
		Panel A: Accounting Return on Asset					
ROA	Bad Bank Days	-0.429	-0.315	0.167	0.084	0.018	450
		(-6.568)	(-6.885)				
ROA	Bad Market Days	-0.412	-0.325	0.161	0.073	0.023	449
		(-6.554)	(-6.476)				
		Panel B: Accounting Return on Equity					
ROE	Bad Bank Days	-0.498	-0.420	0.315	0.150	0.088	450
		(-10.190)	(-11.010)				
ROE	Bad Market Days	-0.465	-0.423	0.295	0.126	0.095	449
		(-9.594)	(-10.440)				

Table 6: CEO Compensation: Descriptive Statistics

This table presents the summary statistics for CEO's compensation in 2006 for our sample banks. All compensation level variables are reported in thousands of dollars. Total Compensation is the amount of compensation reported by the company to the SEC in its Def 14a filing. Stock and option awards represent the amount of expensing incurred by the bank with respect to these awards to the CEO as per the rules of accounting standard FASB 123R. The sample consists of all banks covered in the Executive Compensation database as well as non-covered banks with available Def 14a filing on the SEC website.

	Mean	Std Dev	Median	Min	Max
Total Compensation ('000)	1597.51	4124.28	563.60	120.39	39066.11
Salary ('000)	387.11	233.89	310.00	0.00	1500.00
Bonus ('000)	342.37	1023.77	95.00	0.00	13000.00
Stock Grants ('000)	240.21	1071.57	0.00	0.00	11698.86
Option Grants ('000)	331.92	1655.92	13.00	0.00	18012.05
CEO's Total Comp/Asset	0.05	0.04	0.04	0.00	0.36
Salary/Asset	0.03	0.02	0.02	0.00	0.16
Bonus/Asset	0.01	0.01	0.01	0.00	0.13
Stock+Option/Asset	0.01	0.01	0.00	0.00	0.15
Salary/Total Comp	0.52	0.22	0.53	0.00	0.99
Bonus/Total Comp	0.18	0.14	0.17	0.00	0.67
Stock+Option/Total Comp	0.13	0.18	0.06	0.00	0.94
Observations	421				

Table 7: Payouts to CEOs

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and managerial payouts as measured by the CEO's total compensation (scaled by assets) as well as its components. The dependent variable is the return on 'Bad bank days'. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses. All regressions include fixed effects for bank size based on grouping banks into twenty size buckets by total assets.

	I	II	III	IV	V
Total Comp/Asset	-0.10				
	(-2.84)				
Salary/Asset		-0.09			-0.04
		(-1.75)			(-0.78)
Bonus/Asset			-0.09		-0.09
			(-2.65)		(-2.50)
Stock+Option/Asset				-0.04	-0.04
				(-2.08)	(-1.80)
Constant	-0.02	-0.02	-0.02	-0.02	-0.02
	(-0.90)	(-0.90)	(-0.91)	(-0.90)	(-0.91)
Observations	421	421	421	421	421
R^2	0.72	0.72	0.73	0.72	0.73
Absorbed FE	Size_Grp	Size_Grp	Size_Grp	Size_Grp	Size_Grp

Table 8: Cash Incentives, Profits and Risk

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk, profitability and the CEO's cash incentives. The dependent variable is the return on 'Bad bank days'. *Bonus/Total Comp* represents the fraction of total compensation that is paid out as short term cash bonus (including non-equity incentive grants). *High Bonus* is an indicator variable that equals one for banks that pay their CEO above median *Bonus/Total Comp*. The dependent variable is the return on 'Bad bank days'. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses. All regressions include fixed effects for bank size based on grouping banks into twenty size buckets by total assets.

	I	II	III	IV	V
Bonus/Total Comp	-0.10				
	(-3.49)				
High Bonus		-0.18	-0.15	-0.15	-0.15
		(-3.62)	(-2.85)	(-2.93)	(-2.88)
ROAs			-0.06	0.02	
			(-2.18)	(0.57)	
High Bonus x ROA				-0.16	
				(-3.27)	
ROEs					-0.03
					(-0.78)
High Bonus x ROE					-0.12
					(-2.40)
Constant	-0.02	0.07	0.05	0.08	0.07
	(-0.91)	(1.93)	(1.41)	(2.13)	(1.83)
Observations	421	421	421	421	421
R^2	0.73	0.73	0.73	0.74	0.74
Absorbed FE	Size_Grp	Size_Grp	Size_Grp	Size_Grp	Size_Grp

Table 9: Profitability versus regulatory measures of risk

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk, regulatory measures of risk, and prior accounting returns using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \beta_2 \times \left(\frac{RWA}{Asset}\right)_i^{\text{prior}} + \epsilon_i.$$

The explanatory variable P_i is a measure of accounting profit for bank i in 2006, and $(\frac{RWA}{Asset})_i$ is the regulator's model-based measure of risk. Each row in the table corresponds to one cross-sectional regression based on a given measure of profit and tail risk. The table also provides the R^2 of the regression model when estimated with only both variables, only the profit measure, and only the regulatory risk model. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses.

Income Measure	Tail Risk Measure	Profit Coeff.	Model Coeff.	Joint R^2	Profit R^2	Model R^2	Obs
ROA	Bad Bank Days	-0.321	-0.005	0.100	0.115	0.006	388
		(-6.854)	(-0.097)				
ROE	Bad Bank Days	-0.524	-0.006	0.287	0.300	0.006	388
		(-14.630)	(-0.126)				
ROA	Bad Market Days	-0.328	-0.003	0.104	0.119	0.006	387
		(-5.899)	(-0.054)				
ROE	Bad Market Days	-0.513	-0.010	0.273	0.286	0.006	387
		(-12.540)	(-0.214)				

Table 10: Summary statistics: Savings and loan crisis

This table presents the summary statistics of key variables for the S&L crisis sample. Average bad-day returns are calculated from bad days between between July 1, 1988, and June 30, 1990, and accounting profitability measures are from the firm's fiscal year ending in 1986. *ROA* measures accounting return on asset without deducting interest expenses. *ROE* is pre-tax income scaled by book value of equity. *ROA: Interest Income* and *ROE: Interest Income* measures profitability from the interest based income of the bank. To compute this measure, we attribute non-interest expenses to interest and non-interest income based on the proportion of revenue that comes from each source. The construction of these variables, along with an example, is provided in Appendix Table A1.

	Obs	Mean	Std Dev	Median	Min	Max
Return on Bad Bank Days (%)	137	-1.6	1.1	-1.5	-4.7	1.5
Return on Bad Market Days (%)	137	-1.4	1.0	-1.4	-4.0	3.1
Equity ($ billions)	137	0.6	1.0	0.3	0.0	6.7
Assets ($ billions)	137	12.9	24.0	4.7	0.2	196.1
Return on Asset (%)	137	5.417	0.802	5.543	2.097	7.544
Return on Equity (%)	137	15.360	12.201	17.486	-54.774	44.215
Dividends / Equity	137	4.082	1.931	4.372	0.000	12.393
Dividends / Assets	137	0.236	0.120	0.243	0.000	0.795

Table 11: Profits and risk: Savings and loan crisis

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and prior accounting returns using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \epsilon_i.$$

The explanatory variable P_i is a measure of accounting profit for bank i in 1986. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the income measure. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses.

Income Measure	Tail Risk Measure	Coefficient	R^2	Obs
ROA	Bad Bank Days	-0.216	0.111	137
		(-4.539)		
ROA	Bad Market Days	-0.200	0.094	137
		(-3.431)		
ROE	Bad Bank Days	-0.154	0.056	137
		(-2.471)		
ROE	Bad Market Days	-0.161	0.060	137
		(-2.166)		

Table 12: Pooled crises

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and prior accounting returns in the pooled sample of banks from the mortgage crisis and the S&L crisis:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times P_i^{\text{prior}} + \beta_2 \times mortgage_i + \beta_3 \times P_i^{\text{prior}} \times mortgage_i + \epsilon_i.$$

The explanatory variable P_i is a measure of accounting profit for bank i in 1986 or 2006; $mortgage_i$ equals one for all observations belonging to the mortgage crisis subsample and zero for the S&L crisis. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the income measure. The dependent and explanatory variables are standardized to have mean equal to zero and standard deviation equal to one; t-statistics are shown in parentheses.

		Coefficients				
Income Measure	Tail Risk Measure	Profits	Mortgage	Interaction	R^2	Obs
		Panel A: Return on Asset				
ROA	Bad Bank Days	-0.275	-0.576	-0.154	0.118	587
		(-4.557)	(-5.946)	(-1.969)		
ROA	Bad Market Days	-0.205	-0.804	-0.239	0.150	586
		(-3.444)	(-8.337)	(-2.910)		
		Panel B: Return on Equity				
ROE	Bad Bank Days	-0.152	-0.067	-0.437	0.277	587
		(-2.481)	(-0.957)	(-6.088)		
ROE	Bad Market Days	-0.128	-0.371	-0.459	0.296	586
		(-2.175)	(-6.005)	(-6.406)		

Table 13: Estimates from Other Crises

This table presents results from a set of OLS regressions that estimate the relationship between systematic tail risk and prior accounting returns,

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times ROE_i^{\text{prior}} + \epsilon_i,$$

in for four different crises samples. The dependent variable R_i is the return during "Bad Bank Days" of the respective crisis episodes (shown under the column "Crisis Episode"); ROE_i measures return on equity before the crisis (shown under the column "Profits in Year"). For the European Crisis sample, the regression model includes country fixed effects.

Crisis	ROE Coeff.	t-stat.	Crisis Episode	Profits In Year
Mortgage Crisis	-0.530	-14.320	9/1/2007 – 9/30/2010	2006
S&L Crisis	-0.161	-2.471	7/1/1988 – 6/30/1990	1986
Russian Crisis	-0.245	-4.090	6/1/1998 – 12/31/1998	1997
European Crisis	-0.278	-3.800	1/1/2008 – 12/31/2008	2006
			1/1/2011 – 12/31/2011	
European Crisis	-0.235	-3.350	1/1/2008 – 12/31/2012	2006

Figure 1: Cross-sectional distribution of pre-crisis accounting profitability and in-crisis systematic tail risk realization

Accounting profitability is measured in 2006 and our systematic tail risk measure (i.e., average return on bad bank days) during the mortgage crisis.

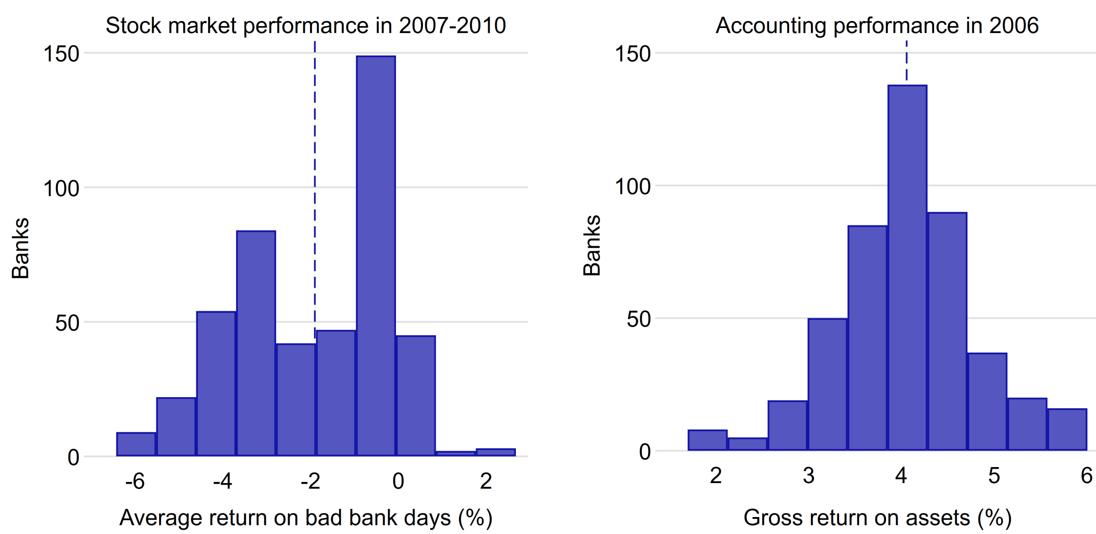


Figure 2: Bank stock returns during bad days across ROE deciles
This figure plots the average return on bad days during the mortgage crisis across deciles of pre-crisis bank profitability as measured by ROE in 2006. The plot on the left-hand side shows returns on days with low bank index returns; the right-hand side plot shows returns on days with low market index returns.

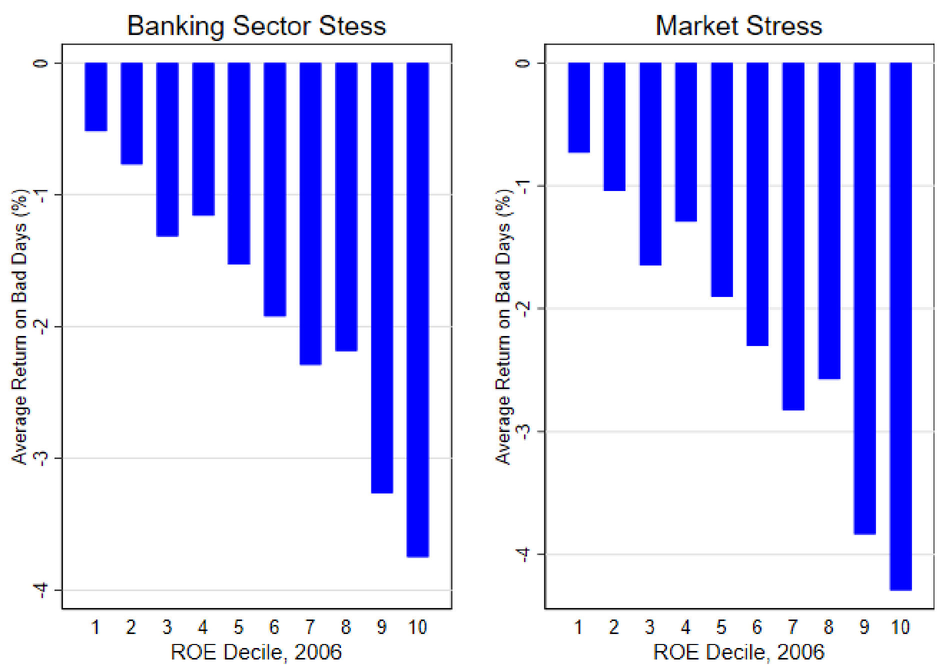
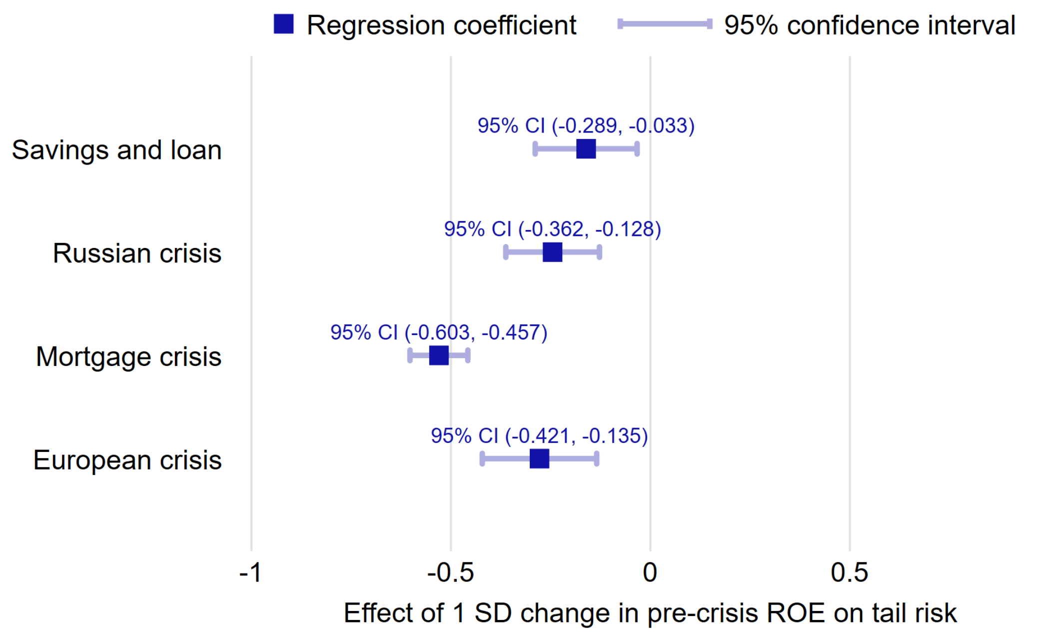


Figure 3: Results from other crises

This figure reports regression slope coefficients, along with 95% confidence intervals, from a regression of in-crisis systematic tail risk exposure, measured as the bank stock return on bad bank days, on pre-crisis ROE. The model is estimated separately for four different cross-sections: the S&L crisis, the mortgage crisis, the Russian crisis, and the European crisis. The model for the European crisis includes country fixed effects.



Appendices

A Data

Our sample covers all banks in the intersection of Fed NY Database of banks, CRSP-COMPUSTAT database and Call Reports. Daily stock market returns are from the Center for Research in Security Prices (CRSP). Equity, assets, pretax income, net interest income, and dividends are from the merged CRSP / Compustat Fundamentals Annual database for banks. Risk-weighted assets for commercial banks and bank holding companies are from call reports.

We construct a measure of contribution to systemic risk consisting of stock market performance on bad market days. We define bad market days as the 5% of days from 1 July 1926 to 31 December 2014 with the lowest value-weighted returns according to the bank industry portfolio index from Fama and French (industry 44 of 48). We aggregate CRSP daily stock market returns on a value-weighted basis to the level of PERMCO, permanent company identifier. By PERMCO and calendar year, we compute the simple annual average of daily stock market returns on bad days.

The merged CRSP / Compustat database has PERMCO, GVKEY, and stock market ticker identifiers. To merge information from call reports, we use a mapping between PERMCO and the call report identifier RSSDID that spans from 1990 to 2012 created by the New York Federal Reserve. Prior to 1990, we assume that PERMCO-RSSDID links identified by the New York Federal Reserve are valid as long as the bank name is consistent in both the Call Reports and CRSP.

We construct an unbalanced panel with 2,674 financial service firms that spans from 1976 to 2014. Average annual stock market returns on bad days are merged with income and balance sheet items from Fundamentals Annual by year and PERMCO. Risk-weighted assets from call reports are merged with income and balance sheet items from Fundamentals Annual by year and PERMCO, using the New York Fed's mapping from RSSDID to PERMCO. Data in Fundamentals Annual files are by fiscal year. We aggregate stock market returns and risk-weighted assets by calendar year.

Equity (CEQT), assets (AT), pretax income (PI), and dividends (DVT) are available from the merged CRSP / Compustat database over the full 1976 to 2014 date range. Dividends includes both dividends on common stock and on preferred stock. Net interest income (NIINT) is available from 1982 to 2014. Noninterest income is calculated as pretax income minus net interest income. Risk weighted assets from call reports are only available from 1996 to 2014.

B Additional tables

Table A1: Construction of variables with an example from Bank of America (BAC)

Variable	$ billions, 2006	Compustat Variable
Income Statement		
Interest Income (1)	78.585	IDIT
Interest Expense (2)	43.994	XINT
Net Interest Income (3)	34.591	NIINT
Non-interest Income (4)	38.432	Note 1 below
Provision for Credit Losses (5)	5.01	PCLC
Gain(loss) on Securities (6)	-0.443	Note 1 below
Non-interest Expenses (7)	35.597	Note 2 below
Profit Before Tax (8)	31.973	PI
Balance Sheet		
Total Assets (9)	1459.737	AT
Book Equity (tangible) (10)	54.292	CEQT
Our Measures	Ratios in %	Construction
Return on Assets (ROA)	5.20%	[(8)+(2)] / (9)
Return on Equity (ROE)	58.89%	[(8)] / (10)
Non-interest Expense Allocated to Lending (11)	24.00	(7)*(1)/[(1)+(4)+(6)]
Non-interest Expense Allocated to Rest (12)	11.60	(7)*[(4)+(6)]/[(1)+(4)+(6)]
ROA: Interest Income	3.40%	[(1)-(11)-(5)]/(9)
ROA: Non-interest Income	1.81%	[(4)+(6)-(12)]/(9)
ROE: Interest Income	10.28%	[(1)-(2)-(11)-(5)]/(10)
ROE: Non-interest Income	48.61%	[(4)+(6)-(12)]/(10)

Note 1: Compustat variable TNII gives the sum of non-interest income (item 4) and gains/losses on securities (item 6). Since we only need the sum of these two variables in our calculation, we do not need any further breakdown of TNII into these parts.

Note 2: Non-interest expense is calculated with the accounting identity using all other items in the Table.

Table A2: Profitability versus stock market beta based measures

Note: See data appendix. T-statistics in parentheses.

Income Measure	Beta Measure	Profit Coefficient	Beta Coefficient	R^2 Joint	R^2 Profit	R^2 Beta	Obs
Panel A: Accounting Return on Asset							
ROA	Bad Bank Days	-0.136	-0.724	0.612	0.115	0.596	450
		(-3.916)	(-23.410)				
ROA-Interest	Bad Bank Days	-0.060	-0.755	0.598	0.021	0.596	450
		(-1.706)	(-24.980)				
ROA-NonInterest	Bad Bank Days	-0.162	-0.714	0.615	0.147	0.596	450
		(-4.452)	(-22.620)				
Dividends / Assets	Bad Bank Days	-0.078	-0.734	0.600	0.115	0.596	450
		(-2.587)	(-24.340)				
ROA	Bad Market Days	-0.160	-0.670	0.552	0.119	0.525	449
		(-3.540)	(-22.450)				
ROA-Interest	Bad Market Days	-0.064	-0.704	0.532	0.026	0.525	449
		(-1.373)	(-24.700)				
ROA-NonInterest	Bad Market Days	-0.200	-0.666	0.560	0.131	0.525	449
		(-5.348)	(-22.090)				
Dividends / Assets	Bad Market Days	-0.092	-0.684	0.535	0.101	0.525	449
		(-2.747)	(-22.680)				
Panel B: Accounting Return on Equity							
ROE	Bad Bank Days	-0.259	-0.649	0.650	0.300	0.596	450
		(-8.971)	(-20.890)				
ROE-Interest	Bad Bank Days	-0.100	-0.738	0.604	0.080	0.596	450
		(-2.505)	(-23.160)				
ROE-NonInterest	Bad Bank Days	-0.197	-0.708	0.625	0.156	0.596	450
		(-4.817)	(-22.830)				
Dividends / Equity	Bad Bank Days	-0.168	-0.695	0.619	0.202	0.596	450
		(-5.461)	(-22.460)				
ROE	Bad Market Days	-0.299	-0.600	0.606	0.286	0.525	449
		(-7.862)	(-19.560)				
ROE-Interest	Bad Market Days	-0.118	-0.684	0.541	0.085	0.525	449
		(-2.162)	(-22.070)				
ROE-NonInterest	Bad Market Days	-0.236	-0.665	0.574	0.137	0.525	449
		(-5.613)	(-22.680)				
Dividends / Equity	Bad Market Days	-0.187	-0.650	0.559	0.171	0.525	449
		(-5.585)	(-21.100)				

Table A3: Alternative Specifications: ROE

This table presents results from a set of OLS regressions that estimate the relationship between tail risk and prior accounting returns using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times ROE_i^{\text{prior}} + \gamma \times X_i + \epsilon_i$$

ROE_i is a measure of accounting returns for bank 'i' in 2006, and X_i is a set of control variables that differ across columns. Each column in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on accounting returns and controls. The regressors and regressands are standardized to have mean equal to zero and standard deviation equal to one. *Size_Grp* denotes the size group that the bank falls into after dividing all banks into 20 bins based on their total assets. T-statistics in parentheses.

	I	II	III	IV	V
ROEs	-0.13	-0.15	-0.13	-0.15	-0.16
	(-2.81)	(-4.20)	(-2.80)	(-4.16)	(-4.65)
Ln(Assets)	-0.45		-0.46		
	(-15.21)		(-15.01)		
Growth Rate			-0.07	-0.08	-0.08
			(-2.49)	(-2.84)	(-2.98)
Deposit/Asset					0.06
					(2.10)
Loan Loss/Asset					-0.01
					(-0.22)
Constant	3.37	0.02	3.40	0.02	0.02
	(15.81)	(0.97)	(15.60)	(0.77)	(0.78)
Observations	450	450	448	448	448
R^2	0.62	0.72	0.62	0.72	0.72
Absorbed FE		Size_Grp		Size_Grp	Size_Grp

t statistics in parentheses

Table A4: Evolution of Profitability over time

This table presents results from a set of OLS regressions that estimate the relationship between tail risk and prior accounting returns for every year from 2001 to 2006 using the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times ROE_i^{\text{prior}} + \epsilon_i$$

ROE_i is a measure of accounting returns for bank 'i' in a prior year. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on accounting returns for a specific year. The regressors and regressands are standardized to have mean equal to zero and standard deviation equal to one.

Income Measure	Tail Risk Measure	Coefficient	R^2	Obs
Panel A: Accounting Return on Asset				
ROA-2006	Bad Bank Days	-0.335	0.115	450
		(-8.669)		
ROA-2005	Bad Bank Days	-0.270	0.075	424
		(-4.536)		
ROA-2004	Bad Bank Days	-0.221	0.050	396
		(-4.823)		
ROA-2003	Bad Bank Days	-0.110	0.012	373
		(-2.034)		
ROA-2002	Bad Bank Days	-0.083	0.007	350
		(-1.736)		
ROA-2001	Bad Bank Days	-0.021	0.000	330
		(-0.409)		
Panel B: Accounting Return on Equity				
ROE-2006	Bad Bank Days	-0.544	0.300	450
		(-15.750)		
ROE-2005	Bad Bank Days	-0.424	0.182	424
		(-3.560)		
ROE-2004	Bad Bank Days	-0.510	0.257	396
		(-9.418)		
ROE-2003	Bad Bank Days	-0.365	0.134	373
		(-2.570)		
ROE-2002	Bad Bank Days	-0.361	0.129	350
		(-3.182)		
ROE-2001	Bad Bank Days	-0.046	0.002	330
		(-2.820)		

Table A5: Sample of Large Banks

This table presents results from a set of OLS regressions that estimate the relationship between tail risk and prior accounting returns for banks that fall in the top half of size distribution the following regression model:

$$R_i^{\text{crisis}} = \beta_0 + \beta_1 \times ROE_i^{\text{prior}} + \epsilon_i$$

ROE_i is a measure of accounting returns for bank 'i' in a prior year. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on accounting returns for a specific year. The regressors and regressands are standardized to have mean equal to zero and standard deviation equal to one.

Income Measure	Tail Risk Measure	Coefficient	R^2	Obs
Panel A: Accounting Return on Asset				
ROA	Bad Bank Days	-0.152	0.022	227
		(-2.064)		
ROA-Interest	Bad Bank Days	0.037	0.001	227
		(0.518)		
ROA-NonInterest	Bad Bank Days	-0.300	0.071	227
		(-4.729)		
ROA	Bad Market Days	-0.139	0.019	226
		(-1.994)		
ROA-Interest	Bad Market Days	0.015	0.000	226
		(0.205)		
ROA-NonInterest	Bad Market Days	-0.245	0.047	226
		(-3.901)		
Panel B: Accounting Return on Equity				
ROE	Bad Bank Days	-0.366	0.129	227
		(-6.468)		
ROE-Interest	Bad Bank Days	-0.082	0.006	227
		(-1.160)		
ROE-NonInterest	Bad Bank Days	-0.317	0.082	227
		(-4.596)		
ROE	Bad Market Days	-0.313	0.095	226
		(-5.393)		
ROE-Interest	Bad Market Days	-0.081	0.006	226
		(-1.163)		
ROE-NonInterest	Bad Market Days	-0.262	0.056	226
		(-4.266)		