Profits, Credit Spreads, and Fragility of Banks

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Abstract

We provide evidence that the sensitivity of bank profits to credit spreads captures systematic tail risk exposure of banks associated with sentiment in the US. In the cross section, higher profit sensitivity predicts lower equity returns in systematic tail events. Furthermore, prior to the global financial crisis, banks in the top quartile of profit sensitivity decreased their holdings of short-term securities and US government and agency securities more than banks in the bottom quartile, which particularly helped increase their interest income. These portfolio shifts and associated increases in interest income, however, reversed in the crisis. In the time series, the average profit sensitivity more robustly predicts future economic outcomes than loan growth.

1 Introduction

Measurement of systematic tail risk exposure of banks associated with sentiment is particularly important,[1] as elevated sentiment during credit booms may induce banks to take more systematic tail risk (Baron and Xiong, 2017), which can result in the buildup of financial fragility and set the stage for economic downturns and financial crises (Krishnamurthy and Muir, 2017).[2] In the wake of the 2007-2009 global financial crisis, various measures of banks' risk-taking have been proposed, such as short-term funding of Beltratti, and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012), noninterest income of Brunnermeier, Dong, and Palia (2019), loan growth of Fahlenbrach, Prilmeier, and Stulz (2018), and bank profits of Meiselman, Nagel, and Purnanandam (2018). These measures, however, are not designed to specifically capture risk-taking of banks associated with sentiment. We therefore explore in this paper if a sentiment-based systematic tail risk exposure measure provides incremental information.

Our proposed measure is the sensitivity of bank profits to credit spreads. Bank profits manifest banks' risk-taking during credit booms. In a competitive market, "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." (Meiselman, Nagel, and Purnanandam, 2018, p. 11) Credit spreads proxy sentiment in the banking system and the corporate bond market (Lopez-Salido, Stein, and Zakrajsek, 2017; Greenwood and Hanson, 2013). If elevated sentiment (i.e., narrowing spreads) induces a bank to choose a combination of risky assets and/or high leverage in the good state, the bank's profits will rise, resulting in a significantly negative loading of bank profits on credit spreads. For the ease of exposition, we define "profit sensitivity" in this paper as the estimated loading of bank profits on credit spreads multiplied by -1 so that a larger value indicates a higher systematic tail risk exposure under our null hypothesis that elevated sentiment leads to

[1] In the same spirit of Lopez-Salido, Stein, and Zakrajsek (2017), when we talk about sentiment, we mean more precisely the expected return to bearing credit risk based on a particular forecasting model. Thus, when we say that sentiment is elevated, this is equivalent to saying that the expected return to bearing credit risk is low.
[2] Risk-taking of banks driven by sentiment could lead to correlation in banks' asset portfolios and therefore systemic risk (e.g., Elsinger, Lehar, and Summer, 2006). Furthermore, banks are also particularly vulnerable to large negative systematic shocks due to their payoff non-linearity (Nagel and Purnanandam, 2019).

more risk-taking in the good state. Empirically, to capture the state dependence of banks' risk-taking, we estimate banks' profit sensitivities with quarterly data and rolling regressions.

Profit sensitivity, however, could also reflect expectations about economic fundamentals. For instance, good news about the economy may lead to declines in credit spreads and increases in the credit demand as well as bank profits. To weigh against this alternative hypothesis, we flesh out two testable predications under our null hypothesis.

- *Prediction 1: In the cross section, banks with higher profit sensitivity, manifesting higher systematic tail risk exposure, should experience lower equity returns in systematic tail events.*
- *Prediction 2: In the time series, an increase in the average profit sensitivity, capturing the buildup of the financial fragility, should predict a subsequent economic downturn.*

Under the alternative hypothesis, high profit sensitivity, reflecting positive economic fundamentals, should not predict adverse economic outcomes in the cross section and the time series.

We first test Prediction 1. Following Brunnermeier, Dong, and Palia (2019), we proxy equity returns in systematic tail events with the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017), which is defined as the average of a bank's daily equity returns during the 5% worst days for the banking industry in any given year. Thus, in our setting, asking whether profit sensitivity captures systematic tail risk exposure and predicts equity returns in systematic tail events boils down to asking whether profit sensitivity predicts subsequent MES. Empirically, in the same spirit of Fahlenbrach, Prilmeier, and Stulz (2018), we divide banks in our sample in quartiles of profit sensitivity, and find that banks in the top quartile of profit sensitivity in year $t-1$ experience significantly lower MES in year t than banks in the bottom quartile. In quantitative terms, we observe that on the 5% (or about 13) worst days in a year for the banking industry a bank in the highest sensitivity quartile has an about 2.69% lower return than a bank in the lowest sensitivity quartile. Our results are robust in the subsample periods and to alternative panel-regression specifications, systematic tail risk measures, profitability proxies, time horizons to estimate MES and profit sensitivities, and bank samples. Furthermore, we find that equity losses of banks in the top quartile of profit sensitivity increase with the magnitude of negative systematic tail shocks, and profit sensitivity also predicts capital losses in hypothetical systematic tail events based on the Federal Reserve's Dodd-Frank Act Stress Tests results. All the evidence provides robust support for Prediction 1 that profit sensitivity is informative about systematic tail risk exposure of banks in the cross section.

If profit sensitivity is not driven by elevated sentiment, expected equity returns should be higher for banks with higher profit sensitivity to compensate for higher systematic tail risk exposure of these banks (Baron and Xiong, 2017). However, we find that banks in the top quartile of profit sensitivity in year $t-1$ experience a 4% lower return in year t than banks in the bottom quartile. Furthermore, we find that the sensitivity of bank profits to a more explicit measure of credit-market sentiment, namely the excess bond premium of Gilchrist and Zakrajšek (2012), has similar predictive power over subsequent MES. In addition, sensitivities of bank profits to credit spreads after controlling for common macroeconomic variables (e.g., GDP growth, the unemployment rate, the inflation rate, and the term spread) still have significant predictive power. Taken together, the evidence supports the notion that profit sensitivity captures risk-taking associated with elevated sentiment.

We further provide evidence of reaching-for-yield, a mechanism of risk-taking associated with elevated sentiment. Under our null hypothesis, elevated sentiment in the good state may induce banks to rebalance from safe and/or short-term assets to risky and/or long-term assets that have higher yields to boost banks' current income. To test this mechanism, along the same line of Hanson and Stein (2015), we utilize the FR Y9-C (Consolidated Financial Statements for Holding Companies) data, which reports banks' non-trading account security holdings by issuer and maturity/next re-pricing date. We find that prior to the global financial crisis, banks in the top quartile of profit sensitivity decreased their holdings of US government and agency securities as well as short-term securities more than banks in the bottom quartile, which particularly helped increase their interest income. These portfolio shifts and associated increases in interest income, however, reversed in the crisis, consistent with notion that elevated sentiment leads to more risk-taking.

The reaching-for-yield results suggest that interest income is important to understand banks' risk-taking associated with sentiment. In particular, interest income is not only the dominant source of banks' profits (about 78%) but also varies more with credit spreads across banks and over time. For instance, the standard deviations of the sensitivities of interest and noninterest income to credit spreads are 3.50 and 0.91, respectively. To provide more formal evidence, we divide banks in quartiles of interest income sensitivity to credit spreads, and find that banks in the top quartile have significantly lower subsequent MES than banks in the bottom quartile. However, we do not find similar results when we divide banks by noninterest income sensitivity to credit spreads. Our results are consistent with Granja, Leuz, and Rajan (2019) who find that banks' lending is significantly cyclical. Note that our results are not inconsistent with Brunnermeier, Dong, and Palia (2019), as Brunnermeier, Dong, and Palia (2019) focus on the level of noninterest income, not the sensitivity of noninterest income to credit spreads.

We also show that profit sensitivity has incremental information relative to the existing measures of banks' risk-taking (e.g., short-term funding, noninterest income, loan growth, and profits). First, the correlations of profit sensitivity with existing risk exposure measures are low, below 10%. Second, conditional on the existing exposure measures, profit sensitivity still has incremental predictive power over subsequent MES in both portfolio and regression analyses. For instance, we construct portfolios double-sorted on noninterest income and profit sensitivity. Given the first-pass sort on noninterest income, the second-pass sort on profit sensitivity still produces significant variation in subsequent MES. In panel regressions, controlling for noninterest income (as well as short-term funding, loan growth, and profits) yields materially similar results. Therefore, by capturing the specific risk-taking associated with sentiment, our proposed measure complements the existing bank-level risk exposure measures.

We next test Prediction 2. Under our null hypothesis, elevated sentiment in the good state leads to increases in risk-taking across banks and therefore increases in the average profit sensitivity. Since the buildup of the financial fragility sets the stage for economic downturns (Krishnamurthy and Muir, 2017), increases in the average profit sensitivity should negatively predict aggregate economic activities. We indeed find supporting evidence for this prediction. In quantitative terms, our estimates over the period from 1975 to 2018 indicate that when the average profit sensitivity in year $t-1$ increases from the 25th to the 75th percentile of its historical distribution, this change predicts a cumulative decline in real per capita GDP growth of about 1.87 percentage points over years t to $t+2$ and an increase in the unemployment rate of 1.07 percentage points over the same period.

A popular financial fragility measure in the literature is loan/credit growth. Rapid loan growth predicts economic downturns in international panels (Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013). However, consistent with Lopez-Salido, Stein, and Zakrajsek (2017), we find that loan growth does not have consistent predictive power in the US sample. Therefore, the predictive power of our bottom-up fragility measure, the average profit sensitivity, suggests that it could be particularly useful as an early warning indicator for the US banking system.

The remainder of the paper is organized as follows: Section 2 describes our sample and data; Section 3 proposes our systematic tail risk exposure measure; Section 4 tests Prediction 1; Section 5 examines Prediction 2; Section 6 concludes the paper with a brief summary.

2 Data

In Section 2.1, we describe the construction of our sample. In Section 2.2, we define the main variables used in the empirical analysis.

2.1 Sample construction

Following Meiselman, Nagel, and Purnanandam (2018), we start with 1,388 public bank holding companies (BHC) and commercial banks (hereafter banks) in the mapping file maintained by the Federal Reserve Bank of New York (FRB).[3] With the mapping, we can merge stock returns from the University of Chicago's Center for Research in Security Prices (CRSP) with accounting data from the CRSP-Compustat

[3] https://www.newyorkfed.org/research/banking_research/datasets.html.

Merged Bank database (CCM-Bank).[4] 76 banks in the FRB mapping are not in the annual CCM-Bank.[5] For these 76 banks, 30 banks can be identified in the CRSP-Compustat Merged North America (CCM-NA) and are added to the CCM-Bank.[6]. After dropping 14 banks with missing total assets, our augmented CCM-Bank covers 1,327 banks from 1962 to 2018.

We impose three filters to construct our sample. First, the coverage of CCM-Bank is very limited prior to 1972, only 70 bank-year observations from 1962 to 1971. Therefore, following Fahlenbrach, Prilmeier, and Stulz (2018), we focus on the period from 1972 to 2018. Second, we drop 402 banks without sufficient data for our empirical analysis. For instance, we need three years' profits data to estimate profit sensitivities of banks. Third, CCM-Bank started to cover small banks in 1993,[7] resulting in a substantial increase in the number of banks. To ensure that our results are not driven by small banks, we follow Fahlenbrach, Prilmeier, and Stulz (2018) and exclude small banks with total assets below \$2 billion in 2013 US dollars. Fig. 1 shows the numbers and total assets of banks before and after the \$2 billion exclusion. As we can see, the exclusion helps remove the spike in the number of banks in 1993 but has trivial impact on the system total assets. After removing small banks, our final sample contains 510 unique banks and 8.057 bank-year observations from 1972 to 2018. In robustness checks, we report the results without excluding small banks, which are materially similar.

2.2 Main variables

Sentiment proxies - We use the credit spread as our sentiment proxy. First, the credit spread is known to capture credit-market sentiment (Greenwood and Hanson, 2013). Second, as Lopez-Salido, Stein, and Zakrajsek (2017) point out, banking-system sentiment should be closely correlated with credit-market

[4] The mapping also helps merge CRSP with the FR Y-9C (Consolidated Financial Statements for Holding Companies).
[5] Companies collected in the Bank Format in Compustat are determined by their SIC codes. The SICs collected in the Bank Files are: 6020 (Commercial Banks), 6021 (National Commercial Banks), 6022 (State Commercial Banks), 6029 (Commercial Banks, Nec), 6035 (Savings Instn, Fed Chartered), and 6036 (Savings Instn, Not Fed Chart).
[6] The rest 46 banks do not have reliable PERMCO-GVKEY links.
[7] In our email communication with S&P Global Market Intelligence, we were told "Compustat covered the top 250 Bank Holding companies up until 1993 only".

sentiment. Empirically, Lopez-Salido, Stein, and Zakrajsek (2017) find that in years in which the credit spread is low (i.e., credit-market sentiment is elevated), bank loan officers also tend to ease credit standards on loans, consistent with the notion of buoyant sentiment in the banking system. Third, the credit spread, relative to lending standards, is available for a longer sample period. Following Lopez-Salido, Stein, and Zakrajsek (2017), our baseline credit spread is defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities. For robustness, we also explore an alternative measure of credit-market sentiment, namely the excess bond premium of Gilchrist and Zakrajšek (2012).[8]

Systematic tail risk measures - Our baseline measure of systematic tail risk is the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017), which is defined as the average of a bank's daily equity returns during the 5% worst days in any given year for the banking industry index from Kenneth French (industry 44 of 48).[9] [10] We aggregate CRSP daily stock returns on a value-weighted basis to the level of PERMCO. By PERMCO and calendar year, we compute the simple annual average of daily returns on bad bank days, which we refer as MES^{Bank}. For robustness, we also consider three alternative systematic tail risk measures. The first one is MES on bad market days, MES^{Market}, which is defined as the annual average of a bank's daily equity returns on the worst 5% of trading days in any given year for the value-weighted market returns. The second alternative measure is tail equity returns of Meiselman, Nagel, and Purnanandam (2018), *MNP*, which is defined as the annual average of a bank's daily equity returns during the 5% worst days from 1926 to 2018 for the banking industry. The third alternative measure is $\Delta CoVaR$ of Adrian and Brunnermeier (2016). To construct $\Delta CoVaR$, we need the systematic state variables at the weekly frequency. This data limitation dictates that our $\Delta CoVaR$ estimates for banks start in 1986.

Existing bank-level risk exposure measures – Noninterest income of Brunnermeier, Dong, and Palia (2019), *Noninterest*, is defined as the ratio of noninterest income to total assets. Three-year loan growth of

[8] https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv.
[9] Baron, Emil, and Xiong (2018) find that compared to non-financial equity returns, the banking sector index is more informative about banking crises.
[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Fahlenbrach, Prilmeier, and Stulz (2018), $\Delta Loan$, is computed as a bank's total loan growth from year $t-3$ to year t. Short-term funding of Beltratti and Stulz (2012), *Funding*, is calculated as debt with maturities of less than one year divided by total liabilities. As for bank profits, we follow Meiselman, Nagel, and Purnanandam (2018) and use ROE^{MNP} as the baseline measure, which is defined as the ratio of pre-tax income plus interest expenses to tangible equity. For robustness, we also explore three alternative profitability measures: ROA^{MNP} is the ratio of pre-tax income plus interest expenses to total assets; ROE^{PI} is the ratio of pre-tax income to tangible equity; ROE^{NI} is the ratio of net income to tangible equity.

We define other variables in Table 1. In terms of data sources, bond yields as well as macroeconomic data (e.g., CPI, real per capita GDP, unemployment, and the term spread) are retrieved from the Federal Reserve Economic Data (FRED); daily/monthly equity returns are from CRSP; quarterly/annual accounting data of banks are from CCM-Bank or FR Y-9C. To mitigate the effects of outliers in accounting variables, following Fahlenbrach, Prilmeier, and Stulz (2018), we winsorize our accounting variables at the 1% and 99% levels.

Table 2 presents the summary statistics of the main variables. The mean (median) MES^{Bank} in the sample is -2.07% (-1.66%). Since MES is daily, its mean (median) implies that on the 5% (or about 0.05 × 250 = 13) worst trading days in a year for the banking industry, banks experience an average (median) equity loss of 2.07×13 = 26.91% (1.66 × 13 = 21.58%). Therefore, systematic tail risk is substantial. Furthermore, its standard deviation of 1.93% suggests that there is considerable variation in systematic tail risk across banks and over time. The mean equity return (r) for our sample is 0.06% per day or about 0.06 ×250 = 15% per year, very close to the mean one-year return of 15.5% reported in Fahlenbrach, Prilmeier, and Stulz (2018) (see their Table 2 on p. 1025). The mean (median) total assets in current dollars is $39.72 ($4.99) billion with a standard deviation of $181.34 billion, suggesting that in terms of total assets, the banking system is dominated by large banks.

3 Profit sensitivity to credit spreads

Influential studies of financial crises by Minsky (1977, 1986), Kindleberger (1978), and Reinhart and Rogoff (2009) emphasize the role of sentiment as an important driver of credit cycles. Gennaioli, Shleifer, and Vishny (2012, 2015) and Bordalo, Gennaioli, and Shleifer (2018) develop behavioral models of credit cycles. Baron and Xiong (2017) and Fahlenbrach, Prilmeier, and Stulz (2018) find empirical evidence that sentiment influences banks' risk-taking.[11] Built on these studies, we propose an empirical measure of banks' risk-taking associated with sentiment.

More specifically, we capture risk-taking in the good state with bank profits (Meiselman, Nagel, and Purnanandam, 2018) and proxy sentiment with credit spreads (Lopez-Salido, Stein, and Zakrajsek, 2017). Fig. 2 depicts the asset-weighted average ROE^{MNP} and the credit spread over our sample period from 1972 to 2018. The shaded vertical bars denote the NBER dated recessions. The negative correlation between bank profits and credit spreads is evident. For instance, prior to the global financial crisis, while the credit spread narrows, bank profitability rises, consistent with the notion that elevated sentiment leads to increased risk-taking and higher yields in the good state. To capture risk-taking associated with sentiment, we consider the following one-factor model of bank profits:

$$P_{i,t} = a_{i,t} + b_{i,t}CS_t + e_{i,t} \tag{1}$$

where $P_{i,t}$ is profitability of bank i (e.g., ROE^{MNP}), CS_t is the credit spread, and $b_{i,t}$ is the loading of bank profits on credit spreads. Profit sensitivity, $s_{i,t}$, is defined as the estimated loading of bank profits on credit spreads multiplied by -1 so that a larger value indicates higher risk-taking under our null hypothesis. That is, $s_{i,t} = -b_{i,t}$. In robustness checks, we also account for common macroeconomic variables (e.g., GDP growth) to estimate profit sensitivities of banks, and find similar results.

Under our null hypothesis, driven by elevated sentiment, banks' risk-taking may be particularly high in the good state. To allow the state dependence in banks' risk exposure, we estimate Eq. (1) for each bank with quarterly data and three-year rolling regressions. In robustness checks, we report the results based

[11] See also Danielsson, Valenzuela, and Zer (2018).

on four-year rolling regressions, which are materially similar. To convert the quarterly series to annual frequency, we take the fourth-quarter value for each calendar year.

A natural question is: are the rolling estimates meaningful? We provide two sets of results to address this concern. The first set focuses on the statistical significance of the rolling regressions. To put the results in perspective, we use monthly data and three-year rolling regressions to estimate CAPM betas of banks (*beta*). The results are reported in Panel A of Table 3. First, the mean (median) absolute t-statistic for the profit-sensitivity estimates is 2.61 (1.83), suggesting that the credit spread is a significant factor of bank profits. Second, the mean (median) R^2 for the profit-sensitivity regressions is 0.23 (0.15), compatible to that for the beta regressions, which is 0.24 (0.22). Therefore, the rolling regressions of Eq. (1) are not particularly noisy in relation to the CAPM regressions.

The second set of evidence shows that the cross-sectional and time-series variation in profit sensitivity seems to be economically plausible. Specifically, each year, we divide our sample into quartiles by profit sensitivity. Panel B of Table 3 presents the means bank characteristics by profit-sensitivity quartiles. Relative to the average bank in the lowest sensitivity quartile, the average bank in the highest sensitivity quartile has higher leverage and experiences higher subsequent charge-offs, provisions, and non-performing assets, suggesting that banks in the highest sensitivity quartile hold more risky assets and use more leverage. We also plot the mean profit sensitivities for the lowest and highest sensitivity quartiles over the entire sample period in Fig. 3a. As we can see, in the good state (e.g., prior to the global financial crisis), profit sensitivities increase particularly for banks in the highest sensitivity quartile, consistent with the notion that profit sensitivity captures the risk-taking associate with elevated sentiment during credit booms.

The rolling regressions of Eq. (1), unsurprisingly, produce outliers. For instance, Panel A of Table 3 shows that while the mean (median) profit sensitivity is 1.33 (0.59), the minimum and maximum are -50.88 and 45.26, respectively. Therefore, to mitigate the effects of outliers, we winsorize the profit-sensitivity estimates of banks in our sample at the 1% and 99% levels.

4 Profit sensitivity in the cross section

Under our null hypothesis, higher profit sensitivity manifests higher systematic tail risk exposure in the good state and should predict lower equity returns in systematic tail events (Prediction 1). In Sections 4.1 and 4.2, we provide robust evidence that higher profit sensitivity predicts lower MES in the cross section. In Section 4.3, we show that the predictive power of profit sensitivity is associated with sentiment, as opposed to economic fundamentals. In Section 4.4, we provide evidence of reaching-for-yield, an economic mechanism of risk-taking associated with sentiment. In Section 4.5, we demonstrate that profit sensitivity has incremental information relative to the existing risk exposure measures. In Section 4.6, we provide further evidence to support our proposed measure, profit sensitivity.

4.1 Baseline results

We first explore our data by plotting the time-series of the average MES^{Bank} (i.e., MES based on the 5% worst days for the banking industry) in year $t + 1$ for two groups of banks over the sample period in Fig. 3b. While the solid line corresponds to the average MES^{Bank} in $t + 1$ for banks in the year-t lowest sensitivity quartile (quartile 1), the dashed line represents the average MES^{Bank} in $t + 1$ for banks in the year-t highest sensitivity quartile (quartile 4). The figure shows that subsequent MES^{Bank} for banks in quartile 4 is generally lower than that for banks in quartile 1, particularly in economic downturns (e.g., the global financial crisis). Panel B of Table 3 shows that the difference in the mean MES^{Bank} in $t + 1$ between the two groups of banks is -0.36% per day, both statistically and economically significant. Note that two groups of banks also differ in terms of size, beta, book-to-market, idiosyncratic volatility, and leverage (see Panel B of Table 3). To control for these known risk characteristics, we estimate fixed-effects panel regressions.

More specifically, in the same spirit of Baron and Xiong (2017) and Fahlenbrach, Prilmeier, and Stulz (2018), we estimate the following regressions:

$$MES_{i,t}^{Bank} = \sum_{k=2}^{4} \beta^k q_{i,t-1}^k + \gamma_1 \log\left(Assets_{i,t-1}\right) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1}$$

$$+\gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \mu_t + \varepsilon_{i,t} \qquad \text{(2a)}$$

and

$$MES_{i,t}^{Bank} = \sum_{k=2}^{4} \beta^k q_{i,t-1}^k + \gamma_1 \log(Assets_{i,t-1}) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1}$$
$$+\gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \mu_t + \mu_i + \varepsilon_{i,t} \quad (2b)$$

where $MES_{i,t}^{Bank}$ is MES in year t for bank i based on the worst 5% days for the banking industry, and $q_{i,t-1}^k$ is an indicator variable equal to 1 if profit sensitivity of bank i is in the kth profit-sensitivity quartile of all banks in year $t-1$. We control for observable bank characteristics, namely log total assets ($\log(Assets)$), CAPM beta ($beta$), book-to-market (BM), idiosyncratic volatility ($Volatility$), and leverage ($Leverage$). By including μ_t (the year fixed effects) in Eq. (2a), we focus on the variation across banks depicted in Fig. 3b. Eq. (2b) further accounts for the bank fixed effects, μ_i, to control for time-invariant unobservable heterogeneity across banks. Our variable of interest is q_{t-1}^4, which captures the difference in MES between banks in the highest sensitivity quartile and banks in the lowest sensitivity quartile. We expect β^4 to be significantly negative under our null hypothesis, as higher systematic tail risk exposure (measured by higher profit sensitivity) should predict lower equity returns in systematic tail events. We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Table 4 reports our baseline results. Since we need three years' data to estimate profit sensitivities and our data starts in 1972, the panel regressions are estimated over the period from 1975 to 2018. In Columns (1), we estimate Eq. (2a) without any observable bank characteristics. The coefficient on q_{t-1}^4 is -0.387 (t-statistic = -3.65), very close to the difference in the mean MES^{Bank} between quartile 4 and quartile 1 we report in Panel B of Table 3. Note that the small difference is due to that all the regressions in Table 4 require that all independent variables have no missing values. In Column (2), we use the bank fixed effects to control for time-invariant heterogeneity across banks. As we can see, MES now monotonically decreases across the sensitivity quartiles. Furthermore, the coefficient on q_{t-1}^4, not surprisingly, decreases in magnitude compared to that in Column (1). However, it is still significant with a t-statistic of -2.76. In terms of economic significance, our coefficient estimate of -0.207 in Column (2) suggests that about $\frac{0.207}{0.387} =$

53% of the difference in MES between quartile 4 and quartile 1 is due to the difference in profit-sensitivity. Alternatively, our estimate suggests that on the 5% (or about 0.05 × 250 = 13) worst days in a year for the banking industry a bank in the highest sensitivity quartile has an about -0.207 × 13 = 2.69% lower return than a bank in the lowest quartile even after controlling for time-invariant heterogeneity across banks.

In Columns (3), we estimate Eq. (2a) with the observable bank characteristics. First, the observable bank characteristics generally have expected signs. For instance, consistent with prior research,[12] bank size, $\log(Assets_{i,t-1})$, has a negative impact on equity returns. Second, interestingly, both the coefficients on the quartile indicators and Adj-R^2 in Column (3) are very similar to those reported in Column (2), suggesting that the observable bank characteristics and the bank fixed effects contain similar information. This is confirmed in Column (4) in that including both the observable bank characteristics and the bank fixed effects does not change the coefficient estimates on the quartile indicators materially.

The results in Table 4 supports Prediction 1. That is, higher profit sensitivity manifests higher systematic tail risk exposure and predicts lower equity returns in systematic tail events even after we account for observable and unobservable bank characteristics.

4.2 Robustness checks

Subsample periods - Are the results in Table 4 driven entirely by the global financial crisis? To address this concern, we repeat our exercises for two equal subsamples. The early subsample, in Columns (1) and (2) of Table 5, covers the period from 1975 to 1996, thereby excluding the global financial crisis. The recent subsample, in Columns (3) and (4) of Table 5, covers the period from 1997 to 2018. Not surprisingly, the results for the early subsample are weaker, although still statistically and economically significant. For instance, with the observable bank characteristics and the year fixed effects, the coefficients on q_{t-1}^4, are -0.153 (t = -2.50) and -0.255 (t = -2.40) for the early and recent subsamples, respectively. The

[12] See for instance Kashyap and Stein (2000) and Gandhi and Lustig (2015).

evidence therefore suggests that the predictive power of profit sensitivity is not entirely driven by the global financial crisis.

Alternative specifications - We explore alternative panel specifications. In Columns (5) and (6) of Table 5, we use profit sensitivity instead of its indicator variables. In Columns (7) and (8) of Table 5, we account for more bank-level controls, including the loans to assets ratio (*Loans/Assets*), the interest expense to assets ratio (*XINT/Assets*), the log change in total assets (Δ*Assets*), the deposits to assets ratio (*DPTC/Assets*), and the loan loss provisions to assets ratio (*PCL/Assets*). As we can see, profit sensitivity still has statistically and economically significant predictive power in these alternative specifications. For instance, in Column (5), with the observable bank characteristics and the year fixed effects, the lagged profit sensitivity enters with a coefficient of -0.025 (t = -4.23). Therefore, an increase in profit sensitivity from the quartile-1 mean (which is -2.21) to the quartile-4 mean (which is 5.49) predicts a lower MES of (5.49 + 2.21) × 0.025 = 0.19% per day, very close to the estimate of 0.21% in Column (3) of Table 4.

Alternative systematic tail risk measures - We consider three alternative systematic tail risk measures, namely MES on bad market days (MES^{Market}), tail equity returns of Meiselman, Nagel, and Purnanandam (2018) (*MNP)*, and $\Delta CoVaR$ of Adrian and Brunnermeier (2016). In Panel B of Table 3, we show that banks in the highest sensitivity quartile experience lower subsequent MES^{Market}, *MNP*, and $\Delta CoVaR$ than banks in the lowest sensitivity quartile. In Table 6, we estimate panel regressions to control for observable and unobservable bank characteristics. In Columns (1), (3) and (5), we account for the year fixed effects. In Columns (2), (4) and (6), we further include the bank fixed effects. Note that these systematic tail risk measures differ. For instance, while MES and MNP are conditional on the whole system being in distress, $\Delta CoVaR$ is conditional on the distress of a particular bank. This difference helps explain why the results for $\Delta CoVaR$ are weaker. However, in general, we observe that profit sensitivity has significant predictive power over alternative systematic tail risk measures.

Alternative profitability measures - In Table 7, we estimate profit sensitivities of banks with alternative profitability measures, namely the ratio of pre-tax income plus interest expenses to total assets

(ROA^{MNP}), the ratio of pre-tax income to tangible equity (ROE^{PI}), and the ratio of net income to tangible equity (ROE^{NI}). In Columns (1), (3) and (5), we account for the year fixed effects. In Columns (2), (4) and (6), we further include the bank fixed effects. Note that excluding interest expenses as in ROE^{PI} and ROE^{NI} may not fully capture banks' risk taking on the liabilities side. This shortcoming explains weaker results based on these measures. However, in general, our results are robust to alternative profitability measures.

Additional robustness checks - We perform additional robustness checks and report the results in Table 8. In Columns (1) and (2), we skip one quarter between the profit-sensitivity estimation period and the MES calculation period, to address the potential concern that accounting information disclosed at the end of year t - 1 (which is used to estimate profit sensitivity) may not be available to equity investors in the first quarter of year t (to impact stock returns and MES). That is, we estimate MES for year t based on equity returns from April of year t to March of year t + 1, as opposed to from January to December of year t. In Columns (3) and (4), we estimate profit sensitivities with four-year rolling windows, as opposed to three-year rolling windows. In Columns (5) and (6), we include all banks, as opposed to only banks with total assets of more than \$2 billion in 2013 US dollars. As we can see, all the results in Table 8 are not materially different from our baseline results in Table 4.

Systematic tail shocks - Bank equity returns in systematic tail events (i.e., MES) depend on both the magnitude of negative systematic tail shocks and the exposure of banks to such shocks. Therefore, the predictive power of profit sensitivity over MES should vary over time with the magnitude of negative systematic tail shocks, if it indeed captures systematic tail risk exposure of banks. We provide supporting evidence here. First, we estimate the cross-sectional version of Eq. (2a) by year to allow the coefficients of the independent variables to vary over time. Then, we proxy the systematic tail shock in each year by the average of the banking industry's daily returns on the 5% worst days in the year. Finally, we plot a scatter with the systematic tail shock on the horizonal axis and the coefficient of q_{t-1}^4 on the vertical axis. A positive correlation emerges: in years in which there are plausibly large negative systematic shocks, the coefficient on q_{t-1}^4 is particularly negative. For instance, in 1987 (the savings and loan crisis), 1998 (the

Long-Term Capital Management crisis), and 2008-2010 (the global financial crisis), the coefficient estimates on q_{t-1}^{4} are around -0.5, more than two time as much as the panel estimates in Table 4.

Stress tests – We utilize the Federal Reserve (Fed)'s Dodd-Frank Act Stress Tests (DFAST) results as an alternative test.[13] DFAST is an annual quantitative exercise in which the Fed uses detailed data from banks (i.e., BHCs with $100 billion or more in total consolidated assets and U.S. IHCs) and its own independent suite of empirical models to project bank income, expenses, loss provisions, and capital, over a nine-quarter horizon and under three hypothetical scenarios: baseline, adverse, and severely adverse. Differences in assets and liabilities (i.e., systematic tail risk exposure) across banks generate cross-sectional variation in banks' capital losses, providing a unique alternative test opportunity. For DFAST 2018, the Fed conducted supervisory stress tests on 35 banks, of which 23 are US public banks in our sample. We use the severely adverse scenario to proxy "hypothetical" systematic tail events, and the difference between the projected minimum common equity tier 1 ratio (CET1) over the nine-quarter horizon from 2018:Q1 to 2020:Q1 and the actual CET1 prior to the exercise in 2017:Q4 to proxy the capital loss in such systematic tail events. Furthermore, we measure banks' systematic tail risk exposure with their profit sensitivities estimated over the period from 2015 to 2017. Fig. 5a shows that the capital loss is positively associated with MES^{Bank} in 2018, confirming that MES is informative about systematic tail risk of banks. Fig. 5b indicates that higher profit sensitivity predicts more capital losses, reinforcing the notion that profit sensitivity is informative about systematic tail risk exposure of banks in the cross section.

4.3 Further evidence

Sections 4.1 and 4.2 present evidence that banks with higher profit sensitivity experience lower equity returns in systematic tail events, suggesting that profit sensitivity helps capture systematic tail risk exposure of banks. In this section, we provide evidence that such systematic tail risk exposure is associated with sentiment.

[13] The data are publically available at https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm.

Mean equity returns - As Baron and Xiong (2017) imply, if banks and their shareholders are not driven by elevated sentiment, mean equity returns should be higher for banks with higher profit sensitivity to compensate for higher systematic tail risk exposure of these banks. Lower instead of higher mean returns for banks with higher profit sensitivity therefore would be consistent with the notion that elevated sentiment leads to more risk-taking. Panel B of Table 3 shows that banks in the highest sensitivity quartile indeed have lower subsequent mean returns (r) than banks in the lowest sensitivity quartile. The difference is 0.01% per day or 0.01 × 250 = 2.5% per year, both statistically and economically significant. To account for bank-level controls, we re-estimate Eqs. (2a) and (2b), except that the dependent variable is average daily returns (r) instead of MES. The results are reported in Columns (1) and (2) of Table 9. As we can see, controlling for observable and unobservable bank characteristics does not explain away the differences in mean returns across banks. For instance, in Column (2), with both the year and bank fixed effects as well as the observable bank characteristics (e.g., *beta*), the coefficient on q_{t-1}^{4} is -0.016 (t = -2.54), implying that banks in the highest sensitivity quartile in year $t-1$ experience a 0.016 × 250 = 4% lower return in year t than banks in the lowest sensitivity quartile.

Excess bond premium – One concern is that profit sensitivity we construct may proxy the effects of economic fundamentals instead of sentiment, as the credit spread is known to predict economic fundamentals. To address this concern, we employ the excess bond premium of Gilchrist and Zakrajšek (2012), which is unrelated to expected defaults and more explicitly measures credit-market sentiment. In Fig. 6, we depict the excess bond premium and various banking-system sentiment measures from Senior Loan Officer Option Surveys retrieved from FRED. Consistent with Lopez-Salido, Stein, and Zakrajsek (2017), there is a close correlation between credit-market and banking-system sentiment. In years in which the excess bond premium is low (i.e., credit-market sentiment is elevated), loan officers tend to ease credit standards on loans and to increase their willingness to make loans (i.e., banking-system sentiment is buoyant). If the predictivity of profit sensitivity is driven by sentiment, as opposed to economic fundamentals, profit sensitivity to the excess bond premium should have similar predictive power over subsequent MES. We test this prediction by re-estimating Eqs. (2a) and (2b), except that the indicator variables are based on the sensitivity of bank profits to the excess bond premium. The results are presented in Columns (3) and (4) of Table 9 and are consistent with our expectation. For instance, in Column (4), with both the year and bank fixed effects as well as the observable bank characteristics, the coefficient on $q_{t-1}^{EBP,4}$ is -0.165 (t = -2.50), close to the coefficient estimate on q_{t-1}^{4} based on profit sensitivity to credit spreads in Column (4) of Table 4.

Controlling for macroeconomic variables – To provide further support that profit sensitivity we propose captures effects of sentiment, we repeat our exercises except that we estimate profit sensitivities with a two-factor model:

$$P_{i,t} = a_{i,t} + b_{i,t}CS_t + c_{i,t}M_t + e_{i,t} \tag{3}$$

where *M* is a common macroeconomic variable (e.g., GDP growth, the unemployment rate, the inflation rate, and the term spread). That is, we first estimate Eq. (3) to obtain the sensitivities of ROE^{MNP} to credit spreads with quarterly data and four-year rolling regressions, and then re-estimate Eqs. (2a) and (2b). The results are presented in Table 10. As we can see, profit sensitivities to credit spreads still have significant predictive power, even after we control for the effects of macroeconomic variables on bank profits.

4.4 Reaching-for-yield

If sentiment is an important driver of banks' risk taking, elevated sentiment in the good state may induce banks to rebalance from safe and/or short-term assets to risky and/or long-term assets that have higher yields to boost banks' current income. In this section, we provide evidence of such reaching-for-yield, an economic mechanism of risk-taking associated with sentiment.

4.4.1 Data

To test for reaching-for-yield, along the same line of Hanson and Stein (2015), we utilize the FR Y9-C (Consolidated Financial Statements for Holding Companies) data. The FR Y-9C reports richer financial data of banks on a consolidated basis in the form of a balance sheet, an income statement, and detailed supporting schedules. For instance, the FR Y-9C reports banks' non-trading account security holdings by issuer and maturity/next re-pricing date. Note that the FR Y-9C started in 1986 and changed over time. For instance, the asset-size threshold for filing the FR Y-9C increased from \$150 million to \$500 million in 2006, and then to \$1 billion and \$3 billion in 2015 and 2018, respectively.

With the FRB mapping, we can identify 484 (out of 506) sample banks in the FR Y-9C. Using the FR Y-9C data, we construct ROE^{MNP} and its two components associated with interest income ($\text{ROE}^{\text{Interest Income}}$) and noninterest income ($\text{ROE}^{\text{Noninterest Income}}$), and estimate the sensitivities of ROE^{MNP} and its two components to credit spreads with quarterly data and three-year rolling regressions. We also construct the fraction of the non-trading account securities with a maturity/next re-pricing date of less than five years (which is referred to as short-term security holdings), and the fraction of the non-trading account securities in US Treasury securities and U.S. government agency and sponsored agency obligations (which is referred to as government security holdings). To mitigate the effects of outliers, we winsorize the variables we construct at the 1% and 99% levels.

Table 11 presents the summary statistics for the FR Y-9C sample over the period from 1986 to 2018. The means of $\text{ROE}^{\text{Interest Income}}$ and $\text{ROE}^{\text{Noninterest Income}}$ are 35.66% and 9.69%, respectively, suggesting that interest income is the dominant source of banks' profits (about $\frac{35.66}{45.55} = 78\%$). The standard deviations of sensitivities of $\text{ROE}^{\text{Interest Income}}$ and $\text{ROE}^{\text{Noninterest Income}}$ to credit spreads are 3.50 and 0.91, respectively, implying that there is more cross-sectional and time-series variation in $\text{ROE}^{\text{Interest Income}}$ sensitivities to credit spreads. The mean (median) of short-term security holdings is 45.06% (43.31%), with a standard deviation of 27.80%. The mean (median) of government security holdings is 4.20% (0.49%), with a standard deviation of 9.19%. Thus, there is substantial cross-sectional and time-series variation in banks' security holdings to potentially help identify the reaching-for-yield mechanism.

4.4.2 Empirical results

Security holdings - Empirically, we focus on the boom-bust period of the global financial crisis from 2003 to 2010, and split the sample into quartiles by banks' profit sensitivities measured at the end of 2006. Fig. 7a plots the asset-weighted average government security holdings for the lowest and highest sensitivity quartiles. As we can see, during the credit boom, while banks in the highest sensitivity quartile (quartile 4) reduced their government security holdings from 11.1% in 2003 to 3.6% in 2006, banks in the lowest sensitivity quartile (quartile 1) did not change their government security holdings materially. Given that the security holdings of banks in quartile 4 in 2006 were about $565 billion, a 11.1 – 3.6 = 7.5% decrease in the government security holdings would be equivalent to about $42 billion, which is economically significant. Interestingly, the reduction in the government security holdings of banks in quartile 4 partially reversed during the crisis, consistent with the notion of reaching-for-yield driven by elevated sentiment during credit booms. Similar evidence is found for the short-term security holdings in Fig. 7b. While banks in quartile 4 reduced their short-term security holdings during the boom, banks in quartile 1 increased their short-term security holdings. Furthermore, the decrease in the short-term security holdings by banks in quartile 4 completely reversed during the crisis.

Interest and noninterest income - Banks can reach for yield through other channels (e.g., subprime lending). To shed more light, we examine banks' profits associated with interest and noninterest income. Note that interest income accounts for not only interest and fee income on loans but also interest and dividend income on securities. In Figs. 7c, we depict the asset-weighted average $ROE^{\text{Interest Income}}$ for the lowest and highest sensitivity quartiles measured at the end of 2006. through portfolio shifts as well as other adjustments, banks in quartile 4 increased their interest income substantially from 22.7% in 2003 to 38.9% in 2006. In contrast, banks in quartile 1 increased their interest income by about 2% over the same period. Consistent with the portfolio shifts evidence in Figs. 6a and 6b, the increase in interest income for banks in quartile 4 reversed in the crisis. Similar evidence is found for noninterest income in Fig. 7d, although economic magnitudes are much smaller. More specifically, while noninterest income of banks in quartile 4 increased from 21.0% in 2003 to 24.9% in 2006, noninterest income of banks in quartile 1 decreased slightly from 13.1% in 2003 to 11.8% in 2006. Again, the increase in noninterest income of banks in quartile 4 reversed in the crisis.

Sensitivities of interest and noninterest income to credit spreads – We find that interest income is about 78% of banks' profits (recall Table 10) and exhibits a stronger boom-bust pattern. These findings suggest that banks reach for yield mainly through interest income, and therefore the sensitivity of interest income to credit spreads should be particularly informative about banks' risk-taking associated with sentiment. Here we provide two sets of supporting evidence.

The first set of evidence is based on portfolio analysis. Each year, we split our sample into quartiles by the sensitivity of interest income to credit spreads ($s^{\text{Interest Income}}$), and report the summary statistics in Panel A of Table 12. As we can see, banks in the highest quartile (quartile 4) experience a significantly lower subsequent MES^{Bank} than banks in the lowest quartile. The difference is -0.39%, significant at the 1% level. We repeat the same exercise based on the sensitivity of noninterest income to credit spreads ($s^{\text{Noninterest Income}}$), and report the results in Panel B. The difference in the subsequent MES^{Bank} based on $s^{\text{Noninterest Income}}$ is -0.26%, which is about 30% smaller than the MES difference based on $s^{\text{Interest Income}}$. In Panel C, we construct portfolios double-sorted on $s^{\text{Interest Income}}$ and $s^{\text{Noninterest Income}}$. Regardless of the first-pass sort on $s^{\text{Noninterest Income}}$, the second-pass sort on $s^{\text{Interest Income}}$ produces significant variation in subsequent MES. For instance, within low $s^{\text{Noninterest Income}}$ banks, the MES difference between high and low $s^{\text{Interest Income}}$ is -0.21%, significant at the 1% level. However, given the first-pass sort on $s^{\text{Interest Income}}$, the second-pass sort on $s^{\text{Noninterest Income}}$ does not consistently result in significant differences in subsequent MES. For instance, within low $s^{\text{Interest Income}}$ banks, the MES difference between high and low $s^{\text{Noninterest Income}}$ is -0.06%, insignificant at the conventional levels.

Our second set of evidence is derived from panel regressions that account for bank-level controls. Panels A and B of Table 12 show that the sensitivities of interest and noninterest income to credit spreads are correlated with known bank characteristics. For instance, the mean total assets of banks in the highest and lowest $s^{\text{Noninterest Income}}$ quartiles are \$95 billion and \$51 billion, respectively. We therefore estimate Eqs. (2a) and (2b) with alternative sets of the indicator variables and report the results in Table 13. In Columns

(1), (3), (5), and (7), we include the year fixed effects. In Columns (2), (4), (6), and (8), we further account for the bank fixed effects to control for unobserved heterogeneity across banks. In Columns (1) and (2), the indicator variables are defined by the sensitivity of ROE^{MNP} to credit spreads. As we can see, the results here based on the FR Y-9C data are similar to those based on the CCM-Bank data reported in Table 4, although slighter weaker (which is due to the shorter sample period for the FR Y-9C). In Columns (3) to (8), we repeat our exercises, except that the indicator variables are based on the sensitivities of interest and noninterest income to credit spreads. Consistent with our expectations, the results suggest that the sensitivity of interest income to spreads is particularly informative. For instance, in Column (8), with all the controls and fixed effects, $q_{t-1}^{Interest,4}$ enters with a coefficient of -0.196% (t = -2.63), suggesting that banks in the highest interest-income-sensitivity quartile experience a 0.196% lower MES^{Bank} than banks in the lowest interest-income-sensitivity quartile. In contrast, , $q_{t-1}^{Noninterest,4}$ is statistically insignificant.

Our results here are consistent with Granja, Leuz, and Rajan (2019) who find that banks' lending is significantly cyclical. Note that our results are not inconsistent with Brunnermeier, Dong, and Palia (2019), as they focus on the level of noninterest income, not the sensitivity of noninterest income to credit spreads.

4.5 Existing risk-taking measures

Various measures of banks' risk-taking have been proposed, such as short-term funding of Beltratti, and Stulz (2012) and Fahlenbrach, Prilmeier, and Stulz (2012), noninterest income of Brunnermeier, Dong, and Palia (2019), loan growth of Fahlenbrach, Prilmeier, and Stulz (2018), and bank profits of Meiselman, Nagel, and Purnanandam (2018). In this section, we show that profit sensitivity complements these existing measures. We provide three sets of evidence based on the CCM-Bank sample.

Correlations - Panel A of Table 14 shows that the correlations of profit sensitivity with existing risk exposure measures are low, below 10%. For instance, its correlation with noninterest income of Brunnermeier, Dong, and Palia (2019) is only 3%., suggesting that the predictive power of profit sensitivity is not simply due to that banks with higher profit sensitivity hold more credit-sensitive securities and generate more noninterest income.

Double-sorted portfolios - We construct portfolios double-sorted on an existing risk exposure measure (e.g., noninterest income) and profit sensitivity, and report the results in Panel B of Table 14. As we can see, given the first-pass sort on an existing risk exposure measure, the second-pass sort on profit sensitivity still produces significant variation in profit sensitivity and subsequent MES. For instance, within banks with low noninterest income, we further sort banks by profit sensitivity. The mean profit sensitivities for the two groups of banks with low noninterest income are -1.34 and 2.98, respectively. The difference of 4.32 is significant at the 1% level. For these two groups of banks, the subsequent MES^{Bank} are -2.45% and -2.72%, respectively. Therefore, within banks with low noninterest income, banks with high profit sensitivity experience a significantly 2.72 – 2.45 = 0.27% lower MES than banks with low profit sensitivity.

Panel regressions - To account for bank-level controls, we estimate Eq. (2b) with existing risk exposure measures and report the results in Panel C of Table 14. As we can see, with the presence of existing risk exposure measures, profit sensitivity is still a significant predictor of subsequent MES. For instance, in Column (5), we include all bank-level controls, the fixed effects, and the existing risk exposure measures, the coefficient on q_{t-1}^{4} is still -0.26% with a t-statistic of -2.45. Therefore, the evidence suggests that by capturing the specific risk-taking associated with sentiment, our proposed measure complements the existing bank-level risk exposure measures.

4.6 Equity returns and loan growth

Knaup and Wagner (2012) propose a credit risk indicator (CRI) based on equity returns and CDS spreads. In a cross section of 150 banks, CRI estimated prior to June 15, 2007 predicts equity performance of banks from June 15, 2007 to June 15, 2008, although the predictive power of CRI depends on the enthronization method In this paper, we focus on bank profits, not stock returns, because profits better capture yields of banks in the good state (Meiselman, Nagel, and Purnanandam, 2018) and equity investors neglect tail risk (Baron and Xiong, 2017). Nevertheless, it is interesting to examine if a return-based measure has general predictive power even outside of the global financial crisis. More specifically, we experiment with two models of equity returns. The first model only includes the credit spread as a single factor of bank equity returns (One-factor), and the second model also accounts for the market factor (Two-factor). We estimate the sensitivity of equity returns to credit spreads with three-year rolling regressions based on these two models, and re-estimate Eqs. (2a) and (2b) with the indicator variables based on return sensitivities. The results are presented in Table 15. In Columns (1) and (3), we include the year fixed effects. In Columns (2) and (4), we further account for the bank fixed effects. As we can see, the coefficients on the return sensitivity indicators are generally insignificant. For instance, in Column (4), with all the controls, the coefficient on q_{t-1}^{4} is -0.099% with a t-statistic of -1.52.

Fahlenbrach, Prilmeier, and Stulz (2018) emphasize the role of loan growth in predicting average returns of banks. We do not use loan growth, because banks have not only lending but also capital market as well as off-balance-sheet activities. Furthermore, loan growth does not capture the risk-taking associated with changes in the composition of loans. For instance, an increase in the share of leveraged lending will not change loan growth but may increase the systematic tail risk exposure of banks. Nevertheless, it is interesting to examine empirically if the sensitivity of loan growth to credit spreads has predictive power over MES. Again, we estimate the sensitivity of three-year loan growth to the credit spread with three-year rolling regressions, and repeat the panel regressions with the indicator variables based on the sensitivity of loan growth to spreads. The results are reported in Columns (5) and (6) of Table 15. As we can see, in general, the sensitivity of loan growth to credit spreads does not have significant predictive power over subsequent MES. Note that our results are not inconsistent with Fahlenbrach, Prilmeier, and Stulz (2018), as they focus on mean equity returns not MES (i.e., equity returns in systematic tail events).

5 Profit Sensitivity in the Time Series

Fig. 3 shows that profit sensitivities of banks not only differ in the cross section but also co-move in the time series. Fig. 8 depicts the asset-weighted average profit sensitivity from 1975 to 2018, which highlights the time-series variation in the average profit sensitivity. The shaded vertical bars denote the NBER dated recessions. If the average profit sensitivity captures the buildup of the financial fragility associated with sentiment which sets the stage for economic downturns (Krishnamurthy and Muir, 2017), increases in the average profit sensitivity should negatively predict aggregate economic activities (Prediction 2). We test this prediction in this section.

Average profit sensitivity - The time-series predictive regression results for the period from 1975 to 2018 are presented in Table 16. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994). Our macroeconomic measures are real per capita GDP growth and the change in unemployment. Since macroeconomic variables respond to shocks with delay and only gradually, we use the average profit sensitivity in year $t-1$ (F_{t-1}) to predict economic activities from year t to year $t+2$. We control for economic activities in year $t-1$ to rule out the concern that the predictive power of our financial fragility measure is due to confounding effects. Consistent with Prediction 2, the average profit sensitivity to credit spreads consistently predicts future aggregate economic activities. In quantitative terms, our estimates indicate that when the average profit sensitivity in year $t-1$ increases from the 25th to the 75th percentile of its historical distribution, this change predicts a cumulative decline in real per capita GDP growth of about 1.87 percentage points over years t to $t+2$ and an increase in the unemployment rate of 1.07 percentage points over the same period.

Triggering events - In theory, economic downturns are the interaction of financial fragility and triggering events (Krishnamurthy and Muir, 2017). Lopez-Salido, Stein, and Zakrajsek (2017) find that in the US sample, the predicted increase in credit spreads ($\Delta\widehat{CS}_t$). is a triggering event and forecasts future economic activities. Therefore, it is interesting to examine if our financial fragility measure complements the trigger measure of Lopez-Salido, Stein, and Zakrajsek (2017) in predicting future economic outcomes. We follow Lopez-Salido, Stein, and Zakrajsek (2017) to construct $\Delta\widehat{CS}_t$ (i.e., the predicted change in the credit spread), and report the results in Panel A of Table 17. More specifically, we forecast the cumulative real GDP per capita growth and unemployment change from year t to year $t + 2$ with the average profit sensitivity and the trigger measure of Lopez-Salido, Stein, and Zakrajsek (2017). In columns (1) and (4), we only include the average profit sensitivity in year t - 1 as well as the lagged economic performance measure. The results mirror those in Table 16 and show the cumulative effects of the lagged financial fragility. In columns (2) and (5), we account for the trigger measure of Lopez-Salido, Stein, and Zakrajsek (2017). Interestingly, the triggering measure does not eliminate the predictive power of the average profit sensitivity, suggesting that our bottom-up fragility measure complements the trigger proxy of Lopez-Salido, Stein, and Zakrajsek (2017). In columns (3) and (6), we further include their interactive term. Consistent with the theory, the interaction terms have expected signs, although the interaction term in the real GDP growth regression is statistically insignificant.

In Panel B of Table 17, we repeat the same analysis with the average three-year loan growth, a popular financial fragility measure in the extant literature (Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013; Mian, Sufi, and Verner, 2017). In columns (1) and (4), we only include the average three-year loan growth ending in year $t - 1$ as well as the lagged economic performance measure. The lagged loan growth seems to predict unemployment change, but not real GDP growth. In Columns (2) and (5), we take into account the trigger measure. Consistent with Lopez-Salido, Stein, and Zakrajsek (2017), the trigger measure absorbs the predictive power of loan growth in the unemployment change regression and results in a wrong sign in the GDP growth regression. In columns (3) and (6), we further account for the interaction of loan growth and the trigger measure. For the GDP growth regression, loan growth still has a wrong sign. For the unemployment change regression, both loan growth and the interaction term are statistically insignificant. Therefore, the evidence suggests that our proposed measure could be particularly useful as an early warning indicator for the US banking system in relation to the popular financial fragility measure of loan growth.

Financial fragility after the global financial crisis - Fig. 8 shows that the financial fragility of the US banking sector associated with sentiment is low after the global financial crisis. For instance, the average

ROE^{MNP} sensitivity to credit spreads was above the 75^{th} percentile of its historical distribution prior to the crisis but below the 50^{th} percentile at the end of 2018. The observed financial fragility after the global financial crisis is consistent with behavioral theories (e.g., "stability is destabilizing"), as there has not been prolonged stability to induce elevated sentiment and increased risk-taking in the banking system. For instance, as we point out, low credit spreads indicate elevated sentiment in the credit market and the banking system While the credit spread dropped steadily below the 25^{th} percentile of its historical distribution from 2002 to 2006, it has generally remained above the 50^{th} percentile of its distribution since the global financial crisis (see Fig. 2).

6 Conclusions

There is evidence that elevated sentiment leads to more risk-taking by banks in the good state (Baron and Xiong, 2017), which makes it particularly important to capture systematic tail risk exposure of banks associated with sentiment. Our proposed measure is the sensitivity of bank profits to credit spreads. Bank profits manifest banks' risk-taking in the good state (Meiselman, Nagel, and Purnanandam, 2018). Credit spreads proxy the sentiment in the banking system and the corporate bond market (Lopez-Salido, Stein, and Zakrajsek, 2017; Greenwood and Hanson, 2013). For the cross section of US banks, we find that banks with higher profit sensitivity to credit spreads experience lower equity returns in systematic tail events, and that the predictive power of profit sensitivity to credit spreads is associated with sentiment and reaching-for-yield. Furthermore, we find that the average profit sensitivity to credit spreads, a bottom-up financial fragility measure, more robustly predicts aggregate economic activities in the US than loan growth.

Our paper is related to the literature on measuring systematic risk exposure of banks (e.g., Beltratti, and Stulz, 2012; Fahlenbrach, Prilmeier, and Stulz, 2018; Meiselman, Nagel, and Purnanandam, 2018). We add to this literature by focusing on systematic tail risk exposure of banks associated with sentiment. Our paper is also related to the macroeconomic literature on credit cycles. Much of the research identifies credit booms with credit/loan growth (e.g., Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013), which as Lopez-Salido, Stein, and Zakrajsek (2017) find is not particularly informative for the US. We add to this literature with our bottom-up financial fragility measure which provides a more timely and accurate description of the buildup of vulnerabilities in the US banking sector.

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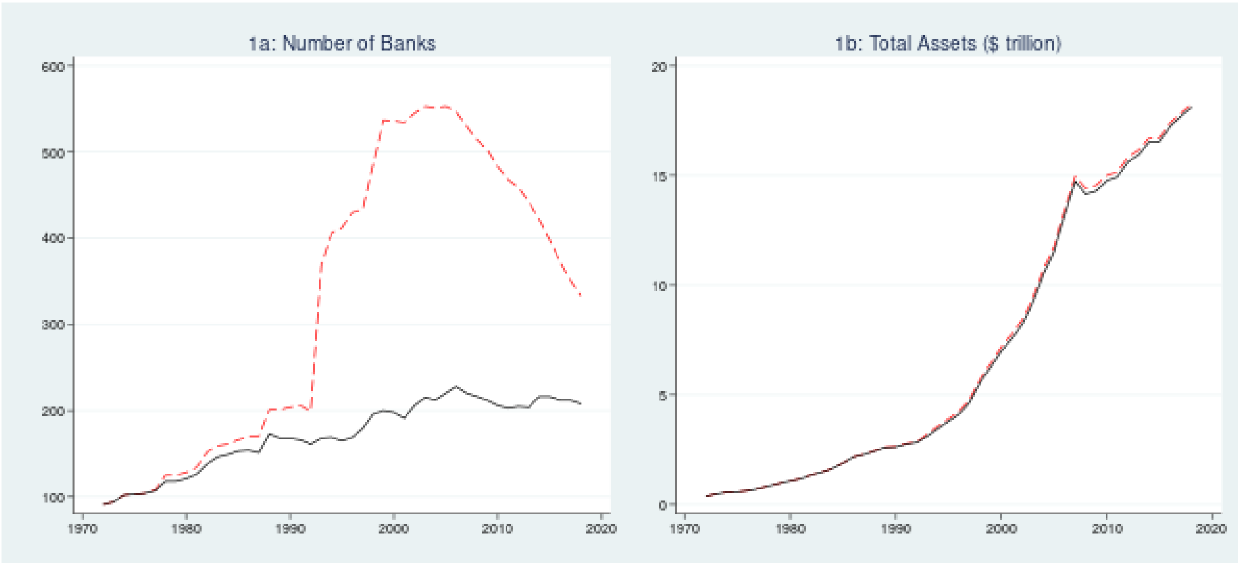
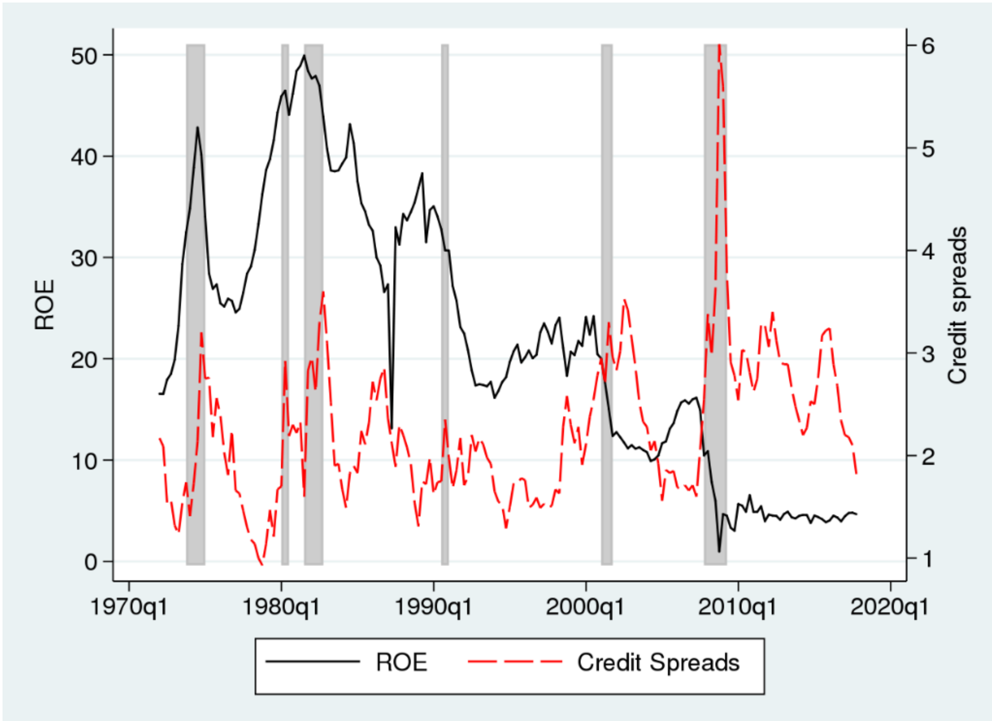
Figure 1 Number and total assets of banks



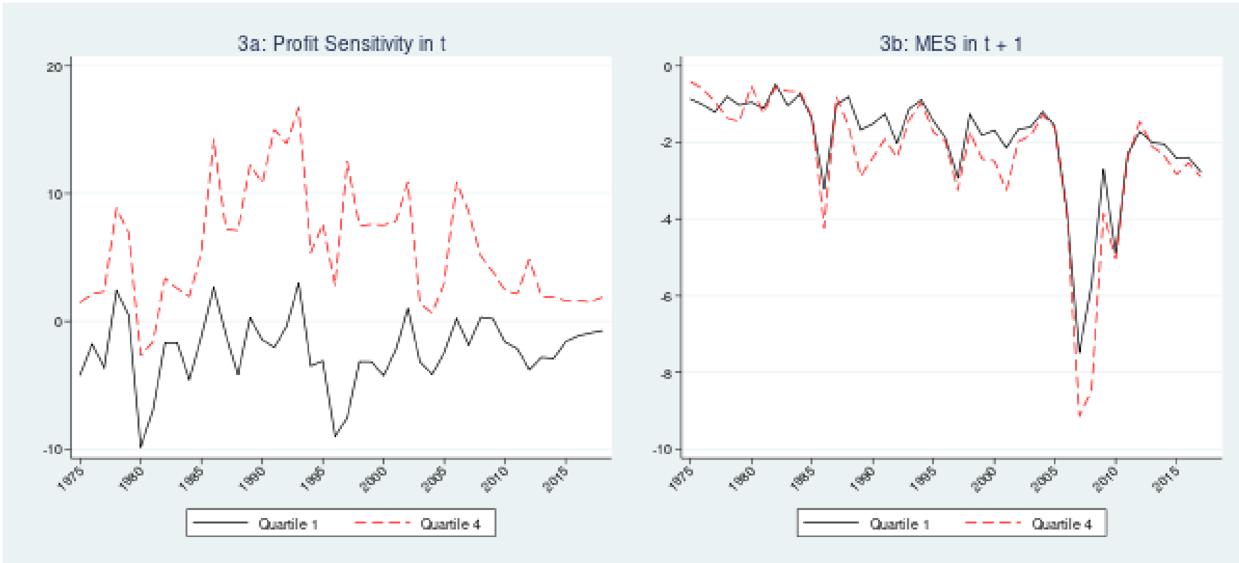
To ensure that our results are not driven by small banks, we follow Fahlenbrach, Prilmeier, and Stulz (2018) and exclude small banks with total assets below $2 billion in 2013 US dollars. Fig. 1 shows the numbers and total assets of banks before and after the $2 billion exclusion. The solid line corresponds to the sample after the exclusion, and the dashed line represents the sample before the exclusion.

Figure 2 Bank profits and credit spreads



This figure depicts the asset-weighted average quarterly ROE of our bank sample as well as the credit spread over the period from 1972 to 2018. The shaded vertical bars denote the NBER dated recessions. ROE is defined as the ratio of pre-tax income plus interest expenses to book equity. The credit spread is defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities.

Figure 3 Cross-sectional and time-series variation in profit sensitivity to credit spreads

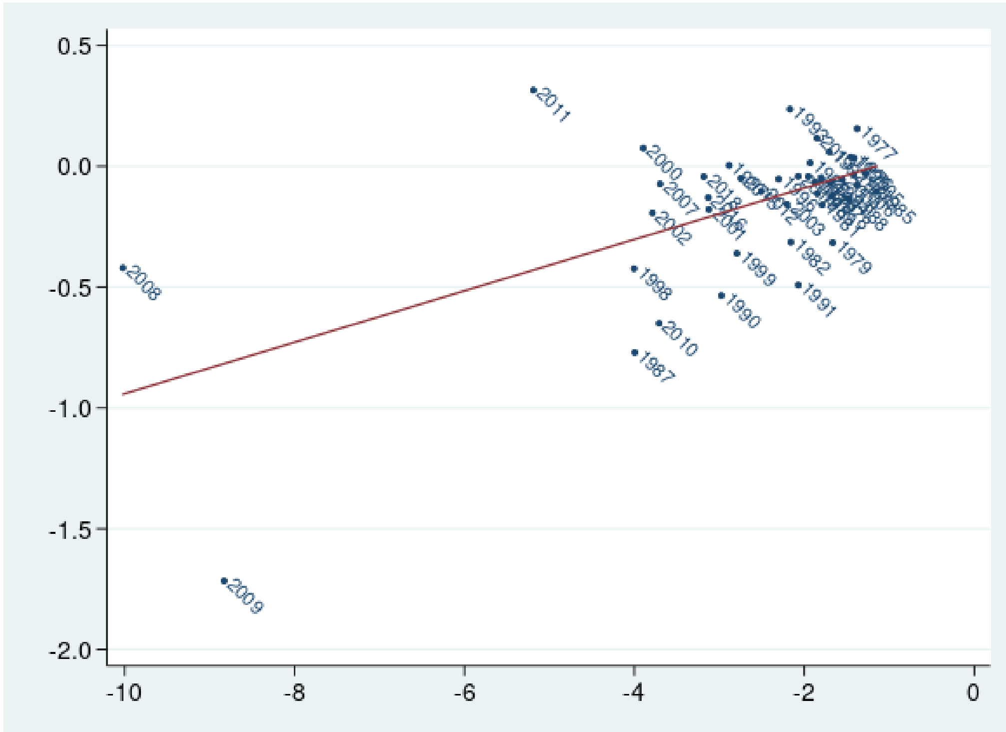


To allow time-varying systematic tail risk exposure of banks, we estimate the following one-factor model with quarterly data and three-year rolling regressions.

$$P_{i,t} = a_i + b_{i,t}CS_t + e_{i,t}$$

where $P_{i,t}$ is ROE of bank i, and CS_t is the credit spreads. ROE is defined as the ratio of pre-tax income plus interest expenses to book equity. The credit spread is defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities. For the ease of exposition, we define "profit sensitivity" as the estimated loading of bank profits on credit spreads multiplied by -1 so that a larger value indicates a greater systematic tail risk exposure under our null hypothesis. That is, profit sensitivity is defined as $s_{i,t} = -b_{i,t}$. We take the last quarterly estimate in each year for each bank to obtain the bank-level systematic tail risk exposure at the annual frequency. To mitigate the effects of outliers, we winsorize sensitivity estimates at the 1% and 99% levels. To visualize the cross-sectional and time-series variation in our proposed measure, we form sensitivity quartiles. That is, each year, we divide our sample by *profit* into quartiles. We report the medians *S* by sensitivity quartiles over the entire sample in Fig. 4.

Figure 4 Cross-sectional regressions by year

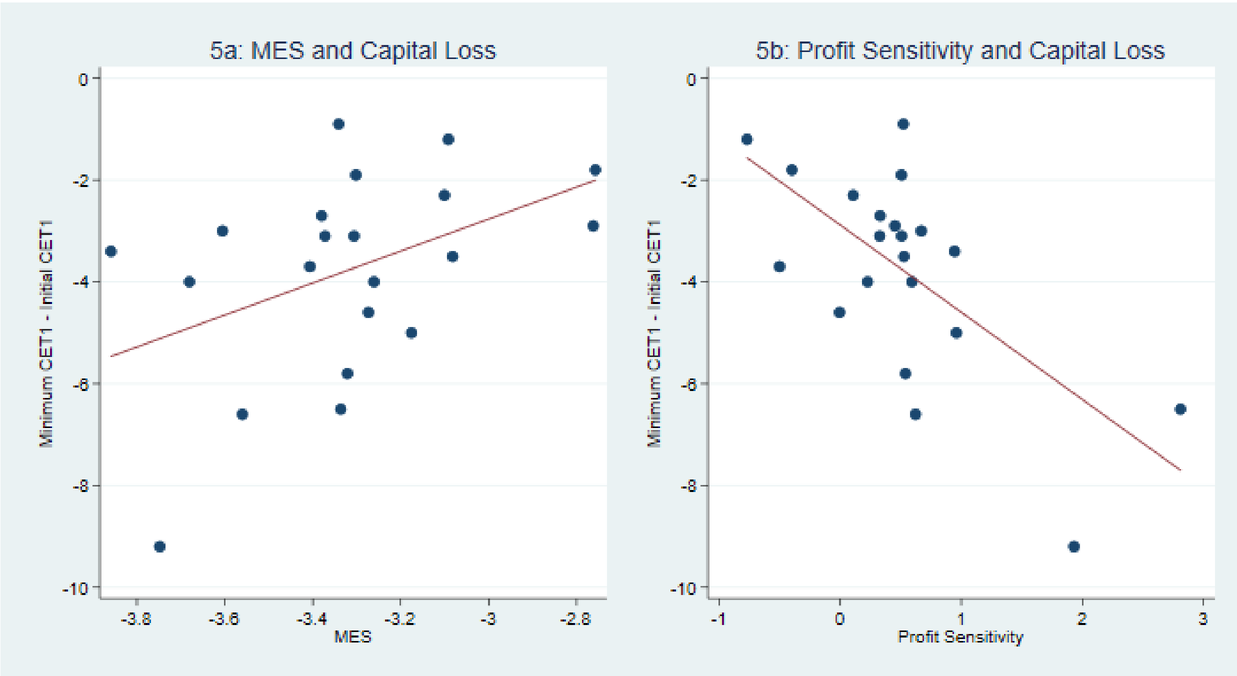


First, we estimate the following regression by year to allow the coefficients of the independent variables to vary over time:

$$MES_{i,t}^{Bank} = \sum_{k=2}^{4} \beta^k q_{i,t-1}^k + \gamma_1 \log(Assets_{i,t-1}) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1} + \gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \varepsilon_{i,t}$$

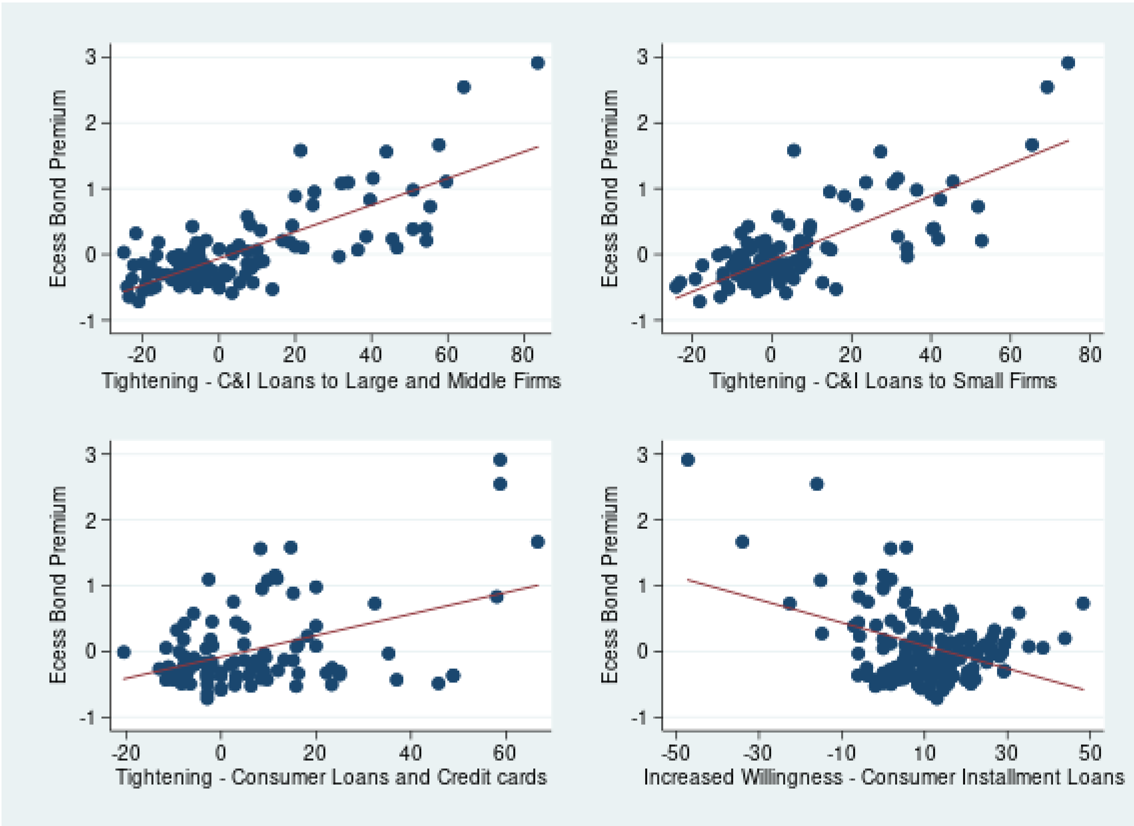
where $MES_{i,t}^{Bank}$ is MES in year t for bank i based on the worst 5% days for the banking industry, and $q_{i,t-1}^k$ is an indicator variable equal to 1 if profit sensitivity of bank i is in the kth profit-sensitivity quartile of all banks in year t – 1. We control for observable bank characteristics, such as log total assets ($\log(Assets)$), CAPM beta ($beta$), book-to-market (BM), idiosyncratic volatility ($Volatility$), and leverage ($Leverage$). Then, we proxy the systematic tail shock in each year by the average of the banking industry's daily returns on the 5% worst days in the year. Finally, we plot a scatter with the systematic tail shock on the horizonal axis and the coefficient of q_{t-1}^4 on the vertical axis.

Figure 5 Profit sensitivity and capital losses in stress Tests



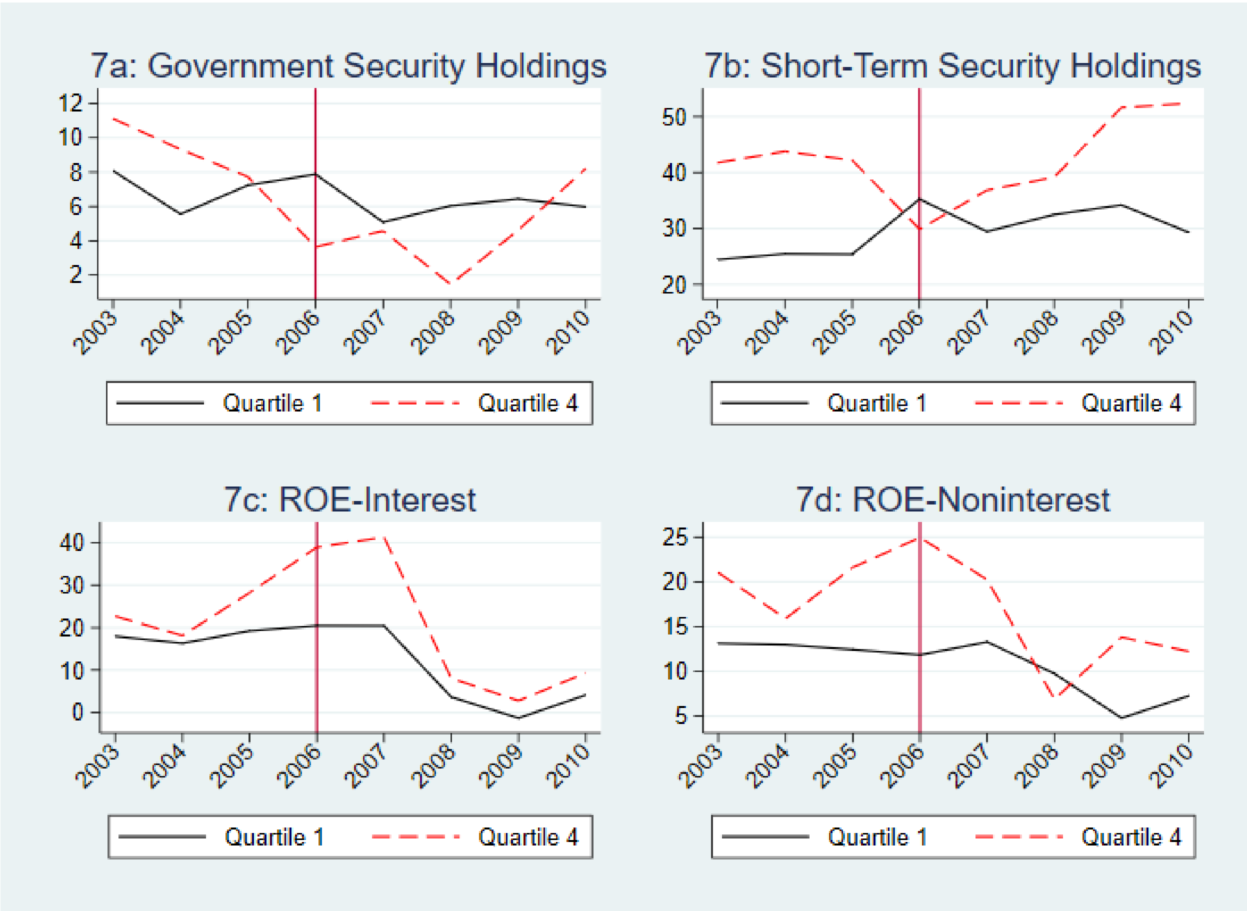
We focus on the Federal Reserve's Dodd-Frank Act Stress Tests (DFAST) results for 2018, and use the severely adverse scenario to capture systematic tail events. The difference between the projected minimum common equity tier 1 ratio (CET1) and the actual CET1 prior to the exercise is employed to proxy the capital losses in systematic tail events. Fig. A1 shows the relationship between the time-series average of a bank's capital losses under the severely adverse scenario and the time-series average of its systematic tail risk exposure measured by three-year loan growth, short-term funding, profits, or profit sensitivity to credit spreads prior to the exercise.

Figure 6 Excess bond premium and banking system sentiment



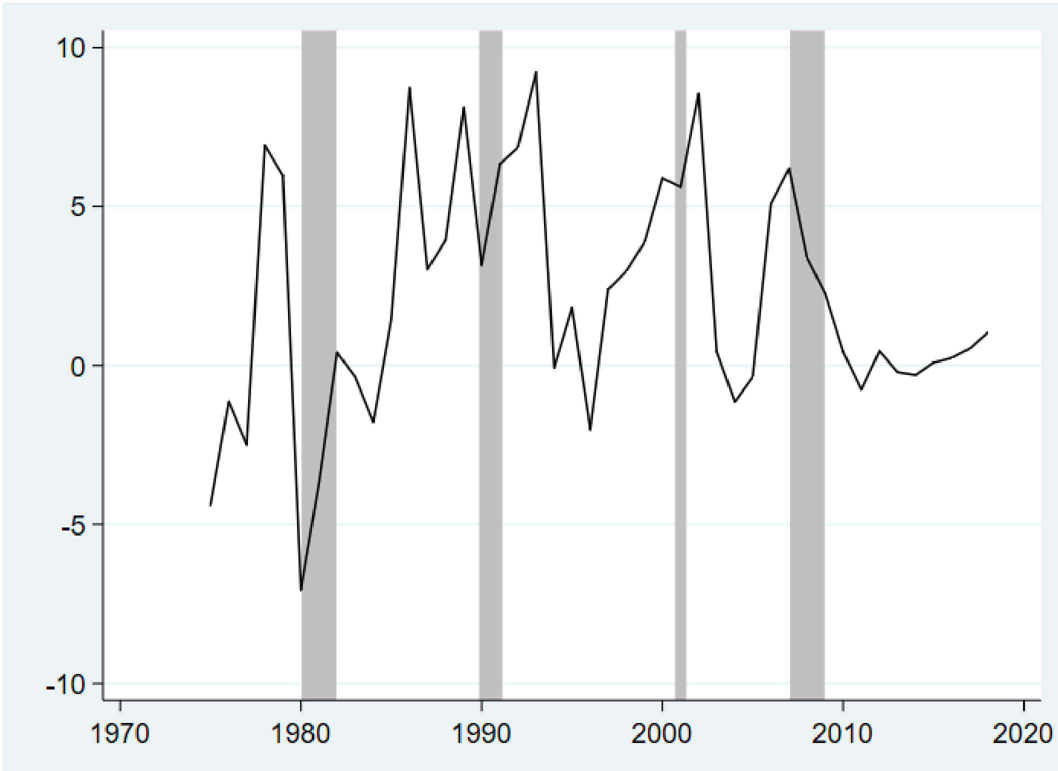
We employ the excess bond premium of Gilchrist and Zakrajšek (2012), which is unrelated to expected defaults and more explicitly measures credit-market sentiment. In this figure, we depict the excess bond premium and various banking-system sentiment measures from Senior Loan Officer Option Surveys. Consistent with Lopez-Salido, Stein, and Zakrajsek (2017).

Figure 7 Reaching for yields



We focus on the boom-bust period of the global financial crisis from 2003 to 2010, and split the sample into quartiles by banks' profit sensitivities at the end of 2006. Fig. 6a plots the asset-weighted average government security holdings for the lowest and highest sensitivity quartiles. Similar evidence is presented for the short-term security holdings in Fig. 6b. In Figs. 6c, we depict the asset-weighted average $ROE^{\text{Interest Income}}$ for the lowest and highest sensitivity quartiles. Similar evidence is presented for noninterest income in Fig. 6d,

Figure 8 Average profit sensitivity



We plot (asset-weighted) average profit sensitivities to credit spreads.

Table 1: Variable definitions and sources

Variable	Definition
MES^{Bank}	MES on bad bank days defined as the average of a bank's daily equity returns during the worst 5% of trading days in any given year for the banking industry index from Kenneth French (industry 44 of 48).
MES^{Market}	MES on bad market days defined as the average of a bank's daily equity returns during the worst 5% of trading days in any given year for the value-weighted market returns.
MNP	Tail equity returns defined as the annual average of a bank's daily equity returns on the 5% of trading days from 1926 to 2018 with the lowest value-weighted returns according to the bank industry portfolio index from Kenneth French (industry 44 of 48)
ΔCoVaR	Change in the value at risk of the financial system conditional on an institution being under distress relative to its median state.
ROE^{MNP}	Ratio of pre-tax income plus interest expenses to book equity.
ROA^{MNP}	Ratio of pre-tax income plus interest expenses to total assets.
ROE^{PI}	Ratio of pre-tax income to book equity.
ROE^{NI}	Ratio of net-tax income to book equity.
$ROE^{Interest\ Income}$	(Interest income – Noninterest Expense Allocated to Lending – Provision for Credit Losses)/Book Equity
$ROE^{Noninterest\ Income}$	(Noninterest income + Gain/Loss on Securities – Noninterest Expense Allocated to Rest)/Book Equity
Noninterest	Noninterest income defined as the ratio of non-interest income to total assets
ΔLoan	Three-year loan growth from year *t* -3 to year *t*.
Funding	Short term funding defined as debt in current liabilities divided by total liabilities.
beta	CAPM beta calculated with three-year rolling regressions and monthly data
Volatility	Idiosyncratic volatility from the CAPM regressions.
BM	Book value of common equity divided by market value of common equity.
Leverage	Book leverage defined as the ratio of total assets to book equity
Credit spreads	The spread between yields on corporate BAA bonds and yields on 10-year Treasury securities.
s	Sensitivity of bank profits to credit spreads
$s^{Interest\ Income}$	Sensitivity of $ROE^{Interest\ Income}$ to credit spreads
$s^{Noninterest\ Income}$	Sensitivity of $ROE^{Noninterest\ Income}$ to credit spreads

Table 2 Summary statistics for the CCM-Bank sample, 1972-2018

	N	Mean	Median	Std. Dev.	Min	Max
$\mathrm{MES}^{\mathrm{Bank}}$ (%)	7,982	-2.07	-1.66	1.93	-17.07	3.33
$\mathrm{MES}^{\mathrm{Market}}$ (%)	8,050	-1.90	-1.51	1.85	-19.88	2.63
MNP (%)	7,607	-1.99	-2.00	1.41	-10.89	9.52
ΔCoVaR (%)	6,194	-2.93	-2.79	1.40	-14.02	0.74
r (%)	8,056	0.06	0.06	0.14	-3.32	1.01
ROE^{MNP} (%)	7,506	69.27	62.54	48.29	-28.02	266.61
ROA^{MNP} (%)	7,952	4.30	4.23	9.36	-14.22	805.32
ROE^{PI} (%)	7,515	17.05	18.19	16.21	-76.22	61.61
ROE^{NI} (%)	7,589	11.94	13.38	12.76	-72.36	40.13
Noninterest Income/Assests (%)	4,280	1.29	1.09	0.95	0.03	5.75
ΔLoan (%)	7,009	11.53	10.68	11.00	-16.67	46.46
Short Term Funding (%)	7,944	10.08	8.65	7.78	0.00	40.46
Assets ($ billion)	8,057	39.72	4.99	181.34	0.55	2,622.53
beta	7,685	0.89	0.85	0.51	-1.14	4.05
Idiosyncratic Volatility	7,685	7.28	6.34	3.76	1.76	49.34
Book to Market	8,056	0.87	0.74	0.51	0.20	3.27
Leverage	8,057	13.62	12.74	5.21	3.95	33.00
Loans/Assets (%)	8,029	57.92	61.21	17.08	0.00	85.72
Interest Expense/Assets (%)	7,957	2.92	2.83	1.98	0.12	8.41
Assets Growth (%)	7,813	10.77	8.32	13.53	-17.30	67.72
Deposits/Assets (%)	8,022	71.99	76.14	16.67	0.00	90.04
Provisions/assets (%)	7,833	0.41	0.23	0.58	-0.12	3.60

The table presents the summary statistics of the main variables used in the tests. Please refer to Table 1 for variable definitions.

Table 3 Profits sensitivity and bank characteristics

Panel A: Summary statistics for profit sensitivity and beta

	Mean	Std. Dev.	Min	p1	p25	p50	p75	p99	Max
$s = -1 \times b$	1.33	5.18	-50.88	-11.39	-0.81	0.59	3.05	19.53	45.26
se_b	1.84	2.40	0.00	0.06	0.49	1.09	2.19	11.67	30.67
$\lvert t_s \rvert$	2.61	2.79	0.00	0.03	0.81	1.83	3.40	12.85	44.29
R_s^2	0.23	0.23	0.00	0.00	0.03	0.15	0.37	0.85	0.97
$beta$	0.89	0.51	-1.14	-0.11	0.54	0.85	1.16	2.40	4.05
se_{beta}	0.24	0.14	0.02	0.06	0.15	0.21	0.29	0.76	1.93
$\lvert t_{beta} \rvert$	4.58	3.27	0.00	0.16	2.36	3.85	5.91	16.17	39.74
R_{beta}^2	0.24	0.17	0.00	0.00	0.10	0.22	0.36	0.68	0.83

Panel B: Summary statistics for profit sensitivity quartiles

		1	2	3	4	4 - 1
	$s = -1 \times b$	-2.21	0.39	1.80	5.49	7.70***
	Assets ($ billion)	31.87	29.61	43.80	53.03	21.16***
	beta	0.88	0.83	0.87	1.02	0.14***
year *t*	Book to Market	0.86	0.79	0.84	0.94	0.08***
	Idiosyncratic Volatility	7.31	6.63	6.97	8.16	0.85***
	Leverage	13.42	12.72	13.09	14.43	1.01***
	MES^{Bank} (%)	-2.15	-2.15	-2.32	-2.51	-0.36***
	MES^{Market} (%)	-1.96	-1.97	-2.12	-2.31	-0.35***
	MNP (%)	-2.09	-2.06	-2.15	-2.41	-0.32***
	ΔCoVaR (%)	-2.89	-3.02	-3.00	-3.11	-0.21***
year *t* + 1	r (%)	0.06	0.06	0.06	0.05	-0.01***
	Charge-Offs/Loans (%)	0.53	0.47	0.57	0.80	0.28***
	Provisions/Loans (%)	0.62	0.60	0.73	1.00	0.38***
	Nonperforming Loans/Loans (%)	1.52	1.40	1.52	2.13	0.61***

We estimate profit sensitivity, *s*, for each bank with quarterly data and three-year rolling regressions. For comparison, we also use monthly data and three-year rolling regression to estimate CAPM beta, *beta*. We convert the quarterly series to annual frequency by taking the last value for each calendar year. Panel A shows the summary statistics for these rolling regressions. Panel B presents the means bank characteristics by profit-sensitivity quartiles. Specifically, each year (*t*), we divide our sample into quartiles by profit sensitivity, and examine their characteristics in year *t* and subsequent performance in year *t* + 1.

Table 4 Benchmark regressions with MES^{Bank}

	(1)	(2)	(3)	(4)
q^2_{t-1}	0.027	-0.009	-0.022	-0.021
	(0.60)	(-0.27)	(-0.61)	(-0.63)
q^3_{t-1}	-0.148	-0.123	-0.125	-0.124*
	(-1.56)	(-1.65)	(-1.65)	(-1.75)
q^4_{t-1}	-0.387***	-0.207***	-0.211***	-0.189***
	(-3.65)	(-2.76)	(-2.93)	(-2.87)
$\log(Assets_{t-1})$			-0.319***	-0.386***
			(-5.40)	(-3.79)
$beta_{t-1}$			-0.401***	-0.163
			(-4.78)	(-1.62)
BM_{t-1}			0.063	-0.062
			(0.67)	(-0.70)
$Volatility_{t-1}$			-0.034*	-0.020
			(-1.87)	(-1.30)
$Leverage_{t-1}$			-0.002	-0.003
			(-0.36)	(-0.42)
Year FEs	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes
Observations	6,228	6,228	6,228	6,228
Adj-R^2	0.691	0.778	0.755	0.784

We estimate the following regressions:

$$MES^{Bank}_{i,t} = \sum_{k=2}^{4} \beta^k q^k_{i,t-1} + \gamma_1 \log(Assets_{i,t-1}) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1} + \gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \mu_t + \varepsilon_{i,t}$$

and

$$MES^{Bank}_{i,t} = \sum_{k=2}^{4} \beta^k q^k_{i,t-1} + \gamma_1 \log(Assets_{i,t-1}) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1} + \gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \mu_t + \mu_i + \varepsilon_{i,t}$$

where $MES^{Bank}_{i,t}$ is MES in year *t* for bank *i* based on the worst 5% days for the banking industry, and $q^k_{i,t-1}$ is an indicator variable equal to 1 if profit sensitivity of bank *i* is in the *k*th profit-sensitivity quartile of all banks in year *t* – 1. We control for observable bank characteristics, such as log total assets ($\log(Assets)$), CAPM beta ($beta$), book-to-market (BM), idiosyncratic volatility ($Volatility$), and leverage ($Leverage$). μ_t is the year fixed effects, and μ_i the bank fixed effects. We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Subsamples and alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
q^2_{t-1}	-0.022	-0.011	-0.030	-0.018			-0.019	-0.020
	(-0.72)	(-0.29)	(-0.56)	(-0.38)			(-0.62)	(-0.59)
q^3_{t-1}	-0.033	0.009	-0.192*	-0.203*			-0.115*	-0.110
	(-0.49)	(0.19)	(-1.77)	(-1.99)			(-1.74)	(-1.58)
q^4_{t-1}	-0.153**	-0.097*	-0.255**	-0.238**			-0.170***	-0.154***
	(-2.50)	(-2.02)	(-2.40)	(-2.55)			(-3.08)	(-2.73)
s_{t-1}					-0.025***	-0.022***		
					(-4.23)	(-3.84)		
$\log(Assets_{t-1})$	-0.369***	-0.273***	-0.300***	-0.565***	-0.320***	-0.380***	-0.311***	-0.351***
	(-10.93)	(-4.47)	(-4.15)	(-3.10)	(-5.34)	(-3.76)	(-5.49)	(-3.44)
$beta_{t-1}$	-0.340***	-0.034	-0.420***	-0.145	-0.400***	-0.161	-0.368***	-0.152
	(-5.78)	(-0.46)	(-3.79)	(-0.99)	(-4.72)	(-1.59)	(-4.37)	(-1.56)
BM_{t-1}	-0.013	-0.008	0.134	-0.075	0.064	-0.062	0.130	0.071
	(-0.11)	(-0.07)	(0.92)	(-0.60)	(0.70)	(-0.68)	(1.44)	(0.86)
$Volatility_{t-1}$	-0.046***	-0.031*	-0.036	-0.016	-0.036*	-0.021	-0.020	-0.009
	(-3.15)	(-1.82)	(-1.69)	(-0.91)	(-1.97)	(-1.39)	(-1.29)	(-0.67)
$Leverage_{t-1}$	-0.006	0.007	0.009	-0.002	-0.002	-0.003	-0.006	0.002
	(-1.05)	(1.02)	(1.38)	(-0.21)	(-0.32)	(-0.40)	(-0.81)	(0.24)
$Loans/Assets_{t-1}$							-0.004*	-0.010***
							(-1.95)	(-2.92)
$XINT/Assets_{t-1}$							0.062	0.050
							(1.30)	(1.07)
$\Delta Assets_{t-1}$							-0.002	-0.001
							(-1.33)	(-0.79)
$DPTC/Assets_{t-1}$							0.005*	0.011**
							(1.84)	(2.60)
$PCL/Assets_{t-1}$							-0.317***	-0.337***
							(-3.36)	(-3.92)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Sample	75-96	75-96	97-18	97-18	75-18	75-18	75-18	75-18
Observations	2,296	2,292	3,932	3,922	6,228	6,228	6,137	6,136
Adj-R^2	0.602	0.655	0.728	0.761	0.756	0.784	0.761	0.790

In Columns (1) to (4), we repeat our exercises for two equal subsamples, 1975-1996 and 1997-2018. In Columns (5) and (6), we use profit sensitivity instead of its indicator variables. In Columns (7) and (8), we account for more bank-level controls, including the loans to assets ratio (*Loans/Assets*), the interest expense to assets ratio (*XINT/Assets*), the log change in total assets (Δ*Assets*), the deposits to assets ratio (*DPTC/Assets*), and the loan loss provisions to assets ratio (*PCL/Assets*). We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Alternative systematic tail risk measures

	(1) MES_t^{Market}	(2) MES_t^{Market}	(3) MNP_t	(4) MNP_t	(5) $\Delta CoVaR_t$	(6) $\Delta CoVaR_t$
q_{t-1}^2	-0.034	-0.036	-0.007	-0.014	-0.070	-0.011
	(-0.81)	(-0.97)	(-0.19)	(-0.35)	(-1.27)	(-0.69)
q_{t-1}^3	-0.125*	-0.134*	-0.011	-0.014	0.012	-0.025
	(-1.70)	(-1.93)	(-0.19)	(-0.27)	(0.20)	(-0.93)
q_{t-1}^4	-0.222**	-0.191**	-0.134**	-0.102*	-0.087	-0.061**
	(-2.48)	(-2.23)	(-2.09)	(-1.86)	(-1.40)	(-2.22)
log ($Assets_{t-1}$)	-0.230***	-0.302***	-0.315***	-0.302***	-0.428***	-0.046
	(-4.93)	(-3.16)	(-7.49)	(-3.63)	(-7.68)	(-1.25)
$beta_{t-1}$	-0.416***	-0.143**	-0.456***	-0.261***	-0.110	0.069
	(-7.70)	(-2.17)	(-5.96)	(-3.06)	(-1.45)	(1.21)
BM_{t-1}	-0.069	-0.222*	0.054	-0.049	0.344***	-0.030
	(-0.71)	(-1.72)	(0.52)	(-0.55)	(3.83)	(-0.72)
$Volatility_{t-1}$	-0.035**	-0.020	-0.020	-0.013	0.025***	-0.022***
	(-2.06)	(-1.51)	(-1.29)	(-0.99)	(2.78)	(-4.32)
$Leverage_{t-1}$	-0.003	-0.003	-0.016*	-0.009	0.018*	-0.009**
	(-0.59)	(-0.40)	(-1.77)	(-0.96)	(1.78)	(-2.04)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Observations	6,228	6,228	5,922	5,919	5,064	5,063
Adj-R^2	0.761	0.788	0.451	0.506	0.394	0.884

We consider three alternative systematic tail risk measures, namely MES on bad market days (MES^{Market}), tail equity returns of Meiselman, Nagel, and Purnanandam (2018) (*MNP)*, and $\Delta CoVaR$ of Adrian and Brunnermeier (2016). We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 Alternative profitability measures

	(1) ROA^{MNP}	(2) ROA^{MNP}	(3) ROE^{PI}	(4) ROE^{PI}	(5) ROE^{NI}	(6) ROE^{NI}
q_{t-1}^{2}	-0.045	-0.063	0.001	0.004	-0.022	-0.021
	(-0.94)	(-1.45)	(0.01)	(0.09)	(-0.42)	(-0.47)
q_{t-1}^{3}	-0.095	-0.094	-0.156*	-0.138*	-0.142	-0.133
	(-1.08)	(-1.29)	(-1.80)	(-1.82)	(-1.60)	(-1.63)
q_{t-1}^{4}	-0.200**	-0.165**	-0.164**	-0.142**	-0.158**	-0.131*
	(-2.19)	(-2.06)	(-2.41)	(-2.21)	(-2.20)	(-1.96)
log ($Assets_{t-1}$)	-0.318***	-0.386***	-0.321***	-0.386***	-0.321***	-0.385***
	(-5.40)	(-3.77)	(-5.38)	(-3.78)	(-5.38)	(-3.77)
$beta_{t-1}$	-0.403***	-0.165	-0.403***	-0.166	-0.404***	-0.166
	(-4.67)	(-1.62)	(-4.76)	(-1.67)	(-4.75)	(-1.65)
BM_{t-1}	0.063	-0.063	0.063	-0.061	0.064	-0.063
	(0.70)	(-0.72)	(0.69)	(-0.70)	(0.70)	(-0.73)
$Volatility_{t-1}$	-0.034*	-0.020	-0.035*	-0.020	-0.036*	-0.020
	(-1.85)	(-1.32)	(-1.86)	(-1.29)	(-1.87)	(-1.31)
$Leverage_{t-1}$	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(-0.70)	(-0.62)	(-0.63)	(-0.56)	(-0.65)	(-0.57)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Observations	6,228	6,228	6,228	6,228	6,228	6,228
Adj-R^2	0.755	0.784	0.755	0.784	0.755	0.784

We estimate profit sensitivities of banks with alternative profitability measures, namely the ratio of pre-tax income plus interest expenses to total assets (ROA^{MNP}), the ratio of pre-tax income to tangible equity (ROE^{PI}), and the ratio of net income to tangible equity (ROE^{NI}). We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Additional robustness checks

	Skipping One Quarter		Four-Year Window		All Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
q^2_{t-1}	-0.010	-0.009	-0.010	-0.017	-0.090	-0.074
	(-0.33)	(-0.27)	(-0.24)	(-0.44)	(-1.46)	(-1.58)
q^3_{t-1}	-0.100	-0.098*	-0.160*	-0.144**	-0.190*	-0.153**
	(-1.65)	(-1.80)	(-2.00)	(-2.03)	(-2.00)	(-2.09)
q^4_{t-1}	-0.206**	-0.175**	-0.185**	-0.159**	-0.284**	-0.228**
	(-2.46)	(-2.31)	(-2.67)	(-2.26)	(-2.56)	(-2.64)
$\log(Assets_{t-1})$	-0.322***	-0.395***	-0.316***	-0.390***	-0.572***	-0.620***
	(-5.86)	(-3.32)	(-5.15)	(-3.92)	(-6.39)	(-5.66)
$beta_{t-1}$	-0.355***	-0.109	-0.404***	-0.159	-0.257**	0.049
	(-4.07)	(-1.09)	(-4.63)	(-1.55)	(-2.13)	(0.30)
BM_{t-1}	0.058	-0.029	0.064	-0.056	0.385***	0.244*
	(0.65)	(-0.40)	(0.65)	(-0.61)	(3.09)	(1.98)
$Volatility_{t-1}$	-0.031**	-0.013	-0.034*	-0.018	-0.067**	-0.059***
	(-2.13)	(-1.04)	(-1.87)	(-1.20)	(-2.62)	(-2.79)
$Leverage_{t-1}$	0.001	0.004	-0.000	-0.000	0.031***	0.017*
	(0.11)	(0.62)	(-0.04)	(-0.03)	(3.03)	(1.72)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Observations	6,217	6,217	5,990	5,990	11,596	11,596
Adj-R^2	0.747	0.776	0.754	0.784	0.513	0.571

We estimate the following regressions:

$$MES^{Bank}_{i,t} = \sum_{k=2}^{4} \beta^k q^k_{i,t-1} + \gamma_1 \log(Assets_{i,t-1}) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1} + \gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \mu_t + \varepsilon_{i,t}$$

and

$$MES^{Bank}_{i,t} = \sum_{k=2}^{4} \beta^k q^k_{i,t-1} + \gamma_1 \log(Assets_{i,t-1}) + \gamma_2 beta_{i,t-1} + \gamma_3 BM_{i,t-1} + \gamma_4 Volatility_{i,t-1} + \gamma_5 Leverage_{i,t-1} + \mu_t + \mu_i + \varepsilon_{i,t}$$

where $MES^{Bank}_{i,t}$ is MES for bank *i* based on the worst 5% days for the banking industry, and $q^k_{i,t-1}$ is an indicator variable equal to 1 if profit sensitivity of bank *i* is in the *k*th profit-sensitivity quartile of all banks in year *t* – 1. We control for observable bank characteristics, such as log total assets ($\log(Assets)$), CAPM beta ($beta$), book-to-market (BM), idiosyncratic volatility ($Volatility$), and leverage ($Leverage$). μ_t is the year fixed effects, and μ_i the bank fixed effects. In Columns (1) and (2), we estimate MES for year *t* based on equity returns from April of year *t* to March of year *t* + 1, as opposed to from January to December of year *t*. In Columns (3) and (4), we estimate profit sensitivities with four-year rolling windows, as opposed to three-year rolling window. In Columns (5) and (6), we include all banks, as opposed to only banks with total assets of more than $2 billion in 2013 US dollars. We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 Sentiment and risk-taking of banks

	r_t		MES_t	
	(1)	(2)	(3)	(4)
q_{t-1}^{2}	-0.003	-0.005		
	(-0.89)	(-1.21)		
q_{t-1}^{3}	-0.004	-0.007		
	(-0.85)	(-1.44)		
q_{t-1}^{4}	-0.013*	-0.016**		
	(-1.99)	(-2.54)		
$q_{t-1}^{EBP,2}$			-0.054	-0.073**
			(-1.44)	(-2.28)
$q_{t-1}^{EBP,3}$			-0.120	-0.120*
			(-1.55)	(-1.82)
$q_{t-1}^{EBP,4}$			-0.178**	-0.165**
			(-2.43)	(-2.50)
log ($Assets_{t-1}$)	-0.005**	-0.050***	-0.320***	-0.384***
	(-2.25)	(-7.96)	(-5.38)	(-3.76)
$beta_{t-1}$	0.015**	0.004	-0.413***	-0.167
	(2.62)	(0.65)	(-4.96)	(-1.68)
BM_{t-1}	0.018	0.043***	0.051	-0.080
	(1.42)	(3.22)	(0.55)	(-0.90)
$Volatility_{t-1}$	-0.001	0.002	-0.035*	-0.020
	(-0.49)	(0.88)	(-1.87)	(-1.31)
$Leverage_{t-1}$	0.000	0.002	-0.004	-0.004
	(0.14)	(1.39)	(-0.68)	(-0.64)
Year FEs	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes
Observations	6,228	6,228	6,205	6,205
Adj-R^2	0.389	0.425	0.755	0.784

The dependent variable is the average daily return in Columns (1) and (2). In Columns (3) and (4), we employ the excess bond premium of Gilchrist and Zakrajšek (2012) to estimate profit sensitivity. We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10 Profit sensitivities based on two-factor models

	$M = \Delta\ln(GDP)$		$M = \Delta CPI$		$M = UN$		$M = Term\ Spread$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
q_{t-1}^{2}	-0.044	-0.043	-0.048	-0.037	-0.017	-0.013	-0.064	-0.067
	(-1.24)	(-1.27)	(-1.36)	(-1.03)	(-0.50)	(-0.42)	(-1.02)	(-1.33)
q_{t-1}^{3}	-0.104*	-0.121*	-0.110	-0.125*	-0.080	-0.074	-0.152*	-0.130**
	(-1.82)	(-1.99)	(-1.64)	(-1.75)	(-1.34)	(-1.49)	(-1.97)	(-2.06)
q_{t-1}^{4}	-0.204***	-0.174***	-0.195**	-0.150**	-0.141**	-0.119*	-0.227**	-0.180**
	(-2.94)	(-2.71)	(-2.68)	(-2.34)	(-2.27)	(-1.98)	(-2.45)	(-2.19)
log $(Assets_{t-1})$	-0.317***	-0.388***	-0.318***	-0.391***	-0.320***	-0.385***	-0.317***	-0.386***
	(-5.17)	(-3.91)	(-5.18)	(-3.90)	(-5.14)	(-3.89)	(-5.16)	(-3.92)
$beta_{t-1}$	-0.404***	-0.161	-0.406***	-0.162	-0.407***	-0.157	-0.402***	-0.156
	(-4.64)	(-1.59)	(-4.66)	(-1.59)	(-4.65)	(-1.52)	(-4.54)	(-1.50)
BM_{t-1}	0.066	-0.053	0.065	-0.056	0.060	-0.062	0.057	-0.063
	(0.66)	(-0.57)	(0.65)	(-0.61)	(0.59)	(-0.66)	(0.58)	(-0.68)
$Volatility_{t-1}$	-0.035*	-0.018	-0.034*	-0.018	-0.035*	-0.018	-0.033*	-0.018
	(-1.90)	(-1.22)	(-1.89)	(-1.21)	(-1.88)	(-1.21)	(-1.81)	(-1.16)
$Leverage_{t-1}$	0.000	-0.000	-0.001	-0.000	-0.002	-0.002	-0.002	-0.001
	(0.05)	(-0.01)	(-0.08)	(-0.05)	(-0.30)	(-0.26)	(-0.35)	(-0.16)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	5,990	5,990	5,990	5,990	5,990	5,990	5,990	5,990
Adj-R^2	0.754	0.784	0.754	0.784	0.753	0.783	0.754	0.784

We repeat our exercises except that we estimate profit sensitivities with a two-factor model:

$$P_{i,t} = a_{i,t} + b_{i,t}CS_t + c_{i,t}M_t + e_{i,t}$$

where $P_{i,t}$ is profitability of bank *i* (e.g., ROE^{MNP}), CS_t is the credit spread, and *M* is a common macroeconomic variable (e.g., GDP growth, the inflation rate, the unemployment rate, and the term spread). $b_{i,t}$ is the loading of bank profits on credit spreads. Profit sensitivity, $s_{i,t}$, is defined as the estimated loading of bank profits on credit spreads multiplied by -1. $q_{i,t-1}^{k}$ is an indicator variable equal to 1 if profit sensitivity of bank *i* is in the *k*th profit-sensitivity quartile of all banks in year *t* – 1. We control for observable bank characteristics, such as log total assets (log($Assets$)), CAPM beta ($beta$), book-to-market (BM), idiosyncratic volatility ($Volatility$), and leverage ($Leverage$). μ_t is the year fixed effects, and μ_i the bank fixed effects. We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11 Summary statistics for the FR Y9-C sample, 1986-2018

	N	Mean	Median	Std. Dev.	Min	Max
Total Assets	5,549	46.53	5.91	208.16	1.00	2,622.53
Leverage	5,549	11.87	11.39	3.54	5.10	23.89
Short-term Security Holding (%)	5,542	45.06	43.31	27.80	0.68	99.59
Government Security Holding (%)	3,087	4.20	0.49	9.19	0.00	54.27
ROE	5,549	45.55	43.62	30.32	-22.00	128.63
$ROE^{\text{Interest Income}}$	5,548	35.66	32.83	26.45	-24.44	107.71
$ROE^{\text{Noninterest Income}}$	5,549	9.69	7.81	7.78	-0.30	42.12
s	4,830	1.27	0.51	3.78	-8.52	15.60
$s^{\text{Interest Income}}$	4,822	1.33	0.50	3.50	-7.06	15.65
$s^{\text{Noninterest Income}}$	4,830	-0.01	-0.02	0.91	-3.26	3.42

With the FRB mapping, we can identify 484 (out of 506) sample banks in the FR Y-9C. Using the FR Y-9C data, we construct ROE^{MNP} and its two components associated with interest and noninterest income, and estimate the sensitivities of ROE^{MNP} and its two components to credit spreads with quarterly data and three-year rolling regressions. We also construct the fraction of the non-trading account securities with a maturity/next re-pricing date of less than five years (which is referred to as short-term security holdings), and the fraction of the non-trading account securities in US Treasury securities and U.S. government agency and sponsored agency obligations (which is referred to as government security holdings). To mitigate the effects of outliers, we winsorize the variables we construct at the 1% and 99% levels. Table 10 presents the summary statistics for the FR Y-9C sample over the period from 1986 to 2018.

Table 12 Sensitivity sorted portfolios

Panel A: Quartiles by $s^{\text{Interest Income}}$					
	1	2	3	4	4 - 1
$s^{\text{Interest Income}}$	-1.29	0.59	1.66	4.39	5.68***
Assets ($ billion)	30.24	46.94	67.70	56.09	25.85***
beta	0.86	0.80	0.86	1.01	0.15***
Book to Market	0.74	0.69	0.73	0.84	0.10***
Idiosyncratic Volatility	7.55	6.59	6.91	8.52	0.97***
Leverage	11.89	11.39	11.64	13.02	1.13***
MES in *t* + 1	-2.38	-2.37	-2.53	-2.77	-0.39***

Panel B: Quartiles by $s^{\text{Noninterest Income}}$					
	1	2	3	4	4 - 1
$s^{\text{Noninterest Income}}$	-0.92	-0.16	0.13	0.92	1.84***
Assets ($ billion)	51.73	24.00	30.61	95.19	43.46***
beta	0.88	0.82	0.84	0.98	0.09***
Book to Market	0.80	0.73	0.73	0.73	-0.07***
Idiosyncratic Volatility	7.82	6.98	7.05	7.70	-0.12
Leverage	12.48	11.51	11.54	12.40	-0.07
MES in *t* + 1	-2.50	-2.37	-2.41	-2.76	-0.26***

Panel C: MES in t + 1 of Double sorted portfolios				
		$s^{\text{Interest Income}}$		
		Low	High	High - Low
$s^{\text{Noninterest Income}}$	Low	-2.28	-2.50	-0.21***
	High	-2.35	-2.65	-0.31***
	High - Low	-0.06	-0.15***	

Each year, we split our sample into quartiles by sensitivity of interest income to credit spreads ($s^{\text{Interest Income}}$), and report the summary statistics in Panel A. We repeat the same exercise based on sensitivity of noninterest income to credit spreads ($s^{\text{Noninterest Income}}$), and report the results in Panel B. In Panel C, we construct portfolios double-sorted on $s^{\text{Interest Income}}$ and $s^{\text{Noninterest Income}}$.

Table 13 Sensitivities to interest and noninterest income, 1986-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
q_{t-1}^{2}	-0.004	0.011						
	(-0.10)	(0.23)						
q_{t-1}^{3}	-0.132*	-0.157*						
	(-1.74)	(-1.73)						
q_{t-1}^{4}	-0.170**	-0.153*						
	(-2.34)	(-1.78)						
$q_{t-1}^{Interest,2}$			0.039	0.037			0.042	0.039
			(1.01)	(0.84)			(1.11)	(0.92)
$q_{t-1}^{Interest,3}$			-0.023	-0.035			-0.015	-0.028
			(-0.48)	(-0.58)			(-0.39)	(-0.56)
$q_{t-1}^{Interest,4}$			-0.214***	-0.212**			-0.202***	-0.196**
			(-3.06)	(-2.39)			(-3.35)	(-2.63)
$q_{t-1}^{Noninterest,2}$					0.000	0.009	-0.002	0.014
					(0.00)	(0.15)	(-0.05)	(0.24)
$q_{t-1}^{Noninterest,3}$					-0.047	-0.033	-0.036	-0.015
					(-0.58)	(-0.35)	(-0.47)	(-0.17)
$q_{t-1}^{Noninterest,4}$					-0.086	-0.107	-0.042	-0.064
					(-0.87)	(-0.85)	(-0.47)	(-0.55)
$\log(Assets_{t-1})$	-0.311***	-0.411***	-0.313***	-0.409***	-0.314***	-0.408***	-0.312***	-0.411***
	(-4.77)	(-3.21)	(-4.78)	(-3.22)	(-4.73)	(-3.15)	(-4.79)	(-3.21)
$Beta_{t-1}$	-0.379***	-0.132	-0.376***	-0.130	-0.388***	-0.136	-0.374***	-0.129
	(-3.75)	(-1.14)	(-3.72)	(-1.13)	(-3.77)	(-1.16)	(-3.62)	(-1.11)
BM_{t-1}	0.043	-0.055	0.056	-0.042	0.029	-0.073	0.052	-0.046
	(0.29)	(-0.36)	(0.38)	(-0.27)	(0.19)	(-0.45)	(0.35)	(-0.29)
$Volatility_{t-1}$	-0.043**	-0.024**	-0.040**	-0.022**	-0.044**	-0.024**	-0.040**	-0.021*
	(-2.29)	(-2.23)	(-2.17)	(-2.09)	(-2.28)	(-2.22)	(-2.14)	(-2.02)
$Leverage_{t-1}$	0.010	-0.000	0.012	0.001	0.008	-0.002	0.011	0.000
	(0.70)	(-0.03)	(0.83)	(0.05)	(0.63)	(-0.13)	(0.84)	(0.03)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,321	4,321	4,321	4,321	4,321	4,321	4,321	4,321
Adj-R^2	0.756	0.789	0.757	0.789	0.755	0.788	0.757	0.789

We estimate the panel regressions for the FR Y-9C sample, and report the results in Table 12. In Columns (1) and (2), the indicator variables are defined by the sensitivity of ROE^{MNP} to credit spreads. In Columns (3) to (8), we repeat our exercises, except that the indicator variables are based on the sensitivities of interest and noninterest income to credit spreads. We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14 Profit sensitivity and existing risk-exposure measures

Panel A: Correlations

	ROE	Noninterest income/Assets	Short term funding	Loan growth
s	0.10	0.03	0.05	0.09

Panel B: Prior profit sensitivity and MES of double sorted portfolios

	1	2	3	4	2 - 1	4 - 3
	Low ROE_{t-1}		$High\ ROE_{t-1}$			
s_{t-1}	-0.67	3.36	-1.06	3.89	4.03***	4.95***
MES_t	-1.74	-1.94	-2.07	-2.30	-0.20***	-0.23**
	$Low\ Noninterest_{t-1}$		$High\ Noninterest_{t-1}$			
s_{t-1}	-1.34	2.98	-1.13	2.92	4.32***	4.05***
MES_t	-2.45	-2.72	-2.67	-3.03	-0.27***	-0.36***
	$Low\ Funding_{t-1}$		$High\ Funding_{t-1}$			
s_{t-1}	-0.95	3.77	-0.86	3.81	4.72***	4.67***
MES_t	-1.83	-2.05	-2.01	-2.28	-0.22**	-0.27**
	$Low\ \Delta Loan_{t-1}$		$High\ \Delta Loan_{t-1}$			
s_{t-1}	-0.92	3.82	-0.89	3.62	4.74***	4.51***
MES_t	-1.90	-2.21	-1.92	-2.13	-0.30***	-0.21**

Panel C: Regressions

	(1)	(2)	(3)	(4)	(5)
q^2_{t-1}	-0.042	-0.035	-0.015	-0.019	-0.026
	(-1.32)	(-0.74)	(-0.46)	(-0.58)	(-0.55)
q^3_{t-1}	-0.137*	-0.232**	-0.121*	-0.125*	-0.226*
	(-1.98)	(-2.19)	(-1.69)	(-1.72)	(-2.07)
q^4_{t-1}	-0.215***	-0.269**	-0.181***	-0.188***	-0.260**
	(-3.17)	(-2.63)	(-2.76)	(-2.82)	(-2.45)
ROE_{t-1}	0.000				0.000
	(0.08)				(0.09)
$Noninterest_{t-1}$		0.026			0.020
		(0.31)			(0.25)
$Funding$			-0.007*		-0.005
			(-1.80)		(-0.88)
$\Delta Loan_{t-1}$				-0.003	-0.002
				(-1.22)	(-0.59)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes
Observations	5,932	3,486	6,197	6,078	3,450
Adj-R^2	0.786	0.768	0.785	0.786	0.768

Panel A shows that the correlations of profit sensitivity with existing risk exposure measures. We construct portfolios double-sorted on an existing risk-taking measure (e.g., noninterest income) and profit sensitivity, and report the results in Panel B. We estimate the panel regressions with existing risk exposure measures, and report the results in Panel C. We control for log total assets ($\log(Assets)$), CAPM beta ($beta$), book-to-market (BM), idiosyncratic volatility ($Volatility$), and leverage ($Leverage$). We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15 Stock returns and loan growth

	One-Factor		Two-Factor		Loan Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
q^2_{t-1}	0.023	0.051	0.025	0.014	0.057	0.050
	(0.61)	(1.42)	(0.72)	(0.37)	(1.33)	(1.23)
q^3_{t-1}	0.019	0.030	0.014	0.016	0.040	0.043
	(0.31)	(0.51)	(0.31)	(0.36)	(0.86)	(0.94)
q^4_{t-1}	-0.072	-0.049	-0.111*	-0.099	-0.068	-0.051
	(-1.02)	(-0.75)	(-1.73)	(-1.52)	(-1.61)	(-1.33)
$\log(Assets_{t-1})$	-0.439***	-0.181*	-0.433***	-0.177*	-0.328***	-0.038
	(-5.38)	(-1.82)	(-5.22)	(-1.76)	(-3.45)	(-0.30)
$Beta_{t-1}$	0.043	-0.104	0.047	-0.099	0.024	-0.153
	(0.48)	(-1.07)	(0.53)	(-1.04)	(0.24)	(-1.54)
BM_{t-1}	-0.029	-0.012	-0.029	-0.012	-0.037*	-0.020
	(-1.58)	(-0.78)	(-1.60)	(-0.83)	(-1.80)	(-1.46)
$Volatility_{t-1}$	-0.308***	-0.349***	-0.307***	-0.349***	-0.326***	-0.304***
	(-5.06)	(-3.36)	(-5.05)	(-3.34)	(-4.77)	(-2.90)
$Leverage_{t-1}$	-0.006	-0.007	-0.006	-0.007	-0.002	0.003
	(-0.94)	(-1.02)	(-0.87)	(-0.98)	(-0.21)	(0.30)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes
Observations	6,061	6,048	6,061	6,048	4,899	4,883
Adj-R^2	0.760	0.792	0.760	0.792	0.761	0.796

We experiment with two models of equity returns. The first model only includes the credit spread (One-factor), and the second model also accounts for the market factor (Two-factor). We estimate return sensitivities to credit spreads with three-year rolling regressions based on these two models, and re-estimate the panel regressions with the indicator variables based on return sensitivity estimates in in Columns (1) to (4). We also examine if sensitivity of loan growth to credit spreads has predictive power over MES. Specifically, we estimate the sensitivity of three-year loan growth to the credit spread with three-year rolling regressions, and repeat the panel regressions. The results are reported in Columns (5) and (6). We cluster standard errors by both bank and year to allow not only serial correlation within banks but also spatial correlation across banks.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 Average profit sensitivity and macroeconomic outcomes

	$y = \Delta\ln(GDP_t)$			$y = \Delta UN_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
F_{t-1}	-0.071*	-0.125**	-0.117**	0.023	0.070*	0.086**
	(-1.84)	(-2.55)	(-2.35)	(0.59)	(1.87)	(2.63)
y_{t-1}	0.325***	-0.002	-0.194***	0.358***	-0.096*	-0.281***
	(4.38)	(-0.03)	(-2.89)	(3.72)	(-1.81)	(-4.03)
Observations	44	43	42	44	43	42
Adj-R^2	0.079	0.031	0.085	0.106	0.046	0.178

The time-series predictive regression results for the period from 1975 to 2018 are presented in Table 15. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994). Our macroeconomic measures are real per capita GDP growth and the change in unemployment. Since macroeconomic variables respond to shocks with delay and only gradually, we use the average profit sensitivity in year $t - 1$ (F_{t-1}) to predict economic activities from year t to year $t + 2$. We control for economic activities in year $t - 1$ to rule out the concern that the predictive power of our financial fragility measure is due to confounding effects.

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 Average profit sensitivity, triggering events, and aggregate economic activities

	y = Log real per capita GDP			*y* = Unemployment		
	Δy from *t* to *t* + 2			Δy from *t* to *t* + 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Profit sensitivity to credit spreads						
F_{t-1}	-0.311***	-0.279***	-0.268***	0.178**	0.150**	0.138**
	(-3.44)	(-4.54)	(-4.95)	(2.36)	(2.69)	(2.71)
$\Delta\widehat{CS}_t$		-5.303***	-4.986**		3.852***	3.479***
		(-4.50)	(-2.58)		(5.43)	(5.69)
$F_{t-1} \times \Delta\widehat{CS}_t$			-0.527			0.469***
			(-1.56)			(4.36)
Δy_{t-1}	0.129	0.167	0.258	-0.021	-0.197	-0.080
	(0.78)	(0.53)	(0.70)	(-0.15)	(-0.73)	(-0.29)
N	42	42	42	42	42	42
Adj-R^2	0.065	0.240	0.252	0.073	0.380	0.449
Panel B: Three-year loan growth						
$\Delta loan_{t-1}$	-0.032	0.305**	0.292**	0.238***	0.112	0.118
	(-0.25)	(2.45)	(2.60)	(3.39)	(1.48)	(1.38)
$\Delta\widehat{CS}_t$		-8.125***	-0.843		3.122***	0.407
		(-5.92)	(-0.43)		(4.62)	(0.24)
$\Delta loan_{t-1} \times \Delta\widehat{CS}_t$			-0.715***			0.268
			(-2.84)			(1.68)
Δy_{t-1}	0.055	0.016	-0.029	-0.205	-0.267	-0.306
	(0.20)	(0.04)	(-0.09)	(-0.76)	(-0.80)	(-0.87)
N	42	42	42	42	42	42
Adj-R^2	-0.049	0.233	0.261	0.204	0.329	0.333

We follow Lopez-Salido, Stein, and Zakrajsek (2017) to construct their trigger measure of $\Delta\widehat{CS}_t$. We forecast the cumulative real GDP per capita growth and unemployment change from year *t* to year *t* + 2 with the average profit sensitivity and the trigger measure of Lopez-Salido, Stein, and Zakrajsek (2017) in Panel A. In Panel B, we repeat the same analysis with the average three-year loan growth. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994).

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1