Bank Failure Prediction and the Subprime Mortgage Crisis

Lynn K. Kendall*

University of Dallas

Walter R. Kendall

Tarleton State University

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Corresponding author: College of Business, Univeristy of Dallas, 1845 E. Northgate Dr., Irving, TX 75062-4736. Phone: 970-396-2089, Fax: 972-721-4007, lkendall@udallas.edu

1. Introduction and background

Not since the late 1980s has the U.S. seen as many bank failures as in recent years. Between July 2009 and December 2012, the Federal Deposit Insurance Corporation (FDIC) reported the closure of 395 banks. Because of the relatively high rate of failures during that period we chose it as the study period for development of our model. During previous periods of high failure rates in the late 1980s and early 1990s, there were as many as 500 financial institution failures in a single year, with a total of nearly 2325 failures between 1982 and 1993 (FDIC, 2015).

Bank failures clearly can produce serious repercussions. While the FDIC presently protects depositors up to $250,000 there are other economic consequences to bank failure. There are many notable consequences pointed out in the literature. Friedman and Schwartz (1963) find that a banking crisis (in this case, a series of bank failures) can result in a severe and unexpected contraction in the money supply, which can then lead to a recession. Bernanke (1983) discusses how the 'credit channel' is impaired as banks fail. As some banks fail, other banks may become capital constrained, reducing the amount of available credit. As credit dries up, businesses reduce investment and households cut expenditures. When liquidity suddenly dries up there is "fragility" in market liquidity due to market and information imperfections (Brunnermeier and Pedersen, 2009). This market liquidity and fragility co-move across assets as investors' liquidity is affected across all of their assets. In the most recent spate of bank failures a spiral of declines in the real economy, beginning with the subprime mortgage crisis, led to bank failures and the loss of easy credit, which in turn led to further declines in GDP and the real U.S. economy (Bailey & Elliott, 2009). Clearly, bank failures are not a positive economic or financial event.

Academic interest in bank failure prediction models tends to increase in concert with an increase in bank failures. It is important for banking regulators to have early warning models, and it is proposed by Jagtiani et al. (2003) that simple linear models which can identify financial distress in commercial banks up to one year in advance may aid in bank supervision. Following this recommendation, we developed a model which uses bank Call Report data for June 2009 to predict bank failures in the following 18 months which identifies nearly 90% of actual bank failures.

The financial crisis beginning in 2008, and the resulting high number of bank failures, led to a body of research which address the underlying issues, particularly liquidity, lending and leverage (e.g., Adrian and Shin, 2010; Brunnermeier, 2008; Ivashina and Scharfstein, 2010; and Peck and Shell, 2010). Inside debt relative to inside equity by a CEO is considered by Bennett, Güntaya, and Unal (2015). The link between market prices of loan volatility and systematic banking risk is examined by Shleifer and Vishny (2010), who find that profit-maximizing behavior by banks creates systemic risk.

There is considerable empirical research related to bank failure prediction models using Bank Call Report-based data and other available bank-specific accounting and market-based data. Wide-ranging literature reviews on the overall subject of bank failure prediction models have been conducted by Torna (2010) and Demyanyk and Hason (2009). In this paper we discuss the more recent bank failure research, and as such, a broader literature review will not be presented here.

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A widely known bank rating system is "CAMELS", which stands for Capital adequacy, Asset quality, Management, Earnings, Liquidity and Systemic risk. This is based on the Uniform Financial Rating System. Cole and White (2012) study the relationship between bank financial characteristics which proxy the CAMELs factors as well as loan portfolio characteristics and 2009 bank failures. The authors use logistic regression to identify which factors are the best indicators of bank failure. The authors find that a higher likelihood of bank failure is associated with higher levels of real estate construction and development loans, commercial real estate loans and multi-family mortgages. In examining the failed bank loan structure for five years prior to failure, Cole and White conclude that real estate loans are very important factors related to this most recent wave of bank failures.

The Cole and White (2012) research differs from what is presented here in that our focus is to develop a short-term, forward-looking model that might be used to identify banks which are more likely to fail in the near future. Such a model allow additional investigation and supervision of identified banks, which might reduce the ultimate number of banks which fail. Cole and White look at bank loan portfolio composition historically, finding that as early as five years prior to failure, higher proportions of certain real estate loans may indicate future failure. As Jagiani et al. (2003) suggest bank financial health can deteriorate as quickly as six months after supervisory ratings have been issued. Our model is intended to help identify potentially troubled banks up to 18 months prior to failure.

Torna (2010) examines the role of modern banking activities with commercial bank insolvency and financial distress. Using proportional hazard and logit analysis, the author examines the differences in what causes a troubled bank to fail vs. a relatively healthy bank to fail.

Ng and Roychowdhury (2010) use 2007 data with a Cox proportional hazard model to analyze 2008 and 2009 bank failures, citing additions to loan loss reserves as an important indicator of potential failure. DeYoung and Torna (2013) consider the role of fee-based nontraditional banking activities in the likelihood of bank failure. Empirical analysis

2. Discussion of variables

Table 1 illustrates the variables which were found to indicate differences between failed and non-failed banks in previous research. These variables represent the logical starting point for development of our bank failure model.

Capital adequacy measures the amount of capital relative to assets. There are two such ratios included in this analysis, equity capital/total assets, and equity capital/risk assets. Risk-weighted assets are defined by the appropriate federal regulator for prompt corrective action during that time period (FDIC data description). Capital ratios for non-failed banks averaged two to three times that of failed banks.

Asset quality can be defined by a very broad range of measures. In this analysis we focus on bank loan portfolios. Real estate backed loans are made up of 1-4 family residences, multi-family residences (5+ residences), commercial and industrial properties, and construction and development properties. Overall, non-failed banks held lower total loans as a percent of total assets. Examining the loan portfolios by sector, single family mortgages made up 43.5% of the non-failed bank portfolios, compared with fewer than 30% for the failed banks. Multi-family mortgages were more heavily represented in the failed bank portfolios. It is in the construction and development loans were we see a large difference in the two categories, for failed banks, this sector represented nearly one quarter of the overall loan holdings. For non-failed banks, these

Table 1: Key bank statistics and ratios (Q2, 2009 data)

Non-failed banks are those which did not fail prior to 2013 and failed banks are defined in this table as those banks which failed between July 2009 and December

		Non-Failed Banks			Failed Banks			T-test of Difference in Means	
		Mean	Median	Std. Dev	Mean	Median	Std. Dev		
Capital Adequacy									
TE_TA	Total equity/Total assets	11.7%	10.0%	7.4%	4.9%	5.1%	0.04	25.79	***
TE_RA	Total equity/Total risk-weighted assets	21.7%	14.3%	>100%	6.5%	7.0%	0.06	8.37	***
Asset Quality									
TL_TA	Total loans and lease financing receivables, net of unearned income/Total assets	65.6%	68.8%	17.0%	74.0%	74.8%	0.11	-11.70	***
RE_TL	Real estate backed loans/Total loans and leases (L&L)	71.1%	75.0%	20.0%	84.5%	87.7%	0.13	-15.87	***
M_TL	1-4 family real estate backed loans/Total L&L	43.5%	26.4%	267.0%	29.8%	20.3%	0.63	2.74	***
MULTI_TL	>4 family real estate backed loans/Total L&L	2.4%	1.1%	4.6%	5.0%	2.5%	0.07	-5.47	***
COMRE_TL	Commercial & industrial real estate backed loans/Total L&L	23.2%	21.8%	15.2%	29.7%	28.6%	0.13	-7.52	***
CONSDEV_TL	Construction & development real estate backed loans/Total L&L	8.5%	5.9%	8.8%	24.0%	21.6%	0.15	-16.38	***
CI_TL	Commercial & Industrial non-real estate backed loans/Total L&L	13.6%	11.7%	10.7%	11.4%	8.6%	0.10	3.44	***
NONP_TA	Non-performing loans/Total assets	2.1%	1.3%	2.5%	12.2%	10.4%	0.08	-19.57	***
L90A_TA	Loans past due 90 days or more & still accruing/total assets	0.2%	0.0%	0.5%	0.5%	0.0%	0.01	-3.78	***
NA_TA	Nonaccrual loans/total assets	1.4%	0.7%	1.9%	8.6%	7.4%	0.06	-18.25	***
ORE_TA	Other real estate owned/total assets	0.5%	0.1%	0.9%	3.1%	1.7%	0.04	-10.73	***
LA_TL	Loan allowance/total loans	1.0%	0.9%	0.7%	2.5%	2.2%	0.02	-14.24	***
CO_TL	Charge off loans/total loans	0.4%	0.1%	3.9%	1.7%	0.9%	0.02	-0.09	***
Management Decisions									
NI_OI	Net income/operating income	-66.4%	9.5%	>100%	-44.4%	-62.3%	>100%	0.82	
Earnings Ability									
NI_TA	Net Income/Total Assets (ROA)	0.1%	0.3%	5.2%	-2.5%	-1.7%	0.03	12.31	***
OI_TA	Operating expenses/total assets	4.2%	2.9%	17.8%	3.1%	2.6%	0.05	2.71	***
NI_TE	Net income/Total Equity (ROE)	0.7%	2.5%	49.9%	>100%	-22.1%	>100%	-0.95	
Liquidity									
CSE_TA	Cash and investment securities/total assets	27.0%	23.8%	16.5%	17.5%	16.1%	0.10	14.23	***
C_TA	Cash/total assets	7.0%	4.5%	8.0%	7.9%	7.0%	0.07	-2.05	**
IS_TA	Investment securities/total assets	20.0%	16.9%	15.5%	9.6%	8.2%	0.08	19.77	***

***, ** and * indicate 1%, 5% and 10% significance, respectively.

loans only made up 8.5% of all loans. Commercial and industrial real estate backed loans were also a larger portion of the failed bank loans than at the non-failed banks.

Beyond loan portfolios, other asset quality measures are also examined. Non-performing loans are made up of loans past due 90 days or more and still accruing, nonaccrual loans and other real estate owned plus the value of repossessed real estate to total assets (ORE). As a percent of total assets, these non-performing loans were only 2.1% for non-failed banks while for failed banks the level exceeded 12%. Loan allowances measure the amount of loans the banks consider to be bad debts. Charge-offs, are the value of loans removed from the books and charged against loss reserves.

The single management decision criterion, net income/operating income, serves as a proxy for management's operating level decisions. There is not a significant difference in this measure when comparing non-failed and failed banks. Earnings ability is a measure of how well a bank is able to survive. Like any business enterprise, both earnings and operating expenses must be examined. Net income/total assets, or return on assets (ROA) is the most commonly used ratio among the models researched as a part of this analysis, is a measure of effective expense control with respect to bank assets. As reported in Table 1, ROA and operating income/total assets are both significantly different for failed vs. non-failed banks. Differences in net income/total equity (ROE) for failed vs. non-failed banks are significant.

Liquidity, or lack thereof, can very quickly bring even the largest financial firms to ruin, as evidenced by the 2008 failure (and subsequent acquisition) of Bear Stearns (Cohan, 2010). Liquidity measures a bank's ability to meet unforeseen deposit outflow in a short time. Two distinct measures are examined in this analysis, cash/total assets, and investment securities/total assets, along with the aggregate of these two measures, cash and securities/total assets. As reported in Table 1, cash/total assets ratios are not significantly different between failed and non-failed banks, while investment securities/total assets are significantly higher for non-failed banks. This would indicate that the significance of cash plus securities/total assets is driven by the securities rather than by cash holdings.

In Table 2 we compare the mean values for these same key variables for banks which failed in the model period (July 2009 to December 2010) with those that failed in subsequent periods, 2011 and 2012. Capital adequacy for banks failing in 2009 and 2010 is significantly lower than that for banks failing in later years. What is of interest, is that within the loan portfolio makeup, only the multi-family loan category is substantially different for banks failing in 2009 and 2010 compared to those which later fail. The key construction and development loan category is not substantially different for banks failing in 2011, indicating (and confirmed by Cole and White, 2012), that this type of loan is an early indicator of potential failure. Banks failing in 2012 held lower proportions of these loans than did banks that failed earlier. The other key indicators of bank financial health, such as non-performing loans and ROA are very different for banks failing prior to 2010 than those which subsequently failed.

3. Model Development and Selection

Using the variables described in Table 1, we found that a number of the variables were, in effect, proxies for other variables, and when combined in probit models, little or no additional predictive power was gained from their inclusion. Our goal was to develop a model that is a very good predictor of whether a particular bank is likely to fail. The data are based on two outcomes: 1) bank failure, where $Y_i = 1$; or 2) bank does not fail, where $Y_i = 0$. Thus, our predictions must be correct for those cases where the bank fails as well as for those cases where the bank does not fail. A model that correctly predicts one of the outcomes but is a poor predictor of the alternative is a poor model – both outcomes must be predicted as accurately as possible. In the case of prediction of 0, or the bank does not fail, when in reality, the bank is likely to fail diverts potential regulatory scrutiny away from the bank. The 252 banks which failed in the second half of 2009 and 2010 represented an estimated loss of $37 billion according to the Federal Deposit Insurance Co. The other "bad" outcome is if the model predicts failure when in reality the bank is relatively sound. In this case, regulatory resources are expended in the wrong place.

Consider the model that correctly predicts all bank failures, but it does this by classifying all banks as potential failures. It is incorrectly predicting bank non-failure. This model is virtually worthless. Likewise, the model that correctly predicts all bank non-failures by saying all banks are good; again, a rather worthless model. It is the balance between correctly identifying failures as well as successes that is important. Model accuracy must be measured by examining both Type 1 and Type 2 errors. As Jagtiani et al. (2003) conclude the "best" model is one that has the lowest number of type 1 errors.

In the sample data set, 252 banks actually failed during the July 2009 through December, 2010 period. Following Martin (1977) and Thomson (1991), we use the number of failed banks in the population/total number of banks as the cutoff for predicted failure vs. non-failure. In other words, with 252 out of the total 7809 banks (the 252 failed banks plus all other banks which did not fail prior to 2013) failing in the July 2009 through December 2010 time period, 3.1% of the banks failed. Predicted values above this level are considered to be “failed banks”.

In each model, rather than directly estimating the probability of $Y_i = 1$, we instead use a continuous variable, Y_i^* that can be considered in this analysis to the (unobservable) continuous “ability” of a bank to fail, that is, the probability of failure. The model for t becomes:

$$Y_i^* = \beta_0 + \beta_1 X1_i + \beta_2 X2_i + \ldots\ldots + \beta_K X3_i + \varepsilon_i$$

Where X1, X2, etc. represent the various financial ratios and other financial characteristics for each failed and non-failed bank based on the June 2009 Call Report data.

The basis for our probit model is whether a bank failed in the July 2009 – December 2010 period or it did not fail (prior to 2013). Banks that failed in 2011 or 2012 were not included in the probit model.

Table 2: Comparison of key variables for banks failing during the model period (July 2009-December 2010) to those failing in 2011 and 2012

	Mean for Banks Which Failed in 2011	Mean for Banks Which Failed in 7/09-12/10	Ttest of Difference in Means (2011 failures vs. 7/09-12/10 failures)		Mean for Banks Which Failed in 2012	Ttest of Difference in Means (2012 failures vs. 7/09-12/10 failures)	
Capital Adequacy							
TE_TA	8.3%	4.9%	9.90	***	8.5%	8.64	***
TE_RA	10.5%	6.5%	8.17	***	11.1%	7.81	***
Asset Quality							
TL_TA	76.0%	74.0%	1.80	*	74.9%	0.59	
RE_TL	83.4%	84.5%	-0.71		83.3%	-0.58	
M_TL	27.5%	29.8%	-0.29		30.5%	0.15	
MULTI_TL	2.9%	5.0%	-3.86	***	2.9%	-3.17	***
COMRE_TL	32.8%	29.7%	1.88	*	30.2%	0.22	
CONSDEV_TL	25.3%	24.0%	0.74		18.4%	-2.57	**
CI_TL	12.1%	11.4%	0.60		12.1%	0.45	
NONP_TA	8.0%	12.2%	-5.96	***	6.7%	-6.01	***
L90A_TA	0.4%	0.5%	-0.59		0.4%	-0.52	
NA_TA	5.3%	8.6%	-6.18	***	4.4%	-6.05	***
ORE_TA	2.2%	3.1%	-2.61	***	1.9%	-2.86	***
LA_TL	1.9%	2.5%	-4.04	***	1.5%	-5.68	***
CO_TL	0.8%	1.7%	-4.41	***	0.5%	-6.98	***
Management Decisions							
NI_OI	-33.3%	-44.4%	0.24		-43.7%	0.01	
Earnings Ability							
NI_TA	-0.5%	-2.5%	5.26	***	-0.9%	3.39	***
OI_TA	4.9%	3.1%	0.84		2.9%	-0.57	
NI_TE	6.9%	>100%	-0.95		-13.3%	-0.96	
Liquidity							
CSE_TA	16.5%	17.5%	-0.90		16.4%	-0.73	
C_TA	6.5%	7.9%	-2.11	**	5.1%	-3.69	***
IS_TA	10.0%	9.6%	0.50		11.2%	1.27	

***, ** and * indicate 1%, 5% and 10% significance,, respectively.

Model development started with a range of potential explanatory variables which proxy for CAMELs factors as well as loan portfolio elements. Loan portfolio composition has been identified as a major factor related potential bank failure (Cole and White, 2012 and GAO, 2013); key categories of real estate backed loans were included in model development as well as CAMEL related factors discussed above.

Table 3: Probit Models

Dependent Variable: Y=1 if bank failed between July 2009 and December 2010 and Y1=0 if bank did not fail prior to 2013.

All financial data are as of June 30, 2009

	Model 1			Model 2		
	Coeff.	Z-Stat		Coeff.	Z-Stat	
Capital Adequacy						
TE_TA	-40.94	-3.67	***	-40.41	-4.44	***
M_TL	0.05	0.85				
Asset Quality						
MULTI_TL	6.46	3.56	***	6.44	4.67	***
COMRE_TL	1.35	2.06	**	1.40	1.87	*
CONSDEV_TL	3.34	2.68	**	3.39	2.65	***
CI_TL	1.98	2.12	**	2.09	1.48	
NONP_TA	13.48	2.75	***	15.46	3.48	***
LA_TL	22.33	1.45				
Earnings Ability						
NI_TA	-8.68	-0.87				
Liquidity						
IS_TA	-0.42	-0.31		-1.30	-0.81	
Constant	-1.00	-2.13	**	-0.60	-1.38	
# Obs	2763			2763		
Like Likelihood	-173			-179		
Wald Chi Sq	25			74.67		

***, ** and * indicate 1%, 5% and 10% significance,, respectively.
Robust standard errors
Heteroskedasticity corrected

Capital adequacy as measured by total equity/total assets proved to be a definitive variable in all models tested. Model 1 includes five types of loans (each as a percent of total liabilities);

single family mortgages, multi-family mortgages, commercial real estate loans, construction & development loans and commercial loans. In addition, non-performing loans as a percent of total assets, loan loss allowance as a percent of total liabilities, ROA and liquidity as measured by investment securities, are included. In Model 2, single family mortgages, loan loss allocation and ROA are excluded.

4. Discussion of the Findings for the Final Model

Financial ratios providing the greatest predictive power are based on only two of the key "CAMELS" categories: Capital adequacy as measured by total assets/total equity, and asset quality. In terms of asset quality, higher percentages of real estate backed commercial & industrial and construction & development loans were major contributing factors to the failure of banks during the analysis period. Lower capital adequacy, relatively high percentages of non-performing loans and lower levels of liquidity are key explanatory factors. Liquidity, as measured by investment securities/total assets, is not a statistically significant predictor variable. However, we find that bank liquidity provides improved Type 1 error control and is therefore included in both models.

Earnings ability as measured by net income as a percent of total assets was significantly higher for non-failed banks, but this variable did not provide additional explanatory power and was not included in the final model (2).

Table 4: Goodness of fit measures for Probit models

	Model 1			Model 2		
	Actual Fail/Not Fail			Actual Fail/Not Fail		
	Fail	Not Fail	Total	Fail	Not Fail	Total
Training Sample						
Bank fails 7/09-2010	108	100	208	98	46	144
Bank does not fail < 2013	15	2560	2575	25	2614	2639
Total	**123**	**2660**	**2783**	**123**	**2660**	**2783**
% Correct when Y=1		87.8%			79.7%	
% Correct when Y=0		96.2%			98.3%	
Overall % correct		95.9%			97.4%	
Holdout Sample						
Bank fails 7/09-2010	115	216	331	105	110	215
Bank does not fail < 2013	14	4933	4947	24	5039	5063
Total	**129**	**5149**	**5278**	**129**	**5149**	**5278**
% Correct when Y=1		89.1%			81.4%	
% Correct when Y=0		95.8%			97.9%	
Overall % correct		95.6%			97.5%	
Out of Sample Prediction						
Bank fails in 2011	56	316	372	41	156	197
Bank does not fail < 2013	36	7493	7529	51	7653	7704
Total	**92**	**7809**	**7901**	**92**	**7809**	**7901**
% Correct when Y=1		60.9%			44.6%	
% Correct when Y=0		96.0%			98.0%	
Overall % correct		95.5%			97.4%	
Out of Sample Prediction						
Bank fails in 2012	21	216	237	10	110	120
Bank does not fail < 2013	30	4933	4963	41	5039	5080
Total	**51**	**5149**	**5200**	**51**	**5149**	**5200**
% Correct when Y=1		41.2%			19.6%	
% Correct when Y=0		95.8%			97.9%	
Overall % correct		95.3%			97.1%	

Model predictive accuracy

Models were developed by using a “training” model, based on roughly one half of the July 2009-December 2012 failed banks and a holdout sample. The unmatched non-failed banks in the training model were randomly selected (following Lanine and Vennet, 2005). Using coefficients from the probit model, the accuracy of the model is then tested on the holdout sample of failed and non-failed banks. Additional out of sample analysis was conducted testing model predictive ability for banks which failed in 2011 and those which failed in 2012.

Goodness of fit for each of the models is shown in Table 4. Model 1 has the highest training sample overall predictive ability. However, this model suffers from higher Type 1 errors, both for the training sample and the holdout sample. Model 2 exhibits 89.4% correct failure prediction in the training sample and 92.2% in the holdout sample. This lower Type 1 error indicates that Model 2 is the superior model. The elimination of single family mortgages, loan loss allowances and ROA actually improved the predictive ability of the model.

Out of sample predictive accuracy

Moving forward, both models lose their predictive power with respect to 2011 bank failures. Model 1 only predicts 51.1% of the actual 2011 failures while Model 2 successfully identifies over 65% of the actual failures. It should be noted that the models were developed to identify short-term failures, those occurring within 18 months of the base data. By moving to 2011 and 2012, it is not surprising that the predictive power declines. This is in line with Jagtiani et al. (2003), who state that banks generally have on-site examinations every 12 to 18 months in order to identify potential problems.

5. Conclusions and Recommendations

This research was conducted in order to understand the factors which led to bank failure subsequent to the financial crisis which began in 2008. Further, we sought to identify which of these factors were the strongest predictors of potential bank failure over the short term of 6-18 months. We find that despite significant differences between failed banks and non-failed banks across a wide range of financial variables and loan portfolios, not all of these differences represent factors which are effective differentiators in modeling bank failures. Despite home mortgages being an underpinning of the subprime mortgage crisis, higher proportions of multi-family mortgages, commercial real estate loans, construction & development loans as well as commercial loans help us identify potential bank failures. At the same time, three of the most common financial ratios used in prior bank failure prediction models (total equity as a percent of total assets, non-performing loans as a percent of total assets and investment securities as a percent of total assets) remain as key model determinants.

Our findings indicate that financial ratios and loan portfolio structure are key determinants of bank financial health; and when predicting potential failure over a reasonable time period, such as up to 18 months, models can be highly predictive. The high degree of correct categorization combined with simple nature of the model and the use of readily available data allows for wide-spread usage among practitioners as well as academics.

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