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An Analysis of Economic Efficiency in Agriculture: A Nonparametric Approach

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A nonparametric analysis of technical, allocative, scale, and scope efficiency of agricultural production is presented based on a sample of Wisconsin farmers. The results indicate the existence of important economies of scale on very small farms, and of some diseconomies of scale for the larger farms. Also, it is found that most farms exhibit substantial economies of scope, but that such economies tend to decline sharply with the size of the enterprises. Finally, the empirical evidence suggests significant linkages between the financial structure of the farms and their economic efficiency.

Key words: efficiency, financial structure, nonparametric, production, scope.

Introduction

Much research has focused on the economic efficiency of agricultural production. Issues related to the structure of agriculture, the survival of the family farm, as well as the effects of agricultural policy on smaller farmers have remained controversial. The analysis typically has centered on the technical, allocative,[1] and scale efficiency of farm production (e.g., Timmer; Lau and Yotopoulos; Yotopoulos and Lau; Sidhu and Baanante; Hall and Leveen; Kalirajan; Garcia, Sonka, and Yoo). It has been motivated in large part by an attempt to identify the factors influencing the efficiency of resource allocation in agriculture. For example, Sidhu and Baanante; Kalirajan; and Garcia, Sonka, and Yoo found empirical evidence suggesting that small farms are as efficient as larger farms.

The analysis of efficiency has fallen into two broad categories: parametric and nonparametric. The parametric approach relies on a parametric specification of the production function, cost function, or profit function (e.g., Forsund, Lovell, and Schmidt; Bauer). For example, the profit function specification proposed by Lau and Yotopoulos, and Yotopoulos and Lau has been fairly popular in the investigation of farm production efficiency (e.g., Sidhu and Baanante; Kalirajan; Garcia, Sonka, and Yoo). It provides a consistent framework for investigating econometrically the technical, allocative, and scale efficiency of profit-maximizing production units. However, it relies on a fairly restrictive Cobb–Douglas technology, which implies unitary Allen elasticity of substitution among inputs. This illustrates an important weakness of the parametric approach: in general, it requires imposing parametric restrictions on the technology and the distribution of the inefficiency terms (Bauer).

Alternatively, production efficiency analysis can rely on nonparametric methods (e.g., Seiford and Thrall). Building on the work of Farrell and of Afriat, the nonparametric approach has the advantage of imposing no a priori parametric restrictions on the un-

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derlying technology (e.g., Färe, Grosskopf, and Lovell). Also, it can easily handle disaggregated inputs and multiple output technologies. As the nonparametric approach develops (e.g., Hanoch and Rothschild; Varian; Banker, Charnes, and Cooper; Färe, Grosskopf, and Lovell; Byrnes et al.; Chavas and Cox 1988, 1990; Cox and Chavas; Deller and Nelson), its applications to production analysis have become more refined. This provides some new opportunities for the empirical analysis of economic efficiency.

This article focuses on various aspects of production efficiency based on a nonparametric approach. First, we review the characterization of technical, allocative, and scale efficiency. We also consider scope efficiency. Economies of scope relate to the benefits of integrated multiproduct firms (compared to specialized enterprises) (see Baumol, Panzar, and Willig). This is of special interest in agriculture since most farms produce more than one output. Second, we propose nonparametric measures of various indexes of efficiency: technical, allocative, scale, and scope efficiency. Our empirical measurement of scope efficiency appears to be new in the literature. All indexes are easy to measure empirically; they involve only the solutions of linear programming problems. Third, we illustrate the usefulness of the approach by applying it to a sample of Wisconsin farms. The results identify various sources of inefficiency on Wisconsin farms. They indicate the existence of important economies of scale on very small farms and show some diseconomies of scale on the larger farms. Also, it is found that, while most farms exhibit substantial economies of scope, such economies tend to decline sharply with the size of the enterprises. Finally, the empirical evidence suggests significant linkages between the financial structure of the farms and their economic efficiency.

The Measurement of Production Efficiency

This section provides a brief literature review on production efficiency. Consider a firm using an $(M \times 1)$ input vector $x = (x_1, x_2, \ldots, x_M)' \in \Re^{M+}$ in the production of an $(N \times 1)$ output vector $y = (y_1, y_2, \ldots, y_N)' \in \Re^{N+}$. Characterize the underlying technology by the production possibility set T_v, where $(y, -x) \in T_v$. We assume that T_v is a non-empty, closed, convex, and negative monotonic set[2] that represents a general technology under variable return to scale (VRTS).

We will also make use of the cone technology T_c defined as

$$T_c = \mathrm{cl}\{(y, -x): (ky, -kx) \in T_v \ \forall\ k \in \Re^+\},$$

where $\mathrm{cl}\{\cdot\}$ denotes the closure of the set $\{\cdot\}$. Note that T_c exhibits constant returns to scale (CRTS) and satisfies $T_v \subseteq T_c$. The cone technology T_c generated by T_v is the smallest closed CRTS technology that contains T_v.

Let the $(M \times 1)$ vector $r = (r_1, r_2, \ldots, r_M)' \in \Re^{M+}$ denote the market prices for inputs x. Under competition, consider the cost minimization problem

$$C(r, y, T) = r'x^* = \min_x\{r'x: (y, -x) \in T, x \in \Re^{M+}\},$$

where $x^* = \mathrm{argmin}_x\{r'x: (y, -x) \in T, x \in \Re^{M+}\}$ is the cost minimizing input demand functions under technology T.

Technical Efficiency

The concept of technical efficiency relates to the question of whether a firm uses the best available technology in its production process. Following the work of Debreu; Farrell; Farrell and Fieldhouse; and Färe, Grosskopf, and Lovell, technical efficiency can be defined as the minimal proportion by which a vector of inputs x can be rescaled while still producing outputs y.[3] For a firm choosing the output–input vectors (y, x), this corresponds to the Farrell technical efficiency index, TE:

$$TE(y, x, T_v) = \inf_k\{k: (y, -kx) \in T_v, k \in \Re^+\}. \tag{1}$$

In general, $0 < TE \leq 1$, where $TE = 1$ implies that the firm is producing on the production frontier and is said to be technically efficient. Alternatively, $TE < 1$ implies that the firm is not technically efficient. In this case, $(1 - TE)$ is the largest proportional reduction in inputs x that can be achieved in the production of outputs y. Alternatively, $(1 - TE)$ can be written as $[r'x - (TE)r'x]/(r'x)$, implying that $(1 - TE)$ can be interpreted as the largest percentage cost saving that can be achieved by moving the firm toward the frontier-isoquant through a radial rescaling of all inputs x.

Allocative Efficiency

Following Farrell, and Farrell and Fieldhouse, the concept of allocative efficiency (also called "price efficiency") is related to the ability of the firm to choose its inputs in a cost minimizing way. It reflects whether a technically efficient firm produces at the lowest possible cost. For a given input choice x, this generates the Farrell allocative efficiency index AE:

$$AE(r, y, T_v) = C(r, y, T_v)/[r'(TE)x], \tag{2}$$

where $C(r, y, T_v)$ is the cost function under technology T_v, and $[(TE)x]$ is a technically efficient input vector from (1). In general, $0 < AE \leq 1$, where $AE = 1$ corresponds to cost minimizing behavior where the firm is said to be allocatively efficient. Alternatively, $AE < 1$ implies allocative inefficiency. In this case, $(1 - AE)$ measures the maximal proportion of cost the technically efficient firm can save by behaving in a cost minimizing way.

Note that the two indexes TE and AE in (1) and (2) both depend on outputs y. Thus, they can be interpreted as being conditional on scale y (Seitz). Also, they can be combined into an economic efficiency index given scale y, defined to be the product of the two indexes (1) and (2):

$$(TE\ AE) = C(r, y, T_v)/r'x,$$

where $0 < (TE\ AE) \leq 1$. Then, $(TE\ AE) = 1$ implies that the firm is both technically and allocatively efficient. Alternatively, $(TE\ AE) < 1$ indicates that the firm is not efficient, $[1 - (TE\ AE)]$ measuring the proportional reduction in cost that the firm can achieve by becoming both technically and allocatively efficient.

Scale Efficiency

While the indexes TE and AE in (1) and (2) are conditional on outputs y, the choice of y involves efficiency considerations as well. Whether a firm is producing optimally at y has been analyzed through the measurement of returns to scale. Returns to scale can be characterized from the production technology T_v as well as from the cost function $C(r, y, T_v)$. Following Baumol, Panzar, and Willig (p. 55), multiproduct returns to scale can be measured from the production technology by considering the function:

$$S(y, x, T_v) = \sup_k\{k\colon \exists\ \delta > 1 \text{ such that } (\lambda^k y, -\lambda x) \in T_v,\ 1 \leq \lambda \leq \delta\}.$$

The function $S(y, x, T_v)$ measures the maximal proportionate increase in outputs y as all inputs x are expanded proportionally. It is the local degree of homogeneity of the production set. Then, returns to scale at the point (y, x) are defined to be increasing, constant, or decreasing whenever $S > 1$, $S = 1$, or $S < 1$, respectively.

Alternatively, returns to scale can be expressed from the cost function in terms of the ray average cost (RAC):

$$RAC(k, r, y, T_v) = C(r, ky, T_v)/k,$$

where $k \in \Re^+$ and $y \neq 0$. Assuming differentiability, let the elasticity of the ray average cost function with respect to k (evaluated at $k = 1$) be denoted by $e = \partial\ln(RAC)/\partial\ln(k)$.

Then, under competition, the function $S(y, x, T_v)$ evaluated at the cost minimizing solution x^* can be expressed as (see Baumol, Panzar, and Willig, p. 55)

$$S(y, x^*, T_v) = 1/(1 + e).$$

Given the above definition of returns to scale in terms of S, it follows that returns to scale at the point y are increasing, constant, or decreasing whenever the elasticity e is negative, zero, or positive, respectively. This implies that, when returns to scale are increasing, then the ray average cost $RAC(k, r, y, T_v)$ is a decreasing function of k (where a proportional increase in outputs leads to a less than proportional increase in cost). Similarly, when returns to scale are decreasing, then the ray average cost $RAC(k, r, y, T_v)$ is an increasing function of k (where a proportional increase in outputs leads to a more than proportional increase in cost). And in the case where the $RAC(k, \cdot)$ function has a U-shape, then constant returns to scale are attained at the minimum of the RAC with respect to k.

This suggests the following index of scale efficiency:

$$SE(r, y, T_v) = AC(r, y, T_v)/C(r, y, T_v), \tag{3a}$$

where

$$AC(r, y, T_v) = \inf_k \left\{\frac{C(r, ky, T_v)}{k}: k > 0\right\}$$

denotes the minimal ray average cost function with respect to k. Clearly, $0 < SE \leq 1$. Values of the vector y satisfying $SE(r, y, T_v) = 1$ identify an efficient scale of operation corresponding to the smallest ray average cost. Alternatively, finding $SE(r, y, T_v) < 1$ implies that the value of the vector y is not an efficient scale of operation. In this case, $(1 - SE)$ can be interpreted as the maximal relative decrease in the ray average cost that can be achieved by proportionally rescaling all outputs toward an efficient scale of operation (where the output vector y exhibits locally constant return to scale). And $SE(r, y, T_v)$ rises (declines) with a proportional augmentation in y under increasing (decreasing) return to scale.

Note that $AC(r, y, T_v)$ can be expressed alternatively as

$$\begin{aligned} AC(r, y, T_v) &= \inf_{k,x}\{r'x/k: (ky, -x) \in T_v\} \\ &= \inf_{k,X}\{r'X: (ky, -kX) \in T_v\} \\ &= \inf_X\{r'X: (y, -X) \in T_c\} \\ &= C(r, y, T_c). \end{aligned}$$

It follows that the scale efficiency index $SE(r, y, T_v)$ can be alternatively written as[4]

$$SE(r, y, T_v) = C(r, y, T_c)/C(r, y, T_v). \tag{3b}$$

The index of scale efficiency SE in (3) can be combined with the efficiency indexes TE and AE in (1) and (2). In particular, we can define the overall efficiency index as the product of the three indexes (1), (2), and (3):

$$\begin{aligned} (TE\ AE\ SE) &= AC(r, y, T_v)/(r'x), \\ &= C(r, y, T_c)/(r'x), \end{aligned}$$

where $0 < (TE\ AE\ SE) \leq 1$. Then, $(TE\ AE\ SE) = 1$ implies that the firm is technically and allocatively as well as scale efficient. Alternatively, $(TE\ AE\ SE) < 1$ indicates the presence of inefficiency, where $[1 - (TE\ AE\ SE)]$ measures the proportional reduction in ray average cost RAC that a firm can achieve by becoming technically, allocatively, and scale efficient.

Scope Efficiency

The concept of scale economies helps assess the efficiency of firm size. However, it does not address the issue of why some firms decide to produce more than one output. The motivation for multiple product firms is linked with the concept of economies of scope (Baumol, Panzar, and Willig). To define such a concept, let $P = \{1, 2, \ldots, N\}$ denote the set of output indexes. Partition the set P into s mutually exclusive subsets P_k, satisfying $P_k \neq \varnothing$, $k = 1, 2, \ldots, s \leq N$, $\{\cup_k P_k\} = P$, and $\{P_k \cap P_j\} = \varnothing$ for $k \neq j$. Let $Y_k = \{y\colon y_j \geq 0$ for $j \in P_k$, $y_j = 0$ for $j \notin P_k\}$ denote the kth specialized product line, $k = 1, 2, \ldots, s$. Then, following Baumol, Panzar, and Willig (p. 72), economies (diseconomies) of scope are said to exist if $C(r, y, T_v) < (>) \Sigma_k C(r, Y_k, T_v)$, where $y = \Sigma_k Y_k$. Thus, economies of scope reflect the fact that splintering the production of the output vector $y = \Sigma_k Y_k$ into the product lines $(Y_1, \ldots, Y_s)$ would increase the cost of producing y. This suggests the following index of scope efficiency:

$$SC(r, y, T_v) = \left\{ \frac{\sum_{k=1}^{s} C(r, Y_k, T_v)}{C(r, y, T_v)} : y = \sum_{k=1}^{s} Y_k \right\}, \tag{4}$$

where $SC > 1$ (<1) implies economies (diseconomies) of scope. More specifically, a fragmentation of the firm producing y would increase (decrease) total production cost whenever the scope index $SC(r, y, T_v)$ is greater than one (less than one).[5]

The Nonparametric Approach

Consider a sample of n observations on firms in a given competitive industry. Let y^i and x^i be the output vector and input vector, respectively, chosen by the ith firm, $i = 1, 2, \ldots, n$. Denote the production possibility set of each firm in the industry by $\check{T}$, with $(y^i, -x^i) \in \check{T}$, $i = 1, \ldots, n$, where $\check{T}$ is a non-empty, closed, convex, and negative monotonic set. The question then is: how to use the production data, (y^i, x^i), $i = 1, \ldots, n$, to provide a representation of the set $\check{T}$. Following Afriat, and Färe, Grosskopf, and Lovell, consider the following nonparametric representation of $\check{T}$:

$$T_v = \left\{ (y, -x)\colon y \leq \sum_{i=1}^{n} \lambda_i y^i,\ x \geq \sum_{i=1}^{n} \lambda_i x^i,\ \sum_{i=1}^{n} \lambda_i = 1,\ \lambda_i \in \Re^+,\ \forall\ i \right\}. \tag{5}$$

The set T_v in (5) is closed, convex, and negative monotonic. Under variable returns to scale, it is the smallest convex set that satisfies the monotonicity property and includes all the observations (y^i, x^i), $i = 1, \ldots, n$. As such, it corresponds to the inner bound of the underlying production possibility set $\check{T}$ (Banker and Maindiratta).

Using T_v in (5) as a representation of technology, the measurement of the Farrell technical efficiency index TE in (1) for the ith firm is obtained from the following linear programming problem:

$$TE(y^i, x^i, T_v) = \min_{k,\lambda} \left\{ k_i\colon y^i \leq \sum_{j=1}^{n} \lambda_j y^j,\ k_i x^i \geq \sum_{j=1}^{n} \lambda_j x^j \ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \in \Re^+,\ \forall\ j \right\}. \tag{6}$$

Let r be the price vector for x. Then, based on T_v in (5), the measurement of the Farrell allocative efficiency index AE for the ith firm is obtained from (2), the cost function $C(r, y^i, T_v)$ being calculated from the following linear programming problem:

$$C(r, y^i, T_v) = \min_{x,\lambda} \left\{ r'x\colon y^i \leq \sum_{j=1}^{n} \lambda_j y^j,\ x \geq \sum_{j=1}^{n} \lambda_j x^j,\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \in \Re^+,\ \forall\ j \right\}. \tag{7}$$

Alternatively, under constant return to scale (CRTS), consider the following nonparametric representation of $\check{T}$:

$$T_c = \left\{ (y, -x)\colon y \leq \sum_{i=1}^{n} \lambda_i y^i,\ x \geq \sum_{i=1}^{n} \lambda_i x^i,\ \lambda_i \in \Re^+,\ \forall\ i \right\}. \tag{8}$$

Comparing (5) and (8), note that $T_v \subseteq T_c$. The set T_c in (8) is closed, convex, negative monotonic, and exhibits CRTS (Afriat; Färe, Grosskopf, and Lovell). It is the smallest convex cone that satisfies the monotonicity property and includes all the observations (y^i, x^i), $i = 1, \ldots, n$. As such, it corresponds to the CRTS inner bound of the underlying production possibility set $\check{T}$. Based on T_c in (8) as a representation of the CRTS technology, consider calculating $C(r, y^i, T_c)$ from the following linear programming problem:

$$(9) \qquad C(r, y^i, T_c) = \min_{x,\lambda}\left\{r'x: y^i \le \sum_{j=1}^{n} \lambda_j y^j,\ x \ge \sum_{j=1}^{n} \lambda_j x^j,\ \lambda_j \in \Re^+,\ \forall j\right\}.$$

Then, the scale efficiency index SE for the ith firm can be obtained from (3b), where $C(r, y^i, T_v)$ and $C(r, y^i, T_c)$ are given in (7) and (9).

Finally, the scope efficiency measure SC for the ith firm can be obtained from (4). The cost of producing outputs y^i, $C(r, y^i, T_v)$, is given in (7). And the cost of producing the specialized product line Y_k^i, $C(r, Y_k^i, T_v)$, is calculated from the following linear programming problem:

$$(10) \qquad C(r, Y_k^i, T_v) = \min_{x,\lambda}\left\{r'x: Y_k^i \le \sum_{j=1}^{n} \lambda_j y^j,\ x \ge \sum_{j=1}^{n} \lambda_j x^j,\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \in \Re^+,\ \forall j\right\},$$

where $k = 1, \ldots, s$. Note that both equations (7) and (10) rely on the same underlying technology T_v in (5). However, while equation (7) gives the smallest cost of producing all outputs y, equation (10) gives the cost of producing only those outputs included in the product line Y_k. These results indicate that the analysis of production efficiency can be easily conducted using standard tools. This is illustrated next by an application to Wisconsin farming.

An Application to Wisconsin Farms

The Data

The data used in the analysis were collected in 1987 by the Farm Credit Service of St. Paul, Minnesota, and cover a sample of more than 1,000 farms in Wisconsin. After elimination of incomplete records and outliers, usable data consisted of observations on 545 Wisconsin farms. The analysis is conducted at the district level, Wisconsin being divided into nine agricultural districts: 1 = northwest, 2 = north central, 3 = northeast, 4 = central west, 5 = central central, 6 = central east, 7 = southwest, 8 = south central, and 9 = southeast. Choosing the district as the unit of analysis is motivated by the existence of important agro-climatic differences across districts. For example, the length of the growing season in Wisconsin is shortest in the northwest district and longest in the southeast district. Because of such climatic differences, a crop such as soybeans cannot be grown in the northern districts. Also, although corn grain is an important crop in the southern districts, it may not reach maturity before the end of the growing season in the northern districts. As a result, farmers in different districts clearly face different agro-climatic conditions. This motivated us to conduct our analysis one district at a time, thus implicitly assuming that the production technology is constant within a district, but potentially different across districts.

The data for each farm in the sample involve inputs and outputs. The outputs used in the analysis include two categories: (*a*) crops, and (*b*) livestock.[6] The inputs include seven categories: (*a*) family labor; (*b*) hired labor; (*c*) miscellaneous inputs (repairs, rent, custom hiring, supplies, insurance, gas, oil, and utilities); (*d*) animal inputs (purchased feed, breeding, and veterinary services); (*e*) crop inputs (seeds, fertilizers, and chemicals); (*f*) intermediate-run assets; and (*g*) long-run assets.[7] Assets are classified according to their average useful life: between one and 10 years for intermediate-run assets, and more than 10 years for long-run assets.

The measurement of input and output quantities was problematic. Both outputs and most categories of inputs defined above are aggregates (e.g., animal inputs, assets, etc.). This raises the issue of obtaining quantity indexes for these aggregates. A typical approach is to measure quantity indexes as a ratio of expenditures, holding prices fixed (e.g., see Diewert). This requires knowledge of farm level prices. Unfortunately, farm level prices were not collected for all commodities in our sample. As a result, we were forced to make some restrictive assumptions about the nature of prices. We assumed that all sampled farmers in a given district face the same prices in 1987, i.e., that the "law of one price" holds at the district level. We then measured input and output quantity indexes by their monetary value. This amounts to assuming that the corresponding implicit price indexes are unity. Given the data limitations, this approach has the advantage of being empirically tractable. Although it allows for price difference across districts, it has the disadvantage of neglecting possible price variations across farms within any particular district. While such price variations may be relatively small, they cannot be ruled out.[8] Given this shortcoming, the results presented below should be interpreted with caution.

All quantity measurements are annual flow variables. The values of intermediate and long-run assets were reported as stock variables in the original data set. These asset values were transformed into flow variables by calculating the equivalent annuities based on an 8.94% interest rate in 1987 and five years (30 years) of useful life for intermediate-run (long-run) assets. Thus, the analysis presented below measures all inputs and outputs as annual flows expressed in monetary values. A summary of the data for each of the nine districts is presented in table 1.

Efficiency Results

The efficiency of each farm in the sample was investigated using either T_v in (5) or T_c in (8) as a representation of the technology associated with the farms within a district. For each farm, the optimal objective functions for problems (6), (7), (9), and (10) were then calculated from the solution of the corresponding linear programming problems.[9]

The analysis of efficiency was done under two scenarios: a long-run situation where all inputs are variable, and a short-run situation where "long-run asset" is treated as a fixed input. This implicitly assumes that "long-run assets" cannot be changed in the short run. The long-run estimate of the Farrell technical efficiency index *TE* is given by equation (6) (where all inputs are rescaled toward the frontier isoquant). Similarly, the long-run estimate of the Farrell allocative efficiency index *AE* is given by equations (2) and (7) [where all inputs are treated as variable in the definition of the cost function (7)]. In contrast, the short-run estimates of technical and allocative efficiency involve a distinction between variable inputs and fixed input. Let $x = (x_1, x_2)$, where x_1 denotes the vector of variable inputs, while x_2 is the fixed input ("long-run asset" in our case). Then, the short-run *TE* index is obtained from a modification of equation (7), where only the variable inputs x_1 are rescaled toward the frontier isoquant. The short-run estimate of *AE* is obtained from the following modifications to equation (2). First, the *TE* index in (2) is the short-run *TE* index just discussed. Second, the cost in (2) is the short-run cost function defined as

$$C(r, x_2, y^i, T_v) = \min_{x_1,\lambda} \left\{ r_1' x_1 : y^i \leq \sum_{j=1}^{n} \lambda_j y^j,\ x \geq \sum_{j=1}^{n} \lambda_j x^j,\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \in \Re^+,\ \forall\, j \right\},$$

where $x = (x_1, x_2)$ and r_1 is the price vector for the variable input x_1. This provides the empirical basis for investigating short-run as well as long-run technical and allocative efficiency.

The analysis of scale and scope efficiency was conducted only in the long-run situation.

Table 1. Data Summary for Nine Wisconsin Agricultural Districts Sampled

		Crop Output	Livestock Output	Family Labor	Hired Labor	Miscel. Inputs	Animal Expend.	Crop Expend.
District 1	Min.	0	76,771	9,366	0	17,250	10,281	3,001
(N = 15)	Max.	20,293	224,433	32,436	28,497	67,280	60,402	28,221
	Avg.	4,205	146,373	23,509	8,696	35,164	29,513	12,625
	SD	6,738	44,393	6,706	8,726	18,311	15,499	6,801
District 2	Min.	0	20,046	3,442	0	5,270	3,695	191
(N = 82)	Max.	88,000	271,363	33,933	44,692	116,593	77,270	65,937
	Avg.	3,521	115,368	17,990	8,583	25,302	25,873	8,204
	SD	13,157	50,822	6,775	8,275	17,110	15,303	9,581
District 3	Min.	0	47,062	3,668	0	6,365	6,197	1,342
(N = 57)	Max.	75,698	481,166	43,540	74,969	120,297	112,158	36,053
	Avg.	3,049	150,121	19,909	10,714	30,043	29,737	10,442
	SD	10,751	79,489	8,472	13,269	19,937	18,842	8,070
District 4	Min.	0	61,170	11,029	30	15,300	9,316	1,867
(N = 21)	Max.	39,001	445,416	77,195	64,179	96,715	105,448	27,575
	Avg.	4,849	157,830	21,216	12,442	39,140	26,163	12,685
	SD	9,638	88,149	13,703	15,738	22,955	20,982	7,912
District 5	Min.	0	0	1,773	0	8,896	0	711
(N = 57)	Max.	590,611	298,307	45,968	93,479	184,149	62,454	199,406
	Avg.	33,325	116,238	19,849	10,069	35,097	21,370	19,424
	SD	102,539	60,213	8,743	13,493	31,932	14,065	32,342
District 6	Min.	0	0	2,086	0	5,086	0	0
(N = 158)	Max.	290,187	475,312	81,102	75,935	145,981	159,499	105,224
	Avg.	5,010	140,560	22,887	8,728	31,725	28,885	12,090
	SD	24,731	85,950	11,388	11,709	22,471	23,152	11,779
District 7	Min.	0	52,620	1,526	0	11,610	6,222	1,292
(N = 19)	Max.	22,291	332,809	44,691	33,764	101,731	57,786	44,708
	Avg.	3,898	155,288	19,831	9,688	36,110	29,233	14,713
	SD	7,102	83,106	10,722	9,492	25,275	15,501	11,750
District 8	Min.	0	0	3,228	0	3,960	0	881
(N = 114)	Max.	518,569	426,396	54,335	115,625	204,513	76,436	100,288
	Avg.	31,262	115,898	19,448	9,100	37,829	21,895	16,562
	SD	73,979	74,148	8,915	13,316	32,268	16,692	18,084
District 9	Min.	0	72,181	3,011	0	14,596	10,581	1,023
(N = 22)	Max.	49,276	370,370	82,205	30,292	97,249	111,087	42,137
	Avg.	8,132	168,833	22,907	12,581	41,929	37,472	15,747
	SD	13,171	85,296	18,290	10,585	20,438	27,924	11,436

This seems reasonable to the extent that the concepts of scale and scope efficiency are typically motivated in a long-run context. Thus, treating all inputs as variables, the scale efficiency indexes were obtained from equation (3b), and the scope efficiency indexes from (4).

A summary of the results is presented in table 2. The mean technical efficiency index *TE* varies across districts from .85 to 1 in the short run, and from .92 to 1 in the long run (see table 2). In general, farms are found to have a slightly lower technical efficiency index in the short run (where "long-run assets" are treated as fixed) than in the long run. Although the gains from improving technical efficiency exist, they tend to be of limited magnitude. The percentage of technically efficient farms (with $TE = 1$) goes from a low of 32% (short run, district 6) to a high of 100% in district 1.

Table 2 shows that the mean allocative efficiency index *AE* goes from .76 in district 6 to .95 in district 1 in the short run, and from .82 in district 8 to .96 in district 1 in the long run. The percentage of price efficient farms (with $AE = 1$) ranges from 4% (short

Table 1. (Continued)

Int.-Run Asset	Long-Run Asset	Int.-Run Debt/ Int.-Run Asset	Long-Run Debt/ Long-Run Asset	Nonfarm Income/ Total Income
26,909	10,328	.16	.24	.00
114,734	37,909	.96	1.70	.19
54,121	20,042	.58	.64	.06
24,063	8,876	.21	.35	.06
14,188	4,066	.01	.02	−.04
107,355	43,470	1.49	2.64	2.17
39,592	19,322	.59	.72	.11
18,321	7,580	.37	.44	.25
9,766	6,292	.04	.02	.00
181,153	68,650	1.89	1.31	.55
49,825	24,038	.67	.69	.07
31,898	13,355	.31	.27	.09
18,091	9,673	.04	.07	.00
138,440	77,154	.92	1.48	.27
57,607	31,086	.52	.66	.07
31,385	19,537	.30	.35	.08
18,301	7,744	.00	.05	.00
112,098	152,807	3.02	1.82	.33
45,281	29,334	.68	.74	.08
18,822	20,942	.44	.34	.08
4,711	4,356	.01	.00	−.06
146,961	89,075	2.99	2.48	1.20
45,310	22,825	.68	.81	.11
26,146	13,511	.43	.44	.16
21,576	14,782	.03	.14	.00
137,668	59,395	1.30	1.99	.31
51,514	30,263	.46	.68	.07
25,857	14,067	.37	.39	.09
9,111	5,808	.00	.00	.00
146,387	102,228	3.76	1.93	1.07
44,547	27,470	.84	.71	.13
22,334	16,025	.69	.39	.20
21,269	5,826	.06	.00	.00
124,126	67,800	2.40	1.57	.41
53,390	25,076	.83	.65	.08
30,256	16,973	.48	.39	.10

run, district 2) to 42% in district 7. This indicates that improving allocative efficiency can help reduce production cost on many farms. The mean economic efficiency index given scale (*TE AE*) reported in table 2 varies across districts from .65 to .95 in the short run, and from .76 to .96 in the long run.

The scale efficiency index *SE* ranges from .87 in district 7 to .94 in districts 3, 5, and 6 (see table 2). This suggests that the gains from attaining an efficient scale appear to be moderate in our sample. However, the percentage of scale efficient farms tends to be low: from 3% in district 6 to a high of 18% in district 9. The inverse of the scale efficiency index ($1/SE$) is plotted against outputs in figure 1 for selected districts.[10] Note that, given the discussion presented earlier, this inverse can be interpreted in a way similar to an average cost function: ($1/SE$) is a declining function of outputs under increasing returns to scale, and an increasing function under decreasing returns to scale. Figure 1 indicates the existence of substantial economies of scale for very small farms. Also, it provides some evidence of diseconomies of scale for larger farms. Such diseconomies of scale

Table 2. Short-Run and Long-Run Efficiency Indexes for Nine Wisconsin Agricultural Districts Sampled

		Short Run			Long Run					
		TE	*AE*	(*TE AE*)	*TE*	*AE*	(*TE AE*)	*SE*	(*TE AE SE*)	Scope[a]
District 1	Mean	1.00	.95	.95	1.00	.96	.96	.93	.89	1.74
($N = 15$)	SD	.00	.05	.05	.00	.06	.06	.09	.11	.18
	% 1's	100%	40%	40%	100%	40%	40%	13%	13%	
	Cond. Mean[b]	–	.92	.92	–	.93	.93	.91	.87	
District 2	Mean	.95	.83	.79	.96	.83	.79	.86	.68	1.55
($N = 82$)	SD	.07	.10	.12	.07	.10	.12	.12	.13	.17
	% 1's	55%	10%	10%	62%	9%	9%	4%	4%	
	Cond. Mean	.88	.81	.77	.89	.81	.78	.85	.66	
District 3	Mean	.95	.88	.84	.96	.85	.82	.94	.77	1.56
($N = 57$)	SD	.07	.09	.11	.06	.10	.11	.07	.10	.20
	% 1's	56%	16%	16%	61%	12%	12%	4%	4%	
	Cond. Mean	.89	.86	.81	.91	.83	.80	.94	.76	
District 4	Mean	.99	.88	.87	.99	.86	.85	.91	.77	1.67
($N = 21$)	SD	.04	.12	.13	.04	.14	.15	.07	.13	.25
	% 1's	90%	33%	33%	90%	24%	24%	10%	10%	
	Cond. Mean	.87	.82	.81	.87	.81	.80	.90	.74	
District 5	Mean	.96	.89	.85	.98	.89	.87	.94	.82	1.51
($N = 57$)	SD	.08	.08	.11	.06	.09	.11	.07	.12	.21
	% 1's	63%	14%	14%	79%	16%	16%	5%	5%	
	Cond. Mean	.88	.87	.83	.89	.86	.84	.94	.81	
District 6	Mean	.85	.76	.65	.92	.83	.76	.94	.71	1.49
($N = 158$)	SD	.14	.12	.15	.10	.09	.12	.10	.11	.23
	% 1's	32%	4%	4%	44%	6%	6%	3%	1%	
	Cond. Mean	.79	.75	.64	.85	.82	.75	.93	.71	
District 7	Mean	.98	.93	.92	.99	.94	.93	.87	.80	1.67
($N = 19$)	SD	.05	.07	.09	.04	.08	.10	.12	.14	.22
	% 1's	89%	42%	42%	89%	42%	42%	11%	11%	
	Cond. Mean	.85	.89	.86	.86	.89	.87	.86	.78	
District 8	Mean	.94	.81	.76	.96	.82	.79	.89	.70	1.36
($N = 114$)	SD	.09	.11	.13	.07	.11	.12	.12	.14	.15
	% 1's	58%	8%	8%	68%	8%	8%	3%	2%	
	Cond. Mean	.85	.80	.74	.89	.80	.77	.88	.69	
District 9	Mean	.99	.89	.88	.99	.93	.92	.93	.85	1.55
($N = 22$)	SD	.04	.10	.12	.03	.08	.09	.07	.09	.23
	% 1's	86%	32%	32%	86%	41%	41%	18%	14%	
	Cond. Mean	.92	.85	.83	.92	.88	.86	.92	.83	

[a] Scope Index = [C(livestock) + C(crops)]/C(livestock, crops).
[b] The conditional mean is the mean efficiency among the farms that exhibit an efficiency index less than 1.

appear to be fairly small. This helps explain the high scale efficiency indexes reported in table 2.

Note that the diseconomies of scale vary with the output mix. Within the range of the data, diseconomies of scale are found to be virtually nonexistent with respect to crops, although they can be important with respect to livestock (see districts 4, 7, and 9 in fig. 1). This implies that the average cost function for crops has a general L-shape, as typically found in previous research (e.g., Hall and Leveen). However, the average cost of producing livestock follows a different pattern (see fig. 1). It exhibits strong economies of scale for small operations. This is consistent with the results obtained, for example, by Matulich. But it also exhibits some diseconomies of scale for a livestock enterprise with a gross income beyond $100,000 to $200,000.

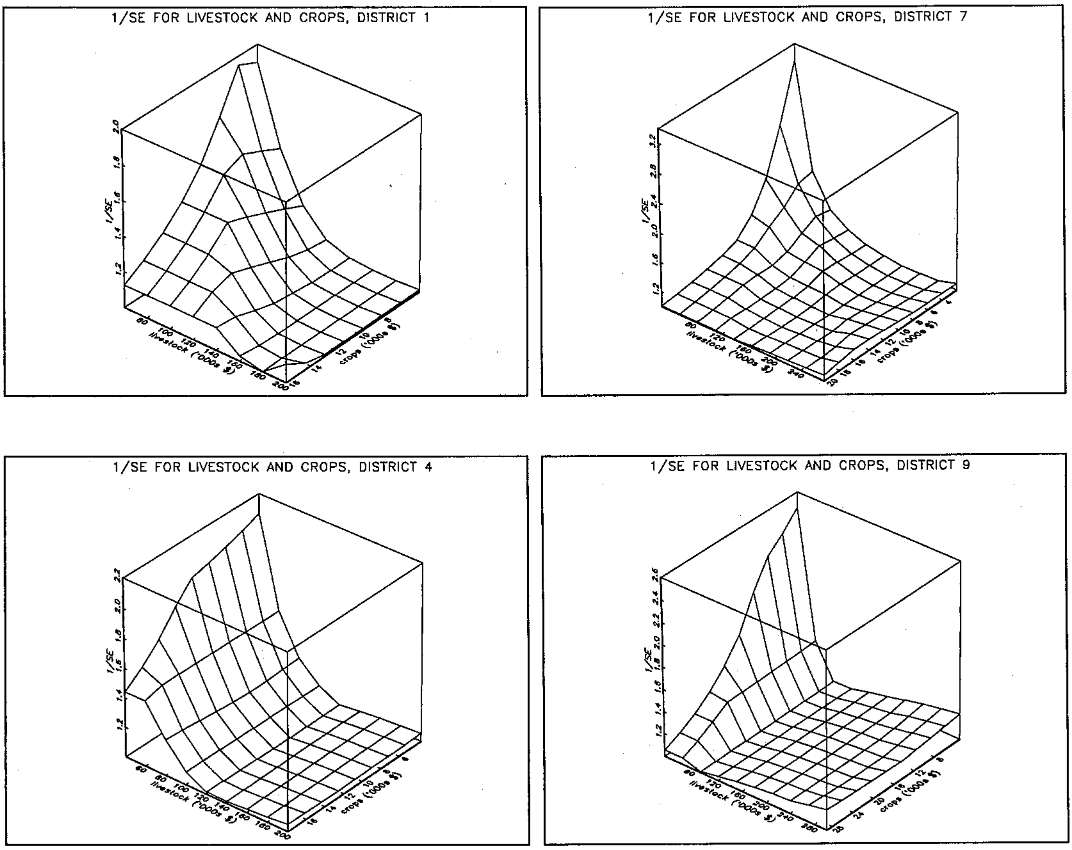

Figure 1. Economies of scale for selected districts

In the long-run scenario, the mean overall efficiency index (*TE AE SE*) varies across districts from .68 to .89 (see table 2). This implies that, although each of the measured inefficiencies (i.e., technical, price, or scale) is not very large on the average, their combined effects on average cost appear important. Also, the percentage of farms that are technically, allocatively, and scale efficient is found to be quite small, varying from 1% in district 6 to 13% in district 1. This suggests that most farms can find ways of improving their production practices.

The indexes of scope efficiency reported in table 2 measure the relative cost of producing livestock and crops separately, compared to producing them jointly. They indicate the existence of fairly large economies of scope. This is interpreted as evidence that the underlying technology is characterized by a joint production process (Leathers). The mean scope index *SC* varies from 1.36 in district 8 to 1.74 in district 1. This implies that there are strong benefits associated with the joint production of both crops and livestock on the same farm. It shows that crops and livestock can be produced at a much lower cost in an integrated farm enterprise as compared to specialized enterprises. This evidence of strong economies of scope is consistent with the fact that most Wisconsin farms are multiproduct enterprises, integrating crop and dairy activities in their production practices. Additional information on the nature of economies of scope is presented in figure 2, where the scope efficiency index *SC* is plotted against outputs for selected districts.[11] Figure 2 shows that economies of scope tend to be very large for small farms, implying that small operations tend to generate important benefits from crop–livestock integration. It also shows that, although economies of scope seem to exist for a wide variety of sizes, they

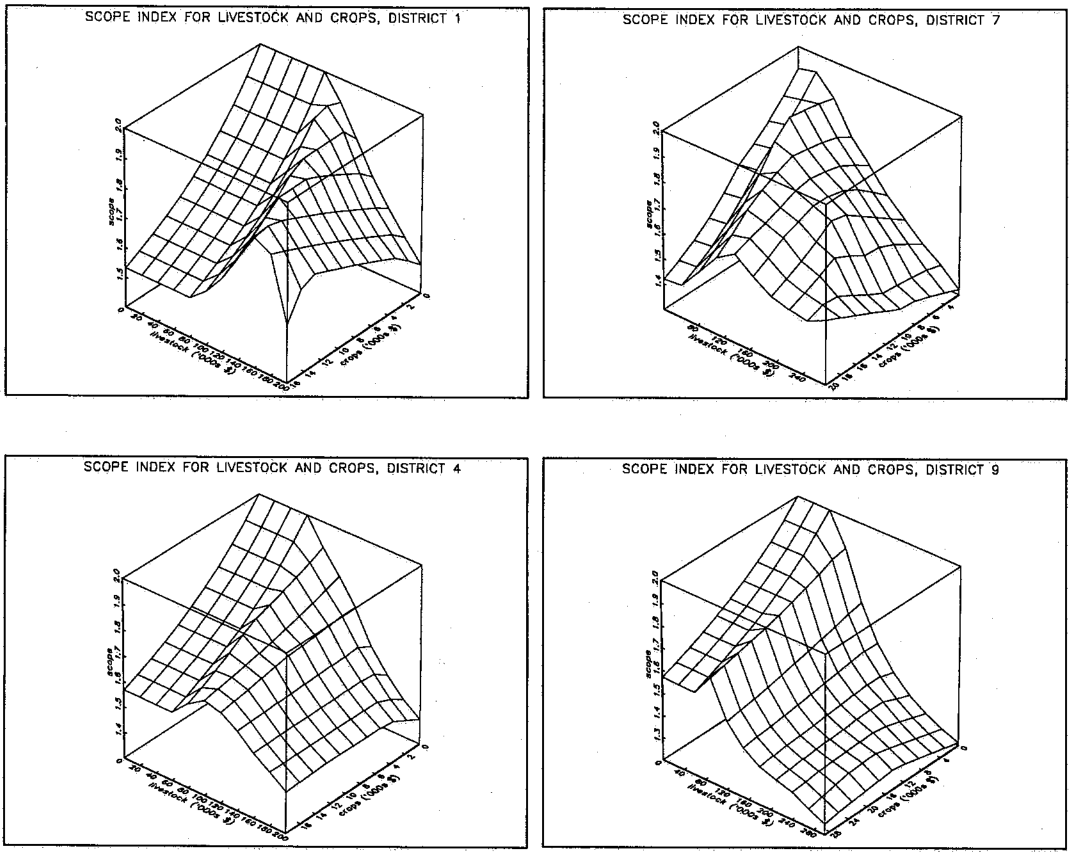

Figure 2. Economies of scope for selected districts

tend to decrease significantly with larger operations. Thus, the cost reductions generated by crop–livestock integration appear to decline with farm size. In other words, incentives for specialization in agricultural production are found to increase with farm size.

Additional Interpretation

Although measuring production inefficiencies is of interest by itself, it would be helpful to identify the sources of such inefficiencies. In an attempt to do so, we propose estimating an econometric model regressing the efficiency indexes on a set of explanatory variables. With the largest possible values of the efficiency indexes *TE, AE,* or *SE* being 1, this generates the following Tobit model:

$$EI_i = X_i\beta + e_i \quad \text{if } X_i\beta + e_i < 1, \qquad = 1 \quad \text{otherwise,} \tag{11}$$

where EI_i is one of the efficiency indexes (*TE, AE,* or *SE*) calculated above for farm i, X_i is a vector of explanatory variables, β is a parameter to be estimated, and e_i is an error term distributed $\sim N(0, \sigma^2)$.

The data set used in the analysis of Wisconsin farmers provided some detailed information on the financial structure of each farm. This gives an opportunity to investigate possible linkages between financial structure and production efficiency.[12] Thus, the explanatory variables used in model (11) are: (*a*) short-run debt-to-asset ratio, (*b*) intermediate-run debt-to-asset ratio, (*c*) long-run debt-to-asset ratio,[13] and (*d*) the ratio of nonfarm income to total income.

Table 3. Tobit Estimates

Explanatory Variable	Dependent Variable: Short Run *TE*	Short Run *AE*	Long Run *TE*	Long Run *AE*	Long Run *SE* (IRTS)	Long Run *SE* (DRTS)
Intercept–District 1	1.860 (.043)	.958 (.036)	1.860 (.036)	.956 (.031)	.933 (.040)	.973 (.028)
Intercept–District 2	.976 (.029)	.802 (.019)	.975 (.026)	.793 (.016)	.840 (.022)	.940 (.017)
Intercept–District 3	.986 (.034)	.856 (.021)	.983 (.028)	.819 (.018)	.876 (.051)	.960 (.012)
Intercept–District 4	1.159 (.056)	.873 (.030)	1.120 (.044)	.833 (.026)	.892 (.044)	.944 (.018)
Intercept–District 5	.998 (.035)	.863 (.021)	1.038 (.033)	.853 (.019)	.940 (.024)	.972 (.024)
Intercept–District 6	.824 (.027)	.727 (.017)	.882 (.022)	.792 (.015)	.913 (.025)	.957 (.011)
Intercept–District 7	1.151 (.056)	.940 (.032)	1.116 (.035)	.934 (.028)	.851 (.036)	.956 (.024)
Intercept–District 8	.956 (.030)	.726 (.019)	.980 (.022)	.780 (.016)	.885 (.022)	.940 (.017)
Intercept–District 9	1.122 (.060)	.881 (.031)	1.088 (.021)	.916 (.027)	1.060 (.058)	.940 (.017)
Short-Run Debt/ Asset	−.016 (.013)	.007 (.009)	−.013 (.012)	.002 (.008)	−.006 (.010)	.010 (.006)
Int.-Run Debt/Asset	.060 (.020)	.022 (.012)	.059 (.017)	.016 (.010)	−.034 (.014)	.0001 (.009)
Long-Run Debt/ Asset	.035 (.022)	.026 (.014)	.059 (.020)	.040 (.012)	.043 (.018)	−.014 (.010)
Nonfarm Income/ Total Income	-3×10^{-4} (3×10^{-4})	8×10^{-5} (2×10^{-4})	-8×10^{-5} (3×10^{-4})	-5×10^{-5} (2×10^{-4})	6×10^{-6} (8×10^{-4})	9×10^{-5} (1×10^{4})
σ^2	.029 (.003)	.015 (.001)	.024 (.002)	.011 (8×10^{-4})	.015 (.001)	.003 (3×10^{-4})
N	544	544	544	544	325	244
Log-Likelihood Function	−84.25	253.69	−83.00	313.90	179.09	290.19

Note: Figures in parentheses below the parameter estimates are asymptotic standard errors.

Allowing for a different intercept in each district, equation (11) generated several models according to the choice of the dependent variable: the technical efficiency index *TE* in the short run (where "long-run assets" are fixed) as well as in the long run, the allocative efficiency index *AE* in the short run and in the long run, the scale efficiency index *SE* for farms exhibiting increasing returns to scale (IRTS), and the scale efficiency index *SE* for farms exhibiting decreasing returns to scale (DRTS). Estimating two models for *SE* allows the explanatory variables to have a different effect on scale efficiency under IRTS compared to DRTS. The models were estimated by the maximum likelihood method. The results are presented in table 3.

Two variables are found to have no significant effect on any of the efficiency indexes: the short-run debt-to-asset ratio, and the ratio of nonfarm income to total income (see table 3). Thus, there is no statistical evidence that either short-term debt or nonfarm income affects production efficiency. This suggests that part-time farmers are as efficient in their use of resources as full-time farmers.

Both intermediate and long-run debt-to-asset ratios are found to have positive and significant effects on technical efficiency (*TE*) and allocative efficiency (*AE*) (see table 3). The effects of the intermediate-run debt-to-asset ratio are fairly similar between the short-run scenario (where "long-run assets" are fixed) and the long-run scenario. However, the long-run debt-to-asset ratio tends to have a stronger and more significant effect on *TE* and *AE* in the long-run scenario (compared to the short-run scenario). These results may reflect the existence of embodied technical change in agriculture. If technical progress is embodied in intermediate and long-run assets, then improving productivity will be associated with the acquisition of such assets, the purchase of which is typically financed (at least partially) through debt. This would help explain the positive relationship found between indebtedness and technical efficiency. The positive relationship between debt and price efficiency could be interpreted as follows. If the early adopters of a new technology tend to have a superior managerial ability, then good management would likely be associated with debt financing of the assets embodying the new technology. Alternatively, the late adopters may exhibit below-average managerial ability, but also fewer recently-purchased assets embodying the new technology, and thus less debt.

The effects of intermediate and long-run debt-to-asset ratios on scale efficiency appear to be more complex (see table 3). First, such ratios are found to have no significant relationship with scale efficiency under decreasing returns to scale (DRTS). Thus, there is no statistical evidence that the financial structure of the larger farms affects their scale efficiency. Second, the intermediate-run (long-run) debt-to-asset ratio is found to have a significant negative (positive) relationship with scale efficiency under increasing returns to scale (IRTS). This indicates that the financial structure of small farms affects their ability to attain an efficient scale. For example, our results show that among the small farms, those operating at a more efficient scale (and thus larger) tend to have a higher long-run debt-to-asset ratio. This may reflect imperfections in the credit market as well as the relatively high cost of entry in agriculture (where entry typically involves the purchase and debt financing of long-term assets). These results call for additional research on the exact nature of the relationships between debt financing and economic efficiency.

Conclusion

This article has presented a nonparametric approach to the measurement of technical, allocative, scale, and scope efficiencies. The proposed methodology is flexible in the sense that it does not require imposing functional restrictions on technology, as typically done using a parametric approach. Also, it is easy to implement empirically since it involves only the solutions of appropriately formulated linear programming models. Finally, it provides firm-specific information on the source and magnitude of production efficiency. The main drawback of the methodology is probably the lack of statistical inference associated with the estimates of the efficiency indexes.

The analysis is applied to a sample of Wisconsin farms. The results generate farm-specific indexes for technical, allocative, scale, and scope efficiencies. While technical inefficiencies are of limited magnitude, it is found that economic losses are commonly generated by allocative inefficiencies and scale inefficiencies. A majority of farms exhibit at least one form of inefficiency. This suggests that most farms can find ways of improving on their production practices. The analysis shows strong economies of scale for very small farms, and some diseconomies of scale for large livestock operations (but not large crop operations). It also presents evidence of important economies of scope in Wisconsin agriculture. However, economies of scope are found to decline sharply with farm size, indicating that the incentives to specialize, while nonexistent on small farms, become stronger on larger farms. Finally, an econometric analysis of the efficiency indexes suggests that the financial structure of farms can have some significant influence on their ability to attain economic efficiency.

The investigation reported here illustrates the usefulness of the nonparametric approach to production efficiency analysis. It is hoped that it will help stimulate additional research on this important topic.

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Notes

[1] Allocative efficiency has also been called "price efficiency" in the literature.

[2] A set T is said to be negative monotonic if $t_1 \in T$ and $t_2 \leq t_1$ implies that $t_2 \in T$. This has been termed "strong disposability" in the literature (see Zieschang; Färe, Grosskopf, and Lovell).

[3] Alternative measures of technical efficiency have been proposed in the literature. For example, an index of technical efficiency can be measured by radially rescaling outputs instead of inputs (see Färe, Grosskopf, and Lovell, chapter 4). Although output-based and input-based indexes of technical efficiency are identical under CRTS, they differ under general VRTS (Färe, Grosskopf, and Lovell, p. 132). More specifically, the input-based index of technical efficiency is lower (higher) than the corresponding output-based index under decreasing (increasing) return to scale (Färe, Grosskopf, and Lovell, p. 133). Also, Zieschang, and Färe, Grosskopf, and Lovell have proposed analyzing technical efficiency without the "negative monotonicity" assumption (where our "strong disposability" assumption is replaced by a "weak disposability" assumption). Finally, non-radial measures of technical efficiency have also been proposed (e.g., Färe, Grosskopf, and Lovell, chapter 7).

[4] Färe and Grosskopf have shown that measuring scale efficiency from the production technology versus the cost function can generate different results. More specifically, the two scale efficiency indexes are different if $AE(r, y, T_v) \neq AE(r, y, T_c)$, i.e., if the allocative efficiency index (2) differs using T_v versus using the associated cone technology T_c (see Färe and Grosskopf, p. 603).

[5] Färe proposed measuring scope efficiency directly from the production technology. However, in contrast with the scope index SC in (4), Färe's proposed approach requires measurements of the inputs used by each plant producing the product line Y_k, $k = 1, \ldots, s$. This information may not be readily available in many production data sets (such as the Wisconsin data set used in the empirical analysis presented below).

[6] Our analysis implicitly neglects possible production uncertainty (e.g., due to weather effects). This amounts to assuming that farmers face similar production uncertainty. This may be appropriate given that our analysis is conducted for a given year (1987) and one district at a time.

[7] This choice of input and output aggregates appears reasonable for our purpose. However, it should be kept in mind that different commodity aggregations could influence the results presented below. The investigation of aggregation issues in efficiency analysis appears to be a good topic for further research.

[8] Price differences across farms could exist for two reasons. First, the "law of one price" may not hold, implying that different farmers face different prices due to transaction costs and/or market imperfections. Second, the commodities may not be of homogeneous quality. In this case, different farmers may face different prices because they purchase inputs or sell outputs of different quality. Although the investigation of these issues is clearly of interest, it is beyond the scope of this research.

[9] These linear programming problems are fairly standard. They were solved numerically by the Simplex method, using GAMS software.

[10] Figure 1 was obtained from (3b), where $C(r, y, T_c)$ and $C(r, y, T_v)$ were derived by solving (7) and (9) parametrically for different values of outputs y. Note that outputs are increasing towards the front of the graph, small farms being situated towards the rear.

[11] Figure 2 was obtained from (4), where $C(r, y, T_v)$ and $C(r, Y_k, T_v)$ were derived by solving (7) and (10) parametrically for different values of the outputs y. Note that outputs are increasing towards the front of the graph, small farms being situated towards the rear.

[12] Other variables (such as education or experience of the decision makers) may also be hypothesized to influence production efficiency. Unfortunately, such variables were not part of the data set and could not be incorporated into the analysis. The results presented below should be interpreted cautiously in light of these data limitations.

[13] Debts and assets are classified according to their duration or expected life: less than a year for the short run, between one and 10 years for the intermediate run, and more than 10 years for the long run.

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