Technical Efficiency and the Probability of Bank Failure among Agricultural and Non-Agricultural Banks

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ABSTRACT

This study is designed to analyze bank failures from the technical efficiency standpoint under a stochastic cost frontier framework and evaluate the reliability of the technical efficiency measure as a determinant of the financial health of banks and probability to succeed or fail at the height of the current recessionary period. Results of this analysis confirm that successful agricultural banks have been operating more efficiently than surviving nonagricultural banks. This result helps to refute the contention that farm loans are at a relatively higher level of riskiness.

Key Words: Agricultural Banking, Stochastic Frontier Analysis, Technical Efficiency

Introduction

The financial crisis of the late 2000s led to a surge of bank failures in the United States at an overwhelming rate. The cycle of seizures started in 2007. Some 25 banks closed in 2008 followed by 140 bank seizures in 2009. The rate of bank bankruptcy did not slow in 2010 with 157 bank failures, the highest level since the savings and loan crisis in 1992 (FDIC).

The breakdown of the real estate industry was widely believed to trigger the onset of economic crisis in the United States. The housing downturn started in 2006 when housing prices dropped significantly after just reaching peak levels. This resulted in an abrupt increase in loan defaults and mortgage foreclosures that led to widespread crisis in the banking industry (Isidore, 2009).

The subprime residential mortgage fiasco, one of the first indicators of the financial crisis, was also considered 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). Moral hazard and slack financial regulation have been indicated as contributing factors to the subprime mortgage crisis. Low interest rates and large inflows of foreign funds created an easy credit condition which fueled the housing market boom with real estate prices dramatically increasing after 2002. However, the housing bubble burst after housing prices peaked in early 2006.The inability to make payments and tightening financial market conditions caused defaults by hundreds of thousands of borrowers within a short period in the subprime lending market, resulting in a number of major U.S. subprime lending institutions going out of business. Meanwhile, the bad residential real estate loans, including the subprime mortgages, hit the banking industry hard leading the FDIC to increase the pace of shutting down failed banks (Steverman,2009).

Over the years the agricultural sector has been indentified as problematic to the financial industry since agriculture is naturally vulnerable to business and financial risks. In the early 1980s more than 1,600 banks closed due to the large number of delinquent farm loans caused by farm operating losses and the decline in agricultural land values. Some experts suspect that significant loan exposure to agricultural activities could increase the probability of bank failure.

However, the true state of the agricultural industry during this recessionary period may tell a different story. On the lending side, Ellinger and Sherrick (2010) claim that the agricultural lenders are generally in strong financial health because most of the agriculturally related institutions did not lend heavily in real estate, or invest in the structured securities (packaged collateralized debt obligations sold through private treaty) that have lost substantial market value. These assertions are supported by data provided in the Agricultural Finance Data book compiled and released by the Federal Reserve Board. The Federal Reserve Bank of Atlanta, for instance, reports that agricultural banks in its region (including Georgia and other southeastern states) posted improvements in loan deposit ratios that dropped from 0.84 in 2008 to 0.78 as of early 2010 which is almost at pre-recession levels. Moreover, the agricultural loan delinquency rates have consistently been below the overall loan delinquency rates of banks since the 1st quarter of 2004 (Figure 1). The gap between overall and agricultural loan delinquency rates has widened since then. Another report published by the Economic Research Service of the U. S. Department of Agriculture (ERS-USDA) indicates that the farm sector has consistently maintained growth rates in farm assets and equity that far exceed the growth in farm debt (Figure 2). In more than two decades, both the rate of increase and the absolute increase in asset values have significantly exceeded those of farm debt.

This study is designed to analyze bank failures from the technical efficiency standpoint under a stochastic cost frontier framework and evaluate the reliability of the technical efficiency measure (vis-à-vis external, macroeconomic factors) as a determinant of the financial health of banks and probability to succeed or fail at the height of the current recessionary period.

In addressing this objective, a technical efficiency model based on the stochastic cost frontier framework is developed. A technical efficiency score for each bank (both failed and surviving entities) is calculated using a set of operational input and output variables estimated under the stochastic cost frontier approach. Instrumental variables estimation using the Probit approach (IV Probit) is employed with a dataset focusing on the failed and non-failed banks in the two most recent years, 2009 and 2010 (Call Report Dataset). The calculated technical efficiency scores are endogenously determined by an array of instrumental that include the bank performance factors considered in the bank failure prediction models. The IV Probit model is also used to evaluate the relative performance of the TE variable, which becomes a collective measure of overall bank financial performance, vis-à-vis variables that capture the prevailing macroeconomic conditions. The results of this analysis offer important insights on the determinants of bank failure. The analysis identifies sources of inefficiency which should aid bankers in developing approaches to improve management decisions, operational strategies, financial conditions, and performance.

Literature Review

Inefficient banker decisions and operations increase bank operating costs and increase the risk of failure. Facing an increasingly competitive environment and realizing the importance of efficiency analysis, the banking industry has conducted a variety of efficiency analyses. Empirical studies have examined many issues related to the operations of financial institutions such as economies of scale and scope, technical and allocative inefficiency, efficiency implications of bank mergers and branch banking.

Technical efficiency measures the ability of a firm to produce optimal output from a given set of inputs (Farrell, 1957). Allocative efficiency measures the ability of a firm to use inputs in optimal proportions and quantities to achieve cost minimization where price equals marginal cost assuming pure competition in the long run (Arindam and Kuri, 2010).

A common approach to examine bank efficiency is to utilize a frontier cost function. One of its subareas, the parametric frontier model, maximizes possible output which is assumed to be a function of certain inputs. Based on this model, Aigner (1976) introduced a stochastic component into the production frontier model in developing an efficiency analytical framework. This Stochastic Frontier Analysis (SFA) is one of the most widely used methods applied to the parametric approach. A functional form and two-part error terms have been used in the stochastic frontier approach. The Maximum Likelihood (ML) estimation or corrected ordinary least squares is used to estimate the frontier given appropriate distributional assumptions for the error components (Färe et al., 1985). Elyasiani and Mehdian (1990) also specify a production frontier for banks in their study and evaluate bank performance based on measured deviation between actual and potential output. Several studies use the stochastic parametric cost frontier which models the bank cost structure using a translog cost functional form (Ellinger and Neff, 1993; Neff et al., 1994). The translog cost function has been used extensively in banking cost studies for its flexible functional form which contains both the Cobb-Douglas and Constant Elasticity of Substitution (CES) as special cases (Ellinger and Neff, 1993).

As an alternative to the parametric approach, Aly et al. (1990) use a nonparametric frontier approach to calculate the overall, technical, allocative, and scale efficiencies for hundreds of banks. In the nonparametric approach, linear programming is used to construct a piecewise-linear, best-practice frontier for each bank. The nonparametric approach avoids the need to specify a particular functional form of the bank cost relationship. In addition, the nonparametric approach is deterministic, where all deviations from the frontier are interpreted as inefficiencies.

Other researchers use profit functions. Neff et al. (1994) estimate profit functions using the Fuss normalized quadratic functional form which treats a normalized profit variable as a function of some specified outputs, inputs, and fixed netputs (transaction deposits and physical capital). The constructed system is estimated using nonlinear Seemingly Unrelated Regression, also used by Berger, Hancock and Humphrey (1993).

The majority of bank studies have been primarily focused on commercial banks with only a few empirical works directed towards agricultural banking and bank efficiency. Agricultural banks, by the FDIC criterion, are those financial institutions where the agricultural loan to total loan ratio is at least 25% and therefore represent a focused set of banks supporting agricultural activities. The bank can limit the chance of failure by diversifying loan portfolios into different categories. Nonetheless, agricultural banking has been criticized for limited portfolio diversification opportunities and is perceived or expected to be more likely to fail when the economy experiences a slowdown in activity such as the economic recession of the late 2000s. With such a perception of the alleged vulnerability of agricultural banks to economic downturns, Kliesen and Gilbert (1996) offer some suggestions for bank survival. For instance, small agricultural banks are advised to merge with large banking organizations, while banks with the highest percentages of assets invested in agricultural loans should maintain a higher ratio of equity to total assets..

Ellinger and Neff (1993) discuss the major issues associated with efficiency measurement of financial institutions and evaluate the efficiency of a sample of agricultural banks by comparing the Stochastic Cost Frontier and the Nonparametric Cost Frontier models which are the two most commonly used methods in the efficiency analysis of commercial banks. Their results indicate that each model or empirical approach has distinct advantages and disadvantages. Compared to the nonparametric models, which usually result in larger and more disperse measures of bank inefficiency, stochastic models are more applicable to the efficiency measurement of agricultural banks with the use of Call Report data.

Neff et al. (1994) present one the earlier empirical works on agricultural bank efficiency. They compare the efficiency analysis methods such as nonparametric, stochastic parametric, and thick frontier methods, and use a stochastic parametric cost frontier and profit model to estimate the efficiencies. They find bank size to be strongly and negatively related to profit inefficiency while the agricultural loan ratio is positively related to profit inefficiency. However, the latter result is questionable because larger banks have smaller agricultural loan-to-deposit ratios (Neff, et al., 1994).

Another study measures economies of scale and scope in agricultural banking (Featherstone and Moss, 1994). Instead of using the normal translog cost function in multiproduct cost analysis, they use a normalized quadratic translog functional form to avoid the possibility of having the translog specification produce a poor fit when applied to all bank sizes. Their results indicate that, regardless of whether curvature was or was not imposed on the function, economies of diversification are not realized when agricultural lending is combined into an institution that has not been previously engaged in agricultural lending.

Yu (2009) looks into the effect of bank specialization (with banks being classified as agricultural and nonagricultural banks) and size categories on various measures of efficiency. A stochastic input distance function is used to compute technical and allocative efficiency. His research shows certain advantages for agricultural banks regarding structural and operating characteristics. His findings indicate that agricultural banks are more efficient at making labor and capital adjustment decisions than nonagricultural banks. Moreover, his study also contends that agricultural banks are more technically efficient than nonagricultural banks.

In the face of the recent economic downturn and concomitant crisis in the financial industry, Ellinger and Sherrick (2010) conducted a study that suggests that agricultural lenders are generally in strong financial health because most of the agriculturally related institutions did not engage in residential home lending nor invest in the structured securities that have lost substantial market value. They observe that the general health of commercial banks that make agricultural loans remains strong, as only 13 of a total of 6,071 such banks have been classified as undercapitalized by the FDIC.

Methodology

Previous literature suggests that technical efficiency can be used as an indicator to evaluate the financial health of banks. The general approach for this type of analysis is the derivation of the levels of technical efficiency for banks under a stochastic cost frontier framework. The technical efficiency scores are then used in an econometric model that relates them, along with macroeconomic factors, to the probability of bank failure.

Stochastic production frontier models were introduced by Aigner, Lovell, and Schmidt and Meeusen and van Den Broeck (Aigner et al., 1976; Meeusen and van Den Broeck, 1977). Since then, these models have become a popular subfield in econometrics and are widely used in efficiency measurement.

The nature of the stochastic frontier problem can be described as follows: suppose a producer has a production function(x_{it}, β), where x_{it} is a vector of n inputs used by the producer, and β is a vector of technology parameters to be estimated. In a world without error or inefficiency, in time t, the ith producer would produce

$$y_{it} = f(x_{it}, \beta),$$

where y_{it} is the observed scalar output of the producer.

A fundamental element of stochastic frontier analysis is that the firm produces less than it potentially might because of a degree of inefficiency, so the production frontier model can be written as

$$y_{it} = f(x_{it}, \beta)\xi_{it},$$

where ξ_{it} is the level of efficiency defined as the ratio of observed output to maximum feasible output for firm i at time t. ξ_{it} must lie in the interval (0,1]. ξ_{it} =1 shows that the ith firm achieves the optimal output with the technology embodied in the production function (x_{it}, β) , while $\xi_{it} < \mathbf{1}$ provides a measure of the shortfall of the observed output from the technology embodied in the production function (Kumbhakar and Lovell, 2003).

A stochastic component that represents random shocks was added in the model so the frontier model can be rewritten as

$$y_{it} = f(x_{it}, \beta)\xi_{it}\exp(v_{it}),$$

where $\exp(v_{it})$ denotes the random shocks. Although each producer faces different types of shocks, we assume the shocks are random and described by a common distribution.

Taking the natural log of both sides, we write the model as

$$\ln(y_{it}) = \ln\{f(x_{it}, \beta)\} + \ln(\xi_{it}) + v_{it}.$$

This study assumes that there are k inputs and the production function is linear in logs, and u_{it}=$\ln(\xi_{it})$ yields

$$\ln(y_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(x_{jit}) + v_{it} - u_{it}$$

.

This is also known as the single-output Cobb-Douglas stochastic frontier functional form, used in several studies (Battese and Coelli, 1993; Kumbhakar and Lovell, 2003; Coelli et al., 2005). In the log-linear model, y_{it} is a scalar output, x_{jit} is a vector of kth inputs, β_j is the vector of the unknown technology parameters, v_{it} is a two-sided random-noise component, and u_{it} is a nonnegative cost inefficiency component of the composed error term $\varepsilon_{it} = v_{it} - u_{it}$ (Kumbhakar and Lovell , 2003).

In this study, we apply the Stochastic Frontier Analysis (SFA) to measure both the failed and solvent bank technical efficiency. Technical efficiency measures the ability of a firm to obtain optimal outputs from a given set of inputs (Drake and Hall, 2003). The efficiency score is in ratio form with observed output divided by potential maximum output. Thus, given the Cobb-Douglas stochastic frontier function, as introduced by Battese and Coelli (1993), the technical efficiency of the i_{th} bank in the t_{th} quarter is defined by:

$$TE_{it} = \frac{Observed\ output}{potential\ maximum\ output} = \frac{Y_{it}}{Y_{it}^*} = \frac{\exp\,(x_{it}\beta + v_{it} - u_{it})}{\exp\,(x_{it}\beta)} = \exp\,(-u_{it})$$

,

where Y_{it} is the frontier output and u_{it} denotes the specifications of the inefficiency component. The score of technical efficiency is between zero and one. The more efficiently a bank operates, a higher efficiency score is denoted. In this study, the post-estimation procedure, using panel data to estimate the stochastic frontier in STATA, is applied to get the technical efficiency score.

In determining the role of technical efficiency in bank failure analysis, this study employs an instrumental variables probit (IV Probit) approach. The IV Probit method used in this analysis uses maximum likelihood estimation technique that fits models with dichotomous dependent variables and endogenous explanatory variables. For a single endogenous regression, the model can be stated as:

$$
\begin{aligned}
z_{1i}^{*} &= \alpha z_{2i}\alpha + \omega W_i + \mu_i \\
z_{2i} &= \pi_1 W_i + \pi_2 V_i + v_i
\end{aligned}
,
$$

where i=1, …, N, z_{1i}^{*} is a dichotomous dependent variable, z_{2i}^{*} is a vector of endogenous variables, W_i is a vector of exogenous variables, V_i is a vector of instruments that satisfy conditions of instrumental exogeneity and relevance, α and ω are vectors of structural parameters, and π_1 and π_2 are matrices of reduced form parameters. The z_{2i} equation is written in reduced form and both equations are estimated simultaneously using maximum likelihood techniques. As a discrete choice model, z_{1i}^{*} is not observed as the model instead fits z_{1i} =1 for $z_{1i} \geq 0$ and z_{1i} =0 for $z_{1i} < 0$.

In this analysis, the IV Probit model is formulated using technical efficiency (TE) scores (as the instrumented variable) and relevant macroeconomic variables. The idea is to test whether the TE scores, which involve instrumented variables among the various bank financial performance factors used previously in the bank prediction models, are significant determinants of the probability of bank failure. Specifically, the model is estimated as follows:

$$PROB_{it}^{*} = \gamma_0 + \alpha TE + \omega W(MACRO) + \mu_i$$
$$TE = \pi_1 W(FV, ST) + v_i \qquad ,$$

where $PROB_{it}^{*}$ is the same binary dependent variable defined in the bank failure prediction models; TE, the instrumented variable (z_{2i}^{*}) in this model, is the bank technical efficiency score; FV and ST are the same set of financial measures and structural/demographic variables relating to the financial performance of banks, respectively, included in the bank failure prediction model; and MACRO, consisting of state-level unemployment growth rates (UNEMPL) and bankruptcy rates (BF) that capture the state level macroeconomic conditions. Separate regressions are made for 2009 and 2010 datasets. These years were chosen for this analysis as these were the years that recorded high numbers of bank failures.

Data Description

Technical efficiency analysis utilizes a panel data collected from the Call Reports Database published on the website of Federal Reserve Board of Chicago (FRB).We focus our study on the two years when majority of the bank failures were experienced (2009 and 2010), and collect sample banks' data from 2005 until the date they failed. 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.

In this analysis, a smaller sample of non-failed banks from Call Reports was randomly selected in a manner that ensures the panel data stochastic frontier approach can successfully converge to the log-likelihood value. In this case, 800 non-failed banks and 258 failed banks were selected, with 23227 observations in total across 6 years.

The stochastic cost frontier framework usually requires two general data categories: bank outputs, and bank inputs. Bank output data used in this study include Agricultural loans (y_1), Non-agricultural loans (y_2), Consumer loans (y_3), Fee-based financial services (y_4), and Other assets in the banks' balance sheets that could not be categorized under the previous output categories (y_5). The single output in the Cobb-Douglas frontier functional form is calculated from the aggregation of the above outputs. The input data categories considered are Number of full time employees(x_1), Premises and fixed assets(including capitalized leases) (x_2), Federal funds purchased and securities sold under agreements to repurchase plus Total time deposits of $100,000 or more($x_3$), and Total deposits($x_4$). These were collected from the Call Report dataset.

Most bank efficiency studies in corporate finance literature consider only the above three data categories. In this study, the stochastic cost function model is extended to include two important variables: loan quality index (z_1) and financial risk index (z_2). These additional variables are intended to introduce a risk dimension to the efficiency model. The index z_1 is calculated from the ratio of non-performing loans to total loans to capture the quality of bank's loan portfolios. The index z_2 is based on banks' capital to asset ratio, which is used by many studies as a proxy for financial risk. The detailed variable definitions are presented in table 1.

Results and Discussion

Stochastic frontier estimation is applied to calculate the technical efficiency scores for each bank using a panel dataset of 255 banks that failed in 2009-2010 and 1,109 surviving banks that passed the filtering criteria previously imposed on the dataset for the prediction model.

A comparative summary of the technical efficiency scores obtained is presented in table 2. The summary presents mean technical efficiency scores for each year in the dataset and aggregate measures to draw some comparisons between failed and surviving banks as well as agricultural and nonagricultural banks. The FDIC criterion of categorizing banks as agricultural and nonagricultural is used in this analysis. The FDIC classifies a bank as agricultural if the ratio of its agricultural loans to total loan portfolio exceeds 25%.

Based on the summary in table 2, both the surviving and failed banks registered mean technical efficiency scores that are well below 0.50. This implies that in general, banks, regardless of solvency conditions, have been operating quite inefficiently during the years 2005-2010. It is worth noting that banks that failed in 2009 and 2010 retain their classification as failed banks during the earlier time periods (2005 to 2008) when they were supposed to be still in "favorable financial health." The average technical efficiency score for surviving banks over the six-year period is 25.59%, while failed banks registered an average six-year technical efficiency score of only 16.46%. During the entire six-year period, surviving banks consistently outperformed failed banks in technical efficiency. These results indicate that the failed banks were actually already not operating efficiently even before the recession of the late 2000s.

The comparison of TE scores for agricultural and nonagricultural banks provides an interesting twist (table 3). An important result in this analysis is that successful (or surviving) agricultural banks have been shown to be operating more efficiently than surviving nonagricultural banks. This is important evidence that refutes the contention that loans extended to farm borrowers are at relatively higher levels of riskiness.

Moreover, a comparison of average TE scores for failed agricultural and nonagricultural banks reinforces the earlier result. Not only is the average TE score of failed agricultural banks higher than that of failed nonagricultural banks, the average TE score of failed agricultural banks even exceeds the average TE score of surviving agricultural banks. While this result could be counterintuitive, it could be due to the smaller sample of failed agricultural banks as a majority of banks with higher agricultural loan portfolios, operating during the Great Recession of the late 2000s, have managed to survive the economic crisis.

The instrumental variables probit (IV Probit) approach is used to determine the role of technical efficiency in bank failure analysis. In the IV Probit model, technical efficiency scores (TE) were estimated by a set of instruments that include all financial variables[1] used in bank failure prediction models. In addition to TE, the probability of bank failure is also determined by two macroeconomic variables, state-level unemployment (UNEMPL) and bankruptcy rates (BF). The original panel dataset was converted to cross-sectional data because of the limitation of IV probit in STATA that does not allow panel data estimation.

Separate regressions are applied to the 2009 and 2010 datasets which are compiled using the last quarter of the year reported by the failed banks (or the quarter prior to the time they were declared insolvent or failed) and the year-end report for surviving, solvent, or successful banks.

As reported in table 4, the Wald test for exogeneity applied to the IV probit model yields significant Chi-square statistics (χ^2) both for the 2009 and 2010 models which establishes the endogeneity of the TE variable and reinforces the use of the IVProbit method. The results indicate the strong significance of both macroeconomic variables (unemployment rate and bankruptcy rate) in determining the probability of bank failure. The coefficient results of UNEMRATE and BF suggest that banks located in states with higher rates of unemployment and business bankruptcy are more likely to fail. The results for BF are consistent with the results of

[1] Instruments: UNEMRATE, BF, RWCAPRATIO, AGNR, AGR, INDUS, CONSUM, LOANHER, AGTOTAL, CONSTOTAL, INDUSTOTAL, RETOTAL, LIQM1, LIQM2, OVERHEAD, INSIDELN, PROFIT, SIZE, PURCHASEDTL2, DEPLIAB, GAP (See table 5 for details).

the previous bank failure prediction models in this study. The consistent performance of UNEMRATE in the 2009 and 2010 models shows its important role in analyzing bank financial conditions.

The marginal effects reported in table 4 also provide some important insights. The unemployment rate is an importance determinant of the probability of bank failure, with a 1% increase in the unemployment rate increasing the probability of bank failure by 135% in 2009 and 199% in 2010. On the hand, a percentage change in the bankruptcy ratio increases the probability of bank failure by 78% in 2009 and 119% in 2010.

The relationship between the probability of bank failure and technical efficiency scores also corresponds to the results of the stochastic frontier analysis. The negative and significant coefficients of TE in both 2009 and 2010 models indicate that banks with lower efficiency scores are more likely to experience insolvency. A 1% increase in technical efficiency scores (TE) will decrease the probability of bank failure by 12% in 2009 and 72% in 2010.

Conclusions

The objective of this study is to understand the determinants of bank failures through technical efficiency analysis using the stochastic cost frontier frame work.

The stochastic frontier analysis allows for the calculation of technical efficiency scores, which are then incorporated into an IV Probit model as an instrumented variable that represents all bank performance variables considered in the bank failure prediction models. The IV Probit model allowed for the evaluation of the TE variable, which is a collective (aggregated) measure that captures or represents all bank decisions, strategies, and resulting financial predicaments, as a determinant of the probability of bank failure vis-à-vis macroeconomic factors. In other words, the IV Probit allows for the comparison of effects of internal (TE) and external (macroeconomic) factors in affecting the financial health and fate of banks during the most difficult periods of the Great Recession of the late 2000s.

The results of the IV Probit analysis emphasize the importance of both internal and external factors in determining the probability of bank failure. As the TE variable is instrumented by a host of financial variables representing various facets of banking business decisions, it stress the fact that bank failures are a result of poor business decisions made by bank managers and administrators. However, more than just the internal decision-related factors, banking business conditions can be significantly affected by the prevailing macroeconomic conditions. Our results suggest that when unemployment conditions worsen and more business failures occur, the general depressing mood in the economy will certainly affect banking businesses to the point that some will end up in bankruptcy.

The TE analysis also allows the validation of the relative financial strength of agricultural banks vis-à-vis nonagricultural counterparts. Results of this analysis confirm that successful agricultural banks have been operating more efficiently than surviving nonagricultural banks. This result helps to refute the contention that farm loans are at a relatively higher level of riskiness. The average TE scores of agricultural banks have also dominated in comparisons between agricultural and nonagricultural failed banks.

This study embodies the emphatic contention that the agricultural sector, regarded as a very volatile sector and thus more likely to be vulnerable to current economic turbulence, has not significantly ignited the rush of bank failures. In the future, alternative formulations for the stochastic frontier framework should perhaps be explored to evaluate the relative efficiency of the Cobb-Douglas functional from.

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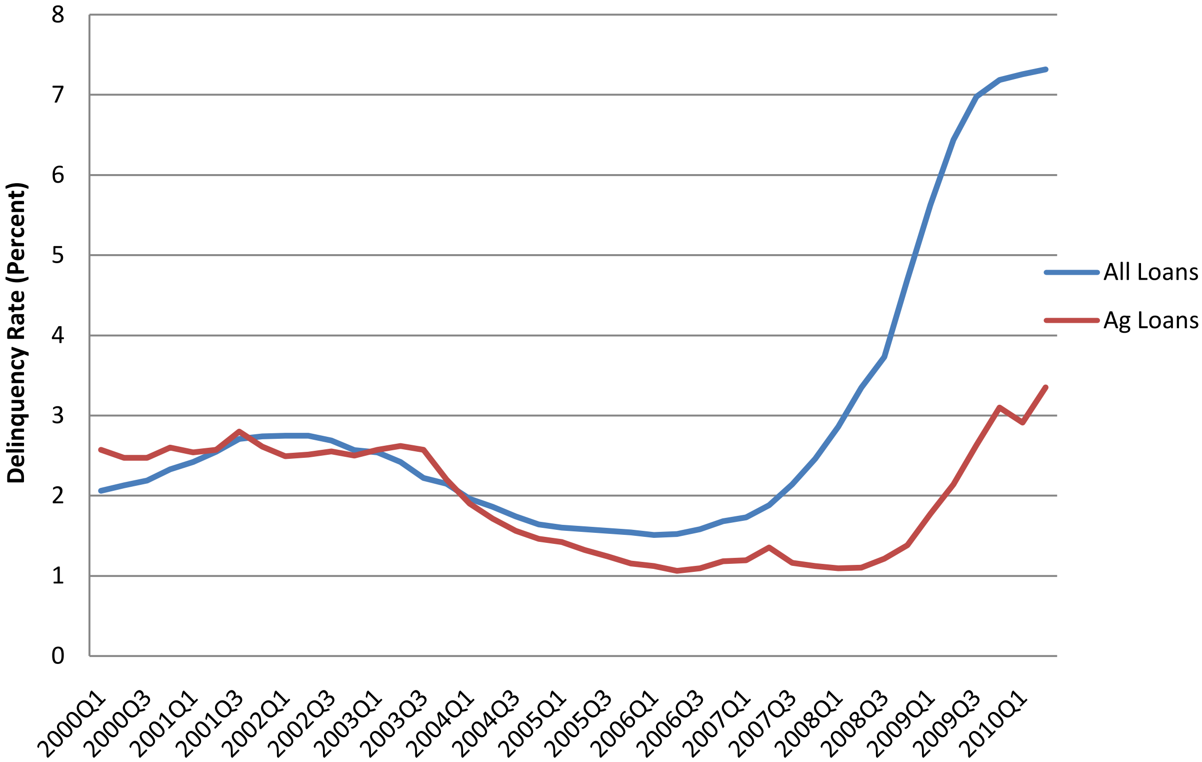

Figure 1: National Loan Delinquency Rates, Quarterly, 2000-2010

Source: Federal Reserve Board

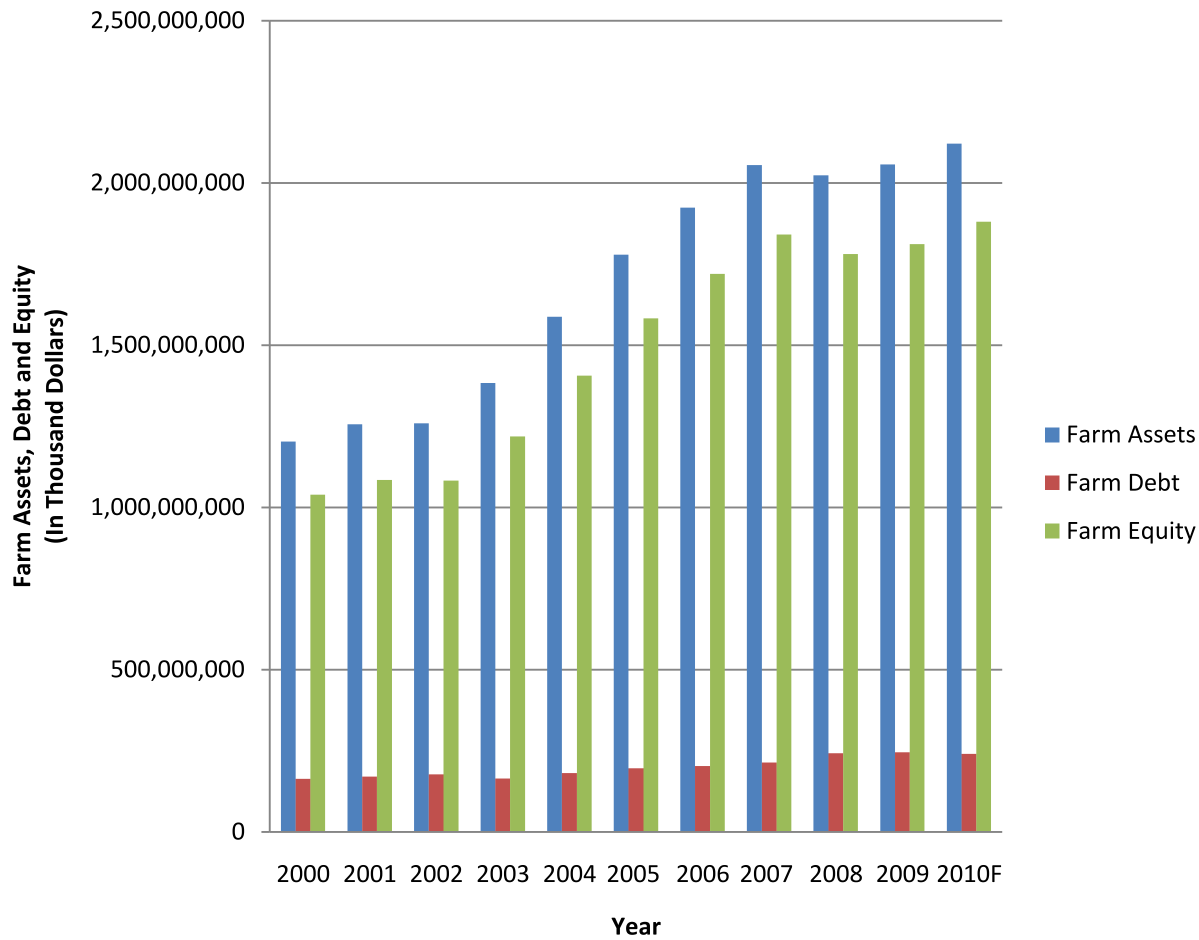

Figure 2: Total Assets, Debt, and Equity of U.S. Farms, 2000-2010

Source: Economic Research Service (ERS), USDA

Table 1. Definitions of Variables for the Stochastic Cost Frontier

Variable	Description
Output	
y_1	Agricultural loans
y_2	Nonagricultural loans, composed of real estate loans, commercial and industrial loans, and lease financing receivables
y_3	Consumer loans
y_4	Fee-based financial services
y_5	Other assets
Input	
x_1	Number of full-time equivalent employees on payroll at end of current period
x_2	Premises and fixed Assets (including capitalized leases)
x_3	Quarterly average of federal funds purchased and securities sold under agreements to repurchase
	Total time deposits of $100,000 or more
x_4	Total deposits
Exogenous	
z_1	Ratio of nonperforming loans to total loans (NPL)
z_2	Ratio of bank capital to assets.

Table 2. Technical Efficiency Comparison between Failed Banks and Non-failed Banks

TE Difference Between Non-failed Banks and Failed Banks			
Bank Characteristics	Mean	Standard Error	Standard Deviation
Non-failed banks	0.2559	0.0008	0.1269
Failed banks	0.1646	0.0014	0.0883

Comparison	Estimate	Standard Error	T value	Pr>|t|
Non-failed banks vs Failed banks	0.0913	0.0016	56.3620	0.0000

Annual Breakdown of Technical Efficiency Scores of Surviving and Failed Banks 2005-2010			
Bank Characteristics	Mean	Standard Error	Standard Deviation
2005			
Non-failed banks	0.2533	0.0019	0.1268
Failed banks	0.1626	0.0029	0.0808
2006			
Non-failed banks	0.2544	0.0019	0.1268
Failed banks	0.1620	0.0030	0.0880
2007			
Non-failed banks	0.2555	0.0019	0.1268
Failed banks	0.1641	0.0032	0.0920
2008			
Non-failed banks	0.2566	0.0019	0.1269
Failed banks	0.1650	0.0031	0.0870
2009			
Non-failed banks	0.2576	0.0019	0.1270
Failed banks	0.1721	0.0042	0.0956
2010			
Non-failed banks	0.2586	0.0022	0.1270
Failed banks	0.1642	0.0079	0.0871

Comparison	Estimate	Standard Error	T value	Pr>|t|
2005	0.0907	0.0047	19.4231	0.0000
2006	0.0924	0.0049	20.1498	0.0000
2007	0.0914	0.0046	19.9843	0.0000
2008	0.0916	0.0047	19.5927	0.0000
2009	0.0855	0.0058	14.8719	0.0000
2010	0.0944	0.0116	8.1339	0.0000

Table 3. Technical Efficiency Comparison between Agricultural and Nonagricultural Banks

TE Difference Between Ag Banks and Non-Ag Banks				
Bank Characteristics	Observation	Mean	Standard Error	Standard Deviation
Agricultural banks				
Non-failed banks	3427	0.4629	0.0024	0.1379
Failed banks	26	0.7741	0.0530	0.2705
Nonagricultural banks				
Non-failed banks	22080	0.2238	0.0006	0.0893
Failed banks	3888	0.1605	0.0011	0.0698

Comparison	Estimate	Standard Error	T value	Pr>|t|
Ag-failed vs Ag-non-failed	-0.3111	-.0274	-11.3412	0.0000
Non-Ag failed vs Non-Ag-non-failed	0.0632	0.0015	41.9678	0.0000
Ag-non-failed Vs Non-Ag-non-failed	-0.2392	0.0018	-1.3e+02	0.0000
Ag-failed vs Non-Ag failed	-0.6135	0.1434	-41.7742	0.0000

Table 4. Results of Instrumental Variables Probit (IV Probit) Estimation

	IV Probit			
	2009		2010	
Variables	Coefficient	Marginal effect	Coefficient	Marginal effect
Intercept	-2.2626***		-0.1564	
	(0.2387)		(0.3012)	
A. Instrumented variable				
TE[a]	-2.2172**	-0.1224**	-5.5464***	-0.7264***
	(0.9083)	(0.0460)	(0.8723)	(0.1843)
B. Macroeconomic variables				
UNEMRATE	24.5442***	1.3546***	15.2088***	1.9918***
	(2.0413)	(0.2462)	(1.9907)	(0.2778)
BF	14.1488***	0.7809***	9.1156***	1.1938***
	(2.3740)	(0.1696)	(2.3857)	(0.2484)
Model's Explanatory Power (χ^2)	195.82***		209.56***	
Wald Test of Exogeneity (χ^2)	11.78***		5.63**	

Note:

*** Significantly different from zero at the 1% level.
** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level.
Standard errors are in parentheses.
[a] The instruments used for TE in the IV Probit model are UNEMRATE, BF, RWCAPRATIO, AGNR, AGR, INDUS, CONSUM, LOANHER, AGTOTAL, CONSTOTAL, INDUSTOTAL, RETOTAL, LIQM1, LIQM2, OVERHEAD, INSIDELN, PROFIT, SIZE, PURCHASEDTL2, DEPLIAB, GAP.

Table 5. Definitions of Financial Variables

Variables	Descriptions
RWCAPRATIO	Risk-weighted capital ratio
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 & 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 & industrial loans, and agricultural loans.
AGTOTAL	Agricultural loans / total loans
CONSTOTAL	Consumer loans/total loans
INDUSTOTAL	Commercial & 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