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Banks performance evaluation: A hybrid DEA-SVM- The case of U.S. agricultural banks

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ABSTRACT

Data Envelopment Analysis (DEA) is a well-known method used to measure the efficiency of decision making units. In this paper, we study the impact of the financial crisis while integrating DEA efficiency measures with Support Vector Machines (SVM). Moreover, to account for the heterogeneity effect in the efficiency measures, the gap statistical method of Tibshirani, et al., (2001) [Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology), 63*(2), 411-423.] is applied in order to achieve the optimal number of cluster. This study uses December quarterly panel data consisting of Farm Credit Agricultural Banks data from 2005 to 2016. We find strong evidence that the efficiency measures were stationary prior to the financial crisis (2005-2006), during the financial crisis (2007-2009) and post financial crisis (2010-2016). The results further show that the integrated DEA-SVM provide a lower performance during 2007-2009. Furthermore, the results show that the Agricultural banking sector was both efficient and stable over the period being analysed.

1. Introduction

In economic theory, the efficient and effective utilization of resources are the main objectives of every bank. The study of bank efficiency has shown to be important during the recent financial crisis of 2007-2009, which not only impacted the United States (U.S) but also Europe and the whole world. Since then, the prediction of bank failures has become an important issue studied by researchers (Ataullah & Le, 2006). Previous studies have produced mixed results regarding the effects of efficiency in the banking sector (Drake, 2001; Hao et al., 2001; Ataullah and Le, 2006; Andrews & Pregibon, 1978). Hence, frontier efficiency analyses have become preferred methods of evaluating performance in the banking sector. Efficiency benchmarking allows banks to estimate production, cost and profit functions. There are two main techniques used to evaluate these efficiencies: parametric methods, exemplified by the Stochastic Frontier Analysis (SFA), and the non-parametric methods exemplified by Data Envelopment Analysis (DEA). DEA, a non-parametric method based on the linear programming framework, can manage complex production environments with multiple inputs and outputs. On the other hand, SFA is a statistical method that can discriminate between efficient units,

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and decomposes the statistical error, ε, into a noise term, v, and an inefficiency term, u. DEA has an advantage over SFA because it does not account for a statistical error term. Hence, it does not deal with the distributional assumptions of u and v. This paper is concerned with the DEA approach.

A fundamental assumption of the DEA method is that the decision-making units (DMUs) such as banks in a sample must all have a functional similarity. However, this can become problematic in the presence of noise (Fried et al., 2002). Moreover, given the amount of data available, literature has shown that there is still a need to address the importance of noise on the performance of DEA measures.[1] Proponents of DEA have suggested integrating machine learning techniques with DEA efficiency measures to alleviate the issues of noise (Wu et al., 2006; Azadeh et al., 2007; Favero & Papi, 1995). One such technique that has shown good performance in the prediction/classification of the financial markets is Support Vector Machine (SVM) (Cao and Tay, 2003; Racine, 2000). SVM has a literature that is relatively small compared to other statistical methods such as Random Forest, K-Nearest Neighbor, and neural networks (Boyacioglu et al., 2009). The recent approach of integrating DEA efficiency measures with SVM has some drawbacks including uncontrolled dependence of the efficiency measures. Hence, in this paper, a new combination of DEA and SVM method with four kernel functions (linear, sigmoid, polynomial and Radial Basis Function (RBF)) is proposed. Our research contributes to the literature by accounting for the heterogeneity effect in the efficiency measures while applying SVM methodology to assess any inconsistency between the efficiency estimates produced using the U.S. Federal Agricultural Banks data from 2005 to 2016.

In this paper, our contribution is in three-fold: First, we estimate the efficiency measures. Second, to account for heterogeneity among the banks, we determine the optimal number of cluster using the gap statistical method and then cluster the efficiency measures of the U.S Federal Agricultural Banks prior to the financial crisis (2005-2006), during the financial crisis (2007-2009) and post the financial crisis (2010-2016) using k-means algorithm. Third, we integrate the DEA efficiency measures estimated with SVM while accounting for four variety of kernel functions: linear, sigmoid, polynomial, and Radial Basis Function (RBF). The remainder of this paper is structured as follows: Section 2 introduces the DEA and SVM model, and the integration of DEA and SVM. Section 3 presents the empirical data set and the input and output variables. Section 4 presents the results. Section 5 summarizes the research and provides additional discussion.

2. Theoretical framework

Primal production theory assumes that the relationship between multiple outputs, $y=\left(y_1,y_2,...,y_j\right)\in\Re_+^J$ and inputs, $x=\left(x_1,x_2,...,x_i\right)\in\Re_+^I$ is reflected by the concept of *production function*. The production function framework forms the bases in the estimation of the DMUs efficiency using linear programming DEA.

2.1. DEA model

The technology that transforms inputs into outputs can be represented by input set $L(\mathbf{y})$. The input set satisfying constant returns to scale and strong disposability of input is defined as:

$$L\left(\mathbf{y}\right)=\left\{\mathbf{x}:\mathbf{y}\ \text{is produced by}\ \mathbf{x};\qquad \mathbf{x}\in\Re_+^I\quad \mathbf{y}\in\Re_+^J\right\} \tag{1}$$

1 See: Holland and Lee, 2002; Ondrich and Ruggiero, 2002; Banker and Chang, 2006; Simar and Zelenyuk, 2011.

The input set $L(\mathbf{y})$ denotes the collection of input vector that yield output vector. This concept is represented by an input distance function evaluated for any DMU a reference production possibility set T, as:

$$D_i^T\left(y^t, x^t\right)^{-1} = \min\left\{\lambda : \lambda x^t \in L^T\left(y^t\right)\right\}$$

or

$$\begin{aligned} &\min_{\theta,z}\ st. && y^t \le Yz && Y = y_1,\dots,y_T \\ &\text{subject to} && && \\ & && \lambda x^t \ge Xz && X = x_1,\dots,x_T \\ & && z \ge 0 && \end{aligned} \tag{2}$$

Here, the second expression of Eq. (2) identifies the linear program that is used to calculate the distance function, with the z's being a *Tx1* vector of intensity variables that identify the constant return to scale (CRS) boundaries of the reference set. Once the traditional DEA analysis has been performed it may be difficult to interpret the efficiency measures obtained for each bank because of the non-homogeneity of the banks. In our paper, we solve the issue of heterogeneity by determining the optimal number of clustering group within the years using the gap statistic method, first by developed by Tibshirani, et al., (2001). The results suggest that the efficiency measures can be classified into four groups: Highly Efficient (HE), Efficient (E), Highly Inefficient (HI), and Inefficient (I).

2.2. Support Vector Machine

Support Vector Machine (SVM), a relatively young classification algorithm that has been proposed by Vapnick (Xu et al., 2006), is devised to provide a computationally efficient way of separating hyperplanes in a high dimensional feature space. Given a training data (X_1,y_1).....,(X_n,y_n) where $X_i \in \mathrm{R}^m$ and $y_i \in \mathrm{R}$, the goal is to find a function to classify g(x) where:

$$g(x) = w^T \Phi(X) + b, \tag{3}$$

where $\varphi(i) : \mathrm{R}^m \rightarrow \mathrm{R}$ and w and b are the parameters learned from the training data. w is the weight that defines a direction that is perpendicular to the hyperplane, b is the bias term that moves the hyperplane parallel to itself and x is the support of the support machine. In the binary classification[2] with $y_i \in \{-1, +1\}$ corresponding to the class label of x_i, the function margin that is defined as the margin measured by the function output of $g(x)$is:

$$\text{g(x)=}\begin{cases} \langle w.x^{+} + b\rangle = +1 \\ \langle w.x^{-} + b\rangle = -1 \end{cases} \tag{4}$$

The goal of the algorithm is to maximize the distance between the training data that are closest to the decision boundary. The margin of separation is related to the so called Vapnik-Chervonenkis dimension, which measures how complex the learning machine is (Vapnick, 1998). Given a linearly separable training data, the hyperplane (w,b) that solves the optimization problem

$$\begin{aligned} &\min_{w,b}\{\langle w \cdot w\rangle\} \\ &\text{subject to} \\ &y_i[\langle w.x_i\rangle + b] \ge 1, \forall i \end{aligned} \tag{5}$$

2 In the multi-classification, SVM performs one versus the other classification framework. Therefore, we will always get back to the binary classification framework.

realizes the maximal margin hyper-plane with a geometric margin $\frac{1}{\|w\|_2}$ which is the minimal distance between two classes. The transformation of the optimization problem in (4) into a dual problem gives us the primal Lagrangian:

$$L(w,b,\alpha)=\frac{1}{2}\langle w \cdot w\rangle - \sum_{i=1}^{l} \alpha_i [\, y_i [\langle w. x_i\rangle + b] - 1] \tag{6}$$

This dual is found by differentiation with respect to w and b, and it is only dependable on the Lagrange multipliers α_i. Furthermore, Cortes and Vapnick (1995) suggested a modification to the original optimization statement that will penalize the failure of a training data point to reach the correct margin. The proposed modification is conducted by introducing the slack variable that accounts for any data that were wrongly misclassified. As a result, the algorithm could be generalized to a nonlinear classification by the introduction of a kernel function K that maps the input data into a high-dimensional feature space (Vapnik, 1982). The kernels function used in this paper are:

Linear : $K(x,y) = x^T y$; Gaussian (RBF): $K(x,y) = \exp(-\gamma kx - yk^2)$; Sigmoid: $K(x,y) = \tanh(a + \gamma x^T y)$; Polynomial: $K(x,y) = (\gamma + x^T y)^d$ where a, γ, d are the parameters associated with each kernel function.

The empirical framework is as follow:

1. Partition the data into three groups: prior to the financial crisis (2005-2006), during the financial crisis (2007-2009), and post financial crisis (2010-2016).
2. Estimate the efficiency measures assuming an input oriented DEA model by year.
3. Test for stationarity of the efficiency measures across each group of the financial crisis.
4. Using the efficiency measures of each group, a cluster analysis (kmeans) is implemented with four clustering groups
5. Apply SVM classification technique by splitting the data into two sets: training set and a testing set.
6. Using the training set within each group of the financial crisis, perform a grid search to optimize the parameters associated with the kernels of SVM.
7. Apply the trained SVM model to the testing data and calculate the prediction error and the accuracy under the four kernels.

3. Data and construction of the variables

This study uses the annual data for most of the agricultural banks located in the U.S from 2005 to 2016. The data was provided by the Farm Credit Administration (FCA) Web Site. Farm Credit System institutions submit Call Reports to FCA on a quarterly basis. These reports contain the institutions financial data. A random sample of 363 banks were selected from 2010-2016, 121 banks were selected from 2005-2006, and 182 banks were selected from 2007-2009.

Within DEA methodology, the efficiency measures are only relative to the best DMUs in the data; that is the choice of the input-output variables (Martić and Savić, 2001). Following the works of Sealey and Lindley (1977), and Casu and Molyneux (2003), we considered the intermediate approach with two inputs: (total interest expenses and total non-interest expenses), and two outputs (total loan and other earning assets). Moreover, the input total cost is measured as the sum of the two inputs variables: total interest expenses and total non-interest expenses. The output, total loan, is measured as the sum of all loan accounts by the banks listed in FCA and the output, other earning assets is measured as the sum of total securities (treasury bills, government bonds and other securities), deposits with banks, and equity investments.

4. Results and Discussions

4.1. Unit Roots Test

SVM is a method that assumes that the data is stationary. In the literature of the unit root tests, the augmented Dickey Fuller (ADF) test of Said and Dickey (1984) and the KPSS test of Kwiatkowski et al., (1992) are the most popular. However, because of the drawback of ADF that is, the ADF test has low power, KPSS test of stationarity is considered in this paper. Hence, the hypothesis for this test can be written as:

Hypothesis 1 *each time series follow a straight line time trend with stationary errors.*

Hypothesis 2 *each time series is non-stationary.*

Table 1 shows the results of the KPSS test. While applying the KPSS test, the null hypothesis is not statistically rejected at 1% for each of the period of the financial crisis. Therefore, we conclude that the efficiency measures are stationary. Hence, SVM can be applied on the efficiency measures obtained during the periods of 2005-2006, 2007-2009, and 2010- 2016.

Table 1
KPSS Test of the efficiency measures for prior, during and post the financial crisis

	2005-2006	2007-2009	2010-2016
p-value	0.0216	0.1	0.0172

4.2. Prior to the financial crisis

The efficiency measures of agricultural financial banks for the period of 2005-2006 are evaluated using the input oriented BCC model. Tables 2 summarizes the efficiency measures of banks in our sample by year. Tables 2 shows a significant dynamic change.

Table 2
Efficiency Measure Prior (2005-2006)

Name of the Bank	Year	Efficiency Scores	Cluster group	Name of the Bank	Year	Efficiency Scores	Cluster group
FCB of Texas	2005	1.000	4	Legacy Ag Credit, ACA	2005	0.627	3
FCB of Texas	2006	0.951	4	Legacy Ag Credit, ACA	2006	0.804	2
AgFirst FCB	2005	0.677	1	First South ACA	2005	0.665	1
AgFirst FCB	2006	1.000	4	First South ACA	2006	0.822	2
AgriBank, FCB	2005	0.913	4	Central Kentucky ACA	2005	0.719	1
AgriBank, FCB	2006	1.000	4	Central Kentucky ACA	2006	0.936	4
U.S. AgBank, FCB	2005	0.699	1	Valley ACA	2005	0.803	2
U.S. AgBank, FCB	2006	1.000	4	Valley ACA	2006	0.921	4
AgCredit of South Texas ACA	2005	0.827	2	Puerto Rico ACA	2005	0.556	3
AgCredit of South Texas ACA	2006	0.959	4	Puerto Rico ACA	2006	0.742	1
Louisiana Ag Credit, ACA	2005	1.000	4	Chattanooga ACA	2005	0.727	1
Louisiana Ag Credit, ACA	2006	0.942	4	Chattanooga ACA	2006	0.825	2
First Ag Credit FCS	2005	0.752	1	Cape Fear ACA	2005	0.579	3
First Ag Credit FCS	2006	1.000	4	Cape Fear ACA	2006	0.762	2
Ag New Mexico, FCS, ACA	2005	0.729	1	MidAtlantic ACA	2005	0.675	1
Ag New Mexico, FCS, ACA	2006	0.888	4	MidAtlantic ACA	2006	0.799	2
Texas AgFinance FCS	2005	0.690	1	ArborOne, ACA	2005	0.643	3
Texas AgFinance FCS	2006	0.929	4	ArborOne, ACA	2006	1.000	4
Great Plains Ag Credit, ACA	2005	0.612	3	Colonial ACA	2005	0.612	3
Great Plains Ag Credit, ACA	2006	0.770	2	Colonial ACA	2006	0.741	1
AgriLand FCS	2005	0.718	1	Southwest Georgia ACA	2005	0.587	3
AgriLand FCS	2006	0.868	2	Southwest Georgia ACA	2006	0.903	4

Table 2
Efficiency Measure Prior (2005-2006) (Continued)

Name of the Bank	Year	Efficiency Scores	Cluster group	Name of the Bank	Year	Efficiency Scores	Cluster group
Capital Farm Credit ACA	2005	0.700	1	AgChoice ACA	2005	0.703	1
Capital Farm Credit ACA	2006	1.000	4	AgChoice ACA	2006	0.838	2
AgTexas FCS	2005	0.840	2	Northwest Florida ACA	2005	0.567	3
AgTexas FCS	2006	1.000	4	Northwest Florida ACA	2006	0.738	1
Southwest Texas ACA	2005	0.669	1	South Florida ACA	2005	0.582	3
Southwest Texas ACA	2006	0.990	4	South Florida ACA	2006	0.668	1
Central Texas ACA	2006	0.890	4	Central Florida ACA	2005	0.597	3
Heritage Land Bank, ACA	2005	0.750	1	Central Florida ACA	2006	0.745	1
Heritage Land Bank, ACA	2006	0.896	4	North Florida ACA	2005	0.608	3
Lone Star, ACA	2005	0.805	2	North Florida ACA	2006	0.774	2
Lone Star, ACA	2006	1.000	4	FC of the Virginias ACA	2005	0.703	1
Southwest Florida ACA	2005	0.594	3	FC of the Virginias ACA	2006	0.823	2
Southwest Florida ACA	2006	0.806	2	Carolina ACA	2005	0.776	2
Carolina ACA	2005	0.776	2	Carolina ACA	2006	0.956	4
Carolina ACA	2006	0.956	4	AgCarolina ACA	2005	0.627	3
AgCarolina ACA	2005	0.627	3	AgCarolina ACA	2006	0.868	2
AgCarolina ACA	2006	0.868	2	AgGeorgia ACA	2005	0.675	1
AgGeorgia ACA	2005	0.675	1	AgGeorgia ACA	2006	0.816	2
AgGeorgia ACA	2006	0.816	2	AgSouth ACA	2005	0.776	2
AgSouth ACA	2005	0.776	2	AgSouth ACA	2006	0.910	4
AgSouth ACA	2006	0.910	4	Jackson Purchase ACA	2005	0.668	1
Jackson Purchase ACA	2005	0.668	1	Jackson Purchase ACA	2006	0.848	2
Jackson Purchase ACA	2006	0.848	2	Western Arkansas ACA	2005	0.622	3
Grand Forks ACA	2005	0.534	3	Western Arkansas ACA	2006	0.774	2
Grand Forks ACA	2006	0.724	1	Badgerland ACA	2005	0.601	3
Mandan ACA	2005	0.610	3	Badgerland ACA	2006	0.815	2
Mandan ACA	2006	0.738	1	AgHeritage ACA	2005	0.615	3
FCS of Illinois ACA	2005	0.629	3	AgHeritage ACA	2006	0.739	1
FCS of Illinois ACA	2006	0.803	2	AgCountry ACA	2005	0.631	3
FCS of America ACA	2005	0.779	2	AgCountry ACA	2006	0.825	2
FCS of America ACA	2006	0.918	4	Progressive FCS, ACA	2005	0.571	3
Midsouth ACA	2005	0.597	3	Progressive FCS, ACA	2006	0.733	1
Midsouth ACA	2006	0.711	1	Mid-America ACA	2005	0.700	1
1st Farm Credit Services, ACA	2005	0.595	3	Mid-America ACA	2006	0.804	2
1st Farm Credit Services, ACA	2006	0.774	2	Maine ACA	2006	0.873	2
United ACA	2005	0.599	3	Yankee ACA	2006	0.767	2
United ACA	2006	0.785	2	Western New York ACA	2005	0.490	3
FCS Financial, ACA	2005	0.687	1	First Pioneer ACA	2005	0.682	1
FCS Financial, ACA	2006	0.825	2				

The calculated efficiency measures vary from 0.490 to 1.000. The input-oriented efficiency analysis provides information on how much the bank should increase the level of inputs of an inefficient bank to become DEA-efficient whilst keeping the current level of output fixed. In Tables 2, the cluster group column, 1 indicates inefficient banks (I), 2 indicates efficient bank (E), 3 indicates highly inefficient banks (HI), and 4 indicates highly efficient banks (HE). For example, Table 2 shows that the bank FCB of Texas is highly efficient in 2005, but in 2006, its efficiency measure decreased from 1.000 in 2005 to 0.951 in 2006. After classifying the efficiency measures into four clusters, Table 3 shows the accuracy, confidence interval, and the parameters associated with the different kernel functions of SVM.

Table 3
Performance criteria from 2005 to 2006

	Linear	RBF	Sigmoid	Polynomial
Accuracy	0.930	0.972	0.971	0.860
Error	0.170	0.28	0.29	0.240
95%CI	0.840, 0.963	0.857, 0.993	0.854, 0.990	0.80, 0.93
a			1.683	
γ		4.463	0.951	0.444
d				3

The basic SVM framework is designed to determine the optimal decision boundary. To obtain an unbiased performance estimate, cross-validation was performed (See Table 4) with a total of 36 banks in the testing data set comprised of 13 inefficient banks, 8 efficient banks, 11 highly inefficient banks and 4 highly efficient banks. While applying the RBF kernel, 12 banks were correctly classified as inefficient, 8 banks were correctly classified as efficient, 11 banks were correctly classified as highly inefficient, and 4 banks were correctly classified as highly efficient. Using the linear kernel function, 13 banks were correctly classified as inefficient, 8 banks were correctly classified as efficient, 10 banks were correctly classified as highly inefficient, and 3 banks were correctly classified as highly efficient. With the polynomial kernel function, 10 banks were correctly classified as inefficient, 7 banks were correctly classified as efficient, 10 banks were correctly classified as highly inefficient, and 4 banks were correctly classified as highly efficient. When applying the sigmoid kernel function, 12 banks were correctly classified as inefficient, 8 banks were correctly classified as efficient, 11 banks were correctly classified as highly inefficient, and 4 banks were correctly classified as highly efficient.

4.3. During the financial crisis

Tables 4 presents a summary of the efficiency measures of banks in our sample by year. Column 2 gives the year of the technical efficiency for each individual bank, followed by technical efficiency measures in column 3. Table 4 provides the efficiency measures that changed on the year basis. The results of our analysis show that there was a big fluctuation in the efficiency scores. In column 4 of Table 4, the cluster group of the technical efficiency measure is presented in which 1 indicates highly inefficient banks (HI), 2 indicates highly efficient bank (HE), 3 indicates efficient banks (E), and 4 indicates inefficient banks (I). Additionally, Table 4 shows the cluster group of the individual bank is changing. This is for example seen with the bank of FCB of Texas. Table 8 shows the accuracy, confidence interval, and the parameters associated with the different kernel functions of SVM.

Table 4
Efficiency Measure (2007-2009)

Name of the Bank	Year	Efficiency	Cluster group	Name of the Bank	Year	Efficiency	Cluster group
FCB of Texas	2007	1	2	AgCountry ACA	2009	0.526	4
FCB of Texas	2008	0.797	3	ArborOne, ACA	2007	1	2
FCB of Texas	2009	0.596	1	ArborOne, ACA	2008	1	2
AgFirst FCB	2007	1	2	ArborOne, ACA	2009	0.912	2
AgFirst FCB	2008	0.744	3	Colonial ACA	2007	0.77	3
AgFirst FCB	2009	0.446	4	Colonial ACA	2008	0.682	1
AgriBank, FCB	2007	1	2	Colonial ACA	2009	0.603	1
AgriBank, FCB	2008	0.683	1	MidAtlantic ACA	2009	0.668	1
AgriBank, FCB	2009	0.42	4	Southwest Georgia	2007	0.965	2
U.S. AgBank, FCB	2007	0.967	2	Southwest Georgia	2008	0.798	3
U.S. AgBank, FCB	2008	0.693	1	Southwest Georgia	2009	0.8	3
U.S. AgBank, FCB	2009	0.459	4	AgChoice ACA	2007	0.856	3
AgCredit of South Texas ACA	2007	1	2	AgChoice ACA	2008	0.714	1
AgCredit of South Texas ACA	2008	0.992	2	AgChoice ACA	2009	0.608	1
AgCredit of South Texas ACA	2009	0.825	3	Northwest Florida ACA	2007	0.757	3
Louisiana Ag Credit, ACA	2007	0.871	3	Northwest Florida ACA	2008	0.648	1
Louisiana Ag Credit, ACA	2008	0.887	3	Northwest Florida ACA	2009	0.631	1
Louisiana Ag Credit, ACA	2009	0.825	3	South Florida ACA	2007	0.737	3
First Ag Credit FCS	2007	1	2	South Florida ACA	2008	0.617	1
First Ag Credit FCS	2008	0.819	3	South Florida ACA	2009	0.514	4
Ag New Mexico, FCS, ACA	2007	0.96	2	Central Florida ACA	2007	0.858	3
Ag New Mexico, FCS, ACA	2008	0.769	3	Central Florida ACA	2008	0.725	1
Ag New Mexico, FCS, ACA	2009	0.621	1	Central Florida ACA	2009	0.614	1
Texas AgFinance FCS	2007	1	2	North Florida ACA	2007	0.826	3
Texas AgFinance FCS	2008	0.793	3	North Florida ACA	2008	0.692	1
Texas AgFinance FCS	2009	0.651	1	North Florida ACA	2009	0.614	1
Great Plains Ag Credit, ACA	2007	0.812	3	Southwest Florida ACA	2007	0.971	2
Great Plains Ag Credit, ACA	2008	0.621	1	Southwest Florida ACA	2008	0.841	3
Great Plains Ag Credit, ACA	2009	0.489	4	Southwest Florida ACA	2009	0.756	3
AgriLand FCS	2007	0.881	3	FC of the Virginias	2007	0.838	3
AgriLand FCS	2008	0.745	3	FC of the Virginias	2008	0.789	3
AgriLand FCS	2009	0.664	1	FC of the Virginias	2009	0.744	3

Table 4

Efficiency Measure (2007-2009) (Continued)

Name of the Bank	Year	Efficiency	Cluster group	Name of the Bank	Year	Efficiency	Cluster group
AgTexas FCS	2007	1	2	Carolina ACA	2007	0.929	2
AgTexas FCS	2008	0.853	3	Carolina ACA	2008	0.794	3
AgTexas FCS	2009	0.847	3	Carolina ACA	2009	0.703	1
Capital Farm Credit ACA	2007	1	2	AgCarolina ACA	2007	0.857	3
Capital Farm Credit ACA	2008	0.833	3	AgCarolina ACA	2008	0.714	1
Central Texas ACA	2007	0.985	2	AgCarolina ACA	2009	0.596	1
Central Texas ACA	2008	0.704	1	AgGeorgia ACA	2007	0.821	3
Central Texas ACA	2009	0.527	4	AgGeorgia ACA	2008	0.74	3
Heritage Land Bank, ACA	2007	0.991	2	AgGeorgia ACA	2009	0.65	1
Heritage Land Bank, ACA	2008	0.808	3	AgSouth ACA	2007	0.884	3
Heritage Land Bank, ACA	2009	0.651	1	AgSouth ACA	2008	0.758	3
Capital Farm Credit, ACA	2009	0.649	1	AgSouth ACA	2009	0.7	1
Texas Land Bank, ACA	2007	0.952	2	Jackson Purchase ACA	2007	0.927	2
Texas Land Bank, ACA	2008	0.782	3	Jackson Purchase ACA	2008	0.769	3
Texas Land Bank, ACA	2009	0.623	1	Jackson Purchase ACA	2009	0.712	1
Lone Star, ACA	2007	1	2	AG CREDIT ACA	2007	0.773	3
Lone Star, ACA	2008	0.831	3	AG CREDIT ACA	2008	0.697	1
Lone Star, ACA	2009	0.606	1	AG CREDIT ACA	2009	0.574	1
Legacy Ag Credit, ACA	2007	1	2	GreenStone ACA	2007	0.769	3
Legacy Ag Credit, ACA	2008	0.911	2	GreenStone ACA	2008	0.674	1
Legacy Ag Credit, ACA	2009	0.794	3	GreenStone ACA	2009	0.509	4
Southern AgCredit, ACA	2009	0.585	1	AgStar ACA	2007	1	2
First South ACA	2007	0.834	3	AgStar ACA	2008	0.834	3
First South ACA	2008	0.784	3	AgStar ACA	2009	0.666	1
First South ACA	2009	0.717	1	North Dakota ACA	2007	0.768	3
Central Kentucky ACA	2007	1	2	North Dakota ACA	2008	0.575	1
Central Kentucky ACA	2008	0.895	2	North Dakota ACA	2009	0.398	4
Central Kentucky ACA	2009	0.796	3	Delta ACA	2007	1	2
Valley ACA	2007	0.941	2	Delta ACA	2008	1	2
Valley ACA	2008	0.86	3	Delta ACA	2009	0.925	2
Puerto Rico ACA	2007	0.788	3	Grand Forks ACA	2007	0.728	3
Puerto Rico ACA	2008	0.583	1	Mandan ACA	2007	0.784	3
Puerto Rico ACA	2009	0.495	4	Mandan ACA	2008	0.614	1
Chattanooga ACA	2007	0.869	3	Mandan ACA	2009	0.441	4
Chattanooga ACA	2008	0.764	3	FCS of Illinois ACA	2007	0.834	3
Chattanooga ACA	2009	0.836	3	FCS of Illinois ACA	2008	0.722	1
Cape Fear ACA	2007	0.81	3	FCS of Illinois ACA	2009	0.509	4
Cape Fear ACA	2008	0.69	1	FCS of America ACA	2007	1	2
Cape Fear ACA	2009	0.594	1	FCS of America ACA	2008	0.862	3
Cape Fear ACA	2009	0.594	1	1st Farm Credit	2007	0.756	3
MidAtlantic ACA	2007	0.794	3	1st Farm Credit	2008	0.663	1
MidAtlantic ACA	2008	0.695	1	1st Farm Credit	2009	0.516	4
FCS of America ACA	2009	0.656	1	United ACA	2007	0.812	3
Midsouth ACA	2007	0.74	3	United ACA	2008	0.655	1
Midsouth ACA	2008	0.583	1	United ACA	2009	0.481	4
Midsouth ACA	2009	0.46	4	FCS Financial, ACA	2007	0.848	3
Western Arkansas ACA	2007	0.804	3	FCS Financial, ACA	2008	0.748	3
Western Arkansas ACA	2008	0.693	1	FCS Financial, ACA	2009	0.525	4
Western Arkansas ACA	2009	0.53	4	Mid-America ACA	2007	0.765	3
Badgerland ACA	2007	0.815	3	Mid-America ACA	2008	0.762	3
Badgerland ACA	2008	0.637	1	Mid-America ACA	2009	0.656	1
Badgerland ACA	2009	0.42	4	Maine ACA	2007	0.938	2
AgHeritage ACA	2007	0.78	3	Maine ACA	2008	0.667	1
AgHeritage ACA	2008	0.703	1	Yankee ACA	2008	0.594	1
AgHeritage ACA	2009	0.504	4	Western New York	2008	0.432	4
AgCountry ACA	2007	0.79	3	Western New York	2009	0.314	4
Progressive FCS, ACA	2007	0.784	3	First Pioneer ACA	2008	0.541	4
Progressive FCS, ACA	2008	0.59	1	First Pioneer ACA	2009	0.388	4
Progressive FCS, ACA	2009	0.427	4	American AgCredit	2009	0.539	4
AgCountry ACA	2008	0.638	1				

During 2007-2009, only 54 banks (6 inefficient banks, 20 efficient banks, 17 highly inefficient banks and 11 highly efficient banks) were considered in the testing data set. Using the RBF kernel, to validate whether the training was efficient, 15 banks were correctly classified as highly inefficient, 8 banks were correctly classified as highly efficient, 19 banks were correctly classified as efficient, and 6 banks were correctly classified as inefficient. For the linear kernel, 16 banks were correctly classified as highly inefficient, 9 banks were correctly classified as highly efficient, 20 banks were correctly classified as efficient and 6 banks were correctly classified as inefficient. Using the polynomial kernel, 12 banks were correctly classified as highly inefficient, 10 were correctly classified as highly efficient, 19 banks were correctly classified as efficient, and 6 banks were correctly classified as inefficient. Using the sigmoid kernel, 16 banks were correctly classified as highly inefficient, 8 were correctly classified as highly efficient, 18 banks were correctly classified as efficient, and 5 banks were correctly classified as inefficient.

Table 5
Performance criteria from 2007-2009

	Linear	RBF	Sigmoid	Polynomial
Accuracy	0.944	0.899	0.870	0.850
Error	0.56	0.111	0.130	0.150
95%CI	0.846, 0.988	0.774, 0.958	0.751, 0.946	0.751, 0.946
a			1.683	
γ		4.43	0.950	0.446
d				3

4.4. After the financial crisis of 2007-2009

Tables 9-13 present the efficiency measures for 2010-2016 using the input oriented BCC model. The stationary test of the efficiency measures was conducted and resulted in not having enough evidence to reject the null hypothesis of stationarity at 1%. In Table 6, four columns are present: 1) The bank name; 2) The year of the estimated efficiency measures; 3) The estimated efficiency measure and 4) The cluster group of the efficiency measure. While accounting for the cluster group in Tables 9-13, 1 indicates highly efficient banks (HE), 2 indicates efficient bank (E), 3 indicates highly inefficient banks (HI), and 4 indicates inefficient banks (I). To observe the impact of DEA measure on the bank performance, Table 14 shows the accuracy, confidence interval, and the parameters associated with the different kernel functions of SVM.

Table 6
Efficiency Measure (2010-2016)

Name of the Bank	Year	Efficiency Scores	Cluster group	Name of the Bank	Year	Efficiency Scores	Cluster group
FCB of Texas	2010	0.975	1	Texas Land Bank, ACA	2010	0.844	2
FCB of Texas	2011	0.731	2	Texas Land Bank, ACA	2011	0.712	3
FCB of Texas	2012	0.618	3	Texas Land Bank, ACA	2012	0.611	3
FCB of Texas	2013	0.539	4	Texas Land Bank, ACA	2013	0.594	3
FCB of Texas	2015	0.575	4	Lone Star, ACA	2010	0.866	2
FCB of Texas	2016	0.672	3	Lone Star, ACA	2011	0.815	2
AgFirst FCB	2010	0.733	2	Lone Star, ACA	2012	0.739	2
AgFirst FCB	2011	0.572	4	Lone Star, ACA	2013	0.638	3
AgFirst FCB	2012	0.429	4	Legacy Ag Credit, ACA	2010	0.916	1
AgFirst FCB	2013	0.408	4	Legacy Ag Credit, ACA	2011	0.992	1
AgFirst FCB	2015	0.518	4	Legacy Ag Credit, ACA	2012	1	1
AgFirst FCB	2016	0.643	3	Legacy Ag Credit, ACA	2013	1	1
AgriBank, FCB	2010	1	1	Legacy Ag Credit, ACA	2015	1	1
AgriBank, FCB	2011	0.958	1	Legacy Ag Credit, ACA	2016	0.967	1
AgriBank, FCB	2012	0.812	2	Louisiana Land Bank,	2010	0.816	2
AgriBank, FCB	2013	0.715	3	Louisiana Land Bank,	2011	0.718	3
AgriBank, FCB	2015	0.958	1	Louisiana Land Bank,	2012	0.819	2
AgriBank, FCB	2016	1	1	Louisiana Land Bank,	2013	0.707	3
U.S. AgBank, FCB	2010	0.814	2	Louisiana Land Bank,	2015	0.753	2
U.S. AgBank, FCB	2011	0.621	3	Louisiana Land Bank,	2016	0.714	3
AgCredit of South Texas ACA	2010	1	1	Mississippi Land Bank,	2010	0.839	2
Louisiana Ag Credit, ACA	2010	0.976	1	Mississippi Land Bank,	2011	0.734	2
Ag New Mexico, FCS, ACA	2010	0.901	1	Mississippi Land Bank,	2012	0.683	3
Ag New Mexico, FCS, ACA	2011	0.86	2	Mississippi Land Bank,	2013	0.64	3
Ag New Mexico, FCS, ACA	2012	0.816	2	Mississippi Land Bank,	2015	0.675	3
Ag New Mexico, FCS, ACA	2013	0.775	2	Mississippi Land Bank,	2016	0.67	3
Ag New Mexico, FCS, ACA	2015	0.889	1	Southern AgCredit, ACA	2010	0.792	2

Table 6

Efficiency Measure (2010-2016)

Name of the Bank	Year	Efficiency Scores	Cluster group	Name of the Bank	Year	Efficiency Scores	Cluster group
Ag New Mexico, FCS, ACA	2016	0.846	2	Southern AgCredit, ACA	2011	0.682	3
Texas AgFinance FCS	2010	0.883	1	Southern AgCredit, ACA	2012	0.607	3
Great Plains Ag Credit, ACA	2010	0.569	4	Southern AgCredit, ACA	2013	0.565	4
Great Plains Ag Credit, ACA	2011	0.521	4	Southern AgCredit, ACA	2015	0.567	4
Great Plains Ag Credit, ACA	2012	0.504	4	Southern AgCredit, ACA	2016	0.613	3
Great Plains Ag Credit, ACA	2013	0.489	4	Alabama ACA	2010	0.907	1
AgriLand FCS	2010	0.739	2	Alabama ACA	2011	0.763	2
AgriLand FCS	2011	0.726	2	Alabama ACA	2012	0.692	3
AgriLand FCS	2012	0.71	3	Alabama ACA	2013	0.645	3
AgriLand FCS	2013	0.738	2	Alabama ACA	2015	0.683	3
Texas AgFinance FCS	2011	0.639	3	Alabama ACA	2016	0.73	2
Texas AgFinance FCS	2012	0.7	3	Alabama Ag Credit, ACA	2010	0.799	2
Texas AgFinance FCS	2013	0.634	3	Alabama Ag Credit, ACA	2011	0.712	3
AgTexas FCS	2010	1	1	Alabama Ag Credit, ACA	2012	0.688	3
AgTexas FCS	2011	0.981	1	Alabama Ag Credit, ACA	2013	0.652	3
AgTexas FCS	2012	0.779	2	Alabama Ag Credit, ACA	2015	0.698	3
AgTexas FCS	2013	0.688	3	Alabama Ag Credit, ACA	2016	0.709	3
Texas FCS	2015	0.768	2	First South ACA	2010	1	1
Texas FCS	2016	0.72	3	First South ACA	2011	0.978	1
AgTexas FCS	2015	0.737	2	First South ACA	2012	0.924	1
AgTexas FCS	2016	0.726	2	First South ACA	2013	0.934	1
Lone Star, ACA	2015	0.711	3	First South ACA	2015	0.979	1
Lone Star, ACA	2016	0.705	3	First South ACA	2016	1	1
Central Texas ACA	2010	0.703	3	Central Kentucky ACA	2010	0.918	1
Central Texas ACA	2011	0.648	3	Central Kentucky ACA	2011	0.79	2
Central Texas ACA	2012	0.601	3	Central Kentucky ACA	2012	0.727	2
Central Texas ACA	2013	0.585	4	Central Kentucky ACA	2013	0.689	3
Central Texas ACA	2015	0.663	3	Central Kentucky ACA	2015	0.687	3
Central Texas ACA	2016	0.816	2	Central Kentucky ACA	2016	0.655	3
Heritage Land Bank, ACA	2010	0.889	1	Puerto Rico ACA	2010	0.621	3
Heritage Land Bank, ACA	2011	0.903	1	Puerto Rico ACA	2011	0.644	3
Heritage Land Bank, ACA	2012	0.845	2	Puerto Rico ACA	2012	0.682	3
Heritage Land Bank, ACA	2013	0.837	2	Puerto Rico ACA	2013	0.674	3
Heritage Land Bank, ACA	2015	0.965	1	Puerto Rico ACA	2015	0.778	2
Heritage Land Bank, ACA	2016	0.923	1	Puerto Rico ACA	2016	0.828	2
Capital Farm Credit, ACA	2010	1	1	Chattanooga ACA	2010	1	1
Capital Farm Credit, ACA	2011	0.865	2	Chattanooga ACA	2011	0.946	1
Capital Farm Credit, ACA	2012	0.761	2	Chattanooga ACA	2012	0.924	1
Capital Farm Credit, ACA	2013	0.679	3	Cape Fear ACA	2010	0.713	3
Capital Farm Credit, ACA	2015	0.769	2	Cape Fear ACA	2011	0.618	3
Capital Farm Credit, ACA	2016	0.811	2	Cape Fear ACA	2012	0.599	3
Cape Fear ACA	2013	0.593	3	AgCarolina ACA	2010	0.748	2
Cape Fear ACA	2015	0.636	3	AgCarolina ACA	2011	0.686	3
Cape Fear ACA	2016	0.683	3	AgCarolina ACA	2012	0.649	3
ArborOne, ACA	2010	1	1	AgCarolina ACA	2013	0.613	3
ArborOne, ACA	2011	0.979	1	AgCarolina ACA	2015	0.616	3
ArborOne, ACA	2012	0.914	1	AgCarolina ACA	2016	0.646	3
ArborOne, ACA	2013	0.757	2	AgGeorgia ACA	2010	0.889	1
ArborOne, ACA	2015	0.698	3	AgGeorgia ACA	2011	0.814	2
ArborOne, ACA	2016	0.681	3	AgGeorgia ACA	2012	0.784	2
Colonial ACA	2010	0.651	3	AgGeorgia ACA	2013	0.741	2
Colonial ACA	2011	0.617	3	AgGeorgia ACA	2015	0.743	2
Colonial ACA	2012	0.599	3	AgGeorgia ACA	2016	0.755	2
Colonial ACA	2013	0.619	3	Florida ACA	2011	0.741	2
Colonial ACA	2015	0.694	3	Florida ACA	2012	0.793	2
Colonial ACA	2016	0.741	2	Florida ACA	2013	0.859	2
MidAtlantic ACA	2010	0.959	1	Florida ACA	2015	0.708	3
MidAtlantic ACA	2011	0.855	2	Florida ACA	2016	0.73	2
MidAtlantic ACA	2012	0.807	2	AgSouth ACA	2010	0.974	1
MidAtlantic ACA	2013	0.763	2	AgSouth ACA	2011	0.958	1
MidAtlantic ACA	2015	0.818	2	AgSouth ACA	2012	0.901	1
MidAtlantic ACA	2016	0.848	2	AgSouth ACA	2013	0.915	1
Southwest Georgia ACA	2010	0.818	2	AgSouth ACA	2015	0.962	1
Southwest Georgia ACA	2011	0.777	2	AgSouth ACA	2016	0.995	1
Southwest Georgia ACA	2012	0.723	3	Jackson Purchase ACA	2010	0.87	2
Southwest Georgia ACA	2013	0.659	3	Jackson Purchase ACA	2011	0.825	2
Southwest Georgia ACA	2015	0.721	3	Jackson Purchase ACA	2012	0.811	2

Table 6
Efficiency Measure (2010-2016) (Continued)

Name of the Bank	Year	Efficiency Scores	Cluster group	Name of the Bank	Year	Efficiency Scores	Cluster group
Southwest Georgia ACA	2016	0.775	2	AG CREDIT ACA	2010	0.751	2
AgChoice ACA	2010	0.813	2	AG CREDIT ACA	2011	0.733	2
AgChoice ACA	2011	0.771	2	AG CREDIT ACA	2012	0.694	3
AgChoice ACA	2012	0.751	2	AG CREDIT ACA	2013	0.654	3
AgChoice ACA	2013	0.709	3	AG CREDIT ACA	2015	0.655	3
AgChoice ACA	2015	0.743	2	AG CREDIT ACA	2016	0.685	3
AgChoice ACA	2016	0.753	2	River Valley AgCredit, ACA	2012	0.897	1
Northwest Florida ACA	2010	0.74	2	River Valley AgCredit, ACA	2013	0.866	2
Northwest Florida ACA	2011	0.704	3	River Valley AgCredit, ACA	2015	0.864	2
Northwest Florida ACA	2012	0.688	3	River Valley AgCredit, ACA	2016	0.73	2
Northwest Florida ACA	2013	0.686	3	GreenStone ACA	2010	0.76	2
Northwest Florida ACA	2015	0.64	3	GreenStone ACA	2011	0.704	3
Northwest Florida ACA	2016	0.68	3	GreenStone ACA	2012	0.664	3
South Florida ACA	2010	0.547	4	GreenStone ACA	2013	0.63	3
Central Florida ACA	2010	0.621	3	GreenStone ACA	2015	0.692	3
Central Florida ACA	2011	0.622	3	GreenStone ACA	2016	0.699	3
Central Florida ACA	2012	0.615	3	AgStar ACA	2010	1	1
Central Florida ACA	2013	0.611	3	AgStar ACA	2011	0.936	1
Central Florida ACA	2015	0.621	3	AgStar ACA	2012	0.88	1
Central Florida ACA	2016	0.639	3	AgStar ACA	2013	0.784	2
North Florida ACA	2010	0.698	3	AgStar ACA	2015	0.773	2
Southwest Florida ACA	2010	0.977	1	AgStar ACA	2016	0.823	2
FC of the Virginias ACA	2010	1	1	North Dakota ACA	2010	0.479	4
FC of the Virginias ACA	2011	0.947	1	North Dakota ACA	2011	0.483	4
FC of the Virginias ACA	2012	0.873	1	North Dakota ACA	2012	0.488	4
FC of the Virginias ACA	2013	0.813	2	North Dakota ACA	2013	0.449	4
FC of the Virginias ACA	2015	0.808	2	North Dakota ACA	2015	0.503	4
FC of the Virginias ACA	2016	0.83	2	North Dakota ACA	2016	0.586	4
Carolina ACA	2010	0.976	1	Delta ACA	2010	1	1
Carolina ACA	2011	0.925	1	Delta ACA	2011	0.993	1
Carolina ACA	2012	0.905	1	Delta ACA	2012	0.999	1
Carolina ACA	2013	0.872	1	Delta ACA	2013	1	1
Carolina ACA	2015	0.849	2	Delta ACA	2015	0.976	1
Carolina ACA	2016	0.899	1	Delta ACA	2016	0.969	1
Badgerland Financial ACA	2013	0.559	4	Farm Credit West, ACA	2013	0.47	4
Badgerland Financial ACA	2015	0.633	3	Farm Credit West, ACA	2015	0.425	4
Badgerland Financial ACA	2016	0.671	3	Oklahoma AgCredit, ACA	2016	0.629	3
AgHeritage ACA	2010	0.638	3	Chisholm Trail ACA	2012	0.68	3
AgHeritage ACA	2011	0.6	3	Chisholm Trail ACA	2013	0.655	3
AgHeritage ACA	2012	0.575	4	Chisholm Trail ACA	2015	0.667	3
AgHeritage ACA	2013	0.551	4	American AgCredit, ACA	2015	0.804	2
AgHeritage ACA	2015	0.56	4	American AgCredit, ACA	2016	0.866	2
AgHeritage ACA	2016	0.542	4	Western AgCredit, ACA	2015	0.537	4
Progressive FCS, ACA	2010	0.489	4	Western AgCredit, ACA	2016	0.522	4
Progressive FCS, ACA	2011	0.478	4	Farm Credit East, ACA	2015	0.546	4
Progressive FCS, ACA	2012	0.448	4	Farm Credit East, ACA	2016	0.614	3
Progressive FCS, ACA	2013	0.485	4	FCS Southwest ACA	2015	0.48	4
Progressive FCS, ACA	2015	0.491	4	Western Oklahoma ACA	2016	0.709	3
Progressive FCS, ACA	2016	0.541	4	Southwest Kansas ACA	2016	0.652	3
AgCountry ACA	2010	0.71	3	1st Farm Credit Services, ACA	2010	0.666	3
AgCountry ACA	2011	0.69	3	1st Farm Credit Services, ACA	2011	0.617	3
AgCountry ACA	2012	0.643	3	1st Farm Credit Services, ACA	2012	0.589	3
AgCountry ACA	2013	0.558	4	1st Farm Credit Services, ACA	2013	0.536	4
AgCountry ACA	2015	0.546	4	1st Farm Credit Services, ACA	2015	0.637	3
AgCountry ACA	2016	0.555	4				

To validate our model during 2010-2016, 108 banks (48 highly inefficient banks, 22 efficient banks, 15 inefficient banks, and 23 highly efficient banks) were considered in the testing data set. Using the RBF kernel, 22 banks were correctly classified as highly efficient, 22 banks were correctly classified as efficient, 45 banks were correctly classified as highly inefficient, and 15 banks were correctly classified as inefficient. For the linear kernel, 23 banks were correctly classified as highly efficient, 22 were correctly classified as efficient, 45 banks were correctly classified as highly inefficient, and 15 banks were correctly classified as inefficient. Using the polynomial kernel, 22 banks were correctly classified as highly efficient, 21 banks were correctly classified as efficient, 46 banks were correctly classified as highly inefficient, and 15 banks were correctly classified as inefficient. Additionally, using the sigmoid kernel, 20 banks were correctly classified as highly efficient, 14 banks were correctly classified as efficient, 43 banks were correctly classified as highly inefficient, and 15 banks were correctly classified as inefficient.

Table 7
Performance criteria from 2010-2016

	Linear	RBF	Sigmoid	Polynomial
Accuracy	0.972	0.963	0.852	0.960
Error	0.028	0.037	0.148	0.040
95%CI	0.921, 0.994	0.908, 0.989	0.771, 0.913	0.910, 0.989
a			2.223	
γ		4.428	0.951	0.442
d				2

5. Conclusions

This study applies Data Envelopment Analysis (DEA) under the input oriented BCC model to measure the efficiency scores of the FCA Banks from 2005-2016 while accounting for the time dependence between the efficiency measures. The study focuses on three periods: prior to the financial crisis (2005-2006), during the financial crisis (2007-2009) and post the financial crisis (2010-2016). These time periods enabled us to analyze the performance of the Financial Crisis on the U.S Agricultural banking sector as a whole. We applied a DEA-SVM model while accounting for the time dependency with the purpose of classifying the banks into four categories: (i) highly efficient (HE), (ii) highly inefficient (HI), (iii) efficient (E), and (iv) inefficient (I). Overall, the results revealed that technological progression declined due to financial crisis. More precisely, the performance of SVM declined during the financial crisis. The results show that the overall efficiency and performance using the integrated DEA-SVM during 2005-2006 and 2010-2016 were high. Furthermore, the integrated DEA-SVM had a lower performance during the financial crisis (2007-2009). The overall performance of all the kernels decreased during the financial crisis. Overall, the results show that the Agricultural banking sector is both efficient and stable over the time period being analyzed.

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