A Comparative Analysis of Technical Efficiency and Input Allocation Decisions of Farm Lenders in the Commercial Banking Industry and the Farm Credit System during the Late 2000s Recession

Introduction

Towards the end of 2007, a recessionary period dawned upon the U.S. and global economies that was dubbed as the worst economic crises since the Great Depression of 1930s. Investments in subprime residential mortgage-backed securities (RMBS) have been singled out as having triggered these financial crises. 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 through financial distress. After the industry witnessed 25 bank closures in 2008, a total of 140 banks shut down in 2009. The number of bank closure reached its peak level in 2010 with 157 bank failures, the highest level since the savings-and loan crisis in 1992. By October 2013, a total of 488 banks failed in the last five years.

After the farm crises of the 1980s and through the implementation of several federal and banking reforms in the 1990s, farm lending has been sustained by both federal and private lending institutions. Despite the vigorous lending activities of federally sponsored farm credit programs, commercial banks have long been financing agricultural borrowers. The amount of bank lending to agriculture is shared by a few large banks holding a large portion of the total portfolio and thousands of small sized community-oriented banks. The five largest U.S. institutions lending to agriculture hold 15% of the portfolio of banks loans to agriculture, with Wells Fargo as the nation's top agricultural business lender for 15 consecutive years with $9.2

billion in agricultural loans in 2010 (Ellinger, 2011). Notably, very minimal incidence of bank failures was observed among agricultural lenders in the commercial banking industry during the recent recession-induced banking crises. Analysts attribute such financial endurance to more prudent operating decisions made by most agricultural banks. For instance, these banks did not lend aggressively to their commercial real estate clientele and did not invest in the structured securities that have lost substantial market values (Ellinger and Sherrick, 2010).

Aside from commercial banks, the Farm Credit System (FCS) accounts for a significant portion of the nation's agricultural loan portfolio (FDIC, 1997). As a government sponsored enterprise founded in 1916, FCS is a network of borrower-owned financial institutions to provide credit and financial service to farmers, ranchers, rural homeowners, aquatic producers, timber harvesters, agribusinesses, and agricultural and rural utility cooperatives. The system raises funds by selling securities in the national and international money markets. In 2013, FCS has more than $260 billion assets and nearly 500,000 member borrowers. Unlike commercial banks, FCS lending units are not depository institutions. In lieu of deposits, they rely on the U.S. and international capital market to raise funds by issuing system-wide debt notes and bonds. As of January 2013, FCS is composed of four banks and 82 associations. The Banks of FCS provide loans to its affiliated associations, and those associations make short, intermediate, and long term loans to qualified borrowers. FCS provides more than $191 billion loans, which consist of more than one third of the credit needed by American people living and working in rural areas. The Farm Credit mission is to provide a reliable source of credit for American agriculture by making loans to qualified borrowers at competitive rates and providing insurance and related services.

The banking industry and the FCS, though rivals in farm lending, have altogether provided crucial financial assistance to farm businesses with synergistic impacts on the growth and expansion of the U.S. agricultural industry. Overall, commercial banks and the FCS hold 84% of total agricultural debt (Ellinger, 2011). As the major forces in the farm lending industry, these institutions' financial conditions can more aptly be considered as an important gauge of the financial health of the farm sector.

These institutions' financial performance may be analyzed under an efficiency analysis framework. In corporate finance literature, efficiency studies have proven to be important and beneficial in analyzing several facets of the banking industry operations. The information obtained from banking efficiency analysis can be helpful in policy formulation by assessing the effects of deregulation, mergers, or market structure on efficiency, or to improve managerial performance by identifying "best practices" and "worst practices" associated with high and low measure efficiency, respectively (Berger and Humphrey, 1997). However, only a few studies have addressed the efficiency issues from U.S. commercial banks' standpoint during the recent recession (Barth 2013; Paradi 2011), while there are hardly any studies on the application of the efficiency framework on FCS lending units[1].

This paper uses the late 2000s recession as a backdrop for scrutinizing the operating decisions of commercial banks and FCS lending units. Specifically, these lenders' input allocation decisions will be analyzed and compared to discern any inherent differences in their operating or management styles that define these lenders' strategies for enduring the financial crises. An efficiency analytical framework using a Translog stochastic frontier model will be

[1] The only paper that studied technical efficiency of Farm Credit System focusing on recent recession is: Leatham,D., Dang, T., McCarl, B.A., and Wu, X.,2014. Measuring efficiency of the Farm Credit System. Agricultural Finance Review, Vol.74 Issue: 1(upcoming).

employed to calculate and compare the technical and allocative efficiencies of commercial banks and FCS lending units. As a comparative study, this article will shed light on the nature of survival strategies employed by these two sets of lenders faced with different operating constraints, but similarly aligned to the goal of servicing the volatile farm industry even under the most adverse economic conditions.

Moreover, under the same efficiency analytical framework, this study also investigates on the effect of the size of lending operations on the lenders' efficiency and input allocation decisions. Previous studies have asserted that larger banks under a given amount of total assets could actually perform more efficiently. This implies that expanding the bank size through mergers or acquisition could be an effective strategy to improve the operational efficiency at some specific stage (Berger, 1998; Akhavein et al., 1997; Mitchell et al., 1996). In this regard, this study seeks to evaluate the relative survival capability of larger lending institutions, regardless of whether they are from the commercial banking industry or the FCS, vis-à-vis their smaller lending counterparts. This analysis may clarify any differences in input allocations and other operating decisions that define small and large lenders' strategies to survive the tight financial conditions of the late 2000s.

The Theoretical Model

A discussion of the theoretical foundation of this study is presented in this section. The discussion begins with a layout of the economic efficiency framework that provides an understanding of an agency's operating environment, goals and constraints. Then, the firm's owner's motivations for making input allocation decisions are analyzed that require controlling or monitoring the use of certain production inputs vis-à-vis other inputs.

The Technical Efficiency Model

In developing the efficiency analysis model under the stochastic frontier framework, a generic form of the input distance function is first defined as follows (Shephard, 1953):

$$(1)\quad D^{I}(\mathbf{x},\mathbf{y}) = \sup_{\rho}\{\rho > 0 : (\mathbf{x}/\rho) \in L(\mathbf{y})\}$$

where the superscript I implies that it is the input distance function; the input set $L(\mathbf{y}) = \{\mathbf{x} \in \mathbf{R}_{N}^{+} : \mathbf{x}\,\text{can produce}\,\mathbf{y} \in \mathbf{R}_{\mathbf{M}}^{+}\}$ represents the set of all input vectors, $\mathbf{x}$, that can produce the output vector, $\mathbf{y}$; and ρ measures the possible proportion of the inputs that can be reduced to produce the quantity of outputs not less than $\mathbf{y}$. In other words, the input distance function determines the maximum proportion of retraction in input levels to achieve the output levels defined along the production frontier.

The stochastic frontier analysis (SFA) approach is introduced to estimate the flexible Translog distance function. Distance functions can be used to estimate the characteristics of multiple output production technologies in the absence of price information and whenever the cost minimization or revenue maximization assumptions are inappropriate. This analytical framework applies well to banking operations as well as Farm Credit System’s operations since their operations are often characterized by multi-outputs and multi-inputs. Moreover, these agencies usually have greater grasp or control over operating inputs instead of their outputs.

This analysis adopts the Translog function that overcomes the shortcomings of the usual Cobb-Douglas function form, which assumes that all firms have the same production elasticities, which sum up to one. The Translog function is more flexible with less restriction on production and substitution elasticities. The flexibility reduces the possibility of producing biased estimates due to erroneous assumption on the functional form.

Hence, the stochastic input distance function for each observation i can be estimated by:

(2)
$$\begin{aligned}\ln D_{it}^{I} &= \beta_0 + \sum_{k=1}^{M}\beta_{y_k}\ln y_{ikt} + \frac{1}{2}\sum_{k=1}^{M}\sum_{l=1}^{M}\beta_{y_{kl}}\ln y_{ikt}\ln y_{ilt} + \sum_{j=1}^{N}\beta_{x_j}\ln x_{ijt} + \frac{1}{2}\sum_{j=1}^{N}\sum_{h=1}^{N}\beta_{x_{jh}}\ln x_{ijt}\ln x_{iht} \\ &+ \sum_{j=1}^{N}\sum_{k=1}^{M}\beta_{xy_{jk}}\ln x_{ijt}\ln y_{ikt} + \sum_{d=1}^{P}\beta_{z_d}\ln z_{idt} + \frac{1}{2}\sum_{d=1}^{P}\sum_{f=1}^{P}\beta_{z_{df}}\ln z_{idt}\ln z_{ift} + \sum_{k=1}^{M}\sum_{d=1}^{P}\beta_{yz_{kd}}\ln y_{ikt}\ln z_{idt} \\ &+ \sum_{j=1}^{N}\sum_{d=1}^{P}\beta_{xz_{jd}}\ln x_{ijt}\ln z_{idt} + \sum_{k=1}^{M}\alpha_k(t\ln y_{ikt}) + \sum_{j=1}^{N}\delta_j(t\ln x_{ijt}) + \sum_{d=1}^{P}\theta_d(t\ln z_{idt}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\ &+ \sum_{g=1}^{G-1} d_g\, dum_{igt} + d_F\, dum_{iFt} + d_b\, dum_{ibt}\end{aligned}$$

where $dum_{g,it}$ is the dummy variable to present the agency size in group g ; dum_{iFt} is the dummy variable to identify Farm Credit System (FCS); k, l = 1, … M and M = 3 (number of outputs); j, h = 1, … N and N = 3 (number of inputs); d, f = 1, … P and P = 2 (number of indexes to measure financial risks and loan’s quality), g=1,…(G-1) and G=5 (number of groups). The dum_{iFt} is a dummy variable, which is 1 for FCS and 0 for banks; the dum_{ibt} is the dummy variable, which is 0 for time before the recession.

A necessary property of the input distance function is homogeneity of degree one in input quantities, which required the parameters in equation (2) to satisfy the following constraints:

$$\sum_{j=1}^{N}\beta_{x_j} = 1 \qquad \text{(R1)}$$

$$\sum_{j=1}^{N}\beta_{x_{jh}} = 0, \qquad \forall\ h = 1,\ldots,N \qquad \text{(R2)}$$

$$\sum_{j=1}^{N}\beta_{xy_{jk}} = 0, \qquad \forall\ k = 1,\ldots,M \qquad \text{(R3)}$$

$$\sum_{j=1}^{N}\beta_{xz_{jd}} = 0, \qquad \forall\ d = 1,\ldots,P \qquad \text{(R4)}$$

$$\sum_{j=1}^{N}\delta_j = 0 \qquad \text{(R5)}$$

In addition, the property of homogeneity can be expressed mathematically as:

(3) $D_{it}^{I}(\lambda \mathbf{x}, \mathbf{y}) = \lambda D_{it}^{I}(\mathbf{x}, \mathbf{y}), \qquad \forall \lambda > 0$.

Assuming that $\lambda = 1/x_{N,it}$ [2], equation (3) can be expressed in the logarithmic form as:

(4) $\ln D_{it}^{I}(\mathbf{x}/x_{N,it}, \mathbf{y}) = \ln D_{it}^{I}(\mathbf{x}, \mathbf{y}) - \ln x_{N,it}$

According to the definition of the input distance function, the logarithm of the distance function in (4) measures the deviation (ε_{it}) of each observation $(\mathbf{x}, \mathbf{y})$ from the efficient production frontier $L(\mathbf{y})$:

(5) $\ln D_{it}^{I}(\mathbf{x}, \mathbf{y}) = \varepsilon_{it}$

Such deviation from the production frontier (ε_{it}) can be decomposed as $\varepsilon_{it} = v_{it} - u_{it}$.

Thus, equation (5) can be rewritten as:

(6) $\ln D_{it}^{I}(\mathbf{x}, \mathbf{y}) = u_{it} - v_{it}$

where u_{it} measures the technical inefficiency that follows the positive half normal distribution as $u_{it} \overset{iid}{\sim} N^{+}(\mu, \sigma_u^{\ 2})$ while v_{it} measures the pure random error that follows the normal distribution as $v_{it} \overset{iid}{\sim} N(0, \sigma_v^{\ 2})$.

Substituting equation (6) into equation (4), equation (4) can then be rewritten as:

(7) $-\ln x_{N,it} = \ln D_{it}^{I}(\mathbf{x}/x_{N,it}, \mathbf{y}) + v_{it} - u_{it}$

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[2] λ is selected as arbitrary input to serve as the denominator considering the input distance function's property of homogeneity of degree one in inputs (here the N^{th} input is selected as the denominator).

Aside from the homogeneity restrictions, symmetric restrictions also need to be imposed in estimating the Translog input distance function. The symmetric restrictions require the parameters in equation (2) to satisfy the following constraints:

$$\beta_{y_{kl}} = \beta_{y_{lk}}, \text{ where } k,l = 1,....,M \quad \text{(R6)}$$

$$\beta_{x_{jh}} = \beta_{x_{hj}}, \text{ where } j,h = 1,....,N \quad \text{(R7)}$$

$$\beta_{z_{df}} = \beta_{z_{fd}}, \text{ where d}, f = 1,....,P \quad \text{(R8)}$$

Imposing restrictions (R1) through (R8) on equations (2) and (7) yields the following estimating form of the input distance function:

(8)

$$\begin{aligned}
-\ln x_{N,it} = {} & \beta_0 + \sum_{k=1}^{M}\beta_{y_k}\ln y_{k,it} + \sum_{j=1}^{N-1}\beta_{x_j}\ln x_{j,it}^{*} + \sum_{d=1}^{P}\beta_{z_d}\ln z_{d,it} \\
& + \frac{1}{2}\left[\sum_{k=1}^{M}\beta_{y_{kk}}(\ln y_{k,it})^2 + \sum_{j=1}^{N-1}\beta_{x_{jj}}(\ln x_{j,it})^2 + \sum_{d=1}^{P}\beta_{z_{dd}}(\ln z_{d,it})^2\right] \\
& + \sum_{k=1}^{M}\sum_{l=1,\, for\ l>k}^{M}\beta_{y_{kl}}\ln y_{k,it}\ln y_{l,it} + \sum_{j=1}^{N}\sum_{h=1,\, for\ h>j}^{N-1}\beta_{x_{jh}}\ln x_{j,it}^{*}\ln x_{h,it}^{*} + \sum_{d=1}^{P}\sum_{f=1,\, for\ f>d}^{P}\beta_{z_{df}}\ln z_{d,it}\ln z_{f,it} \\
& + \sum_{j=1}^{N-1}\sum_{k=1}^{M}\beta_{xy_{jk}}\ln x_{j,it}^{*}\ln y_{k,it} + \sum_{k=1}^{M}\sum_{d=1}^{P}\beta_{yz_{kd}}\ln y_{k,it}\ln z_{d,it} + \sum_{j=1}^{N-1}\sum_{d=1}^{P}\beta_{xz_{jd}}\ln x_{j,it}^{*}\ln z_{d,it} \\
& + \sum_{k=1}^{M}\alpha_k(t\ln y_{k,it}) + \sum_{j=1}^{N-1}\delta_j(t\ln x_{j,it}^{*}) + \sum_{d=1}^{P}\theta_d(t\ln z_{d,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\
& + \sum_{g=1}^{G-1}d_g dum_{g,it} + d_F dum_{iFt} + d_b dum_{ibt} + v_{it} - u_{it}
\end{aligned}$$

where $x_{j,it}^{*} = x_{j,it} / x_{N,it}$ is the normalized input *j*.

Since our model is estimated for panel data, the hypothesis of time-invariance ($\eta = 0$) needs to be tested. For the general model form, the inefficiency effects can be modeled as

$$u_{it} = \exp\{-\eta(t - T_i)\}.u_i$$

where $u_i \overset{iid}{\sim} N^{+}(\mu, \sigma_{\mu}^{2})$. If $\eta = 0,$ then the time-invariance hypothesis cannot be rejected and the model becomes a time-invariant model. If the hypothesis is rejected, then a time variant model results and time-variant constraint ($\eta \neq 0$) will be imposed in estimating equation (8). Additionally, the sign of the η can indicate the nature of the change in efficiency across the time series. A positive sign means an achievement of efficiency, while a negative sign indicates deterioration in efficiency. After estimating all coefficients in equation (8), the coefficients for the N^{th} input can be calculated by imposing the homothetic restrictions (R1) to (R5).

Input Allocation Efficiency

Moreover, efficiency can be decomposed into two separate components: technical efficiency (TA) and allocative efficiency (AE). Unfortunately, as Bauer (1990) has pointed out, it is difficult to obtain separate TE and AE measures. Figure 1 will help understand the mechanics of such decomposition. In the plots, assume a firm that uses two inputs(x1 and x2) to produce the output *y*. Technical inefficiency would occur at point A since it is possible that the same amount of output could be produced with fewer inputs by a movement from point A to point C. The percentage of input savings that will result from that movement is actually the TE measure calculated as $TE = OC / OA$. Recalling the definition of the input distance function, the following linkage can be established between $D^{I}(\mathbf{x}, \mathbf{y})$ and *TE.*

(9) $TE = 1 / D^{I}(\mathbf{x}, \mathbf{y})$

Given the input prices p_1 and p_2, the AE concept can also be illustrated in Figure 1. The move from C to D in the isoquantity curve shows that the firm's output has been maintained at the same level even while operating at a lower isocost curve *f1*. This implies that the firm could realize cost savings even without incurring any decrease in output production. The cost savings can be represented by AE that can be calculated as $AE = OB/OC$.

The estimated input distance function will be used to further differentiate technical and allocative efficiencies. TE levels can be calculated by

$$(10)\ TE_{it} = 1/D_{it}^{I} = 1/E[\exp(u_{it}) \mid v_{it} - u_{it}]$$

where $0 \le TE_{it} \le 1$. The closer TE_{it} is to unity, the more technically efficient a company is. Considering the panel data nature of this analysis, u_{it} can be expressed as equation

$$(11)\ u_{it} = \exp\{-\eta(t - T_i)\}u_i.$$

$\eta = 0$ implies that the distance function is time invariant and, hence, will not fluctuate throughout the time series; otherwise, the model is time-variant.

Allocative efficiency can be assessed by estimating the inputs' shadow prices. Earlier studies on allocative efficiency were based on the estimation of a system of equations composed of the cost function and cost share equations (Atkinson and Halvorsen, 1986; Eakin and Kniesner, 1988). However, this approach requires imposing the condition of cost minimization. Recent studies have shown an alternative method for obtaining input shadow prices using Shephard's distance function (Fare and Grosskopf, 1990; Banos-Pino et al., 2002; Atkinson and Primont, 2002; Rodriguez-Alvarez et al., 2004). This new approach no longer requires the cost minimization condition to produce consistent estimates. This method analyses differences between the market and shadow prices with respect to the minimum costs.

Recalling the plots in Figure 1, the shadow price ratio p_1^s / p_2^s is the slope of the isocost curve *f3*, which indicates the minimum cost of production at a given levels of inputs to produce the same output quantity. In other words, a firm would be allocative efficient if it operates at point C, which is on the isocost curve *f3* to satisfy the condition required by allocative efficiency. This condition requires that the marginal rate of technical substitution (MRTS) between any two of its inputs is equal to the ratio of the corresponding input prices (p_1^s / p_2^s). So the deviation of the market price ratio (p_1/p_2) from the shadow price ratio (p_1^s / p_2^s) reflects allocative inefficiency. The price ratio can be expressed as $k_{12} = \dfrac{p_1^s / p_2^s}{p_1/p_2}$. Specifically, if the ratio equals to 1, allocative efficiency is achieved.

In general, the allocative inefficiency for each observation *i* at time *t* can be measured by the relative input price correction indices (herein also referred to as the input allocation ratio):

$$(12)\quad k_{jh,it} = k_{j,it} / k_{h,it} = \frac{p_{j,it}^{\ s} / p_{j,it}}{p_{h,it}^{\ s} / p_{h,it}} = \frac{p_{j,it}^{\ s}}{p_{h,it}^{\ s}} \cdot \frac{p_{h,it}}{p_{j,it}}$$

where $k_{j,it} = p_{j,it}^{\ s} / p_{j,it}$ is the ratio of the shadow price, $p_{j,it}^{\ s}$, to the market price, $p_{j,it}$, for input *j* of firm *i* at time *t*. If $k_{jh,it} = 1$, allocative efficiency is achieved. If $k_{jh,it} > 1$, input *j* is being underutilized relative to input *h*. If $k_{jh,it} < 1$, input *j* is being over-utilized relative to input *h*.

Atkinson and Primont (2002) derived the shadow cost function from a shadow distance system. In the shadow distance system, the cost function can be expressed as:

$$(13)\quad C(\mathbf{y},\mathbf{p}) = \min_{\mathbf{x}} \{\mathbf{px} : D(\mathbf{y},\mathbf{x}) \geq 1\}$$

Implementing the duality theory and imposing input distance function's linear homogeneity property, the study demonstrated that the dual Shephard's lemma can be derived as:

$$(14)\quad \frac{\partial D_{it}^{I}(\mathbf{x},\mathbf{y})}{\partial x_{j,it}} = \frac{p_{j,it}^{s}}{C(\mathbf{y},\mathbf{p}^{s})}.$$

From equation (14), the ratio of the shadow prices can be calculated as:

$$(15)\quad \frac{p_{j,it}{}^{s}}{p_{h,it}{}^{s}} = \frac{\partial D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial x_{j,it}}{\partial D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial x_{h,it}}$$

Applying the derivative envelope theory to the numerator and denominator of equation (15) results in the following:

$$(16)\quad \begin{aligned} \frac{p_{j,it}{}^{s}}{p_{h,it}{}^{s}} &= \frac{\partial D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial x_{j,it}}{\partial D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial x_{h,it}} = \frac{\left[1\big/\left(D_{it}^{I}(\mathbf{x},\mathbf{y})\cdot x_{j,it}\right)\right]\cdot\left[\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial \ln x_{j,it}\right]}{\left[1\big/\left(D_{it}^{I}(\mathbf{x},\mathbf{y})\cdot x_{h,it}\right)\right]\cdot\left[\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial \ln x_{h,it}\right]} \\ &= \frac{x_{h,it}}{x_{j,it}}\cdot\frac{\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial \ln x_{j,it}}{\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y})\big/\partial \ln x_{h,it}} \end{aligned}$$

Finally, substituting equation (16) into equation (12), the relative allocative inefficiency shown by the relative input price correction indices can then be expressed as:

$$(17)\quad \begin{aligned} k_{jh,it} &= \frac{p_{h,it}}{p_{j,it}}\cdot\frac{x_{h,it}}{x_{j,it}}\cdot\frac{\partial \ln D_{\mathrm{it}}^{I}(\mathbf{x},\mathbf{y})\big/\partial \ln x_{j,it}}{\partial \ln D_{\mathrm{it}}^{I}(\mathbf{x},\mathbf{y})\big/\partial \ln x_{h,it}} \\ &= \frac{p_{h,it}x_{h,it}}{p_{j,it}x_{j,it}}\cdot\frac{\beta_{x_j}+\sum_{h=1}^{N}\beta_{x_{jh}}\ln x_{h,it}+\sum_{k=1}^{M}\beta_{xy_{jk}}\ln y_{k,it}+\sum_{d=1}^{P}\beta_{xz_{jd}}\ln z_{d,it}+\delta_j t}{\beta_{x_j}+\sum_{j=1}^{N}\beta_{x_{jh}}\ln x_{j,it}+\sum_{k=1}^{M}\beta_{xy_{jk}}\ln y_{k,it}+\sum_{d=1}^{P}\beta_{xz_{jd}}\ln z_{d,it}+\delta_j t} \end{aligned}$$

Data Measurement

This study will utilize a panel dataset of financial information on commercial banks and FCS lending units compiled on a quarterly basis from 2005 to 2010. The sample time period allows for the analysis of operating decisions made by both banks and Farm Credit Systems (FCS) from two years prior to the beginning of recession in 2007 until one year after the end of the recession as declared in 2009. Hence, in this analysis, the years 2005 and 2006 will be referred to as the pre-recession years while 2010 will capture the post-recession period.

The bank data were collected from the call report database published online by Federal Reserve Board of Chicago. Instead of using branch-level data, this study used financial information from consolidated banking financial statements since overall operating decisions, especially concerning input use, are usually made at banks' head offices. In this study 500 banks are randomly selected to form a panel dataset of 3,507 observations.

The data for the FCS lenders were collected from the Call Report Database published online by the Farm Credit Administration. There are a total of 5 banks and 100 associations that comprise the panel dataset of 2,202 observations across 8 years.

The analyses are conducted on two levels of comparisons: according to lender type (commercial banks and FCS lenders) and size categories where all lenders, regardless of type, are classified into 5 groups. The size categories were determined as follows: lenders with total assets of less than $1 billion are grouped under Group 1; Group 2 lenders have assets between $1 billion and $2 billion; Group 3 lenders' assets range from $2 billion to $5 billion; Group 4 lenders' total assets are between $5 billion and $10 billion; and the largest lenders fall under Group 5 with assets over $10 billion.

In this study, three output variables were considered: total dollar amounts of agricultural loans (y_1), non-agricultural loans which include Real estate loans, Commercial and Consumer loans (y_2), and other assets which consist of fee-based financial services and those assets that cannot be classified under the available asset accounts in the balance sheet (y_3). The input data categories considered are number of full-time equivalent employees(x_1), physical capital (premises and fixed assets, x_2), and financial inputs (include expense of federal funds purchased and securities sold and interest on time deposits of $100,000 or more and total deposits, x_3).

Measures of loan quality index (z_1) and financial risk index (z_2) are also included in this analysis to introduce a risk dimension to the efficiency models. The index z_1 is calculated as the ratio of non-performing loans (NPL) to total loans to capture the quality of the banks' loan portfolios (Stiroh and Metli, 2003). The index z_2 is based on the banks' capital to asset ratio, which is used in this study as proxy for financial risk. The role of equity has been understated in efficiency and risk analyses that focus more on NPL and other liability-related measures (Hughes et al., 2001). Actually, as a supplemental funding source to liabilities, equity capital can provide cushion to protect banks from loan losses and financial distress. Banks with lower capital to asset ratios (CAR) would be inclined to increasingly rely on debt financing, which, in turn, increases the probability of insolvency.

The variables measured in dollar amount were adjusted by Consumer Price Index (CPI) using 2005 as base year. The summary statistics are reported in table 1.

Empirical Results

The estimates of the components of the input distance function (defined in equation 8) are summarized in table 2. The hypothesis that all coefficients of the distance function are equal to zero is rejected at 0.01 level by an LM test (p-value<.0001). The hypothesis that the function takes on Cobb-Douglas form, which requires that all parameters except for β_{y_k} and β_{x_j} in equation (2) equals to 0, is rejected at 1% level by the LM test. This result indicates that the flexible Translog function form is more applicable in this study.

The coefficient of the dummy variable dum_{iFt} that captures the effect of lender type is significantly different from 0 at 1% level. This indicates that differences in operating structure between commercial banks and FCS can influence the cost structure of these lenders. On the other hand, the time dummy dum_{ibt} that separates the time period into the pre-efficiency and efficiency phases is also significant level at 5%, thereby suggesting a notable change in efficiency levels during the recession.

The significant coefficient results for the risk variables also conform to logical expectations. The positive coefficient for the loan quality index variable z_1 shows the additional cost burden brought about by higher rates of loan delinquency. The financial risk index variable z_2 has a negative coefficient that suggests that lenders' increasing reliance on debt financing for additional funds can translate to additional costs for them.

The t statistics for η given in table 2 shows a significant result (P-value<.0001), which indicates that the hypothesis of a time-invariant model is rejected in favor of a time-variant model. This allows the system to face a time-variant technical efficiency level from 2005 to 2010.

Overall Technical Efficiency

Table 3 presents the resulting mean Technical Efficiency (TE) levels for the different lenders and size categories. The summary also includes the results of t-tests conducted on the differences between pairings of annual TE results.

The results indicate that the overall TE levels of both commercial and FCS are below 0.50, thereby suggesting that these lenders in general have been operating below efficiency during the sample period. The mean TE level for FCS is 42% while the commercial banks posted a mean TE level of 37%. According to the t-test result, the 5% difference in these TE results is significantly different from zero. These results are further confirmed by a visual representation of the results through the plots presented in Figure 2. As can be gleaned from the plots, there is a wider gap in the TE levels of FCS and banks during the recessionary period. Interestingly, the gap diminished after the end of the recession (2010). The drop in TE levels from the pre-recession to post-recession period has been larger among commercial banks vis-à-vis the FCS lenders' TE results.

Table 3 also shows that lenders' size can also be an important factor that can influence the TE levels of the lenders. Based on the summary in that table, all size categories registered TE levels below 0.50 during the sample period. However, among these size categories, the smaller lenders tend to have relatively higher TE levels than the larger lenders. The pairwise differences in TE levels have been found to be significant, except for the groups 2 and 3 pair.

Differences in Input Allocation Decisions

As laid out earlier in the theoretical model, $k_{jh,it}$ calculated by equation (17) can be used to measure the relative allocative inefficiency level. Tables 4 and 5 present a summary of the average values of the k_{jh} (input allocation ratios) for the different lender and size categories.

The summaries in Tables 4 and 5 are best analyzed using graphical aids. Figure 4 provides a comparison of the plots of input allocation ratios (k_{jh}) of FCS and banks.

The k_{12} ratio is the input allocation ratio between labor and physical capital. Inputs are most efficiently used if the ratio is equal or closer to one. In the plots, the FCS k_{12} results lie above the critical boundary (k_{12} =1) while the banks' k_{12} ratios lie below that line. These results indicate that banks over utilized their physical asset endowment relative to their labor input. Conversely, FCS lenders over utilized their labor input while underutilizing their physical assets. These trends actually are consistent with the actual operating structures of these lenders. Compared to FCS lenders, banks tend to be more geographically dispersed across the country as they tend to operate more branch offices for the sake of greater visibility and representation in as many areas as possible. This could very well be both a marketing ploy for banks, but could also be dictated by the necessity for proximity to their clientele to better service depository, lending and other financial transactions. FCS, on the other hand, are relatively less dispersed geographically as they tend to concentrate mostly on farming communities and, since they do not provide in depository services, the need for greater geographical visibility is not too much.

The k_{13} ratio, which shows tradeoffs in allocation between labor and financial assets, also present some interesting results. The plot of the k_{13} ratios of FCS lenders has been above unity (k=1) during the entire sample period while the bank's k_{13} ratio plot was below unity before the recession, then crossed the critical unity line during the recession, and then reverted to its pre-recession condition in 2010. These results indicate that FCS lenders over utilized their financial assets while underutilizing their labor inputs. On the other hand, banks initially underutilized their financial assets before and after the recession, with a radical shift to over utilizing their financial assets vis-à-vis labor during the recession years. The k_{23} ratio is the input allocation ratio between physical assets and financial assets. These results indicate that financial inputs have been an important concern for FCS lenders, regardless of overall economic conditions, given the fact that these lenders have more limited funding alternatives.

On the other hand, banks may not be pressured to over utilize their financial inputs under favorable economic conditions. Recessionary conditions may, however, bring about some funding constraints to banks, which then have to resort to some belt-tightening measures of over utilizing available financial input endowments when alternative, supplementary financial capital funds are more difficult to procure.

The k_{23} ratios reflect decisions of lenders in allocating physical and financial capital inputs. The k_{23} results for the banks are close to one, thereby suggesting that when banks usually make near optimal decisions when allocating these two inputs. The k_{23} ratios for FCS lenders, on the other hand, are significantly more than one. This trend suggests that FCS tend to underutilize their physical assets while over utilizing their financial inputs. These results only confirm the earlier contentions made in the discussions of the previous input allocation ratio results. FCS tend to maintain a relatively low physical asset profile but are constrained by limited funding alternatives that they tend to over utilize or exhaust any available financial capital they have to maintain and sustain their operating viability. Notably, the k_{23} ratio of FCS went down after the recession, which indicates that they have tempered down their tendency to over utilize their financial inputs when economic conditions improved.

Figure 5 shows the graphs for the different input allocation ratios (k_{jh}) for the various lender size categories. The plots of the k_{12} ratios indicate that smaller lenders (group 1 and group 2) tend to underutilize their labor inputs vis-a-vis their physical capital given that $k_{12} > 1$ consistently through all six years. On the other hand, larger lenders tend to maintain their allocative efficiency closer to unity or efficiency. These results indicate that smaller lenders may have resorted to exhausting their physical capital (through branch expansions, perhaps) to cope with increasing competitive pressure from the larger lenders.

The results for the k_{13} ratios show that all size categories have shown tendencies to increase this ratio before the recession and then making adjustments in their operating decisions to bring down the ratio afterwards. The results for the larger institutions (group 3-5) indicate that they were underutilizing their labor inputs vis-à-vis their financial capital inputs before the recession. These lenders then made some adjustments in their operations by making decisions to reallocate these two inputs more efficiently during and after the recession. Smaller lenders over utilized their labor inputs against financial inputs in all six years.

Generally, all lender groups underutilized their physical capital inputs vis-a-vis financial inputs ($k_{23} > 1$) in most years, except for group 1 in 2009 and 2010. Larger groups (3-5) showed greater tendencies to underutilize their physical capital compared to the smaller lenders (1-2). The largest group (group 5), however, has made better input allocation decisions compared to the other groups as their ratios have been closer to the critical unity line since 2007.

Summary and Implications

As two major suppliers of farm credit, commercial banks and Farm Credit System (FCS) have long been serving the agricultural industry. Even when these two lenders work (or compete) for a common clientele and pursue the same goal of servicing the nation's agricultural industry, their operating styles and structures are inherently different. For instance, their physical capital management and strategies are contrasting – perhaps defined more by their strategic principles, the nature of the financial services they offer, or even the inherent differences in alternative fund procurement opportunities.

After the worst economic crises hit the nation and the global community in the late 2000s, the farm lending sector emerged as one of the notable survivors, registering a very minimal rate of institutional failure while the rest of the industry was dealt with more significant blows in alarming rates of bank failures and borrower delinquencies. Some analysts have recognized farm borrowers for their impressive minimal loan delinquency record (compared to borrowers from other industries) that has been maintained before, during and after the recessionary period. However, would the farm operators' prudent business management practices that translate to good loan repayment records be the only reason for the farm lending industry's endurance and survival of the economic recession?

This study provides an additional perspective in explaining the farm lending industry's performance during the last recession. The overall results of technical and allocative efficiency analyses confirm that both groups of lenders are plagued with higher costs that could diminish their overall levels of efficiency. However, this liability does not need to constrain these lenders' capability to operate successfully even under a period of recession. The key strategies to these lenders' survival are their input allocations decisions.

This study's results indicate that even when FCS lenders are relatively more constrained in their financial capital procurement, these lenders make offsetting decisions to underutilize their labor and physical capital inputs. On the other hand, banks may have greater flexibility in enhancing their financial capital endowment, but these lenders have made some adjustments in their input allocation decisions where they exercised control or caution in using their financial capital inputs while regulating (either by postponing or diminishing) the use of physical and labor inputs. Smaller lenders, though a mixed group of FCS and bank lenders, also tend to exhibit the same predicament faced by FCS lenders in general. The operating decisions of smaller lenders notably mirror those made by FCS lenders. The larger lenders also have shown to have made some operating adjustments similar to those made by banks, in an effort to survive the most difficult economic conditions of the late 2000s.

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Table 1. Summary Statistics of Banks and FCS, 2005-2010

Variables	Sample Mean	Std. Deviation	Minimum	Maximum
Banks				
Agricultural Loans (y_1)	26,530.79	69,820.56	2.00	1,567,007.00
Non-Agricultural Loans (y_2)	564,563.71	3,381,465.56	2,037.00	85,791,415.00
Others (y_3)	35,757.13	241,984.69	55.00	7,131,994.00
Labor (x_1)	183.39	686.62	3.00	12,502.00
Physical Capital (x_2)	11,898.37	40,757.59	13.00	672,414.00
Financial Inputs (x_3)	805,880.12	4,474,349.02	6,826.00	119,500,000.00
Loan Quality Index (z_1)	0.99	0.02	0.63	1.00
Financial Risk Index (z_2)	0.90	0.03	0.59	0.99
Farm Credit System				
Agricultural Loans (y_1)	1,218,687.18	2,086,098.96	44,352.10	20,323,464.00
Non-Agricultural Loans (y_2)	1,148,265.66	5,301,168.97	21.60	48,433,996.00
Others (y_3)	20,091.33	99,475.21	1.00	1,687,746.30
Labor (x_1)	120.97	340.52	2.00	2,496.00
Physical Capital (x_2)	5,704.76	9,683.84	140.20	94,581.30
Financial Inputs (x_3)	2,483,113.80	7,445,202.53	29,794.90	60,561,572.00
Loan Quality Index (z_1)	0.99	0.01	0.88	1.00
Financial Risk Index (z_2)	0.83	0.05	0.65	0.96

Table 2. Estimation Results for the Input Distance Function

Model Coefficients and Parameter Estimates							
Intercept	1.454*** (0.051)	$\beta_{x_{12}}$	0.021** (0.011)	$\beta_{xz_{21}}$	0.123 (0.111)	d_b	0.012** (0.004)
β_{y_1}	-0.134*** (0.006)	$\beta_{x_{13}}$	0.137*** (0.029)	$\beta_{xz_{31}}$	-0.436** (0.224)	η	-0.003*** (0.001)
β_{y_2}	-0.517*** (0.010)	$\beta_{x_{23}}$	-0.021** (0.010)	$\beta_{xz_{12}}$	-0.246 (0.200)		
β_{y_3}	-0.054*** (0.006)	$\beta_{z_{12}}$	1.981 (1.478)	$\beta_{xz_{22}}$	-0.004 (0.063)		
β_{x_1}	0.383*** (0.016)	$\beta_{xy_{11}}$	0.055*** (0.006)	$\beta_{xz_{32}}$	0.250 (0.198)		
β_{x_2}	-0.012 (0.008)	$\beta_{xy_{12}}$	0.052*** (0.011)	α_1	0.000 (0.0002)		
β_{x_3}	0.629*** (0.016)	$\beta_{xy_{13}}$	-0.057*** (0.110)	α_2	0.001** (0.0002)		
β_{z_1}	0.525** (0.211)	$\beta_{xy_{21}}$	-0.006** (0.003)	α_3	0.000 (0.0002)		
β_{z_2}	-0.199* (0.108)	$\beta_{xy_{22}}$	0.003 (0.002)	δ_1	-0.001 (0.001)		
$\beta_{y_{11}}$	-0.040*** (0.002)	$\beta_{xy_{23}}$	-0.003 (0.003)	δ_2	0.001** (0.0002)		
$\beta_{y_{22}}$	-0.084*** (0.002)	$\beta_{xy_{31}}$	-0.049*** (0.006)	δ_3	0.000 (0.001)		
$\beta_{y_{33}}$	-0.008*** (0.001)	$\beta_{xy_{32}}$	-0.055*** (0.011)	θ_1	0.020* (0.011)		
$\beta_{x_{11}}$	-0.158*** (0.031)	$\beta_{xy_{33}}$	0.061*** (0.011)	θ_2	-0.025*** (0.005)		
$\beta_{x_{22}}$	-0.000 (0.005)	$\beta_{yz_{11}}$	0.234** (0.070)	λ_1	0.002* (0.001)		
$\beta_{x_{33}}$	-0.116*** (0.029)	$\beta_{yz_{21}}$	0.207** (0.072)	λ_2	0.000** (0.00005)		
$\beta_{z_{11}}$	1.983 (1.345)	$\beta_{yz_{31}}$	-0.103 (0.083)	d_{g_1}	0.290*** (0.016)		
$\beta_{z_{22}}$	-10.459*** (1.093)	$\beta_{yz_{12}}$	-0.040 (0.038)	d_{g_2}	0.190*** (0.013)		
$\beta_{y_{12}}$	0.050*** (0.002)	$\beta_{yz_{22}}$	0.448*** (0.033)	d_{g_3}	0.102*** (0.011)		
$\beta_{y_{13}}$	-0.004** (0.002)	$\beta_{yz_{32}}$	0.029 (0.039)	d_{g_4}	0.031*** (0.008)		
$\beta_{y_{23}}$	-0.001 (0.001)	$\beta_{xz_{11}}$	0.313 (0.222)	d_F	-0.711*** (0.046)		

Notes: *** Significantly different from zero at the 1% confidence level.
** Significantly different from zero at the 5% confidence level.
* Significantly different from zero at the 10% confidence level.

Table 3. Technical Efficiency Levels and Mean Differences, comparison between Commercial banks and Farm Credit System (FCS)

Category	Estimate	Standard Error	t Value	Pr > |t|	Number of Observations
By Type					
Commercial Banks	0.37	0.003			3507
Farm Credit System (FCS)	0.42	0.004			2237
Difference between Means	-0.05	0.005	-10.13	<.0001	
By Size					
Group 1	0.52	0.005			1425
Group 2	0.41	0.005			1027
Group 3	0.41	0.004			1390
Group 4	0.31	0.003			823
Group 5	0.22	0.002			1079
Difference between Means					
Group1-Group2	0.11	0.007	16.35	**<.0001**	
Group1-Group3	0.11	0.006	18.66	**<.0001**	
Group1-Group4	0.21	0.007	36.45	**<.0001**	
Group1-Group5	0.30	0.006	56.65	**<.0001**	
Group2-Group3	-0.002	0.006	-0.24	0.8072	
Group2-Group4	0.09	0.105	15.61	**<.0001**	
Group2-Group5	0.19	0.006	33.30	**<.0001**	
Group3-Group4	0.09	0.005	19.59	**<.0001**	
Group3-Group5	0.19	0.005	42.88	**<.0001**	
Group4-Group5	0.09	0.004	23.96	**<.0001**	

Table 4. Input Allocation Ratios (k_{jh}) by Agency Categories, Annual Averages, 2006-2010

Bank Categories	Year	k12[a]	k13[b]	k23 [c]
Commercial Banks	2005	1.40***	0.67***	1.09***
	2006	1.98***	0.95***	0.83***
	2007	1.92***	1.16***	1.05***
	2008	2.00***	1.08***	1.03***
	2009	1.93***	0.91***	0.82***
	2010	1.69***	0.66***	0.65***
Farm Credit System (FCS)	2005	0.53***	1.42***	8.97***
	2006	0.50***	1.97***	9.93***
	2007	0.56***	2.28***	9.90***
	2008	0.52***	1.99***	9.28***
	2009	0.49***	1.43***	7.07***
	2010	0.56***	1.32***	5.77***
Pair Wise T-test Between Groups [d]		30.42***	-34.90***	-50.70***

Notes: [a] Input 1 is labor while input 2 is physical capital.
[b] Input 3 is financial inputs which include: purchased financial capital and deposit.
[c] k ratios significant different between groups are marked using "*"
[d] T value for difference test between commercial banks and FCS
*** Significantly different from zero at the 1% level.
** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level.

Table 5. Input Allocation Ratios (k_{jh}) by Group Categories, Annual Averages, 2006-2010

Bank Categories	Year	k12[a]	k13[b]	k23
Group 1	2005	1.46	0.57	0.99
	2006	1.93	0.74	1.06
	2007	1.68	0.92	1.30
	2008	1.81	0.87	1.92
	2009	1.67	0.66	0.83
	2010	2.23	0.52	0.34
Group 2	2005	1.29	0.64	1.84
	2006	1.95	0.96	1.67
	2007	2.16	1.18	1.71
	2008	2.03	1.07	1.93
	2009	1.96	0.92	1.92
	2010	1.15	0.80	3.72
Group 3	2005	0.98	1.06	4.59
	2006	1.39	1.48	5.40
	2007	1.30	1.62	5.30
	2008	1.19	1.57	6.01
	2009	1.10	1.26	5.35
	2010	0.90	1.09	4.97
Group 4	2005	0.83	1.12	5.64
	2006	1.12	1.50	5.33
	2007	1.32	1.80	4.98
	2008	0.92	1.72	6.73
	2009	0.81	1.23	5.54
	2010	0.75	1.11	5.07
Group 5	2005	1.06	1.29	4.33
	2006	0.96	1.78	6.06
	2007	1.00	2.12	6.19
	2008	1.11	1.92	5.01
	2009	1.07	1.42	3.32
	2010	0.86	1.27	2.82

Notes: [a] Input 1 is labor while input 2 is physical capital.
[b] Input 3 is financial inputs which include: purchased financial capital and deposit.

Table 6. Two sample t-test for Input Allocation Ratios (k_{jh}) by Group Categories

Category	Estimate	Standard Error	t Value	Pr > |t|
k_{12}				
Group1-Group2	-0.08	0.08	-1.03	0.3046
Group1-Group3	0.50	0.07	7.24	**<.0001**
Group1-Group4	0.67	0.07	9.55	**<.0001**
Group1-Group5	0.61	0.07	9.59	**<.0001**
Group2-Group3	0.58	0.08	7.11	**<.0001**
Group2-Group4	0.75	0.08	9.09	**<.0001**
Group2-Group5	0.69	0.08	8.95	**<.0001**
Group3-Group4	0.17	0.07	2.47	**0.0138**
Group3-Group5	0.11	0.07	1.77	**0.0768**
Group4-Group5	-0.06	0.07	-0.92	0.3555
k_{13}				
Group1-Group2	-0.21	0.02	-8.65	**<.0001**
Group1-Group3	-0.64	0.03	-22.70	**<.0001**
Group1-Group4	-0.72	0.58	-21.76	**<.0001**
Group1-Group5	-0.93	0.03	-28.01	**<.0001**
Group2-Group3	-0.43	0.03	-13.31	**<.0001**
Group2-Group4	-0.51	0.04	-13.93	**<.0001**
Group2-Group5	-0.72	0.04	-19.61	**<.0001**
Group3-Group4	-0.08	0.04	-2.03	**0.0421**
Group3-Group5	-0.29	0.04	-7.37	**<.0001**
Group4-Group5	-0.21	0.04	-4.90	**<.0001**
k_{23}				
Group1-Group2	-0.86	0.15	-5.48	**<.0001**
Group1-Group3	-4.10	0.20	-20.90	**<.0001**
Group1-Group4	-4.44	0.20	-19.23	**<.0001**
Group1-Group5	-3.44	0.17	-18.76	**<.0001**
Group2-Group3	-3.24	0.24	-14.20	**<.0001**
Group2-Group4	-3.58	0.25	-13.84	**<.0001**
Group2-Group5	-2.58	0.22	-11.87	**<.0001**
Group3-Group4	-0.34	0.29	-1.18	0.2399
Group3-Group5	0.66	0.25	2.68	**0.0074**
Group4-Group5	1.00	0.27	3.36	**0.0003**

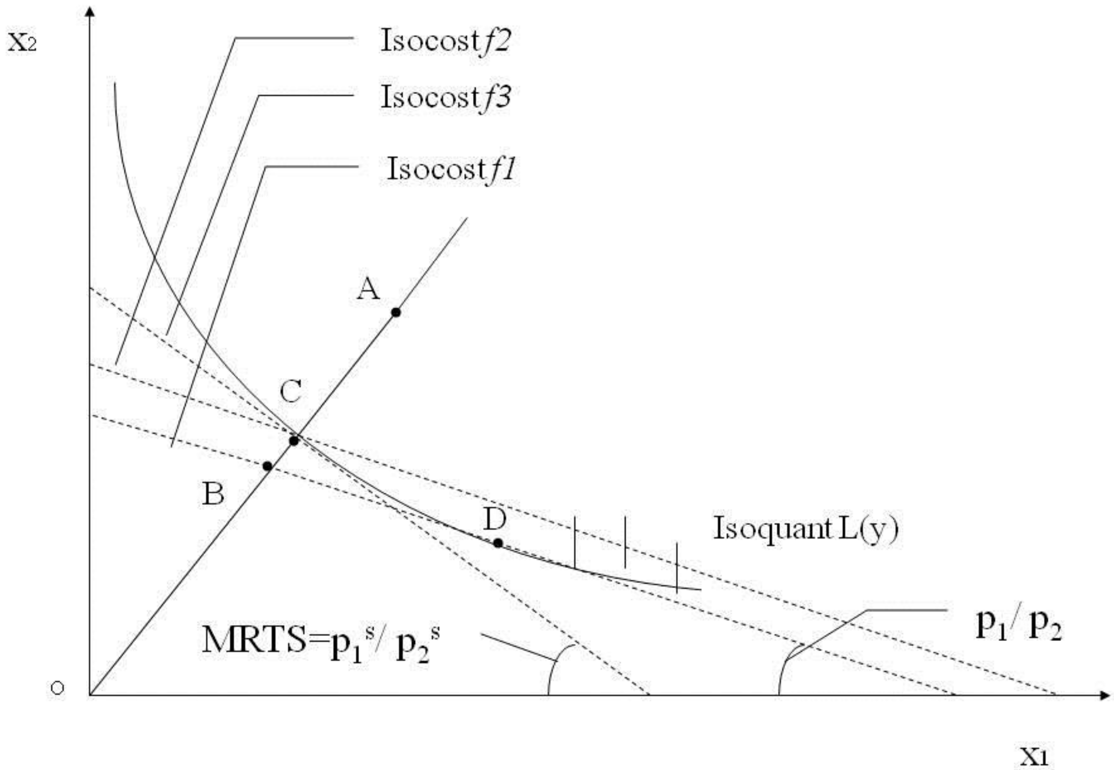

Figure 1. Technical and Allocative Efficiency Identified by Input Distance Function

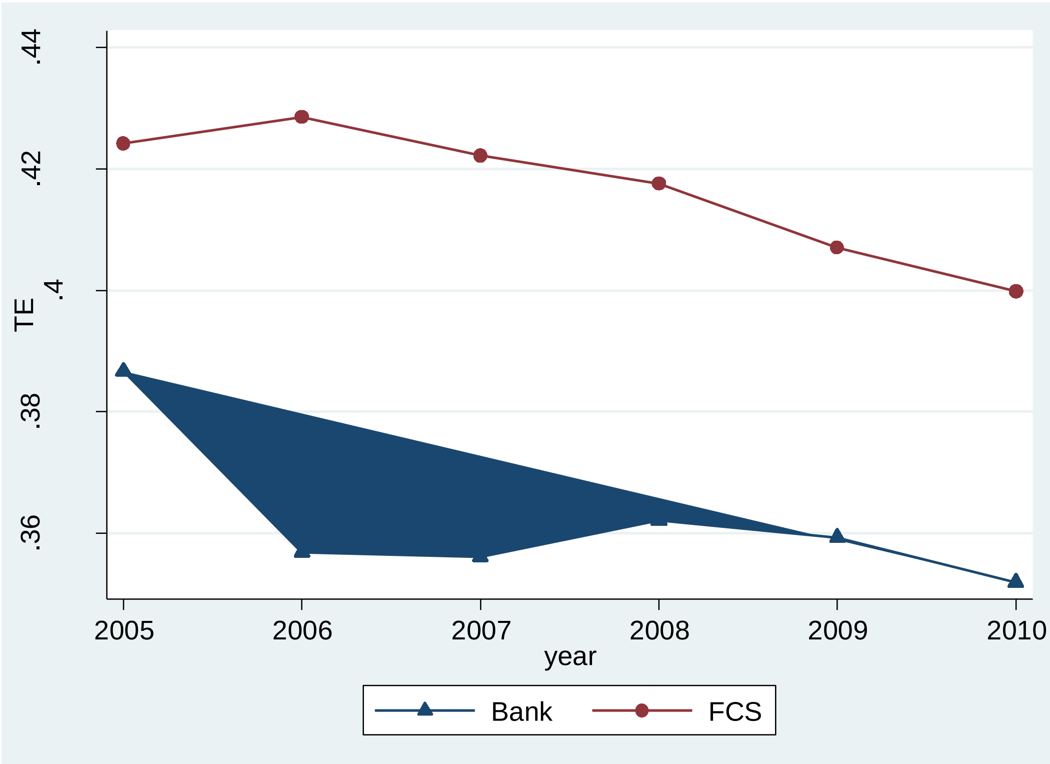

Figure 2. Trends in Technical Efficiency Levels, By Institution Type, 2005-2010

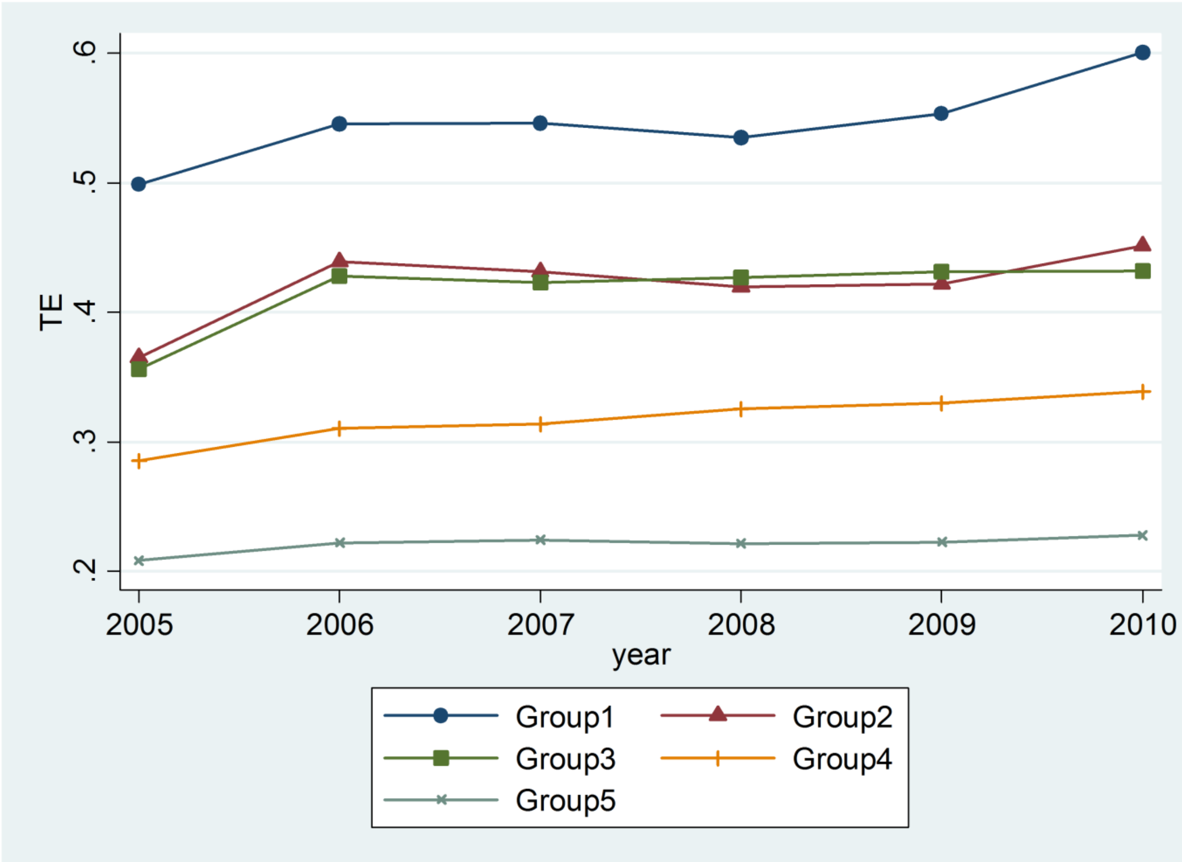

Figure 3: Trends in Technical Efficiency Levels, By Group, 2005-2010

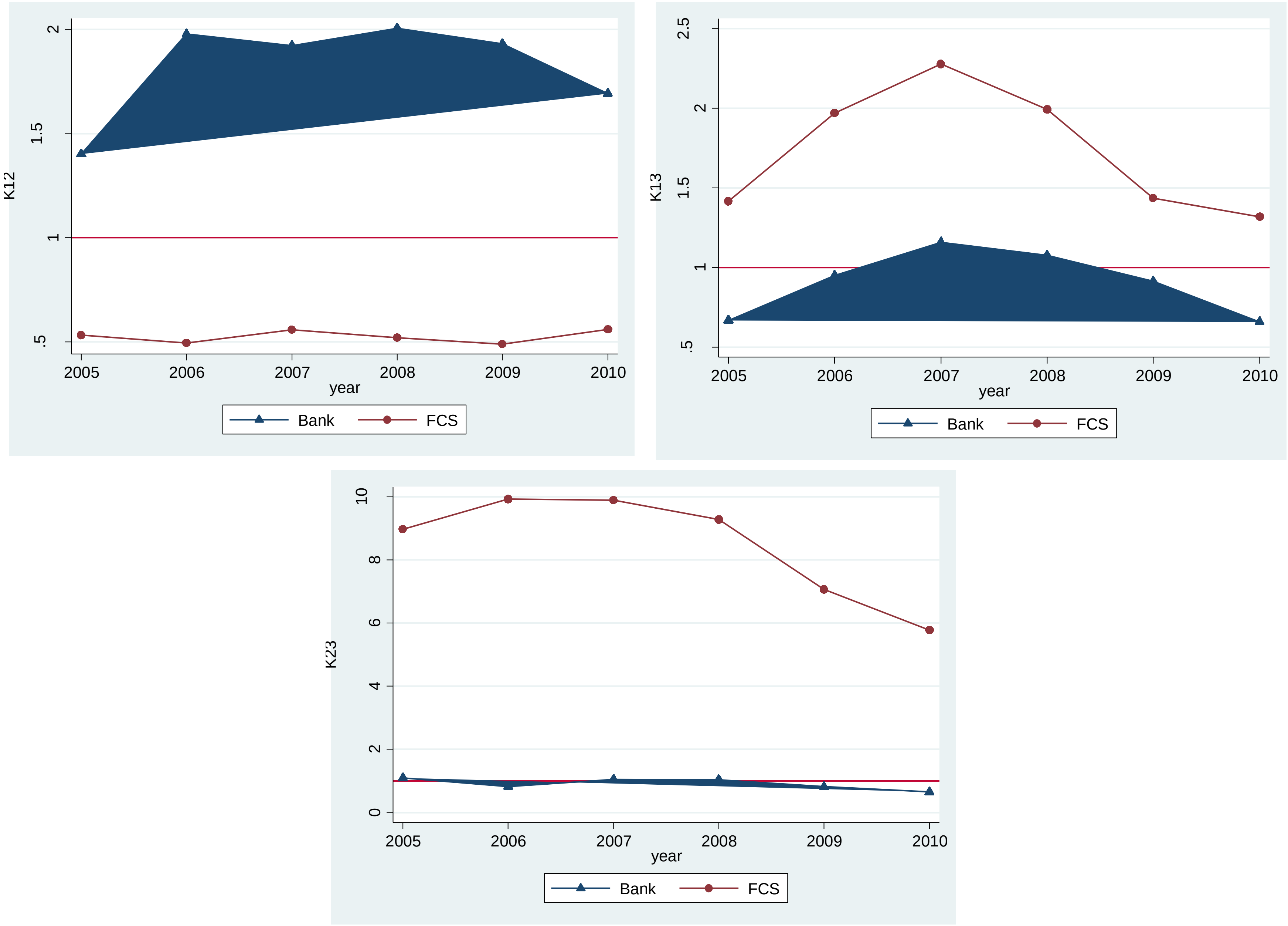

Figure 4: Plots of Input Allocation Ratios (k_{jh}) by Agency Category, 2005-2010

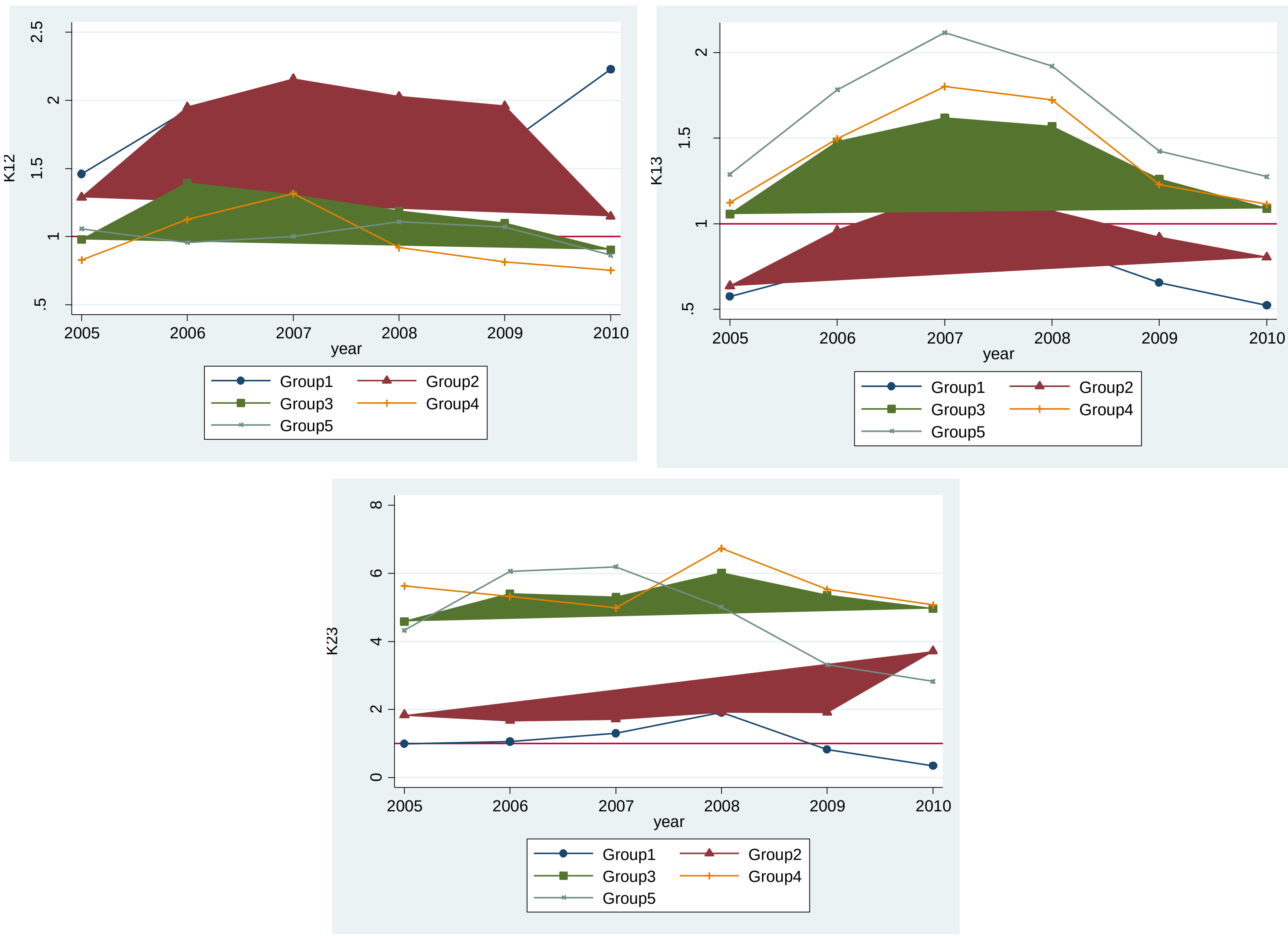

Figure 5: Plots of Input Allocation Ratios (k_{jh}), by Group Category, 2005-2010