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The Financial Distress Pricing Puzzle in Banking Firms

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This papers examines whether the financial distress pricing puzzle observed for non-financial firms is also observed for financial firms and how this puzzle differs according to the extent of short sale constraints. By using the eight distress measures developed for financial firms, we find that there is a strong negative relation in the cross-section between financial distress and subsequent bank stock returns, regardless of adjustment for risk. However, this distress pricing puzzle is statistically significant only for high short-sale constrained banks, but not for low short-sale constrained banks. Thus, short sale constraints are at least one non-risk attribute that causes the distress pricing puzzle for financial firms. We also find that despite its simple form, compared to the other complex distress measures, non-performing loan (NPL) is most informative in predicting future bank stock returns as well as bankruptcy and failure.

Keywords: Distress pricing puzzle; Financial firms; Bank stock returns; Short sale constraints; Abnormal returns

JEL classification: G12; G14

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Abstract

This papers examines whether the financial distress pricing puzzle observed for non-financial firms is also observed for financial firms and how this puzzle differs according to the extent of short sale constraints. By using the eight distress measures developed for financial firms, we find that there is a strong negative relation in the cross-section between financial distress and subsequent bank stock returns, regardless of adjustment for risk. However, this distress pricing puzzle is statistically significant only for high short-sale constrained banks, but not for low short-sale constrained banks. Thus, short sale constraints are at least one non-risk attribute that causes the distress pricing puzzle for financial firms. We also find that despite its simple form, compared to the other complex distress measures, non-performing loan (NPL) is most informative in predicting future bank stock returns as well as bankruptcy and failure.

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1. Introduction

A fundamental principle of asset pricing is that higher risk assets should compensate investors with higher returns. Contrary to this asset pricing principle, recent empirical studies show that firms with higher (lower) financial distress tend to earn lower (greater) subsequent return (Dichev, 1998; Griffin, and Lemmon, 2002; Ferguson and Shockley, 2003; Campbell, Hilscher, and Szilagyi, 2008; Garlappi, Shu, and Yan, 2008; Avramov et al., 2009; Chen, Chollete, and Ray, 2010; Chou, Ko, and Lin, 2010; and Kim, Lee, and Na, 2019; among many others). In other words, there is a negative relation between financial distress and subsequent stock returns in the cross-section. Since this implies that investors even pay a premium for bearing distress risk and, thus, the above risk-return tradeoff principle is violated, it is a challenge to standard rational asset pricing models. This negative relation between financial distress and subsequent returns in the cross-section is dubbed the distress pricing puzzle.

Studies suggest several explanations for the causes of the distress pricing puzzle. One group of studies attempts to provide risk-based rational explanations for the distress pricing puzzle (e.g., Garlappi, Shu, and Yan, 2008; Chen, Chollete, and Ray, 2010; George and Hwang, 2010; Garlappi and Yan, 2011),[3] and other group of studies argue that market frictions, such as short-

[3] In their theoretical model, Garlappi, Shu, and Yan (2008) argue that firms whose shareholders have a stronger advantage in extracting rents from negotiation with other claimholders have lower risk for equity and, hence, lower expected return as the probability of default increases. George and Hwang (2010) argue that since firms with high distress costs tend to choose low leverage, low-leverage firms have greater exposure to systematic risk relating to distress costs; therefore, expected returns are negatively related to leverage. By choosing low leverage, high-cost firms achieve low probabilities of financial distress, and thus, expected returns are negatively related to distress measures. Chen, Chollete, and Ray (2010) suggest a corrected single-beta CAPM to explain the distress puzzle. In their theoretical model, Garlappi and Yan (2011) argue that while higher leverage increases equity beta at low levels of default probability, equity betas do not increase with leverage at high levels of default probability, due to the possibility of debt renegotiation and subsequent asset redistribution on financial distress, which actually de-levers equity betas and thus reduces equity risk. As a consequence, the relationship between

sale constraints, play the important role in incurring the financial distress pricing puzzle (e.g., Griffin and Lemmon, 2002; Campbell et al., 2008; Avramov et al., 2009; Chen, Chollete, and Ray, 2010; Stambaugh et al. 2012; Kim and Lee, 2015, 2016; Kim, Lee, and Na, 2019). For example, Avramov et al. (2009) and Kim, Lee, and Na (2019) report that the negative relation between default risk and future returns is prominent among stocks with severe short sale constraints. These authors argue that short sale constraints prevent arbitrageurs from eliminating the inefficiency in pricing. In other words, the distress pricing puzzle is a consequence of systematic mispricing due to short sale constraints.

In most studies on the distress pricing puzzle, however, financial firms are excluded from analysis. Those studies are focused only on non-financial firms and concentrate on development of default/bankruptcy prediction models (equivalently, financial distress measures) for non-financial firms. A main reason for excluding financial firms is that the implication of accounting variables of financial firms is not necessarily the same as that of non-financial firms. For example, the high leverage that is regarded as normal for financial firms does not have the same meaning as for non-financial firms. In fact, the distress pricing puzzle may be a more important issue for financial firms/banks than for non-financial firms, since it could have an implication on bank-runs, which would have serious impacts on the whole financial system. To our knowledge, no studies in the literature yet thoroughly examine the distress pricing puzzle for financial firms.

The purpose of this paper is two-fold. First, we examine whether the distress pricing puzzle observed in non-financial firms is also observed for financial firms. Second, if the distress

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expected returns and default probability is hump-shaped, not positive, in the presence of shareholder recovery.

pricing puzzle is prominent in financial firms, we examine how it differs according the degree of short sale constraints. To measure financial distress for financial firms, we use the following eight default/bankruptcy prediction models developed for financial firms: Bank Z-score; distance to default suggested by KMV; distance to default suggested by Duan and Wang (2012) for financial firms; each of four components included in CAEL, which is used to rate Capital adequacy, Asset quality, Earnings, and Liquidity of banks (hence the name CAEL) by bank supervisory authorities, such as the Federal Deposit Insurance Corporation (FDIC); and the CAEL composite score, which is obtained from estimating the logit model using all four components of CAEL.[4] For financial firms, we select commercial banks that are listed on exchanges. We do not include unlisted banks, since banks should have information available to compute their distress measures and stock returns.

In univariate tests at the portfolio level as well as multivariate regression tests at the firm level, we find that there is a strong negative relation in the cross-section between financial distress and subsequent bank stock returns, regardless of adjustment for risk. That is, the distress pricing puzzle is observed for financial firms, as observed for non-financial firms. However, the distress pricing puzzle is statistically significant only for high short-sale constrained firms, but not for low short-sale constrained firms. As proxies for short sale constraints, we use Markit's stock borrowing costs, institutional ownership ratio, and status of exchange-traded stock options. We therefore argue that short sale constraints are at least one possible non-risk attribute that causes the distress

[4] Other distress measures for financial firms are also suggested in the literature. For example, the multivariate discriminant analysis in Sinkey et al. (1987), the logit model in Martin (1977), and the hazard model in Lane et al. (1986) and Whalen (1991) are developed for listed firms as well as unlisted firms. These distress models are estimated using accounting information for both listed and unlisted firms. We do not use these distress measures, due to possible sample selection bias that can occur when they are applied only to listed banks.

pricing puzzle for financial firms.

We also find that among the eight distress measures considered in this paper, NPL, a component in CAEL to measure asset quality, has the strongest negative relation with subsequent bank stock returns in the cross-section. It also performs best in predicting bankruptcy and failure for banks in terms of forecasting accuracy. Despite its simple form, compared to the other complex distress measures, NPL is most informative in predicting future bank stock returns as well as bankruptcy and failure. These results provide an important policy implication for investors, bank rating agencies, as well as financial supervisory authorities.

The rest of this paper proceeds as follows. Section 2 describes our data. Section 3 introduces the eight distress measures for financial firms. Section 4 provides empirical results, and Section 5 sets forth our conclusions.

2. Data

We collect data on stock prices, returns, and number of common shares outstanding for all U.S. commercial banks from the Center for Research in Security Prices (CRSP), and their accounting variables from the Compustat Bank Quarterly database. For proxies for short sale constraints, we obtain institutional investor holdings data from Thomson Reuters Institutional (13f) holdings S34 files, stock borrowing costs from the Markit (formerly Data Explorers) Securities Finance Analytics database, which are measured by daily costs to borrow score (DCBS) and indicative fee, and option status data from OptionMetrics. The full sample period for the data is January 1996 to December 2015, except for stock borrowing costs and option status data, whose sample periods are September 2004 to December 2015 and January 1996 to August 2015, respectively.

Following Gandhi and Lustig (2015), we define commercial banks as firms with header Standard Industrial Classification (SIC) codes 60 or historical SIC code 6712 on the CRSP data file. According to Gandhi and Lustig (2015), this definition ensures that bank holding companies are included in the sample. Since banks that belong to a holding company are not publicly traded themselves, bank holding companies need to be included. We define failed firms as firms that are delisted from exchanges due to financial reasons as stipulated in the CRSP delisting codes. The CRSP delisting codes for financial reasons are listed in Appendix Table A1.

Appendix Table A2 presents the number of bank and non-bank firms listed in the CRSP database for the period from 1996 to 2015 as being in bankruptcy or failure. Firms in bankruptcy (failure) are defined as those delisted due to financial reasons of the CRSP delisting code 574 (other delisting codes). Non-bank firms includes all firms listed in the CRSP database except for bank firms. Banks in failure is much more than banks in bankruptcy (178 versus 17 in total). Banks in bankruptcy are rare over the sample period and exist only during the financial crisis period 2009 to 2011.

3. Financial Distress Measures for Financial Firms

3.1. Definitions of the Financial Distress Measures

A. Bank Z-score

The first financial distress measure is Bank Z-score, which was developed in the spirit of the safety-first criterion of Roy (1952) and is currently widely used to measure probability of bank insolvency (e.g., Hanman and Hanweck, 1988; Boyd et al., 1993; Fiordelisi and Marqués-Ibañez, 2013; Lepetit and Strobel, 2013; and Kanas, 2013). It is defined as

$$\text{Bank Z} - \text{score} = \frac{\mu_{ROA} + \mu_{CAP}}{\sigma_{ROA}}, \tag{1}$$

where μ_{ROA} and μ_{CAP} are the averages of return on assets (ROA) and capital ratio (CAP), defined as the ratio of equities to total assets, respectively, and σ_{ROA} is the standard deviation of ROA. This definition compares buffers (returns and capitalization) with risk (volatility of returns). Thus, higher Z-score values suggest that a bank is less likely to default due to higher profitability and capitalization levels and/or more stable earnings. Since the Z-score needs only accounting information, it is applicable to unlisted financial firms, contrary to market-based distress measures. To differentiate this from the Altman (1968) Z-score, which measures financial distress of non-financial firms, we call this the *Bank Z-score* hereafter. Every quarter, we calculate the Bank Z-score using the preceding 5 years data available up to that quarter.

B. Distant-to-Default (DD)

The Merton (1974) model provides a framework to compute default measures for individual firms. In this model, the market value of equity, V_E, is determined as

$$V_E = V_A\, N(d_1) - e^{-r_f T} X\, N(d_2) \tag{2}$$

$$\sigma_E = (V_A/V_E)\, N(d_1)\, \sigma_A \tag{3}$$

where V_A is market value of assets, r_f is riskless rate of return, T is time to maturity, X is book value of debt, $d_1 = \left[ln(V_A/X) + \left(r_f + 0.5\sigma_A^2\right)T\right]/\sigma_A\sqrt{T}$, $d_2 = d_1 - \sigma_A\sqrt{T}$, $N(\cdot)$ is the cumulative density function of the standard normal distribution, and σ_E and σ_A are standard deviations of equity and assets, respectively. Based on the reasoning that default probability is the probability that the firm's assets (A) will be less than the book value of the firm's debts (X) (total liabilities), the probability of the company's default at maturity T evaluated at time t is computed as $N(-DD)$, where DD is defined as

$$\mathrm{DD} = \frac{ln(V_A/X) + (\mu_A - 0.5\sigma_A^2)\,T}{\sigma_A\sqrt{T}}, \tag{4}$$

where μ_A is the expected return of assets. Higher DD values suggest that a bank has a lower probability of default.

The distance-to-default of equation (4) is based on the reasoning that the firm is in default when its assets are less than the book value of its debts; that is, the default point, the asset value at which the firm will default, is the book value of debt, X. However, in general, firms do not default even though their asset value reaches the book value of their total liabilities. Some firms actually default at this point, but many continue to trade and service their debts. According to Crosbie and Bohn (2003), the default point generally lies somewhere between total liabilities and short-term debt. Thus, KMV sets the default point to $\mathrm{X} = \text{short-term debt} + 0.5 \times \text{long-term debt}$. We call the distance-to-default with this default point DD_all.[5] However, the default point of financial firms needs to be set differently from non-financial firms, since the capital structure of financial firms has not the same implication as that of non-financial firms. As mentioned, the high leverage that is regarded as normal for financial firms does not have the same meaning as for non-financial

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[5] To compute the value of DD of equation (4), we need σ_A, μ_A, and V_A. To first compute the volatility of assets, σ_A, we conduct an iterative procedure using equation (2), following Crosbie and Bohn (2003) and Vassalou and Xing (2004). To do this, we first compute the volatility of equity, σ_E, by using daily returns from the past 12 months to use an initial value for σ_A. For each trading day over the preceding 12 months, we compute V_A using V_E from equation (2). Using the computed daily values of V_A, we then compute σ_A for the next iteration. This procedure is repeated until the value of σ_A converges. Our convergence criterion is that the difference in the value of σ_A between two consecutive iterations is less than 10^{-3}. Using the daily values of V_A obtained from the final iteration, we compute μ_A.

firms. Duan and Wang (2012) argue that financial firms typically have higher leverage than non-financial firms, and they require special treatment of their default points, and, thus, the popular KMV default point seems ill-suited for financial firms. As the default point for financial firms, these authors suggest $\mathrm{X} = \text{short-term debt} + 0.5 \times \text{long-term debt} + \delta \times \text{other liabilities}$, where δ is the parameter to be estimated together with μ_A and σ_A. We call the distance-to-default with this default point DD_fin.[6] We use both DD_all and DD_fin as distress measures; every month we compute these two DDs.

C. Components of CAEL

The FDIC developed CAEL to monitor the financial solvency of individual banks. CAEL uses basic financial ratios from Call Reports (the quarterly financial reports filed by banks) to rate capital adequacy, asset quality, earnings (profitability), and liquidity (hence the name CAEL). The CAEL rating combines the four components by means of a complex system of weights to produce a composite score. CAEL does not include the management component because the quality of management cannot readily be identified with any financial ratio. We measure each component of CAEL using the following financial ratios: (i) CAR ($= \text{equity/total assets}$) for capital adequacy; (ii) $\text{NPL} (= \text{non-performing loan/total assets})$ for asset quality; (iii) RETA ($= \text{retained earnings/total assets}$) for earnings (see Altman, 1967, 1977; Sinkey et al., 1987); and (iv) CATA ($= \text{cash and cash equivalent/total assets}$) for liquidity (see Martin, 1977). We use these definitions of the CAEL components as our four individual measures of financial

6 We obtain the values of DD_fin from the website: http://rmicri.org (National University of Singapore, Risk Management Institute, CRI database).

distress.

D. CAEL composite score

Rather than considering individually each of the four components of CAEL, we develop a composite score that aggregates information from the four components.[7] To do this, we estimate the following pooled logit regression model:

$$P_{t-1}\left(Y_{i,t-1+K}=1\right)=\frac{1}{1+exp(-\alpha-\beta X_{i,t-1})}, \tag{5}$$

where $Y_{i,t-1+K}$ is a dichotomy variable, which equals 1 if bank i is in bankruptcy or financial failure over the next K months (forecasting horizon) in month t-1, and zero otherwise; $X_{i,t-1}$ is a vector of explanatory variables of bank i in month t-1, which are the four components of CAEL available in month t-1 (i.e., CAR, NPL, RETA, and CATA); and $P_{t-1}(\cdot)$ is the probability that bank i is in bankruptcy or failure over the next K months, which is evaluated based on information available up to t-1.

Appendix Table A3 reports estimation results of the logit model (5) with various forecasting horizons (K) over the sample period January 1996 to December 2015; $K=$ 3, 6, 9, and 12 months. Among the four components, the coefficient estimates on NPL and CAR are

[7] The CAEL ratings are reported as a composite score from 1 (best) to 5 (worst) by many private rating firms, which are not affiliated with the FDIC. One such firm is Bankrate.com. The reasons we develop our CAEL composite score rather than using the composite scores developed by such private firms are as follows. First, it is difficult to obtain historical time-series data of the composite score developed by private firms, which is critical to this study. Second, the distribution of their available composite scores is quite skewed. For example, almost 70% of all U.S. banks have a composite score of 4. Third, it is difficult to match banks analyzed by the private firms with banks on the CRSP and Compustat database, since the private firms reveal the identification of the banks as their name and address, not the identification commonly used in the database, such as CUSIP or PERM number.

strongly statistically significant at the 1 percent level for all considered forecasting horizons, while those on RETA and CATA are statistically insignificant, irrespective of forecasting horizon. These results indicate that NPL and CAR are the strongest predictors for bankruptcy or financial failure among the four components of CAEL. We compute the fitted value of the dependent variable based on the coefficient estimates in equation (5) with $K = 12$ months and use it as our CAEL composite score.[8] Thus, the greater the CAEL composite score, the higher the distress and the likelihood of bankruptcy.

3.2. Basic Characteristics of the Distress Measures

The four components of CAEL, the CAEL composite score (Comp), and the Bank Z-score are computed using quarterly accounting variables from the Compustat Bank Quarterly database, and these quarterly distress measures are assigned the same value for the months of the quarter. DD_fin and DD_all are computed every month. Thus, we use all eight distress measures at a monthly frequency. The definitions of all measures and variables are summarized in Appendix Table A4.

Table 1 presents basic statistics (Panel A) and correlation coefficients (Panel B) of the pooled sample for all eight distress measures of U.S. banks over the period January 1996 to December 2015. Note that greater NPL and CAEL composite score indicate a higher probability of default, while greater values of the other six distress measures indicate a lower probability of default. Thus, NPL and the CAEL composite score are expected to have a negative correlation with the other six distress measures, and the six distress measures are expected to have a positive

[8] When the different forecasting horizons of $K = 3$, 6, and 9 months, the results are qualitatively similar.

correlation with each other. Overall, the observed correlation coefficients tend to have signs consistent with this expectation, except for a few cases. In general, the correlation coefficients among NPL, CAEL composite score, Bank Z-score, DD_fin, and DD_all have signs consistent with our expectation, while those among the three components of CAEL, except for NPL, have signs inconsistent with our expectation in several cases.

To examine whether failed banks, which are in bankruptcy or failure, differ from non-failed banks with respect to distress measures, we conduct t-tests for the difference in distress measure between failed and non-failed banks for each distress measure. Table 2 presents test results, showing that failed banks are significantly differentiated from non-failed banks with respect to all distress measures, except for CATA. In particular, these two groups of banks are most significantly differentiated with respect to NPL in that the t-statistic for the difference in NPL between these two groups is greatest.

It is noteworthy to mention that, in tests of assessing forecasting accuracy of bankruptcy and failure, NPL performs best among all eight distress measures considered in predicting bankruptcy and failure (not reported).[9] NPL performs even better than the CAEL composite score, which aggregates information of all components of CAEL. The components of CAEL, except for NPL, generally perform poorly in predicting bankruptcy and failure. In particular, CATA performs worst and hardly contains information with respect to forecasting bankruptcy. NPL is a simple

[9] We compared forecasting accuracy of bankruptcy and failure for all eight distress measures with respect to the receiver operating characteristics (ROC) curve and the hitting ratio. With respect to the ROC curve, NPL is best. DD_fin, DD_all, Bank Z-score, CAEL composite score, CAR, RETA, and CATA are next best in this order. With respect to the hitting ratio, NPL is also best. CAEL composite score, DD_fin, DD_all, CAR, Bank Z-score, RETA, and CATA are next best in this order. The detailed results are available upon request.

measure, compared to the other, more complex measures, such as Bank Z-score, DD measures, and the CAEL composite score. Nonetheless, NPL, which is a proxy for asset quality, is most informative in terms of predicting bankruptcy and failure.

4. Empirical Results

4.1. The Distress Pricing Puzzle in Bank Stock Returns

In this section, we examine the predictive power of the distress measures for future bank stock returns in the cross-section. In other words, we examine a cross-sectional relation between the distress measures and subsequent bank stock returns. To do this, we construct portfolios by sorting all banks each month into one of 10 decile portfolios based on the value of the financial distress measure most recently available up to the portfolio formation month. Portfolios are held with value weight for the next month and are rebalanced every month.

Table 3 presents average monthly raw returns (Panel A) and abnormal returns (Panel B) of the 10 decile portfolios sorted on each financial distress measure over the entire sample period. Portfolio 1 (10) includes the least (most) distressed banks. Abnormal returns are calculated as the intercept estimate $(\hat{\alpha})$ in the time-series regression of portfolio returns on the Fama and French (1993) three factors (FF3). It is observed that average raw and abnormal returns tend to decrease across the distress-sorted portfolios for all distress measures, except for CATA; more distressed portfolios tend to earn lower subsequent returns, no matter which distress measure (except for CATA) is used as a sorting variable. That is, a significant negative relation between financial distress and subsequent stock returns is observed in the cross-section for bank firms.

Specifically, when NPL is used as a sorting variable, Portfolio 1 (P1; least distressed) earns 1.31 percent raw return per month on average, while Portfolio 10 (P10; most distressed) earns -0.35 percent raw return per month on average. The difference in average raw return between P10 and P1 ("High−Low"), which is the zero-investment portfolio return by buying long P10 and selling short P1, is negative and statistically significant at the 1 percent level; it is -1.66 percent (t-statistic of -3.37). Even after FF3 is adjusted, High−Low is also statistically significant at the 1 percent level; it is -1.97 percent (t-statistic of -4.13). When the CAEL composite score and the Bank Z-score are used as sorting variables, we find similar results, although the economic and statistical significance of the differences is smaller than in the case of using NPL. When the CAEL composite score is used as a sorting variable, "High−Low" is -0.98 percent (t-statistic of -2.00) for raw returns and -1.33 percent (t-statistic of -2.87) for abnormal returns. When the Bank Z-score is used as a sorting variable, "High−Low" is -0.89 percent (t-statistic of -2.36) for raw returns and -1.22 percent (t-statistic of -3.44) for abnormal returns. However, when the other distress measures are used as sorting variables, "High−Low" is statistically insignificant, although negative. That is, NPL, CAEL composite score, and Bank Z-score have stronger predictive power for future bank stock returns in the cross-section than the other distress measures.

Since the above portfolio approach is a univariate test at the portfolio level, it is difficult to control for some bank firm characteristics in examining the cross-sectional relation between distress measures and subsequent bank stock returns at the individual firm level. To do this, we estimate the following multivariate regression model:

$$\begin{aligned}\mathrm{Ret}_{i,t} = \beta_0 + \beta_1 \mathrm{Distress}_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 \mathrm{BM}_{i,t-1} + \beta_4 \mathrm{ILLIQ}_{i,t-1} + \beta_5 \mathrm{Beta}_{i,t-1} \\ + \beta_6 \mathrm{IVOL}_{i,t-1} + \varepsilon_{i,t}, \qquad (6)\end{aligned}$$

where $\mathrm{Ret}_{i,t}$ is the raw return of bank *i* in month t and $\mathrm{Distress}_{i,t-1}$ is the value of the distress measure of bank i in month t-1. As control variables, we select firm characteristics, which are known in the literature as factors affecting stock returns. The selected control variables are as follows: *Size* is natural logarithm of the market value of common equities (Banz, 1981; Keim, 1983; Fama and French, 1992); *BM* is book-to-market ratio (Fama and French, 1992); *ILLIQ* is the Amihud (2002) illiquidity; *Beta* is market beta obtained from regressions of the market model using 36 monthly returns available up to month *t*; *IVOL* is idiosyncratic volatility (Ang et al., 2009), which is the standard deviation of the residuals obtained from regressions of the Fama and French (1993) three-factor model using 36 monthly returns available up to month t. Note that "month t-1" in equation (6) means "most recently available up to month t."

Table 4 presents estimation results of equation (6) using the pooled regression method (Panel A) and the Fama and MacBeth (1973) method (Panel B). Thus, the coefficient estimates in Panel B are time-series averages of the month-by-month cross-sectional regression coefficient estimates. Note that we multiply the financial distress measures by -1, except for NPL and the CAEL composite score, to indicate greater value as more distressed, as do NPL and the CAEL composite score. Thus, negative coefficient estimates indicate the distress pricing puzzle; that is, more distressed banks earn lower subsequent bank stock returns. Panel A shows that when each distress measure is individually included in the model with the control variables, the pooled regression coefficient estimates on the distress measures, $\hat{\beta}_1$, are all negative and statistically significant at the 1 percent level, except for CAR which is significant at the 5 percent level. When all eight distress measures are included together in the model, the coefficient estimates on the eight measures, except for the CAEL composite score, are negative. However, the coefficient estimates only on CAR, NPL, CATA, and DD_all are statistically negatively significant at the 1 percent level. Among these four distress measures, NPL has the strongest statistical significance.

The statistical significance of the Fama and MacBeth coefficient estimates is lower than that of the pooled regression coefficient estimates. Note that the Fama and MacBeth (1973) regression estimates the coefficients more conservatively with respect to statistical significance than does the pooled regression. Panel B of Table 4 shows that when each distress measure is individually included in the model, the coefficient estimates on the distress measures are mostly negative. However, the coefficient estimates are statistically negatively significant only for NPL and Bank Z-score. When all eight distress measures are included together in the model, the coefficient estimates only on NPL, RETA, and Bank Z-score are statistically negatively significant at the 5 percent level. Based on the estimation results of the pooled regression and the Fama and MacBeth regression, the coefficient estimate only on NPL is negatively statistically significant in any circumstance.

Overall, the regression coefficient estimates on the distress measures are negative and generally statistically significant; that is, banks with higher financial distress tend to earn lower subsequent stock returns. This is consistent with the univariate portfolio test results. Among the eight distress measures, NPL has the strongest negative relation with subsequent bank stock returns in the cross-section. That is, NPL has the strongest predictive power for future bank stock returns as well as for bankruptcy and failure. This means that, despite its simple form, compared with the other distress measures, NPL is most informative in predicting future bank stock returns and bankruptcy. This provides an important policy implication for investors, bank rating agencies, and financial supervisory authorities.

4.2. Effects of Short-Sale Constraints on the Distress Pricing Puzzle

Several studies argue that market frictions, such as short sale constraints, play the important role of incurring the distress pricing puzzle (e.g., Griffin and Lemmon, 2002; Campbell et al., 2008; Avramov et al., 2009; Chen, Chollete, and Ray, 2010; Stambaugh et al. 2012). In this section, we examine how the distress pricing puzzle observed in bank stock returns differs according to the degree of short sale constraints. Based on the results in Section 4.1., we use NPL as a representative distress measure to examine the effects of short sale constraints on the distress pricing puzzle, hereafter.

4.2.1. Proxies for Short Sale Constraints

Short sellers must borrow shares from an investor willing to lend. Stocks are short-sale constrained when there is a strong demand to sell short and a limited supply of shares to borrow. Thus, loan supply and demand are the key elements of short sale constraints. As proxies for short sale constraints, we use four variables: Markit's DCBS and indicative fee (FEE), institutional ownership ratio (IOR), which is defined as the ratio of shares owned by institutions to the total number of shares outstanding, and option status (OS) (i.e., presence of exchange-traded stock options). Among these, institutional ownership is a proxy for loan supply, while DCBS and the indicative fee are proxies for loan demand. Using a proprietary database from a single lender, D'Avolio (2002) shows that the main suppliers of stock loans are institutional investors, such as passive index funds, insurance companies, and pension funds. Investors can take short positions in stocks by buying put options and/or writing call options without selling short directly. Stocks with exchange-traded options are therefore less short-sale constrained, since investors can more easily establish short positions via options at lower cost than in the case of directly borrowing stocks. Boehme, Danielsen, and Sorescu (2006) show that stocks with listed options have lower average fee levels than non-optioned stocks after controlling for short interest. In this sense, option status is an indirect proxy for loan demand.

We use two measures of stock borrowing costs, and these are the most direct measures of short sale constraints; one is DCBS, and the other is the indicative fee. DCBS is a measure of the relative cost of borrowing for each stock which is computed by Markit for each stock-day based on actual lending fees. DCBS is an integer categorization ranging from 1 (low cost; easy to borrow) to 10 (high cost; hard to borrow). The indicative fee, which is observed on the last trading day of each month from the Markit data set, is the fee paid by the borrower for a new stock loan, based on both borrowing costs between agent lenders and prime brokers as well as rates from hedge funds to produce an indication of the current market rate.[10] This is the fee data on the buy-side for a new loan and, thus, is paid by stock borrowers. Meanwhile, DCBS is the fee data on the sell-side, which is the average fee on currently outstanding loans and, thus, are received by stock lenders.[11] Thus, the fee data on the buy-side reflect, a priori, the fees for new stock loans, while the fee data on the sell-side reflect the fees for outstanding loans.

In summary, banks are more short-sale constrained with stock borrowing costs (DCBS

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[10] Based on the Markit (2015) data description, this is Markit's estimate of expected borrow cost, in fee terms, for a hedge fund on a given day. This is a derived rate using the Markit Securities Finance proprietary analytics and data set.

[11] The difference between the fees on the buy-side and on the sell-side is the spread charged by brokers.

and FEE) higher, institutional ownership ratio lower, and absence of exchange-traded option.

4.2.2. Revisiting the Distress Pricing Puzzle

We first examine how the financial distress measure for banks, NPL, is related with their firm characteristics. To do this, we construct portfolios by assigning all banks each month into one of five quintiles based on NPL. Table 5 presents time-series averages of value-weighted monthly excess returns and several firm characteristic variables in the NPL-sorted portfolios. In general, high NPL portfolios tend to have firm characteristics indicating greater risk. That is, higher NPL portfolios have greater standard deviation of stock returns, market beta, idiosyncratic volatility, the Amihud (2003) illiquidity, book-to-market, and smaller firm size and lower profitability than do lower NPL portfolios. Nonetheless, higher NPL portfolios tend to earn lower subsequent stock returns. Table 5 also shows the relation between NPL and the proxy variables for short sale constraints. We observe that DCBS and FEE monotonically increase across NPL-sorted portfolios, while institutional ownership and availability of exchange-traded stock options decrease. This indicates that high NPL banks are more short-sale constrained.

To confirm the distress pricing puzzle in bank stock returns, we re-examine the relation between NPL and subsequent bank stock returns after adjustment for risk. For adjustment for risk, we use the well-known existing models: the CAPM, FF3, the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2014) q-factor model (HXZ). Table 6 presents abnormal returns of the five quintile portfolios sorted on NPL, which are measured as the intercept estimate ($\hat{\alpha}_p$) from regressing monthly excess returns of each portfolio on the factors included in the model over the whole sample period.

Table 6 shows that no matter which model is used for adjustment for risk, risk-adjusted abnormal returns monotonically decrease across NPL-sorted portfolios. Further, the differences in abnormal return between the highest (P5) and lowest (P1) NPL-sorted portfolios, $\hat{\alpha}_H - \hat{\alpha}_L$, are all negative and statistically significant at the 1 percent level for all models considered; they are -0.99 percent (t-statistic of -3.22) from the CAPM, -1.10 percent (t-statistic of -3.65) from FF3, -0.84 percent (t-statistic of -2.71) from FF5, and -0.98 percent (t-statistic of -3.05) from HXZ. These differences indicate monthly risk-adjusted profits from the long-short zero-investment strategy based simply on NPL. These risk-adjusted zero-investment profits, $\hat{\alpha}_H - \hat{\alpha}_L$, are similar in magnitude to the zero-investment profits even without adjustment for risk, $\bar{R}_H - \bar{R}_L$, which is -0.86 percent per month (t-statistic of -2.73). This indicates that the distress pricing puzzle in bank stock returns is hardly explained by the risk factors included in the existing models in the literature. In other words, the distress pricing puzzle is at least not attributable to the risk(s) included in the models.

4.2.3. Portfolio Tests

In the previous section, we show that the distress pricing puzzle in bank stock returns is not explained by the risks included in the well-known existing models. It can be argued, therefore, that the distress pricing puzzle in bank stock returns is hardly attributable to the well-known risk factors. In this section and the following section, we examine whether short sale constraints are one of the possible non-risk attributes that cause the distress pricing puzzle in bank stock returns. As proxy variables for short sale constraints, we use DCBS, indicative fee (FEE), IOR, and OS, as explained in Section 4.2.1. Among these, DCBS and FEE are direct measures of costs of short selling, while

IOR and OS are indirect measures of such costs.

To carry out univariate portfolio tests, we construct portfolios in a two-way independent sorting. That is, we sort bank stocks on the intersection of five break points of NPL and one or two break points of the short sale constraints proxy variable. The break points of each short-sale constraint proxy variable are determined as follows: (i) if the DCBS of a bank is greater than 1 (equal to 1), it is assigned into a high (low) DCBS portfolio; (ii) the high (low) FEE portfolio includes the top (bottom) 40 percent of bank stocks sorted on indicative fee; (iii) the low IOR (high IOR) portfolio includes the bottom (top) 30 percent of banks sorted on IOR; (iv) portfolios sorted on OS are NO and YES, depending on whether the bank stock has exchange-traded options trading prior to the first day of the month. High DCBS, high FEE, low IOR, and No exchange-traded option (absence of option status) indicate more short-sale constrained.

Table 7 presents abnormal returns (in percent) of the portfolios, which are constructed by assigning all banks each month into one of 10 (=5×2) portfolios sorted on NPL and the short sale constraints proxy variable. Abnormal returns are FF3-adjusted returns. The overall results show that the distress pricing puzzle is statistically significant only for the high short-sale constrained group, but not for the low short-sale constrained group, and that the difference in the measure of the distress pricing puzzle between these two groups is statistically significant. Specifically, when DCBS is used as a proxy for short sale constraints, the differences in abnormal return between the highest and lowest NPL portfolios, $\hat{\alpha}_H - \hat{\alpha}_L$, which is a measure of the distress pricing puzzle, are -2.62 percent (t-statistic of -3.25) for the high DCBS group and -0.50 percent (t-statistic of -1.27) for the low DCBS group. The difference in $\hat{\alpha}_H - \hat{\alpha}_L$ between the high and low DCBS groups (i.e., difference in difference; DiD) is statistically significant; it is -2.12 percent (t-statistic of -2.37).

We obtain similar results for the other short-sale constraint proxy variables. That is, the difference in $\hat{\alpha}_H - \hat{\alpha}_L$ between the more and less short-sale constrained groups (i.e., DiD) are also statistically significant; they are -2.09 percent (t-statistic of -2.67) for FEE, -0.95 percent (t-statistic of -1.69) for IOR, and -0.93 percent (t-statistic of -2.14) for option status.

The above results apparently indicate that short sale constraints are one of the non-risk attributes that cause the distress pricing puzzle in bank stock returns.

4.2.4. Multivariate Pooled Regression Tests

The portfolio tests in the previous section perform a univariate test at the portfolio level on the effect of short sale constraints on the distress pricing puzzle. In this section, we conduct a multivariate test to examine this effect at the individual stock level. To do this, we estimate the following pooled regression model.

$$\begin{aligned}\mathrm{Aret}_{i,t} = \beta_0 + \beta_1\mathrm{NPL}_{i,t-1} + \beta_2\left(\mathrm{NPL}_{i,t-1} \times \mathrm{Crisis}\right) + \beta_3\mathrm{Cost}_{i,t-1} + \beta_4\left(\mathrm{NPL}_{i,t-1} \times \mathrm{Cost}_{i,t-1}\right)\\ +\beta_5\left(\mathrm{NPL}_{i,t-1} \times \mathrm{Cost}_{i,t-1} \times \mathrm{Crisis}\right) + \mathrm{Z}_{i,t-1} + \mathrm{Year}_t + e_{i,t-1} \qquad (7),\end{aligned}$$

where $\mathrm{Aret}_{i,t}$ is the abnormal return of firm *i* at month *t*, which is the sum of the intercept estimate and residuals obtained from regressing the excess monthly returns of bank i on the Fama and French (1993) three factors; $\mathrm{NPL}_{i,t-1}$ is the NPL divided by total assets of bank i at month t-1; $\mathrm{Cost}_{i,t-1}$ is the stock loan cost of bank i at month t-1, which is either DCBS or FEE;[12] Crisis is a dummy variable, which equals 1 if month t is included in the financial crisis period February

[12] In the pooled regression tests, we use only DCBS and FEE as short-sale constraint proxy variables. When we use the other short-sale constraint proxy variables, such as institutional ownership ratio (IOR) and option status (OS), we also obtain similar results.

2007 to April 2011 and zero otherwise. We include the crisis dummy variable to examine whether the distress pricing puzzle is different between the financial crisis period and the period excluding the financial crisis period. Z is a vector of the control variables, and Year is the year dummy variable. We include year dummies in the model to capture shocks of market-wide credit conditions on financial distress possibly due to macroeconomic environments. Improving (deteriorating) market-wide credit conditions could ease (worsen) financial distress on individual stocks and thus reduce (magnify) the financial distress effect.

We consider the following control variables (Z) in equation (7). Since Ericsson and Renault (2006) and Da and Gao (2010) argue that the return spread by financial distress is attributable to illiquidity, we include ILLIQ as a measure of illiquidity, which is the Amihud (2002) illiquidity. Chen, Chollete, and Ray (2010) show that the distress pricing puzzle is empirically connected to the idiosyncratic volatility puzzle. We thus include IVOL as a measure of idiosyncratic volatility, which is measured as the standard deviation of the residuals obtained from regressions of the Fama and French (1993) three-factor model using 36 monthly returns available up to month *t*. Campbell, Hilscher, and Szilagyi (2011) show that profitability is strongly negatively related to default probability. Hou, Xue, and Zhang (2015) show that the distress pricing puzzle is explained by their q-factor model, which includes the four factors related to the market, size, investment, and profitability. Among these four factors, the profitability factor is most closely related to the distress pricing puzzle. Therefore, we include NITA, the ratio of net income to total assets, as a measure of profitability. To control for variation with the market, we include Beta, which is obtained from regressions of the market model using 36 monthly returns available up to month *t*.

Table 8 presents estimation results of the pooled regression model of equation (7). When the financial distress variable, NPL, is alone in the model, the coefficient estimate on NPL is strongly negatively significant (i.e., $\hat{\beta}_1$ is -43.04, with t-statistic of -16.04), which confirms the distress pricing puzzle in bank stock returns at the individual firm level. When the multiplicative term NPL×Crisis is added, the coefficient estimates on NPL and NPL×Crisis are both negatively statistically significant; they are $\hat{\beta}_1 = -10.59$ (t-statistic of -2.80) and $\hat{\beta}_2 = -57.66$ (t-statistic of -12.18), respectively. This means that the distress pricing puzzle is observed, regardless of the financial crisis period, but the distress pricing puzzle is much stronger during the financial crisis period. When the multiplicative term of NPL with Cost, NPL×Cost, is added with Cost to the model, the coefficient estimates on NPL×Cost, $\hat{\beta}_4$, are negatively statistically significant at the 1 percent level; they are -2.98 (t-statistic of -6.06) for DCBS and -67.26 (t-statistic of -2.91) for FEE. However, the coefficient estimates on Cost, $\hat{\beta}_3$, are statistically insignificant for both stock loan fee variables. This indicates that the distress pricing puzzle is insignificant for low stock loan cost (i.e., less short-sale constrained) stocks, but the distress pricing puzzle is much stronger for high stock loan costs (i.e., more short-sale constrained) stocks than low stock loan costs stocks, and the difference in the pricing puzzle between these two groups of stocks is statistically significant. In fact, these results are consistent with those of the univariate portfolio tests.

When the triple multiplicative term of NPL with Crisis and Cost, NPL×Crisis×Cost, is added to the model with all control variables, the coefficient estimate on the term $\hat{\beta}_5$ is negative and statistically significant; it is -6.98 (t-statistic of -4.66) for DCBS and -60.61 (t-statistic of -2.54) for FEE. These results indicate that the stronger distress pricing puzzle observed during the financial crisis period becomes more severe for stocks with high stock loan costs (i.e., more short-sale constraints). These results are similar when excluding the control variables.

5. Conclusion

This paper examines whether the distress pricing puzzle observed in non-financial firms is observed for financial firms as well and, if any, how it differs according the degree of short sale constraints. To do this, we use the default/bankruptcy prediction models developed for financial firms. To our knowledge, there are no studies in the literature that examine the distress pricing puzzle for financial firms.

In univariate portfolio tests and multivariate regression tests, we find that there is a significant negative relation in the cross-section between financial distress and subsequent bank stock returns, regardless of adjustment for risk. That is, the distress pricing puzzle is also observed for financial firms, as observed for non-financial firms. However, the distress pricing puzzle is statistically significant only for high short-sale constrained banks, but not for low short-sale constrained bank. We therefore argue that short sale constraints are at least one of the possible non-risk attributes that cause the distress pricing puzzle for financial firms.

Among the eight distress measures considered in this paper, NPL, a component in CAEL to measure asset quality, has the strongest negative relation with subsequent bank stock returns in the cross-section. It also performs best in predicting bankruptcy and failure for banks in terms of forecasting accuracy. Despite its simple form, NPL is most informative in predicting future bank stock returns as well as bankruptcy and failure. These results provide an important policy implication for investors, bank rating agencies, as well as financial supervisory authorities.

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Table 1. Summary Statistics of Financial Distress Measures for Banks

This table presents basic statistics (Panel A) and correlation coefficients (Panel B) of the financial distress measures for U.S. bank firms. The components of CAEL are CAR (capital adequacy ratio; equity to total assets), NPL (non-performing loan assets to total assets), RETA (retained earnings to total assets), and CATA (cash and due, U.S. Treasury securities and net federal funds to total assets). "Comp" (×100) is the CAEL composite score calculated by the logit model using the four components of CAEL as explanatory variables. DD_all and DD_fin are the distances to default (DD) assuming that the default point equals short-term liabilities+0.5×long-term liabilities and short-term liabilities+0.5×long-term liabilities+δ×other liabilities, respectively. 'Ave #firms' indicates time-series average of the firms with available data. The four components of CAEL and Bank Z-score are computed using the Compustat Bank quarterly accounting variables, and these quarterly distress measures are assigned the same value for the months of the quarter. DD_fin and DD_all are of monthly frequency. The basic statistics and correlation coefficients are based on the pooled sample. The sample period is January 1996 to December 2015.

Panel A: Basic statistics

Distress measure		Ave #firms	Mean	Std dev	Skew-ness	Min	Q1	Median	Q3	Max
CAEL	CAR	540	0.100	0.041	4.613	-0.117	0.077	0.092	0.112	0.922
	NPL	500	0.012	0.020	7.739	0.000	0.003	0.006	0.013	0.623
	RETA	539	0.045	0.039	-0.691	-0.256	0.023	0.046	0.068	0.265
	CATA	540	0.086	0.101	1.919	-0.432	0.025	0.058	0.120	0.959
	Comp	499	0.137	1.005	68.747	0.000	0.073	0.098	0.128	94.662
Bank Z		447	5.210	5.813	2.358	-1.910	1.303	3.436	7.344	67.504
DD_fin		407	2.429	1.610	0.501	-2.301	1.300	2.338	3.398	12.192
DD_all		510	2.964	2.706	2.397	-3.833	1.289	2.571	4.132	65.300

Panel B: Correlation coefficients

Distress measure		CAEL					Bank Z	DD_fin	DD_all
		CAR	NPL	RETA	CATA	Comp			
CAEL	CAR	1.000							
	NPL	0.043	1.000						
	RETA	0.356	-0.120	1.000					
	CATA	-0.041	0.059	0.026	1.000				
	Comp	-0.854	0.314	-0.436	-0.127	1.000			
Bank Z		-0.002	-0.494	0.280	0.018	-0.258	1.000		
DD_fin		0.312	-0.217	0.256	0.057	-0.413	0.354	1.000	
DD_all		0.330	-0.249	0.248	-0.041	-0.417	0.357	0.689	1.000

Table 2. Tests for the Difference in Distress Measure between Non-Failed and Failed Banks

This table presents t-test results for the difference in distress measure between failed and non-failed firms for all seven distress measures considered. "Failed" banks include banks in bankruptcy or failure, which are defined in Table 1. The components of CAEL are CAR (capital adequacy ratio; equity to total assets), NPL (non-performing loan assets to total assets), RETA (retained earnings to total assets), and CATA (cash or cash equivalents to total assets). "Comp" (×100) is the CAEL composite score calculated by the logit model using the four components of CAEL as explanatory variables. DD_all and DD_fin are the distances to default (DD) assuming that the default point equals short-term liabilities+0.5×long-term liabilities and short-term liabilities+0.5×long-term liabilities+delta× other liabilities, respectively.

Distress measure		Average value		Difference	t-statistic
		Non-failed banks	Failed banks		
CAEL	CAR	0.100	0.064	0.036	8.81
	NPL	0.012	0.068	-0.056	-28.44
	RETA	0.045	0.008	0.038	9.71
	CATA	0.086	0.090	-0.004	-0.39
	Comp	0.135	2.267	-2.132	-20.40
Bank-Z		5.214	1.111	4.103	6.95
DD_fin		2.431	0.623	1.808	9.40
DD_all		2.966	0.258	2.708	9.75

Table 3. Portfolio Returns Sorted on Financial Distress Measures

This table presents average monthly raw returns (Panel A) (in percent) and abnormal returns (Panel B) (in percent) of portfolios sorted on each financial distress measure. Portfolios are constructed by assigning all banks each month to one of 10 decile portfolios according to the magnitude of the financial distress measure most recently available up to the portfolio formation month. Portfolios are held with value weight for the next one month. Portfolio 1 (10) includes the least (most) distress banks. Abnormal returns are calculated as the intercept estimate $(\hat{\alpha})$ in the regression, $R_{i,t} = \alpha + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t}$, where $R_{i,t}$ is the excess return in month t, and MKT_t, SMB_t, and HML_t are the Fama and French (1993) three factors. "Comp" is the composite score calculated by the logit model using the four components of CAEL as explanatory variables. The sample period is from January 1996 to December 2015. Numbers in parentheses indicate t-statistics.

Distress measure		Distress-Sorted Portfolio										High−Low
		1 (low)	2	3	4	5	6	7	8	9	10 (high)	
		Panel A: Raw return										
CAEL	CAR	0.49	0.78	0.77	0.95	0.62	0.89	0.85	1.04	0.89	0.28	-0.21
		(1.50)	(1.91)	(2.03)	(2.15)	(1.22)	(2.11)	(2.06)	(2.26)	(2.12)	(0.55)	(-0.57)
	NPL	1.31	1.45	0.91	0.71	0.88	0.73	0.37	0.47	0.73	-0.35	-1.66
		(3.39)	(4.11)	(1.93)	(1.37)	(2.06)	(1.69)	(0.75)	(1.01)	(1.60)	(-0.60)	(-3.37)
	RETA	0.91	1.03	1.14	0.84	0.73	0.76	1.17	0.55	0.66	0.60	-0.31
		(2.29)	(2.78)	(2.77)	(2.29)	(1.68)	(1.39)	(2.20)	(1.32)	(1.48)	(1.20)	(-0.68)
	CATA	0.76	0.73	0.97	0.83	0.72	0.89	0.79	0.82	0.52	0.84	0.08
		(2.02)	(1.44)	(1.89)	(1.91)	(1.67)	(2.07)	(2.06)	(2.06)	(1.20)	(1.95)	(0.25)
	Comp	0.50	0.83	0.99	0.76	0.78	0.91	1.08	0.85	0.46	-0.48	-0.98
		(1.48)	(2.43)	(2.42)	(1.60)	(1.80)	(1.83)	(2.42)	(2.07)	(0.87)	(-0.81)	(-2.00)
Bank-Z		1.15	0.95	1.05	0.82	0.86	0.60	0.46	0.82	0.83	0.26	-0.89
		(3.47)	(2.46)	(2.50)	(2.12)	(2.06)	(1.23)	(0.93)	(1.74)	(1.50)	(0.49)	(-2.36)
DD_fin		0.69	1.03	0.47	1.01	0.76	1.31	0.83	1.21	1.12	0.16	-0.54
		(2.23)	(2.62)	(1.15)	(2.30)	(1.61)	(2.79)	(1.64)	(2.43)	(2.14)	(0.30)	(-1.26)
DD_all		0.78	0.83	0.64	0.72	0.75	0.68	0.81	0.78	1.15	0.42	-0.36
		(2.98)	(2.33)	(1.77)	(1.79)	(1.71)	(1.52)	(1.67)	(1.56)	(1.83)	(0.59)	(-0.59)

Panel B: FF3-adjusted abnormal return												
CAEL	CAR	-0.26	-0.06	-0.07	-0.01	-0.48	-0.05	-0.01	0.06	-0.01	-0.77	-0.51
		(-1.10)	(-0.22)	(-0.25)	(-0.01)	(-1.59)	(-0.17)	(-0.05)	(0.21)	(-0.01)	(-2.23)	(-1.50)
	NPL	0.51	0.64	-0.13	-0.38	0.01	-0.18	-0.56	-0.55	-0.33	-1.46	-1.97
		(1.86)	(2.68)	(-0.44)	(-1.11)	(0.02)	(-0.64)	(-1.49)	(-1.73)	(-1.18)	(-3.29)	(-4.13)
	RETA	0.06	0.19	0.23	0.10	-0.21	-0.39	0.08	-0.32	-0.33	-0.30	-0.37
		(0.23)	(0.77)	(0.89)	(0.37)	(-0.75)	(-1.08)	(0.23)	(-1.06)	(-1.13)	(-0.75)	(-0.81)
	CATA	-0.11	-0.34	-0.11	-0.13	-0.17	-0.09	-0.09	-0.07	-0.21	-0.03	0.07
		(-0.48)	(-1.07)	(-0.34)	(-0.46)	(-0.58)	(-0.32)	(-0.33)	(-0.24)	(-0.57)	(-0.10)	(0.22)
	Comp	-0.28	0.04	0.11	-0.28	-0.20	-0.14	0.14	-0.07	-0.64	-1.62	-1.33
		(-1.20)	(0.19)	(0.43)	(-0.93)	(-0.73)	(-0.45)	(0.48)	(-0.26)	(-1.80)	(-3.64)	(-2.87)
Bank-Z		0.42	0.08	0.17	-0.06	-0.09	-0.44	-0.57	-0.16	-0.17	-0.80	-1.22
		(1.85)	(0.33)	(0.58)	(-0.25)	(-0.34)	(-1.38)	(-1.67)	(-0.50)	(-0.39)	(-2.12)	(-3.44)
DD_fin		0.05	0.21	-0.43	0.06	-0.25	0.29	-0.24	0.21	0.12	-0.73	-0.77
		(0.21)	(0.80)	(-1.60)	(0.19)	(-0.75)	(0.90)	(-0.67)	(0.56)	(0.30)	(-1.66)	(-1.85)
DD_all		0.16	0.05	-0.14	-0.15	-0.21	-0.31	-0.23	-0.25	-0.07	-0.73	-0.89
		(0.83)	(0.21)	(-0.56)	(-0.57)	(-0.73)	(-1.10)	(-0.74)	(-0.71)	(-0.16)	(-1.25)	(-1.54)

Table 4. Cross-Sectional Regressions of Bank Returns on Financial Distress Measures

This table presents estimation results of the following regression model individual bank stock returns on the financial distress measures by using the pooled regression framework (Panel A) and the Fama and MacBeth (1973) framework (Panel B):

$$\text{Ret}_{i,t} = \beta_0 + \beta_1\text{Distress}_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3\text{BM}_{i,t-1} + \beta_4\text{ILLIQ}_{i,t-1} + \beta_5\text{Beta}_{i,t-1} + \beta_6\text{IVOL}_{i,t-1} + \varepsilon_{i,t},$$

where $\text{Ret}_{i,t}$ is the raw return (in percent) of bank *i* in month *t*; Distress is the financial distress measure; Size is the natural logarithm of the market value of common equities; BM is the book-to-market ratio, respectively; ILLIQ is the Amihud (2002) illiquidity; Beta is the market beta obtained from regressions of the market model using 36 monthly returns available up to month *t*; IVOL is the idiosyncratic volatility, which is the standard deviations of the residuals obtained from regressions of the Fama and French (1993) three-factor model using 36 monthly returns available up to month t. "(−)Distress" is the distress value multiplied by −1 to indicate the greater value the more distressed. "Comp" is the CAEL composite score calculated by the logit model using the four components of CAEL as explanatory variables. Numbers in parentheses indicate t-statistic. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The sample period is January 1996 to December 2015.

Explana.	Model								
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Estimated by the pooled regression				
(−)CAR	-2.15**								-4.27***
	(-2.36)								(-3.15)
NPL		-37.90***							-27.60***
		(-17.98)							(-10.19)
(−)RETA			-3.26***						-0.73
			(-3.48)						(-0.63)
(−)CATA				-1.53***					-1.98***
				(-4.66)					(-4.64)
Comp					-0.23***				0.04
					(-7.25)				(1.06)
(−)Bank-Z						-0.03***			-0.01
						(-4.59)			(-1.32)
(−)DD_fin							-0.14***		-0.06*
							(-5.22)		(-1.68)
(−)DD_all								-0.12***	-0.06***
								(-8.62)	(-3.14)
Size	-0.11***	-0.12***	-0.11***	-0.12***	-0.11***	-0.11***	-0.17***	-0.12***	-0.18***
	(-5.41)	(-5.73)	(-5.32)	(-5.97)	(-5.13)	(-5.05)	(-6.87)	(-6.05)	(-6.78)
BM	0.14***	0.29***	0.15***	0.14***	0.17***	0.15***	0.17***	0.17***	0.28***
	(6.33)	(12.02)	(6.58)	(6.12)	(7.59)	(6.79)	(5.90)	(7.33)	(8.94)
ILLIQ	0.30***	0.31***	0.30***	0.30***	3.03***	0.31***	0.31***	0.30***	3.21***
	(13.37)	(13.66)	(13.40)	(13.35)	(13.33)	(13.45)	(14.06)	(13.54)	(14.27)
Beta	0.38***	0.37***	0.38***	0.36***	0.42***	0.41***	0.54***	0.44***	0.61***
	(5.78)	(5.48)	(5.85)	(5.49)	(6.19)	(6.06)	(7.35)	(6.63)	(7.64)
IVOL	-0.08***	-0.01	-0.07***	-0.08***	-0.08***	-0.08***	-0.04***	-0.07***	0.02*
	(-9.47)	(-0.52)	(-7.76)	(-9.77)	(-8.78)	(-8.19)	(-4.51)	(-7.09)	(1.86)
Constant	2.29***	2.41***	2.24***	2.55***	2.42***	2.22***	2.41***	2.14***	1.64***
	(8.30)	(8.71)	(8.27)	(9.68)	(8.75)	(7.99)	(8.26)	(7.92)	(4.75)
#Obs.	107,430	100,926	107,312	107,412	100,817	100,351	84,762	104,621	74,714
R-squared	0.003	0.006	0.003	0.003	0.004	0.003	0.004	0.004	0.007

Explan. variable	Model (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Panel B: Estimated by the Fama and MacBeth (1973) framework						
(−)CAR	-0.47								-3.62
	(-0.32)								(-0.96)
NPL		-34.68***							-38.28***
		(-6.77)							(-4.02)
(−)RETA			-1.28						-3.03**
			(-0.96)						(-2.28)
(−)CATA				-0.06					-0.44
				(-0.15)					(-0.90)
Comp					-0.30				3.87
					(-0.34)				(1.40)
(−)Bank-Z						-0.03**			-0.03***
						(-2.42)			(-2.71)
(−)DD_fin							0.05		0.12**
							(0.92)		(2.31)
(−)DD_all								0.02	0.05*
								(0.54)	(1.92)
Size	-0.04	-0.06	-0.02	-0.03	-0.05	-0.05	-0.01	-0.03	-0.04
	(-0.69)	(-0.94)	(-0.38)	(-0.42)	(-0.75)	(-0.74)	(-0.19)	(-0.52)	(-0.59)
BM	0.45***	0.58***	0.44***	0.39**	0.39**	0.40***	0.49***	0.38**	0.79***
	(2.87)	(3.74)	(2.85)	(2.52)	(2.45)	(2.60)	(2.77)	(2.44)	(3.98)
ILLIQ	-0.21	0.05	-0.21	-0.20	-3.33	-1.05	-0.67	-0.73	-48.78*
	(-0.17)	(0.03)	(-0.17)	(-0.16)	(-0.23)	(-0.68)	(-0.37)	(-0.56)	(-1.80)
Beta	0.20	0.22	0.21	0.21	0.20	0.27*	0.29*	0.21	0.27*
	(1.30)	(1.43)	(1.34)	(1.34)	(1.30)	(1.70)	(1.95)	(1.40)	(1.79)
IVOL	-0.08***	-0.04	-0.08***	-0.08***	-0.07***	-0.08***	-0.06***	-0.08***	-0.03
	(-3.12)	(-1.55)	(-3.16)	(-3.16)	(-2.75)	(-2.96)	(-2.60)	(-3.55)	(-1.30)
Constant	1.53*	1.78**	1.32*	1.46*	1.65**	1.51*	1.20	1.62**	0.59
	(1.89)	(2.24)	(1.65)	(1.84)	(2.05)	(1.87)	(1.48)	(2.07)	(0.57)
#Month	240	240	240	240	240	240	240	240	240
Adj R^2	0.088	0.094	0.088	0.086	0.097	0.089	0.096	0.089	0.153

Table 5. Summary Statistics of Portfolios Sorted on NPL

This table presents time-series averages of the characteristic variables in the portfolios sorted on NPL. Portfolios are constructed by assigning all bank firms each month into one of five quintile portfolios according to the magnitude of NPL from the highest (P5) to the lowest (P1) NPL portfolios. Raw returns are monthly value-weighted portfolio returns. Size is the market value of common equities. Illiquidity is computed as in Amihud (2002). Market beta is the time-series average of the slope coefficient estimates obtained from month-by-month regressions of the market model using 36 rolling-over monthly returns. Idiosyncratic volatility is the time-series average of the standard deviations of the residuals obtained from month-by-month regressions of the Fama and French (1993) three-factor model using 36 rolling-over monthly returns. NITA is the ratio of net income to total assets. DCBS (daily cost to borrow score) is an integer categorization ranging from 1 (low cost; easy to borrow) to 10 (high cost; hard to borrow), which is computed by Markit for each stock-day based on actual lending fees. FEE is the indicative fee observed on the last trading day of each month from the Markit database, which is paid by the borrower for a new stock loan. IOR is measured as the ratio of shares owned by institutions to the total number of shares outstanding. OS is a dichotomy variable that equals 1 if the stock has exchange-traded options and zero if the stock does not. The sample period is January 1996 to December 2015 except for DCBS and FEE, which are available from January 2004 to December 2015.

Variable	NPL-sorted portfolios					
	1(low NPL)	2	3	4	5(high NPL)	High−Low
NPL (%)	0.24	0.58	0.92	1.46	3.28	3.04
Raw excess return (%)	1.15	0.53	0.73	0.17	0.30	-0.86
Standard deviation (%)	6.78	6.90	7.28	8.29	11.82	5.03
Size ($b)	2.01	2.66	2.83	1.21	0.44	-1.57
Book-to-market	0.73	0.76	0.83	1.01	1.81	1.08
Illiquidity	4.29	3.84	5.31	6.59	16.2	11.91
Market beta	0.55	0.60	0.62	0.60	0.63	0.08
Idiosyncratic vol.	6.29	6.39	6.80	7.49	9.74	3.45
NITA (%)	0.23	0.24	0.22	0.16	0.04	-0.19
DCBS	1.35	1.38	1.39	1.46	1.98	0.63
FEE (%)	1.12	1.23	1.37	1.47	4.09	2.97
Instit ownership ratio	0.30	0.31	0.31	0.28	0.21	-0.09
Option status	0.18	0.22	0.23	0.17	0.10	-0.08

Table 6. Abnormal Returns of Portfolios Sorted on Financial Distress

This table presents abnormal returns (in percent) of the portfolios sorted on NPL, which are computed as an intercept estimate ($\hat{\alpha}_p$) from regressing monthly excess returns on the factors of each model over the whole sample period. Portfolio excess returns (in percent) are value-weighted. FF3 and FF5 indicate the Fama and French (1993, 2015) three- and five-factor models, respectively, and HXZ is the Hou, Xue, and Zhang (2015) q-factor model, including four factors related to the market, size, investment, and ROE. Numbers in parentheses indicate t-statistic. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Model	NPL-sorted portfolio					High–Low
	1 (low NPL)	2	3	4	5 (high NPL)	
	Panel A: Whole period (January 1996 – December 2015)					
Excess return	1.15***	0.53	0.73*	0.17	0.30	-0.86***
	(3.28)	(1.11)	(1.71)	(0.36)	(0.62)	(-2.73)
CAPM	0.68***	-0.08	0.27	-0.38	-0.31	-0.99***
	(2.64)	(-0.23)	(0.75)	(-1.00)	(-0.83)	(-3.22)
FF3	0.51**	-0.34	0.02	-0.63**	-0.59*	-1.10***
	(2.36)	(-1.19)	(0.08)	(-1.98)	(-1.91)	(-3.65)
FF5	0.56**	0.08	0.17	-0.51	-0.29	-0.84***
	(2.43)	(0.27)	(0.60)	(-1.53)	(-0.91)	(-2.71)
HXZ	0.27	-0.40	-0.19	-0.79**	-0.71*	-0.98***
	(1.08)	(-1.11)	(-0.57)	(-2.14)	(-1.94)	(-3.05)

Table 7. Abnormal Returns of Portfolios Sorted on Financial Distress and Short-Sale Constraints

This tables presents abnormal returns (in percent) of the portfolios, which are constructed by assigning all banks each month to one of 10 (=5×2) portfolios based on the intersection of the five break-points of NPL and the two-break points of the short-sale constraint proxy variable. The proxy variables for short-sale constraints are Markit's daily costs to borrow score (DCBS) and indicative fee (FEE), institutional ownership ratio (IOR), and option status (OS). The two-break points of each short-sale constraint proxy variable are determined as follows. (i) DCBS is an integer categorization ranging from 1 (low cost; easy to borrow) to 10 (high cost; hard to borrow). If the DCBS of a bank is greater than 1 (equal to 1), it is assigned into high (low) DCBS portfolio; (ii) Indicative fee is the fee paid by the borrower for a new stock loan. The high (low) FEE portfolio includes top (bottom) 40% percent of bank stocks sorted on indicative fee; (iii) The low IOR (high IOR) portfolio includes the bottom (top) 30 percent of banks sorted on IOR; (iv) Option status indicates whether the bank stock has exchange-traded options trading prior to the first day of the month, No or Yes. Abnormal returns are computed as an intercept estimate ($\hat{\alpha}_p$) from regressing monthly excess returns of each portfolio on the Fama and French (1993) three factors by using monthly observations over the whole sample period January 1996 to December 2015. Numbers in parentheses indicate t-statistic. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

SS constraint-sorted portfolio	NPL-sorted portfolio					High–Low
	1 (low NPL)	2	3	4	5 (high NPL)	
	Panel A: Daily costs to borrow score (DCBS)					
High DCBS	-0.21	0.28	-0.25	-1.02**	-2.84***	-2.62***
	(-0.49)	(0.71)	(-0.58)	(-1.99)	(-3.65)	(-3.25)
Low DCBS	-0.15	-0.20	-0.08	-0.79	-0.64	-0.50
	(-0.51)	(-0.52)	(-0.23)	(-1.54)	(-1.62)	(-1.27)
High–Low	-0.07	0.48	-0.17	-0.23	-2.19***	-2.12**
	(-0.13)	(0.87)	(-0.31)	(-0.32)	(-2.51)	(-2.37)
	Panel B: Indicative fee (FEE)					
High FEE	-0.08	0.66	-0.08	-0.38	-2.67***	-2.59***
	(-0.24)	(1.44)	(-0.19)	(-0.80)	(-4.15)	(-3.97)
Low FEE	-0.04	-0.30	0.21	-0.80	-0.54	-0.50
	(-0.14)	(-0.70)	(0.56)	(-1.37)	(-1.42)	(-1.14)
High–Low	-0.04	0.96	-0.29	0.42	-2.13***	-2.09***
	(-0.08)	(1.53)	(-0.52)	(0.55)	(-2.85)	(-2.67)
	Panel C: Institutional ownership ratio (IOR)					
Low IOR	0.63**	0.54**	0.43	0.06	-0.89**	-1.52***
	(2.17)	(2.45)	(1.42)	(0.14)	(-2.07)	(-3.62)
High IOR	0.42	-0.41	-0.12	-0.43	-0.16	-0.57
	(1.52)	(-1.50)	(-0.39)	(-1.42)	(-0.46)	(-1.56)
Low–High	0.22	0.95	0.55	0.49	-0.73	-0.95*
	(0.54)	(2.71)	(1.27)	(0.90)	(-1.34)	(-1.69)
	Panel D: Option status					
No	0.55***	0.26	0.24	-0.25	-0.88***	-1.44***
	(3.15)	(1.11)	(1.26)	(-1.09)	(-3.15)	(-5.24)
Yes	0.20	-0.52	0.00	-0.68*	-0.32	-0.51
	(0.76)	(-1.57)	(0.00)	(-1.92)	(-0.96)	(-1.54)
No–Yes	0.36	0.78*	0.24	0.43	-0.57	-0.93**
	(1.14)	(1.93)	(0.66)	(1.02)	(-1.31)	(-2.14)

Table 8. Pooled Regression Estimates

This table presents the coefficient estimates of the following pooled regression model:

$$\mathrm{Aret}_{i,t} = \beta_0 + \beta_1 \mathrm{NPL}_{i,t-1} + \beta_2(\mathrm{NPL}_{i,t-1} \times \mathrm{Crisis}) + \beta_3 \mathrm{Cost}_{i,t-1} + \beta_4(\mathrm{NPL}_{i,t-1} \times \mathrm{Cost}_{i,t-1}) + \beta_5(\mathrm{NPL}_{i,t-1} \times \mathrm{Cost}_{i,t-1} \times \mathrm{Crisis}) + \mathrm{Z}_{i,t-1} + \mathrm{Year}_t + e_{i,t-1},$$

where $\mathrm{Aret}_{i,t}$ is the abnormal return of firm i at month t, which is the sum of the intercept estimate and residuals obtained from regressing the excess monthly returns of bank i on the Fama and French (1993) three factors; $\mathrm{NPL}_{i,t-1}$ is the non-performing loan divided by total assets of bank i at month t-1; $\mathrm{Cost}_{i,t-1}$ is the stock loan cost of bank i at month t-1, which is either DCBS (daily costs of borrowing score) or FEE (indicative fee); Crisis is a dummy variable, which equals 1 if month t is included in the financial crisis period February 2007 to April 2011 and zero otherwise. Control variables, $\mathrm{Z}_{i,t-1}$, are as follows. ILLIQ is the Amihud (2002) illiquidity; Beta is the market beta obtained from regressions of the market model using 36 monthly returns available up to month t. IVOL is the idiosyncratic volatility, which is the standard deviations of the residuals obtained from regressions of the Fama and French (1993) three-factor model using 36 monthly returns available up to month t. NITA indicates the ratio of net income to total assets. Year is the year dummy variable. Numbers in parentheses indicate t-statistic. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Explanatory variable	Coeff-icient	Model (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NPL	β_1	-43.04***	-10.59***	-0.70	0.44	7.20*	2.21	2.31	-0.75	5.19	1.64
		(-16.04)	(-2.80)	(-0.17)	(0.10)	(1.69)	(0.54)	(0.43)	(-0.17)	(0.90)	(0.34)
NPL×Crisis	β_2		-57.66***	-61.44***	-59.58***	-58.52***	-58.65***	-36.10***	-53.47***	-31.22***	-48.06***
			(-12.18)	(-12.08)	(-11.69)	(-11.46)	(-11.49)	(-5.37)	(-9.78)	(-4.46)	(-8.40)
DCBS	β_3			-0.17***		-0.03		0.08		0.11**	
				(-4.98)		(-0.76)		(1.61)		(1.99)	
FEE	β_3				-5.67***		-1.38		-1.76		-1.13
					(-7.40)		(-0.83)		(-1.06)		(-0.62)
NPL×DCBS	β_4					-2.98***		-2.33		-2.66*	
						(-6.06)		(-1.60)		(-1.74)	
NPL×FEE	β_4						-67.26***		-18.66		-24.81
							(-2.91)		(-0.63)		(-0.80)
NPL×Crisis×DCBS	β_5							-7.18***		-6.98***	
								(-4.90)		(-4.66)	
NPL×Crisis×FEE	β_5								-62.12***		-60.61**
									(-2.65)		(-2.54)
Control variables											
ILLIQ										0.90	0.90
										(1.55)	(1.55)
Beta										0.22**	0.21**
										(2.43)	(2.32)
IVOL										-0.01	-0.01
										(-0.77)	(-0.64)
NITA										28.37***	30.23***
										(3.50)	(3.74)
Constant	β_0	0.53***	0.35***	0.58***	0.41**	0.24	0.39**	0.30*	0.41**	0.12	0.24
		(3.96)	(2.59)	(3.34)	(2.31)	(1.34)	(2.28)	(1.68)	(2.37)	(0.58)	(1.24)
Year dummy		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations		66,997	66,997	55,799	55,799	55,799	55,799	55,799	55,799	51,263	51,263
R-square		0.016	0.018	0.020	0.020	0.020	0.020	0.021	0.020	0.021	0.020

Table A1. Delisting reasons

CRSP delisting code (DLSTCD)	Delisting reasons
560	Delisted - insufficient capital, surplus, and/or equity.
552	Delisted - price fell below acceptable level.
580	Delisted - delinquent in filing, non-payment of fees.
584	Delisted - does not meet exchange's financial guidelines for continued listing.
561	Delisted - insufficient (or non-compliance with rules of) float or assets.
574	Delisted - bankruptcy, declared insolvent.
500	Stopped trading - reason unavailable.
550	Delisted - insufficient number of market makers.
570	Delisted - company request (no reason given).
520	Stopped trading - trading Over-the-Counter.
400-499,500, 520-599	Delisted/Liquidated - all other reasons

Table A2. Number of U.S. Firms in Bankruptcy and Financial Failure

This table presents the number of bank and non-bank firms listed on the CRSP database that are in bankruptcy and failure. Firms in bankruptcy (in failure) are defined as the ones that are delisted due to financial reasons of delisting code 574 (the other delisting codes). Explanations for the delisting codes are in Appendix Table 1. Bank firms are defined as firms with the first two-digit header SIC codes 60 or historical SIC code 6712. Non-bank firms includes all firms listed on the CRSP database except for bank firms. Numbers in parentheses indicate the portion of the firms in percentage relative to all firms.

Year	Non-bank firms					Bank firms				
	All	Failures		bankruptcies		All	Failures		bankruptcies	
1996	7245	159	(2.19)	8	(0.11)	761	2	(0.26)	0	(0.00)
1997	7361	219	(2.98)	10	(0.14)	793	2	(0.25)	0	(0.00)
1998	7094	365	(5.15)	23	(0.32)	855	7	(0.82)	0	(0.00)
1999	6787	349	(5.14)	20	(0.29)	846	0	(0.00)	0	(0.00)
2000	6424	276	(4.30)	34	(0.53)	817	3	(0.37)	0	(0.00)
2001	5778	411	(7.11)	45	(0.78)	768	2	(0.26)	0	(0.00)
2002	5104	324	(6.35)	48	(0.94)	729	5	(0.69)	0	(0.00)
2003	4700	241	(5.13)	27	(0.57)	713	7	(0.98)	0	(0.00)
2004	4511	104	(2.31)	15	(0.33)	700	7	(1.00)	0	(0.00)
2005	4484	133	(2.97)	12	(0.27)	668	13	(1.95)	0	(0.00)
2006	4410	84	(1.90)	2	(0.05)	658	5	(0.76)	0	(0.00)
2007	4406	82	(1.86)	2	(0.05)	641	8	(1.25)	0	(0.00)
2008	4142	150	(3.62)	17	(0.41)	601	18	(3.00)	0	(0.00)
2009	3908	201	(5.14)	38	(0.97)	561	33	(5.88)	6	(1.07)
2010	3753	100	(2.66)	10	(0.27)	520	26	(5.00)	9	(1.73)
2011	3613	78	(2.16)	9	(0.25)	488	19	(3.89)	1	(0.20)
2012	3496	82	(2.35)	13	(0.37)	456	14	(3.07)	1	(0.22)
2013	3486	53	(1.52)	8	(0.23)	420	4	(0.95)	0	(0.00)
2014	3590	46	(1.28)	9	(0.25)	405	0	(0.00)	0	(0.00)
2015	3635	65	(1.79)	14	(0.39)	391	3	(0.77)	0	(0.00)
Average	4896	176.1	(3.60)	18.2	(0.37)	639	8.9	(1.39)	0.85	(0.13)

Table A3. Estimation Results of the Logit Model for Bankruptcy and Financial Failure

This table presents estimation results of the pooled logit model for bankruptcy and financial failure using the components of CAEL as explanatory variables. The model to be estimated is

$$P_{t-1}\left(Y_{i,t-1+K} = 1\right) = 1/\left[1 + \exp\left(-\alpha - \beta X_{i,t-1}\right)\right],$$

where $Y_{i,t-1+K}$ is a dichotomy variable which equals 1 if bank *i* is in bankruptcy or financial failure over the next *K* months (forecasting horizon) in month t-1 and zero otherwise, and *X* is a vector of explanatory variables, which are the components of CAEL; they are CAR (capital adequacy ratio; equity to total assets), NPL (non-performing loan assets to total assets), RETA (retained earnings to total assets), and CATA (cash and due, U.S. Treasury securities and net federal funds to total assets). Numbers in parentheses indicate t-statistic. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The sample period is January 1996 to December 2015.

Explanatory	Forecasting horizon (K)			
variable	3 months	6 months	9 months	12 months
CAR	-28.47***	-21.13***	-18.30***	-15.27***
	(-7.46)	(-6.30)	(-6.41)	(-6.06)
NPL	15.18***	16.67***	17.71***	16.90***
	(14.44)	(14.76)	(13.24)	(11.40)
RETA	-3.21	-3.37*	-2.29	-1.10
	(-1.45)	(-1.66)	(-1.14)	(-0.55)
CATA	-0.70	-0.61	-1.65*	-0.90
	(-0.76)	(-0.68)	(-1.70)	(-0.98)
Constant	-4.73***	-5.17***	-5.31***	-5.55***
	(-15.55)	(-18.25)	(-20.97)	(-23.78)
Observations	119,451	119,068	118,670	118,266
Pseudo R^2	0.157	0.116	0.0934	0.0596

Table A4. Definitions of Variables

CAR	Capital adequacy ratio; equity to total assets
NPL	Non-performing loan assets to total assets
RETA	Retained earnings to total assets
CATA	Cash or cash equivalents to total assets
Comp	Composite score calculated by the logit model using the four components of CAEL (CAR, NPL, RETA, CATA) as explanatory variables.
NITA	Net income to total assets
Bank Z-score	Measure of probability of bank insolvency, defined as $(\mu_{ROA} + \mu_{CAP})/\sigma_{ROA}$, where μ_{ROA} and μ_{CAP} are the averages of return on assets (ROA) and capital ratio (CAP), defined as the ratio of equities to total assets, respectively, and σ_{ROA} is the standard deviation of ROA
DD_all	Distance-to-default with the default point equal to short-term debt + 0.5×long-term debt
DD_fin	Distance-to-default with the default point equal to short-term debt + 0.5×long-term debt + δ×other liabilities, where δ is a parameter to adjust for other liabilities and is estimated using an MLE method.
DCBS	Daily Cost to Borrow Score provided by Markit; an integer categorization ranging from 1 (low cost; easy to borrow) to 10 (high cost; hard to borrow)
FEE	Indicative fee, which is paid by the borrower for a new stock loan
IOR	Institutional ownership ratio; the ratio of shares owned by institutions to the total number of shares outstanding
ILLIQ	The Amihud's (2002) illiquidity measure, which is defined as the time-series average of absolute daily returns divided by daily dollar trading volume over the past one year ending in June of year t.
IVOL	Idiosyncratic volatility, which is measured as the standard deviations of the residuals obtained from regressing monthly excess returns on the Fama and French (1993) three factors using 36 monthly returns available up to month t.