Determinants of Financial and Temporal Endurance of Commercial Banks during the Late 2000s Recession: A Split-Population Duration Analysis of Bank Failures

Xiaofei Li*
University of Georgia,
Department of Agricultural and Applied Economics
306 Conner Hall, Athens, GA 30602

Cesar L. Escalante*
University of Georgia,
Department of Agricultural and Applied Economics
315 Conner Hall, Athens, GA 30602

Submitted: April 2016

Abstract

This paper presents an application of the split-population duration model in identifying operating strategies and structural attributes of commercial banks that increased their financial and temporal endurance (translated into probability and duration of survival, respectively) during the late 2000s recession. This study's results identify the isolated effects of certain variables on a bank's temporal endurance that have not been captured by other commonly used survival models. For instance, delinquency rates for consumer and industrial loans have separate adverse effects on the banks' chances of survival and temporal endurance, respectively, while real estate loan delinquency rates negatively affect both survival parameters. Aside from the loan portfolio composition effects, interest rate risk, fund sourcing strategies, and business size could also significantly influence a bank's survival through the financial crises.

Keywords: agricultural loans, real estate loans, bank failures, proportional hazard model, late 2000s recession, loan diversification, split population duration model

JEL Classifications: C41, G21, Q14

* Xiaofei Li, frank.xiaofeili@gmail.com; Cesar Escalante, cescalan@uga.edu.

Determinants of Financial and Temporal Endurance of Commercial Banks during the Late 2000s Recession: A Split-Population Duration Analysis of Bank Failures

I. Introduction

The National Bureau of Economic Research (NBER) contends that the late 2000s economic recession caused some serious economic repercussions for the local and global economies (NBER 2010). This most recent recession, characterized by high unemployment, declining real estate values, bankruptcies and foreclosures, affected the banking industry so severely that nearly 500 banks failed from 2007 until the end of 2014. During this time, the number of critically insolvent banks included in the "High Risk of Failing Watch List" maintained by Federal Deposit Insurance Corporation (FDIC) also increased dramatically.

Daniel Rozycki, associate economist of Federal Reserve Bank of Minneapolis, actually pointed out some similarities of the late 2000s recession to the 1980s farm crisis in recent agricultural sector trends (Rozycki 2009). He observed that the prices of some key crops doubled or tripled from 2006 to 2008 but started on a downhill trend thereafter (except in 2012 and 2013) while farmland prices were falling after reaching record high levels in 2008. There has been some concern that a continued decline in land and crop prices could lead to deterioration in the agricultural loan portfolios of commercial banks and other farm lenders.

It has been argued that no financial crisis can be dismissed as insignificant since any crisis that affects all or even just a part of the banking sector may result in a decline in shareholders' equity value, the loss of depositors' savings, and insufficient funding for borrowers. These would translate to increasing costs on the economy as a whole or parts within it (Hoggarth et al. 2002). In this regard, it is important to probe more deeply and understand the causes of the bank failures experienced in the banking industry during the last recession as this could provide insights on more effective, cautious operating decisions that could help prevent the duplication of failures in the future.

Most early warning banking studies that have already been published have employed probit/logit techniques in their analyses (Hanweck 1977; Martin 1977; Pantalone and Platt 1987; Thomson 1991; Cole and Gunther 1998). The analyses are usually focused on identifying retroactive determinants of a bank's probability of failure versus survival.

Duration (hazard) models were introduced as an alternative to the probit/logit technique in identifying the determinants of the probability of bank failure. The original application of this model was introduced by Cox in a biomedical framework (Cox 1972). In banking, the Cox proportional hazard model was first applied in 1986 to explain bank failure (Lane et al. 1986). The cox model adopts a semi-parametric function that offers the advantage of avoiding some of the strong distributional assumptions associated with parametric survival-time models. However, just as in other parametric duration models, the Cox proportional model suffers from one shortcoming whereby it forces the strong assumption of the eventual failure of every single observation analyzed by the model. Hence, the model is incapable of isolating specific determinants of bank failure from factors that influence the timing of failure.

The split-population duration model was conceived as a remedy to such shortcoming. The model was first used by Schmidt and Witte (1989) in a study on making predictions on criminal recidivism. The study recognizes the irrationality in assuming that every individual would eventually return to prison. As such, the study's sample has been "split" into those that "(did go) back to prison" and "(did) not (go) back to prison". The model was actually applied to the analyses of bank failures in previous economic episodes other than the more recent banking crises caused by the last recession (Cole and Gunter 1995; Hunter et al. 1996; Deyoung 2003).

This paper presents an application of the split-population duration model to the banking crisis in the late 2000s recession. Specifically, this article will identify early bank failure warning signals that can be deduced from the operating decisions made and lessons learned by banks that either failed or survived the last recession. This study differentiates itself from previous empirical works through its focus on factors that affect both the comparative financial (probability of survival) and temporal (length of survival) endurance of commercial banks. The strength and reliability of this study's results lie in its underlying analytical framework's capability to capture more realistic and intuitively reasonable assumptions on the probability and timing of failure that should rectify results in other studies that do not account for such conditions.

II. The Analytical Framework

This study's analytical framework is derived from basic survival analysis techniques used in previous empirical studies (Schmidt and Witte, 1989; Cole and Gunther, 1995; Deyoung, 2003). The likelihood function for the basic parametric survival model can be written as:

(1) $$L = \prod_{i=1}^{N} [\mathrm{f}(\mathrm{t_i} \mid \mathrm{p}, \lambda)]^{1-\mathrm{D_i}} [\mathrm{S}(\mathrm{t_i} \mid \mathrm{p}, \lambda)]^{\mathrm{D_i}}$$

where $f(\mathrm{t})$ is the probability density function of duration t and $S(\mathrm{t})$ is the survival function. D_i is the indicator variable that would equal to one if a bank survived the entire sample period and would equal to zero if the bank was shut down during the period. As pointed out in previous split-population duration studies (Schmidt and Witte 1989; Cole and Gunther 1995; Deyoung 2003), the basic duration model's shortcoming lies in its forced assumption that every observation in the dataset will eventually experience the event of interest; or as applied to this analysis, the assumption that every bank would eventually fail as time at risk becomes sufficiently large. The other shortcoming, as pointed out by Cole and Gunther (1995), is that the likelihood function fails to distinguish between the determinants of failure and those influencing the timing of failure. These issues are addressed in the subsequent discussions.

Using the notation from Schmidt and Witte (1989), F is defined to be an unobservable variable that equals to 1 if the bank eventually fails and 0 otherwise. Then,

(2) $$P(\mathrm{F}=1)=\delta, \qquad P(\mathrm{F}=0)=1-\delta$$

where the estimable parameter δ is the probability that a bank will eventually fail. With this additional parameter, the basic likelihood function to be estimated is modified as follows:

(3) $$L = \prod_{i=1}^{N} [\delta\, \mathrm{f}(\mathrm{t_i} \mid \mathrm{p}, \lambda)]^{1-\mathrm{D_i}} [(1-\delta)+\delta\, \mathrm{S}(\mathrm{t_i} \mid \mathrm{p}, \lambda)]^{\mathrm{D_i}}$$

If $\delta = 1$, then the likelihood function reduces into a "basic" duration model that assumes all banks will eventually fail. If $\delta < 1$, then both $S(\mathrm{t})$ and $f(\mathrm{t})$ are estimated conditional on the probability of bank failure.

In bank failure studies, the log-logistic distribution has been widely used (Cole and Gunther 1995; Deyoung 2003) since it is a non-monotonic hazard function that can generate a hazard rate that increases initially before eventually decreasing. The log-logistic distribution imposes the following form on the survival function $S(\mathrm{t})$ and hazard function $h(\mathrm{t})$:

(4) $$S(t) = \frac{1}{1+(\lambda t)^{p}}$$

(5) $$h(t) = \frac{f(t)}{S(t)} = \frac{\lambda p(\lambda t)^{p-1}}{1+(\lambda t)^{p}}$$

Given the above, the shape of probability density function can be obtained from the product of equations (4) and (5) as shown below:

(6) $$f(t) = S(t)\,h(t) = \frac{\lambda p(\lambda t)^{p-1}}{[1+(\lambda t)^{p}]^{2}}$$

where parameters p and λ are positive parameters that define the exact shape of this hazard function.

The probability of eventual bank failure δ and the timing of failure λ can be made bank-specific as follows:

(7) $$\delta = \frac{1}{1+e^{\alpha' X}}$$

$$\lambda = e^{-\beta' X}$$

where X is a vector of covariates that capture the influence of a bank's financial condition on δ and λ.

The parameters α and β are estimated in the split-population duration model, with α representing a direct relationship between bank specific covariates and the probability of survival, and β indicating a direct relationship between those covariates and survival time.

The variables used in this study and their descriptive statistics are shown in table 1. In order to distinguish each variable' effect on both the probability of survival and length of survival, identical regressors are used in the estimation of α and β parameters. This approach has been employed in several empirical studies (Douglas and Hariharan 1994; Cole and Gunther 1995; DeYoung 2003) and this study is an attempt to duplicate such analytical method. The following sub-sections discuss the measurement of the explanatory variables considered in this analysis and their expected relationships with the dependent variables (also listed in table 1).

[Place Table 1 Approximately Here]

A. Asset Quality and Management Risk Variables

Bank loan concentration is measured in this model by HHI, calculated as the Herfindahl-Hirschman Index, which is bounded as follows:

$$\frac{1}{n} \leq HHI \leq 1$$

where n stands for the loan segments. This index will approach 1 under higher levels of client specialization (or if banks tend to concentrate their loan portfolios around one or just a few client categories). An index that approaches 0 indicates a more diversified loan portfolio. This variable is designed to measure portfolio diversification that is usually regarded as a risk reduction strategy (Markowitz 1952; Thomson 1991; DeYoung and Hasan 1998). This index is expected to be negatively related to both the probability of bank's survival and expected survival time[1].

Management risk will be captured in the model by two measures: overhead cost ratios (OVERHEAD) and insider loan ratios (INSIDER) (Whalen 1991; Thomson 1991). OVERHEAD is calculated as the sum of salaries and employee benefits, expense on premises and fixed assets, and total noninterest expense divided by average total assets. This ratio is expected to negatively influence the likelihood of survival since improved management of these expenses would increase bank's efficiency and therefore increase its survival probability. The insider loan ratios (INSIDER) is calculated by dividing the aggregate amount of credit extended to the banks' officers, directors and stockholders to total assets. Thomson (1991) used this ratio to capture management risk in the form of fraud or insider abuse, and it is expected to be negatively related to both the probability of survival and expected survival time.

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

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

B. Profitability Potential and Structural Variables

PROFIT, represented by the rate of return on assets, captures the banks' earnings capability and it is expected to increase both the probability of survival and expected survival time. To capture the effect of the size and scale of banking operations, the logarithm of total assets (SIZE) is included in this model (Cole and Gunther 1995; Wheelock and Wilson 2000; Shaffer 2012). Compared to smaller banks that possibly do not have adequate resource capability to withstand economic crises, larger banks are more likely expected to survive since they possess greater financial flexibility and larger resource bases to weather economic fluctuations.

C. Loan Portfolio Composition and Non-Performing Loan Variables

The banks' loan exposures to different industry sectors are also accounted for in the model, as suggested by previous literatures (Cole and Gunter 1995; Wheelock and Wilson 2000; DeYoung 2003). These variables include the proportion to total loans of loan exposures to specific industry segments such as agriculture (AGLOANS), consumer (CONSUMLOANS), and commercial & industrial (CILOANS) sectors[2]. These variables' impact on survival probability and time may vary depending on the relative financial health of each sector.

The banks' credit risk conditions are captured by several variables that capture the actual delinquency rates experienced in certain loan categories. These categories or transaction categories include agricultural (AGNP), real estate (REALESTNP), commercial and industrial (CINP), and consumer (CONSUMNP) loan transactions. The aggregate value of actual non-performing loans in each transaction category is calculated as the sum of "past due up to 89 days", "past due 90 plus days", and "nonaccrual or charge-offs". The measures for these variables are calculated as the proportion of delinquencies in each transaction category to the aggregate value of the loan portfolio in each category, and weighted by their corresponding loan categories to total loan ratio.

D. Funding Arrangement Variables (FA)

Banks may hold portfolios of assets and liabilities with different maturities and a change in interest rates will affect the portfolios' market value and net income. Interest rate risk is represented by three variables. The first variable is measured as the proportion of Purchased Liabilities to Total Liabilities (PURFUNDS). As a price-taker

[2] Real Estate Loans to Total Loan ratio is removed due to multicollinearity issue in this sample.

in the national market, banks that rely more on external markets through higher purchases of liabilities will incur greater interest expenses and, hence, may have lower probabilities of survival (Belongia and Gilbert 1990).

The other measure is GAP and is derived by first subtracting "liabilities with maturities less than one year" from "assets with maturities less than one year" and then dividing the difference by total assets (Belongia and Gilbert 1990). This GAP ratio is expected to be negatively related to both the probability of survival and survival time since banks can lose their market value when interest rates rise.

The third variable, DEPLIAB, is calculated by taking the ratio of total deposits to total liabilities. This ratio is expected to be positively related to the likelihood of survival and bank's survival time because bank's tendency to thrive in the business is enhanced by their ability to attract deposits to provide loans.

III. Data Description

The banking data used in this study are collected from the quarterly Consolidated Reports of Condition and Income (call reports) published online by the Federal Reserve Bank of Chicago (FRB). A dataset of banks that either failed or survived after December 2007 through the fourth quarter of 2012 was developed for this study. This time period adequately captures the late 2000s recession, which was said to have formally started in December 2007 (NBER 2008). The reckoning (starting) point for each bank's survival period is set at the end of the 4th quarter of 2007. Some previous studies have considered using time-varying covariates in their duration models applied to panel datasets (Wheelock and Wilson 2000; Dixon et al. 2011). However, Chung (1991) contends that the unique design of the split-population duration model does not allow the explanatory variables to vary over time while it is relatively straightforward and feasible to incorporate the time-varying design in a proportional hazard model. Hence, this analysis employs the more applicable cross-sectional data analysis for its split-population model.

The maximum survival time is censored at 21 quarters. Banks that commenced operations after December 2007 were not included in the dataset to ensure the right censoring of data. The right censoring design used in this analysis follows the approach used in earlier studies that does not account for the interval censoring of failed banks (Cole and Gunter 1995; Deyoung 2003; Maggiolini and Mistrulli 2005)[3]. Surviving or successful banks during the

[3] An interval censoring design approach is beyond the scope and capability of this paper, as has also been the case of similar studies this article is drawn from. Future research efforts may be devoted to validating the use of such design.

time period that have missing values for any financial data being collected were discarded. Given these data restrictions, the resulting sample of 6,839 banks consists of 6,461 surviving and 378 failed bank observations. These banks' financial performance indicators measured by the end of 2007 were used for this analysis.

IV. Estimation Results

Prior to estimation, an important preliminary step is to check the appropriateness of the distributional assumption by comparing the split-population's hazard rate[4] and the actual hazard rate (Douglas and Hariharan 1994; Cole and Gunter 1995). This is achieved by estimating a split-population model without covariates and comparing the predicted hazard to a nonparametric estimate. The nonparametric hazard estimate is calculated by dividing the number of failed banks at time t by the number of banks that neither failed nor were censored in prior periods.

[Place Figure 1 Approximately Here]

As shown in figure 1, the nonparametric hazard rate rises rapidly from quarter 2 to quarter 8 (2009 third quarter) and would decrease at a slower pace from quarter 11 to quarter 21 ($S(\mathrm{T}) = 1$ at quarter 1). This trend in the changes in the hazard rate is closely replicated by the behavior of the forecasts by the split-population model using the log-logistic distribution as the underlying parametric distribution.

Table 2 presents the estimation results for both the determinants of the probability of survival and each bank's survival time under the split population duration model.

[Place Table 2 Approximately Here]

A. Determinants of the Probability of Survival

As laid out in this study's analytical model, the covariates associated with α measure their impact on the probability of a bank's survival. A positive coefficient result indicates a higher probability of survival.

---

[4] The hazard rate is calculated from an unconditional hazard function
$h(\mathrm{t}) = \delta(\mathrm{t}) / [(1-\delta) + \delta S(\mathrm{t})]$.

This study’s results focused on certain loan portfolio composition variables that identify specific sectors that can be accommodated by banks in order to enhance their chances of survival. Results indicate that the banks’ consumer loan exposure (CONSUMLOANS) has a significant, favorable effect on their probability of survival, which is consistent with the findings from Cole and Whitt (2012) who claimed that banks have comparative advantage in well-behaved consumer loans. The estimated coefficients for agricultural (AGLOANS) and industrial (CILOANS) loans, on the other hand, are not significant.

Among the non-performing loan variables that capture client delinquency in several loan categories, this study’s most compelling result is the insignificance of the agricultural loans-related variable (AGNP). These results suggest that the delinquency ratio of those loans extended to agricultural businesses cannot be used as an effective indicator for predicting bank failures. It has been observed that the agricultural economy, supported by strong global demand for agricultural products and an expanding biofuel sector, was booming. This finding is also confirmed by some empirical studies on the latest recession (Li et al. 2012; Sundell and Shane 2012) that provide further support on the financial strength of the agricultural sector.

In contrast, delinquency loan ratio variables for real estate loans (REALESTNP), and consumer loans (CONSUMNP) are significant negative regressors. The significant effect of problematic real estate loan accounts in this analysis supports the contention of Cole and White (2012) that banks’ decisions to heavily invest in residential mortgage-backed securities (RMBS) have been singled out as one of the major triggers of the last recession. Other studies have also singled out real estate loan accommodations for their important role in predicting bank failure (Jin et al. 2011; Cole and White 2012). On the other hand, as the banking industry’s consumer loan portfolio has grown in recent years, the quality of such loans was found to have a significant effect on the banks’ probability of survival (El-Ghazaly and Gopalan 2010).

Results also confirm the effectiveness of the loan portfolio diversification strategy. In this analysis, the HHI variable is significantly negative, which emphasizes the risk-reducing effect of the loan portfolio diversification strategy that ultimately increases the banks’ survival probability. The positive and significant coefficient on PROFIT conforms to logical expectations. Higher earnings enhance the value of the banks’ net worth and thus, greater wealth translates to greater financial strength and higher probability of survival.

Results also indicate that interest rate risk management and more appropriate fund sourcing strategies can enhance banks' chances of survival. The coefficient result for DEPLIAB is positive and significant, which is consistent with the expectation that the banks' capability to thrive in their businesses is enhanced by their ability to generate an adequate deposit base to meet their business funding requirements. The GAP variable that captures interest rate risk has a significantly negative effect on the probability of survival as higher GAP values are associated with higher interest rate risk.

The SIZE variable is significantly and negatively related to the probability of survival. For the banks observed in this sample, this result suggests that larger banks were more likely to fail during the last recession, which seems to disagree with Thomas (1991)' "too big to fail" doctrine. Thomas argued in his study that endangered or at-risk larger financial institutions will tend to receive financial and other assistance from regulatory authorities because their failures are thought to impose severe repercussions to the economy. A cursory look at the profiles of the banks that failed in the last recession suggests that their median assets and deposits were considerably larger than non-failed banks (Aubuchon and Wheelock 2010). Moreover, given that today's "more consolidated" banking industry consists of too many small institutions and very few large institutions (thus skewing the median asset-size downward), the Thomas doctrine hardly applies to the average bank observation and to this study's findings where banking units are not necessarily too large to have the industry effect the doctrine suggests.

B. *Determinants of Temporal Endurance*

The split-population model offers the advantage of being able to separate the factors that influence survival time from those that affect the probability of survival. This section analyzes the results for the vector of β coefficients that measure the influence of covariates on the bank's survival time. This analysis can also be labeled as temporal endurance analysis where the focus is on how certain factors can either expedite a bank's retrogression into failure or enhance the period of endurance of pressures to survive the financial crisis over time. In this case, a positive coefficient indicates that the covariate is associated with a longer duration time (or endurance over time), while a negative coefficient implies a more immediate incidence of failure.

Compared to the α parameters estimates where 9 regressors (exclude intercept) are statistically significant, 8 variables are significant in the β parameters model. Among these significant variables are those that were already identified as significant variables in the α model: consumer loans portfolio ratio (CONSUMLOANS), the loan risk or delinquency variables for real estate loans (REALESTNP), bank earnings (PROFIT), the banks' deposits to liabilities ratio (DEPLIAB), and bank size (SIZE). These variables also produced the same directional effects (coefficient signs) as those estimated for the probability of survival (α parameters).

Two other variables were previously insignificant in the probability model are significant in the β model for the determinants of survival time. The variable CINP has a significant negative coefficient in the β model, thereby suggesting that banks with higher accumulation of delinquent industrial loans may fail in a shorter time. Moreover, the variable INSIDER has a significantly positive relationship with survival time. Although seemingly counter-intuitive, this result may suggest that extending higher credit accommodation to the banks' management and owners may be regarded as an effective incentive strategy. Such incentives could have elicited the much needed loyalty and productivity that could help enhance their institutions' temporal endurance or extend the banks' survival time. On the other hand, this result could also reflect the confidence of insiders in their institutions' financial strength, perhaps derived from unobservable "insider" information on the banks' real conditions. Such confidence is translated to greater patronage of insiders' credit dealings with their own employer that could ultimately serve as a good signaling strategy directed to prospective investors and other market players.

One variable has contrasting coefficient sign results for the α and β models. The estimated coefficient of PURFUNDS, previously with a positive result in the α model, has a negative sign in the β model. The latter result indicates that banks that hold larger proportions of purchased liabilities obtained from national markets may have shorter survival periods as such purchases may have exerted some immediate liquidity pressures for the purchasing bank. However, on a medium- to long-term perspective, such transactions may prove to be strategic purchases for building up funding endowments to cover eventual needs to bolster liquidity and thus, would actually enhance a bank's chances of survival.

V. Conclusions and Implications

A split-population duration model developed by Schmidt and Witte (1989) is used in this study to examine the determinants of a bank's survival and temporal endurance. In contrast to the parametric duration model used in previous studies, the split-population model treats failed and survival banks differently by estimating an extra parameter δ , which stands for the probability of bank's eventual failure. This study's results identify the isolated effects of certain variables on a bank's temporal endurance that have not been captured by other commonly used survival models, such as the Cox proportional hazard model. Such lapses in other duration models can understate the real determinants of a bank's probability of survival and its temporal endurance.

The most compelling result in this study is the insignificance of the delinquency measure for agricultural loan portfolios in both the survival probability and time models. This validates the true state of the farm lending industry in the late 2000s that refute the more pessimistic regard of experts and analysts on the farm sector. During the recession, agricultural lenders have, in fact, made cautious, prudent operating decisions as majority of them 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 (Ellinger and Sherrick 2008). Moreover, data compiled and released by the Federal Reserve Bank show that while the entire banking industry experienced significant increases in overall loan delinquency rates from 1.73% (1st quarter 2007) to 7.36% (1st quarter 2010), the comparable delinquency rates of the banks' agricultural loan portfolios posted very modest increases – from 1.18% to just 2.89% during the same period (Agricultural Finance Databook). The agricultural loan delinquency rates have consistently been below the banking industry's overall loan delinquency rates since the 1st quarter of 2004, and the gap has widened since then. On the other hand, agricultural production price and demand has been strong before the recession because of the combination of increased demand from developing countries, the falling dollar, and the growing importance of biofuels. These factors has boosted the agricultural economy and helped agricultural sector to weather the financial crisis.

This study presents an emphatic contention that while the agricultural sector has usually been regarded as a volatile sector potentially vulnerable in periods of economic crises, the commercial banks' dealings with farm clients during the late 2000s did not have significant adverse effects on the banks' financial health. Farm credit transactions in the last recession neither increased the commercial bank lenders' chances of failure nor expedited the deterioration of their financial conditions.

On the other hand, this study's results direct the attention to the banks' real estate, industrial, and consumer loan accommodations as delinquency rates for consumer and industrial loans adversely affected the banks' chances of survival and temporal endurance, respectively, while real estate loan delinquency rates have negative effects on both the probability of survival and temporal endurance. Important lessons and policy implications can be derived from the repercussions of such lending decisions. Recalling that the deterioration of the quality of real estate loan portfolios during the recession began when real estate prices started to decline in 2006, lenders should become more attentive to and more cautious about economic bubbles in the different industries they lend to. Notably, in the pre-recession period, real estate loan clients only were required by banks to put up around 20% to 30% equity infusion. The losses from unpaid real estate loans would have been minimized if only such requirement was set higher to around 50%, which banks now actually require. This argument further underscores the need for banks to closely monitor unsecured loan accommodations, especially their consumer loan portfolios that, according to latest statistics, have grown tremendously after the recessionary period (El-Ghazaly and Gopalan 2010).

Even with the implementation of several federal programs designed to provide relief and assistance to surviving banks (such as the Federal Reserve's discount window, interest rate policies and other open market operations, among others), these institutions need to supplement such efforts with improved internal controls for better monitoring of performance efficiencies of various operating units, more protective loan covenants especially for unsecured or less secured loan transactions, more prudent business decisions (such as greater portfolio diversification, strategic liquidity-enhancing, and more practical asset expansion decisions), and greater caution in dealing with business opportunities in various sectors of the economy, including their clients in the farm industry.

Reference

Aubuchon, Craig P. and David C. Wheelock (2010). The geographic distribution and characteristics of US bank failures, 2007-2010: Do bank failures still reflect local economic conditions? Federal Reserve Bank of St. Louis Review 92(05):395-415.

Belongia, M.T., and R.A. Gilbert (1987). Agricultural Banks:Causes of Failures and the Condition of Survivors. Federal Reserve Bank of St. Louis Review 69(5): 30-37.

Belongia, M.T., and R.A. Gilbert (1990). The effects of management decisions on agricultural bank failures." *American journal of agricultural economics* 72(4):901-910.

Chung, C.F., P. Schmidt, and A.D. Witte (1991). Survival analysis: A survey. *Journal of Quantitative Criminology* 7(1):59-98.

Cox, D.R (1972). Regression models and life-tables. *Journal of Royal Statistical Society*. Series B (Methodological) 34(2):187-220.

Cole, R.A., and J.W. Gunther (1995). Separating the likelihood and timing of bank failure." *Journal of Banking & Finance* 19(6):1073-1089.

Cole, R.A., and J.W. Gunther (1998). Predicting bank failures: A comparison of on-and off-site monitoring systems. *Journal of Financial Services Research* 13 (2): 103-117.

Cole, R.A., White, L.J (2012). De´ja vu all over again: the causes of US commercial bank failures this time around. *Journal of Financial Services Research* 42:5–29.

DeYoung, R., and I. Hasan (1998). The performance of de novo commercial banks: A profit efficiency approach. *Journal of Banking & Finance* 22(5):565-587.

DeYoung, R (2003). The failure of new entrants in commercial banking markets: a split-population duration analysis.” *Review of Financial Economics* 12 (1):7-33.

Dixon, B.L., B.L. Ahrendsen, B.R. McFadden, D.M. Danforth, M. Foianini, S.J. Hamm (2011). Competing Risks Models of Farm Service Agency Seven Year Direct Operating Loans. *Agricultural Finance Review* 71(1): 5-24.

Douglas, S. and Hariharan, G (1994). The hazard of staring smoking: estimates from a split population duration model. *Journal of Health Economics* 13:213-230.

El-Ghazaly, H. and Y. Gopalan (2010). A jump in consumer loans? Economic Synopses. Federal Bank of St. Louis. 18:1-2.

Ellinger, P. and B. Sherrick, *Financial markets in agriculture*. Illinois: Illinois Farm Economics Update, October 15, 2008. http://www.farmdoc.illinois.edu/ifeu/IFEU_08_02/IFEU_08_02.pdf (Accessed 1st April 2016)

Hanweck, G.A (1977). Predicting bank failure. Working Paper, Board of Governors of the Federal Reserve System.

Henderson, J. and M. Akers (2010). Financial challenges facing farm enterprises. Ag Decision Maker, Cooperative Service Extension, Iowa State University.

Hoggarth, G., Reis, R., and Saporta, V (2002). Costs of banking system instability: some empirical evidence. *Journal of Banking and Finance* 26:825-855

Hunter, W.C., Verbrugge, J.A., and Whidbee, D.A (1996). Risk taking and failure in de novo savings and loans in the 1980s. *Journal of Financial Services Research* 10:235-272.

Jin, J. Y., K. Kanagaretnam, and G.J. Lobo (2011). Ability of accounting and audit quality variables to predict bank failure during the financial crisis. *Journal of Banking and Finance* 35(11): 2811-2819.

Lane, W.R., S.W. Looney and J.W. Wansley (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance* 10:511-531

Li, X., C.L. Escalante, J.E. Epperson, and L.F. Gunter (2013). Agricultural lending and early warning models of bank failures for the late 2000s Great Recession. *Agricultural Finance Review* 73(1):119-135.

Martin, D (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking & Finance* 1(3):249-276.

Markowitz, H (1952). Portfolio selection. *Journal of Finance* 7 (1):77-91.

Maggiolini P., and P.E. Mistrulli (2005). A survival analysis of de novo co-operative credit banks. *Empirical Economics* 30: 359-378.

National Bureau of Economic Research (NBER). Determination of the December 2007 Peak in Economic Activity. Business Cycle Dating Committee, Cambridge,MA. Internet site:

http://www.nber.org/cycles/dec2008.html (Accessed 1st April 2016)

National Bureau of Economic Research (NBER). Announcement made by Business Cycle Dating Committee, Cambridge, MA. Internet site: http://www.nber.org/cycles/sept2010.html (Accessed 1st April 2016)

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

Peoples, K.L., F. Freshwater, G.D. Hanson, P.T. Prentice, and E.P. Thor (1992). Anatomy of an American Agricultural Credit Crisis. A Farm Credit System Assistance Board Publication. Rowman and Littlefield Publishers, Inc., Lanham, MD.

Rozycki, D (2009) Ag banks: A walk down (bad) memory lane? fedgazette, Federal Reserve Bank of Minneapolis. https://www.minneapolisfed.org/publications/fedgazette/ ag-banks-a-walk-down-bad-memory-lane (Accessed 1st April 2016)

Schmidt, P., and A.D. Whitte (1989). Predicting criminal recidvism using 'split population' survival time models. *Journal of Econometrics* 40:141-159.

Shaffer, S (2012). Bank failure risk: Different now? *Economics Letters* 116(3):613-616.

Sundell, P., and M. Shane (2012). The 2008-09 Recession and Recovery: Implications for the Growth and Financial Health of U.S. Agriculture." United States Department of Agriculture, Economic Research Service (USDA, ERS) Online publication.

http://www.ers.usda.gov/publications/wrs-international-agriculture-and-trade-outlook/wrs1201.aspx (Accessed 1st April 2016)

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

Vogt, W. "Agriculture feeling the impact of recession." *Farm Futures.* http://farmfutures.com/story-agriculture-feeling-the-impact-of-recession-8-23071 (Accessed 1st April 2016)

Whalen, G (1991). A proportional hazards model of bank failure: an examination of its usefulness as an early warning tool. *Economic Review* 27(1):21-30.

Wheelock, D.C., and P.W. Wilson (2000). Why do banks disappear? The determinants of US bank failures and acquisitions. *Review of Economics and Statistics* 82(1): 127-138.

Table 1. Definitions and Summary Statistics of Duration Model Variables

Variables	Descriptions	Sample Mean	Std. Deviation	Min	Max	Expected Sign	
						Survival	Survival Time
Dependent variable							
T	Length of time between t=1 and the subsequent failure date T	20.4287	2.5599	1	21		
Explanatory variables							
AGLOANS	Agricultural loans / total loans	0.0772	0.1275	0	0.7636	+/-	+/-
CONSUMLOANS	Consumer loans/total loans	0.0775	0.0880	0	1.0000	+/-	+/-
CILOANS	Commercial & Industrial loans / total loans	0.1530	0.0988	0	0.9668	+/-	+/-
REALESTNP	Aggregate past due/non-accrual real estate loans/total loans	0.0142	0.0198	0	0.3597	-	-
AGNP	Aggregate past due/non-accrual agricultural loans/total loans	0.0007	0.0039	0	0.1597	-	-
CINP	Aggregate past due/non-accrual Commercial & Industrial loans /total loans	0.0008	0.0023	0	0.0549	-	-
CONSUMNP	Aggregate past due/non-accrual Consumer loans /total loans	0.0005	0.0023	0	0.0731	-	-
HHI	Herfindahl index constructed from the following loan classifications: real estate loans, loans to depository institutions, loans to individuals, commercial & industrial loans, and agricultural loans.	0.5606	0.1692	0	1.0000	-	-

Table 1. Continued

Variables	Descriptions	Sample Mean	Std. Deviation	Min	Max	Expected Sign	
						Survival	Survival Time
PROFIT	Return on assets (Earnings)	0.0507	0.0481	-0.4452	0.4612	+	+
PURFUNDS	Purchased funds to total liabilities	0.5085	0.1398	0	0.9952	-	-
DEPLIAB	Total deposits/ total liabilities	0.9254	0.0866	0.00001	0.9996	+	+
GAP	Duration GAP measure [a]	-0.0403	0.2100	-2.1587	0.9468	-	-
OVERHEAD	Overhead costs/total assets	0.0211	0.0115	0	0.3747	-	-
INSIDER	Loans to insiders/total assets	0.0154	0.0181	0	0.1973	-	-
SIZE	Natural logarithm of total assets	11.8331	1.1820	8.1137	18.1842	+	+

[a] GAP = Rate sensitive assets – Rate sensitive liabilities + Small longer-term deposits.

Table 2. Maximum Likelihood Parameter Estimates [a] and Standard Errors [b] for Split-Population Duration Model

Variable	Label	Split-Population Model †			
		α Survival	P-value	β Survival time	P-value
Intercept		**7.4449 (1.5131)**	**<.0001**	**2.6189 (0.8027)**	**0.0006**
Ag loans	AGLOANS	0.1752 (0.1661)	0.1457	-0.0251 (0.1374)	0.4277
Consumer loans	CONSUMLOANS	**0.9304 (0.3255)**	**0.0021**	**0.3473 (0.2494)**	**0.0819**
C&I loans	CILOANS	-0.2342 (1.9150)	0.4513	0.9773 (0.9876)	0.1612
Real Estate Non-performing loan	REALESTNP	**-19.4559 (3.3798)**	**<.0001**	**-3.8449 (0.5384)**	**<.0001**
Ag Non-performing loan	AGNP	-0.2247 (0.4967)	0.3255	-0.3573 (0.3048)	0.1205
C&I Non-performing loan	CINP	-0.1779 (0.3792)	0.3195	**-0.4654 (0.1395)**	**0.0004**
Consumer Non-performing loan	CONSUMNP	**-0.9756 (0.6967)**	**0.0807**	-3.4148 (4.5155)	0.2248
Herfindahl Index	HHI	**-2.2766 (1.1865)**	**0.0275**	0.7827 (0.6772)	0.1239
Profit	PROFIT	**0.9073 (0.2257)**	**<.0001**	**0.3780 (0.1326)**	**0.0022**
Purchased Liabilities to total liabilities	PURFUNDS	**0.9182 (0.5646)**	**0.0520**	**-0.2812 (0.1926)**	**0.0721**
Deposits to liabilities	DEPLIAB	**1.6242 (0.8828)**	**0.0329**	**0.5275 (0.3693)**	**0.0766**
Duration GAP	GAP	**-0.4236 (0.0377)**	**<.0001**	0.0018 (0.0160)	0.4541
Overhead cost	OVERHEAD	0.3514 (0.7111)	0.3106	0.1548 (0.1531)	0.1560
Insider loan	INSIDER	-0.1262 (0.3572)	0.3620	**0.3133 (0.1793)**	**0.0403**
Size, log(total assets)	SIZE	**-0.4611 (0.0710)**	**<.0001**	**-0.1072 (0.0330)**	**0.0006**
	P	3.8894 (0.2468)	<.0001		

† Log likelihood at convergence is: -2032.6016, convergence criterion achieved is: 0.0100
[a] Results in boldface are significant at least at the 90% confidence level.
[b] Number in parentheses is the estimate's standard error.

Figure 1. Estimated Hazard Rate for Bank Failure, 2008 Q1-2012 Q4