Agricultural lending and early warning models of bank failures for the late 2000s Great Recession

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Abstract

Purpose – The late 2000s Great Recession led to a surge of bank failures in the USA with nearly 300 banks failing from 2009 to 2010. Recalling the farm crises of the 1980s where the farm sector was pinpointed as one of the major precursors of such crises, this study is an attempt to validate if the agricultural sector can once again be considered as a major instigator of the current financial crises.

Design/methodology/approach – An early warning model is developed based on factors that may cause bank failures, with special attention given to the role of the agricultural lending portfolios of commercial banks. The model will have several time period versions that will determine the length of time prior to the actual bank bankruptcy declarations that early warning signals could be detected.

Findings – The empirical results indicate that credit exposure to the farm sector does not necessarily enhance a bank's tendency to fail or its probability of success or survival. This lends support to the reality that agricultural loan delinquency rates are consistently below the banks' overall loan delinquency rates, thus confirming that agricultural lenders are in relatively stronger financial health. This study instead finds that costly funding arrangements, increasing interest rate risk, and declining asset quality can be possible early warning signals that can be detected as far back as two or three years before eventual bank failure.

Originality/value – This study differentiates itself from previous studies by its special focus on the role of the agricultural finance industry in the ensuing economic crises. This study's early warning model also presents an extended version of previous empirical models as it accounts for measures of capital adequacy, asset quality, management risk, profitability, liquidity risk, loan portfolio composition and risk, funding arrangement, structural and macroeconomic variables.

Keywords Agricultural loans, Bank failures, Early warning signals, Funding arrangements, Interest rate risk, Late 2000s Great Recession, Liquidity risk, Loan portfolio risk, Risk-weighted capital ratio, Agriculture, Banks, Financing

Paper type Research paper

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 Second World War and the longest downturn since the 1930s Great Depression. Dubbed as the Great Recession (Wessel, 2010), it was said to have started, according to the National Bureau of Economic Research (NBER), in December 2007

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when labor market and the overall global economic conditions started deteriorating (NBER, 2008; Isidore, 2009).

The US 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 (Rutenberg and Thee-Brenan, 2011). A widely accepted theory was that the breakdown of the real estate industry significantly launched the onset of the economic crises in the USA (Demyank and Van Hemert, 2011; Isidore, 2009). The housing downturn started in 2006 when housing prices 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.

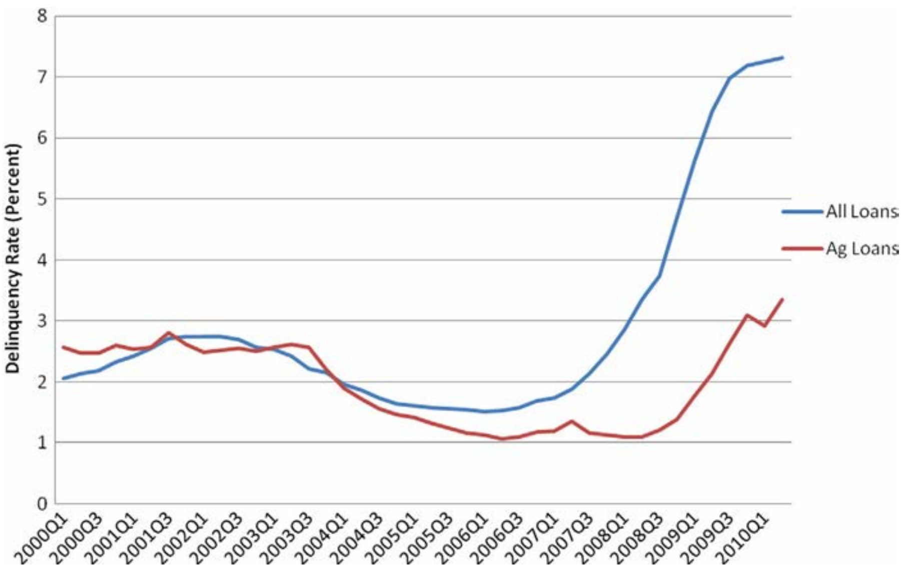
The late 2000s financial crisis led to a surge of bank failures in the USA at an overwhelming rate not observed in many years. A total of 325 bank failures were recorded between 2007and 2010. In contrast, only 24 banks had failed in the seven-year period prior to 2007.

Delinquencies in subprime residential loan accommodations were said to have delivered the coup de grace to the country's banking system and consequently led to the wave of bank failures since 2007. The subprime mortgage is viewed as riskier than a regular loan because its expected probability of default is higher (Demyanyk and Hasan, 2010). Speculative borrowing in residential real estate has been pinpointed as a contributing factor to the subprime mortgage crisis. Under earlier favorable economic conditions, lower interest rates and large inflows of foreign funds created an easy access to credit and fueled the housing market boom with real estate prices dramatically increasing since 2002. However, the housing bubble burst when housing prices started dropping in late 2006 after peaking in early 2006. High inflation and tight financial market conditions caused the default by hundreds of thousands of borrowers within a short period of time and resulted in a number of major US lending institutions closing their businesses. Following 25 bank closures in 2008, a total of 140 banks closed down in 2009. The rate of bank bankruptcy even increased in 2010, with 157 bank failures, the highest level since the savings-and-loan crisis in 1992.

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 during the latest recessionary period.

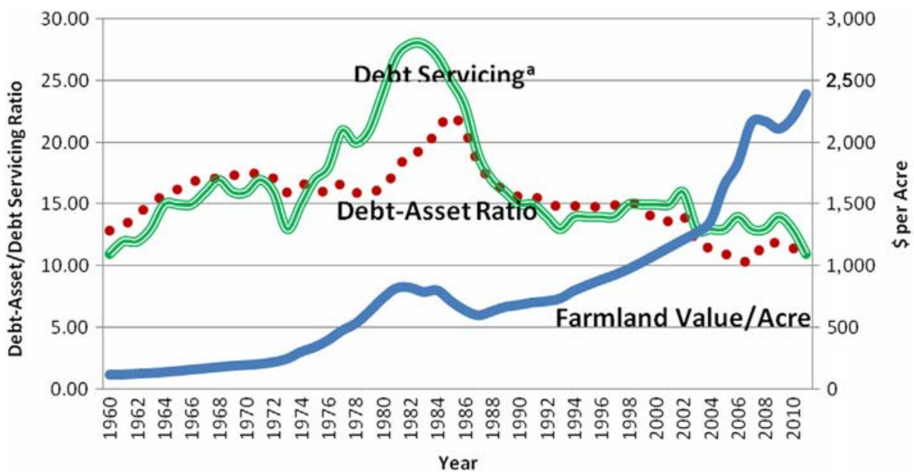
However, the true state of agricultural industry during this recessionary period may tell a different story. In the lending side, Ellinger and Sherrick (2010) claimed that the agricultural lenders are actually generally in strong financial health because most of the agricultural-related institutions did not lend heavily to the real estate industry, and agricultural banks did not invest in the structured securities that have lost substantial market value. In recent years, the agricultural loan delinquency rates have consistently been below the banks' overall loan delinquency rates since the 1st quarter of 2004 (Figure 1).

Figure 2 shows trends in farmland values and farm debt-related measures collected for the years 1960-2010. This historical summary clearly depicts significant differences



Source: Board of Governors of the Federal Reserve System (2010)

Figure 1.
National loan delinquency rates, quarterly, 2000-2010



Note: [a]Debt servicing ratio is scaled by 100 for plotting purposes
Source: Economic Research Service, USDA

Figure 2.
US average farmland values, debt servicing and debt-asset ratios, 1960-2010

between the financial conditions of the farm sector in recent years (2000s onwards) and during certain episodes of recessionary periods since 1960. A case in point is a comparison between the 1980s and the late 2000s recessions. The booming farm incomes and commodity prices in the 1970s have led to increasing farmland values that peaked in 1981. This ignited a spike in farmland purchases as the farm's debt-asset ratio started increasing (Figure 2). However, farmland values declined by about 50 percent over the next six years and then reached its lowest value in 1987. Farm bankruptcies and foreclosures led to tight money conditions and a surge in interest rates. At that period, one-third of bank failures from 1984 to 1987 were agricultural banks (Thomson, 1991).

The farm sector has learned its lessons since then. It is worth noting that from a debt-to-asset ratio of 22.19 in 1985, the farm sector has managed to bring that ratio down to 11.33 in 2009 (Figure 2) – which actually has improved further to 10.74 in 2010. Since the 1980s, the farm sector's debt repayment capacity utilization (DRCU), which accounts for all debt obligations and compares them with maximum debt repayment capabilities, has improved tremendously. In more than two decades, both the rate of increase and the absolute increase in asset values have significantly exceeded those of farm debt. Under a regime of low interest rates, more income protection (such as crop insurance) and steady gains in farmland values, the farm sector of the late 2000s has been in much better financial health than the 1980s farms.

This study nonetheless would like to validate the above contention and determine if the agricultural lending portfolio of any commercial bank has enhanced its probability of failure during the late 2000s recession. In the face of the current recession, 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; DeYoung and Hasan, 1998), introducing different capital ratios as predictors of bank performance (Estrella *et al.*, 2000), and analyze the impact of audit quality on bank failure (Jin *et al.*, 2011). Different bankruptcy prediction models have been developed in those studies, with the basic probit/logit model (Cole and Gunther, 1995; Hanweck, 1977; Martin, 1977; Pantalone and Platt, 1987; Thomson, 1991) as the widely used analytical tool. What these studies have in common is that they divided the banks into failure and non-failure groups and treated the classification as binary dependent variable regressed against a host of explanatory variables that could influence a bank's probability of failure.

This study differentiates itself from previous empirical works by its special focus on the role of the banks' agricultural loan exposures in the ensuing credit crises. Specifically, this study will develop an early warning model that considers factors that can predict the eventual occurrence of 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.

Empirical design for bank failure analysis

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:

(1) the addition of state-level variables that capture macroeconomic factors, in addition to bank performance variables; and
(2) 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 empirical design includes defining an equation for estimating $PROB_{it}$ for each observation that involves the following categories of explanatory variables:

$$\begin{aligned} PROB_{it} &= x'_{\iota\tau}\beta \\ &= \beta_0 + \beta_1 AQCA_{it} + \beta_2 MR_{it} + \beta_3 PL_{it} + \beta_4 LPC_{it} + \beta_5 LPR_{it} + \beta_6 FA_{it} \\ &\quad + \beta_7 SIZE_{it} + \beta_8 STECON_{it} + u_t \end{aligned}$$

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]. Hence, in this study, the term "insolvency" will be used synonymously with "failure" as determined by the FDIC using the above criterion.

$AQCA_{it}$ 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 and bank earnings potential; LPC_{it} are variables for loan portfolio composition measures; LPR_{it} capture loan portfolio risk measures; FA_{it} are variables for 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 denotes the period of time prior to bank failure.

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 I.

In the different time period models, PROB is the identifier for banks that eventually failed during the entire sample period. The early warning models will be applied to the 2009 failed bank dataset and other banks surviving as of the end of 2009. For example, if Bank A was declared insolvent in the 3rd quarter of 2009 while Bank B went into insolvency in the 1st quarter of 2009, and Bank C is a bank that survived, the delineation rules in Table I are used in defining the observations for Banks A, B and C in the different cross-sectional time period models.

Data sources and 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 web site of Federal Reserve Board of Chicago (FRB). The banking

Table I.
Time period delineation for determining quarterly Call Report data used

Model	Quarterly Call Report data used Bank A (insolvent in 3rd qtr 2009)	Bank B (insolvent in 1st qtr 2009)	Bank C (surviving bank)
6-month model	1st qtr 2009	3rd qtr 2008	2nd qtr 2009[a]
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

Notes: [a]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

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. The same restriction was applied to the subset of failed banks. In compiling the dataset, special attention was given to banks that failed in 2009 and 2010, the two years with the largest number of bank failures since 1992.

In this study, six time period models (i.e. six, 12, 18, 24, 36, and 48 months) are developed utilizing a common dataset of 1,180 surviving banks and 95 failed banks (in 2009)[3]. Table I explains the derivation of the quarterly data points for each observation in every time period model. In the cross-sectional dataset for each time period, the data points for surviving banks are fixed (Bank C in Table I). A failed bank's data point, however, depends on the quarter in 2009 when the bank was declared failed or insolvent by FDIC (Banks A and B in Table I capturing two out of four possible cases of quarterly failures).

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.

Categories of variables

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. Some of the explanatory variables are selected to be proxies for the components of the CAMELS rating system[4], which is used by regulators during on-site examinations to determine a bank's financial conditions. These variables, summarized in Table II with summary statistics presented in Table III, are organized under different categories and defined as follows.

Capital adequacy, asset quality and management risk variables

LOANHER, which is calculated as the loan portfolio diversification index[5], captures the extent of diversification of the bank's risky asset (loans) among various loan types. OVERHEAD and INSIDELN are used in this study as proxies for management risk systems (Thomson, 1991). OVERHEAD is a measure of operating efficiency that was introduced in the model in a ratio form (dividing overhead costs by total assets). Using the Call Report item "Aggregate amount of all extensions of credit to executive officers, directors, and principal shareholders" as a proxy for insider loan, we use the ratio of insider loan to total assets (INSIDELN) to capture of management risk in the form of fraud or insider abuse.

Profitability potential and liquidity risk variables

PROFIT[6], or return on assets, is the proxy for the banks' earnings capability in the CAMELS 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.

Variables	Descriptions
Dependent variable	
PROB	Dummy variables, equals to one for failed banks and zero for non-failed banks
Explanatory variables	
AGNR	Aggregate past due/non-accrual agricultural non-real estate loans/total loans
AGR	Aggregate past due/non-accrual agricultural real estate loans/total loans
INDUS	Aggregate past due/non-accrual commercial and industrial loans/total loans
CONSUM	Aggregate past due/non-accrual Consumer loans/total loans
LOANHER	Loan portfolio Herfindahl index constructed from the following loan classifications: real estate loans, loans to depository institutions, loans to individuals, commercial and industrial loans, and agricultural loans
AGTOTAL	Agricultural loans/total loans
CONSTOTAL	Consumer loans/total loans
INDUSTOTAL	Commercial and Industrial loans/total loans
RETOTAL	Real Estate loans/total loans
LIQM1	Non-deposit liabilities/cash and investment securities
LIQM2	Total loans/total deposits
OVERHEAD	Overhead costs/total assets
INSIDELN	Loans to insiders/total assets
PROFIT	Return on assets
SIZE	Natural logarithm of total assets
PURCHASEDTL	Purchased funds to total liabilities
DEPLIAB	Total deposits/total liabilities
GAP	Duration GAP measure
UNEMRATE	Percentage change of unemployment rate
BF	Business failure ratio

Table II. Definitions of variables for the bank failure prediction model

Variable	Mean	SD	Minimum	Maximum
AGNR	0.0020	0.0068	0	0.3761
AGR	0.0029	0.0060	0	0.0974
INDUS	0.0050	0.0074	0	0.1516
CONSUM	0.0030	0.0045	0	0.1206
LOANHER	0.5519	0.1627	0.0028	1.0000
AGTOTAL	0.0913	0.1332	0	0.8123
CONSTOTAL	0.0826	0.0718	0	0.8917
INDUSTOTAL	0.1344	0.0805	0	1.0000
RETOTAL	0.6772	0.1735	0	1.0000
LIQM1	0.2645	0.8538	0.0006	87.3232
LIQM2	0.8180	0.2270	0.0350	18.5314
OVERHEAD	0.0123	0.0070	−0.0016	0.1866
INSIDELN	0.0128	0.0148	0	0.1839
PROFIT	0.0581	0.0476	−1.1943	0.2913
SIZE	12.0436	1.1307	8.3885	16.7375
PURCHASEDTL	1.0880	0.1432	0.0317	1.7592
DEPLIAB	0.9244	0.0742	0.0317	0.9996
GAP	−0.0773	0.1928	−0.7183	0.9225
UNEMRATE	0.0227	0.0737	−0.5393	0.3791
BF	0.0262	0.0207	0	0.1689

Table III.
Data summary for bank failure prediction model

Lon portfolio composition and risk variables

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. The ratios were calculated by dividing the total loan portfolio for each client sector or group to the total loan portfolio of the bank.

Beyond the previous category of loan portfolio-based variables, this study also considers risk measures associated with specific components of the loan portfolio 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 and industrial loans (INDUS), and consumer loans (CONSUM). These portfolio risk ratios are calculated by aggregating such loan delinquency figures as "past due up to 89 days", "past due 90 plus days", and "nonaccrual or charge offs" together for each loan category (as enumerated above) and dividing the total delinquencies by the aggregate value of the loan portfolio. 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.

Funding arrangement variables

Three 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 (Belongia and Gilbert, 1990). DEPLIAB, was calculated by taking the ratio of total deposits to total liabilities.

This study also considers repricing gap, GAP, which is used to measure interest-rate risk but usually ignored by previous bank failure prediction studies. Belongia and Gilbert (1990) introduced this concept by specifying a measure calculated by taking assets with maturities under one year minus liabilities with maturities under one year, and dividing the difference by total assets.

Structural and macroeconomic variables

SIZE variable was included in the model by taking the natural logarithm of total assets to determine if smaller banks would be more vulnerable to economic fluctuations and failure.

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 US bankruptcy filings was also used as a proxy for general business conditions of each state. BF, was calculated by aggregating each state's quarterly business filings and non-business filings together, and dividing the total by the number of total filings of all states.

Bank failure prediction model results

In determining early warning signals for predicting bank failures, logistic regression techniques were applied to six time period models[7] dating back from six months to 48 months before a bank is declared insolvent by the FDIC, which is otherwise known in this study as bank failure. Table IV summarizes the logistic regression results for all time period model versions, which are useful for determining the relative significance of variables and their directional relationship with the dependent variable. Table V provides the results for marginal effects that show the magnitude of influence the explanatory variables have on the dependent variable.

The regression results indicate that banks may consider loan exposures to their consumer credit clientele (CONSTOTAL) from one to two years prior to bank failures but should be cautioned about real estate loan exposures (RETOTAL) that could increase probability of eventual failure in the 12- and 18-month models.

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 either bank failure or survival. 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. However, this study's results do not imply that the lenders' agricultural loan exposures contribute to the banks' success or survival.

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 six 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. As shown in Table V, a 1 percent increase in the industrial loan

Table IV. Cross-sectional logit regression results for bank failure prediction model

Variables	Months to failure after quarterly Call Report publication					
	6 months	12 months	18 months	24 months	36 months	48 months
AGNR	4.36	−74.41	−766.18	−499.20	−1,298.61	−123.52
	(24.95)	(127.70)	(649.06)	(477.59)	(1,066.54)	(287.81)
AGR	−12.87	−13.98	−13.45	−128.8	−326.23	−195.64
	(23.80)	(47.23)	(55.85)	(143.34)	(232.82)	(212.83)
INDUS	49.65	102.24**	30.92	75.69**	18.63	33.90
	(33.48)	(40.36)	(20.03)	(32.76)	(33.88)	(31.09)
CONSUM	143.59***	171.49*	80.83**	−18.50	123.67	8.52
	(41.27)	(103.08)	(38.26)	(131.05)	(127.63)	(136.54)
LOANHER	2.51	−10.17	−2.70	0.68	−4.11	1.51
	(5.17)	(6.62)	(4.04)	(3.14)	(4.38)	(3.51)
AGTOTAL	−2.69	4.02	3.28	3.74	7.79	0.09
	(8.27)	(4.94)	(6.25)	(4.67)	(11.44)	(7.86)
CONSTOTAL	−21.18**	−27.14**	−30.52**	−22.67*	−18.57	−14.31
	(9.47)	(12.52)	(11.51)	(11.78)	(13.68)	(10.13)
INDUSTOTAL	−7.63	0.89	6.64	1.86	6.60	3.12
	(7.25)	(5.10)	(4.24)	(4.28)	(10.92)	(8.02)
RETOTAL	−0.11	24.88***	13.87***	5.90	15.65	5.37
	(9.98)	(6.59)	(4.29)	(4.63)	(13.90)	(9.12)
LIQM1	0.66*	0.74	0.31	0.38	−0.74	−0.83*
	(0.37)	(0.54)	(0.21)	(0.32)	(1.10)	(0.50)
LIQM2	−7.67***	−4.94***	−0.36	−1.47	1.22	−0.29
	(1.48)	(1.36)	(1.56)	(1.45)	(1.30)	(0.57)
OVERHEAD	75.82	−86.81***	9.79	−100.80**	−113.51**	−131.06***
	(72.78)	(23.41)	(29.16)	(31.94)	(48.84)	(27.91)
INSIDELN	0.38	6.84	14.90	−1.77	5.70	0.46
	(14.93)	(10.72)	(9.08)	(10.53)	(10.04)	(9.70)
PROFIT	−32.18***	−33.76***	−6.70	−21.94***	−23.46***	−21.85***
	(6.37)	(6.08)	(7.26)	(5.87)	(5.32)	(4.01)

(continued)

Variables	Months to failure after quarterly Call Report publication					
	6 months	12 months	18 months	24 months	36 months	48 months
SIZE	0.62***	0.05	0.17	0.07	0.03	−0.14
	(0.18)	(0.16)	(0.17)	(0.17)	(0.17)	(0.15)
PURCHASEDTL	1.29	5.07**	−0.29	2.89*	2.51*	4.20**
	(2.29)	(1.62)	(1.72)	(1.50)	(1.42)	(1.61)
DEPLIAB	−11.38**	−14.71***	−5.61	−6.66*	−9.40**	−12.43**
	(4.90)	(4.05)	(4.42)	(3.75)	(3.96)	(3.92)
GAP	6.87***	6.39***	4.36***	4.18***	4.16***	4.74***
	(1.80)	(1.39)	(1.10)	(1.03)	(0.98)	(0.99)
UNEMRATE	30.09***	−15.43***	−31.69***	17.50***	17.07**	4.23*
	(6.41)	(4.76)	(5.13)	(4.81)	(5.55)	(2.31)
BF	35.72***	27.52***	43.95***	13.69**	32.59***	26.06***
	(10.64)	(6.40)	(8.68)	(6.59)	(7.84)	(7.38)
Constant	−0.77	−0.41	−7.23**	−1.72	−5.22	4.62
	(7.65)	(3.88)	(3.58)	(5.13)	(11.87)	(8.83)
Log pseudo likelihood ratio	−80.15	−116.24	−149.02	−154.42	−146.26	−166.23
Wald χ^2	141.21***	128.78***	146.12***	124.05***	128.16***	163.19***
Pseudo R^2	0.7629	0.6562	0.5592	0.5397	0.5499	0.4756

Notes: Significant at: *10, **5, ***1 percent levels; standard errors are reported in the parentheses

Table IV.

Table V.
Marginal effects of the logit results

Variables	Months to failure after quarterly Call Report publication					
	6 months	12 months	18 months	24 months	36 months	48 months
AGNR	0.07	−1.93	−25.98	−17.50	−43.53	−4.65
	(0.43)	(3.31)	(21.39)	(16.63)	(35.19)	(10.77)
AGR	−0.22	−0.36	−0.46	−4.52	−10.94	−7.36
	(0.41)	(1.23)	(1.89)	(4.93)	(7.42)	(7.86)
INDUS	0.85	2.65**	1.05	2.65**	0.62	1.28
	(0.57)	(1.01)	(0.67)	(1.13)	(1.12)	(1.16)
CONSUM	2.45***	4.44*	2.74**	−0.65	4.15	0.32
	(0.73)	(2.64)	(1.24)	(4.60)	(4.22)	(5.14)
LOANHER	0.04	−0.26	−0.09	0.02	−0.14	0.06
	(0.09)	(0.18)	(0.14)	(0.11)	(0.15)	(0.13)
AGTOTAL	−0.05	0.10	0.11	0.13	0.26	0.004
	(0.14)	(0.13)	(0.21)	(0.16)	(0.39)	(0.30)
CONSTOTAL	−0.36**	−0.70**	−1.03**	−0.79**	−0.62	−0.54
	(0.17)	(0.33)	(0.38)	(0.40)	(0.45)	(0.38)
INDUSTOTAL	−0.13	0.02	0.23	0.07	0.22	0.12
	(0.12)	(0.13)	(0.14)	(0.15)	(0.37)	(0.30)
RETOTAL	0.002	0.64***	0.47***	0.21	0.52	0.20
	− (0.17)	(0.17)	(0.14)	(0.17)	(0.47)	(0.34)
LIQM1	0.01*	0.02	0.01	0.01	−0.03	−0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)
LIQM2	−0.13***	−0.13***	−0.01	−0.05	0.04	−0.01
	(0.02)	(0.03)	(0.05)	(0.05)	(0.04)	(0.02)
OVERHEAD	1.30	−2.25***	0.33	−3.53***	−3.80**	−4.93***
	(1.27)	(0.58)	(0.99)	(1.10)	(1.59)	(1.04)
INSIDELN	0.01	0.18	0.51	−0.06	0.19	0.02
	(0.26)	(0.28)	(0.31)	(0.37)	(0.34)	(0.37)
PROFIT	−0.55***	−0.87***	−0.23	−0.77***	−0.79***	−0.82***
	(0.09)	(0.15)	(0.24)	(0.21)	(0.18)	(0.16)
SIZE	0.01***	0.001	0.01	0.002	0.001	−0.01
	(0.003)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)
PURCHASEDTL	0.02	0.13***	−0.01	0.10**	0.08*	0.16**
	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.06)
DEPLIAB	−0.19**	−0.38***	−0.19	−0.23*	−0.32**	−0.47***
	(0.09)	(0.10)	(0.15)	(0.13)	(0.13)	(0.15)
GAP	0.12***	0.17***	0.15***	0.15***	0.14***	0.18***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
UNEMRATE	0.51***	−0.40***	−1.07***	0.61***	0.57***	0.16*
	(0.11)	(0.11)	(0.16)	(0.16)	(0.18)	(0.09)
BF	0.61***	0.71***	1.49***	0.48**	1.09***	0.98***
	(0.17)	(0.17)	(0.28)	(0.23)	(0.26)	(0.27)

Notes: Significant at: *10, **5, ***1 percent levels; standard errors are reported in the parentheses

delinquency ratio will increase the probability of bank failure by 265 percent around 12 and 24 months before bank failure. The magnitude of the marginal effects for CONSUM is even larger. In fact, the CONSUM marginal effects are one of the largest among those calculated for the significant predictors of bank failure. Based on the results (Table IV), a 1 percent increase in the consumer loan delinquency ratio could increase the probability of bank failure by 245, 444 and 274 percent around six, 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 previous studies' results, 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 six 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 (denominator of the OVERHEAD ratio) 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 have been mostly insignificant across all time period models, except in the six- and 48-month models.

The other liquidity measurement, LIQM2, calculated as the loan-to-deposit ratio, produced more significant results for the six- 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. 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 18-month model) 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 (1990), the liabilities purchased from national market will have higher interest rate. The coefficient results are robust across all time period models (except for the six- and 18-month models) 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, except in the 18-month model. 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 positively related to the probability of failure in the six-month model, while remaining insignificant in the other time period models. This means that there is a higher probability of failure among larger banks vis-à-vis their smaller counterparts.

The original list of economic variables includes unemployment rate, bankruptcy rate, changes in personal incomes (PI), and farm-related bankruptcy (Chapter 12) rates. However, PI and Chapter 12 variables were dropped from the final version of the estimating equations due to collinearity problems. 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 positive and significant coefficients imply that a higher incidence of business or non-business failures or insolvencies in each state would further depress the general economic conditions that would, in turn, influence the surge of bank failures.

Based on the foregoing discussions, important early warning signals are then identified by period to stress the importance of paying attention to such factors long before they cause more serious operating problems for the banks. Table VI categorizes the early warning signals according to time periods, or the length of time before the actual occurrence of bank failures.

Three to four years prior to failure	About two years prior to failure	Six to 12 months prior to failure
Costly funding arrangements	Costly funding arrangements	Costly funding arrangements
Increasing interest rate risk	Increasing interest rate risk	Increasing interest rate risk
Declining profits	Declining profits	Declining profits
Asset adequacy and quality (sale of low risk assets)	Asset adequacy and quality (sale of low risk assets)	Asset adequacy and quality (sale of low risk assets and less diversification)
Worsening macroeconomic conditions	Worsening macroeconomic conditions	Worsening macroeconomic conditions
	Increasing loan portfolio risk (especially consumer and industrial loans)	Increasing loan portfolio risk (especially consumer and industrial loans)

Table VI.
Summary of findings on early warning signals of eventual bank failure

Conclusions

In the light of the recent surge in bank failures during the recession of the late 2000s, 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 three to four years prior to a bank's declaration of insolvency. 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. This study's result contend that 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. It is, however, important to clarify that this study's results do not necessarily imply that agricultural lending has significantly enhanced a bank's survival during such period of financial crises.

Moreover, delinquency rates for consumer loans and commercial and 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.

Overall, this study has laid out some important foundation in the analysis of the causes of the banking crises during the late 2000s Great Recession. This study's bank failure prediction models have identified early warning signals that could offer insights on future banking strategies to employ that should minimize the likelihood of bank failures. More importantly, this study presents evidence that banks' decisions to lend to the agricultural sector, which was always regarded as a very volatile sector and thus, more likely to be vulnerable to current economic pandemonium, have neither significantly ignited the rush of bank failures nor enhanced a bank's survival during this particular time period. After all, the farm sector of today is a far cry from the distressed farm economy of the 1980s that leaves no doubt that it is healthy and resilient enough to be more likely to endure episodes of financial crises.

This study's results on the insignificance of farm lending variables can serve as motivation for future research on the real contributions of agricultural lending to sustaining rural economies. The changing structure of today's farm sector in terms of size, ownership, goals and production methods could enhance the farms' financial strength vis-à-vis their counterparts in previous periods. Whether or not these changes are enough for them to positively steer rural economic development efforts should be an interesting issue for further research.

Notes

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.
2. When a bank's risk-based capital ratio drops below 2 percent, 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).

3. This sample size is the result of a restriction imposed in developing the common time period dataset where only banks with continuous (non-missing) observations since the 1st quarter of 2005 (earliest quarterly cut-off) until the 4th quarter of 2009 have been considered.
4. CAMELS stands for capital adequacy, asset quality, management quality, liquidity, and sensitivity to market risk as defined by the Federal Deposit Insurance Corporation (FDIC).
5. 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:

$$\mathrm{LOANHER} = \sum\left[\left(\frac{\text{Real Estate Loans}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Loans to Depository Institutions}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Individual Loans}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Commercial and Industrial Loans}}{\text{Total Loans}}\right)^2 + \left(\frac{\text{Agricultural Loans}}{\text{Total Loans}}\right)^2\right]$$

6. 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.
7. 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 absence of heteroskedasticity problem in our datasets.

References

Board of Governors of the Federal Reserve System (2010), *Agricultural Finance Databook 2010*, Board of Governors of the Federal Reserve System, Washington, DC, available at: http://federalreserve.gov/releases/e15/default_2010.htm

Belongia, M.T. and Gilbert, R.A. (1990), "The effects of management decisions on agricultural bank failures", *American Journal of Agricultural Economics*, Vol. 72 No. 4, pp. 901-910.

Cole, R.A. and Gunther, J.W. (1995), "Separating the likelihood and timing of bank failure", *Journal of Banking & Finance*, Vol. 19 No. 6, pp. 1073-1089.

DeYoung, R. and Hasan, I. (1998), "The performance of de novo commercial banks: a profit efficiency approach", *Journal of Banking & Finance*, Vol. 22 No. 5, pp. 565-587.

Demirguc-Kunt, A., Laeven, L. and Levine, R. (2003), *Regulations, Market Structure, Institutions, and the Cost of Financial Intermediation*, National Bureau of Economic Research, Cambridge, MA.

Demyank, Y. and Van Hemert, O. (2011), "Understanding the subprime mortgage crisis", *Review of Financial Studies*, Vol. 24, pp. 1848-1881.

Demyanyk, Y. and Hasan, I. (2010), "Financial crises and bank failures: a review of prediction methods", *Omega*, Vol. 38 No. 5, pp. 315-324.

Ellinger, P. and Sherrick, B. (2010), *Financial Markets in Agriculture*, Illinois Farm Economics Update, Urbana, IL, October 15, available at: www.farmdoc.illinois.edu/ifeu/IFEU_08_02/IFEU_08_02.html

Estrella, A., Park, S. and Peristiani, S. (2000), "Capital ratios as predictors of bank failure", *Economic Policy Review*, Vol. 6 No. 2, pp. 33-52.

Graham, F.C. and Horner, J.E. (1988), *Bank Failure: An Evaluation of the Factors Contributing to the Failure of National Banks*, Federal Reserve Bank of Chicago, Chicago, IL, pp. 405-435.

Hanweck, G.A. (1977), "Predicting bank failure", Research Papers in Banking and Financial Economics.

Isidore, C. (2009), *It's Official: Recession Since Dec'07*, CNNMoney, Atlanta, GA, December 1, available at: http://money.cnn.com/2008/12/01/news/economy/recession/index.htm?postversion=2008120112

Jin, J.Y., Kanagaretnam, K. and Lobo, G.J. (2011), "Ability of accounting and audit quality variables to predict bank failures during the recent financial crisis", *Journal of Banking & Finance*.

Martin, D. (1977), "Early warning of bank failure: a logit regression approach", *Journal of Banking & Finance*, Vol. 1 No. 3, pp. 249-276.

NBER (2008), *Determination of the December 2007 Peak in Economic Activity*, Business Cycle Dating Committee, National Bureau of Economic Research, Cambridge, MA, available at: www.nber.org/cycles/dec2008.html (accessed September 2012).

Pantalone, C.C. and Platt, M.B. (1987), "Predicting commercial bank failure since deregulation", *New England Economic Review*, July, pp. 37-47.

Rutenberg, J. and Thee-Brenan, M. (2011), "Nation's mood at lowest level in two years, poll shows", *New York Times*, April 21, available at: www.nytimes.com/2011/04/22/us/22poll.html?_r=1

Seballos, L.D. and Thomson, J.B. (1990), "Underlying causes of commercial bank failures in the 1980s", Economic Commentary.

Thomson, J.B. (1991), "Predicting bank failures in the 1980s", *Economic Review*, Vol. 27, pp. 9-20.

Wessel, D. (2010), "Did 'great recession' live up to the name?", *Wall Street Journal*, April 8, available at: http://online.wsj.com/article/SB10001424052702303591204575169693166352882.html

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