Journal of Agricultural and Applied Economics, 43,4(November 2011):515–528

Does Farm Size and Specialization Matter for Productive Efficiency? Results from Kansas

Amin W. Mugera and Michael R. Langemeier

In this article, we used bootstrap data envelopment analysis techniques to examine technical and scale efficiency scores for a balanced panel of 564 farms in Kansas for the period 1993–2007. The production technology is estimated under three different assumptions of returns to scale and the results are compared. Technical and scale efficiency is disaggregated by farm size and specialization. Our results suggest that farms are both scale and technically inefficient. On average, technical efficiency has deteriorated over the sample period. Technical efficiency varies directly by farm size and the differences are significant. Differences across farm specializations are not significant.

Key Words: bootstrap, data envelopment analysis, efficiency, farms

JEL Classifications: D24, Q12

Productivity analysis of U.S. farms has received substantial attention in empirical research. Differences in technical efficiency across farms have been identified as one of the major factors explaining differences in farm survival and growth, and changes in farm industry structure. The general trend across the United States is a decline in the number of farms, an increase in the average farm size, and a decrease in labor use. Serious concerns have emerged about the economic health of family farms as traditional farming communities have experienced declines in profitability and competitiveness. The increasingly strong move toward larger farms is perceived as a threat to the long-term economic viability of the small family farm. Thus, there has been political pressure to support farmers while at the same time a desire by policy-makers to increase production efficiency. The passage of the Federal Agricultural Improvement and Reform (FAIR) Act in 1996 introduced decoupled payments that created an opportunity to transition into a more market oriented agricultural policy.

There is an emerging consensus that technical efficiency and overall performance of farms are influenced by farm size so that larger and more diversified farms are more productive or efficient than small farms[1] (Byrnes et al., 1987; Chavas and Aliber, 1993; Featherstone, Langemeier, and Ismet, 1997; Kalaitzandonakes, Wu, and Ma, 1992; Key, McBride, and Mosheim, 2008; Olson and Vu, 2009; Serra, Zilberman, and Gil, 2008; Weersink, Turvey, and Godah, 1990; Wu, Devadoss, and Lu, 2003). Byrnes et al. (1987) investigated the relative technical performance

Amin W. Mugera is assistant professor, Institute of Agriculture and School of Agriculture and Resource Economics, Faculty of Agriculture and Natural Sciences, The University of Western Australia, Perth, Australia. Michael R. Langemeier is professor, Department of Agricultural Economics, Kansas State University, Manhattan, Kansas.

[1] Technical efficiency is only one component of productivity. Other components include scale efficiency and allocative efficiency. Productivity measures over time include total factor productivity, technical change, and efficiency change.

of Illinois grain farms and observed that the major source of inefficiency was scale inefficiency, particularly for the large farms in the sample. Weersink, Turvey, and Godah (1990) examined the relationship between farm size and technical efficiency using data from Missouri grain farms and found efficiency to be positively related to farm size. Kalaitzandonakes, Wu, and Ma (1992), using both the parametric and nonparametric methods, examined the relationship between farm size and technical efficiency using data from Missouri grain farms. The authors reported that farm efficiency was positively related to farm size irrespective of the estimation methods used. Chavas and Aliber (1993) analyzed economic, scale, and scope efficiency of Wisconsin crop and livestock farmers. The authors found that scale and scope efficiency measures depend on the farm size and financial structure. Featherstone, Langemeier, and Ismet (1997) investigated technical, allocative, and scale efficiency for a sample of Kansas beef-cow farms and found that profitability was positively correlated with overall technical efficiency, and that inefficiency was negatively related to herd size and positively related to the degree of specialization. Wu, Devadoss, and Lu (2003) computed technical efficiency indices for Idaho sugarbeet farms and decomposed these indices into pure technical efficiency, scale efficiency, and congestion efficiency using nonparametric procedures. Improper scale of operation and input over-utilization were found to be the major sources of inefficiency but technical efficiency was independent of farm size. Key, McBride, and Mosheim (2008) estimated total factor productivity growth for U.S. hog enterprises for 12 years (1992–2004). Productivity gains were found to be driven by technical progress and improvements in scale efficiency rather than by efficiency gains. Serra, Zilberman, and Gil (2008) investigated the influence of the decoupling of government payments on production efficiencies of a sample of Kansas farmers using a stochastic frontier model. Results indicated that an increase in decoupling will likely decrease technical efficiencies. Olson and Vu (2009) estimated the technical, allocative, and scale efficiencies of farms in southern Minnesota using bootstrap nonparametric output-based data envelopment analysis. The authors found that large farm sizes are consistently associated with higher technical efficiency.

Two competing methods are often used to compute technical efficiency, the parametric stochastic frontier analysis and the nonparametric data envelopment analysis (DEA). The DEA method has several advantages over the stochastic frontier analysis method: DEA is nonparametric and does not require any parametric assumptions on the structure of technology or the inefficiency term. Another advantage is that as long as inputs and outputs are measured in the same unit of measurement, an assumption about complete homogeneity of the economic agents included in the analysis is not needed (Henderson and Zelenyuk, 2007). However, DEA also has some drawbacks: the traditional DEA approach does not have a solid statistical foundation behind it and is sensitive to outliers.

To overcome those problems, Simar and Wilson (1998, 2000) and others have introduced bootstrapping into the DEA framework. Their method, based on statistical well-defined models, allows for consistent estimation of the production frontier, corresponding efficiency scores, as well as standard errors and confidence intervals. These advances have not been included in many recent studies that have examined farm level technical efficiency of U.S. agriculture. An exception is the Olson and Vu (2009) study which estimated technical, allocative, and scale efficiencies of farms in southern Minnesota using the bootstrap output-based DEA approach.

This paper used the Simar and Wilson (1998, 2000) smoothed bootstrap procedure to investigate the bias, variance, and confidence intervals for technical efficiency scores for the Kansas farm sector. The study also investigates whether both technical and scale efficiencies vary by farm size and farm specialization. Results of this study have policy implications pertaining to enhancing the competitiveness and long-term viability of farms through expansion and diversification.

Methodology

This article follows the approach by Henderson and Zelenyuk (2007) to define the underlying production technology. For each farm i (i = 1,

2. . . n), the period-t input vector is $x_i^t = \left(K_i^t, L_i^t\right)$ where K_i^t is physical capital and L_i^t is labor. Let y_i^t be a single output for farm i in period t. The technology for converting inputs for each farm i in each time period t can be characterized by the technology set:

$$T_i^t \equiv \left\{\left(x_i^t, y_i^t\right)|\text{can produce} y_i^t\right\}. \tag{1}$$

The same technology can be characterized by the following input sets

$$C_i^t\left(y_i^t\right) \equiv \left(x_i^t|x_i^t \text{ can produce } y_i^t\right),\ x_i^t \in \Re_+^2\ . \tag{2}$$

We assume that the technology follows standard regularity assumptions under which the Farrell input-oriented distance function[2] can be represented as:

$$\begin{aligned} TE_i^t &\equiv TE_i^t\left(x_i^t, y_i^t|C_i^t\left(y_i^t\right)\right) \\ &= \text{supremum}\left\{\theta > 0|x_i^t/\theta \in C_i^t\left(y_i^t\right)\right\}\forall y_i^t \in \Re_+^1. \end{aligned} \tag{3}$$

A farm is considered to be technically efficient when $TE_i^t = 1$ and technically inefficient when $0 < TE_i^t < 1$. The true technology and input sets are unknown and thus, the individual value of technical efficiency must be estimated using either the nonparametric (data envelopment analysis) or parametric (stochastic frontier analysis) techniques.

Given the production technology in Equation (3), we use linear programming to estimate the input distance function. The Farrell input-based efficiency index for farm i at time t is defined as:

$$e\left(x_i^t, y_i^t\right) = \min\left\{\theta|\langle x_i^t/\theta,\ y_i^t\rangle \in T^t\right\}. \tag{4}$$

In the above equation Y is output, K is capital, and L is labor.[3] The subscript i refers to an individual farm and the superscript t represents the individual time period. The efficiency index value for each farm is found using the following linear program:

$$\begin{aligned} &\underset{\theta, z^1, \ldots, z^j}{\text{Minimize}}\ \theta_i \\ &\text{subject to} \left\{\begin{array}{l} Y_i \leq \sum_k z_k Y_k^t \\ \theta K_i \geq \sum_k z_k K_k^t \\ \theta L_i \geq \sum_k z_k L_k^t \\ z_k \geq 0 \forall k. \end{array}\right\} \end{aligned} \tag{5}$$

where θ_i is the efficiency measure to be calculated for farm i at time t, and z_k is the intensity variable for farm i. One advantage of the DEA approach is that it jointly calculates the intensity variable and efficiency score in the same programming problem. The above model assumes constant return to scale (CRTS). Constant returns to scale suggest that all firms operate at an optimal scale. However, imperfect competition and financial constraints may cause farms to operate below optimal scale. Adding $\sum_{k=1}^{k} z_k = 1$ to the constraints in the above model imposes variable returns to scale (VRTS) while adding the equation $\sum_{k=1}^{k} z_k < 1$ imposes decreasing returns to scale (DRTS).

Scale efficiency shows the degree of inefficiency that a unit is facing due to its scale of operation. It is computed as a ratio of a farm's technical efficiency under CRTS to its technical efficiency under VRTS:

$$\text{SE}_1 = \text{TECRTS}/\text{TEVRTS}. \tag{6}$$

Since TECRTS $\leq$ TEVRTS, $\text{SE}_1 \leq 1$. A farm with $\text{SE}_1 = 1$ is scale efficient in the sense that the chosen input-output mix is optimal and maximizes the average productivity. If $\text{SE}_1 < 1$, the input-output mix is not scale efficient and the farm in question is operating either in a region of increasing returns (inefficient small scale) to scale or decreasing returns to scale (inefficient large scale).[4]

The smooth homogenous bootstrap DEA approach introduced by Simar and Wilson (1998,

---

2 The input distance function determines where a farm is located in the input space relative to the isoquant. It aims at reducing the input amounts by as much as possible while keeping at least the present output levels.

3 Working in smaller dimensions (in this case one output and two inputs) tends to provide better estimates of the frontier and helps overcome the "curse of dimensionality" always present in nonparametric estimation (Daraio and Simar, 2007). Adding more variables not only inflates DEA efficiency scores but it may also conceal the actual magnitude of inefficiency (Hughes and Yaisawarng, 2004).

4 The ratio $\text{SE}_2 = \text{TE}_{\text{CRTS}}/\text{TE}_{\text{NIRTS}}$ can be used to indicate whether the scale inefficiency is due to a too small scale or a too large scale. Increasing returns to scale is inferred when $\text{SE}_2 = 1$ given that $\text{SE}_1 < 1$, and decreasing returns to scale when $\text{SE}_2 < 1$ given that $\text{SE}_1 < 1$.

2000) is used to allow for consistent estimation of the production frontier, corresponding efficiency scores, bias, bias corrected efficiency scores, as well as standard errors and confidence intervals. Bootstrapping investigates the reliability of a data set by creating a pseudo-replicate data set. Bootstrapping allows the assessment of whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates that cannot be derived analytically. Random samples are obtained by sampling, assuming a standard normal distribution, with replacement from the original data set. This provides an estimator of the parameter of interest. With DEA bootstrapping, the data generation process (DGP) is repeatedly simulated by resampling the sample data and applying the original estimator to each simulated sample. It is expected that the bootstrap distribution will mimic the original unknown sampling distribution of the estimators of interest (using a nonparametric estimate of their densities). Hence, a bootstrap procedure can simulate the DGP by using Monte Carlo approximation and may provide a reasonable estimator of the true unknown DGP. The bootstrap estimates are biased by construction and the empirical bootstrap distribution is used to estimate the bias. An estimate of the bias is defined as the difference between the empirical mean of the bootstrap distribution and the original efficiency point estimates. The bias-corrected estimator is obtained by subtracting the bias from the original efficiency estimates. Details of the DEA bootstrapping process are well documented in Simar and Wilson (1998, 2000).

Bootstrapping enables the investigation of the sensitivity of efficiency scores to sampling variations. However, this comes at a cost because the ranking of original efficiencies may change if compared with the bias-corrected efficiencies. The main drawback of using bootstrapping in DEA used to be computation time in running the replications; this is no longer a problem with the computation power of the new generation of computers.

Data Description

Data for this study comes from the Kansas Farm Management Association (Langemeier, 2010). We use a balanced panel of 564 farm households for the period 1993–2007. The estimated model includes one output, gross farm income (GFI), and two inputs, capital and labor. Gross farm income is an aggregation of crop and livestock income while capital is an aggregation of asset charges and purchased inputs.[5]

The nominal GFI is deflated by the Personal Consumption Expenditure Index, with 2007 as the base year. Real capital is calculated in the following manner: first, total capital is calculated as the sum of asset charges and purchased inputs. Second, a deflator is constructed using the price indices for purchased inputs (Purinp) and asset charges (Capp) by farm and year, with 2007 as the base year, and weighted with total capital:[6]

$$\text{deflator} = \left(\frac{\text{Purchased Inputs}}{\text{Total Capital}}\right) \times \text{Purinp} + \left(\frac{\text{Asset Charges}}{\text{Total Capital}}\right) \times \text{Capp} \tag{7}$$

Third, estimates of real capital by farm and year are computed by dividing the nominal capital by the deflator:

$$\text{Real Capital} = \frac{\text{Assets Charges} + \text{Purchased Inputs}}{\text{deflator}} = \frac{\text{Nominal Capital}}{\text{deflator}} \tag{8}$$

Labor is measured as the number of farm workers per farm per year. To obtain this value, we deflate the total annual cost of labor (includes hired and unpaid labor) by a labor price index with 2007 as the base year. This value is

[5] Two outputs and three inputs were aggregated into one output and two inputs in computing technical efficiencies because this study was a preliminary analysis of a major study that investigated the dynamics of labor productivity growth in the farm sector. Asset charges include repairs, rental charges for land and machinery, auto and conservation expense, cash interest, real estate and property taxes, general farm insurance, depreciation, and opportunity interest charged on owned equity. Purchased inputs include fuel and oil, seed, fertilizer and lime, chemicals, feed, utilities, and crop insurance.

[6] The deflator is a sum of the ratio of the relative prices of purchased inputs and assets charges (with 2007 as base year), multiplied by the value shares of each input. The weights (value shares) reflect the importance of each input in the production process.

Table 1. Mean and Standard Deviation of Output and Inputs

Year	Real Gross Farm Income (in \$10,000)	Real Capital (in \$10,000)	Labor Inputs (in Persons/Farm)
1993	19.610 (15.057)	23.732 (17.365)	1.560 (1.010)
1994	19.566 (14.842)	25.162 (18.841)	1.560 (0.970)
1995	19.764 (16.513)	25.416 (19.324)	1.570 (1.040)
1996	25.351 (21.216)	26.245 (20.161)	1.560 (1.000)
1997	27.171 (21.106)	28.244 (20.847)	1.590 (1.100)
1998	20.885 (16.521)	28.395 (20.919)	1.590 (1.080)
1999	23.325 (18.936)	29.115 (22.245)	1.550 (1.020)
2000	23.926 (19.419)	29.476 (22.473)	1.490 (0.920)
2001	24.274 (20.576)	30.458 (23.803)	1.500 (1.050)
2002	22.487 (19.300)	29.878 (23.118)	1.480 (1.000)
2003	26.508 (22.600)	30.590 (23.745)	1.470 (0.980)
2004	29.337 (26.572)	31.682 (25.137)	1.460 (0.960)
2005	29.730 (26.705)	33.557 (26.294)	1.440 (0.950)
2006	30.532 (26.273)	34.265 (26.831)	1.420 (0.920)
2007	38.459 (34.821)	36.831 (29.188)	1.380 (0.970)
Mean	25.395 (22.527)	29.536 (23.149)	1.510 (1.000)

then divided by the average annual salary of a farm worker. No attempt is made to account for quality differences in inputs because of lack of such information in the database. However, scatter plots are used in conjunction with box plots to identify and eliminate outliers leaving only 564 farms from the original 583 farms.[7]

The descriptive statistics of the data are presented in Table 1. In general, the series indicates an upward trend for both real GFI and real capital, although real GFI exhibits more fluctuations than real capital possibly due to weather pattern fluctuations. Average GFI increased from \$196,099 in 1993 to \$384,593 by 2007. Real capital increased from \$237,324 to \$368,311. However, labor input decreased from 1.56 workers to 1.38 workers during the same time period, respectively.

The farms are grouped according to farm size and specialization. Farm size is defined by gross farm income levels: very small farms (GFI < \$100,000); (2) small farms (\$100,000 < GFI < \$250,000; medium farms (\$250,000 < GFI < \$500,000); and large farms (GFI > \$500,000). Specialization is defined by percentage of time (T) devoted to crop production: livestock farms (T < 50%), crop farms (T = 100%), and diversified farms (50% < T < 100%). The justification for this segregation is that the farm categories may face different constraints, which could subsequently impact efficiency measures.

Empirical Results

Bootstrapping DEA Efficiency Estimates

The input oriented framework was used to estimate technical efficiency. The orientation aims at reducing the input amount by as much as possible while keeping at least the present output levels. For all the estimates, 2000 bootstrap iterations (i.e., B = 2000) were employed and the models were estimated using the FEAR package that is linked to the statistical package R (Wilson, 2008). Tables 2 and 3 present the mean technical efficiency scores of the 564 farms under two assumptions of the technological set: variable returns to scale, and non-increasing returns to scale (NIRTS).[8] For each table, the

[7] Outliers are observations that appear to be inconsistent with the remainder of the data. For this study, those are abnormally high or low capital inputs relative to gross farm incomes in real values.

[8] Results for technical efficiency under CRTS are not presented. Each of those three technological sets is necessary in identifying the nature of returns to scale. It is important to note that efficiency scores are relative measures, in this case, relative to best practice producers in Kansas.

Table 2. Input Oriented Technical Efficiency Scores with Variable Returns to Scale (VRTS) Model for Kansas Farms

Year	Efficiency Score	Bias Corrected Efficiency	Bias	Standard Error	Lower Bound	Upper Bound
1993	0.6250	0.5870	0.0379	2.3959	0.5691	0.6200
1994	0.6242	0.5871	0.0370	2.3480	0.5686	0.6182
1995	0.5770	0.5329	0.0440	1.7584	0.5161	0.5705
1996	0.6096	0.5693	0.0403	2.2858	0.5515	0.6027
1997	0.6223	0.5884	0.0338	1.9060	0.5675	0.6175
1998	0.6122	0.5746	0.0376	2.5520	0.5580	0.6070
1999	0.5628	0.5195	0.0433	1.6573	0.4997	0.5564
2000	0.6386	0.6007	0.0378	2.7297	0.5838	0.6329
2001	0.6447	0.6048	0.0398	2.5808	0.5865	0.6387
2002	0.5768	0.5268	0.0500	1.4289	0.5095	0.5696
2003	0.5297	0.4769	0.0528	0.6964	0.4577	0.5215
2004	0.6232	0.5854	0.0378	1.9847	0.5668	0.6172
2005	0.5159	0.4584	0.0575	0.5532	0.4411	0.5061
2006	0.5563	0.5081	0.0481	1.5576	0.4912	0.5492
2007	0.5699	0.5291	0.0407	2.1151	0.5150	0.5591
Mean	0.5925	0.5499	0.0426	1.9033	0.5321	0.5858

The above table reports mean technical efficiency scores bootstrapped with 2000 iterations. The total number of farms for each year is 564. The equality of means test for the standard and bias corrected efficiency scores is rejected at 1% level of significance.

second through seventh columns represent the mean of the DEA-estimates, the bias corrected DEA estimates, the estimated bias, the estimated standard errors, and the 95% confidence lower and upper bounds, respectively. The confidence intervals are based on the bias corrected efficiency scores. Daraio and Simar (2007) note that when the bias is larger than the

Table 3. Input Oriented Technical Efficiency Scores with Non-Increasing Returns to Scale (NIRTS) Model for Kansas Farms

Year	Efficiency Score	Efficiency Bias Corrected	Bias	Standard Error	Lower Bound	Upper Bound
1993	0.6151	0.5861	0.0289	2.8142	0.5654	0.6105
1994	0.6072	0.5755	0.0316	2.6167	0.5552	0.6015
1995	0.5627	0.5299	0.0328	2.0051	0.5091	0.5576
1996	0.5790	0.5439	0.0351	1.8244	0.5234	0.5728
1997	0.6119	0.5867	0.0251	2.2664	0.5670	0.6083
1998	0.6022	0.5756	0.0266	2.8741	0.5560	0.5983
1999	0.5344	0.4977	0.0367	1.4940	0.4760	0.5291
2000	0.6243	0.5950	0.0292	3.1120	0.5758	0.6191
2001	0.6167	0.5815	0.0351	2.1617	0.5614	0.6107
2002	0.5529	0.5143	0.0386	1.4117	0.4928	0.5475
2003	0.5154	0.4702	0.0452	0.8092	0.4483	0.5089
2004	0.5956	0.5648	0.0308	2.1771	0.5453	0.5899
2005	0.4993	0.4501	0.0491	0.7552	0.4307	0.4907
2006	0.5307	0.4921	0.0386	1.8583	0.4713	0.5249
2007	0.5434	0.5159	0.0274	2.0740	0.4986	0.5399
Mean	0.5727	0.5386	0.0340	2.0169	0.5184	0.5673

The above table reports mean technical efficiency scores bootstrapped with 2000 iterations. The total number of farms for each year is 564. The equality of means test for the standard and bias corrected efficiency scores is rejected at 1% level of significance.

standard deviation, the bias corrected estimates are preferred to the original estimates. In this case, the original estimates are preferred because the standard deviation is larger than the bias.

Table 2 presents the mean technical efficiency, across years, under VRTS. The efficiency score varied from a minimum of 52% (2005) to a maximum of 65% (2001). For the bias corrected technical efficiency score, the minimum was 46% (2005) and the maximum was 60% (2001). The lower bound ranged from 44% to 59% while the upper bound ranged from 51% to 64%. The mean difference between the lower and upper bounds throughout the study period is 5.4%, with the highest value being 6.5% (2005) and the lowest value being 4.4% (2007).

Results for the mean technical efficiency, across years, under NIRTS are presented in Table 3. The average efficiency score varied from a minimum of 50% (2005) to a maximum of 62% (2000). For the bias corrected technical efficiency score, the minimum was 45% (2005) and the maximum was 60% (2000). The lower bound ranged from 43% to 58% while the upper bound ranged from 49% to 62%. The mean difference between the lower and upper efficiency interval throughout the study period is 4.9%, with the highest value being 6.1% (2003) and the lowest value being 4.1% (1997).

The mean technical efficiency, across years, under CRTS varied from a maximum of 60% (2001) to a minimum of 47% (2005). For the bias corrected technical efficiency score, the minimum was 42% (2005) and the maximum was 58% (2000). The lower bound ranged from 40% to 56% while the upper bound ranged from 46% to 60%. The mean difference between the lower and upper efficiency interval throughout the study period is 4.8%, the highest value is 7.2% (2003) and the lowest value is 3.6% (1993).

In general, the mean technical efficiency scores of all farms for the entire sample period were 55, 57, and 59% for the CRTS, NIRTS, and VRTS technology sets, respectively. These results are consistent with production economics theory because VRTS technology set is the least restrictive and the CRTS technology set is the most restrictive, whereas the NIRTS technology set lies in between. The estimated mean confidence intervals for CRTS are narrower (4.8%) than for NIRTS (5.0%) and VRTS (5.4%) because of the greater curvature of the production frontier for the VRTS case. Likewise, the CRTS technology set displays smaller bias (2.8%) compared with NIRTS (3.4%) and VRTS (4.3%), where larger bias indicates a larger degree of noise.

The mean, standard deviation, and coefficient of variation for the original technical efficiency scores under VRTS and the bias corrected efficiency scores are presented in Table 4. The original scores are higher than the bias corrected scores, which have lower standard deviations and coefficients of variation. Ranking of original efficiency scores changed compared with the ranking of bias corrected efficiency scores. Farms that seemed to be perfectly efficient are ranked at a lower level when the bias corrected efficiency scores are considered, suggesting that data for those farms could have been measured with a larger degree of noise. Only 15% of the farms ranked as perfectly efficient under original efficiency scores retain a dominant position with the bias corrected efficiency ranking. Likewise, some farms that were not on the frontier are ranked at higher levels relative to other farms across the years. Indeed, all farms that had perfect original efficiency scores end up with bias corrected efficiency scores of less than unity. These results are not inconsistent but rather an outcome of the theory behind the construction of the homogenous smooth bootstrap procedure as outlined in Simar and Wilson (1998, 2000).

Table 5 presents the estimated farm-specific technical efficiency measures (VRTS) in the form of frequency distribution within a decile range. The results reveal that, in general, Kansas farms have not been successful in employing best-practice production methods and achieving the maximum possible output from new and existing technologies. The majority of the farms had an efficiency score between 40% and 70% throughout the sample period. The estimated results reveal that the number of farms that operate at an efficiency level less than 50% are increasing while those operating above the 50% efficiency level are decreasing. The empirical results suggest that Kansas farms

Table 4. Summary Statistics of Original and Bootstrapped Technical Efficiency Scores under VRTS Model

	Original Technical Efficiency			Bootstrapped Technical Efficiency		
Year	Mean	Standard Deviation	Coefficient of Variation	Mean	Standard Deviation	Coefficient of Variation
1993	0.6250	0.1553	0.2484	0.5870	0.1362	0.2321
1994	0.6242	0.1499	0.2402	0.5871	0.1340	0.2282
1995	0.5770	0.1712	0.2967	0.5329	0.1534	0.2879
1996	0.6096	0.1639	0.2689	0.5693	0.1457	0.2559
1997	0.6223	0.1438	0.2311	0.5884	0.1338	0.2275
1998	0.6122	0.1596	0.2607	0.5746	0.1492	0.2597
1999	0.5628	0.1591	0.2827	0.5195	0.1355	0.2609
2000	0.6386	0.1533	0.2400	0.6007	0.1369	0.2279
2001	0.6447	0.1500	0.2326	0.6048	0.1322	0.2186
2002	0.5768	0.1571	0.2724	0.5268	0.1366	0.2594
2003	0.5297	0.1555	0.2935	0.4769	0.1319	0.2766
2004	0.6232	0.1595	0.2558	0.5854	0.1400	0.2391
2005	0.5159	0.1639	0.3178	0.4584	0.1390	0.3032
2006	0.5563	0.1609	0.2893	0.5081	0.1438	0.2830
2007	0.5699	0.1783	0.3129	0.5291	0.1647	0.3113
Mean	0.5925	0.1635	0.2759	0.5499	0.1479	0.2689

The mean, variance, and coefficient of variation in the second to fourth columns represent the variations within the sample of original efficiency scores. The fifth to seventh columns represent the variations within the bootstrapped efficiency estimates with 2000 replications.

are technically inefficient and have been facing efficiency deterioration over time with low performers getting relatively worse over time. On average, the relative technical efficiency scores under the three technological sets have been declining over the sample period. We do not know if this is solely because the frontier is shifting over time, if the producers are falling further behind a static frontier, or a combination of both factors.

The reported results are consistent with what has been reported in literature. Bravo-Ureta et al. (2007) in a meta-regression analysis study of farm level technical efficiency scores found that efficiency scores in North America range from 45.9% to 100%. The authors

Table 5. Frequency Distribution of Input Efficiency Scores with VRTS Model

TE (%)	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
<20	1	1	8	3	1	0	2	1	0	3	3	2	6	5	9
20–30	6	3	18	11	6	9	18	4	2	18	26	7	38	28	33
30–40	24	32	55	39	22	42	61	26	26	42	92	32	106	59	59
40–50	86	76	94	82	69	95	121	70	59	114	133	79	114	114	95
50–60	142	151	154	148	149	121	148	135	135	150	141	119	138	140	127
60–70	152	146	112	130	170	137	109	144	147	121	92	168	90	123	117
70–80	82	79	65	77	90	99	60	107	112	76	49	83	51	58	71
80–90	40	52	34	42	35	31	27	46	50	20	17	37	8	21	26
90–99	11	11	11	14	13	18	9	15	18	11	5	18	5	6	17
100	20	13	13	18	9	12	9	16	15	9	6	19	9	10	10

The original VRTS efficiency scores are used to indicate the number of farms that defined the best-practice frontier over the sample period.

Table 6. Technical Efficiency Scores by Farm Size

Farm Size	Efficiency Score	Efficiency Bias Corrected	Bias	Standard Error	Lower Bound	Upper Bound
Very Small	0.4872	0.4214	0.0657	2.0021	0.4194	0.4773
Small	0.5631	0.5414	0.0217	2.8421	0.5233	0.5595
Medium	0.6678	0.6245	0.0432	0.7622	0.5977	0.6610
Large	0.7983	0.6958	0.1025	0.0032	0.6677	0.7814
Average	0.5925	0.5499	0.0426	1.9033	0.5321	0.5858

The equality of means test for the standard and bias corrected efficiency scores for each farm size category is rejected at 1% level of significance.

observed that a number of factors influence technical efficiency scores, including the number of variables in the model, number of fixed and variable inputs, and for parametric models, the functional form used to estimate the model.

Technical Efficiency Estimates by Farm Size and Specialization

Estimates of technical efficiency under VRTS technology set by farm size and specialization are presented in Tables 6 and 7. The VRTS technology set is used to report the remaining results because it is less restrictive than the NIRTS and CRTS technology sets. Technical efficiency is found to vary by farm size with large farms being more efficient (80%) compared with medium-sized farms (67%), small farms (56%), and very small farms (49%). The ranking of efficiency scores by farm size does not change when the bias corrected efficiency scores are used (i.e., 70%, 63%, 54%, and 42%, respectively). These results are consistent with the findings of Weersink, Turvey, and Godah (1990) and Paul et al. (2004) that technical efficiency is positively related to farm size.

There was not much variation in technical efficiency scores by farm specialization although crop farms are slightly more efficient (61%) than diversified farms (59%) and livestock farms (59%). Mean technical efficiency decreased over time within each farm size and farm specialization group, as well as over the entire sample. This provides evidence for the presence of efficiency degradation within each farm size group and farm specialization group, between the groups, and over the entire farm sample.

To statistically test technical efficiency differences by farm size and farm specialization, the nonparametric Kruskal-Wallis (KW) test was conducted for all the VRTS efficiency measures.[9] The null hypothesis is that the rank of technical efficiency scores, based on the means, is the same across the different farm sizes and farm specialization groups. Using the KW test, the null hypothesis for farm sizes is rejected at the 1% significance level. However, the null hypothesis for farm specialization groups is not rejected even at 10% significance level. This provides evidence that farm size does matter when comparing farm technical efficiency but specialization does not.

Scale Efficiency

Results for scale efficiency are presented in Table 8. The mean scale efficiency over the sample period was 93%, with the highest scale efficiency attained in 1998 (96%) and the lowest in 1999 (89%). Scale efficiency was consistently high in comparison with technical efficiency. On average, small farms are more scale efficient (97%) compared with medium-sized farms (93%), very small farms (89%), and large farms (84%). However, analysis over time indicates that large and medium-sized

[9] The Kruskal Wallis test is a nonparametric test for the situation where the analysis of variance (ANOVA) normality assumption may not apply. This test was used instead of ANOVA because normality of efficiency scores in the entire sample was rejected using the Shapiro-Wilk, Shapiro-Francia, and Skewness-Kurtosis tests. However, both the KW and ANOVA gave identical results for this case.

Table 7. Technical Efficiency Scores by Specialization

Farm Specialization	Efficiency Score	Efficiency Bias Corrected	Bias	Standard Error	Lower Bound	Upper Bound
Livestock	0.5866	0.5449	0.0417	2.0027	0.5263	0.5802
Mixed	0.5864	0.5480	0.0383	1.9937	0.5294	0.5808
Crops	0.6060	0.5559	0.0501	1.6988	0.5398	0.5984
Average	0.5926	0.5499	0.0426	1.9033	0.5321	0.5858

The equality of means test for the standard and bias corrected efficiency scores for each farm specialization category is rejected at 1% level of significance.

farms are becoming more scale efficient while small and very small farms are becoming scale inefficient.[10] These results are contrary to the results by Paul et al. (2004) who found small family farms to be less efficient in terms of both their scale of operation and technical aspects of production than large farms. The mean difference in scale efficiency by farm specialization was not statistically significant: crop farms (93%), diversified farms (94%), and livestock farms (92%).

Analysis of Returns to Scale

One can ascertain the returns to scale properties of a farm by comparing the technical efficiency levels with reference to CRTS, VRTS, and NIRTS frontiers. Returns to scale expresses the relationship between a proportional change in inputs and the resulting proportional change in output. Constant returns to scale implies that an *n* percent rise in all inputs produces an *n* percent increase in output. When output rises by a larger percentage than inputs, there are increasing returns to scale (IRTS). Decreasing returns to scale holds when output rises by a smaller percentage than inputs.

A variable returns to scale frontier exhibits CRTS, DRTS, and IRTS. When the NIRTS and CRTS measures are equal but differ from the VRTS measure, increasing returns to scale (IRTS) holds (i.e., $TE^{NIRS} = TE^{CRTS} < TE^{VRTS}$). When VRTS and NIRTS measures are equal but differ from the CRTS measure, DRTS holds (i.e., $TE^{VRTS} = TE^{NIRTS} < TE^{CRTS}$). The three measures are equal only at the most productive scale size (MPSS). The MPSS constitutes two groups of farms, those that are both technically and scale efficient and those that are technically inefficient but scale efficient. For the purpose of this analysis, the former group is considered to be operating under CRTS (i.e., $TE^{NIRTS} = TE^{CRTS} = TE^{VRTS} = SE = 1$) and the latter under MPSS (i.e., $TE^{NIRTS} = TE^{CRTS} = TE^{VRTS} < 1$ and $SE = 1$).

Table 9 presents the results of the overall number of farms operating under optimal scale (CRTS), sub-optimal scale (IRTS), supra-optimal scale (DRTS), and most productive scale size over the sample period. The data show that the number of farms that operated under supra-optimal scale increased while those that operated at sub-optimal scales decreased. This implies that, on average, farms gradually grew larger beyond their optimal scale of operation, hence became scale inefficient. The overall returns to scale results indicate that only 8% of the farms in the sample operated under CRTS and MPSS, 39% of the farms operated under sub-optimal returns to scale, and 53% operated under supra-optimal returns to scale. The optimal level of output under CRTS represented a point in the following years: 1994, 1995, 1996, 1998, 1999, 2001, 2004, 2005, and 2006. In the other years, the optimal level of output for CRTS represented a range. On average, the percentage of farms that operate under DRTS is as follows: large farms (6%), medium farms (20%), small farms (61%), and very small farms (92%). In contrast, the percentage of farms operating under IRTS is as follows: large farms (88%), medium farms (70%),

[10] There are significant adjustment costs to changing scale and many farms may be simply locked in. The high adjustment cost may make it difficult for small farms to change the size of their operation, suggesting that new frontier shifting technology may be favoring large-scale farms.

Table 8. Scale Efficiency Scores

	Overall				Farm Size				Farm Specialization		
Year	Mean	Minimum	Standard Deviation	CV	Very Small	Small	Medium	Large	Livestock	Mixed	Crop
1993	0.9416	0.4131	0.0848	0.0901	0.9528	0.9678	0.8821	0.7211	0.9341	0.9475	0.9361
1994	0.9435	0.4963	0.0772	0.0818	0.9194	0.9826	0.8951	0.7175	0.9403	0.9456	0.9422
1995	0.9329	0.2727	0.0955	0.1023	0.9185	0.9714	0.8827	0.7433	0.9298	0.9351	0.9310
1996	0.9181	0.0826	0.1030	0.1122	0.8119	0.9680	0.9282	0.8079	0.9170	0.9230	0.9088
1997	0.9577	0.5126	0.0776	0.0810	0.9224	0.9857	0.9659	0.8177	0.9513	0.9650	0.9491
1998	0.9610	0.3971	0.0692	0.0720	0.9485	0.9750	0.9549	0.8950	0.9448	0.9655	0.9618
1999	0.8888	0.2811	0.1109	0.1248	0.8318	0.9463	0.8547	0.7643	0.8656	0.8993	0.8810
2000	0.9454	0.3341	0.0850	0.0899	0.9224	0.9765	0.9296	0.8344	0.9302	0.9526	0.9405
2001	0.9364	0.1234	0.0876	0.0936	0.8399	0.9784	0.9528	0.8673	0.9238	0.9423	0.9320
2002	0.9506	0.4558	0.0816	0.0859	0.8838	0.9776	0.9757	0.8854	0.9270	0.9606	0.9446
2003	0.9191	0.2040	0.1212	0.1319	0.9080	0.9862	0.8802	0.7563	0.9030	0.9268	0.9147
2004	0.9311	0.2296	0.0947	0.1017	0.8312	0.9682	0.9643	0.8443	0.9161	0.9363	0.9298
2005	0.9129	0.3136	0.1009	0.1105	0.8447	0.9584	0.9191	0.8459	0.8880	0.9233	0.9090
2006	0.9139	0.2230	0.1009	0.1104	0.8217	0.9611	0.9443	0.8290	0.9037	0.9154	0.9157
2007	0.9255	0.2276	0.1044	0.1128	0.8102	0.9520	0.9837	0.8871	0.9016	0.9310	0.9283
Average	0.9319	0.0826	0.0957	0.1027	0.8846	0.9709	0.9296	0.8355	0.9206	0.9381	0.9278

The reported values for farm size and farm specialization categories are annual means. Scale efficiency is represented by the technical efficiency (CRTS) to technical efficiency (VRTS) ratio.

Table 9. Overall Number of Farms Operating under Optimal Scale (CRTS), Sub-optimal Scale (IRTS), and Supra-optimal Scale (DRTS), and Most Productive Scale Size (MPSS)

	CRTS	IRTS	DRTS	MPSS	Total
1993	6	295	148	115	564
1994	4	224	325	11	564
1995	3	212	291	58	564
1996	5	256	273	30	564
1997	2	336	224	2	564
1998	4	261	298	1	564
1999	2	230	287	45	564
2000	4	307	197	56	564
2001	3	193	324	44	564
2002	3	101	453	7	564
2003	2	186	323	53	564
2004	5	155	362	42	564
2005	3	289	113	159	564
2006	2	188	373	1	564
2007	2	98	457	7	564

The values above report the actual number of farms operating under each of the four technological sets. MPSS are farms that are scale efficient (SE = 1), but technically inefficient (TE < 1). Optimal scale farms operate under CRTS, sub-optimal scale farms operate under IRTS, and supra-optimal scale farms operate under DRTS.

small farms (29%), and very small farms (4%). This lends support to the view that competitive forces are reducing the number of small commercial farms and shifting production to larger farms.

Analysis of Efficiency Distributions

Nonparametric kernel density estimation techniques have become common in graphically illustrating various results in nonparametric production efficiency analysis (Henderson and Zelenyuk, 2007; Simar and Zelenyuk, 2006). Compared with histograms, kernel densities have the advantage of providing smoother density estimates and do not depend on the width and number of bins (Wand and Jones, 1995). This method is useful in this study because no distributional assumptions were imposed on the efficiency scores across farms. When using kernel density estimation, Simar and Zelenyuk (2006) note that one has to take care of at least three things: the random variable whose density is to be estimated must have a bounded support, only the consistent estimate of the efficiency scores are used, and there is no violation of the continuity assumption needed to ensure consistency of the density estimation. In this paper, the Silverman reflection method is used to correct for the bounded support, bootstrap DEA is used to compute the consistent efficiency scores, and a Gaussian kernel density is estimated using the bias corrected efficiency scores. The Silverman (1986) rule of thumb is used for bandwidth selection.

Figure 1 reports the kernel destiny estimates of the technical efficiency scores under VRTS

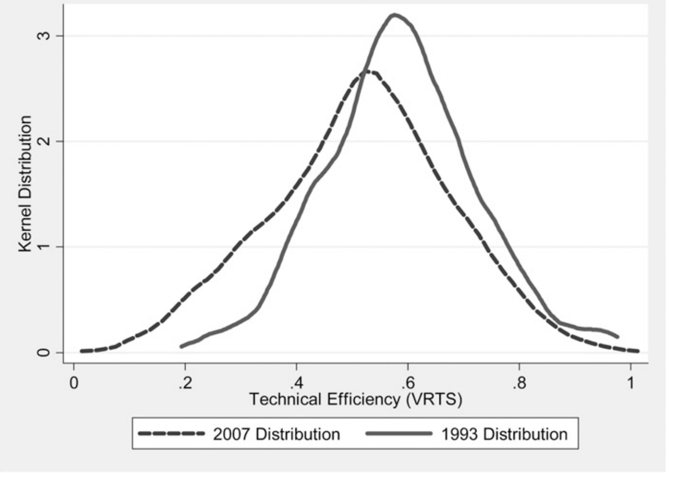

Figure 1. Distributions of Input Efficiency Scores, 1993 and 2007

for 1993 (solid line) and 2007 (dashed line). The figure shows a shift of the entire distribution of efficiency scores for 2007 toward the left, indicating that on average Kansas farms did not move closer to the frontier over the sample period. The shift is more prominent in the left tail, an indication that farms that had low efficiency scores in 1993 moved further away from the frontier relative to farms that had high efficiency scores (i.e., farms are getting left behind). The densities exhibit a single peak suggesting that the distribution of efficiency has remained unimodal over the sample period.

Concluding Remarks

This article introduced recent advances in bootstrapping and data envelopment analysis to investigate technical and scale efficiency indices of the Kansas farm sector using three different technology sets: constant returns to scale (CRTS), variable returns to scale (VRTS), and non-increasing returns to scale (NIRTS). The data consisted of a balanced panel of 564 farms for the sample period 1993–2007. The input oriented approach was used to compute technical efficiency scores, bias corrected efficiency scores, and the 95% confidence interval. Further, the sample was separated into farm size and farm specialization categories. Kernel estimation methods were used to investigate the distribution of efficiency scores in 1993 and 2007.

The following conclusions may be drawn from the analysis. First, the study reveals that there is substantial room for improvement in technical efficiency in the sample of farms analyzed. The mean annual technical efficiency scores over the sample period, assuming VRTS technology, was 59%, with a minimum of 52% and a maximum of 65%. More farms operated under VRTS rather than CRTS. Second, technical efficiency scores differ by farm size, but not by specialization. Larger farms are more technically efficient than smaller farms. Third, scale efficiency analysis reveals that farms are more scale efficient than technically efficient, indicating that inefficiency primarily emanates from poor managerial practices rather than scale of operation. The analyzed farms are, on average, scale inefficient (93%). Small farms (97%) and medium-sized farms (93%) are more scale efficient compared with very small farms (88%) and large farms (84%). However, large and medium-sized farms are becoming more scale efficient over time while small and very small farms are becoming scale inefficient. The difference in scale efficiency by specialization is not significant. Fourth, the study finds no evidence of improvement in technical efficiency (catching-up) over the sample period. Farms that had lower efficiency scores in 1993 moved further away from the frontier by 2007 compared with farms that initially had high efficiency scores. Our results are consistent with the observation by Serra, Zilberman, and Gil (2008) that an increase in decoupled payments would increase farms' technical inefficiencies in Kansas. Decoupled payments are not linked to production or yield; hence, higher production yields are not receiving any premiums. Therefore, producers may not have the incentive to produce the maximum attainable output and may respond to a decline in price supports by reducing the efficiency with which they operate.

In general, the results indicate deterioration in technical efficiency implying that most farms in the sample have either not been able to uptake new technologies adopted by the technological leaders in the sector or become inefficient in their managerial operations, or a combination of both factors. Smaller farms are becoming both technically and scale inefficient compared with larger farms that are becoming less inefficient over time. From a policy viewpoint, the results indicate that any policy to address inefficiency in the farm sector should take into account the relationship between farm size and efficiency. Farms that get both technically and scale efficient by increasing in size should be encouraged to grow larger while those that become both technically and scale inefficient by getting smaller should be allowed to exit. Policies designed to increase technical efficiency could include education, training, and extension programs. Intensification of extension programs is of particular importance because it influences managerial decisions at the farm level. As a policy incentive, the state government could increase the level of assistance to producers by expanding farm lending programs to provide incentives to adopt new technologies. Eliminating all technical inefficiencies would increase the average gross farm income from \$229,972 to \$308,438 without a change in input usage. Alternatively, producers can achieve the current average output levels with less input usage; real capital can be reduced from \$269,406 to \$170,045 and labor from 1.40 to 0.86 persons.

A key question for farm policy makers is whether the increasing relative inefficiency means that the educational systems in Kansas are failing to disseminate appropriate information to producers, whether the rate of technological adoption differs across groups of producers, or a combination of both factors. Therefore, a logical extension of this study would be to identify the determinants of efficiency, especially how the input-output configuration and different managerial practices affect efficiency. Further analysis is also needed to evaluate how the frontier is changing using mixed period distance functions.

[Received March 2010; Accepted May 2011.]

References

Bravo-Ureta, B., D. Solís, V. Moreira, J. Maripani, A. Thiam, and T. Rivas. "Technical Efficiency in Farming: A Meta-regression Analysis." *Journal of Productivity Analysis* 27(2007):57–72.

Byrnes, P., R. Färe, S. Grosskopf, and S. Kraft. "Technical Efficiency and Size: The Case of Illinois Grain Farms." *European Review of Agriculture Economics* 14(1987):367–81.

Chavas, J.V., and M. Aliber. "An Analysis of Economics Efficiency in Agriculture: A Nonparametric Approach." *Journal of Agricultural Research Economics.* 18(1993):1–16.

Daraio, C., and L. Simar. *Advanced Robust and Nonparametric Methods in Efficiency Analysis: Methodology and Applications*. New York: Springer, 2007.

Featherstone, A.M., M.R. Langemeier, and M. Ismet. "A Nonparametric Analysis of Efficiency for a Sample of Kansas Beef Cow Farms." *Journal of Agricultural Economics* 29(1997):175–84.

Henderson, D.J., and V. Zelenyuk. "Testing for (Efficiency) Catching-up." *Southern Economic Journal* 73(2007):1003–19.

Hughes, A., and S. Yaisawarng. "Sensitivity and Dimensionality Tests of DEA Efficiency Scores." *European Journal of Operational Research* 154(2004):410–22.

Kalaitzandonakes, N.G., S. Wu, and J. Ma. "The Relationship between Technical Efficiency and Firm Size Revisited." *Canadian Journal of Agricultural Economics* 40(1992):427–42.

Key, N., W. McBride, and R. Mosheim. "Decomposition of Total Factor Productivity Change in the U.S. Hog Industry." *Journal of Agricultural and Applied Economics* 40(2008):137–49.

Langemeier, M. "Kansas Farm Management SAS Data Bank Documentation." Staff Paper No. 11-01. Department of Agricultural Economics, Kansas State University, August 2010.

Olson, K., and L. Vu. "Economic Efficiency in Farm Households: Trends, Explanatory Factors, and Estimation Methods." *Agricultural Economics* 40(2009):587–99.

Paul, C.M., R. Nehring, D. Banker, and A. Somwaru. "Scale Economies and Efficiency in U.S. Agriculture: Are Traditional Farms History?" *Journal of Productivity Analysis* 22(2004): 185–205.

Serra, T., D. Zilberman, and J.M. Gil. "Farms' Technical Inefficiencies in the Presence of Government Programs." *The Australian Journal of Agricultural and Resource Economics* 52(2008):57–76.

Silverman, R.W. *Density Estimation for Statistical and Data Analysis*. London: Chapman and Hall, 1986.

Simar, L., and P. Wilson. "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models." *Management Science* 44(1998):49–61.

———. "Statistical Inference in Nonparametric Frontier Models: The State of the Art." *Journal of Productivity Analysis* 13(2000):49–78.

Simar, L., and V. Zelenyuk. "On Testing Equality of Distributions of Technical Efficiency Scores." *Economic Review (Federal Reserve Bank of Atlanta)* 25(2006):497–522.

Wand, M.P., and M.C. Jones. *Kernel Smoothing*. New York: Chapman and Hall, 1995.

Weersink, A., C.G. Turvey, and A. Godah. "Decomposition Measures of Technical Efficiency for Ontario Dairy Farms." *Canadian Journal of Agricultural Economics* 38(1990):439–56.

Wilson, P.W. "FEAR: A Package for Frontier Efficiency Analysis with R." *Socio-Economic Planning Sciences* 42(2008):247–54.

Wu, S., S. Devadoss, and Y. Lu. "Estimation and Decomposition of Technical Efficiency for Sugarbeet Farms." *Applied Economics* 35(2003): 471–84.