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PRE AND POST RECESSION INPUT ALLOCATION DECISIONS OF FARM CREDIT SYSTEM LENDING UNITS

Abstract:

This article estimates and analyzes the technical efficiencies and input allocation decisions of lending associations and their own banks under the U.S. Farm Credit System (FCS) during the period 2005-2011. The sample time period allows for the analysis of the operating decisions of FCS lending units under pre- and post-economic recession conditions. Results indicate that even while FCS lending units were plagued with higher funding costs during the recession, their input allocation decisions revealed fund sourcing strategies that leaned towards using more of the cheaper inputs. Moreover, smaller lending associations were found to have maintained relatively higher levels of technical efficiency.

Keywords:

Farm Credit System, allocative efficiency, input allocation, technical efficiency, financial inputs, deposits

JEL Classification: G20, E39, Q14

Introduction

As a government sponsored enterprise in the U.S., the Farm Credit System (FCS) is a network of borrower-owned financial institutions created to provide credit and financial services to farmers, ranchers, producers or harvesters of aquatic products, and agricultural and aquatic cooperatives. The system raises funds by selling securities in the national and international money markets. In 2013, FCS had more than $260 billion assets and nearly 500,000 member borrowers. Unlike commercial banks, FCS lending units are not depository institutions and 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 (see FCS annual report 2013). The banks of FCS provide loans to its affiliated associations (i.e. FCS lending associations), while such 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 system's goal is to meet a broad range of public needs by maintaining liquidity and competition in rural credit markets in both good and bad economic conditions (Briggerman and Kenkel, 2008; Dodson and Koenig, 2004).

The 2007-2009 global recession was sparked by the outbreak of the U.S. subprime mortgage and financial crisis. The economy was threatened by the collapse of financial markets, the expensive bailout of banks by national governments, and the plummet of stock markets around the world. The global recession reduced the demand of farm products, causing declining commodity prices. Thus, the FCS and other lenders, just like other institutions in the lending industry, had to contend with a highly risky operating environment (Escalante, Song, and Dodson, 2016; Li, et al., 2011). Although FCS banks and associations maintained a capital ratio above the minimum regulation requirements, the turmoil in the U.S. and global markets during the recession limited the System's ability to raise third-party capital or issue term debt.

In this paper, we analyze the efficiencies of FCS lending units before and after the 2007-2009 recessions. A specific focus of the analysis is the input allocation decisions and strategies of FCS lending units during the study period. The lending units are analyzed and compared according to their types of operations (banks versus credit associations).

The Theoretical Model

The Technical Efficiency Model

The stochastic frontier model is used in a large literature of studies of production, cost, revenue, profit and other models of goals. The model was first introduced by Aigner, Lovell, and Schmidt (1977). 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):

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

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 reduction in input levels to achieve the output levels defined along the production frontier.

This analysis adopts the Translog function that overcomes the shortcomings of the usual Cobb-Douglas functional form, which assumes that all firms have the same production elasticities, which sum up to one. The stochastic input distance function for each observation *i* can be estimated by:

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

where $dum_{g,it}$ is the dummy variable to present the agency size in group ; g=1,…(G-1) and G=5 (number of groups); *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); *t* is the quarter index during time periods. The dum_{iat} is a dummy variable, which is 1 for FCS banks and 0 for associations; the dum_{ibt} is the dummy variable, which is 0 for periods before the recession.

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 $L(\mathbf{y})$:

$$\ln D_{it}^I(\mathbf{x},\mathbf{y}) = \varepsilon_{it} \tag{3}$$

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

Thus, equation (3) can be rewritten as:

$$\ln D_{it}^{I}(\mathbf{x},\mathbf{y}) = u_{it} - v_{it} \tag{4}$$

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 $v_{it} \overset{iid}{\sim} N(0,\sigma_v^{2})$.

Imposing homogeneity and symmetry restrictions yields the following estimating form:

$$\begin{aligned}
-\ln x_{N,it} &= \beta_0 + \sum_{k=1}^{M}\beta_{y_k}\ln y_{k,it} + \sum_{j=1}^{N-1}\beta_{x_j}\ln x_{j,it}^{*} + \sum_{d=1}^{P}\beta_{z_d}\ln z_{d,it} \\
&+ \frac{1}{2}\left[\sum_{k=1}^{M}\beta_{y_{kk}}(\ln y_{k,it})^2 + \sum_{j=1}^{N-1}\beta_{x_{jj}}(\ln x_{j,it})^2 + \sum_{d=1}^{P}\beta_{z_{dd}}(\ln z_{d,it})^2\right] \\
&+ \sum_{k=1}^{M}\sum_{l=1,\, for\ l>k}^{M}\beta_{y_{kl}}\ln y_{k,it}\ln y_{l,it} + \sum_{j=1}^{N}\sum_{h=1,\, for\ h>j}^{N-1}\beta_{x_{jh}}\ln x_{j,it}^{*}\ln x_{h,it}^{*} + \sum_{d=1}^{P}\sum_{f=1,\, for\ f>d}^{P}\beta_{z_{df}}\ln z_{d,it}\ln z_{f,it} \\
&+ \sum_{j=1}^{N-1}\sum_{k=1}^{M}\beta_{xy_{jk}}\ln x_{j,it}^{*}\ln y_{k,it} + \sum_{k=1}^{M}\sum_{d=1}^{P}\beta_{yz_{kd}}\ln y_{k,it}\ln z_{d,it} + \sum_{j=1}^{N-1}\sum_{d=1}^{P}\beta_{xz_{jd}}\ln x_{j,it}^{*}\ln z_{d,it} \\
&+ \sum_{k=1}^{M}\alpha_k(t\ln y_{k,it}) + \sum_{j=1}^{N-1}\delta_j(t\ln x_{j,it}^{*}) + \sum_{d=1}^{P}\theta_d(t\ln z_{d,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\
&+ \sum_{g=1}^{G-1}d_g dum_{g,it} + d_a dum_{iat} + d_b dum_{ibt} + v_{it} - u_{it}
\end{aligned} \tag{5}$$

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

Efficiency Measures

Efficiency can be decomposed into two separate components: technical efficiency (TE) and allocative efficiency (AE). Unfortunately, as Bauer (1990) has pointed out, it is difficult to obtain separate TE and AE measures. Recalling the definition of the input distance function, the following linkage can be established between $D^{I}(\mathbf{x},\mathbf{y})$ and *TE.*

$$TE = 1/D^{I}(\mathbf{x},\mathbf{y}) \tag{6}$$

Given the input prices p_1 and p_2, the AE concept can also be illustrated in figure 3.1. 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

$$TE_{it} = 1/D_{it}^{I} = 1/E[\exp(u_{it}) \mid v_{it} - u_{it}] \tag{7}$$

where $0 \leq TE_{it} \leq 1$. 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

$$u_{it} = \exp\{-\eta(t - T_i)\}u_i. \tag{8}$$

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

Under this new analysis scheme, the assumption of the cost minimization is not necessary to get the consistent estimates. They allow the difference between the market prices and shadow prices with respect to the minimum costs. As illustrated for simplified situation by figure 3.1, shadow price ratio p_1^s / p_2^s is the slope of the isocost curve *f3* which indicates the minimum cost at given level of inputs to produce the same quantity of the outputs. In other words, a firm would be allocative efficient if it could operate at point C which is on the isocost curve f_3 to satisfy the condition required by the 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 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 the allocative inefficiency. The ratio can be expressed as $k_{12} = \frac{p_1^s / p_2^s}{p_1 / p_2}$. Specifically, if the ratio equals to 1, the allocative efficiency achieved. Otherwise, the allocative inefficiency is detected. The larger does $|k_{12}|$ deviate from 1, the larger allocative inefficiency is.

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):

$$k_{jh,it} = k_{j,it} / k_{h,it} = \frac{p_{j,it}^{\ s} / p_{j,it}}{p_{h,it}^{\ s} / p_{h,it}} = \frac{p_{j,it}^{\ s}}{p_{h,it}^{\ s}} \cdot \frac{p_{h,it}}{p_{j,it}} \tag{9}$$

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*.

Data

This study collected quarterly panel data from the Call Report Database from 2005 to 2011 published online by the Farm Credit Administration. The numbers from the original data are CPI adjusted with year 2005 as the baseline. It is important to use the real dollars because this will allow us to make more accurate year-to-year comparison of efficiencies. There are a total of 5 FCS banks and more than 100 credit associations that altogether produce 2,913 observations across 7 years. Lending institutions are classified as banks and associations.

Lending institutions output data collected include agricultural loans (y1), non-agricultural loans (y2), and other assets (y3). Input data are labor (x1), physical capital (x2), and financial capital (x3). Unlike commercial banks, FCS lending units do not have direct deposits as a source of financial capital. FCS banks raise capital from the financial markets and loan to credit associations.

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 lending units' loan portfolios (Stiroh and Metli, 2003). The index z_2 is based on the lending units' 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 a cushion to protect banks from loan losses and financial distress. Lending units 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 summary statistics are reported in table 1.

Table 1. Summary Statistics of FCS Lending Units, 2005-2011

Variables	Sample Mean	Std. Deviation	Minimum	Maximum
Banks				
Agricultural Loans (y_1)	2,670,943	2,720,737	589	14,970,670
Non-Agricultural Loans (y_2)	20,980,380	14,274,330	73,124	53,897,990
Others (y_3)	124,800	191,916	6,538	1,116,259
Labor (x_1)	8,055	5,114	3,508	33,888
Physical Capital (x_2)	10,795	6,955	2,254	35,416
Financial Inputs (x_3)	28,001,370	17,723,550	8,577,538	72,917,860
Loan Quality Index (z_1)	0.0013	0.0022	0.0000	0.0100
Financial Risk Index (z_2)	0.9427	0.0115	0.9083	0.9585
Associations				
Agricultural Loans (y_1)	1,218,729	2,169,966	63	20,323,460
Non-Agricultural Loans (y_2)	328346	2583113	9	30,428,610
Others (y_3)	16,213	94,479	1	1,687,746
Labor (x_1)	2,860	4,378	100	36,721
Physical Capital (x_2)	5,843	10,507	140	105,511
Financial Inputs (x_3)	1,452,794	4,742,172	29,795	57,248,780
Loan Quality Index (z_1)	0.0073	0.0133	0.0000	0.1251
Financial Risk Index (z_2)	0.8220	0.0410	0.6454	0.9469

Empirical Results

The coefficient estimates of the components of the input distance function are summarized in table 2. The hypothesis that all coefficients of the distance function are equal to zero is rejected at the 0.01 level by an LM test (p-value<.0001). The hypothesis that the function takes a 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 suggests that the flexible Translog function form is more applicable than the Cobb-Doublas function form (Dang et al., 2014) in this study.

Table 2 Estimation Results for the Input Distance Function

Model Coefficients and Parameter Estimates									
Intercept	2.922*** (0.046)	$\beta_{y_{12}}$	-0.001 (0.001)	$\beta_{yz_{22}}$	-0.060** (0.018)	dum_{g_1}	0.155*** (0.017)
β_{y_1}	-0.060*** (0.008)	$\beta_{y_{13}}$	0.000 (0.001)	$\beta_{yz_{32}}$	0.069*** (0.019)	dum_{g_2}	0.104*** (0.010)
β_{y_2}	-0.049*** (0.005)	$\beta_{y_{23}}$	-0.005*** (0.001)	$\beta_{xz_{11}}$	-0.441** (0.184)	dum_{g_3}	0.054*** (0.007)
β_{y_3}	-0.006 (0.004)	$\beta_{x_{12}}$	0.001 (0.003)	$\beta_{xz_{21}}$	0.078 (0.119)	dum_{g_4}	0.016** (0.005)
β_{x_1}	0.084*** (0.009)	$\beta_{z_{12}}$	-5.911*** (1.673)	$\beta_{xz_{12}}$	0.170*** (0.045)	dum_{iat}	-0.765*** (0.107)
β_{x_2}	-0.008 (0.008)	$\beta_{xy_{11}}$	-0.014*** (0.001)	$\beta_{xz_{22}}$	0.209*** (0.044)	dum_{ibt}	0.013*** (0.003)
β_{z_1}	2.308*** (0.472)	$\beta_{xy_{12}}$	0.002* (0.001)	α_1	-0.007*** (0.0002)	d_b	0.012** (0.004)
β_{z_2}	-4.016*** (0.119)	$\beta_{xy_{13}}$	0.008*** (0.001)	α_2	0.0002** (0.0001)	η	-0.003*** (0.001)
$\beta_{y_{11}}$	-0.011*** (0.001)	$\beta_{xy_{21}}$	0.007*** (0.002)	α_3	-0.000 (0.0002)		
$\beta_{y_{22}}$	-0.006*** (0.001)	$\beta_{xy_{22}}$	0.000 (0.001)	δ_1	0.001** (0.0003)		
$\beta_{y_{33}}$	-0.003*** (0.001)	$\beta_{xy_{23}}$	-0.005*** (0.001)	δ_2	0.0002 (0.0002)		
$\beta_{x_{11}}$	0.013*** (0.004)	$\beta_{yz_{11}}$	-0.166 (0.205)	θ_1	-0.131*** (0.015)		
$\beta_{x_{22}}$	0.004 (0.005)	$\beta_{yz_{21}}$	-0.238*** (0.067)	θ_2	-0.005** (0.003)		
$\beta_{z_{11}}$	-12.102*** (3.765)	$\beta_{yz_{31}}$	0.080* (0.050)	λ_1	-0.030*** (0.002)		
$\beta_{z_{22}}$	-10.770*** (0.817)	$\beta_{yz_{12}}$	-0.040 (0.038)	λ_2	0.000*** (0.00003)		

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.

The coefficient of the dummy variable dum_{iat} that captures the effect of lender type is significantly different from 0 at 1% level. This indicates that differences in operating structure between FCS banks and credit associations 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-recession and recession phases is also significant level at 1%, thereby suggesting a notable change in efficiency levels during the recession.

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 2011. The sign of η is slightly negative and suggests that the efficiency of FCS lending units was deteriorating.

Overall Technical Efficiency

Table 3 shows the mean Technical Efficiency (TE) levels for the different lending units and size categories. The summary also includes the results of t-tests conducted on the differences between pairings of annual TE results from different groups.

Table 3. Technical Efficiency Levels and Mean Differences, Comparison between FCS Banks and Credit Associations

Category	Estimate	Standard Errors	Pr > |t|	Number of Observations
FCS Banks	0.09	0.034	<.0001	2816
Credit Associations	0.33	0.187	<.0001	130

The results indicate that the overall TE levels of both FCS banks and credit associations are below 1, thereby suggesting that these lenders in general have been operating below efficiency during the sample period. The mean TE level for FCS banks is 9% while the credit associations posted a mean TE level of 33%. According to the t-test result, these TE results are significantly different from one at 1% level. These results are further confirmed by a visual representation of the results through the plots presented in Figure 1. We find that TE level is improving, though not significantly, for both FCS banks and credit association. Those results can also be confirmed by the improvement of financial strengths of lending units from FCS annual reports from 2005 to 2011.

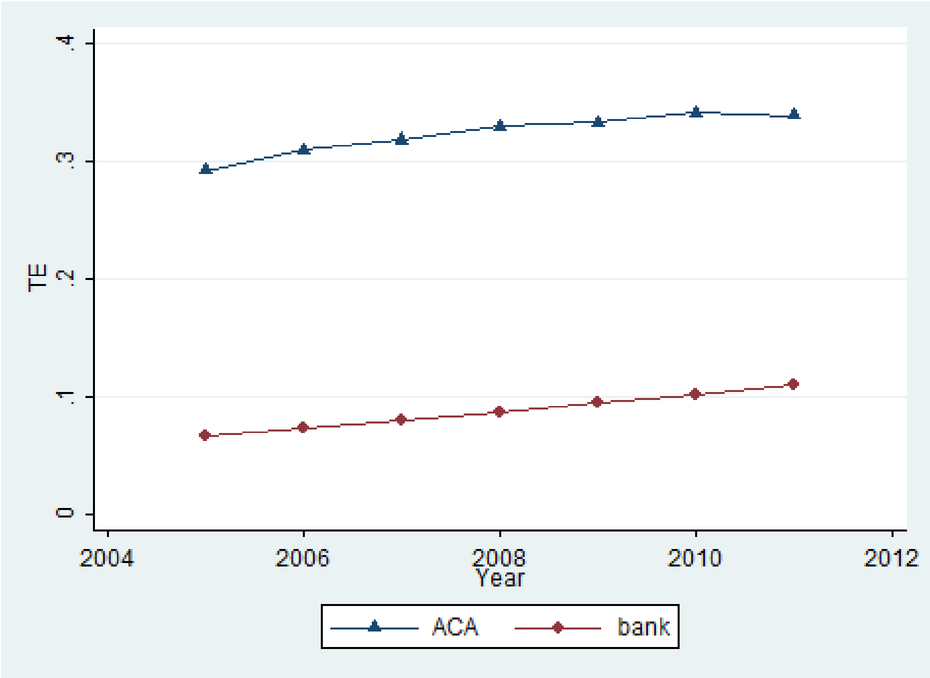

Figure 1: Trends in Technical Efficiency Levels, by Lending Units Type, 2005-2011

Input Allocation Decisions

As explained earlier in the theoretical model, $k_{jh,it}$ calculated by equation (17) can be used to measure the relative allocative inefficiency level. Table 4 presents a summary of the average values of the k_{jh} (input allocation ratios) for the different lending units and size categories. Figure 3.4 provides a comparison of the plots of input allocation ratios (k_{jh}) of FCS banks and credit associations.

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 figure 3.4, both of the FCS banks and credit associations' k_{12} results lie above the critical boundary (k_{12}=1). These results indicate that FCS lending units over utilized their physical assets while underutilizing their labor inputs.

For k_{13} (labor vs. financial assets), FCS banks' ratio lie above the critical boundary (=1) from 2005 to 2010 and the ratio is just below 1 in 2011. Credit associations' k_{13} ratios lie below the critical boundary (=1). These results indicate that banks over utilized their financial inputs most of the time and credit associations over utilized their labor.

For k_{23} (physical assets vs. financial assets), FCS banks' ratios lie above the critical boundary (=1). The credit associations' k_{13} ratios lie above 1 during the recession and lie below 1 after the recession. These results indicate that FCS banks over utilized their financial inputs. Credit Associations over utilized financial inputs during the recession and over utilized physical assets after the recession. There are spikes of the k_{12} and k_{13} ratios for FCS banks during the recession. FCS Banks raise capital for associations through domestic and global money market. It was hard to get capital during the recession and banks had to over utilize their existing financial assets. The ratios went down significantly after the recession, suggesting improving capital market conditions.

Table 4. Input Allocation Ratios (k_{jh}) by Lending Units Categories, Annual Averages, 2005-2011

Lending Units Categories	Year	k12[a]	k13[b]	k23 [c]
FCS Banks	2005	2.39***	1.89***	2.59***
	2006	1.15***	2.97***	4.15***
	2007	2.10***	3.41***	4.21***
	2008	3.57***	2.47***	3.05***
	2009	1.67***	1.45***	2.10***
	2010	1.70***	1.13***	1.66***
	2011	2.11***	0.91***	1.31***
Credit Associations	2005	1.12***	0.33***	1.14***
	2006	1.33***	0.47***	1.49***
	2007	1.41***	0.53***	1.60***
	2008	1.57***	0.45***	1.13***
	2009	1.38***	0.33***	0.77***
	2010	1.39***	0.30***	0.68***
	2011	1.20***	0.25***	0.63***
Pair Wise t-test Between Groups [d]		-3.02***	-55.48***	-12.19***

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

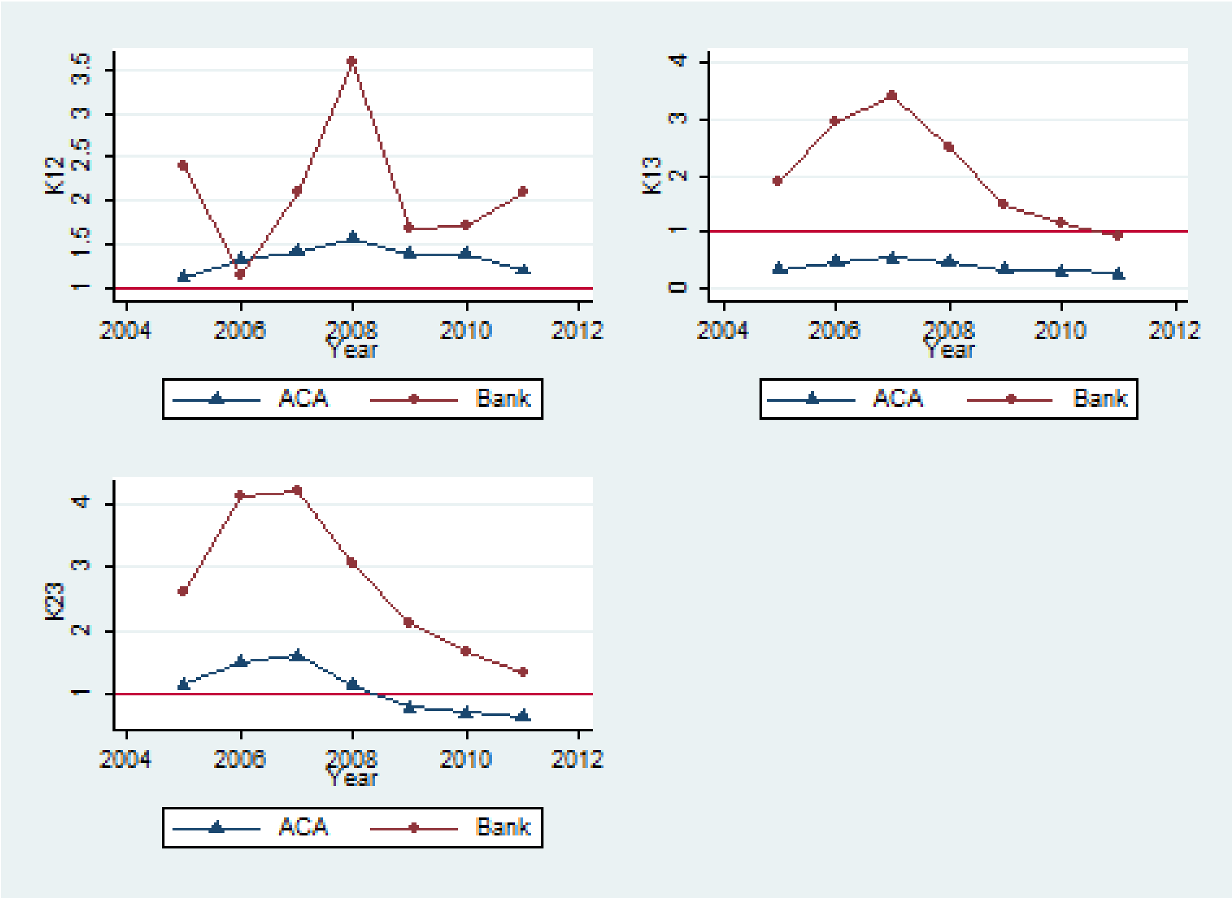

Figure 2: Plots of Input Allocation Ratios (k_{jh}) by Lending Units Category, 2005-2011

Conclusions

As a major supplier of farm credit, Farm Credit System (FCS) lending units have long been serving the agricultural industry. After the 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.

This study provides an additional perspective in explaining the farm credit systems lending units' performance during the last recession. The overall results of technical and allocative efficiency analyses confirm that both FCS banks and credit associations 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 show that the overall TE level of both FCS banks and credit associations (ACA) are below efficiency. Credit associations are more efficient than banks. Small lenders tend to have relatively higher TE than larger lenders. For input allocative ratio k_{12} (labor vs. physical assets), banks and associations over utilized physical assets compared to labor. For ratio k_{13} (labor vs. financial assets), FCS banks over utilized financial inputs and credit associations over utilized labor. For k_{23} (physical assets vs. financial assets), FCS banks over utilized their financial inputs and credit associations over utilized financial inputs during the recession and over utilized physical assets after the recession. FCS lending units do not have deposits as a source of capital and rely on banks to raise funds in the money market. FCS Banks over utilized existing financial assets during the recessions, as they were hard to get capital from the market.

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