



# Measuring the efficiency of the Farm Credit System

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## Abstract

**Purpose** – The purpose of this paper is to develop information on the relative efficiency of Farm Credit System (FCS) lenders. Also the evolution of relative efficiency is examined as influenced by the biofuel boom, the financial crisis, and farm income increases. The paper aims to discuss these issues.

**Design/methodology/approach** – A stochastic frontier production function is used to estimate technical efficiency of FCS banks and associations.

**Findings** – A significant difference is found in efficiency between large and small associations and banks. Larger asset bases and management compensation are found to be positively associated with efficiency. Banks are found to have higher technical efficiency than associations (66-46 percent). Association efficiency is found to be increasing indicating likely effects of recent consolidation. The financial crisis was not found to have a significant effect with the bioenergy and farm income booms being likely countervailing forces.

**Research limitations/implications** – Further work is needed on the impact of the biofuel boom, increases in farm income, and new regulations.

**Practical implications** – The study provides information and indications of strategies for FCS management including additional consolidation.

**Originality/value** – This does an updated assessment of FCS efficiency taking into account changes in consolidation, lending practices, and economic conditions. Implications are developed for management actions such as more consolidation. The study also uses a more advanced methodology compared to older studies.

**Keywords** Technical efficiency, Financial crisis, Agricultural lenders, Banking efficiency, Farm credit system, Stochastic frontier production function

**Paper type** Research paper

The US Farm Credit System (FCS) is a key credit source for the US farmers. As of 2010, the FCS funded 41.4 percent of US farm business debt (USDA, Agricultural Income and Finance Outlook, 2011). The performance of FCS therefore can impact US farmers (Schnepf, 2012). This paper develops information on the relative efficiency of FCS lending entities in producing loans and other output. Such measures will provide indications as to whether FCS lending entities have utilized their government sponsorship and privileges efficiently. In addition, the paper will assess the way relative efficiency has evolved over time including the 2008-2009 financial crisis.

The FCS is a nationwide network of borrower-owned lending institutions that provides credit to US agriculture. As of January 1, 2011, the System was composed of five banks and 81 lending associations. The banks generally only make long-term real estate loans although also make loans directly to cooperatives and other entities (Farm Credit Administration, 2012). The banks also loan to affiliated associations,

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other banks, and non-system lenders. The banks obtain funds through the issuance of system-wide debt securities, common and preferred equities, plus subordinated debt (Federal Farm Credit Banks Funding Corporation, 2010). The associations make short-, intermediate-, and long-term loans to farmers, ranchers, aquaculture firms, farm-related businesses, and rural homeowners. The majority of these associations' funds come from borrowings from FCS banks (Federal Farm Credit Banks Funding Corporation, 2010). The associations may also purchase loan participations from other System entities and non-System lenders.

The stated FCS goal is to provide maximum service to the US agricultural sector at minimum cost subject to maintaining long-run viability (Collender *et al.*, 1991). The FCS institutions are exempted from many reform regulations as a government-sponsored enterprise (GSE). In addition, the FCS also receives subsidized interest rates as a GSE (Jensen, 2000).

A small amount of prior research has focussed on FCS lending efficiency. Collender *et al.* (1991) investigated the FCS direct lender profit efficiency using data envelopment analysis (DEA) and linear programming. However, their results may not apply today due to recent developments in lending and agriculture. Moreover, efficiency estimation methodology has evolved since their study. This paper provides an updated assessment on FCS bank and association efficiency plus develops implications for FCS management. This will be done by estimating an efficiency model using data from 2000 to 2011. The efficiency of the five FCS banks and the associations will be estimated separately as they fundamentally serve different clients with different embodied transactions costs. The change in efficiency from exogenous influences such as the financial crisis, the biofuel boom, and the recent increase in farm income will also be examined.

## Literature review

### *Banking efficiency measurement*

The major methods used to measure efficiency are non-parametric and parametric frontier production function estimation approaches coupled with analysis of deviations from that frontier. DEA is the dominant non-parametric approach and uses linear programming in which the relative performance of a decision-making unit is compared to the frontier. Henderson (2003) indicates DEA makes several assumptions:

- no random error exists in the data and all deviations from the estimated frontier are manifestations of inefficiency;
- all firms produce in a deterministic framework without uncertainty; and
- the production set is convex with free disposability.

Other non-parametric approaches include free disposal hull (FDH), non-parametric stochastic frontier models (SFAs), and semi-parametric stochastic frontier methods (Kumbhakar *et al.*, 2007). The FDH model assumes free disposability and relaxes the convexity assumption on the production set. The non-parametric SFA uses a local maximum likelihood approach in which the parameters of a polynomial model are localized with respect to the covariates of the model. The semi-parametric SFA includes assumptions about the joint distribution of the random firm effects and the regressors in a panel specification. The non-parametric part of the semi-parametric SFA addresses the distribution of the inefficiency terms. However, the estimators in these models are based on the linearity of the efficient frontier (Kumbhakar *et al.*, 2007).

The conventional linear programming-based DEA approach has the drawbacks listed below:

- It is unable to decompose deviations from the efficient frontier into firm effects and external factor effects, thus considering all deviations from the frontier as inefficiencies.
- It assumes a deterministic frontier which is constructed using the outer envelope of the observations, and thus may be influenced by outliers in the data (Wilson, 1993).
- The approach assumes a proportion of the sample is perfectly efficient. These firms in those cases are therefore “self-referencing” and their efficiency estimate is equal to one (Neff *et al.*, 1994).
- Studies typically develop efficiency measures based on a single time period. They do not account for technical progress and do not consider that technical efficiency for a firm might vary over time (Pasiouras *et al.*, 2007).
- The approach does not allow uncertainty in efficiency estimation. By ignoring relevant uncertainty, estimates of economic efficiency may be misleading and may classify activities which are optimal for the decision maker as inefficient (Pasour and Bruce, 1975).

Although statistical inference has been developed for non-parametric deterministic frontier models, the deterministic assumption may be too strong given possible measurement errors and random shocks (Kumbhakar *et al.*, 2007).

The other non-parametric methodologies also have their own strengths and weaknesses. The FDH estimator does not envelop all the data and are more robust to outliers but is still reliant on the deterministic assumption. The non-parametric SFAs allow uncertainty and noise but are implemented in a cross-sectional framework without considering changes over time. The semi-parametric stochastic frontier method works with panel data but the estimators in these panel models assume linearity of the efficient frontier (Kumbhakar *et al.*, 2007).

The parametric frontier approach specifies a functional form for the relationship among inputs, outputs, and environmental factors, and allows for random error. The three main parametric methodologies include the: stochastic frontier approach (SFA), the thick frontier approach (TFA), and the distribution-free approach (DFA). The SFA employs a composed error model and assumes that: inefficiencies follow an asymmetric distribution, usually the half-normal; the random errors follow a symmetric distribution, usually standard normal; and both the inefficiencies and random errors are orthogonal to the regressors. The TFA assumes that deviations from predicted performance within a group of entities represent random error, whereas differences in predicted performance between highest and lowest groups represent inefficiencies. The DFA is a panel estimation method in which the inefficiency for each firm is estimated as the difference between its average residual and the average residual of the firm on the frontier. It assumes that efficiency of each firm is stable, and the random error is averaged out over time (Bauer *et al.*, 1998).

The SFA has several advantages over the deterministic non-parametric approach because it allows for external events beyond the firm's control such as the financial crisis, climate, and government policy by decomposing deviations from the efficient production frontier into firm effects and external factor effects. Additionally, the SFA

model allows for uncertainty in the estimation of efficiency scores which the deterministic non-parametric approach does not. Lastly, the SFA model accounts for time variations in efficiency using time series, cross-sectional panel data rather than a single cross-section (Pasiouras *et al.*, 2007). Pasiouras *et al.* (2007) stated that this allows for time variations in efficiency where firms might learn from previous experience, or that efficiency might change as a result of some regulatory or environmental factors. Panel data has also been argued to be better in studying efficiency by Carbo *et al.* (2002), Cornwell *et al.* (1990), Kumbhakar (1993), and many others.

However, these approaches are not without defect. The SFA requires a particular functional form plus embodies assumptions about distribution of efficiency (Neff *et al.*, 1994). Those assumptions might not truly reflect the firm's underlying technology but studies by Bauer *et al.* (1998) and Vander Vennet (2002) showed when comparing different functions and models estimated under different assumptions, the estimation results are not significantly different (Pasiouras *et al.*, 2007). Furthermore, Gong and Sickles (1992) demonstrated that the stochastic model outperforms the DEA model if the employed technology is close to the given underlying technology.

The TFA puts no restriction on the correlations between inefficiencies and the regressors but the estimation results provide little information on firm specific inefficiency (Neff *et al.*, 1994). The DFA assumes that for a given firm the random errors will average out over time but as Sfiridis and Daniels (2006) pointed out this might not be reasonable, especially for short time periods. The DFA also requires a large amount of data encompassing multiple cross-sections of the studied subjects (Sfiridis and Daniels, 2006).

Bayesian estimation of SFAs has been developed by Van den Broeck *et al.* (1994), Koop *et al.* (1995, 1997), and (Koop and Steel, 2004). These models use Bayesian inference about firm-specific inefficiency in estimating SFAs. They are typically implemented using fixed and random effects models. These two types of models also have weaknesses. The Bayesian fixed effects model does not make a distributional assumption about the inefficiency distribution but it implicitly makes strong and possibly unreasonable prior assumptions. Furthermore, the model can only calculate relative efficiency, as opposed to absolute. The random effects model allows the calculation of absolute efficiency; but it makes explicit distributional assumption about the inefficiency distribution. Those assumptions might lead to improper priors on the parameters that can lead to invalid Bayesian inference because the posterior does not exist (Koop and Steel, 2004).

After considering the advantages and disadvantages of the various models plus the FCS characteristics, we decided to use the SFA. This choice is made for several reasons. First, the SFA accounts for exogenous factors, uncertainty, and time variation in efficiency. Thus the model can incorporate changes in the agricultural lending markets over time. Second, although this model requires a functional form assumption, the findings in the literature indicate the assumption about functional form should not create a serious problem.

#### *Means of estimating efficiency*

One can estimate a variety of efficiency concepts including cost, revenue, technical, and profit efficiency and a choice must be made. Kumbhakar and Lovell (2000) stated that if price data was difficult to find, one might decide to focus on technical efficiency rather than cost, revenue, or profit efficiency. Technical efficiency can be measured without having price information and having to impose a behavioral objective on producers, while the measurement of cost, revenue, and profit efficiency requires both

(Henderson, 2003). Henderson (2003) argues that measuring output based technical efficiency is more relevant because increasing output with a given amount of inputs might be easier than decreasing inputs to produce a given amount of output. Consequently this study estimates technical efficiency as the ratio of an entities production (in these case loans and other earning assets) to the corresponding amount from the frontier production function using the same levels of inputs.

In developing input and output measures for banks, the literature offers four approaches. The first is a production approach (Benston, 1965), where the number of a bank's accounts or its related transactions measure output, while the number of employees and physical capital are considered as inputs. Second, there is an intermediation approach (Aly *et al.*, 1990) which defines volume of loans and other assets as outputs, whereas deposits, labor, physical capital, and other borrowed funds are inputs. Third, there is an operating approach (Jemric and Vujcic, 2002) which classifies total revenue (interest and non-interest income) as a banks' output and the total interest plus non-interest expenses as inputs. Fourth, there is a value added approach (Drake *et al.*, 2006) that identifies balance sheet categories that contribute to the bank value added such as deposits and loans as outputs while labor, capital, and interest expenses are used as inputs (Sufian, 2009).

Due to data availability, the intermediation approach will be used here. The total value of loans, leases, investments, interest receivables, and other earning assets will be characterized as outputs, while inputs include the total amount of system bonds, notes, other borrowings, labor, and fixed assets. Deposits were not considered because the FCS is not allowed to have deposits.

## Methodology

### *Theoretical conceptualization of model*

We will estimate a SFA model following Battese and Coelli (1993). The frontier production function  $f(\cdot)$  gives the maximum feasible volume of outputs that can be produced with a given level of inputs. The actual production function for bank  $i$  in time period  $t$  can be written as:

$$Q_{it} = f(x_{it}; \beta) \exp(v_{it} - u_{it}) \quad 0 \leq u_{it} < \infty \text{ where } i = 1, 2, \dots, n \text{ and } t = 1, 2, \dots, T \quad (1)$$

where  $Q_{it}$  represents the production output of entity  $i$  in period  $t$ ,  $x_{it}$  is a  $(1 \times k)$  vector of production inputs associated for entity  $i$  in time period  $t$ ; and  $\beta$  is a  $(k \times 1)$  vector of parameters to be estimated, which represents the effect of a given input on the quantity of outputs produced;  $v_{it}$  and  $u_{it}$  are two components of the disturbance term where  $u_{it}$  stands for deviation of output from entity  $i$  in time period  $t$  from the production frontier,  $v_{it}$  is a random noise that captures the effects of idiosyncratic errors which are assumed to be i.i.d. normal  $(0, \sigma_v^2)$ . In this case  $u_{it}$  is a one-sided (non-negative) residual term representing the bank technical inefficiency effect which is assumed to have a half-normal, truncated half-normal, exponential or  $\gamma$  distribution (Battese and Coelli, 1993; Kumbhakar and Lovell, 2000). In turn  $u_{it}$  is assumed to be a function of a set of explanatory variables  $z_{it}$  and the unknown  $\delta$ :

$$u_{it} = z_{it} \times \delta + W_{it} \text{ for } i = 1, 2, \dots, n \text{ and } t = 1, 2, \dots, T \quad (2)$$

where  $z_{it}$  is a  $(1 \times m)$  vector of entity  $i$  specific variables at time period  $t$ , and  $\delta$  is an  $(m \times 1)$  vector of unknown coefficients of the firm-specific inefficiency variables.

$W_{it}$  accounts for other firm-specific inefficiency variables which are not included in the model, and defined by the truncation of the normal distribution with zero mean and variance  $\sigma^2$ , such that the point of truncation is  $-z_{it} \times \delta$ , i.e.  $W_{it} > -z_{it} \times \delta$ .

The most efficient case for an entity is obtained when the entity's effect  $u_{it} = 0$ , i.e.  $Q_{it} = f(x_{it}; \beta) \exp(v_{it})$ . Thus for each entity the measure of technical efficiency is equivalent to the ratio of the production for the  $i$ th entity in any given period  $t$ ,  $f(x_{it}; \beta) \exp(v_{it} - u_{it})$  to the corresponding production value if the firm effect  $u_{it}$  was zero,  $Q_{it} = f(x_{it}; \beta) \exp(v_{it})$ .

The technical efficiency of production for the  $i$ th FCS entity at the  $t$ th observation is defined by equation:

$$TE = f(x_{it}; \beta) \exp(v_{it} - u_{it}) / f(x_{it}; \beta) \exp(v_{it}) = \exp(-u_{it}) = \exp(-z_{it} \times \delta - W_{it})$$

which is in effect the production function value for the entity divided by the frontier value, both using the same level of inputs.

Let  $e_{it} = v_{it} - u_{it}$ , following the model specified by Equations (1) and (2), then the mean prediction of TE for entity  $i$  in period  $t$  given the values of the random variable  $e_{it}$  is:

$$TE = E[\exp(-u_{it} | e_{it})] = E[\exp(-z_{it} \times \delta - W_{it}) | e_{it}]$$

Then  $E[\exp(-z_{it} \times \delta - W_{it}) | e_{it}]$  provides the measure of TE of FCS entity  $i$  in period  $t$ .

#### The estimation model

The system stochastic frontier production function is defined as:

$$\begin{aligned} \ln Q_{it} = & \beta_0 + \beta_1 \ln B_{it} + \beta_2 \ln L_{it} \\ & + \beta_3 \ln A_{it} + \sum_{k=2000}^{2011} \beta_{4k} DY_k \\ & + \sum_{q=1}^4 \beta_{5q} DQ_q + v_{it} - u_{it} \end{aligned} \quad (3)$$

$$u_{it} = \sum_{p=1}^4 \delta_{1pt} DS_{ipt} + \sum_{p=1}^5 \delta_{2pt} DR_{ip} + \delta_{3t} Dir_{it} + W_{it} \quad (4)$$

where  $Q_{it}$  represents outputs which include loans, leases, investments, interest receivable, other receivables, cash, and other earning assets for entity  $i$  in period  $t$ . The value of these assets is used as a single output. Inputs include input cost ( $B$ ), the sum of interest paid for system bonds, notes, and other borrowings/payables; expenditures on labor ( $L$ ), which is summed salaries and employee benefits; and fixed assets ( $A$ ) which is from the cost of premises and fixed assets in the FCS call report data.

Following Blair and Kraft (1974), year-specific dummies  $DY_k$  for  $k = 2000, 2001, \dots, 2011$  were used to account for the presence of technical progress and time specific effects. The resultant coefficients of the dummy variables indicate



what Blair and Kraft (1974) call “the marginal change in output per year associated with the occurrence of technological progress in each cross section.” Quarterly dummies with  $q = 1, 2, 3,$  and  $4$  represent the first, second, third, and fourth quarter of the year is also included to account for seasonal effects on farm loan demand.

Due to the unavailability of specific data on each association and bank, dummy variables for director compensation, bank size, and region are used to account for bank and association characteristics. Specifically, at time  $t$  when entity  $i$  has total assets larger than \$1 billion in year 2011 dollars we set  $DS_{i1t} = 1$ , then  $DS_{i2t} = 1$  for entities with total assets between \$1 and \$500 million;  $DS_{i3t} = 1$  for those with total assets between \$500 million and \$250 million, and  $DS_{i4t} = 1$  for associations with total assets less than \$250 million. The dummy variables for bank size give a measure of economies of scale and consequently incorporate the impact of risk on technical efficiency (Hughes and Mester, 1998)[1].

Regional dummies  $DR_{ip}$ ,  $p = 1, 2, 3, 4,$  and  $5$  identify whether the bank or association is located in west, midwest, northeast, south, and Puerto Rico, respectively.  $Dir_{it}$  is management compensation expenditure for entity  $i$  in time period  $t$ . The regional dummies capture regional fixed effects on technical efficiency, and the director compensation variable examines the influence of incentives on each association and bank’s endogenous effort to improve efficiency.

#### Estimation approach

The maximum likelihood approach is used to estimate the model. As shown by Battese and Coelli (1993), the logarithm of the likelihood function is:

$$L^*(\theta; y) = -\frac{1}{2} \left( \sum_{i=1}^N T_i \right) \{ \ln 2\pi + \ln \sigma_s^2 \} - \frac{1}{2} \sum_{I=1}^N \sum_{t=1}^{T_i} \{ (y_{it} - x_{it}\beta + z_{it}\delta)^2 / \sigma_s^2 \} - \frac{1}{2} \sum_{I=1}^N \sum_{t=1}^{T_i} \{ \ln \Phi(d_{it}) - \ln \Phi(d_{it}^*) \} \quad (5)$$

where  $\sigma_s^2 = \sigma_v^2 + \sigma^2$ ,  $\gamma = \sigma^2 / \sigma_s^2$ ,  $d_{it} = z_{it}\delta / (\gamma\sigma_s^2)^{1/2}$ ,  $\mu_{it}^* = (1-\gamma)z_{it}\delta - \gamma(y_{it} - x_{it}\beta)$ ,  $d_{it}^* = \mu_{it}^* / [\gamma(1-\gamma)\sigma_s^2]^{1/2}$ ,  $\theta = (\beta', \delta', \delta_s^2, \gamma)'$ .

In turn maximizing the above log likelihood give estimates of the coefficients  $\beta$ ,  $\delta$ ,  $\sigma_s^2$ , and  $\gamma$ .

The mean prediction of the technical efficiency of the  $i$ th entity at the  $t$ th time period  $TE_{it}$  is:

$$E \left( (e^{-U} | E = e) \right) = \left\{ \exp[-u_* + \frac{1}{2} \sigma_*^2] \right\} \left\{ \Phi \left[ \left( \frac{\mu_*}{\sigma_*} \right) - \sigma_* \right] / \Phi(\mu_*/\sigma_*) \right\} \quad (6)$$

where  $E_i$  represents the  $(T_i \times 1)$  vector of  $E_{it}$ 's associated with the time periods observed for the  $i$ th entity,  $E_{it} = V_{it} - U_{it}$ ,  $\mu_* = (\sigma_v^2 z \delta - \sigma^2 e) / (\sigma_v^2 + \sigma^2)$ , and  $\sigma_*^2 = \sigma^2 \sigma_v^2 / (\sigma^2 + \sigma_v^2)$ .

The model is run separately for the banks and the associations because of their heterogeneous products. Bank size dummies are excluded in the banks' technical inefficiency equation as they are all in the large category. The study uses the computer program Frontier 4.1 (Coelli, 1996).

### Data

Quarterly unbalanced panel data for the period from January 2000 to December 2011 were obtained from the Farm Credit Administration web site on the FCS five banks and all of the member associations. All data are adjusted to 2011\$ using US CPI indices (base = 2011) drawn from the Bureau of Labor Statistics web site ([www.bls.gov/data/#prices](http://www.bls.gov/data/#prices)). Descriptive statistics on the variables in logarithm form for the five banks and for the associations are presented in Table I.

Two observations were found for particular associations in selected quarters which have negative total salary and expenses. These were assumed to be outliers and were excluded from the data. In addition 310 observations for banks and associations with less than five quarters of available data are excluded as that period was too short for precise estimation.

### Empirical results and discussion

Empirical results are reported in Table II for the five banks and Table III for the associations. It is expected that all inputs would have positive effects on output. The estimated results show positive estimated coefficients for interest paid, fixed assets, and labor expenses with most being statistically significant at the 5 percent level. The coefficient estimates for labor expenses and interest payable for banks are 0.38 and 0.64, respectively, compared to 0.08 and 0.26 for associations. These are statistically significantly different and indicate that the banks productivity is higher than the associations in using the same inputs. However, fixed assets seem to be more important in an association's productivity where they have a higher level of significance (5 percent). These findings can be explained from the fact that small

Variable	Observation	Mean	SD	Minimum	Maximum
<i>Banks</i>					
<i>Outputs</i>					
Log (earning assets)	201	17.06	0.65	15.63	18.11
<i>Inputs</i>					
Log (premises and fixed assets)	201	9.33	0.72	7.07	10.41
Log (labor expenses)	201	9.00	0.61	6.85	10.38
Log (interest payable)	201	11.89	0.79	10.28	13.18
Log (directors' compensation)	201	5.50	0.59	0.00	6.51
<i>Associations</i>					
<i>Outputs</i>					
Log (earning assets)	4,917	13.04	1.50	0.00	17.33
<i>Inputs</i>					
Log (premises and fixed assets)	4,917	7.51	1.68	0.00	11.67
Log (labor expenses)	4,917	6.99	1.42	0.00	10.62
Log (interest payable)	4,917	7.30	2.30	0.00	12.92
Log (directors' compensation)	4,917	3.58	1.07	0.00	7.01

**Note:** <sup>a</sup>All variables are measured in thousands of dollars and reported in logarithm

**Source:** Calculations over data from Farm Credit Administration

**Table I.**  
Descriptive statistics for  
The FCS's five banks and  
associations<sup>a</sup>



AFR 74,1	Variable	Coefficient	SD	t-Ratio
46	Constant	5.57	0.42	13.28
	Log (premises and fixed assets)	0.04	0.02	1.77
	Log (labor expenses)	0.38	0.02	22.82
	Log (interest payable)	0.64	0.03	18.56
	Dummy year 2001	0.24	0.08	2.91
	Dummy year 2002	0.51	0.09	5.81
	Dummy year 2003	0.87	0.08	11.41
	Dummy year 2004	0.70	0.08	8.46
	Dummy year 2005	0.51	0.08	6.59
	Dummy year 2006	0.37	0.08	4.76
	Dummy year 2007	0.36	0.08	4.56
	Dummy year 2008	0.55	0.07	7.42
	Dummy year 2009	0.71	0.08	9.29
	Dummy year 2010	0.88	0.08	11.24
	Dummy year 2011	0.97	0.08	11.87
	Dummy quarter 2	0.03	0.03	0.92
	Dummy quarter 3	0.03	0.03	0.88
	Dummy quarter 4	-0.01	0.03	-0.24
	Constant	0.85	0.51	1.67
	Dummy region west	0.61	0.50	1.21
	Dummy region midwest	0.06	0.50	0.13
	Dummy region northeast	0.00	1.00	0.00
	Dummy region south	0.18	0.50	0.36
	Mgmt compensation	-0.11	0.02	-4.91
	$\sigma^2$	0.02	0.00	7.26
	$\gamma$	1.00	0.00	483.49
	LR test of the one-sided error <sup>a</sup>	39.63		

**Table II.** Maximum likelihood estimates of stochastic frontier functions for five banks

**Note:** <sup>a</sup>Critical value at 5 percent level of significance with seven restrictions: 13.401

**Source:** Kodde and Palm (1986)

associations might still need more capital asset investment to work more productively. The five banks might have come to a saturation point where adding more capital assets does not significantly increase outputs. Also the five banks' dependence on the bonds and securities market explains their higher output elasticity with respect to input cost which mainly consists of interest payables.

The coefficients of the year dummy variables in the bank equation have positive signs and all are significant at 5 percent level. The significant, positive sign of the year dummy variables indicates that there is an increasing efficiency over time due to technological progress; however, the magnitude varies among years. The increase in magnitude dropped in 2007 then increased afterwards. Regarding the five banks estimation, the quarterly dummies and regional dummies are not significant which implies that the five banks' inefficiency is not influenced by seasonal or regional effects.

Results from the one-sided generalized likelihood ratio test (Coelli *et al.*, 1997) suggest we reject the null hypothesis of no efficiency effects at 5 percent level of significance for both bank and association models. The estimates from the association equation show an interesting result on bank size for associations. The coefficients of the bank size dummies are significant and increase in magnitude as the asset size increases, meaning that larger associations tend to exhibit higher technical efficiency, *ceteris paribus*. This result is consistent with an average efficiency calculation by bank

Variable	Coefficient	SD	t-Ratio
Constant	11.19	0.09	117.90
Log (premises and fixed assets)	0.05	0.02	2.76
Log (labor expenses)	0.08	0.02	4.06
Log (interest payable)	0.26	0.00	57.57
Dummy year 2001	-0.01	0.06	-0.21
Dummy year 2002	0.09	0.06	1.64
Dummy year 2003	0.16	0.06	2.78
Dummy year 2004	0.14	0.06	2.39
Dummy year 2005	-0.01	0.06	-0.23
Dummy year 2006	-0.15	0.06	-2.57
Dummy year 2007	-0.06	0.06	-1.03
Dummy year 2008	0.01	0.06	0.17
Dummy year 2009	0.10	0.06	1.68
Dummy year 2010	0.10	0.06	1.74
Dummy year 2011	0.15	0.06	2.62
Dummy quarter 2	0.02	0.03	0.68
Dummy quarter 3	0.02	0.04	0.56
Dummy quarter 4	-0.04	0.04	-1.02
Constant	2.49	0.14	17.56
Dummy bank size 1	-3.93	0.09	-41.74
Dummy bank size 2	-1.17	0.04	-29.73
Dummy bank size 3	-0.91	0.03	-26.37
Dummy region west	0.00	0.13	-0.03
Dummy region Midwest	0.37	0.13	2.90
Dummy region northeast	-0.13	0.13	-0.96
Dummy region south	0.12	0.13	0.98
Management compensation	-0.16	0.02	-9.25
$\sigma^2$	0.46	0.01	40.45
$\gamma$	0.18	0.01	16.97
LR test of the one-sided error <sup>a</sup>	2,296.28		

**Note:** <sup>a</sup>Critical value at 5 percent level of significance with ten restrictions: 17.670

**Source:** Kodde and Palm (1986)

**Table III.**  
Maximum likelihood  
estimates of stochastic  
frontier functions for  
associations

asset size (Table IV and Figure 1). On average, associations with more than \$1 billion in assets exhibit an average efficiency of 96.5 percent, while associations which have less than \$250 million in assets show an average 12.2 percent level of efficiency. These results are consistent with the findings of many studies including DeYoung *et al.* (2004), Mehdiian *et al.* (2007), Wheelock and Wilson (2003), Marsh *et al.* (2003), and Akhigbe and McNulty (2005) showing that larger banks are often more efficient than smaller banks. This reflects economies to scale.

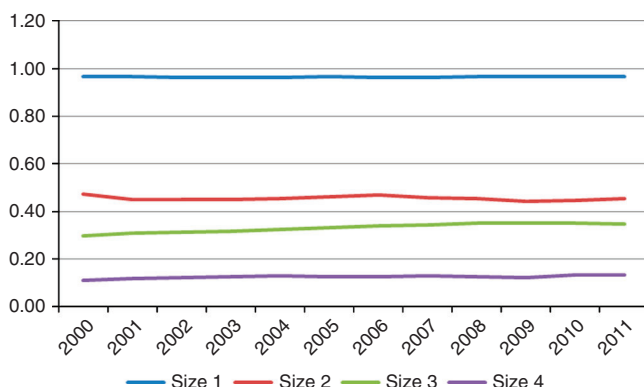
Quarterly dummies are not significant in the model. The regional dummy for the midwest is positive and significant for associations indicating that efficiency in this region might be lower than elsewhere. That negative effect should be further investigated.

Tables V and VI present the average predicted technical efficiencies for the five FCS banks and the FCS associations, respectively, for 2000-2011. Efficiency of the associations as in Figure 2 shows an increasing trend that can likely be explained by several factors. First, the market share of the FCS in the US agricultural lending market has been increasing since 2000, from 27 percent of total US farm business debt in

**Table IV.**  
Predicted efficiency value  
for associations  
2000-2011 by size

Year	Efficiency of size 1 <sup>a</sup>			Efficiency of size 2 <sup>b</sup>			Efficiency of size 3 <sup>c</sup>			Efficiency of size 4 <sup>d</sup>		
	Mean	SD	Frequency	Mean	SD	Frequency	Mean	SD	Frequency	Mean	SD	Frequency
2000	0.967	0.02	70	0.472	0.10	43	0.299	0.07	94	0.110	0.03	229
2001	0.965	0.01	83	0.448	0.09	95	0.307	0.06	124	0.115	0.03	214
2002	0.964	0.01	97	0.448	0.08	105	0.311	0.06	107	0.121	0.03	147
2003	0.964	0.01	96	0.450	0.07	107	0.317	0.05	110	0.126	0.03	107
2004	0.964	0.01	92	0.454	0.08	103	0.323	0.06	118	0.129	0.03	99
2005	0.965	0.01	97	0.462	0.07	99	0.329	0.06	117	0.126	0.04	95
2006	0.964	0.01	108	0.467	0.06	102	0.339	0.07	108	0.124	0.04	85
2007	0.963	0.01	116	0.457	0.07	96	0.342	0.06	108	0.129	0.04	76
2008	0.965	0.01	122	0.454	0.07	96	0.351	0.07	98	0.126	0.03	70
2009	0.966	0.01	126	0.444	0.05	85	0.351	0.08	102	0.122	0.03	59
2010	0.965	0.01	121	0.447	0.06	78	0.351	0.07	101	0.131	0.04	64
2011	0.964	0.01	117	0.455	0.06	78	0.347	0.07	93	0.131	0.03	60
Average/total	0.965	0.01	1,245	0.454	0.07	1,087	0.330	0.07	1,280	0.122	0.03	1,305

**Notes:** <sup>a</sup>Size 1: associations with total assets larger than or equal to \$1 billion in year 2011 dollars; <sup>b</sup>Size 2: associations with total assets larger than or equal to \$500 million and less than \$1 billion in year 2011 dollars; <sup>c</sup>Size 3: associations with total assets larger than or equal to \$250 million and less than \$500 million in year 2011 dollars; <sup>d</sup>Size 4: associations with total assets less than \$250 million in year 2011 dollars



**Figure 1.**  
Mean efficiency estimates  
of associations by size

Year	Mean	SD	Frequency
2000	0.67	0.10	8
2001	0.65	0.16	8
2002	0.68	0.16	8
2003	0.59	0.15	17
2004	0.65	0.10	20
2005	0.66	0.12	20
2006	0.67	0.12	20
2007	0.67	0.13	20
2008	0.66	0.16	20
2009	0.66	0.19	20
2010	0.67	0.20	20
2011	0.68	0.19	20
Average/total	0.66	0.15	201

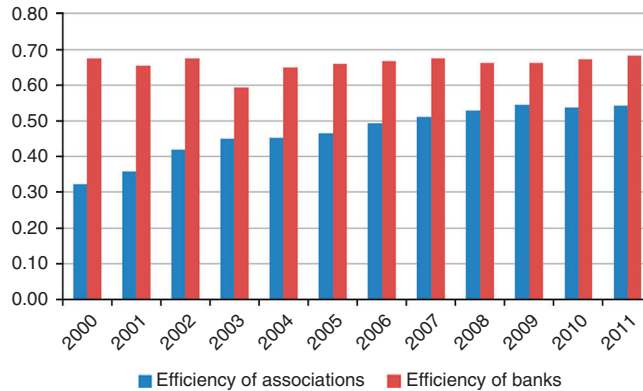
**Table V.**  
Predicted efficiency  
value for the five  
banks 2000-2011

Year	Mean	SD	Frequency
2000	0.32	0.31	436
2001	0.36	0.30	516
2002	0.42	0.31	456
2003	0.45	0.31	420
2004	0.45	0.30	412
2005	0.47	0.31	408
2006	0.49	0.31	403
2007	0.51	0.31	396
2008	0.53	0.32	386
2009	0.54	0.32	372
2010	0.54	0.32	364
2011	0.54	0.32	348
Average/total	0.46	0.32	4,917

**Table VI.**  
Predicted efficiency value  
for associations 2000-2011

2000 to 41.4 percent in 2010 (USDA, Agricultural Income and Finance Outlook, 2011). Second, farm income has been rising which has led to a greater demand for FCS loans again increasing output and efficiency. Lastly, there has been consolidation of associations that is likely contributing to efficiency as will be discussed later in the paper.

**Figure 2.**  
Mean efficiency  
estimates of five banks  
vs all associations



Despite the financial crisis which started in 2008 and the economic recession afterwards, FCS entity efficiency were stable to increasing during these times. The estimates are consistent with the FCS's income performance and the FCS's increasing market share in the lending market. According to the Farm Credit Administration (2009) annual information statement, FCS's net income went up to \$2.92 billion in 2008, rising from less than \$1.77 billion in 2002. Rising farm income associated in part with the biofuel boom and rising crop prices are one likely reason for this rising efficiency. According to Henderson and Akers (2008), rising commodity prices followed by rise in average farm income has resulted in more spending and lending demand by farmers. For this reason, the FCS was somewhat immune to the 2008-2009 financial crisis and economic recession. Henderson and Akers (2010) also concluded the US agricultural banks outperformed the group of all banks nationwide during the recent financial crisis.

Another likely reason for the increase in efficiency of the associations is consolidation. The system associations consolidated from 153 associations in 2000 to 80 associations in 2011 increasing average association size. This finding is consistent with our previous findings where greater size was found to increase efficiency. This was also found in Al-Sharkas *et al.* (2008) who investigated the cost and profit efficiency effects of bank mergers finding that mergers improved the cost and profit efficiencies of non-agricultural banks.

The negative and significant statistics for the management compensation variable in both the banks and association technical inefficiency equations indicate a positive relation between management compensation and technical efficiency. This finding shows higher incentives for the management team might help to increase technical efficiency.

Our estimates of the system efficiency suggest that not all of the FCS's associations have efficiently utilized their inputs. A few associations have efficiency of less than 5 percent and the mean of association technical efficiency values is 46.28 percent. This indicates that an average FCS association operates at 46.28 percent of the efficiency level of the most efficient associations using the same mix of inputs. The five banks average technical efficiency is 65.98 percent (Table IV).

Our average association efficiency estimates are quite similar to those in Collender *et al.*'s (1991) where short run efficiency was 73 percent regionally but only 49 percent nationwide. However, our estimates are much higher than their long-run results where efficiency was found to be 28 percent regionally; 6 percent nationwide for all associations and 18 percent nationwide when the dominant association was dropped.

The difference between our and their efficiency estimates likely arise because of several reasons. First, they measured profit efficiency while we measure technical efficiency. Second, the DEA methodology they used embodied an assumption of a deterministic frontier constructed using the outer envelope of the most efficient observations. Their methodology of pooling all associations without considering the difference in bank size might falsely lower the efficiency of small banks. Third, DEA assumes all deviations from the frontier are inefficiencies. Fourth, the time periods differed substantially between the two studies with Collender *et al.*'s study was conducted in 1991 while this study is for 2000-2011.

The low mean efficiency of associations compared to banks can plausibly be explained as a result of business practices plus as a result of larger variation in efficiency estimates among associations as discussed earlier. In particular the banks are wholesalers with larger loans using traditional relationships leading to likely lower costs of doing business and higher efficiency. Also in terms of associations the more diverse nature of those in the sample plus the associated low efficiency of small associations has undoubtedly drawn the average association efficiency estimate downward.

To check these results, we have experimented with various specification and estimation alternatives, and the results remain quantitatively similar to what are reported[2]. Overall, our estimates are reasonably close to other work on agricultural financial institutes, especially with results in Li *et al.* (2012) who also used stochastic cost frontier framework to measure technical efficiency for agricultural and non-agricultural banks[3].

### Concluding remarks

The paper analyzes the technical efficiency of banks and associations within the US FCS using a stochastic frontier production function model with quarterly unbalanced panel data. The results show smaller bank size and lower levels of management compensation plus location in the midwest are associated with lower efficiency. On average, the banks have technical efficiency of 65.98 percent while the associations have technical efficiency of 46.28 percent. We find the efficiency of the banks is quite stable while the efficiency of the associations, for the most part, is increasing gradually over time. The association results indicate the potential benefits of the last decade's FCS consolidation and show more consolidation may be desirable. These results also indicate a system wide review of compensation policy may be desirable.

We find little effects of the financial crisis on FCS entity efficiency. However, further estimation of the impact of exogenous factors on the system's efficiency is necessary as the biofuel boom, increasing farm income, and new regulations emerged over the same time period. Further work using the FCS's firm specific characteristics would be helpful to derive a clearer picture how specific characteristics might affect technical efficiency.

### Notes

1. The model does not explicitly include a risk variable into the production function but lets the unrestricted error terms reflect the production risk. Since all our covariates for banks and associations are time invariant, modeling the risk explicitly are analogous to clustering the variance of the estimation and therefore does not change the estimation results significantly. In addition, due to small sample size, additional parameterization of the composite error process might lead to numerical difficulties. Moreover, the FCS banks and associations are not allowed to have deposits and will not face liquidity risk as much as other banks.

2. The model was first estimated without separating banks and associations, and with the firm effects assumed to be time – varying with an exponential specification. Estimation results showed the mean technical efficiency of 62.3 percent for banks and 7.7 percent for associations. The models were then run separately for banks and associations with several alternative specifications regarding the firm effects, and dummy variables. Those estimations resulted in an efficiency of the associations below 55 percent. We chose to proceed with the current model specification considering that it allows firm-specific heterogeneity/endogenous effects, differing time effects, and regional heterogeneity. We also found that it provides more reasonable coefficient signs and magnitude.
3. Li *et al.* (2012) recently analyzed bank failures among agricultural banks and non-agricultural banks from the technical efficiency standpoint. Using a stochastic cost frontier framework which included a loan quality index and a financial risk index, they capture the influence of bank loan portfolio quality and financial risk exposure on technical efficiency. They found that during 2005-2010, both surviving and failed banks had mean technical efficiency scores that were well below 50 percent. The average technical efficiency score for surviving banks over the six-year period was 25.59 percent, while failed banks registered an average six-year technical efficiency score of only 16.46 percent. Regarding agricultural banks, mean technical efficiency for non-failed agricultural banks was 46.29 percent while it was 77.41 percent for failed banks. The high technical efficiency of failed agricultural banks was explained as a result from smaller sample of failed agricultural banks (Li *et al.*, 2012).

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