Judging Banks' Risk by the Profits They Report *

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April 26, 2018
First version: February 12, 2018

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. Rather than trying to directly measure asset risks on the balance sheet—the typical (manipulation-prone) approach in model-based regulation—we explore high rates of profit in good times as an indicator of systematic tail risk exposure. We show empirically, for cross-sections of banks in the financial crisis of 2007-2008 as well as the savings and loan crisis of the 1980s, that high accounting profitability prior to the crisis predicts high systematic tail risk of equity market values during the crisis, and most strongly so if pre-crisis profits arise from non-interest income or are paid out as dividends and managerial compensation. 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
JEL Codes: G20, G30

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*We are grateful for comments from Viral Acharya, John Cochrane, Ken French, Robin Greenwood, Randy Krozsner, Philip Strahan, Raghuram Rajan, Uday Rajan, Jeremy Stein, Pietro Veronesi and Vikrant Vig.

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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. Therefore, a number of regulations such as 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 (e.g., to minimize equity capital requirements), but also considerable ability to understate risk exposures. Empirical evidence in Behn, Haselmann, and Vig (2014) and Begley, Purnanandam, and Zheng (2016) 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. In this setting, the asset risk and return of a bank should 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

[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.

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 must have a combination of risky assets and high leverage.

We demonstrate the usefulness of our model-free approach using data from two recent periods of systemic stress: the financial crisis of 2007-08 and the savings and loan crisis of the late 1980s. 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. We show that the pre-crisis ROE helps explain the cross-sectional variation in banks' stock returns on "bad days" during the crisis period.

Bad days are defined as days in which the return on the Fama/French banking industry portfolio is in the bottom 5 percentiles of the empirical distribution generated by the portfolio's daily stock returns during 1926-2015. 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 find that banks with a higher pre-crisis ROE perform significantly worse on bad days. As an additional measure of tail risk, we define "bad days" as days in which the return on the value-weighted market index is in the bottom 5 percentiles of the empirical distribution generated by daily stock returns during 1926-2015. Our results remain similar.

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 (2018) 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 (2016) 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, compared with 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 (2012) that a higher share of non-interest income is associated with higher systemic risk contributions, but our focus here is on the level, not 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: dividend payout to the shareholders and compensation to their managers. We first analyze whether the relationship between profits and tail risk

[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.

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 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.

In our final test, we 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. In economic terms, our profit-based measure is almost three times more effective in detecting cross-sectional variation in tail risk.

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

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

the failure of the previous model. The newer model is typically more complex, which provides even more opportunity for manipulation. 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. However, the fault does not necessarily lie with a particular model. Rather we argue that it is a more fundamental issue: any quantitative model will be subject to manipulation as long as there are incentives to do so, an application of Campbell's Law.

Risk assessment based on reported profitability has several advantages over model-based approaches. First, our proposed approach 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 model-free approach simply infers off-balance sheet risk from the profits that accrue to the sponsoring bank. Second, 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 of 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.

Second, the model-free approach is more incentive compatible than model-based approaches. A bank subject to model-based regulation faces a clear benefit of underreporting risk—raising payouts in normal times to shareholders and managers—but only a remote possibility of punishment from the regulator for underreporting risk. For a bank subject to model-free regulation, underreporting risk could only be achieved by underreporting profits, which would inhibit the ability to distribute returns to shareholders and managers. Finally, since profits are more easily verifiable than risk-weighted assets, the model-free approach generates stronger incentives for truthful reporting (e.g., see Gigler and Hemmer (1998)).

Using reported profits to assess bank risk is a useful but not a perfect tool. The timing of risky activity might not coincide with the timing of profits, so there could be a delay with which risk is assessed. Using the overall measure of profits might raise requirements unnecessarily on banks with high profits due to safe lending, but using the finer measure of 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. Notwithstanding these valid criticisms of our model, its simplicity makes it an attractive additional 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 to set capital requirements based on loan spreads. Calomiris (2011) highlights the incentive-robustness of this approach as circumvention is difficult. 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 and therefore of great importance.

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 requirement is 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 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.[4] 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.

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

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.[5] 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 2007-08, 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.

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 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

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

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 "usual" state and d is a "disaster" state. The available investment opportunities differ in their riskiness θ, which determines their state-dependent payoffs. Given the 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 and 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,

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

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 $R^u_A(\theta) = X^u(\theta) - 1$ (i.e., gross of interest expense). Combining (2) and (1), we get

$$R^d_E(\theta) - R_F = -\frac{1 - \pi}{(1 - D)\pi}(R^u_A(\theta) - R_F) \tag{3}$$

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 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 savings and loan 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 savings and loan 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 2007-08, 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 savings and loan crisis, and a pooled sample including both the mortgage crisis sample and the savings and loan crisis sample. As we present the results, we discuss the relative advantages and disadvantages of each sample—mortgage, savings and loan, and pooled. For each sample, we relate bank profitability before the crisis to performance during the period of systemic stress.

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.[6]

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. Following Acharya, Pedersen, Philippon, and Richardson (2017), we use the average of a bank's stock market returns on the worst 5% of market days to measure its exposure to a systematic tail event. In addition, we also compute a measure of tail risk that focuses exclusively on stress in the banking sector. We define "bad days" as days in which the return on the Fama/French banking industry portfolio is in the bottom 5 percentiles of the empirical distribution generated by the portfolio's stock returns during 1926-2015, and use the average of a bank's stock return during these days as this additional measure of tail risk.

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

[6]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.

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 period. We estimate this model using several accounting measures of profitability, including return on equity.

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) between September 2007 and October 2010. For the savings and loan sample, the period of crisis is not as well defined as the mortgage crisis sample. The savings and loan 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 between July 1988 and July 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. $R^u_A(\theta)$ is measured as gross (of interest expense) profitability on the assets of the bank 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. Thus, the $R^u_A(\theta)$ measure provides us with a measure of all accounting earnings net of some losses in normal times. This closely matches our intuition based on yield on corporate bonds during normal times. We call this measure ROA (Return on Assets) in the rest of the paper. Analogously, $R^u_E(\theta)$ is defined as the sum of pre-tax income and interest expense scaled by the book value of equity. In other words, $R^u_E(\theta) = R^u_A(\theta) \times \frac{A}{E}$, where A measures the total book asset of the bank and E is measured by its tangible common equity. We choose tangible equity value to measure E because this is the cleanest, model-free measure of bank equity available. We call this measure ROE (Return on Equity) in the rest of the paper.

We further break down the gross profit measure (i.e., pre-tax profit plus interest expense) 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.[7] 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. 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

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

returns on "bad days".[8] 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. 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 to October 2010, the most stressful time period associated with the crisis. The savings and loan crisis sample matches income and balance sheet data from fiscal 1986 with stock market returns from July 1988 to July 1990. The pooled crisis sample is a union of the mortgage crisis sample and the savings and loan crisis sample. We match 11,325 bank-year observations from 1986 to 2012, out of which we use 457 cross-sectional observations for the mortgage crisis sample and 138 cross-sectional observations for the savings and loan crisis sample.

5 Empirical relation between profits and systematic risk

To evaluate the extent to which pre-crisis profitability predicts tail risk, we estimate equation (8) for three samples: the mortgage crisis sample, the savings and loan crisis sample, and the

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

pooled sample. For each sample, we relate several measures of profitability to two measures of tail risk—a bank's average return during bad market days and a bank's average return during bad bank days.

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.

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 savings and loan 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 56.774% (55.920%), reflecting the high leverage ratios of banks in the sample.[9] As expected, a large fraction of bank profits are generated through interest income. Average interest income scaled by

[9] Note that our measure of ROE differs from the commonly used ratio of net income to total assets. Crucially, we do not subtract interest expense from gross income. See Appendix Table A1.

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.

Table 2 shows that higher accounting profitability during good times is associated with larger incidence of tail risk. 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 accounting returns on assets are grouped in Panel A, and estimates for accounting returns on equity 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 0.428 (0.409) standard deviation decrease in stock returns during bad bank (market) days. These estimates are statistically significant at the 1% level.

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: Non-interest Income) 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: Non-interest Income). 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 10-15%. Like non-interest income, interest income is positively associated with tail risk, but the relationship is much weaker, especially when we look at the ROA measure.

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: Non-interest Income 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 Income 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 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 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 a strong model fit 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 Table 5 we estimate a model that includes both dividend payouts and remaining profits (i.e. profits minus the dividend 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 paint a clear picture: 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. As expected, the compensation data is large variance and skewness: 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. Do these payouts to CEOs motivate banks to engage in short-term earnings and to take tail risk?

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 the size of the bank. We do so by first breaking all banks into twenty buckets based on their total assets, and then assigning them to one of these 20 size groups for the purpose of fixed effects. 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.

Bank managers' short-term compensation is often tied to specific performance measures linked to the bank's net income and net income to equity ratio. The traditionally used ROE measure in the banking industry is simply the ratio of net-income to equity capital. Our ROE measures are calculated differently, specifically we do not subtract interest expense from the earnings number in calculating the numerator of this ratio. To shed light on the relationship between this specific measure of profitability and CEO bonus payouts, in Table 9 we use ROE net of interest expense as our profitability measure: we call this measure *ROE_net*. Column (I) shows that one standard deviation higher profitability is associated with a 0.51 standard deviation decrease in returns during the crisis. Compared to other measures of profitability used in the paper elsewhere, this measure has the highest impact in economic terms. Further, as shown in Column (V) of the Table, the effect of *ROE_net* is again concentrated within banks in the *High Bonus* group. In sum, when CEOs benefitted from short-term earnings, earnings predicted tail risk.

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 10 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 10 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 10 uses ROA: Non-interest Income 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 0.358 standard deviation decrease in returns during bad bank days. The RWA based measure, in comparison, has a significantly smaller coefficient of just a 0.10 standard deviation decrease in returns on bad bank days for a one standard deviation increase in the RWA-to-asset ratio. The difference in the model fit is even more stark: while the profitability based measure provides an R^2 of over 14%, the model-based risk measure produces an R^2 of less than 1% by itself. When we use dividend payout as the measure of profitability, the results are equally strong. Model-based risk measures have significantly lower coefficient in economic terms; their effect is almost one-third of the effect of profitability and payout ratio on tail risk. Similar patterns hold for variables based on ROE.

The 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 savings and loan 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. Most banks were not yet in distress in 1986, but some were already in distress. 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 savings and loan 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 choice of pre-crisis period), which creates a substantial gap between the pre-crisis period and the performance during the crisis. With these limitations in mind, we proceed with the same set of analyses that we conducted for the mortgage crisis sample on the savings and loan sample.

Table 11 provides the descriptive statistics for the savings and loan 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 98.338%. These numbers are considerably higher than the corresponding estimates for the mortgage crisis period. This is consistent with the general trend of deregulation of the U.S. banking industry: over time the banking markets have become more competitive and therefore the average bank's profitability has declined. For the savings and loan 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 12 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 at the 1% level. A one standard deviation increase in the profitability measure was associated with a 0.2–0.3 decrease in the tail risk measure, depending on the model specification. The model fit ranges between 10–20%. Overall, our key results remain similar for the savings and loan crisis as well.

5.3 Pooled Results

Now we pool the cross-sectional observations from both crises and reproduce these results in Table 13. For this purpose we estimate the following model:

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

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 savings and loan crisis. This specification allows us to evaluate the relative difference in the effect of profits on predicting tail risk across the two crises.

As expected, the effect of ROA and ROS remain strong. A one standard deviation increase in profitability ratios corresponds to a reduction in returns on bad days of $-.27$ to $-.35$ standard deviations depending on the model specification. Interestingly, the effect is much stronger for the mortgage crisis as shown by economically large (-0.14 to 0.21) 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. After a series of banking deregulations in the 1980s and 1990s, banking market is significantly more competitive during this period compared to the savings and loan period. In addition, banks moved their business mix in favor of market related activities in the aftermath of the Glass-Steagall Act. Therefore, profitability in 2006 is likely to contain relatively lower proportion that comes from access to positive net present value projects, and more of it from competitive market risk-taking. These results provide important implications for the interplay between risk measures and industry competitiveness.

5.4 Alternative Specification and Robustness Tests

Table A2 provides regression results for models that also 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 large impact on tail risk, and it can serve as an additional useful tool for banking regulation.

Table A3 produces regression results for the ROA 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 quantiles. We also control for the interest-expense-to-asset ratio of the bank as a measure of the bank's dependence on short-term funding. 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, ROA is a strong predictor of tail risk. Table A4 reproduces the result for ROE and finds the same result.

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 two 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 relatively weaker explanatory power of interest income in predicting tail risk is consistent with some bank profits coming from access to relatively safe positive net present value projects.

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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 2008 crisis period. "Bad bank days" are the 5% of days from July 1926 to July 2015 with the lowest value-weighted return for the Fama/French banking industry portfolio. "Bad market days" are the 5% of days from January 1926 to December 2014 with the lowest CRSP value-weighted market index return (NYSE, AMEX, NASDAQ & ARCA). Average bad-day returns are calculated from bad days between September 1, 2007, and October 1, 2010, and 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 the corresponding measure scaled by book value of equity. *ROA: Interest Income* measures return on asset 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 1.

	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	56.774	22.809	55.920	-8.409	283.895
Return on Equity: Interest Income (%)	450	47.937	17.619	47.177	-10.120	184.420
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

Table 2: Profits and risk: Mortgage crisis

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:

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

P_i is a measure of accounting profit for bank 'i' in 2006. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the income measure. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. T-statistics 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	-0.428	0.190	450
		(-6.021)		
ROE-Interest	Bad Bank Days	-0.351	0.129	450
		(-8.104)		
ROE-NonInterest	Bad Bank Days	-0.425	0.156	450
		(-5.968)		
ROE	Bad Market Days	-0.409	0.174	449
		(-5.788)		
ROE-Interest	Bad Market Days	-0.339	0.121	449
		(-7.340)		
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 tail risk and prior accounting returns, broken down by interest and non-interest sources of income, using the following regression model:

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

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. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. T-statistics in parentheses.

Profit Measure	Tail Measure	Interest Coefficient	Non-Interest Coefficient	R^2 Joint	R^2 Interest	R^2 Non-Interest	Obs
		Panel A: Accounting Return on Asset					
ROA-Interest	Bad Bank Days	-0.233	-0.466	0.200	0.021	0.147	450
		(-5.758)	(-8.930)				
ROA-Interest	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-Interest	Bad Bank Days	-0.235	-0.323	0.205	0.129	0.156	450
		(-4.402)	(-4.087)				
ROE-Interest	Bad Market Days	-0.233	-0.297	0.186	0.121	0.137	449
		(-4.267)	(-3.933)				

Table 4: Payouts to shareholders

This table presents results from a set of OLS regressions that estimate the relationship between tail risk and dividend payouts. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the payout measure. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. T-statistics in parentheses.

Income Measure	Tail Risk Measure	Coefficient	R^2	Obs
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)		

Table 5: Dividend versus other components of profit measures

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

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

div_i is a measure of dividends for bank 'i' in 2006; $nondiv_i$ is a measure of bank's overall profit minus dividend payout. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the dividend measure. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. T-statistics in parentheses.

		Dividend	Non-Dividend		R^2		
Profit Measure	Tail Measure	Coefficient	Coefficient	Joint	Dividend	Non-Dividend	Obs
		Panel A: Accounting Return on Asset					
ROA - Income paid out	Bad Bank Days	-0.340	-0.244	0.176	0.115	0.057	450
		(-7.105)	(-6.064)				
ROA - Income paid out	Bad Market Days	-0.318	-0.256	0.168	0.101	0.063	449
		(-6.797)	(-5.748)				
		Panel B: Accounting Return on Equity					
ROE - Income paid out	Bad Bank Days	-0.349	-0.244	0.255	0.202	0.149	450
		(-5.912)	(-3.382)				
ROE - Income paid out	Bad Market Days	-0.312	-0.245	0.224	0.171	0.139	449
		(-5.398)	(-3.485)				

Table 6: CEO Compensation: Descriptive Statistics

This table presents the summary statistics for CEO's compensation in 2006 for our sample banks. All variables representing the level of compensation are in $'000. 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 tail risk and managerial payouts as measured by CEO's total compensation (scaled by assets) as well as its components. The dependent variable is the return on 'Bad bank days'. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. All models include fixed effects based on the size-bins that the bank falls into. All banks are divided into 20 size buckets based on their total assets, and fixed effects represent these size buckets. T-statistics in parentheses.

	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 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*. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. All models include fixed effects based on the size-bins that the bank falls into. All banks are divided into 20 size buckets based on their total assets, and fixed effects represent these size buckets. T-statistics in parentheses.

	I	II	III	IV	V
Bonus/Total Comp	-0.10				
	(-3.49)				
High Bonus		-0.18	-0.15	-0.15	-0.18
		(-3.62)	(-2.85)	(-2.93)	(-3.53)
ROAs			-0.06	0.02	
			(-2.18)	(0.57)	
High Bonus x ROA				-0.16	
				(-3.27)	
ROEs					0.02
					(0.42)
High Bonus x ROE					-0.10
					(-2.11)
Constant	-0.02	0.07	0.05	0.08	0.07
	(-0.91)	(1.93)	(1.41)	(2.13)	(2.05)
Observations	421	421	421	421	421
R^2	0.73	0.73	0.73	0.74	0.73
Absorbed FE	Size_Grp	Size_Grp	Size_Grp	Size_Grp	Size_Grp

Table 9: Payouts to CEOs: Net ROE

This table presents results from a set of OLS regressions that estimate the relationship between tail risk, profitability and the CEO's cash incentives. The profitability measure *ROE_net* represents return on equity *net* of interest expenses, and calculated as the ratio of profit before tax scaled by tangible common equity. 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*. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. When indicated, models include fixed effects based on the size-bins that the bank falls into. All banks are divided into 20 size buckets based on their total assets, and fixed effects represent these size buckets. T-statistics in parentheses.

	I	II	III	V
ROE_net	-0.51		-0.09	-0.03
	(-13.92)		(-2.70)	(-0.78)
High Bonus		-0.18	-0.15	-0.15
		(-3.62)	(-2.83)	(-2.88)
High Bonus x ROE_net				-0.12
				(-2.40)
Constant	-0.02	0.07	0.05	0.07
	(-0.55)	(1.93)	(1.40)	(1.83)
Observations	421	421	421	421
R^2	0.27	0.73	0.73	0.74
Absorbed FE		Size_Grp	Size_Grp	Size_Grp

Table 10: Profitability versus regulatory measures of risk

This table reports regression results of the following model:

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

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 provides regression results based on a given measure of profit. 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. T-statistics in parentheses.

Income Measure	Tail Risk Measure	Profit Coefficient	Model Coefficient	R^2 Joint	R^2 Profit	R^2 Model	Obs
		Panel A: Accounting Return on Equity					
ROA-NonInterest	Bad Bank Days	-0.358	-0.100	0.135	0.147	0.006	388
		(-6.883)	(-2.123)				
Dividends / Assets	Bad Bank Days	-0.302	-0.113	0.109	0.115	0.006	388
		(-6.336)	(-2.281)				
ROA-NonInterest	Bad Market Days	-0.337	-0.103	0.121	0.131	0.006	387
		(-6.413)	(-2.266)				
Dividends / Assets	Bad Market Days	-0.282	-0.115	0.097	0.101	0.006	387
		(-5.970)	(-2.385)				
		Panel B: Accounting Return on Asset					
ROE-NonInterest	Bad Bank Days	-0.374	-0.120	0.151	0.156	0.006	388
		(-5.540)	(-2.554)				
Dividends / Equity	Bad Bank Days	-0.405	-0.126	0.189	0.202	0.006	388
		(-7.500)	(-2.671)				
ROE-NonInterest	Bad Market Days	-0.349	-0.122	0.132	0.137	0.006	387
		(-5.460)	(-2.690)				
Dividends / Equity	Bad Market Days	-0.371	-0.128	0.160	0.171	0.006	387
		(-7.039)	(-2.765)				

Table 11: Summary statistics: Savings and loan crisis

This Table presents the summary statistics of key variables used in the paper for the savings and loan crisis period. "Bad bank days" are the 5% of days from July 1926 to July 2015 with the lowest value-weighted return for the Fama/French banking industry portfolio. "Bad market days" are the 5% of days from January 1926 to December 2014 with the lowest CRSP value-weighted market index return (NYSE, AMEX, NASDAQ & ARCA). Average bad-day returns are calculated from bad days between between July 1, 1988, to July 1, 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 the corresponding measure scaled by book value of equity. *ROA: Interest Income* measures return on asset 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 1.

	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	98.338	28.222	93.994	35.016	220.244
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 12: Profits and risk: Savings and loan crisis

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:

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

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. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. T-statistics 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	-0.330	0.259	137
		(-8.348)		
ROE	Bad Market Days	-0.335	0.263	137
		(-8.038)		

Table 13: Pooled crises

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 using the pooled sample of banks from the mortgage crisis and the savings and loan crisis:

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

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 savings and loan crisis. Each row in the table corresponds to one cross-sectional regression where the tail risk measure is regressed on the income measure. Both the regressor and regressand are standardized to have mean equal to zero and standard deviation equal to one. T-statistics in parentheses.

		Coefficients				
Income Measure	Tail Risk Measure	P_i	$mortgage_i$	$P_i \times mortgage_i$	R^2	Obs
		Panel A: Return on Asset				
ROA	Bad Bank Days	-0.269	-0.178	-0.136	0.125	587
		(-4.557)	(-1.900)	(-1.800)		
ROA	Bad Market Days	-0.250	-0.238	-0.161	0.121	586
		(-3.444)	(-2.16)	(-1.810)		
		Panel B: Return on Equity				
ROE	Bad Bank Days	-0.348	-0.319	-0.212	0.207	587
		(-8.381)	(-3.690)	(-2.080)		
ROE	Bad Market Days	-0.353	-0.395	-0.182	0.189	586
		(-8.070)	(-4.370)	(-1.781)		

A Data

The data consist of annual income and balance sheet reports and daily stock market returns for financial service firms. 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 database Fundamentals Annual. 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 Appendix 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 Asset (9)	1459.737	AT
Book Equity (tangible) (10)	54.292	CEQT
Our Measures	Ratios in %	Construction
Return on Asset (ROA)	5.20%	[(8)+(2)] / (9)
Return on Equity (ROE)	139.99%	[(8)+(2)] / (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	91.31%	[(1)-(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	Joint R^2	Profit R^2	Beta R^2	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	-0.204	-0.695	0.633	0.190	0.596	450
		(-4.983)	(-22.640)				
ROE-Interest	Bad Bank Days	-0.161	-0.718	0.620	0.129	0.596	450
		(-5.349)	(-23.990)				
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	-0.229	-0.649	0.578	0.174	0.525	449
		(-5.139)	(-22.030)				
ROE-Interest	Bad Market Days	-0.177	-0.670	0.558	0.121	0.525	449
		(-4.908)	(-23.330)				
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: ROA

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:

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

ROA_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
ROAs	-0.17	-0.17	-0.18	-0.18	-0.18
	(-4.35)	(-5.23)	(-4.69)	(-5.67)	(-4.99)
Ln(Assets)	-0.47		-0.47		
	(-18.18)		(-18.15)		
Interest Expenses/Asset	0.11	0.10	0.11	0.09	0.14
	(3.39)	(3.40)	(3.29)	(3.17)	(3.92)
Growth Rate			-0.08	-0.09	-0.09
			(-2.91)	(-3.33)	(-2.72)
Loans/Asset					-0.07
					(-2.46)
Deposit/Asset					0.10
					(2.83)
Loan Loss/Asset					0.01
					(0.20)
Constant	3.50	0.02	3.52	0.02	-0.11
	(19.04)	(0.98)	(19.01)	(0.79)	(-4.09)
Observations	450	450	448	448	386
R^2	0.63	0.73	0.63	0.73	0.71
Absorbed FE		Size_Grp		Size_Grp	Size_Grp

Table A4: 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	-0.28	-0.31	-0.28	-0.31	-0.33
	(-2.99)	(-4.40)	(-2.97)	(-4.32)	(-4.07)
Ln(Assets)	-0.47		-0.47		
	(-15.48)		(-15.33)		
Interest Expenses/Equity	0.28	0.29	0.28	0.28	0.32
	(3.51)	(4.67)	(3.43)	(4.49)	(4.47)
Growth Rate			-0.07	-0.08	-0.08
			(-2.40)	(-2.75)	(-2.44)
Loans/Asset					-0.08
					(-2.85)
Deposit/Asset					0.10
					(2.92)
Loan Loss/Asset					0.01
					(0.33)
Constant	3.47	0.02	3.50	0.02	-0.11
	(16.12)	(0.97)	(15.95)	(0.76)	(-3.98)
Observations	450	450	448	448	386
R^2	0.62	0.72	0.62	0.72	0.70
Absorbed FE		Size_Grp		Size_Grp	Size_Grp