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Cotton Farmers' Technical Efficiency: Stochastic and Nonstochastic Production Function Approaches

Kalyan Chakraborty, Sukant Misra, and Phillip Johnson

Technical efficiency for cotton growers is examined using both stochastic (SFA) and nonstochastic (DEA) production function approaches. The empirical application uses farm-level data from four counties in west Texas. While efficiency scores for the individual farms differed between SFA and DEA, the mean efficiency scores are invariant of the method of estimation under the assumption of constant returns to scale. On average, irrigated farms are 80% and nonirrigated farms are 70% efficient. Findings show that in Texas, the irrigated farms, on average, could reduce their expenditures on other inputs by 10%, and the nonirrigated farms could reduce their expenditures on machinery and labor by 12% and 13%, respectively, while producing the same level of output.

Key Words: cotton, data envelopment analysis, stochastic frontier, technical efficiency

Cotton is the most important agricultural commodity in Texas, after cattle and calves, in terms of cash receipts. In 2000, cash receipts from the sale of cotton lint and seed were $1.15 billion, representing 10% of the total agricultural cash receipts in the state. Texas produced 4 million bales of upland cotton in 2000, which represents 23% of total U.S. cotton production. Recent cotton price decreases, however, have considerably reduced cotton profitability. The average price received by Texas cotton producers for upland cotton lint has decreased from 74.6¢ per pound in 1995 to 51.4¢ per pound in 2000 (U.S. Department of Agriculture, 2000).

The severe economic stress confronting cotton producers today has prompted research efforts in production and marketing risk management strategies. Yet it is equally important to assess the production and scale efficiency of specific farming units, which can help producers focus on necessary adjustments within their operations and improve productivity.

Compared with the number of studies devoted to measuring productive efficiency of other agricultural crops, studies on cotton farmers are limited. Although Brooks (2001) analyzed production and cost estimates for cotton-producing farms in the United States, and Helmers, Weiss, and Shaik (2000) measured regional efficiency and total factor productivity for U.S. cotton-producing regions, there has been no study measuring farm-level technical efficiency for cotton farmers.

The primary objectives of this study are to estimate technical efficiency of cotton-producing farms and compare the results obtained from two alternative methods of estimation—parametric and nonparametric. Other objectives are to investigate the relationship between the farm output and the inputs given the assumption of a specific technology, and to analyze the slack input variables in terms of their excess use in the production process. The present analysis contributes to the existing literature because it is the first comparative study of farm-level efficiency of cotton producers.

The remainder of the article proceeds as follows. First, we provide a background overview on the development and application of parametric and

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nonparametric estimation techniques, highlighting this discussion with references to relevant literature. The measurement of technical efficiency is then addressed, with specific emphasis on the DEA and SFA models employed in our analysis. The description of data and our empirical results are detailed in the next section, followed by a final section presenting our summary and conclusions.

Background

Since the pioneering work by Farrell in 1957, which drew upon the works of Debreu (1951) and Koopmans (1951), a considerable effort has been directed at refining the measurement of technical efficiency. The literature on efficiency analysis is broadly divided into deterministic and stochastic frontier methodologies. The deterministic, nonparametric approach that developed out of mathematical programming to measure efficiency is known as data envelopment analysis (DEA), while the parametric approach which uses a stochastic production, cost, or profit function to estimate efficiency is called the stochastic frontier approach (SFA).

A detailed review of both approaches is provided through the collective works of Lovell and Schmidt (1988); Schmidt (1986); Bauer (1990); Seiford and Thrall (1990); Lovell (1993); Greene (1993); Ali and Seiford (1993); and Coelli (1995a). The most commonly cited models employing DEA are those developed by Charnes, Cooper, and Rhodes (1978), and Banker, Charnes, and Cooper (1984).

In DEA, the performance of a farm is evaluated in terms of its ability to either shrink usage of an input or expand the output level subject to the restrictions imposed by the best-observed practices. This measure of performance is relative, in the sense that the efficiency of each decision-making unit (DMU) is evaluated against the most efficient DMU, and it is measured by the ratio of actual output to maximal potential output. In stochastic frontier production functions (SFA) there are two error terms. One accounts for the existence of technical inefficiency, and the other accounts for random disturbances arising out of measurement error, luck, bad weather, etc.

In the past, common criticisms of DEA related to its inability to account for the measurement error and to test for significance of the efficiency measures. Banker (1993, 1996), and Fare and Grosskopf (1995) proposed several statistical tests which have subsequently made DEA a powerful tool for efficiency analysis. One of the major limitations of the SFA is the restrictive assumption on the functional form of the production function and the distribution of the one-sided error term (Forsund, Lovell, and Schmidt, 1980).

In the agricultural economics literature, stochastic frontier estimation is generally the preferred procedure because of the inherent nature of uncertainty associated with agricultural production. Uncertainty in production can arise due to bad weather, fires, pests, and diseases. However, because of limitations associated with both stochastic and nonstochastic frontier approaches, we use both techniques in the current study to measure technical efficiency of cotton farmers in Texas, and then compare the results.

Earlier studies have investigated the sensitivity of efficiency estimates to estimation methods (Ferrier and Lovell, 1990; Coelli and Perelman, 1999; Ruggiero and Vitaliano, 1999; Chakraborty, Biswas, and Lewis, 2001). By using data applied from farm-level cotton producers, we seek to make an important contribution to the knowledge related to the comparative analysis of alternative methods of measuring technical efficiency.

Measurement of Technical Efficiency

Simple DEA Model

For a given technology and a set of input quantities, the production frontier defines the maximum output possible from a given combination of inputs. In DEA, a linear programming technique envelops the data and defines the best-practice reference technology by using an output distance function. The value of the output distance function serves as the measure of technical efficiency for each farm relative to the best-observed values of inputs and outputs of all farms, and is used to construct the reference technology. The output-oriented DEA measure of technical efficiency seeks a proportionate increase in its output level given its input usage, while remaining on the same production frontier. Hence, this method assumes that outputs are capable of expansion. A simple output-oriented DEA model is presented below. For a detailed procedural discussion, interested readers are referred to Seiford and Thrall (1990); Lovell (1993); Fare, Grosskopf, and Lovell (1994); and Chakraborty and Mohapatra (1997).

Following Fare, Grosskopf, and Lovell (1994), assume there are K farms using N inputs $x = (x_1, ..., x_N) \in \Re^N_+$, producing M outputs $y = (y_1, ..., y_M)$

$\in \Re^M_+$. We denote $\mathbf{N}$ as an (N, K) matrix of N different inputs used by K different farms; $\mathbf{M}$ is denoted as an (M, K) matrix of M different outputs produced by K different farms; and $(\mathbf{x}^k, \mathbf{y}^k)$ represents the input-output vector, or the activity of the kth farm. Assuming inputs and outputs are nonnegative, the piecewise linear output reference satisfying the properties of constant returns to scale and strong disposability of inputs and outputs (C, S) can be formed from $\mathbf{N}$ and $\mathbf{M}$ as:

$$(1) \quad L(x|C, S) = \left\{ y : y \le \mathbf{zM},\ \mathbf{zN} \le x,\ \mathbf{z} \in \Re^K_+ \right\}, \quad x \in \Re^N_+,$$

where $\mathbf{z}$ is the $(K, 1)$ intensity vector ($\mathbf{z} = z_1, ..., z_k$; $\in \Re^K_+$) identifying to what extent a particular activity $(\mathbf{x}^k, \mathbf{y}^k)$ is utilized. This vector allows us to shrink or expand individual observed activities for the purpose of constructing unobserved feasible activities. Thus it provides the weights which help in the construction of the piecewise linear boundaries of the technology (Fare, Grosskopf, and Lovell, 1994).

The assumption of strong disposability of inputs and outputs as a feature of technology implies the same input vector can produce lesser outputs, and a higher input vector can produce the same outputs. Given the technology in the above specification, the Farrell output-oriented measure of technical efficiency for activity k is the solution to the linear programming problem (with θ representing the output distance function):

$$(2) \quad F(\mathbf{x}^k, \mathbf{y}^k)^{-1} = \max_{\theta, \mathbf{z}} \theta \quad \text{s.t.:} \quad \theta \mathbf{y}^k \le \mathbf{zM}, \quad \mathbf{zN} \le \mathbf{x}^k, \quad \mathbf{z} \in \Re^K_+;$$

or

$$(3) \quad F(\mathbf{x}^k, \mathbf{y}^k)^{-1} = \max_{\theta, \mathbf{z}} \theta \quad \text{s.t.:} \quad \theta y_{km} \le \sum_{k=1}^{K} z_k y_{km}, \ m = 1, 2, ..., M, \quad \sum_{k=1}^{K} z_k x_{kn} \le x_{kn}, \ n = 1, 2, ..., N, \quad z_k \ge 0, \ k = 1, 2, ..., K.$$

Hence, if the ratio of the distance functions as measured by θ equals one, then farm k is the most efficient and lies on the frontier, and any value less than one implies the farm is operating below the frontier. The implication of the technical efficiency score using output-oriented DEA is the extent to which that output vector may be increased given the combination of input vector. The restrictive assumption of constant returns to scale ($z_k \ge 0$) on the production technology is further relaxed, and a variable returns to scale with strong disposability (V, S) is imposed with the following restriction on the intensity vector: $\Sigma_K z_k = 1$.

The measure of technical efficiency can be decomposed into a measure of scale efficiency and pure technical efficiency (Fare, Grosskopf, and Lovell, 1994). If a farm is not operating in the range of constant returns to scale (CRS), then conceptually it could increase output without increasing inputs if CRS is realized. The measure of technical efficiency using variable returns to scale (VRS) is termed pure technical efficiency. Pure technical efficiency occurs when a farm operates on its production frontier. Scale efficiency is measured as the ratio of CRS to VRS technical efficiencies (Domazlicky and Weber, 1997; Fare, Grosskopf, and Lovell, 1994). If the ratio is less than one, then the farm has scale error.

Stochastic Frontier Approach (SFA)

The stochastic frontier model proposed independently by Aigner, Lovell, and Schmidt (1977), and Meeusen and van den Broeck (1977) is written as:

$$(4) \quad y_i = \exp(\mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i),$$

where y_i is production of the ith farm, $\mathbf{x}_i$ is the $(k \times 1)$ vector of input quantities of the ith farm, and $\boldsymbol{\beta}$ denotes the $(k \times 1)$ vector of unknown parameters to be estimated. It is postulated that $\varepsilon_i = v_i - u_i$, where white noise $v_i \sim N(0, \sigma^2_v)$ and the one-sided component $u_i \sim N(0, \sigma^2_u)$, with $u_i \ge 0$; the u_i and v_i are assumed to be independently and identically distributed. The one-sided component (u_i) is obtained by truncation at zero of a normal distribution with mean μ and variance σ^2_μ. The term v_i allows for randomness across firms and captures the effect of measurement error, other statistical noise, and random shocks outside the firm's control. The one-sided component u_i captures the effect of inefficiency (Forsund, Lovell, and Schmidt, 1980).

Borrowing from Chakraborty, Biswas, and Lewis (2001), the production function for the ith farm in this study is represented by:

$$(5) \quad y_i = \beta_0 \prod_{k=1}^{K} x_k^{\beta_k} e^{(v_i - u_i)},$$

where y is output, x_k are exogenous inputs, and v is the stochastic disturbance term. The Cobb-Douglas transformation of the above production function for cotton producers is written as:

$$(6) \quad \mathrm{Ln}(y_i) = \beta_0 + \sum_{k=1}^{K} \beta_k \mathrm{Ln}(x_{ki}) + v_i - u_i.$$

Technical efficiency is represented as:

$$(7) \quad TE = \exp(-u_i).$$

A technically efficient farm produces output that is on the stochastic production frontier and is subject to random fluctuations captured by v. However, because of differences in managerial efficiency, actual performance deviates from the frontier.

For maximum-likelihood estimation, following Battese and Coelli (1992) and Battese and Corra (1977), the variances are parameterized as follows:

$$\sigma_s^2 = \sigma_v^2 + \sigma_\mu^2 \quad \text{and} \quad \gamma = \sigma_\mu^2/\sigma_s^2.$$

The parameter γ must lie between 0 and 1 to provide a good starting value for an iterative maximization process. If the coefficient of γ is significantly different from zero, based on a one-sided likelihood-ratio test, this implies inefficiency effects are present in the model, and frontier estimation of the production function is more appropriate than ordinary least squares (OLS) estimation (Coelli, Rao, and Battese, 1998; Coelli, 1995b).

Description of Data and Empirical Results

Description of Data

The data are derived from the Standardized Performance Analysis (SPA) database of revenues and expenditures for cotton farms in the Texas High Plains. The SPA database is maintained by the Department of Agricultural and Applied Economics, Texas Tech University. The sample includes information on multiple input expenditures and production of cotton for 77 farms (54 irrigated and 23 nonirrigated) located in Crosby, Lubbock, Hale, and Terry counties. Data on output and inputs were obtained for the year 1998 on a per acre basis. Output is defined as the average cotton lint production per acre (pounds/acre). Inputs include per acre expenditures on other inputs, fertilizer, chemicals, machinery, and labor. Expenditures on other inputs include gasoline, fuel and oil, seed and plants, and other miscellaneous expenses.

With regard to yield, it is recognized that a portion of the variability among producers may be due to weather and soil conditions. Failure to account for such variability in production due to weather and soil conditions would lead to an incorrect measure of efficiency. By using temperature- and precipitation-adjusted measures, Helmers, Weiss, and Shaik (2000) found increased efficiency and productivity in the cotton-producing states of the Southern Plains.

In this study we therefore assume, ceteris paribus, that the difference in yields among counties is due to differences in soil and weather conditions. Thus, in order to eliminate the effect of weather and soil conditions on farms' productivity, producer-level yields were normalized based on county average yield for that year. For example, for irrigated cotton, the yield per acre for Hale County was higher than for Lubbock, Terry, and Crosby counties by 41.4%, 45%, and 37.34%, respectively. Using Hale County as a base, yield per acre for farms located in Lubbock, Terry, and Crosby counties was increased by those percentages. For nonirrigated cotton, Terry County was used as a base.

Table 1 presents a summary of adjusted yields and input data used in this study. From table 1, considerable variation in yields is evident between irrigated and nonirrigated farms; the average yield of irrigated farms is 34% higher than the yield of nonirrigated farms. Similarly, average expenditures on other inputs, chemicals, and fertilizer for irrigated farms are approximately twice as much as for nonirrigated farms. In contrast, there is little variation in average expenditures on machinery and labor between the two farm types.

Empirical Results

Tables 2 and 3 report technical efficiency (TE) scores for the irrigated and nonirrigated farms obtained from the DEA and SFA models. For the DEA measure, we used a computer program (DEAP V-2.1) developed by Coelli (1992). The DEA efficiency scores are reported under constant returns to scale (CRS) and variable returns to scale (VRS) technology. CRS implies a proportionate change in inputs leads to an equal proportionate change in output, and VRS implies a proportionate change in inputs leads to more than [increasing returns to scale (IRS)] or less than [decreasing returns to scale (DRS)] proportionate change in output. Since there is no reason to assume CRS exists in the production of cotton at the farm level, the measure

Table 1. Descriptive Statistics of Output and Expenditure on Inputs (per acre) Used in the Study

	Irrigated Farms ($N = 54$)			Nonirrigated Farms ($N = 23$)		
Variable	Mean	Maximum	Minimum	Mean	Maximum	Minimum
Adjusted Yield (lbs./acre)	485.75	913.84	233.63	319.98	688.34	55.11
Inputs ($/acre):						
Other Inputs	76.95	172.93	28.02	42.17	86.12	16.40
Chemicals	34.46	90.78	4.68	16.87	43.89	3.93
Fertilizer	17.59	42.75	4.97	9.02	21.14	1.36
Machinery	52.81	95.44	22.64	62.05	190.01	20.34
Labor	27.46	45.11	0.01	27.84	102.79	10.24

Table 2. Technical Efficiency (TE) Scores Estimated for Irrigated Farms Under DEA and SFA Models ($N = 54$)

Farm No.	DEA Efficiency Scores [a] CRS	DEA Efficiency Scores [a] VRS	SFA Efficiency Score	Farm No.	DEA Efficiency Scores [a] CRS	DEA Efficiency Scores [a] VRS	SFA Efficiency Score
1	0.645	1.000	0.682	29	0.793	1.000	0.921
2	1.000	1.000	0.917	30	0.755	0.849	0.823
3	0.576	1.000	0.631	31	0.785	0.812	0.804
4	0.889	0.900	0.866	32	0.981	1.000	0.661
5	1.000	1.000	0.904	33	0.924	0.943	0.876
6	0.911	0.911	0.840	34	1.000	1.000	0.926
7	0.922	1.000	0.894	35	0.800	0.866	0.819
8	1.000	1.000	0.841	36	1.000	1.000	0.907
9	0.692	0.721	0.799	37	0.838	1.000	0.816
10	1.000	1.000	0.919	38	0.735	0.768	0.766
11	0.510	0.533	0.657	39	0.691	1.000	0.819
12	0.807	0.929	0.876	40	1.000	1.000	0.937
13	0.864	1.000	0.898	41	0.889	1.000	0.807
14	0.680	0.721	0.797	42	0.812	0.916	0.855
15	0.971	0.971	0.829	43	0.755	0.788	0.737
16	0.668	0.699	0.784	44	0.889	1.000	0.883
17	0.970	0.971	0.913	45	1.000	1.000	0.844
18	0.495	0.519	0.642	46	0.766	1.000	0.688
19	0.575	0.769	0.765	47	0.705	0.880	0.675
20	0.598	0.838	0.823	48	0.764	1.000	0.808
21	0.437	0.512	0.628	49	1.000	1.000	0.913
22	0.530	0.600	0.708	50	0.904	1.000	0.701
23	0.327	0.433	0.531	51	0.943	1.000	0.737
24	0.375	0.457	0.554	52	0.974	1.000	0.721
25	0.955	1.000	0.887	53	1.000	1.000	0.876
26	0.890	0.995	0.832	54	1.000	1.000	0.869
27	0.621	0.790	0.790				
28	0.545	0.754	0.814	Avg.	0.799	0.886	0.800

[a] CRS denotes constant returns to scale, and VRS denotes variable returns to scale.

of technical efficiency under VRS relaxes this assumption.

Of the 54 irrigated farms listed in table 2, 11 farms under CRS and 27 farms under VRS are fully efficient. Under VRS, there are eight farms with efficiency scores between 90–99%, five farms scoring between 80–89%, eight farms between 70–79%, four farms between 50–69%, and two farms with scores below 50%.

Of the 23 nonirrigated farms listed in table 3, seven farms under CRS and 14 farms under VRS are found to be fully efficient. For inefficient farms,

Table 3. Technical Efficiency (TE) Scores Estimated for Nonirrigated Farms Under DEA and SFA Models ($N = 23$)

Farm No.	DEA Efficiency Scores[a] CRS	DEA Efficiency Scores[a] VRS	SFA Efficiency Score	Farm No.	DEA Efficiency Scores[a] CRS	DEA Efficiency Scores[a] VRS	SFA Efficiency Score
1	0.736	1.000	0.712	13	1.000	1.000	0.966
2	0.756	1.000	0.719	14	1.000	1.000	0.751
3	1.000	1.000	0.933	15	0.344	1.000	0.714
4	0.647	0.771	0.549	16	0.366	0.649	0.775
5	0.319	0.352	0.253	17	0.338	0.662	0.678
6	0.599	1.000	0.555	18	0.208	0.382	0.414
7	0.734	1.000	0.663	19	0.458	1.000	0.973
8	0.648	0.798	0.570	20	1.000	1.000	0.893
9	1.000	1.000	0.845	21	1.000	1.000	0.875
10	0.992	0.992	0.838	22	0.799	0.819	0.759
11	0.408	1.000	0.385	23	1.000	1.000	1.000
12	0.945	0.998	0.496	Avg.	0.708	0.888	0.709

[a] CRS denotes constant returns to scale, and VRS denotes variable returns to scale.

the causes of inefficiency were identified as either inappropriate size or misallocation of resources. Operating at an inappropriate size suggests the farm is not taking advantage of economies of scale, while misallocation of resources refers to inefficient use of input combinations.

The coefficients of the production function in SFA are estimated using Frontier Program Version 4.1 (Coelli, 1996). A Cobb-Douglas production function in log form is assumed for convenience and simplicity. The attractive feature of the Cobb-Douglas form is that a logarithmic transformation provides a model, which is linear in logarithms of the inputs, and the coefficients measure elasticity. It is recognized that the Cobb-Douglas production function uses restrictive assumptions on the returns to scale and elasticity of substitution.

A translog (Greene, 1980) or generalized production function (Forsund and Hjalmarsson, 1979; Kumbhakar, Ghosh, and McGuckin, 1991) was not used because of potential multicollinearity and loss of degrees of freedom (due to the small number of observations in this study). Various other combinations of input variables were examined, and the following production function specification provided the best results:

$$\begin{aligned}\mathrm{Ln}(\mathit{Adjusted\ Yield}) &= \beta_0 + \beta_1 \mathrm{Ln}(\mathit{Other\ Inputs}) \\ &+ \beta_2 \mathrm{Ln}(\mathit{Chemicals}) + \beta_3 \mathrm{Ln}(\mathit{Fertilizer}) \\ &+ \beta_4 \mathrm{Ln}(\mathit{Machinery}) + \beta_5 \mathrm{Ln}(\mathit{Labor}) + v_i - u_i.\end{aligned}$$

The maximum-likelihood estimates of the parameters are reported in table 4. The signs on the coefficients of *Chemicals* and *Labor* are positive and significant for both irrigated and nonirrigated farms. The sign of the coefficient on *Machinery* is negative for both types of farms and is significant for nonirrigated farms, although a positive sign was expected for both types of farms.

The expenditures on *Machinery* include custom hire and depreciation. Based on findings of a recent study by Brooks (2001), smaller farms generally had lower yields per acre and had more custom hire for cultivation and harvesting than larger farms. Examination of our raw data on planted cropland revealed that 44% of irrigated farms and 50% of nonirrigated farms have a size less than 100 acres. The higher share of expenditure on custom hire by smaller farms may have raised the total expenditure on *Machinery* while yield per acre remained unaffected. It is possible this phenomenon contributed to the negative relationship between yield per acre and the *Machinery* variable. Finally, the coefficients for *Other Inputs* and *Fertilizer* are insignificant (table 4). These results are similar to those found by Battese and Hassan (1998) measuring technical efficiency of cotton farmers in Pakistan.

The test statistic for the generalized likelihood-ratio test for $\gamma = 0$ had a value of 5.17 for irrigated farms and 6.57 for nonirrigated farms. The null hypothesis that there is no technical inefficiency in the model is rejected at the 5% level, indicating the coefficients of the frontier production function are significantly different from the average production function estimated by OLS (Battese and Coelli, 1988; and Coelli, 1996). The *Chemical* variable has

Table 4. Maximum-Likelihood Estimates of the Stochastic Frontier Model Using Cobb-Douglas Production Function [dependent variable = Ln(*Adjusted Yield*)]

	Irrigated Farms (N = 54)		Nonirrigated Farms (N = 23)	
Variables	Coefficient	t-Statistic	Coefficient	t-Statistic
Intercept	4.579*	7.067	3.997*	23.36
Ln(*Other Inputs*)	0.121	1.078	0.043	0.133
Ln(*Chemicals*)	0.335*	4.993	0.685*	3.101
Ln(*Fertilizer*)	−0.011	−0.103	0.679	0.775
Ln(*Machinery*)	−0.002	−0.020	−0.945*	−5.928
Ln(*Labor*)	0.006*	3.647	1.143*	1.645
$\sigma_s^2 = \sigma_u^2 + \sigma_v^2$	0.113		0.229	
$\gamma = \sigma_u^2/\sigma_s^2$	0.774		0.999	

* Denotes coefficients are significantly different from zero at the 5% level or below.

the highest partial elasticity for irrigated cotton, and *Machinery* has the highest partial output elasticity for nonirrigated cotton.

The technical efficiency scores from SFA, assuming a half-normal distribution of the inefficiency component (u) for the irrigated and nonirrigated farms, are reported in column 4 of tables 2 and 3, respectively. From table 2, there are eight irrigated farms with SFA efficiency scores above 90%, 24 farms with scores between 80–89%, 12 farms between 70–79%, eight farms between 60–69%, and two farms scoring below 50%. From table 3, there are four nonirrigated farms with SFA efficiency scores above 90%, four farms between 80–89%, six farms between 70–79%, and four farms with scores below 50%.

Although individual efficiency scores for the irrigated and nonirrigated farms differ between DEA and SFA, their mean efficiency scores of 0.80 and 0.70, respectively, are similar (tables 2 and 3). This finding implies the irrigated farms could operate with 80% and nonirrigated farms with 70% of their current input levels and still produce the same level of output. The most inefficient irrigated farm under both DEA and SFA is farm 23 (Hale County), with efficiency scores of 33% and 53%, respectively (table 2). The most inefficient nonirrigated farm under DEA using CRS is farm 18 (Terry County), which is 21% efficient; under SFA, farm 5 (Lubbock County) is the most inefficient, operating at only 25% efficiency (table 3).

The differences in efficiency scores between DEA and SFA arise due to specification of the production function and the distributional assumption of the random disturbance term. This may be explained as follows. Farms appearing more efficient under SFA contain a relatively large random component (v) of the error term compared to the inefficiency component (u). Hence, under DEA, these farms appear less efficient because the production function does not account for randomness, where any deviation from the maximum is measured as inefficiency. Examples of such farms are farms 11, 22, and 23 in table 2, and farms 16 and 18 in table 3. The reverse is the case for farms that appear less efficient under SFA and more efficient under DEA—e.g., farm 11 (table 2) and farm 16 (table 3).

A ratio of technical efficiency scores obtained from DEA under CRS and VRS assumptions measures scale efficiency (SE) (not reported here). A value of SE equal to one implies the farm is scale efficient, and a value less than one suggests the farm is scale inefficient. A farm is scale inefficient because it might be producing inefficiently large output in the face of DRS or producing inefficiently small output in the face of IRS.

Farms identified as scale inefficient were analyzed further in terms of "peer counts" in table 5, and "input slacks" in table 6. For scale-inefficient farms producing in the face of DRS, table 5 reports the number of counts a farm appeared as a peer for other farm(s). Farms appearing more frequently as a peer for other farms are termed robustly efficient. They are robustly efficient because their production practices are such that these farms were frequently used to form the efficient frontier for the inefficient farms in the data. As observed from table 5, irrigated farms 10, 29, and 49, and nonirrigated farms 3 and 23 are identified as robustly efficient.

Table 6 reports input slacks for irrigated and nonirrigated farms. A slack variable represents the

Table 5. Farms and Their Counts Appearing as Peers for Other Farms

IRRIGATED FARMS:															
Farm No.	2	5	7	8	10	13	25	29	32	36	40	41	46	48	49
Peer Counts	8	5	8	2	11	3	7	12	3	8	8	6	2	2	11
NONIRRIGATED FARMS:															
Farm No.	2	3	9	13	19	21	23								
Peer Counts	2	5	2	3	3	2	5								

Table 6. Input Slacks and the Number of Farms Associated with the Slacks

	Irrigated Farms				Nonirrigated Farms			
Input Variables	No. of Farms	Actual Use ($)	Target Use ($)	Excess Use (%)	No. of Farms	Actual Use ($)	Target Use ($)	Excess Use (%)
Other Inputs	13	4,156	3,727	10.3	1	983	961	2.2
Chemicals	3	1,861	1,814	2.5	3	388	377	2.8
Fertilizer	10	950	890	6.3	—	—	—	—
Machinery	16	2,852	2,634	7.6	5	1,427	1,255	12.0
Labor	6	1,483	1,435	3.2	4	640	554	13.4

amount of excess expenditure on an input, i.e., the amount by which the expenditure on a particular input could be reduced without altering the production level. It is evident from table 6 that 13 irrigated farms together could reduce total expenditures on *Other Inputs* by 10.3% without reducing their current level of production. Similarly, excess expenditures on *Machinery* and *Fertilizer* are estimated at 7.6% and 6.3%, involving 16 and 10 irrigated farms, respectively. For nonirrigated farms, the excess expenditures on *Machinery* and *Labor* are 12% and 13.4%, representing five and four farms, respectively.

Summary and Conclusions

This study measured technical efficiency of individual cotton farms employing two commonly used methods of estimation—data envelopment analysis (DEA) and the stochastic frontier approach (SFA). Evidence suggests that under the assumption of constant returns to scale (CRS), mean efficiency estimates for cotton farmers in this study were similar when applied to DEA and SFA. On average, the irrigated farms were more efficient (80%) than their nonirrigated counterparts (70%). Findings also show, on average, irrigated and nonirrigated farms had similar efficiency scores under the assumption of variable returns to scale (VRS) in DEA.

One of the interesting results from this study is that a large number of farms—from both the irrigated and nonirrigated categories—were scale inefficient (as is evident from table 5). The major cause of inefficiency for irrigated farms was the production of large output in the face of decreasing returns to scale (increasing cost conditions), and for nonirrigated farms the production of small output in the face of increasing returns to scale (decreasing cost conditions).

Considering the growing number of large-size farms in the United States over the past 20 years, the above finding seems striking. However, Brooks (2001), in her study investigating the characteristics of production costs for U.S. cotton farms, reported similar results. Brooks found that one-third of the farms in the Prairie Gateway (which includes Texas) and Fruitful Rim regions were high-cost producers. While irrigation in these regions mitigates the effects of adverse weather conditions, it also raises production costs considerably. Hence, in order to improve efficiency, our findings suggest these farms should adjust their scale of operation. Several of these inefficient farms could reduce their operating costs by reducing expenditures on *Other Inputs*, *Machinery*, and *Labor* without decreasing their current level of output.

Although an adjustment was made in this analysis for yields per acre at the farm level based on the difference in yields per acre across counties, the assumption upon which such adjustments was made is restrictive. The assumption that the differences in yields across counties were due solely to variation in weather and soil conditions is not very realistic. Variation in yield among counties may be attributed to several other factors, such as farmers' education, age, farming experience, and contact with extension agents. Consequently, adjusting county yields only for weather and soil conditions leaves the effect of other factors unaccounted for in the measure of efficiency and productivity, and may lead to an inaccurate estimate of technical efficiency.

Thus, one of the limitations of this study was the non-inclusion of variables representing soil quality and weather variability affecting farms' productivity. In future research estimating the technical efficiency of cotton farmers, it would be helpful to include inputs such as soil conditions, annual rainfall, and temperature, as well as the demographic characteristics of the cotton farmers.

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