Agricultural Banking and Early Warning Models for the Bank Failures of the Late 2000s Great Recession

Xiaofei Li
University of Georgia
Department of Ag & Applied Economics
306 Conner Hall, Athens GA 30602
zxmf1128@uga.edu

Cesar L. Escalante
University of Georgia
Department of Ag & Applied Economics
315 Conner Hall, Athens GA 30602
cescalan@uga.edu

James E. Epperson
University of Georgia
Department of Ag & Applied Economics
315 Conner Hall, Athens GA 30602
epperson@uga.edu

Lewell F. Gunter
University of Georgia
Department of Ag & Applied Economics
314 Conner Hall, Athens GA 30602
lgunter@uga.edu

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INTRODUCTION

The global economy experienced a general slowdown in economic activity in the late 2000s that economists and business analysts consider as the worst economic crises experienced since World War II and the longest downturn since the 1930s Great Depression. Dubbed as the Great Recession (Wessel, 2010), worsening global economic conditions began in December 2007 as declared by the National Bureau of Economic Research (NBER) that took cues from the deteriorating conditions in the labor market (Isidore, 2009).

The U.S. economy was not spared from the global crises, with the period of the late 2000s being marked by trends of high unemployment, declining real estate values, bankruptcies and foreclosures, among many other indicators (Rutenber and Thee-Brenan, 2011). A widely accepted theory of the real culprit that significantly launched the onset of the economic crises in the United States was the breakdown of the real estate industry (Isidore, 2009). The housing downturn started in 2006 when housing process dropped significantly after reaching peak levels in the early 2000s. This resulted in an abrupt increase in loan defaults and mortgage foreclosures that led to widespread crises in the banking industry.

The late-2000s financial crisis led to a surge of bank failures in the United States at an overwhelming rate not observed in many years. The cycle of seizures started in 2007, and by the end of 2010, a total of 325 banks had failed. In contrast, only 24 banks had failed in the seven-year period prior to 2007.

In times of economic hardships, there is often less confidence in the resilience and endurance of the agricultural sector in weathering business survival challenges since the farm sector is naturally too vulnerable to business and financial risks. Recalling the farm crises of the

1980s where the farm sector was pinpointed as one of the major precursors of economic turmoil[1], some experts suspect that significant loan exposures to agricultural activities could increase the probability of bank failure.

In the face of the current recession that manifested itself in the financial industry, it is important to probe more deeply and understand the causes of bank failures, which should provide insights on more effective solutions to the current crises or cautionary policies that will prevent its duplication in the future. Bank failures have been analyzed quite extensively in the corporate finance literature. Many previous studies have examined the determinants of bank failures from previous episodes of financial crises by analyzing the nature and consequences of management decisions(Belongia and Gilbert, 1990), investigating the effect of insider loans (Graham and Horner, 1988, Seballos and Thomson,1990, Belongia and Gilbert,1990, Thomson, 1991) as well as overhead costs (Demirguc-Kunt, et al., 2003, Seballos and Thomson, 1990, Thomson, 1991), analyzing the effect of product diversification or level of industry concentration on bank performance (Thomson 1991, and DeYoung and Hasan, 1998), and introducing different capital ratios as predictors of bank performance(Estrella, Park and Peristiani, 2000).

This study differentiates itself from previous empirical works by its special focus on the role of the agricultural finance industry in the ensuing credit crises. Specifically, this study will determine the factors that significantly caused bank failures, with special attention given to the role of the agricultural lending portfolios of commercial banks. Moreover, it will determine the length of time prior to the actual bank bankruptcy declarations that early warning signals among the banks' operating and lending decisions, in addition to certain macroeconomic indicators, could be detected.

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[1] In 1980s, more than 1,600 banks closed due to the large amount of delinquent farm loans caused by farm operating losses and a fall in agricultural land values.

METHODOLOGY

The basic framework of the models used in this study is based on traditional bank failure prediction models presented in the corporate finance literature. Typically, the prediction model is a single equation model, with the primary goal of predicting bank failures. This study presents a variant of the typical model presented in literature differentiated through two model extensions: a) the addition of state-level variables that capture macroeconomic factors, in addition to bank performance variables; and b) the use of different time period versions of the cross-sectional model to determine earliest possible warning signals of bank failures.

The typical single-equation bank failure prediction model employs logistic regression techniques. The logistic function is specified as:

$$F(\,PROB_{it}) = \frac{\exp\,(\,PROB_{it})}{1+\exp\,(\,PROB_{it})} = \frac{\exp\,(x_i'\beta)}{1+\exp\,(x_i'\beta)}$$

The empirical design includes defining an equation for estimating $PROB_{it}$ for each observation i that involves the following categories of explanatory variables:

$$PROB_{it} = x_{it}'\beta = \beta_0 + \beta_1 AQCA_{it} + \beta_2 MR_{it} + \beta_3 PL_{it} + \beta_4 LPC_{it} + \beta_5 LPR_{it} + \beta_6 FA_{it} + \beta_7 Size_{it} + \beta_8 STECON_{it} + u_i$$

where $PROB_{it}$ is the binary dependent variable that takes a value of 1 for banks classified by the FDIC as failed banks and zero for surviving or successful (non-failed) banks. The analyses in this research use the FDIC's criterion that equates insolvency with failure. Thus, the banks categorized as failed banks in this study are those considered by FDIC as severely insolvent or "critically undercapitalized"[2]. $AQCA_{it}$ are variables representing capital adequacy and asset quality; MR_{it} is a set of management risk variables; PL_{it} are variables that capture liquidity risk

2 When a bank's risk-based capital ratio drops below 2%, it is classified by FDIC as "critically undercapitalized." When this happens, FDIC declares the bank as insolvent and will take over management of the bank (FDIC, FDIC Law, Regulations, Related Acts).

and bank earnings (profitability) potential; LPC_{it} are variables that represent loan portfolio composition measures; LPR_{it} capture loan portfolio risk measures; FA_{it} are variables that represent funding arrangements; $Size_{it}$ is a structural factor variable, specifically representing bank size; $STECON_{it}$ are economic variables that capture macroeconomic conditions at the state level; t = t denotes the period of time prior to bank failure.

In order to interpret the coefficients of the logit model, we need to estimate the marginal effect. The marginal effect for logit model is defined as

$$\frac{\partial p}{\partial x_i} = F(x_i'\beta)\{1 - F(x_i'\beta)\}\beta_j$$

The estimating model has six time period model versions. Each time period model utilizes a cross-sectional dataset compiled at specific points in time away from the actual occurrence of bank failure. The time period models considered in this study are explained in detail in Table 1.

In the different time period models, PROB is the identifier for banks that eventually failed during the entire sample period. For example, if Bank A is a bank that was declared bankrupt or insolvent in the 3rd quarter of 2009 while Bank B went into bankruptcy in the 1st quarter of 2009, and Bank C is a bank that successfully survived, the following delineation rules (table 1) are used in defining the observations for Banks A, B and C in the different cross-sectional time period models:

This study will also analyze the robustness of the estimation results by employing in-sample and out-of-sample forecasting methods. Similar to the in-sample classification, the out-of-sample forecasting uses the estimated coefficients from cross-sectional logistic regressions, but applies them to an expanded dataset. The failed sample consists of all banks that failed in 2010, which is a year after the reckoning year for the failed bank observations in the bank prediction or early warning signals models. Then, out-of-sample forecasting uses the estimated coefficients from prediction model to predict the outcomes in 2010, and compare them with the actual outcomes in 2010. Similar to in-sample accuracy, higher percentage of correct classification implies higher prediction efficiency.

DATA MEASUREMENT

In order to determine early warning signals of bank failures among bank performance variables, several cross-sectional datasets are compiled in this study. The data for both failed banks and surviving banks are collected from the Call Reports Database published on the website of Federal Reserve Board of Chicago (FRB). The banking data are available through the banks' quarterly financial statements made publicly available by the FRB. This study's banking data are collected on a quarterly basis from January 2005 to September 2010, a time period that captures the favorable economic times prior to the onset of the current recession and the aggravation of the bank bankruptcy filings in 2009 and 2010.

For the non-failed sample, only banks that continuously reported their financial conditions in the dataset during the time period were included. Surviving or successful banks with missing values for any financial data being collected were discarded. Given these data restrictions, a total of 1109 banks were identified each year and included in the non-failed or successful bank sample.

In compiling the dataset, special attention was given to those banks that failed in 2009 and 2010 because these two years have the largest number of failure since 1992. FDIC records a total of 255 out of 297 failed banks to have been identified just in the two year period (2009-2010) – with 117 in 2009 and 138 in 2010.

In addition to bank performance variables, this study also collected data from other sources that would reflect certain aspects of the local economic conditions during the recessionary period. These variables include state-level monthly unemployment rate data that were obtained from the

Bureau of Labor Statistics and were converted to quarterly data. State-level numbers of bankruptcy were collected from Bankruptcy filing statistics, published online by American Bankruptcy Institute (ABI). These bankruptcy figures were available for business, non-business and even sectoral (including agriculture-related filings under Chapter 12 bankruptcy) filings. The Bureau of Economic Analysis (BEA) provided data on the state-level aggregation of personal incomes.

Categories of Variables for Bank Failure Prediction Models

In order to construct a model that can predict bank failure of all sizes, this study includes proxy variables based on balance-sheet and income data from Call Reports. RWCAPRATIO, the risk-weighted capital ratio, has been used as proxy for capital adequacy in CAMEL rating system. This variable is defined as the ratio of tier 1 capital to risk-weighted assets, where tier 1 capital include common stock, common stock surplus, retained earnings, and some perpetual preferred stock(Estrella, et al., 2000). Another variable considered in this category is LOANHER, measured as the loan portfolio diversification index[3].

OVERHEAD and INSIDELN are proxies for management risk in the CAMEL rating systems. OVERHEAD is a measure of operating efficiency that was introduced in the model in a ratio form (dividing overhead costs by total assets). Using “Aggregate amount of all extensions of credit to executive officers, directors, and principal shareholders” as a proxy for the insider loan, we use the ratio of insider loan to total assets (INSIDELN) to capture another form of management risk: fraud or insider abuse.

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3 The index was developed using the Herfindahl measurement method where the index was constructed from taking the sum of squares of various components of the loan portfolio:

$$\text{LOANCHER} = \sum \left(\frac{\text{Real Estate Loans}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Loans to depository institutions}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Individual Loans}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Commercial and Industrial Loans}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Agricultural Loans}}{\text{Total Loans}}\right)^2$$

PROFIT[4], or return on assets, is the proxy for the banks' earnings capability in the CAMEL rating system. Two types of liquidity measures were added to the model as proxies for liquidity risk. LIQM1 was calculated by dividing non-deposit liabilities with cash and investment securities. LIQM2 was calculated by dividing total loans with total deposits.

Measures that capture the banks' loan exposure to different industry sectors are also included in the analyses. AGTOTAL, CONSTOTAL, INDUSTOTAL and RETOTAL are ratios of loans extended to the agricultural, consumer, industrial and real estate industries, respectively. Beyond the previous category of loan portfolio-based variables, this study also considers loan portfolio risk measures that are expected to even shed more light into the causes of bank failures. In this study, the loan delinquency rates that capture loan portfolio risk are measured for certain categories of loan exposures: agricultural non-real estate loans (AGNR), agricultural real estate loans (AGR), commercial & industrial loans (INDUS), and consumer loans (CONSUM). The delinquency rates for the agricultural loan portfolio were separated for real estate and non-real estate loans in order to isolate the effects of real estate loan exposures to this industry and determine whether the agricultural sector contributed to the popular claim that real estate delinquencies, in general, are being suspected as the significant precursors of recession.

The next three early warning system variables represent the funding arrangements or strategies employed by banks. PURCHASEDTL, purchased liabilities as a percentage of total liabilities, is used to reflect the share of liabilities purchased from national market, as suggested by Belongia and Gilbert(Belongia and Gilbert, 1990). DEPLIAB, was calculated by taking the ratio of total deposits to total liabilities.

4 To calculate return on assets, we need to construct the net income after taxes to total assets ratio. The item net income after taxes are no longer available in Call Report, and item "Undivided profits and capital reserves" was used instead.

This study also considers duration gap, GAP, which is a commonly used tool to measure interest-rate risk. This study uses the definition given by Blasko and Sinkey.[5] Just as in their study, in this study, GAP is defined as the difference between rate-sensitive assets and rate-sensitive liabilities(Blasko and Sinkey, 2006). This approach is more appropriate to calculate GAP when using the Call Reports dataset since all the variables they used can be directly found from the dataset.

SIZE variable was included in the model by taking the natural logarithm of total assets. This variable was added to the failure prediction model to account for the “too big to fail” doctrine.

This study further extends the previous bank failure prediction (early warning) models by considering variables that capture the macroeconomic conditions at the state level. UNEMRATE, is the quarterly percentage change of state-level unemployment rate. The data of U.S. bankruptcy filings was also used as a proxy for general business conditions of each state. BF, was calculated by aggregating each state’s business filings and non-business filings together, and dividing the total by the number of total filings of all states.

RESULTS AND IMPLICATIONS

Bank Failure Prediction Model

In determining early warning signals for predicting bank failures, logistic regression techniques were applied to several time period models dating back from 6 months to 48 months before a bank is declared insolvent by the FDIC, which is otherwise known in this study as bank

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[5] In their study, Blasko and Sinkey (2006) define rate sensitive assets = (Federal funds sold) + (Securities purchased under agreements to resell) + (Customer’s liability) + (Trading assets) + (Fixed and floating debt securities maturing or repricing within 12 months) + (Fixed and floating loans maturing or repricing within 12 months); rate sensitive liabilities = (Federal funds purchased) + (Securities sold under agreements to repurchase) + (Bank’s liability on acceptances executed and outstanding) + (Trading liabilities) + (Other borrowed money) + (Demand notes issued to the U.S. Treasury) + (Time and saving deposits) – (Large long-term time deposits).
And GAP = rate sensitive assets – rate sensitive liabilities + (Small longer-term deposits).

failure. This portion of the analysis considers 6 time period cross-sectional data models[6]: 6months, 12 months, 18months, 24 months, 36 months, and 48 months prior to failure. The in-sample prediction for these 6 model versions is undertaken using a database of 95 banks that failed in 2009 and 1,180 banks that have survived and continued operations through that year.

Table 2 summarizes the logistic regression results for all time period model versions, which are useful for determining the relative significance of variables and their directional (positive or negative) relationship with the dependent variable. Table 3 provides the results for marginal effects that show the magnitude of influence the explanatory variables have on the dependent variable.

Based on the result summaries, one of the notable results was the significance of RWCAPRATIO, the risk-weighted capital ratio, which is being used by the FDIC to identify banks that are still solvent, those that need to be warned about possible insolvency, and those that are eventually closed down because of critically insolvent conditions. This ratio determines the capacity of the bank in terms of facing certain risks such as credit risk, and operational risk. This study's results indicate that RWCAPRATIO is a significant negative determinant (and predictor) of bank failure from 6 months until as long as 18 months prior to failure. The coefficients of this variable tend to become insignificant at longer time lags, which may suggest of its reliability as a predictor of financial stress over the short-run, but not over longer time horizons.

The LOANHER measured using the Herfindahl index approach was also included in Thomson's study and did not fare well as in his regression models. In this study, this variable is also barely significant in the 6-month model as its p-value shows significance under the 10 percent confidence level. The loan portfolio diversification is normally regarded as a risk-

[6] The heteroskedasticity was checked for each cross-sectional model with computing a likelihood ratio test between probit model (prob) and Heteroskedastic probit model (hetprob) in Stata. The results indicate the heteroskedasticity problem is not severe in our datasets.

reducing strategy and, thus, the significant positive coefficient result in the 6-month model suggests that diversification indeed helps minimize the probability of bank failure.

Pursuant to the verified effectiveness of the loan portfolio diversification strategy, the loan portfolio composition variables identify the sectors that banks should consider in their loan servicing operations. The regression results indicate that banks may consider loan exposures to their consumer credit clientele (CONSTOTAL) from 1 to 2 years prior to bank failures. Loan exposures to agricultural (AGTOTAL) and industrial (INDUSTOTAL) may be considered around 1 year before the onset of bank failures. These variables are negatively signed, which suggests that an increase in the portfolio of these loans will decrease the probability of failure.

Among the portfolio risk variables (AGNR, AGR, CONSUM and INDUS, which are loan ratios of past due/ nonaccrual loans), the most notable result that applies to this study's special focus is the insignificance of both the non-real estate and real estate delinquency ratios for agricultural loans (AGNR and AGR) across all time period models. This suggests that agricultural loan ratios cannot be used as indicators for predicting bank failure. This finding is important because it confirms our contention that exposure to clients engaged in seemingly riskier and more uncertain agribusiness operations does not really pose as a risk or enhances a bank's tendency to fail.

On the contrary, the delinquency loan ratios for consumer loans (CONSUM) and commercial/industrial loans (INDUS) are significant positive regressors in some time period models. CONSUM is a significant determinant or predictor of bank failure from 6 months up to 18 months prior to bank failure, while INDUS is a significant bank failure predictor around 12 and 24 months before bank insolvency.

The marginal effects results for these variables provide interesting insights and implications (Table 3). A 1 percent increase in the industrial loan delinquency ratio will increase the probability of bank failure by 253% around 24 months before bank failure. At about a year before bank failure, the marginal effect of INDUS is 1.81. The magnitude of the marginal effects for CONSUM is even larger. In fact, the CONSUM has among the largest marginal effects as a 1% increase in the consumer loan delinquency ratio could increase the probability of bank failure by 227%, 397% and 388% around 6, 12, and 18 months, respectively, before the occurrence of bank failure. It is worth noting that most consumer loans extended by commercial banks are through credit cards and other revolving credit plans.

Variables that capture management risk and insider abuse are expected to be positively related to the probability of bank failure. However, in contrast to the results obtained in previous studies, the coefficients of insider loan (INSIDELN) have remained consistently insignificant across all the time period models. On the other hand, the overhead cost ratio (OVERHEAD) variable has turned up negative and significant results in almost all time period models (except for the 6 month and 18 month models). This contrasting result can be attributed to some plausible strategic moves of banks during the recessionary period. When faced with financial difficulty, especially illiquid conditions, banks may have the tendency to resolve the operating constraint by selling low-risk assets (like Treasury securities) that are relatively more easily marketable. As a result of such probable coping mechanism, the bank loses its asset base (OVERHEAD ratio denominator) while at the same time, overhead costs (ratio's numerator) could possibly be rising as a result of higher degrees of operating inefficiency produced by less prudent operating decisions. Thus, the net effect of these two trends would be the positive relationship between increasing OVERHEAD ratios and the probability of bank failure.

Two measures of liquidity (LIQM1, LIQM2) are included as regressors in the models to capture different facets of bank liquidity. LIQM1 captures liquidity that is attributed to more costly sources of funds (non-deposit liabilities) as opposed to the cheaper deposit sources. As such, this liquidity-enhancing option, while favorable to bank liquidity conditions, is actually unfavorable in terms of enhancing profit potentials and, hence, maximizing equity gains for the bank. Thus, this variable is expected to be positively related to the probability of bank failure. In this study, this variable's coefficients across all time period models have been insignificant.

The other liquidity measurement, LIQM2, calculated as the loan-to-deposit ratio, produced more significant results for the 6-month and 12-month models. The loan-to-deposit ratio captures the bank's financing strategy where bank loans are funded through deposits – which is an ideal, logical operating decision for banks. An upswing in this ratio may suggest that a bank has less of a cushion to fund its growth and to protect itself against a sudden recall of its funding (Feldman 1998). Thus, it should be positively related to the bank failure. The unexpected result for this variable (significantly negative) may indicate that this variable is a poor proxy of liquidity.

The significant negative coefficients of PROFIT in all time period models (except for the 6-month and 18-month models) indicate that the erosion of bank profits can be a strong determinant (and eventual predictor) of the probability of bank failure.

PURCHASEDTL, defined as the percentage of purchased liabilities among total liabilities, captures the national market option for sourcing funds. As described by Belongia and Gilbert(Belongia and Gilbert, 1990), the liabilities purchased from national market will have higher interest rate**.** The coefficient results are robust across all time period models (except for the18 month-model) with significant positive results, indicating that banks are more likely to fail when exposed to the higher interest rate risk. On the other hand, the coefficient for DEPLIAB is negative and significant in all time period models. These results are consistent with the expectation that banks' tendency to thrive in their businesses are enhanced by their ability to maximize the generation of deposits to fund their business funding requirements.

A third measure, duration GAP measurement, is also included in the analysis to further investigate interest rate risk issues. The significant positive coefficient of GAP that all time period models produced is consistent with logical expectations as higher GAP values are associated with higher interest rate risk. These results therefore imply that the probability of bank failure is positively related to the likelihood or incidence of higher interest rate risk or the banks' greater sensitivity to interest rate change.

The SIZE variable was at least significantly negatively related to the probability of failure in the 12-month model, while remaining insignificant in the other time period models. This results confirmed the "too big to fail" doctrine that larger banks could have already established more coping mechanisms that could be relied on in times of financial distress.

Percentage change of state-level unemployment rate (UNEMRATE) is expected to be positively related to the probability of bank failure for a healthy economic condition should have a positive effect on the banking industry. However, it has mixed signs, which is not a new result. Thomson (1991), in his study, also obtained the same result suggesting a negative relationship between bank failure and unemployment rate. He explained his results by citing the increased political constraints as explanation. The state-level bankruptcy filing ratio (BF) variable is more logically acceptable. The negative and significant coefficients imply that a higher incidence of business or non-business failures or bankruptcies in each state would further depress the general economic conditions that would, in turn, influence the surge of bank failures.

In-Sample Classification Accuracy

Table 4 reports the overall classification accuracy for all time period models, along with each model's type I and type II error, and Pseudo R^2. As shown in table 3, the overall classification accuracy ranges from 95.11 to 98.59, where the accuracy level is highest for time period models are closer to the occurrence of bank failure. The overall accuracy level tends to diminish as the time period model moves farther away from the experience of bank failure. Specifically, the accuracy rate is 98.59% for the more current 6-month time period model and 95.11% for the 48-month period model.

In a similar fashion, Pseudo R^2 also decreases as the time period model moves farther away from the time of bank failure. The same trend is not observed in the type I and type II error rates. These rates are calculated as percentages of misclassified observations to the total classifications in a certain category (failure versus non-failure). The range for Type I error is from 10.53% in the 6-month time period model to 56.32% in the 48-month time period model.

Type II error rates are considerably smaller, ranging from 0.68% for the 6-month time period model to 1.19% for the 18-month model.

Out-of-Sample Forecasting

The forecasting efficiency or prediction accuracy of this study's regression results is further tested through out-of-sample forecasting techniques. A separate dataset, consisting of banks that failed in 2010 and 1109 non-failed banks, is compiled for this analysis. The dataset is constructed in the same way that the cross-sectional datasets for the earlier regression were developed.

The estimated coefficients from the previous cross-sectional logistic regression models are used for forecasting or prediction purposes (table 2). As before in the in-sample prediction, the cutoff point is set at 0.5 for separating failed and non-failed banks. The out-of-sample classification accuracy ranges from 99.42 to 95.28 (table 4), reflecting an increasing trend in accuracy rates as the time period models approach the point of bank failure (except for 36 months model, for which the classification error is less than the 24 months). The 48-month model produced the highest rate of type I error (54.08 percent). In contrast, forecasts for the 6-month to 36-month models produced type I error rates that range from 6.93 percent to 41.58 percent.

As before, the type II error rates are much lower than the type I error rates. The range of values for type II error rates are from 0.45% in the 6-month model to 1.53% in the 36-month model.

CONCLUSION

In order to address the perennial question of whether the riskier, more volatile agricultural sector indeed has contributed significantly in causing and provoking the current crises in the financial industry, this study has developed early warning models that involve a host of potential determinants of the probability of bank failure. These factors include a set of variables that represent bank's management decisions, operating strategies, financial conditions and prevailing macroeconomic conditions. The bank failure prediction models produced results that identified important early warning signals that could be detected as far back as 3 to 4 years prior to a bank's declaration of insolvency or bankruptcy. The most compelling result in the analyses of early warning signals is the notable insignificance of any measure related to the banks' agricultural loan portfolios. Even agricultural real and non-real estate loan delinquencies have not been established to significantly influence the likelihood of bank failure across all time period models. These results confirm our contention that exposure to a seemingly riskier and more uncertain agribusiness operations does not necessarily enhance a banks' tendency to fail. On the other hand, delinquency rates for consumer loans and commercial & industrial loans are significant predictors of bank failure. As commercial/industrial loans are typically larger in magnitude, increases in delinquency in this loan category due to depressed economic demand and diminished economic activity will certainly help lead to bank failure.

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Table 1. Delineation of Bank Time Period Observations

Model	Bank A (Bankrupt in 3rd Qtr 2009)	Bank B (Bankrupt in 1st Qtr 2009)	Bank C (Surviving Bank)
6-month model	1st Qtr 2009	3rd Qtr 2008	2nd Qtr 2009[7]
12-month model	3rd Qtr 2008	1st Qtr 2007	4th Qtr 2008
18-month model	1st Qtr 2008	3rd Qtr 2007	2nd Qtr 2008
24-month model	3rd Qtr 2007	1st Qtr 2007	4th Qtr 2007
36-month model	3rd Qtr 2006	1st Qtr 2006	4th Qtr 2006
48 month model	3rd Qtr 2005	1st Qtr 2005	4th Qtr 2005

[7] Data for surviving banks are determined using the entire coverage of the dataset. The banking dataset used in this research extends to the last quarter of 2009. Hence, a surviving bank's data for the 6-month model, for instance, will be its 2nd quarter of 2009 financial conditions.

Table 2. Cross-sectional logit regression results for bank failure prediction model						
Variables	**Months to failure after Call Report issued**					
	6months	**12months**	**18months**	**24months**	**36months**	**48months**
RWCAPRATIO	-79.49***	-58.35***	-24.05**	-2.69	1.04	0.23
	(19.62)	(15.07)	(11.49)	(2.84)	(4.38)	(1.61)
AGNR	43.56	-50.04	-661.713	-477.03	-1317.93	-122.40
	(27.85)	(84.37)	(685.18)	(474.77)	(1088.49)	(287.33)
AGR	-14.43	13.91	7.80	-124.45	-328.72	-196.33
	(24.34)	(50.27)	(58.16)	(139.04)	(235.37)	(213.78)
INDUS	24.08	91.77**	29.15	72.69**	18.98	34.35
	(19.89)	(43.30)	(18.45)	(32.85)	(33.67)	(31.04)
CONSUM	247.84***	201.24*	122.96**	-34.29	18.98	34.35
	(69.65)	(106.13)	(52.89)	(137.76)	(33.67)	(31.04)
LOANHER	9.92*	1.89	2.98	2.32	-4.43	1.38
	(5.44)	(6.53)	(3.63)	(3.07)	(4.60)	(3.52)
AGTOTAL	-9.07	-21.85	-11.05	-3.12	7.96	0.18
	(12.25)	(10.67)	(9.04)	(8.55)	(10.84)	(8.03)
CONSTOTAL	-17.76	-41.34**	-41.02**	-26.37**	-19.31	-14.28
	(11.68)	(15.34)	(12.78)	(13.20)	(13.46)	(10.19)
INDUSTOTAL	-13.97	-24.85**	-7.47	-4.89	6.64	3.24
	(10.69)	(11.22)	(7.85)	(8.51)	(10.07)	(8.21)
RETOTAL	-10.21	-14.51	-5.97	-2.43	16.02	5.62
	(13.22)	(13.27)	(8.72)	(9.14)	(13.00)	(9.39)
LIQM1	0.38	0.63	0.25	0.28	-0.72	-0.82
	(0.59)	(0.48)	(0.24)	(0.31)	(1.12)	(0.51)
LIQM2	-7.79**	-4.70**	-0.95	-1.15	1.23	-0.32
	(2.49)	(1.54)	(1.83)	(1.67)	(1.32)	(0.61)
OVERHEAD	66.130	-115.50**	23.10	-98.63**	-113.36**	-132.03***
	(78.89)	(33.24)	(65.56)	(31.55)	(46.51)	(28.14)
INSIDELN	-1.67	-1.15	12.84	-1.69	5.89	0.51
	(26.45)	(12.20)	(10.34)	(10.32)	(10.13)	(9.67)
PROFIT	-10.67	-32.88**	-4.08	-22.42***	-23.38***	-21.80***
	(10.22)	(5.99)	(3.15)	(6.18)	(5.14)	(4.01)
SIZE	0.33	-0.33	-0.04	0.03	0.05	-0.14
	(0.26)	(0.21)	(0.18)	(0.18)	(0.20)	(0.15)
PURCHASEDTL	5.57*	6.92***	1.49	3.07**	2.47*	4.20**
	(3.24)	(2.00)	(1.61)	(1.52)	(1.42)	(1.60)
DEPLIAB	-20.09**	-16.47***	-8.77*	-7.09*	-9.32**	-12.48**
	(9.57)	(4.47)	(4.62)	(3.87)	(3.94)	(3.94)
GAP	9.24***	6.81***	4.89***	4.35***	4.14***	4.74***
	(2.18)	(1.35)	(1.11)	(1.02)	(0.96)	(0.99)
UNEMRATE	30.62**	-13.62**	-31.09**	17.10***	16.99**	4.23*
	(9.10)	(5.12)	(5.86)	(4.75)	(5.53)	(2.31)
BF	30.32**	32.18***	42.84***	13.36**	32.64***	25.98***
	(14.68)	(8.39)	(8.93)	(6.73)	(7.86)	(7.37)
Constant	17.93	37.96**	14.00	5.80	-5.68	4.49
	(12.32)	(12.25)	(8.90)	(8.50)	(11.50)	(9.06)

Note

*** Significantly different from zero at the 1% level. ** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level. Standard errors are reported in the parentheses.

Table 3. Marginal Effects of the Logit Results

Variables	Months to failure after Call Report issued					
	6months	12months	18months	24months	36months	48months
RWCAPRATIO	-0.73***	-1.15***	-0.76**	-0.09	0.04	0.01
	(0.16)	(0.23)	(0.34)	(0.10)	(0.15)	(0.06)
AGNR	0.40	-0.99	-20.90	-16.63	-44.15	-4.61
	(0.25)	(1.67)	(21.64)	(16.54)	(36.46)	(10.81)
AGR	-0.13	0.27	0.25	-4.34	-11.01	-7.39
	(0.22)	(0.99)	(1.84)	(4.85)	(7.89)	(8.04)
INDUS	0.22	1.81**	0.92	2.53**	0.64	1.29
	(0.18)	(0.85)	(0.58)	(1.14)	(1.13)	(1.17)
CONSUM	2.27***	3.97*	3.88**	-1.20	4.30	0.32
	(0.64)	(2.10)	(1.67)	(4.80)	(4.24)	(5.13)
LOANHER	0.09*	0.04	0.09	0.08	-0.15	0.05
	(0.05)	(0.13)	(0.11)	(0.11)	(0.16)	(0.13)
AGTOTAL	-0.08	-0.43**	-0.35	-0.11	0.27	0.001
	(0.11)	(0.20)	(0.29)	(0.30)	(0.37)	(0.30)
CONSTOTAL	-0.16	-0.82**	-1.30**	-0.92**	-0.65	-0.54
	(0.10)	(0.29)	(0.41)	(0.45)	(0.45)	(0.38)
INDUSTOTAL	-0.13	-0.49**	-0.24	-0.17	0.22	0.12
	(0.09)	(0.21)	(0.25)	(0.39)	(0.34)	(0.31)
RETOTAL	-0.09	-0.29	-0.19	-0.08	0.54	0.21
	(0.12)	(0.25)	(0.28)	(0.32)	(0.44)	(0.35)
LIQM1	0.003	0.01	0.01	0.01	-0.02	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)
LIQM2	-0.07***	-0.09**	-0.03	-0.04	0.04	-0.01
	(0.02)	(0.03)	(0.06)	(0.06)	(0.04)	(0.02)
OVERHEAD	0.61	-2.28***	0.73	-3.44**	-3.80**	-4.97***
	(0.72)	(0.65)	(2.07)	(1.10)	(1.57)	(1.05)
INSIDELN	-0.02	-0.02	0.41	-0.06	0.20	0.02
	(0.24)	(0.24)	(0.33)	(0.36)	(0.34)	(0.36)
PROFIT	-0.10	-0.65***	-0.13	-0.78***	-0.78***	-0.82***
	(0.09)	(0.09)	(0.10)	(0.22)	(0.19)	(0.16)
SIZE	0.003	-0.01*	-0.001	0.001	0.002	-0.01
	(0.002)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
PURCHASEDTL	0.05*	0.14***	0.05	0.11**	0.08*	0.16**
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)
DEPLIAB	-0.18**	-0.033***	-0.28*	-0.25*	-0.31**	-0.47***
	(0.09)	(0.09)	(0.14)	(0.14)	(0.13)	(0.15)
GAP	0.08***	0.13***	0.15***	0.15***	0.14***	0.18***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
UNEMRATE	0.28**	-0.27**	-0.98***	0.60***	0.57***	0.16*
	(0.10)	(0.09)	(0.17)	(0.16)	(0.18)	(0.09)
BF	0.28**	0.64***	1.35***	0.47**	1.09***	0.98***
	(0.14)	(0.16)	(0.28)	(0.23)	(0.27)	(0.28)

Note:

*** Significantly different from zero at the 1% level.
** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level.
Standard errors are reported in the parentheses.

Table 4. In-Sample and Out-of-Sample Forecasting Results

Forecasting Type	Months prior to failure					
	6months	**12months**	**18months**	**24months**	**36months**	**48months**
	A. In-Sample Forecasting					
Classification accuracy (%)	98.59	97.57	96.16	95.21	96.30	95.11
Type I error (%)	10.53	22.11	36.84	44.68	41.11	56.32
Type II error (%)	0.68	0.85	1.19	1.61	0.85	1.10
Pseudo R^2	0.8699	0.7369	0.5878	0.5418	0.5501	0.4756
	B. Out-of-Sample Forecasting					
Classification accuracy (%)	99.42	97.44	95.45	95.29	95.95	95.28
Type I error (%)	6.93	17.82	38.61	41.58	32.00	54.08
Type II error (%)	0.45	1.17	1.44	1.35	1.53	1.08