A Split-Population Duration Approach to Understanding Agricultural Banking Survival Strategies during the Late 2000s Recession

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Abstract

This paper is designed to identify predictors of eventual bank failure as well as factors that could enhance the survival ability of agricultural and non-agricultural banks. This study utilizes a split-population survival model that addresses two shortcomings of the basic duration model. First, this model departs from the restrictive assumption of the traditional model that all bank observations in the sample would eventually fail. Second, this model provides for a clear distinction between the determinants of the probability of failure and factors influencing the timing of the failure. The results of this study suggest that failure to allow for a split population among sample banks represents an important misspecification with serious implications in identifying the determinants of the timing of bank failure, more than just the probability of failure.

Introduction

According to the National Bureau of Economic Research, the late 2000s economic recession that affected both the U.S. and global economies can be considered as the worst economic crises experienced locally and globally since Great Recession of 1930s (NBER, 2010). This recession, characterized by high unemployment, declining real estate values, bankruptcies and foreclosures, has affected the banking industry so hard 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.

Investments in residential mortgage-backed securities (RMBS) have been singled out as having triggered this latest financial crisis. A dramatic increase in delinquencies in subprime residential loan accommodations due to the housing boom-and-bust in 2006 has caused the default by hundreds of thousands of borrowers within a short period of time and resulted in a numbers of banks, particularly those highly involved in the RMBS market, closing down or being taken over due to their insufficient capital and incapability to survive the ensuing financial distress.

It has been argued that no financial crisis can be dismissed as insignificant for any crisis that affects all or even just a part of the banking sector may both 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 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. In other words, the detection of early warning signals of bank’s tendency to fail can offer suggestions in adjusting or modifying banks’ operating decisions and strategies for the sake of building financial strength and endurance through periods of significant financial stress.

In the banking industry, there is a glaring dichotomy between agricultural and non-agricultural banks that have been discussed in agricultural finance literature. Compared to regular commercial banks, agricultural banks[1] usually have more liquidity concerns. Thus, they are unable to diversify their clientele to include other non-agricultural business clientele due to funding constraints. The specialized nature of their lending operations and the large variability of the agricultural products' prices usually result in greater risks and uncertainty. However, during the financial crisis, agricultural banks have managed to maintain their financial composure and survived well through the recession. A cursory look at these banks' operations indicate that most of these specialized banks maintained insignificant exposure to the commercial real estate industry and did not invest aggressively in the structured securities that have lost substantial market value. Moreover, there are possibly other strategic decisions that agricultural banks could have made that enhanced their resilience through the latest recession. Such strategic decisions may either be contemplated by these banks' management or dictated upon as necessary by these banks' inherent structural attributes that differentiate them from their non-specialized (non-agricultural) banking peers. These contrasting decisions, attributes, and operating styles of these groups of banks would provide an interesting backdrop for the identification and analyses of early bank failure warning signals.

Among numerous early warning studies that have already been published, most have employed probit/logit techniques in their analyses (Cole and Gunther, 1998, Hanweck, 1977, Martin, 1977, Pantalone and Platt, 1987, Thomson, 1991). A binary model design allows for the classification of banks into groups of failed and surviving banks. The analysis is focused on identifying the determinants of a bank's probability of failure versus survival. Duration (hazard) models have lately been introduced as an alternative to the probit/logit technique. This approach

[1] FDIC defines Agricultural banks as "Banks whose agricultural production loans plus real estate loans secured by farmland exceed 25 percent of total loans and leases".

has been preferred over the older model given its capability to generate more than just estimates of the probability of bank failure; it also provides estimates of the probable time to 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 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 involving its assumption on 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". Subsequent applications of the model include studies that analyzed bank failures (Cole and Gunter, 1996; Hunter et al., 1996; Deyoung, 2003) other than the more recent incidents in the banking industry caused by the last recession.

This paper presents an application of the split-population duration model to the banking crisis ushered in by 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 special focus on factors that affect the comparative financial endurance of agricultural and non-agricultural 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.

The Analytical Framework

In this survival analysis, the central failure concept is the hazard rate, which defined as the probability that a bank will fail at time T given that it has survived through all of the previous time periods leading up to T. Let $T \geq 0$ denote the duration with the following probability distribution for a population of N banks:

(1) $$F(\mathrm{t}) = \int_0^T f(\mathrm{t})\,\mathrm{dt} = \mathrm{Prob}(\mathrm{T} \leq \mathrm{t})$$

$F(\mathrm{t})$ is the probability of death or failure on or before time t. Then the survival function is defined as follows:

(2) $$S(\mathrm{t}) = 1 - \mathrm{F(t)}$$

This function gives the probability of survival to at least time t.

The hazard function *h(t)* can be written as a function of $f(\mathrm{t})$ and $S(\mathrm{t})$ with:

(3) $$h(\mathrm{t}) = \lim_{\Delta t \to \infty} \frac{F(\mathrm{t} + \Delta\,\mathrm{t}) - \mathrm{F(t)}}{\Delta t S(\mathrm{t})} = \frac{f(\mathrm{t})}{1 - F(\mathrm{t})} = \frac{f(\mathrm{t})}{S(\mathrm{t})}$$

The hazard rate is the rate at which spells or disturbances that enhance the probability of failure are completed after duration t, given that they last at least until t (Greene, 2011). In its estimation, the general shape of the hazard function is constrained by the functional form of the probability distribution $F(\mathrm{t})$ imposed on the data.

In bank failure studies, the log-logistic distribution has been widely used (Cole and Gunther, 1995, Deyoung, 2003) since it is non-monotonic in t with up to two inflection points and can generate a hazard rate that first rises and then falls. The log-logistic imposes the following functional form on the hazard and survival functions:

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

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

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

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

where parameters p and λ give the hazard function its exact shape. The parameter p determines the rate at which hazard rate increases $(\mathrm{p} > 1)$ or decreases $(\mathrm{p} < 1)$ over time, while the parameter λ determines the portion of the hazard rate that is time invariant.

The likelihood function for the basic parametric survival model can be written as:

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

where D 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, 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 the factors influencing the timing of failure. These issues are addressed in the subsequent discussions.

Let F be an unobservable variable that equals to 1 if the bank eventually fails and 0 otherwise. Then,

(8) $$P(\mathrm{F}=1)=\delta, \quad P(\mathrm{F}=0)=1-\delta$$

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:

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

If $\delta=1$, then the likelihood function reduces into a "basic" duration model which 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.

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

(10) $$\delta=\frac{1}{1+e^{\alpha'\mathrm{X}}}$$
$$\lambda=e^{-\beta' X}$$

where X is a vector of bank-specific covariates that includes the following: $AQCA_{it}$ are variables representing capital adequacy and asset quality; MR_{it} is a set of management risk variables; PL_{it} are variables that capture bank earnings (profitability) potential; LPC_{it} are variables that represent loan portfolio composition measures; NPL_{it} capture Non-performing loans; 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 denotes the time when this duration analysis started.

The parameters α and β will be 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. These variables represent the following categories:

Asset Quality and Management Risk Variables (AQMR)

LOANHER is calculated as the loan portfolio diversification index to capture the extent of diversification of the bank's risky asset (loans) among various loan types. OVERHEAD and INSIDELN are used as proxies for management risk measures (Thomson, 1991). OVERHEAD is a measure of operating efficiency derived the proportion of overhead costs to total assets. The ratio of insider loan (obtained from the call report item on aggregate amount of credit extended to the banks' officers, directors and stockholders) to total assets (INSIDELN) is used as a measure to capture management risk in the form of fraud or insider abuse.

Profitability Potential (PL) and Size Variables

PROFIT, represented by return on assets, is the proxy for the banks' earnings capability. SIZE was represented by the natural logarithm of total assets to determine if smaller banks would be more vulnerable to economic fluctuations and failure.

Loan Portfolio Composition and Non-Performing Loan Variables (LPC and NPL)

The banks' loan exposure to different industry sectors are also accounted for in the model. AGTOTAL, CONSTOTAL, and INDUSTOTAL are ratios of loans extended to the agricultural, consumer, and industrial sectors, 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.

The analysis 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 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). In calculating these ratios, the following call report entries for loan accounts "Past due up to 89 days", "Past due 90 plus days", and "Nonaccrual or charge offs" altogether comprise total delinquencies for each loan category. Non-performing loan measurement is given by the proportion of these total delinquencies to the aggregate value of the loan portfolio in each category. 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 (FA)

Three variables capture the banks' fund sourcing strategies. 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 re-pricing gap, GAP, which is used to measure interest-rate risk but usually ignored by previous bank failure prediction studies. Belongia and Gilbert introduced this concept by specifying a measure calculated by taking assets with maturities less than one year minus liabilities with maturities less than one year, and dividing the difference by total assets (Belongia and Gilbert, 1990).

Structural and Macroeconomic Variables (STECON)

The macroeconomic factors of unemployment and general business failures were captured by two variables. UNEMRATE is the quarterly percentage change of state-level unemployment rate. 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.

Data Description

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. The 4th quarter Call Reports database is used to predict survival times during the period from first quarter of 2008 through the fourth quarter of 2012, since the late 2000s recession is formally started from December 2007. The maximum survival time is censored at 21 quarters. The sample consists of all banks that failed between December 2007 and December 2012. Those banks that started after December 2007 were not included in the dataset to ensure the right censoring of data. Surviving or successful banks with missing values for any financial data being collected were discarded. Given these data restrictions, the resulting sample consists of 7337 banks, of which contains 6944 survival banks and 393 failed banks.

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 percentage change of 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.

Estimation Results

Table 2 presents the estimation results for both determinants of the probability of the survival and expected period of survival under the split population duration model. The results of the more basic Cox proportional hazard model are also included in the table for comparison purposes.

I. Determinants of the Probability of Survival

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

The results verified the effectiveness of the loan portfolio diversification strategy and the importance of certain loan portfolio composition variables that identify specific sectors that can be accommodated by banks in their loan servicing operations in order to enhance their chances of survival. The regression results indicate that banks' loan exposure to their consumer credit (CONSTOTAL) has a significant favorable effect to a bank's survival. This is consistent with the finding from Cole and Whitt (2012) who claimed that banks have comparative advantage in well-behaved consumer loans such that the banks' consumer loan exposure should have a negative impact on probability of failure. Similarly, agricultural (AGTOTAL) and industrial (INDUSTOTAL) loans are also significantly positively signed, which suggests that an increase in the portfolio of these loans will decrease the hazard rate and increase the probability of survival.

Among the Non-performing loan variables that capture loan delinquency rates in several loan categories, the most compelling result for this study is the insignificance of both the non-real estate and real estate delinquency ratios for agricultural loans (AGNR and AGR). This suggests that agricultural loan delinquency ratios cannot be used as effective indicators for predicting bank failures. This finding is confirmed by some empirical studies on the latest recession (Ellinger and Sherrick, 2011; Li et al., 2012; Sundell and Shane, 2012) that provide further support on the financial strength of the agricultural sector.

Conversely, the delinquency loan ratios for consumer loans (CONSUM) and commercial/industrial loans (INDUS) are significant negative regressors. The banks' aggressive accommodation of the loan requirements of their consumer and industrial clientele has been seriously impaired by higher rates of delinquency that significantly enhances the banks' probability of failure.

The LOANHER is the Hirschman-Herfindahl Index (HHI) that is used to measure the loan diversification. The boundaries of the HHI are given by

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

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 close to 0 indicates a more diversified loan portfolio. In this analysis, this variable is significantly negative, which emphasizes the risk-reducing effect of the loan portfolio diversification strategy.

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.

The variables that capture interest rate risk and funding arrangements made for the sourcing of capital funds produce interesting results. The coefficient result for DEPLIAB is positive and significant, which is consistent with the expectation that banks' tendency to thrive in their businesses is enhanced by their ability to maximize the generation of deposits to fund their business funding requirements. The GAP variable that captures interest rate risk is has a significant negative effect on the probability of survival, which is also consistent with logical expectations as higher GAP values are associated with higher interest rate risk.

The SIZE variable is significantly negatively related to the probability of survival in the model. This result suggests larger banks are more likely to fail during the last recession, which disproves the finding of Thomas (1991) supporting the "too big to fail doctrine." Thomas argued in his study that endangered or at-risk larger financial institutions will receive financial and other assistance from regulatory authorities because their failures are thought to impose severe damage to economy. However, this study's result verifies that doctrine under a different time period and recessionary conditions where larger banks this time have heavily invested in RMBS (Cole and

White, 2012). 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).

The macroeconomic variables in the model also had significant influences on the probability of survival. The percentage change of state-level unemployment rate (UNEMRATE) produced a highly significant and negative coefficient. The state-level bankruptcy filing ratio (BF)' s negative and significant coefficient implies 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, lead to a surge of bank failures.

II. Determinants of Temporal Endurance

The parameter p determines the rate at which the hazard rate increases or decreases across time. In this study, the model's p is calculated as 3.6938. Since the value is greater than one, this means that there is an overall increasing rate of bank failure in the entire dataset over the sample period. This acceleration of the bank failure rate confirms actual bank failure records where 25 banks closed down in 2008, followed by 140 in 2009, and 157 in 2010.

The split-population model offers the advantage of being able to separate the factors that influence the survival time from those that determine 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 where 13 regressors turned in statistically significant results, only 7 variables are significant in the model with β parameters. Among these significant variables are those that were also identified as significant indicators of the probability of survival: the loan risk or delinquency variables for industrial and consumer loans (INDUS, CONSUM), bank earnings (PROFIT), bank size (SIZE), and the banks' consumer credit portfolio (CONSTOTAL). These variables also produced the same directional effects (coefficient signs) as those produced for the probability of survival (α parameters).

Two other variables were previously insignificant in the α estimation, but turned in significant results in the β estimation for the determinants of survival time. The variable PURCHASEDTL has a significant negative coefficient in the β model, thereby suggesting that banks that hold larger proportions of the more costly purchased liabilities obtained from national markets may lean toward failure in a relatively shorter time. Moreover, the variable INSIDELN 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.

III. The Basic Cox Proportional Hazards Model Results

The last column of table 2 reports the results of the basic Cox proportional hazard model estimation. As laid out earlier, the Cox model results were estimated under a blanket assumption that all banks in the sample will eventually fail. The coefficient results are interpreted in terms of their influence on the hazard rate (instead of the survival rate in the split-population duration model). Hence, a positive coefficient indicates an increasing effect of the variable on the hazard rate. This is the reverse of the expected coefficient results for the α estimation of the split-population duration model (reported in Table 2's column 2).

Based on the Cox model's coefficient estimates, all significant variables produced by the α estimation in the split-population duration model also turned out to be significant regressors with the expected reverse coefficient signs. These variables include those that represent loan portfolio composition variables (AGTOTAL, CONSTOTAL, and INDUSTOTAL), portfolio risk or delinquency (INDUS and CONSUM), portfolio diversification (LOANHER), profitability (PROFIT), business size (SIZE), funding arrangements (DEPLIAB and GAP), and macroeconomic effects (BF and UNEMRATE). The only new result in this model is the significance of OVERHEAD. This variable's negative coefficient indicates that a lower ratio could increase the hazard rate. Although seemingly irregular, this result could suggest that when banks were faced with illiquid conditions during the financial crises, they could have resorted to resolve such operating constraint by selling low-risk assets, such as Treasury securities. Thus, the lower asset base could produce higher OVERHEAD ratio values that may be more associated with enhancing the banks' capability to survive.

Even when the basic Cox and the split-population duration's α model results seem to mirror each other, the former model is incapable of producing the important results and implications derived from the split-population's β model about temporal endurance.

Summary and Conclusions

A split-population duration model is used in this study to examine the determinants of bank survival and bank duration time. In contrast to previous parametric duration model used by studies in the past, the split-population model treats the failed banks and survival banks differently by estimating an extra parameter δ , which stands for the probability of bank's eventual failure. The semi-parametric Cox proportional hazard model is advanced in relaxing the underlying distribution for hazard function, but still fails to distinguish the difference between failing and surviving banks.

The covariates in the model include a set of variables that represent bank's management decisions, operating strategies, financial conditions, and prevailing macroeconomic conditions. However, compared to the determinants that can explain the probability of bank survival, there are certain variables that can only explain temporal endurance, but have not been captured by the basic Cox duration model. This suggests that the typical results obtained from Cox model may provide a distorted view of the determinants of bank survival time, and failure to allow for a split population among banks represents an important misspecification with serious implications in identifying the determinants of the timing of bank failure.

Among the parameters been estimated, the most compelling result in this analysis is the notable insignificance of any measures 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. On the other hand, delinquency rates for consumer loans and commercial & industrial loans are significant in predicting both the probability of survival and survival time. 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 analysis has identified important signals that banks may want to consider with more caution as they devise business strategies for operations in the future.

Table 1. Definitions and Summary Statistics of Duration Model Variables

Variables	Descriptions	Sample Mean	Std. Deviation	Minimum	Maximum
<u>Dependent variable</u>					
T	Length of time between t=1 and the subsequent failure date T	20.4479	2.5201	1	21
<u>Explanatory variables</u>					
AGNR	Aggregate past due/non-accrual agricultural non-real estate loans/total loans	0.0007	0.0041	0	0.1482
AGR	Aggregate past due/non-accrual agricultural real estate loans/total loans	0.0010	0.0035	0	0.0584
INDUS	Aggregate past due/non-accrual Commercial & Industrial loans /total loans	0.0039	0.0074	0	0.0963
CONSUM	Aggregate past due/non-accrual Consumer loans /total loans	0.0026	0.0057	0	0.1530
LOANHER	Loan portfolio Herfindahl index constructed from the following loan classifications: real estate loans, loans to depository institutions, loans to individuals, commercial & industrial loans, and agricultural loans.	0.5784	0.1812	0	1.0000
AGTOTAL	Agricultural loans / total loans	0.0725	0.1248	0	0.7636
CONSTOTAL	Consumer loans/total loans	0.0768	0.0509	0	1.0000
INDUSTOTAL	Commercial & Industrial loans / total loans	0.1471	0.1024	0	1.0000
OVERHEAD	Overhead costs/total assets	0.0210	0.0120	0	0.3747
INSIDELN	Loans to insiders/total assets	0.0149	0.0178	0	0.1973

Table 1. Continued

Variables	Descriptions	Sample Mean	Std. Deviation	Minimum	Maximum
PROFIT	Return on assets (Earnings)	0.0519	0.0502	-0.6023	0.4612
SIZE	Natural logarithm of total assets	11.8777	1.2107	8.1137	18.1842
PURCHASEDTL	Purchased funds to total liabilities	0.5091	0.1408	0	0.9952
DEPLIAB	Total deposits/ total liabilities	0.9210	0.0918	0.00001	0.9996
GAP	Duration GAP measure[2]	-0.0539	0.2166	-2.1587	0.9468
UNEMRATE	Percentage change of unemployment rate	0.0110	0.0225	0	0.0779
BF	Business failure ratio	0.0298	0.0226	0	0.0970

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

Table 2. Maximum Likelihood Result for Duration Model

Log likelihood at convergence: -2153.4084

Convergence criterion achieved: 0.00999

Variable	Split-Population Model				Cox proportional hazards model	
	α Survival	P-value	β Survival time	P-value	Hazard coefficients	P-value
Intercept	**6.0527** **(1.5493)**	**<.001**	**3.5618** **(0.6990)**	**<.001**	_	_
AGNR	0.0161 (0.0519)	0.756	-0.0140 (0.0168)	0.405	-0.0168 (0.0469)	0.720
AGR	0.0170 (0.0288)	0.555	-0.0251 (0.0244)	0.303	-0.0012 (0.0286)	0.966
INDUS	**-0.0289** **(0.0086)**	**0.001**	**-0.0123** **(0.0042)**	**0.003**	**0.0221** **(0.0055)**	**<.001**
CONSUM	**-0.0448** **(0.0215)**	**0.037**	**-0.0525** **(0.0145)**	**0.000**	**0.0564** **(0.0194)**	**0.004**
LOANHER	**-1.3735** **(0.7338)**	**0.061**	-0.2935 (0.3883)	0.450	**1.2484** **(0.4626)**	**0.007**
AGTOTAL	**0.2429** **(0.1437)**	**0.091**	-0.0753 (0.0844)	0.373	**-0.2110** **(0.1247)**	**0.091**
CONSTOTAL	**1.2113** **(0.2834)**	**<.001**	**0.2334** **(0.0885)**	**0.008**	**-1.2533** **(0.2172)**	**<.001**
INDUSTOTAL	**1.8670** **(0.9063)**	**0.039**	-0.0087 (0.4488)	0.985	**-1.2969** **(0.5563)**	**0.020**
OVERHEAD	0.3095 (0.5276)	0.557	0.2330 (0.1530)	0.128	**-0.8496** **(0.3732)**	**0.023**
INSIDELN	-0.0813 (0.3513)	0.817	**0.4717** **(0.1846)**	**0.011**	-0.1358 (0.2435)	0.577
PROFIT	**0.7075** **(0.2083)**	**0.001**	**0.4996** **(0.1639)**	**0.002**	**-0.8195** **(0.0963)**	**<.001**
SIZE	**-0.4134** **(0.0686)**	**<.001**	**-0.1193** **(0.0370)**	**0.001**	**0.4036** **(0.0499)**	**<.001**
PURCHASEDTL	0.2239 (0.5506)	0.684	**-0.4704** **(0.2324)**	**0.043**	-0.0167 (0.4112)	0.968
DEPLIAB	**2.0704** **(0.7675)**	**0.007**	0.6586 (0.4220)	0.119	**-1.4732** **(0.4682)**	**0.002**
GAP	**-0.4311** **(0.0340)**	**<.001**	-0.0153 (0.0181)	0.400	**0.3465** **(0.0214)**	**<.001**
BF	**-0.7460** **(0.2767)**	**0.007**	-0.0888 (0.1406)	0.528	**0.4973** **(0.2218)**	**0.025**
UNEMRATE	**-0.7763** **(0.1933)**	**<.001**	0.0094 (0.0968)	0.923	**0.8279** **(0.1541)**	**<.001**
P	**3.6938** **(0.2334)**	**<.001**	_	_	_	_

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