Economic Efficiency and Factors Explaining Differences

Between Minnesota Farm Households

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Economic efficiency, especially inter-firm differences in efficiency, is one of the major factors explaining differences in firm survival and growth and changes in industry structure. Thus, factors explaining and determining differences in economic efficiency and changes in efficiency between firms are of major interest to owners, managers, and other stakeholders as they strive to improve earnings and improve the chances of firm survival. This current study was undertaken to improve our understanding of the inter-farm differences in and opportunities to improve farm household efficiency in utilizing their land, labor, and capital resources to achieve household objectives.

This study extends current research in several ways. First, it uses a true panel dataset versus the pseudo panel used by Morrison Paul et al (2004). To our knowledge, this study is the first study estimating U.S. agricultural production efficiencies to use bootstrapping procedures to correct the bias generated by the deterministic DEA approach. It is the first to use a weighted Tobit procedure to correct for that same bias. The study is also the first to extend the results of estimating efficiencies and the Tobit identification of explanatory factors to identifying educational opportunities for improving efficiencies.

This study estimated the technical, allocative, and scale efficiencies of farm households in southern Minnesota using a nonparametric, output-based data envelopment analysis (DEA) of a panel dataset of individual farm and household financial records from southern Minnesota from 1993-2005. Technical efficiency (TE) measures the firm's ability to use the best available practices and technology in the most effective way. Allocative efficiency (AE) is dependent on prices and measures the firm's ability to make optimal decisions on product mix and resource allocation. Combining measures of technical and allocative efficiency yields a measure of economic efficiency. Scale efficiency (SE) measures the optimality of the firm's size, so a change in size will not improve output or revenue.

Estimation of efficiency using nonparametric linear programming has its origin with Farrel (1957). Seitz (1970) used linear programming techniques to calculate measures of Farrel-type efficiencies for the single-output case. However, not until Charnes, Cooper and Rhodes (1978) has the generalized linear programming method, known as Data Envelopment Analysis (DEA), been applied widely to estimate technical efficiency, at first within the operating research and management science and later, within the economics community. In US agriculture, Morrison Paul et al. (2004) used survey data collected by the USDA to estimate technical and scale efficiency in US agriculture and found family farms to be both scale and technically inefficient. Wu et al. (2003) computed technical and scale efficiency for Idaho sugar beet farms and concluded that improper scale operation and input over-utilization were the main sources of inefficiency. Tauer (1993) calculated technical and allocative efficiency indices of 395 dairy farms in New York and found that, dairy farms in his sample were more technically efficient but less allocatively efficient in the long run than in the short run.

While most of the studies did not consider nonfarm income and labor in their study, the fact that nonfarm activity now accounts for a large percentage of household income and resources means that they should be incorporated in the calculating of production frontier. As in Morrison Paul et al. (2004) and Chavas et al. (2005), this study incorporated nonfarm income as an output and nonfarm labor as an input in the production technology.

Not many studies using DEA pay much attention to its statistical properties. In the context of the multi-output, multi-input case, the only currently feasible method to establish the statistical property for DEA estimators is by bootstrapping (Simar and Wilson 1998, 2000). Simar and Wilson (1998, 2000) proposed a smoothed bootstrapping method to derive the statistical properties of technical efficiency. This bootstrapping method had been applied empirically to several studies. In agriculture, Latruffe et al. (2005) used bootstrapping in estimating the technical efficiency of crop and livestock farms in Poland. Brümmer (2001) applied it to establish confidence intervals for technical efficiency among private farms in Slovenia. The method was also used in Ortner et al. (2006) for dairy farms in Austria. To our knowledge, bootstrapping the DEA estimators has not been used in studies of US agriculture.

The specific objectives of this study were to (1) estimate technical, allocative, and scale efficiencies of farms using an output based approach, (2) use bootstrap procedures to correct the bias generated by the deterministic DEA method, (3) identify factors that are significant in explaining differences in both levels of efficiency and differences in efficiency among farms and (4) identify educational opportunities for helping farm households improve their efficiencies and, thus, chances for survival.

Methods and Models

Efficiency can be estimated in two ways: parametric and nonparametric. The parametric approach includes specifying and estimating a parametric production frontier (cost or profit function). In contrast, the nonparametric approach, or data envelopment analysis (DEA), has the advantage of no prior parametric restrictions on the technology and thus is less sensitive to misspecification. It is also not subject to assumptions on the distribution of the error term.

Following Chavas et al. (2005), Morrison Paul et al. (2004), and others, we first used nonparametric (DEA) methods to estimate output-based technical, allocative, and scale efficiencies. Based on the smoothed bootstrap procedure for DEA estimators proposed by Simar and Wilson (2000), the study estimated the bias and the confidence interval of the DEA estimators for TE, using the package FEAR developed by Wilson (2005) in the R platform.[1] We then used the estimated efficiencies to identify factors explaining differences among farms by standard and weighted Tobit analysis.

Technical Efficiency

Consider a farm involved in both farm and nonfarm activities with inputs X and producing outputs *(Y, N)* where Y are farm outputs and N is nonfarm income. Nonfarm income is treated as an output because it generates revenue and uses input from the farm family. For the j[th] farm out of n farms, the output-based technical efficiency index, TE, is defined as

$$TE^{j}(X,Y,N) = \min_{q_j, l} q_j \qquad (1)$$

subject to $Y_j / q_j \leq Yl; N_j / q_j \leq Nl; X_j \geq Xl; l \geq 0; \sum_{j=1}^{n} l_j = 1$ where θ is a scalar and λ is a vector of constant λ_j (j=1, …, n).

TE measures the distance between the observed input-output mix and the production frontier. In general, $0 \leq TE \leq 1$; when TE = 1, the farm is producing on the production frontier, and hence, technically efficient. When TE <1, the farm is technically inefficient.

[1] The time for running a bootstrap procedure with 2000 replications for a reference group of 250 farms takes less than one hour for a Pentium IV, 2.8 Ghz computer.

The DEA model above is a variable returns to scale (VRS) DEA model, implying it permits the production frontier to have increasing, constant or decreasing return to scale. In the case of constant return to scale, one can find TE easily by deleting the convexity constraint ($\sum_{j=1}^{n} l_j = 1$).

Allocative Efficiency

The allocative efficiency index can be estimated by using the revenue maximization problem (under VRS):

$$R^j(p, X, Y, N) = \max_{Y,N,l}(p'Y + N) \qquad (2)$$

subject to $Y_j \le Yl; N_j \le Nl; X_j \ge Xl; l \ge 0; \sum_{j=1}^{n} l_j = 1$ where ***p*** is a vector of output prices and other variables are as defined previously. Equation (2) only assumes a well-functioning output market and remains valid despite factor market imperfections. After obtaining maximal revenue $R^j(p, X, Y, N)$ from this problem, we can derive allocative (AE) and economic efficiency (EE) from the equation:

$$EE^j(p, X, Y, N) = (p'Y + N) / R^j(p, X, Y, N)$$

and $AE^j = EE^j / TE^j$.

Thus, EE is the ratio of observed output revenue to maximum revenue for the farm. AE is the economic efficiency after taking out the effect of technical inefficiency. In other words, allocative efficiency is the ratio of the revenue from the hypothetical technical efficient farm to maximal revenue obtained by allocating resources in the “right way”. In general, $0 \le AE \le 1$, where AE=1 represents a farm that is allocatively efficient in output.

Scale Efficiency

Scale efficiency (SE) can be estimated by maximizing the revenue equation (2) under both variable returns to scale (VRS) and constant return to scale (CRS) (Chavas et al. 2005). When assuming CRS, the objective function is similar to (2) but without the condition $\sum_{j=1}^{n} l_j = 1$:

$$R_C^j(p, X, Y, N) = \max_{Y,N,l}(p'Y + N) \tag{3}$$

subject to $Y_j \leq Yl; N_j \leq Nl; X_j \geq Xl; l \geq 0$ where variables are as defined previously. The difference between the two measures is due to scale inefficiency. Thus, the ***scale efficiency index*** (SE) can be expressed as the maximized revenue under VRS divided by the maximized revenue under CRS or $SE^j(p, X, Y, N) = R^j(p, X, Y, N) / R_C^j(p, X, Y, N)$.

In general, $0 \leq SE \leq 1$, with $SE = 1$ representing efficient economy of scale. $SE < 1$ implies that the inputs are not efficient in scale, which can be either increasing returns to scale (IRS) or decreasing returns to scale (DRS). We can decide among farms with scale inefficiency, which farms are "too large" (DRS) or "too small" (IRS) by running a DEA problem with non-increasing returns to scale (NIRS) imposed. This can be done by replacing the constraint $\sum_{j=1}^{n} l_j = 1$ in equation (2) with the constraint $\sum_{j=1}^{n} l_j \leq 1$:

$$R_{NI}^j(p, X, Y, N) = \max_{Y,N,l}\{p'Y + N) \tag{4}$$

subject to $Y_j \leq Yl; N_j \leq Nl; X_j \geq Xl; l \geq 0; \sum_{j=1}^{n} l_j \leq 1$.

Then we can compare the NIRS and the VRS efficiency scores. For a particular farm, if the two scores are unequal and SE<1, the farm is increasing returns to scale. On the other hand, if they are equal and SE< 1, the farm exhibits decreasing returns to scale.

Bootstrapping the DEA estimators

While DEA methods have been widely applied, most researchers largely ignored the statistical properties in the estimators. Any deviation from the frontier is attributed to inefficiency. Ignoring the noise in the estimation can lead to biased DEA estimates and misleading results. This paper applies Simar and Wilson's (1998, 2000) smoothed bootstrap procedure to correct the bias in DEA estimators of TE and establish their confidence interval. Bootstrapping is based on the idea that by resampling the data with replacement, we can mimic the data-generating process characterizing the true data generation. Following Dong and Featherstone (2004), the procedures are the following steps:

i. First we calculated the DEA efficiency scores for each farm among n farms as in equation (1) without the constraint that the sum of λ_i is 1, denoted as $\hat{q}_i$ for the i^th farm.

ii. Then a first, simple bootstrap is made using $\hat{q}_i$ from the first step. Let $b_1^*,....b_n^*$ be a simple bootstrap sample from $\hat{q}_1,..\hat{q}_n$. A random sample of size *n* is generated for the random generator:

$$\tilde{q}_i^* = \begin{cases} b_i^* + he_i^* & if\ b_i^* + he_i^* \le 1 \\ 2 - b_i^* - he_i^* & otherwise \end{cases}$$

where h is the bandwidth of a normal kernel density, calculated from Simar and Wilson's (2000) method of minimizing an approximation to the mean weighted integrated square error, and e_i^* is random deviation.

iii. To obtain the smoothed bootstrap estimates of q_i^*, we now correct the variance of the generated bootstrap sequence since kernel estimators are used by constructing another sequence: $q_i^* = \bar{b}^* + \frac{1}{\sqrt{1+h^2/\hat{s}_q^2}}(\tilde{q}_i^* - \bar{b}^*)$ where $\bar{b}^*$ = (1/N)$\sum_{i=1}^{N} b_i^*$ and

$$\hat{s}_q^2 = \frac{1}{N-1}\sum_{i=1}^{N}(\hat{q}_i - \bar{\hat{q}})^2 .$$

The sequence q_i^* has better properties than the simple bootstrap sequence since the variance of q_i^* is asymptotically correct. We obtain a smoothed bootstrap estimate of DEA efficiency score.

iv. Using the original estimates of technical efficiency, $\hat{q}_i$, and the smoothed bootstrap estimate of efficiency, q_i^*, we construct a pseudo data set of ($x_{i,b}^*$, $y_{i,b}^*$) where $x_{i,b}^*$ = x_i and $y_{i,b}^* = (\hat{q}_i / q_i^*)\, y_i$ with x_i , y_i the original input and output vectors of the i*th* farm, respectively for i=1, .., n and b refers to the iterations done in step vi. The output vector is modified (versus the input vector) since we are estimating efficiency using an output-based DEA.

v. Now we compute the new DEA score $\hat{q}_i^*$ for each farm using the pseudo data set of ($x_{i,b}^*$, $y_{i,b}^*$).

vi. Repeat step (ii) to (v) a sufficiently large number of times, say B, to yield B new DEA technical efficiency scores $\hat{q}_i^*$ for i=1, …, n. In our empirical work, we set B=2000 to ensure the low variability of the bootstrap confidence intervals. The number of bootstrap iterations should be more than 1000 if we are interested in confidence interval estimation. A smaller number of iterations would be enough if we only needed estimates for bias and standard deviation (see Efron and Tibshirani 1993).

vii. Calculate the bootstrap bias estimate for the original estimator $\hat{q}_i$ as

$$\widehat{bias}_B(\hat{q}_i) = B^{-1}\sum_{b=1}^{B}\hat{q}_i^{*} - \hat{q}_i \ .$$

The bias-corrected estimator of $\hat{q}_i$ can be computed as $\hat{\hat{q}}_i = \hat{q}_i - \widehat{bias}_B(\hat{q}_i)$

The percentile method is involved in constructing confidence interval. The confidence interval for the true value of $\hat{q}_i$ can be established by finding value a_a, b_a such that Prob $(-b_a \le \hat{q}_i^{*} - \hat{q}_i \le -a_a) = 1 - a$. Since we do not know the distribution of $(\hat{q}_i^{*} - \hat{q}_i)$, we can use the bootstrap values to find $\hat{a}_a, \hat{b}_a$ such that Prob $(-\hat{b}_a \le \hat{q}_i^{*} - \hat{q}_i \le -\hat{a}_a) = 1 - a$. It involves sorting the value of $(\hat{q}_i^{*} - \hat{q}_i)$ for b =1,…,B in increasing order and deleting $((a/2)\times 100$ percent of the elements at either end of this sorted array and setting $-\hat{a}_a$ and $-\hat{b}_a$ at the two endpoints, with $\hat{a}_a \le \hat{b}_a$.

Tobit analysis

Most authors have used Tobit analysis in the second stage after calculating the efficiency scores to assess the factors influencing efficiency. The use of the Tobit specification is often motivated by the fact that sometimes many values in the efficiency scores are equal to unity. On the other hand, the bias-corrected estimator of technical efficiency generally has higher mean-square error than the original estimates. Simar and Wilson (2000) suggest that one should avoid using the bias-corrected estimates unless $\hat{s}^2 \langle \frac{1}{3}(bias[\hat{q}])^2$ in which $\hat{s}^2$ is the sample variance of the bootstrap values and $\hat{q}$ is the uncorrected estimated efficiency score.

In our sample, this only holds for about 5% of the sample, which could justify the use of the original technical efficiency scores in the second stage. However, the information about the standard error and confidence intervals of the DEA estimator in the first step is very important in indicating the sensitivity of the DEA estimator. The larger the variance is, the more imprecise the calculation of efficiency score might be. Therefore, in the second stage, we apply two Tobit specifications for technical efficiency. The first is the conventional Tobit regression and the second is the weighted Tobit regression with weight equal to the reciprocal of standard error in the first stage. The weighted Tobit regression uses the information on the variances of technical efficiency scores to improve the estimation by prioritizing the observations with lower standard errors and "punishing" those with higher standard errors.

Since the procedures for estimating the bias in DEA estimators for scale and allocative efficiency have not been developed, we use the conventional Tobit analysis for these efficiencies.

Data

For this analysis, we used data from the Southeastern and Southwestern Minnesota Farm Business Associations collected by the Department of Applied Economics at the University of Minnesota. The complete data contains financial and farm characteristic records from about 400 farms, which had been members of either Association in at least one year from 1993 through 2005, and had records of sufficient quality to be included in at least one year. The number of records per year averaged 230 and ranged from a high of 263 in 1995 and 1999 to a minimum of 138 in 2005. Membership in the Associations is not stable; farms have differing frequencies of years in the data. There are 47 farms with only one year of data and

67 farms with 13 years of data. Eighty percent of the observations were from the 211 farms (53% of the total) with 8 to 13 years of data.

The model includes nine inputs: three labor inputs (family labor on farm, hired labor on farm, nonfarm labor), three nonlabor variable inputs categorized into livestock-related, crop-related, and operating-related expenditures, and three inputs for land (rented crop land, owned crop land, and owned pasture land, Table 1). Data for nonlabor and land inputs come directly from the data base. Labor expenses are not included in these expense categories since they are accounted for in other input measures. Income tax expenses are not included in these expenses variables. Family labor working on the farm is the total unpaid labor hours. Hired labor working on the farm is the total (paid) hired labor hours.

Table 1. Summary Statistics of Variables for DEA Estimation

	Variable	Mean	Std. Dev.
Output	Corn production value [a]	34.1	(37.8)
	Soybean production value [a]	26.2	(27)
	Beef production value [a]	4.3	(16)
	Milk production value [a]	14.9	(59.8)
	Hog production value [a]	23.6	(142.6)
	Nonfarm Income [a]	21.8	(29.5)
Inputs	Family labor [b]	2.8	(1.8)
	Hired labor [b]	1.0	(2.9)
	Nonfarm labor [b]	1.0	(1.4)
	Livestock-related expenditures [a]	29.4	(77.6)
	Crop-related expenditures [a]	21.9	(21.1)
	Operating-related expenditures [a]	37.5	(42.7)
	Owned crop land area (acres)	241	287
	Rented crop land area (acres)	439	(438)
	Owned pasture land (acres)	12	(54)
Prices	Corn price ($/bu)	2.10	(0.40)
	Soybean price ($/bu)	5.64	(0.99)
	Beef price ($/cwt)	64.09	(7.29)
	Milk price ($/cwt)	13.88	(1.35)
	Hog price ($/cwt)	43.51	(7.10)

[a] thousand $; [b] thousand hours

Since we did not have direct information on the hours of nonfarm family labor (i.e., working hours not on the farm), we estimated these hours from the available data on total nonfarm wages and salary. A proxy for nonfarm wages was taken from the average nonfarm wages of the counties where the farms reside. The nonfarm wages based on the weighted average wages of nonfarm sectors, specifically construction, manufacturing, and service wages from 2000 to 2004 (NAICS Industries list) and of mining, construction, manufacturing, transportation, finance, services, public administration, and trade wages from 1993-1999 (SIC Industries list). After calculating the nonfarm wages at the county level, we estimated each farm's nonfarm labor hours as that farm's total nonfarm wages and salary divided by the appropriate county's nonfarm wage rate.

The model includes six outputs: two crops (corn and soybean), three livestock products (beef, milk, and hog), and nonfarm income. Corn and soybean were the most important crop outputs in Minnesota. They were produced in more than 90% of our sample and contributed 91% of total crop production value. Among livestock, hog and milk are more important than beef in production value (43%, 40% and 11% of total livestock production value, respectively). Together, these three outputs account for 94% of total livestock production value. Nonfarm income generates about 16% of total output value generated by the six outputs in our study.

Annual output price data were taken from National Agricultural Statistics Service, assuming farms in the region faced the same prices for their outputs in a given year.

Physical crop production for a specific crop on an individual farm in a specific year was calculated by dividing that farm's gross production value by that year's price of that crop. Physical livestock production for a specific livestock enterprise on an individual farm in a specific year was calculated by dividing the total livestock value by the price of livestock.

The variables used in the Tobit analysis to determine factors explaining differences in farm efficiencies include financial condition, farm characteristics, labor characteristics, land tenure, and the relative importance of different outputs (Table 2). Financial condition and farm characteristics were measured by farm income, total asset, debt-asset ratio, depreciation ratio, current asset share, farm investment rate, capital-labor ratio, and land-labor ratio. Labor characteristics were measured by the number of operators, main operator's years farming, and hired labor ratio. Land tenure was measured by the tenancy ratio. The relative importance of different outputs was measured by the nonfarm income ratio and the Herfindahl index. The Herfindahl index measures the degree of output concentration and is defined as $\sum_{i=1}^{n} s_i^2$ in which s_i is the share or ratio of each farm's output of the i^{th} output to the total of that farm's six outputs in this study.

Results

Efficiency estimates obtained from the DEA analysis are presented with technical efficiency first followed by allocative and then scale efficiency. Significant explanatory factors are then identified.

Efficiencies

<u>Technical efficiency.</u> Over all years and farms, the initial estimate of average technical efficiency was 0.87, assuming constant returns to scale (TEC), and 0.90, assuming variable returns to scale (TEV) (Table 3). Over time, both estimates of average technical efficiency

have followed a similar, variable pattern with a slight upward trend: from 0.86 in 1993 to 0.90 in 2005 for TEC, and 0.89 to 0.92 for TEV. These initial estimates showed a majority of farms being technically efficient: 52.8% of farms have an estimated TEC score of 1 and 60.3 % have an estimated TEV score of 1. These estimates of technical efficiency are similar to Morrison Paul et al. (2004) estimates of technical efficiencies for ten corn producing states in the Midwest (which includes Minnesota) using data from USDA's Agricultural Resources Management Study (ARMS) from 1996-2001.

Table 2. Summary Statistics of Explanatory Variables for Tobit Analysis

Description of Variables	Variables	Mean	Standard deviation
Gross farm income [a]	Farm income	397.2	(440.9)
Value of farm and nonfarm asset [a]	Asset	1,159	(948.8)
Number of operators	Number of operators	1.19	(0.65)
Years of farming of the main operator	Years of farming	24.59	(11.28)
Ratio of nonfarm income/ Total income	Nonfarm ratio	0.09	(0.13)
Ratio of hired hours/ Total labor hours	Hired labor ratio	0.14	(0.24)
Ratio of rented land/ Total land	Tenancy ratio	0.6	(0.33)
Debt/Asset Ratio	Debt/Asset Ratio	0.51	(0.23)
Current Asset/ Total assets	Current asset share	0.25	(0.16)
Depreciation expense ratio	Depreciation Ratio	0.08	(0.06)
Herfindahl Index	Herfindahl Index	0.48	(0.14)
Capital/Labor ratio ($thousand/hour)	Capital/Labor ratio	4.44	(4.23)
Land/Labor ratio (acres/hour)	Land/Labor ratio	2.46	(1.86)
Farm investment value/ Gross farm income	Investment rate	0.16	(0.39)
Corporate =1 if corporate or partnership farms; 0 otherwise	Corporate	0.16	(0.37)
Region = 1 if Southeast Minnesota; 0 for Southwest Minnesota	Region	0.23	(0.42)

[a] thousand dollars

Table 3. Average Efficiency Estimates, 1993-2005

	Technical Efficiency by CRS	Allocative Efficiency	Scale Efficiency	Technical Efficiency by VRS	Bias corrected TEV	Lower bound	Higher bound
1993	0.857	0.696	0.845	0.886	0.749	0.675	0.879
1994	0.827	0.730	0.860	0.869	0.707	0.656	0.859
1995	0.812	0.708	0.867	0.850	0.684	0.636	0.840
1996	0.896	0.715	0.871	0.919	0.817	0.716	0.915
1997	0.891	0.789	0.905	0.916	0.827	0.717	0.914
1998	0.892	0.815	0.898	0.913	0.806	0.712	0.908
1999	0.869	0.804	0.891	0.895	0.775	0.695	0.891
2000	0.872	0.703	0.875	0.901	0.792	0.714	0.896
2001	0.875	0.821	0.899	0.904	0.773	0.694	0.898
2002	0.844	0.789	0.862	0.884	0.754	0.684	0.878
2003	0.886	0.855	0.907	0.916	0.816	0.725	0.911
2004	0.901	0.834	0.933	0.913	0.794	0.711	0.908
2005	0.902	0.851	0.911	0.923	0.801	0.703	0.918
All farms	0.869	0.771	0.884	0.897	0.774	0.694	0.892
Median	1.000	0.801	0.934	1.000	0.813	0.694	0.892
Std. Dev.	0.185	0.219	0.139	0.165	0.129	0.114	0.164
Skewness	-1.281	-0.597	-1.692	-1.580	-1.438	-1.090	-1.580
Kurtosis	3.612	2.279	6.369	4.583	5.095	5.259	4.580

Applying the bootstrap procedure by Simar and Wilson (2000), we found that the bias was considerable. While the average initial TEV was 0.90, the bias-corrected point estimate was 0.77, or 86.3% of the initial, uncorrected estimate. Over time the bias-corrected TEV followed a trend similar to, but more accentuated than, that of the initial TEV estimate. The largest group of farms had a bias-corrected TEV between 0.75 and 0.90 compared to the largest group that had an initial TEV estimate of 1.0. When farms are ranked by their bias-corrected TEV (from lowest to highest), the quantitative disparities between the initial and corrected TEV estimates were extremely obvious (Figure 1). This graph also showed that the initial TEV estimates did not provide the same ranking of individual farms since they did not form a smooth line following the corrected TEV. Also visible is the variability in the lower and upper bounds of the corrected TEV, even between farms with similar expected values of corrected TEV. This variability was greatest for those farms with initial TEV estimates of 1.0.

The initial TEV estimate suggested that with a given input, an "average" farm could expand its output by about 11.5 % = (((1/0.90)-1)*100%) if technical efficiency were improved to 1.0. The bias-corrected TEV, however, suggested an expected output expansion of 29.2% = (((1/0.77)-1)*100%). The lower and upper bounds of the 95% confidence interval for the bias-corrected TEV were 0.69 and 0.89, respectively, which suggested that the amount an "average" farm could expand its output by increased technical efficiency ranged from 12.1% to 44.1%.

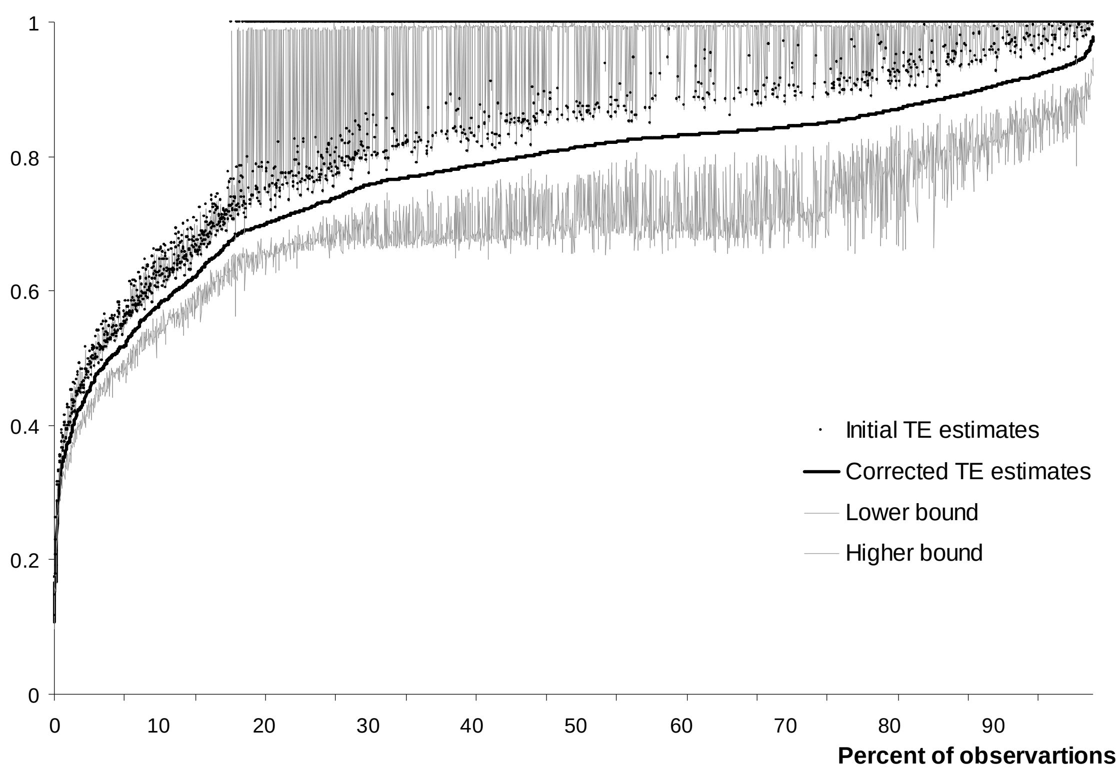

Figure 1. Distribution of technical efficiency with confidence intervals

Allocative efficiency. In terms of allocative efficiency (AE), a majority of the farms in this study are not efficient, that is, these farms did not make the correct allocation of inputs to produce the correct set of outputs to maximize revenue based on the prices received. Over all years, average AE was 0.77 with 30.8% of the farms having a score of 1. Thus, the average farm was estimated to potentially have the ability to increase revenue by 29.7% if price signals had been responded to perfectly. Except for one year (i.e., 2000), average AE followed a fairly stable upward trend over time.

Scale Efficiency. Average scale efficiency (SE) was 0.88 with only 19.9% of the farms having an SE score of 1. However, many farms were near SE: 58.1% of farms had an SE score higher than 0.90 and 45.1% of farms had an SE score higher than 0.95. These estimates of scale efficiency were smaller than those estimated by Morrison Paul et al.'s (2004) estimates of scale efficiencies using USDA ARMS data. Similar to TE and AE, average SE trended upward with some variability over time. Among the farms being scale inefficient (i.e., SE<1), the distribution between farms that are "too large" (having decreasing returns to scale (DRS)) and farms that are "too small" (increasing returns to scale (IRS)) are sharply different. Using the procedures described earlier, 61.8 % of farms were found to be "too large" compared with 18.3 % being "too small" and 19.9% at an optimal scale of operation.

In summary, farms tended to be more technically efficient (using the initial estimates of TEV), followed by scale efficiency, and then by allocative efficiency. However, when using bias-corrected TEV, farms were more scale efficient followed by technical and allocative efficiency. The overall average for scale efficiency is higher than the average allocative efficiency, but the percentage of farms with a score of 1 is higher for allocative efficiency compared to scale efficiency. This apparent difference in signal can be explained in the different distributions shown in the skewness and kurtosis statistics.

Factors explaining differences in efficiencies

Tobit analysis was used to identify significant factors explaining differences in technical, allocative, and scale efficiencies between farms. The estimated efficiency scores of farms during the period 1993-2005 (presented above) were regressed on the explanatory variables.

Technical Efficiency. The Tobit results for explaining technical efficiency (assuming variable returns to scale) are reported in Table 4. A few explanatory variables changed significance levels but no signs of coefficients changed with the weighted Tobit compared to the standard Tobit. When all years and observations are analyzed together, explanatory variables for technical efficiency that had a significant,[2] positive impact in both models were region, current asset share, nonfarm ratio, capital/labor ratio, land/labor ratio, Herfindahl index, and number of operators. Explanatory variables that had a significant, negative impact in both models were tenancy ratio, years of farming, and the farm's debt/asset ratio. The hired labor ratio did not have a significant effect in the standard model but it had a significant, positive impact in the weighted model. Year had a significant, negative coefficient in the weighted Tobit, but it was not significant in the standard Tobit. Significant, positive impacts of the business organization (i.e., Corporate) and the depreciation ratio were found in the standard Tobit but were not significant in the weighted Tobit. Farm income, asset, and investment rate did not have a significant impact in either model.

[2] Tables indicate 95% and 99% significance. When used in the text, "significant" refers to a coefficient with significance greater than 95% (i.e., $p<0.05$). To improve readability, this reference is not included at all points.

Table 4. Tobit Analysis of Technical Efficiency.

	Standard Tobit		Weighted Tobit	
year	0.00	(-1.63)	-0.008	(-3.21)**
Region	0.10	(3.8)**	0.078	(2.64)**
Current asset share	0.76	(10.29)**	0.854	(9.48)**
Tenancy ratio	-0.10	(-3.11)**	-0.101	(-2.48)*
Farm income	0.03	(0.8)	0.056	(1.15)
Asset	0.03	(1.46)	0.048	(1.9)
Years of farming	0.00	(-4.61)**	-0.005	(-5.15)**
Nonfarm ratio	0.64	(7.85)**	0.909	(8.53)**
Capital/Labor ratio	0.02	(3.69)**	0.017	(3.07)**
Land/Labor ratio	0.02	(2.41)*	0.021	(2.59)**
Debt/Asset Ratio	-0.19	(-4.75)**	-0.271	(-6.03)**
Hired labor ratio	0.07	(1.59)	0.117	(2.31)*
Herfindahl Index	0.68	(10.74)**	0.813	(10.78)**
Investment rate	-0.01	(-0.3)	0.000	(0)
Corporate	0.09	(2.14)*	0.060	(1.09)
Depreciation Ratio	0.29	(2.39)*	0.149	(1.08)
Number of operators	0.09	(2.59)**	0.104	(2.05)*
Constant	7.64	(1.73)	16.724	(3.26)**
Number of obs	2503		2436	
LR chi2(17)	554.05		498.24	
Log likelihood =	-968.22		-1105.5	

Note: t- statistics are in parentheses. *, **: significant at 95% and 99% confidence level respectively.

In the weighted Tobit regression, which better accounts for measurement errors as argued above, a higher current asset share and a lower debt-to-asset ratio contributed to higher technical efficiency. Both capital-to-labor and land-to-labor ratios had positive coefficients, indicating that increasing capital and land relative to labor can raise technical efficiency. A higher hired labor ratio (that is, a higher level of hired labor relative to operator labor) had a positive effect, indicating the importance of expanding the total amount of available labor by adding hired labor to the supply of operator labor. Similarly, farms with more operators (i.e., a higher supply of labor and management) had higher technical efficiency. On the other hand, the land tenancy ratio which measures the amount of rented land relative to the farm's total land had a negative effect, similar to the pattern of farms in Central Europe found by Balcombe et al. (2005). Farms which were more specialized, that is, concentrated on a smaller set of outputs, as represented by the Herfindahl index, were found to have a higher technical efficiency than less specialized farms. Having a higher level of nonfarm income relative to total household income was also associated with higher technical efficiency. Years of farming, an indication of both age and experience, had a dampening effect on technical efficiency. Farm size (as represented by farm income, asset level, and the farm investment ratio) had no significant relationship with farm technical efficiency. A slight negative trend was shown by the significant negative coefficient on year; so the slight positive trend seen in Table 3 must be explained by trends in other variables, not as a general trend in TE itself. The region variable indicated farms in Southeast Minnesota were more technically efficient than Southwest farms. Business organization, as indicated by the dummy variable for partnership/corporate farms, was not significant in the weighted Tobit analysis. Nor was the degree of mechanization, as indicated by the depreciation ratio.

Allocative efficiency. The Tobit results for explaining allocative efficiency (assuming variable returns to scale) are reported in Table 5. Those explanatory variables with significant positive impacts on allocative efficiencies were year, current asset share, tenancy ratio, asset, nonfarm ratio, capital/labor ratio, land/labor ratio, hired labor ratio, the Herfindahl index, corporate, depreciation ratio, and the number of operators. Those explanatory variables which have significant, negative impacts on allocative efficiency were farm income, years of farming, and debt/asset ratio. As with technical efficiency, a higher current asset share and a lower debt-to-asset ratio were associated with better allocative efficiency. Nonfarm income opportunities were again found to play a positive role in helping farmers allocate their resources better. Increasing the amount of capital and land relative to labor, as well as the amount of hired labor to total labor, also helped improve allocative efficiency. Higher levels of specialization as measured by the Herfindahl index also were associated with higher allocative efficiency.

Table 5: Tobit Analysis of Allocative Efficiency and Scale Efficiency

	Allocative Efficiency		Scale Efficiency					
					Farms with		Farms with	
	All Farms		All Farms		IRS & CRS		DRS	
year	0.005	(3.35)**	0.002	(2.19)*	-0.007	(-2.27)*	0.005	(5.65)**
Region	0.026	(1.49)	0.006	-0.61	-0.01	(-0.35)	0.016	-1.57
Current asset share	0.171	(3.77)**	0.113	(4.12)**	0.318	(4.33)**	0.002	(0.06)
Tenancy ratio	0.097	(4.35)**	0.083	(6.09)**	0.093	(2.72)**	0.063	(4.65)**
Farm income	-0.106	(-4.95)**	0.004	(0.3)	-0.084	(-1.75)	0.03	(2.74)**
Asset	0.027	(2.46)*	-0.032	(-4.99)**	0.161	(5.7)**	-0.057	(-9.66)**
Years of farming	-0.002	(-3.48)**	0	(0.21)	0	(-0.15)	0	(-0.09)
Nonfarm ratio	0.897	(15.7)**	0.305	(9.25)**	0.795	(9.51)**	-0.038	(-1.01)
Capital/Labor ratio	0.01	(3.66)**	0.012	(7.24)**	0.004	(0.98)	0.007	(3.32)**
Land/Labor ratio	0.032	(7.14)**	0.005	(2.08)**	0.019	(2.95)**	0	(0.11)
Debt/Asset Ratio	-0.099	(-3.6)**	-0.073	(-4.39)**	0.018	(0.38)	-0.088	(-5.65)**
Hired labor ratio	0.138	(4.92)**	0.112	(6.62)**	0.035	(0.77)	0.092	(5.52)**
Herfindahl Index	0.796	(18.7)**	0.206	(8.13)**	0.473	(6.72)**	0.066	(2.66)**
Investment rate	0.016	(1.3)	-0.006	(-0.75)	0.003	(0.22)	-0.02	(-1.93)*
Corporate	0.064	(2.44)*	-0.041	(-2.6)**	-0.097	(-2.41)*	-0.022	(-1.43)
Depreciation Ratio	0.519	(6.15)**	0.105	(2.06)*	0.066	(0.5)	0.051	(1.03)
Number of operators	0.071	(3.33)**	0.013	(1.05)	0.043	(1.33)	-0.012	(-0.93)
Constant	-10.31	(-3.33)**	-3.497	(-1.84)	13.364	(2.33)*	-9.001	(-5.16)**
Number of obs	2503		2503		904		1599	
LR chi2(17)	1114.6		525.56		287.6		285.3	
Log likelihood =	-442		711.8		-168.9		1318.2	

Note: t- statistics are in parentheses.; *, **: significant at 95% and 99% confidence level respectively

Notable differences in significance between factors explaining allocative efficiency compared to those explaining technical efficiency include the positive effects of land tenancy ratio (compared to a negative effect) and total asset value (compared to no effect). Thus, while a higher rented land ratio was associated with lower technical efficiency, it was associated with higher allocative efficiency, perhaps because land rental expanded the available resources for farm production and allowed for a better mix of enterprises. The level of farm income had a significant, negative impact on allocative efficiency compared to no effect on technical efficiency.

Scale efficiency. The Tobit results for explaining scale efficiency are reported in Table 5. When all farmers are grouped together, the explanatory variables that had a significant positive impact were year, current asset share, tenancy ratio, nonfarm ratio, capital/labor ratio, land/labor ratio, hired labor ratio, the Herfindahl index, and the depreciation ratio. As with technical and allocative efficiency, a higher current asset share; a lower debt-to-asset ratio; higher levels of capital, land, and hired labor relative to total labor; and increased specialization (as measured by the Herfindahl index) were associated with better scale efficiency. Variables that had a significant negative impact were asset, debt/asset ratio, and business organization (i.e., corporate). Variables which did not have any significant impact were region, farm income, years of farming, investment rate, and the number of operators.

Farms with scale inefficiency (i.e., SE < 1) were separated into farms with DRS and farms with either CRS or IRS using the NIRS procedure described earlier. Weighted Tobit analysis was then done for the two sub-samples.[3] For both types of farms, higher tenancy ratios and higher specialization (i.e., Herfindahl index) improved scale efficiency. The current asset share and the land/labor ratio had significant positive impact for "too small" farms, but, deviating from the aggregate analysis, they did not have a significant impact on

[3] We group farms with CRS and with IRS to increase the number of observations. The results are not significantly different when we run regression on farms with IRS only.

“too large” farms. Business organization (i.e., corporate) had a negative impact on “too small” farms. For “too large” farms, farm income, capital/labor ratio, hired labor ratio, and the investment rate had significant positive impacts, but they did not have a significant impact on “too small” farms. The debt-to-asset ratio had a significant negative impact on “too large” farms. As should be expected, since we are analyzing scale, the size of farm as measured by asset level had different effects: positive for “too small” farms and negative for “too large” farms. “Too small” farms had a significant negative trend in scale efficiency over time indicating some concern for the future; while “too large” farms had a significant positive trend in scale efficiency. Years of farming, depreciation rate, and the number of operators did not have a significant impact on either group of farms.

Conclusions

The results of the analysis of technical, scale and allocative efficiency show the degree of inefficiency in Minnesota farms to be considerable. The farms tend to be more technically efficient, followed by scale efficiency, and then by allocative efficiency. On average, initial technical efficiency, scale and allocative efficiency are 0.90, 0.88 and 0.77 during the period 1993-2005. In general, farm efficiency improved over the period. The study employed bootstrapping to determine the variability of DEA technical efficiency estimates and to correct for the bias inherent in the deterministic measurement. The bias-corrected point estimate of technical efficiency was 0.77. With bootstrapping, the width of the confidence intervals was estimated to be about 0.2 on average.

These estimates were employed in the second step to evaluate factors influencing efficiency. This Tobit analysis suggested that more specialized farms (as measured by the

Herfindahl index) have higher levels of efficiency by all three measures (Table 6). A higher proportion of rented land (as indicated by the tenancy ratio) is associated with higher allocative and scale efficiency but lower technical efficiency. A higher current asset share and a lower debt-to-asset ratio are positively associated with all three measures of farm efficiency, except the current asset share had no effect on scale efficiency for “too big” farms and the debt-to-asset ratio had no effect on scale efficiency for “too small” farms. A higher proportion of household income coming from nonfarm sources and higher hired labor, capital-to-labor, and land-to-labor ratios had positive effects on all three efficiency measures, except the nonfarm and land-to-labor ratios had no effect on scale efficiency for “too big” farms and the capital-to-labor and hired labor ratios had no effect on scale efficiency for “too small” farms.

Table 6. Summary of Significant Explanatory Variables in Tobit Analysis and their Impact on Each Efficiency Measure*

Explanatory variable	TEV	AE	SE (with all farms)	SE (for farms with IRS & CRS)	SE (for farms with DRS)
year	–	+	+	–	+
Region	+				
Current asset share	+	+	+	+	
Tenancy ratio	–	+	+	+	+
Farm income		–			+
Asset		+	–	+	–
Years of farming	–	–			
Nonfarm ratio	+	+	+	+	
Capital/Labor ratio	+	+	+		+
Land/Labor ratio	+	+	+	+	
Debt/Asset Ratio	–	–	–		–
Hired labor ratio	+	+	+		+
Herfindahl Index	+	+	+	+	+
Investment rate					–
Corporate		+	–	–	
Depreciation Ratio		+	+		
Number of operators	+	+			

*+ and – indicate the sign of those coefficients that have a significance of at least 95%.

Several conclusions and suggestions for improving farm efficiencies can be drawn from these results. First, while these results do not show a direct causal relationship, a higher current asset share and a lower debt-to-asset ratio are associated with higher efficiency levels. Management skills that improve these financial measures likely improve efficiency, so improvement of management skills in general, through education of current and future farmers, appears to be needed. Increasing the amount of rented land relative to owned land has a positive impact on allocative and scale efficiency so improved land markets and the ability to obtain and hold additional land is critical. So improvement in land market negotiation skills and intra-personal skills dealing with absentee landowners can lead to efficiency improvements. However, since a higher tenancy ratio was associated with lower technical efficiency, improvements in managing larger operations and rented properties appears to be needed. The positive impact of nonfarm income shows the need for farm households to take advantage of nonfarm opportunities as well as the need for rural communities to expand and develop those opportunities. Better access to both debt and nonfarm equity capital can improve efficiencies. This includes the identification and use of nonfarm capital (such as partnerships and investments by nonfarmers) and the identification and use of lower cost-debt capital for expansion and improvements as well as the increased management ability to manage higher debt loads. The positive impact of higher capital-to-labor and land-to-labor ratios indicates the need for more intensive use of available labor through increased mechanization and expansion of the land base. These steps can be seen as needing to accompany the ability to access more debt and equity capital. The positive hired labor ratio illustrates the impact of hiring labor and thus, presumably, freeing the farm household to spend more time on management—following the highest and best use argument for the owner's time allocation. The need to increase the relative amount of hired labor points to the need to increase personnel management ability in farmers and thus personnel management educational opportunities for current and future farmers. The positive impact of the Herfindahl index shows the need to increase management skills, and risk management skills especially, to handle more specialized operations that will rely on off-farm tools for protection from uncertainty versus relying on on-farm diversification as a risk decreasing tool.

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