Capital Structure and Monitoring Bank Failure

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This paper attempts to identify the financial symptoms preceding the failure of FDIC insured banks. It also examines the validity of proposed common principal factors that mimick CAMELS to detect meaningful signals prior to the bank failure. From empirical tests, this study finds that our mimicking factors indicate agency problem and large influx of loan size driving undesirable choice of capital structure, and that those mimicking factors are useful indicators to monitor bank performance and to detect the likelihood of bank failure.

INTRODUCTION

The banking system is a key vehicle to maintain the economy on a sound footing. As we observed in the recent 2008 financial crisis, the failure of a bank may trigger risk contagion that spreads to other banks or even the entire financial industry within a short period of time. Thus, the entire financial industry may be swiftly endangered. Therefore, it is very important for federal supervisors and risk managers in each bank to identify and monitor risks effectively.

Several studies suggest that one plausible source of banking risk is an imbalance of capital structure. While Modigliani and Miller (1958, 1963) argue that the value of firms is not irrelevant for capital structure in a perfect capital market, it is actually related to debt and equity structure in the real world. Indeed, Kahane (1977) suggests that there is a negative relationship between capital restriction (i.e. restriction to financial leverage and a composition of asset and liabilities) and the likelihood of insolvency for a bank. Gonzalez (2004) finds that reducing regulatory restrictions induces greater risk-taking in banks. Furlong and Keely (1998) argue that more stringent restrictions are needed to reduce risk-taking because simple capital restriction cannot diminish risk exposure in banks. However, Blum (1999) argues the capital adequacy rule may increase a bank's risk due to leverage effect. In other words, leveraging capital is the only way to increase risk if a highly regulated bank cannot increase equity.

Banking is closely tied to the public interest. As a result, banks are highly regulated to protect public savings, to enhance transparency in financial system, to control money supply and credit, and to monitor bank failures. The U.S. federal government regularly examines banks to promote sound banking and to reduce moral hazard in FDIC's business as suggested by Buser, Chen, and Kane (1981). To monitor the financial condition of banks, federal banking supervisors (the Federal Reserve, the FDIC, and the OCC) have employed the CAMELS rating method that focuses on key factors that highlight a bank's financial condition: Capital Adequacy, Asset Quality, Management, Earnings, Liquidity, and Sensitivity to Market Risk.[1] In short, the CAMELS approach yields summary measures of the private supervisory information gathered during the on-site examination of banks. However, federal banking supervisors do not release these ratings to the public because of the likelihood of bank-runs if they are released. Nevertheless, researchers have investigated the validity of CAMELS. Barker and Holdworth (1993) show that CAMELS ratings are useful to identify and predict bank failure. Cole and Gunther (1998) agree that CAMELS ratings are useful but suggest that they decay very rapidly. Hirtle and Lopez (1999) find that CAMELS ratings provide good information on current bank conditions. According to Lopez (1999), CAMELS contains information useful to both the supervisory and public monitoring of commercial banks. During the bailout of the U.S financial system after the 2008 financial meltdown, the US treasury used CAMELS as a yard stick to identify banks that qualified for the bailout. Thus, CAMELS is the source of standard measures used by US banking regulatory agencies to evaluate the financial soundness of a bank.

The CAMELS process requires an on-site examination that is regarded as the best tool to evaluate a bank's financial condition. However, due to budget and other constraints, on-site examination is not allowed more than once every 12 to 24 months except for banks that are rated as more than average in performance (a score of 3). Cole and Gunther (1998) point out that the condition of banks may worsen since the last on-site examination. Since auditing and regulation prevent moral hazard and help maintain bank performance, more frequent monitoring is advantageous (Jensen and Meckling, 1976). However, it is not feasible for banks to maintain good standing if they undergo on-site CAMELS examination more than once in the stipulated period of time.

To accommodate frequent monitoring and to cope with shortcomings of on-site examination, -researchers have proposed various off-site monitoring methods. Whalen and Thomson (1988) and Bellovary, Giacomino and Akers (2007) summarize two types of off-site monitoring: one approach is fundamental analysis using accounting information (balance sheet and income statement data) and relevant news regarding banks; the other approach is multivariate statistical analysis such as linear discriminant analysis, logistic regression, and survivorship analysis (Altman, 1968; Beaver, 1966; Meyer and Pifer, 1970; Sinkey, 1975; Hanweck, 1977; Martin, 1977; Santomero and Vinso, 1977; Rose and Kolari, 1985; Lane, Looney and Wansley, 1986; Allen and Rose, 2006; Daniel, 2007) or artificial intelligent method such as decision tree, neural networks, and genetic algorithm (Lee, Han and Kwon, 1996; Foster and Stine, 2004; Kim, Street, Russell and Menczer, 2005) to identify problem banks and non-problem banks with the help of financial ratios. Because all the information underlying CAMELS components remain confidential, the off-site monitoring models are only associated with default detection models using financial information. Therefore, this paper studies the symptoms of failure of US FDIC insured banks in order to suggest an off-site monitoring model that potentially overcomes the shortcomings of the on-site CAMELS rating method.

Our research attempts to develop common factors that replicate CAMELS. Using a factor analytical model (West, 1985), our paper tests if our replicating factors explain the capital structure of banks, and if they are appropriately employed as an off-site monitoring tool. We also examine the sensitivity of our factors to capital structure, and test their ability to predict failed banks and non-failed banks.

The remaining sections of this paper are organized as follows: Section 2 outlines our empirical method. Section 3 describes data structure and variables used in our empirical analysis. Section 4 explains the results of empirical tests for our research hypotheses. Section 5 provides concluding remarks.

EMPIRICAL METHODOLOGY

Factor Construction and Model Specifications

We attempt to identify common principal factors that succinctly explain banking performance applying principal component analysis (PCA). As Johnson and Wichern (2001) observe, PCA is concerned with explaining the variance-covariance structure of a set of variables through linear combinations of these variables.

Algebraically, principal components or principal factors are linear combination of the *p* number of random variables $X_1, X_2, \ldots, X_p$. Let the random vector $\mathbf{X}' = [X_1, X_2, \ldots, X_p]$ have the covariance matrix $\boldsymbol{\Sigma}$ with eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$. Let the i^{th} eigenvector $\mathbf{e_i}' = [e_{i1}, e_{i2}, \ldots, e_{ip}]$. Then the i^{th} principal component, or factor, denoted by F_i, is given by[2]

$$F_i = \mathbf{e_i'X} = e_{i1}X_1 + e_{i2}X_2 + \cdots + e_{ip}X_p, \qquad i = 1,2,\ldots, p \tag{2}$$

and

$$\mathrm{Var}(F_i) = \mathbf{e_i'\Sigma e_i} = \lambda_i \qquad i = 1,2, \ldots, p \tag{3}$$

$$\mathrm{Cov}(F_i, F_k) = \mathbf{e_i'\Sigma e_i} = 0 \qquad i \neq k \tag{4}$$

With extracted factors, we specify a research model in equation (5) to test our two hypotheses. The first hypothesis asks if the chosen factor model captures an abnormal pattern of debt relative to equity prior to the bank failure; the second hypothesis asks if our chosen factors are appropriate ones to predict bank failure.

Let the vector of PCA factor $\mathbf{F} = [\mathbf{1}, \mathbf{F_1}, \mathbf{F_2}, \ldots, \mathbf{F_p}]$ where $\mathbf{F_1} = [F_{11}, F_{12}, \ldots, F_{1N}]$, which is *N* number observations. Let the vector of beta $\mathbf{B}' = [\beta_0, \beta_1, \beta_2, \ldots, \beta_p]$ and then

$$y = \mathbf{FB} = \beta_0 + \beta_1 F_1 + \beta_1 F_2 + \cdots + \beta_p F_p \tag{5}$$

where y represents a dependent variable. In our test, it indicates debt to equity ratio or a binary event (where 1 indicates bank failure and 0 represents non-failure). To examine if our factors are appropriate for predicting bank failure, we employ both logistic regression and linear discriminant analysis (see Altman, 1968). As Kolari, Glenno, Shin and Caputo (2004) document, there is no difference between multivariate statistical models and artificial intelligent methods that are tasked to predict failed and non-failed banks. We examine results based on linear discriminant method (Altman, 1968; Beaver, 1966; Meyer and Pifer, 1970; Deakin, 1972; Espahbodi, 1991) and logistic model (Martin, 1977; Hauser, 2001; Jones and Henser, 2004). The logistic regression model is written as

$$\log \frac{p(F)}{1-p(F)} = \beta_0 + \beta_1 F_1 + \cdots + \beta_p F_p \tag{6}$$

where *p(F)* is a linear function of *F*. Solving for *p*, this tells us

$$p(F) = \frac{\exp(\beta_0 + \beta_1 F_1 + \cdots + \beta_p F_p)}{1 + \exp(\beta_0 + \beta_1 F_1 + \cdots + \beta_p F_p)} = \frac{1}{1 + \exp(-\beta_0 - \beta_1 F_1 - \cdots - \beta_p F_p)} \tag{7}$$

Based on this linear classification, we predict y = 1 (bank failure) when $p \geq 0.5$ and predict y = 0 (nonbank failure) when $p < 0.5$.

DATA

We obtain quarterly data on banks listed in the Federal Deposit Insurance Corporation (FDIC)'s Statistics on Depository Institution (SDI) database. For our research purposes, we gather quarterly performance and condition reports, in addition to asset and liability reports for the period December 2000 through December 2013. We use the list of failed banks as of December 2013 that shows that the number of failed banks is 513, representing the cumulative number of failures since October 1, 2000. To merge these three datasets by each bank, we use each bank's certificate number as a matching key.

TABLE 1
THE NUMBER OF FAILED BANKS

Year	Failed Banks	Percentage
2000	2	0.39
2001	4	0.78
2002	11	2.13
2003	3	0.58
2004	4	0.78
2007	3	0.58
2008	25	4.84
2009	140	27.13
2010	157	30.43
2011	92	17.83
2012	50	9.88
2013	24	4.65

Note. The FDIC's failed bank list shows all FDIC-insured banks that have failed since October 1, 2000. As of July 18, 2010, there are a total of 297 reported failed banks. Of those 255 failures have occurred since the September 15, 2008 Lehman Brothers bankruptcy. However, this only represents tips of the entire picture. More specifically, as of March 5, 2009, the FDIC reported a total of 8,284 insured institutions whereas as of July 15, 2010 there were a total of 7,836 insured institutions, implying that a total of 448 (8,284 minus 7,836) institutions have failed, closed, or been acquired since March 5, 2009. This figure shows 5.4% of the FDIC insured banks as of March 5, 2009.

Failed Banks

The FDIC's failed bank list identifies all FDIC-insured banks that have failed since October 1, 2000. As of July 18, 2010, this number amounted to 297. Of these, 255 failures occurred since September 15, 2008 – the bankruptcy date for Lehman Brothers. However, this FDIC's failed bank list does not capture all the available information. More specifically, as of March 5, 2009, the FDIC reported a total of 8,284 insured institutions. As of July 15, 2010, the FDIC reported a total of 7,836 insured institutions. Therefore, we conjecture that a total of 448 (8,284 minus 7,836) institutions failed, closed, or were acquired since March 5, 2009, representing 5.4% of the FDIC insured banks as of March 5, 2009.

Table 1 summarizes the number of failed insured banks for each year. Since September 2008 when Lehman Brothers filed for bankruptcy, the number of failed banks increased substantially until the year 2010: from 25 in 2008 to 157 in 2010. After 2010, the number of failed banks steadily decreased to 24 in 2013, so it appears that the banking sector almost recovered to normalcy in 2013.

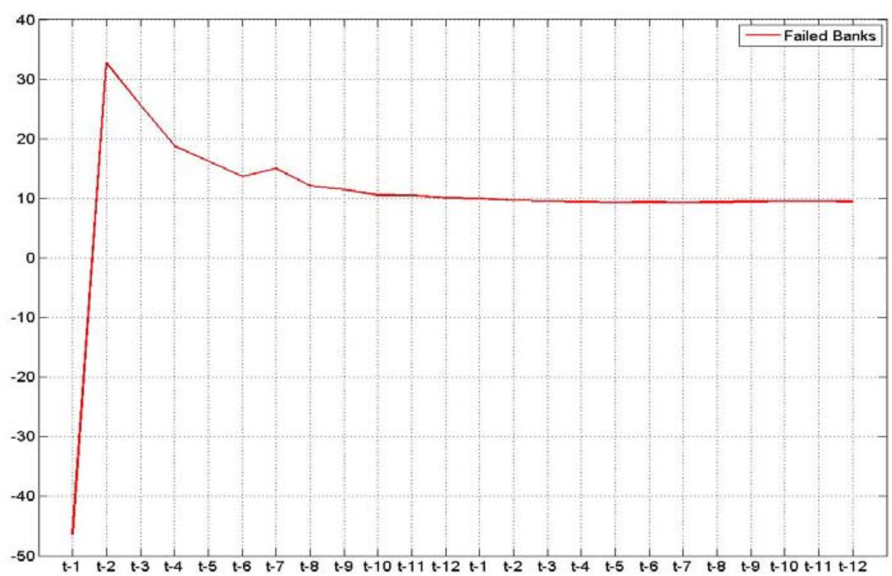
FDIC Asset & Liability, and Performance Condition Reports

To examine the relation between leverage and banks performance, and to develop our factor based model, we use two quarterly reports that explain the behavior and performance of FDIC-insured banks: asset and liability reports; and performance and condition reports from December 2000 to December

2013. Because the dataset for the failed insured banks is available from December 2000, we use this data period as the time window for our analysis.

FIGURE 1
LEVERAGE RATIO FOR NON-FAILED AND FAILED BANKS

FIGURE 2
LEVERAGE RATIO FOR FAILED BANKS BEFORE THE FAILURE



Leverage Exposures for Banks

From asset and liability quarterly reports, we analyze leverage ratio, or debt to equity ratio, using the conventional equation. That is total liability (SDI item: liab) divided by shareholder's equity (SDI item: eqtot). In general, higher leverage indicates that a focal bank carries a bigger debt burden in that principal and interest payments are a large portion of cash flows. Such a bank is highly likely to fail following an increase in interest rates or a financial meltdown. On the other hand, a bank with low leverage is less likely to fail under similar circumstances.

Figure 1 depicts the quarterly trend of debt relative to equity ratio for non-failed banks and failed banks from the year 2000 to 2013. Unlike the solid horizontal-over-time line that represents leverage ratio for non-failed banks, the dotted line for failed banks is volatile. This fluctuation manifests from the first quarter of 2009 and then increases significantly over time. Figure 2 displays debt to equity ratio for failed banks over 12 months tracking history before the failure event. It shows that, on average, the leverage for failed banks reaches its peak at *t-2*. In other words, failed banks continued to lever up over 30 times against equity until *t-2*. At *t-1* their mean of leverage ratio turned negative and eventually they went to default. In summary, these figures suggest that the 2008 collapse of Leman Brothers triggered a risk contagion in the banking industry that drove failed banks to substantially lever their financing sources before they failed, and that the leverage ratio is a useful measure that provides insights about failed banks.

Research Variables and PCA Components

To examine the relation between banks performance and their choice of financing resources, we use financial ratios that focus on bank performance and financial condition. In general, financial ratios were developed by researchers to analyze a firm's credit worthiness. Several researchers have suggested a variety of financial ratios, but there is no widely accepted taxonomy of such ratios. Although liquidity and profitability ratios are widely used (Horrigan, 1965), these two groups of financial ratios are not sufficient for identifying non-failed and failed banks. Because on-site monitoring considers six categories of ratios, we select the most appropriate financial ratios using FDIC data and statistical methods.

The number of FDIC selected financial ratios appears too large to clearly identify the relation between performance and failure of banks. We therefore explore the following data reduction approaches: exploratory factor analysis (EFA) and principal component analysis (PCA). Using VARIMAX rotation, we reduce 35 variables (see Table A.2 in Appendix) to nine variables as shown in Table 2.[3] These nine variables are further classified into five categories. In other words, we identify the respective five dimensions that can be named capital adequacy, asset quality, management experience, earnings, and liquidity respectively, such that those factors are highly associated with the CAMELS (Capital adequacy; Asset quality; Management experience; Earnings; Liquidity; Sensitivity to market) rating method commonly used to examine bank performance. Accordingly, we include market sensitivity ratio, total securities divided by total asset, in our analysis.

TABLE 2
FDIC PERFORMANCE AND CONDITION RATIOS

Classification	FDIC Data Item	Description
Capital Adequacy	*rbc1aaj/rbc1aaj*	Core capital ratio
	rbc1rwaj/rbc1rwaj	Tier 1 risk-based capital ratio
	rbcrwaj/rbcrwaj	Total risk-based capital ratio
Asset Quality	*lnatresr/lnatresr*	Loss allowance to loans
	nperfv/nperfv	Noncurrent assets plus other real estate owned to assets
Management Experience	*nonixay/nonixayq*	Noninterest expense to average assets
Earning	*roe/roeq*	Return on Equity (ROE)
Liquidity Ratio	*lnlsdepr/lnlsdepr*	Net loans and leases to deposits
	idlncorr/idlncorr	Net loans and leases to core deposits
Sensitivity to Market Ratio	*sc/asset*	Total securities over total assets

Note. This table describes ten financial ratios for the performance and condition of the FDIC insured banks.

TABLE 3
SELECTION OF NUMBER OF FACTORS

Num. of Factors	Eigenvalues	Percent of Variance Explained	Cum. % of Variance Explained
1	4.44	0.15	0.15
2	3.93	0.13	0.28
3	2.96	0.10	0.38
4	2.56	0.08	0.46
5	2.00	0.07	0.53
6	1.94	0.06	0.59

Note. This table presents how we select the number of factors based on eigenvalues. The second column shows the respective eigenvalues for each factors. The third column shows the explicability of variance for each corresponding factor. The last column displays the cumulative percent of variance explained in the second column.

On the basis of eigenvalues, we find six principal component factors are able to account for most of the variance of data. To determine the number of factors, several strategies are available, such as Kaiser's stopping rule, scree test, number of non-trivial factors, and percent of cumulative variance explained. Considering these four, a six factor solution appears most appropriate from an overall perspective. Table 3 presents the respective eigenvalues and their variance explicability for each principal factor. Initially, when considering the relationship between eigenvalues and the number of factors, a five factor solution appears appropriate. However, the column for the cumulative percent of variance explained indicates about 59 percent of the variance is accounted for by the six factor model (in contrast to 53 percent of the variance for the five factor model). Thus, six factors appear most suitable. To facilitate comparison with the existing CAMELS rating factors, we label PCA based six factors as PCA-CAMELS hereafter.

We use ten variables as individual indicators of six factors. To analyze the suitability of PCA-CAMELS, we examine if PCA-CAMELS factors explain the substantial variation in debt to equity prior to a bank failure event, and if PCA-CAMELS serves as a common risk factor to identify the risk of bank failure. We also analyze the relationship between the six factors and debt-to-equity ratio and examine whether this suggested model captures signals related to bank failure events. Unlike discriminant analysis, logistic regression does not require normality assumption, so we also report the results from logistic regression analysis.

EMPIRICAL RESULTS

Capital Structure for Failed Banks and Non-Failed Banks

Table 4 summarizes the results of regression of debt to equity ratio on six factors for failed banks and non-failed banks. For failed banks, the slopes of capital adequacy, asset quality, sensitivity to market are negative while the slopes of management experience, earning, and liquidity are positive. The absolute t-statistics for management expense and sensitivity to market are greater than 2.00, indicating failure to reject the null hypothesis. On the other hand, for non-failed banks, the slopes of capital adequacy, management experience, liquidity, and sensitivity to market are negative whereas the coefficients of asset quality and earning are positive. Except for the t-statistic for liquidity, all absolute t-statistics are greater than 2.00, indicating statistical significance at the 95 percent confidence interval. This table showcases substantial differences between failed banks and non-failed banks in their exposure to capital adequacy (for failed and non-failed banks, -10.78 vs. -0.23), management experience (26.8 vs. -0.10), liquidity (55.7 vs. -0.03), and sensitivity to market (-14.2 vs. -0.35). Clearly, the magnitudes of the coefficients for failed banks are much greater than for non-failed banks. For failed banks, our analyses indicate that decreases in capital adequacy, asset quality, and market sensitivity and increases in management expense (management experience) and loan amount (liquidity) trigger a sharp increase in leverage.

TABLE 4
REGRESSION OF LEVERAGE ON PCA-CAMELS FACTORS

	Failed Banks		Non-failed Banks	
	Coefficients	t-statistics	Coefficients	t-statistics
Intercept	14.74	7.24	8.84	289.41
Capital Adequacy	-10.78	-0.53	-0.23	-7.59
Asset Quality	-0.59	-0.72	0.37	11.22
Management Experience	26.8	3.25	-0.1	-3.26
Earnings	0.22	0.32	0.4	12.04
Liquidity	55.07	0.81	-0.03	-1.16
Sensitivity to Market	-14.2	-2.41	-0.35	-11.72
Adjusted R^2	0.26		0.32	

Note. This table reports the results of the regression of debt relative to equity on six PCA-CAMLES factors for failed and non-failed banks. The second and third columns are the regression coefficients and t-statistics for failed banks, respectively. The last two columns are the regression coefficients and t-statistics for non-failed banks, respectively.

Also, this result implies that unless failed banks raise adequate capital and total amount of security (market sensitivity), the excessively negative coefficients for capital adequacy and liquidity point toward negative leverage as depicted in Figure 1. It seems that failed banks encounter agency problem (i.e. moral hazard) because managers of failed banks are likely to sharply increase spending on non-interest expenses before the event of failure. Thus, the findings show that the prominent financial symptoms that precede bank failure are low capital adequacy, low amount of total securities, too much management expense, and sheer increase in loan amount.

PCA-CAMELS and Failed Banks Prediction

Using linear discriminant analysis and logistic regression, we examine whether our CAMELS factors are helpful to identify or predict bank failure events. Table 5 summarizes the linear discriminant function for non-failed banks and failed banks. From these coefficients, we derive Fisher's discriminant function which is specified as $Z = 0.044F_1 - 0.694F_2 + 0.180F_3 + 0.051F_4 + 0.015F_5 + 0.046F_6$. Since the threshold point is -0.236, we classify one into non-failed banks when Z ≤ -0.236 and classify one into failed banks when Z >-0.236. Accordingly, this Fisher's function considers banks with low asset quality as failed banks whereas banks with sufficient asset quality as non-failed banks. The auxiliary test (untabulated) for cross validation points out that the hit ratio, specificity, and sensitivity are 81%, 6.9%, and 96.7%, respectively.

Table 6 reports the results of logistic regression. From the result, the estimated model is specified aslog $\frac{p(F)}{1-p(F)} = -3.47 - 0.10F_1 + 0.24F_2 - 2.70F_3 + 0.00F_4 - 0.18F_5 - 0.60F_6$. Except for the coefficients earning that is almost close to zero, all the p-values for each variable fail to reject the null hypothesis of zero coefficient. It seems unlikely that earning is a critical factor to discern failed banks. Therefore, like the Fisher's function, this model also classifies banks with low asset quality into the failed bank category. The auxiliary test (untabulated) for cross validation suggests that the hit ratio, specificity, and sensitivity are 96%, 2.98%, and 99%, respectively.

In summary, we develop two predictive models based on PCA-CAMELS applying linear discriminant analysis and logistic regression method. We find that the PCA-CAMELS approach contributes useful factors to detect the binary event, failure or non-failure. Potentially, PCA-CAMELS may be one alternative to on-site monitoring to protect against risky events in the banking industry.

TABLE 5
COEFFICIENTS OF LINEAR DISCRIMINANT FUNCTION

	Non-failed Banks	Failed Banks	Fisher's Discriminant Function
Intercept	0.000	-0.236	
Capital Adequacy	0.002	-0.042	0.044
Asset Quality	-0.027	0.667	-0.694
Management Experience	0.007	-0.173	0.180
Earnings	0.002	-0.049	0.051
Liquidity	0.001	-0.015	0.015
Sensitivity to Market	0.002	-0.045	0.046

Note. This table represents the coefficients of linear discriminant functions. The second column and third column suggest linear discriminant functions for failed and non-failed bank, respectively. The last column presents the loadings of Fisher's discriminant function for the respective factors, respectively.

TABLE 6
COEFFICIENTS OF LOGISTIC REGRESSION FOR DETECTION OF FAILED AND NON-FAILED EVENTS

	Coefficients	χ^2	$p(\chi^2)$
Intercept	-3.47	131270.07	0.00
Capital Adequacy	-0.10	6.50	0.01
Asset Quality	0.24	1614.39	0.00
Management Experience	-2.70	4376.26	0.00
Earnings	0.00	0.27	0.60
Liquidity	-0.18	7.39	0.01
Sensitivity to Market	-0.60	3764.64	0.00

Note. This table represents the results of logistic regression. The second column shows estimated coefficients on six factors. The third column shows Wald statistics. The last column presents each p-value for the respective factors.

CONCLUDING REMARKS

In the middle of financial meltdown that occurred several years ago, we observed that many highly leveraged banks went into default. These events paralyzed both the banking system and economy in the US. Subsequently, the US banking industry has experienced stronger regulation (e.g. the Dodd-Frank act; BIS III) and better monitoring systems (see, Adrian et al., 2014).

To evaluate bank performance, federal banking supervisors such as the Federal Reserve, the FDIC, and the OCC usually employ CAMELS rating method as a standard measure to identify banks condition in the US banking system. However, since CAMELS represents on-site examination that may be difficult to implement effectively given budget and other constraints, the examination is limited to once every 12 to 24 months. As Cole and Gunther (1998) point out, the condition of banks tends to generally worsen since the time of the last on-site examination. For more frequent monitoring, our research suggests common factors that replicate CAMELS using FDIC bank performance data that are released on a quarterly basis.

Our empirical results suggest two key findings. First, the common principal factors identified (i.e. PCA-CAMELS) explain financial symptoms preceding the failure of FDIC insured banks. In other words, our mimicking factors indicate that an agency problem and large influx of loans drive failed banks toward an undesirable choice of capital structure. Finally, our common principal factors that mimick CAMELS appear to detect meaningful signals prior to bank failure events.

ENDNOTES

1. Five key factors are referring to as CAMEL and six key factors include CAMELS. The rating ranges from 1 to 5. 1 represents the highest rating, while 5 represents the lowest one. More specifically, a rating of 1 and 2 are given to banks with a good condition. A rating of 3 is given to banks with below average performance and some supervisory concerns. A rating of 4 indicates that banks have serious problems that needed to be revised. Finally, a rating of 5 represents that banks perform poorly and it is highly likely to meet failure within 12 months.
2. Individual factor scores for each time horizon is based on the factor loadings as shown in Table A.1.
3. Sensitivity to market ratio is not initially selected through EFA.

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APPENDIX

TABLE A.1
CAMELS FACTOR LOADINGS FOR THE RESPECTIVE INDICATORS

FDIC Data Item	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
rbc1aaj/rbc1aaj	**0.24**	-0.16	-0.01	-0.31	0.14	-0.01
rbc1rwaj/rbc1rwaj	**0.46**	0.03	0.00	0.01	-0.08	0.00
rbcrwaj/rbcrwaj	**0.46**	0.03	0.00	0.01	-0.08	0.00
lnatresr/lnatresr	-0.01	**0.63**	0.00	0.26	0.11	0.01
nperfv/nperfv	-0.01	**0.59**	-0.01	-0.28	-0.16	0.00
nonixay/nonixayq	-0.05	-0.01	-0.01	0.02	**0.96**	0.00
roe/roeq	0.00	0.01	0.00	-0.01	0.00	**1.00**
lnlsdepr/lnlsdepr	0.00	0.01	**0.64**	-0.01	-0.09	0.00
idlncorr/idlncorr	-0.01	-0.01	**0.63**	0.02	0.06	0.00
sc/asset	-0.05	0.01	0.00	**0.84**	0.02	-0.01

Note. This table describes each variable's factor loading for six individual factors. Based on the magnitude of each factor, the first factor represents capital adequacy; the second factor represents asset quality; the third factor represents liquidity; the fourth factor represents market sensitivity; the fifth factor represents management experience; the last factor represents earning.

TABLE A.2
FDIC PERFORMANCE AND CONDITION RATIOS

FDIC Data Item	Description
idntilr/IDNTILRQ	% of unprofitable institutions
idntigr/idntigrq	% of institutions with earnings gains
intincy/intincyq	Yield on earning assets
intexpy/intexpyq	Cost of funding earning assets
nimy/nimyq	Net interest margin
noniiay/noniiayq	Noninterest income to average assets
nonixay/nonixayq	Noninterest expense to average assets
ELNATRY/ELNATRYQ	Loan and lease loss provision to assets
noijy/noijyq	Net operating income to assets
roa/roaq	Return on assets (ROA)
roaptx/roaptxq	Pretax return on assets
roe/roeq	Return on Equity (ROE)
roeinjr/roeinjr	Retained earnings to average equity (ytd only)
ntlnlsr/ntlnlsqr	Net charge-offs to loans
elnantr/elnatqr	Credit loss provision to net charge-offs
iderncvr/iderncvq	Earnings coverage of net charge-offs (x)
eeffr/eeffqr	Efficiency ratio
astempm/astempm	Assets per employee ($millions)
iddivnir/iddivnir	Cash dividends to net income (ytd only)
lnatresr/lnatresr	Loss allowance to loans
lnresncr/lnresncr	Loan loss allowance to noncurrent loans
nperfv/nperfv	Noncurrent assets plus other real estate owned to assets
nclnlsr/nclnlsr	Noncurrent loans to loans
LNLSNTV/LNLSNTV	Net loans and leases to total assets

lnlsdepr/lnlsdepr	Net loans and leases to deposits
idlncorr/idlncorr	Net loans and leases to core deposits
DEPDASTR/DEPDASTR	Total domestic deposits to total assets
eqv/eqv	Equity capital to assets
rbc1aaj/rbc1aaj	Core capital ratio
rbc1rwaj/rbc1rwaj	Tier 1 risk-based capital ratio
rbcrwaj/rbcrwaj	Total risk-based capital ratio
asset5/asset2	Average total assets
ernast5/ernast2	Average earning assets
eq5/eq2	Average equity
LNLSGR5/LNLSGR2	Average total loans

Note. This table describes thirty five financial ratios for the performance and condition of the FDIC insured banks.