Exploring the Role of Managerial Ability in Determining Firm Efficiency

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Abstract

This paper explores the role of management ability in explaining efficiency on New York dairy farms. Using an unbalanced panel of farm data from 1993 through 2004, we estimate input and output-oriented technical efficiencies, cost efficiencies and revenue efficiencies using stochastic frontier functions. We include various input variables as efficiency effects and find lagged net farm income is a preferred measure of management ability over farmers' own estimates of the value of their labor and management. We also find increasing efficiency with operator education, farm size, and extended participation in a farm management program and decreasing efficiency with operator age.

Keywords: Management and Efficiency, Stochastic Frontier Analysis

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0. Introduction

The notion of efficiency has been an active area of economic research for more than fifty years. Debreu (1951) considered the case of underutilization of resources and proposed what he called the "coefficient of resource utilization" as the radial expansion of resources necessary to achieve optimal production in an economy. In his groundbreaking work, Farrell (1957) proposed numerical measures of efficiency for individual firms. From Farrell's work, in combination with the enumeration of Shephard's (1953) distance functions, came the development of empirical tools to measure efficiency. These encompass stochastic frontier econometric (Aigner, Lovell, and Schmidt 1977) and mathematical programming techniques (Charnes, Cooper, and Rhodes 1978).

The importance of this work notwithstanding, the measurement of inefficiency does not explain why it persists. The ability to explain differences in efficiency across similar firms is necessary if economists are to provide prescriptive advice to firms, recognizing the social benefit of more efficient economic activity. Some explanations of inefficiency predate its measurement, and are based on more general criticisms of neoclassical production theory. Knight (1921) argued that it is not possible for firms to calculate optimal decision rules, and that production functions are mere theoretical ideals. A similar explanation of the inability for individuals to process the vast amounts of information necessary to behave optimally is presented in Hayek (1945). The bounded rationality theory of Simon (1959) and the evolutionary theory of Nelson and Winter (1982) can similarly be invoked to question the existence of known frontiers and, by extension, the meaning of efficiency.

According to Leibenstein (1966), differences in output across firms using the same input sets are due to differences in incentives for workers and managers to perform optimally, or simply differences in inherent capabilities. This view was criticized by Stigler (1976), who argues any variation in output can be attributed to specific inputs, namely management ability. The manager must decide upon, prior to any allocative decisions, the production technology to use and how much knowledge to invest. Once that decision is made, according to Stigler, each firm is operating on an efficient frontier, although not necessarily the same frontier as other firms.

The early efficiency studies attempt to explain differences in computed efficiencies by performing a regression or other statistical exercise of efficiency on a set of explanatory variables, some of which may proxy for management ability. For example, in dairy, Tauer (1993) regressed short-run and long-run technical and allocative efficiencies for a sample of New York dairy farms on a set of variables including operator age and education. In an investigation of the effects of management ability on scale economies for dairy farms in England and Wales, Dawson and Hubbard (1987) define the management ability as returns over feed costs, a method also used in a similar study of scale economies in the South African dairy sector by Beyers (2001). Stefanou and Saxena (1988) find higher levels of education and experience have positive effects on allocative efficiency in Pennsylvania dairy farms.

The purpose of this paper is to test whether computed inefficiency is due to measures of managerial ability. We compute technical, cost, and revenue efficiency for a sample of New York dairy farms using farm-level data. We use two separate proxies for management, including operators' own estimates of the value of their management and labor, and net farm income from the previous year. Following Battese and Coelli (1995), we include these management proxies as explanatory variables in an efficiency effects model. We also estimate an heteroscedastic efficiency model (Hadri, 1999). These approaches allow testing the impact of including management capacity on firm efficiencies, while at the same time controlling for other firm-specific characteristics.

1. The Technology Set, Distance Functions, and Duality

Inefficiency is any deviation from a frontier (Førsund, Lovell and Schmidt, 1980), whether production, cost, revenue, or profit. Implicit in this definition is the existence of these respective frontiers. A production frontier is defined in terms of its technology set, $T = \{(\mathbf{x},\mathbf{y}) \mid \mathbf{x} \in \Re_+^j, \mathbf{y} \in \Re_+^k, \mathbf{x}\ \textit{can produce}\ \mathbf{y}\}$, for **x** and **y** nonnegative (*j* x 1) and (*k* x 1) input and output vectors, respectively. The production frontier for this multi-input, multi-output technology set can be defined in terms of output or input distance functions,

$$D_O(\mathbf{x},\mathbf{y}) = \min\{\phi > 0 \mid (\mathbf{x},\mathbf{y}/\phi) \in T\} \quad [1]$$

$$D_I(\mathbf{x},\mathbf{y}) = \max\{\theta > 0 \mid (\mathbf{x}/\theta,\mathbf{y}) \in T\} \quad [2]$$

where $D_O(\mathbf{x}, \mathbf{y})$ and $D_I(\mathbf{x}, \mathbf{y})$ are the output and input distance functions, respectively. The output distance function seeks the largest possible radial expansion in outputs possible for a given input vector. The input distance function seeks the largest possible radial reduction in inputs for a given output vector. The production frontier is then given by:

$$F = \{(\mathbf{x},\mathbf{y}) \mid D_O(\mathbf{x},\mathbf{y}) = 1\}; \quad [3]$$

or, equivalently,

$$F = \{(\mathbf{x},\mathbf{y}) \mid D_I(\mathbf{x},\mathbf{y}) = 1\}. \quad [4]$$

Thus, $D_O(\mathbf{x}, \mathbf{y}) < 1$ or $D_I(\mathbf{x}, \mathbf{y}) > 1$implies that this particular input-output combination lies "below" the production frontier, indicating technical inefficiency.

Cost efficiency is often derived by first defining the input requirement set (Färe and Grosskopf 2004), $L(\mathbf{y})$ such that $L(\mathbf{y}) = \{\mathbf{x} \mid \mathbf{x} \in T(\mathbf{x},\mathbf{y})$. Then the cost function is

$$C^*(y,w) = \min\{\mathbf{w}^T\mathbf{x} \mid \mathbf{x} \in L(\mathbf{y})\} \quad [5]$$

where **w** is a (*j* x 1) vector of input prices and **y** is the output vector. A dual relationship exists between the input distance function and the cost function, originally proved by Shephard (1953). This relationship is stated as

$$C^*(\mathbf{y},\mathbf{w}) = \min_{\mathbf{x}}\left\{\frac{\mathbf{w}^T\mathbf{x}}{D_I(\mathbf{y},\mathbf{x})}\right\}, \mathbf{w} > 0,$$

*i*f and only if [6]

$$D_I(\mathbf{y},\mathbf{x}) = \inf_{\mathbf{w}}\left\{\frac{\mathbf{w}^T\mathbf{x}}{C^*(\mathbf{y},\mathbf{w})}\right\};$$

Cost efficiency is defined as the ratio $C^*(\mathbf{y},\mathbf{w})/C(\mathbf{y},\mathbf{w})$, where $C(\mathbf{y},\mathbf{w})$ is the observed cost of a particular firm. Given the above duality relationship, it is clear that cost efficiency contains elements of both technical efficiency and allocative efficiency.

Similar to the derivation of cost efficiency, revenue efficiency is often stated in terms of the output set (Färe and Primont 1995), $P(\mathbf{x})$, where

$$P(\mathbf{x}) = \{\mathbf{y} \mid (\mathbf{x},\mathbf{y}) \in T(\mathbf{x},\mathbf{y})\} \quad . \qquad [7]$$

Then the revenue function is defined for input levels and output prices such that,

$$R^*(\mathbf{x},\mathbf{p}) = \max_{\mathbf{y}}\{\mathbf{p}^T\mathbf{y} \mid \mathbf{y} \in P(\mathbf{x})\}, \qquad [8]$$

where **p** is a vector of output prices. $R^*(\mathbf{x},\mathbf{p})$ defines the revenue frontier. Shephard (1970) proved duality between the revenue function and the output distance function as:

$$R^*(\mathbf{x},\mathbf{p}) = \max_{\mathbf{y}}\left\{\frac{\mathbf{p}^T\mathbf{y}}{D_0(\mathbf{y},\mathbf{x})}\right\}, \mathbf{p} > 0,$$

*i*f and only if [9]

$$D_O(\mathbf{y},\mathbf{x}) = \sup_{\mathbf{p}}\left\{\frac{\mathbf{p}^T\mathbf{y}}{R^*(\mathbf{x},\mathbf{p})}\right\};$$

which results in the output oriented Mahler's Inequality,

$$R^*(\mathbf{x},\mathbf{p})D_O(\mathbf{x},\mathbf{y}) \geq R(\mathbf{x},\mathbf{p}); \qquad [10]$$

where $R(\mathbf{x},\mathbf{p})$ is the observed revenue of a particular firm. Revenue efficiency is defined as the ratio of observed revenue to optimal (frontier value) revenue, $R(\mathbf{x},\mathbf{p})/R^*(\mathbf{x},\mathbf{p}) \leq 1$. The above output oriented Mahler's inequality then implies that revenue efficiency is less than or equal to output oriented technical efficiency given by the output distance function.

The above Farrell efficiency measures with their basis in Shephard's distance functions are widely used and will be used for the empirical analyses to follow, but they are by no means comprehensive. For example, profit efficiency is discussed in Coell, Rao, and Battese (1998). Indirect distance functions are presented in Färe and Primont (1995). Directional distance functions, which allow for non-radial scaling of both inputs and outputs, are presented in Färe and Grosskopf (2004).

2. Distance Functions

We elect to model the output distance function using a translog distance function because of its well-known flexibility. The translog distance function for *m* outputs and *k* inputs is given by:

$$\ln D_{O,i} = \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln y_m \ln y_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln y_{m,i} \quad [11]$$

The distance function requires homogeneity of degree one in outputs, which in turn requires that $\sum_m \alpha_m = 1$, $\sum_n \beta_{mn} = 0$, and $\sum_m \beta_{km} = 0$. This is accomplished by normalizing the function by an output. Using y_1 as the normalizing output, the distance function then becomes:

$$\ln\left(\frac{D_{O,i}}{y_{1,i}}\right) = \alpha_0 + \sum_m \alpha_m \ln y^*_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln y^*_{m,i} \ln y^*_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln y^*_m \quad [12]$$

where, $y_m^* = y_m / y_1$. Symmetry requires that $\beta_{mn} = \beta_{nm}$, $\beta_{kl} = \beta_{lk}$, and $\beta_{km} = \beta_{mk}$. Finally, letting $\ln D_{O,i} = u_i$, and appending an error term to the right-hand side, the translog distance function becomes:

$$-\ln y_{1,i} = \alpha_0 + \sum_m \alpha_m \ln y^*_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln y^*_m \ln y^*_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln y^*_m + v_i - u_i; \quad [13]$$

where $v_i - u_i$ is an additive error term with random noise part *v* and efficiency part *u*. The distribution of *v* is assumed $v \sim N(0, \sigma_v^2)$. Defining $e_i \equiv v_i - u_i$, the estimated technical efficiency for the i^{th} firm is $E[\exp(-u_i) \mid e_i]$.

Similarly, we can define an input distance function to measure the extent of technical efficiency from an input-oriented perspective. The input distance function is homogeneous of degree 1 in inputs. Choosing x_1 as the normalizing input, where $x^* = x_k / x_{1,}$, imposing symmetry $\beta_{mn} = \beta_{nm}$, $\beta_{kl} = \beta_{lk}$, and $\beta_{km} = \beta_{mk}$, defining $\ln(D_{I,i}) = u_i$ and appending a random error term, the input distance function becomes:

$$- \ln x_{1,i} = \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + \frac{1}{2} \sum_m \sum_n \beta_{mn} \ln y_m \ln y_{n,i} + \sum_k \alpha_k \ln x^*_{k,i} + \frac{1}{2} \sum_k \sum_l \beta_{kl} \ln x^*_{k,i} \ln x^*_{l,i} + \sum_k \sum_m \beta_{km} \ln x^*_{k,i} \ln y_{m,i} + v_i - u_i \quad [14]$$

Defining $e_i \equiv v_i - u_i$, the estimated technical efficiency for the i^{th} firm is $E[\exp(u_i) \mid e_i]$.

The choice of an output or input specification depends on whether one believes input or output choices are more likely to describe farmers' decision-making processes. The duality of the input distance function and the cost function suggests that if farmers choose inputs to minimize the cost of producing some target output, then an input distance function approach would be most appropriate. On the other hand, if inputs are considered relatively fixed to the farmer, an output distance function would be more appropriate.

3. Stochastic Cost Frontiers

The stochastic cost frontier is specified as a translog cost function with a two-part error structure, *v* + *u*, where *v* and *u* are described above:

$$\ln(TC_i) = \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + \frac{1}{2} \sum_m \sum_n \beta_{mn} \ln y_m \ln y_{n,i} + \sum_k \alpha_k \ln r_{k,i} + \frac{1}{2} \sum_k \sum_l \beta_{kl} \ln r_k \ln r_{l,i} + \sum_k \sum_m \beta_{km} \ln r_{k,i} \ln y_{m,i} + v_i + u_i \quad ; \quad [15]$$

where TC is the total cost of the i^{th} farm, and r_k is the price of the k^{th} input.

The cost function must be homogeneous of degree 1 in input prices. This is accomplished by normalizing the function by one of the input prices. Normalizing by r_1, the cost function becomes:

$$\ln\left(\frac{TC}{r_1}\right)_i = \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + \frac{1}{2}\sum_m\sum_n \beta_{mn} \ln y_m \ln y_{n,i} + \sum_k \alpha_k \ln r^*_{k,i} + \frac{1}{2}\sum_k\sum_l \beta_{kl} \ln r^*_{k,i} \ln r^*_{l,i} + \sum_k\sum_m \beta_{km} \ln r^*_{k,i} \ln y_{m,i} + v_i + u_i; \quad [16]$$

where $r^* = r_k / r_1$. Symmetry requires that $\beta_{mn} = \beta_{nm}$, $\beta_{kl} = \beta_{lk}$, and $\beta_{km} = \beta_{mk}$. The translog cost function also requires that costs are monotonically increasing and concave in input prices. For monotonicity, $\frac{\partial \ln(TC)_i}{\partial \ln r_k} > 0 \quad \forall k$, and for concavity, the matrix β_{kl} must be negative semi-definite.

The distance from the cost frontier is measured by u. Cost efficiency for the i^{th} farm is then computed as $E[\exp(u_i) \mid e_i]$. With this formulation, cost efficiency is greater than or equal to unity. Its inverse, therefore, is the percentage reduction in cost necessary to bring total cost to the frontier.

4. Stochastic Revenue Frontiers

The stochastic revenue frontier is specified as a translog revenue function with a two-part error structure, $v - u$, where v and u are again defined as above:

$$\ln R_i = \alpha_0 + \sum_m \alpha_m \ln p_{m,i} + \frac{1}{2}\sum_m\sum_n \beta_{mn} \ln p_m \ln p_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k\sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k\sum_m \beta_{km} \ln p_{k,i} \ln y_{m,i} + v_i - u_i \quad ; \quad [17]$$

where p_m is the price of the m^{th} output and R_i is the total revenue of the i^{th} farm.

The revenue function must be homogeneous of degree 1 in output prices. This is accomplished by normalizing the function by one of the output prices. Choosing p_1 as the normalizing price, the stochastic revenue frontier function becomes:

$$\ln\left(\frac{R_i}{p_{1,i}}\right) = \alpha_0 + \sum_m \alpha_m \ln p^*_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln p^*_{m,i} \ln p^*_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln p^*_m + v_i - u_i \quad ; \qquad [18]$$

where $p^* = p_k / p_1$. Symmetry requires that $\beta_{mn} = \beta_{nm}$, $\beta_{kl} = \beta_{lk}$, and $\beta_{km} = \beta_{mk}$.

Estimated revenue efficiency for the i^{th} firm is $E[\exp(-u_i) \mid e_i]$.

5. Data Sources

The New York State Dairy Farm Business Summary (DFBS) is a farm management assistance program that collects annual data from New York dairy farmers on a voluntary basis. Data from the years 1993 through 2004 were used. The number of farms participating varies each year and ranged from 354 in 1993 to 199 in 2004. Six inputs and two outputs are defined for the analysis by aggregating accrual accounts. Price indexes taken from *Agricultural Prices* are used to deflate the accrual and inventory accounts to constant dollars. The aggregate inputs are operator labor input, hired labor input, purchased feed input, livestock input, capital input, and crop inputs. The two outputs are milk and other outputs. Summary statistics are in Table 1.

The outputs aggregated to form our measure of "other output" consist largely of what may be considered byproducts of milk production, such as livestock sales (cull cows and calves), government payments, and herd appreciation. Thus we expect the input distance functions and cost functions to show jointness in outputs resulting from the concurrent production of both outputs.

Revenue and cost efficiency problems require knowledge of output and input prices. Price indexes were calculated for the aggregate inputs by means of a weighted average of the price indexes used for the individual DFBS items used in the aggregation process. This ensures that although the quantities of the DFBS items may be different for each farm, all farms face the identical prices for the aggregate input or output.

6. Stochastic Frontier Methods

The final estimation equation for the output distance function is an adaptation of equation [13]. We drop the negative sign from y_1, which results in the signs of the parameters being reversed, but more easily interpreted by standard production theory. The final estimation equation is then:

$$\ln y_{1,i} = -TL(X_i, y_i^* \mid \alpha, \beta) + \sum_s \zeta_s D_{s,i} + \tau T - v_i + u_i \;; \qquad [19]$$

where X is a vector of inputs including Operator Labor, Hired Labor, Purchased Feed, Livestock, Capital, and Crop Inputs, D is a set of dummy variables for the observations with observed zero inputs or negative (accounting) other output, and T is a time trend, α and β are parameter vectors and ζ and τ are parameters to be estimated. We choose y_1 as milk receipts, so that y^* is other output (receipts) normalized by milk receipts.

Equation [14] provides the estimation framework for the input distance function. We again drop the negative sign from in front of x_1, resulting in the estimation equation:

$$\ln x_{1,i} = -TL(X_i^*, Y_i \mid \alpha, \beta) + \sum_s \zeta_s D_{s,i} + \tau T - v_i + u_i \;; \qquad [20]$$

where we now choose x_1 to be the livestock input, X^* is the input vector normalized by the livestock input, $\boldsymbol{Y}$ is a vector output including milk receipts and other receipts and D, T, α, β, ζ, and τ, are described above.

Estimation of cost and revenue frontiers are based on equations [16] and [18], respectively. For cost efficiency, we choose to normalize all prices by the price of the livestock input to impose the homogeneity constraint. A time trend and a dummy variable to account for the observations where no other output is observed are appended to the cost function. The final estimation form for the cost frontier is

$$\ln(TC_i^*) = TL(r_i^*, Y_i \mid \alpha, \beta) + \varsigma D + v_i + u_i \quad . \qquad [21]$$

Dummy variables to account for observation where zero hired labor and crop inputs and a time trend are appended to the revenue function yielding the estimation equation:

$$\ln(TR_i^*) = TL(p_i^*, X_i \mid \alpha, \beta) + \sum_s \varsigma_s D + v_i - u_i \quad ; \qquad [22]$$

where price of milk is used as the normalizing price.

A distributional assumption is required for u in these equations. The pioneering work of Aigner, Lovell, and Schmidt (1977) assumed a half-normal distribution; $u \sim N^+(0, \sigma_u^2)$. The half-normal assumption can be relaxed to allow for other truncations, such that $u \sim N^+(\mu, \sigma_u^2)$, $\mu \geq 0$. Kumbhakar, Ghosh, and McGuckin (1991), Huang and Liu (1994), and Battese and Coelli (1995) examine the effects of exogenous determinants of efficiency by parameterizing the mean of the pre-truncated distribution. In this case, μ, is assumed to follow a linear function of the exogenous variables, $\mu_i = \mathbf{z_i}\delta$; where δ is a vector of parameters to be estimated. Assuming a constant variance, the marginal effect of a change in an element of **z** on the expected value of u is (Wang 2002):

$$\frac{\partial E[u_i]}{\partial z_k} = \delta_k \left(1 - \Delta \frac{\phi(\Delta)}{\Phi(\Delta)} - \left(\frac{\phi(\Delta)}{\Phi(\Delta)} \right)^2 \right) \qquad [23]$$

where $\Delta = \mu_i / \sigma_u^2$ and ϕ and Φ are the standard normal and cumulative standard normal probability density functions, respectively.

Likewise, variance of the efficiency term for the i^{th} farm can be parameterized as:

$$\sigma_{u,i}^2 = \exp(\mathbf{z_i}^T \lambda) \quad ; \qquad [24]$$

where **z** is a vector of exogenous variables (and a constant) and λ is a vector of parameters to be estimated. Wang (2002) shows that the marginal effect of a change in an element of **z** on the expected value of *u* (and hence technical efficiency) is:

$$\frac{\partial E[u_i]}{\partial z_k} = \lambda_k \frac{\sigma_i}{2} \frac{\phi(0)}{\Phi(0)} = \lambda_k \sigma_i \phi(0); \qquad [25]$$

It is not obvious which parameterization (either the mean or the variance) of *u* is best. Kumbhakar and Lovell (2000) show that if *u* is heteroscedastic and is ignored, then the parameters of the production function and the estimates of technical efficiency are biased. If *v* is heteroscedastic and not corrected, then the parameters of the production function are consistent but the estimates of technical efficiency are biased. Wang (2002) suggests that μ, σ_u^2, and σ_v^2 should all be parameterized with the same set of variables, arguing there is no theoretical justification for preferring one parameterization over others.

For panel data, Battese and Coelli (1988) specify the distribution of *u* as a truncated normal with the added restriction that $u_{it} = u_i$ for all *i* and *t*; that is, the efficiency effect is constant over time for all firms in the sample. This time invariant model is estimated via maximum likelihood, but yields results that are quite similar to a simpler fixed-effects model. This is the approach taken by Schmidt and Stickles (1984), who estimate firm effects based on the frontier of the firm with the largest intercept.

7. Technical Efficiency Variables

We focus on two measures of farmer management ability, operators' values of labor and management, and net farm income from the previous year. However, we transform both management variables to a per-cow basis and transform them to their natural logarithms prior to estimation. We include two demographic variables, age and education level. The variable Age is the natural log of the average of all operator ages on the farm. The expected sign on this term is ambiguous. While efficiency may increase with experience (age), younger farmers may have a better understanding of newer production technologies and methods. The variable Education is the natural logarithm of the average number of years of formal schooling of the operators on the farm. We expect the sign of this variable to indicate higher levels of technical efficiency. The variable Milking Frequency takes the value unity for farms that milk more than two times per day, as opposed to the conventional twice-daily milking schedule.

The next three variables included for technical efficiency effects measure the length of farms' participation in the *Dairy Farm Business Summary*. This allows us to test whether farms' participation in the survey affects farm performance. Participation in the *DFBS* is voluntary, and in exchange for their participation, farmers receive a detailed business analysis of their farms as well as a summary of where they stand in relation to peer farms. Because farms can enter and exit the survey at will, we are forced to deal with an unbalanced panel, and it is unclear when the effects of the survey (if any) will become evident in the production performance. To deal with these challenges, three dummy variables are created to measure the number of years that the farm participated in the survey over the twelve-year sample period. We define a dummy variable for participation in the *DFBS* at least four years in the sample period for years 1996 and later. The variable *DFBS* participation 7 years indicates farms that participated in the survey for at least seven years in the sample period for the years 1999 and later. *DFBS* participation 10 years indicates farms that participated for at least ten years in the sample period.

The variable Cows is the natural logarithm of the annual average number of cows in production for each farm. We include this as a measure of farm size to test the effects of farm size on efficiency. We expect larger farms to be more efficient. However, it is possible that the direction of causality runs the other way; that farms are larger because they are more efficient.

The regression models are summarized in Table 2. We begin by estimating conditional mean models. In Model 1, we estimate using a set of explanatory variables for μ including operator value of labor and management per cow, age, education, milking frequency, the survey participation variables, and cows. Model 2 differs from the previous model only by the exclusion of cows in the expression for μ. Model 3 makes use of the unbalanced panel nature of our data set, estimating the function using the Battese, Coelli, and Colby (1989) time-invariant efficiency specification. Models 4 and 5 follow the same parameterizations of Models 1 and 2 with operator value of labor and management per cow variable replaced by net farm income per cow from the previous year. Next, Models 6 and 7 are estimated with parameterized variances of v and u using the same efficiency variables as Models 1 and 2. Models 8 and 9 repeat the analysis with net farm income per cow from the previous year in place of operators' values of labor and management per cow. As stated above, the time-invariant specification in Model 3 is akin to a fixed-effects model, and thus incorporates information contained in the longitudinal characteristics of the data set.

A few words are required regarding the interpretation of the δ and λ parameters. For the output distance functions, estimated technical efficiency is calculated as $E[\exp(-u_i) \mid e_i]$. This implies that if $\delta_k < 0$ (or $\lambda_k < 0$), then an increase in z_k results in a decrease in $E[u]$, and an *increase* in technical efficiency. It follows that if $z_k \notin X \cup Y$,

then for the conditional mean models:

$$-\frac{\partial D_{O,i}}{\partial z_k} = \frac{\partial \ln y_{1,i}}{\partial z_k} = -\frac{\partial E[u_i]}{\partial z_k} = -\delta_k \left(1 - \Delta \frac{\phi(\Delta)}{\Phi(\Delta)} - \left(\frac{\phi(\Delta)}{\Phi(\Delta)} \right)^2 \right) \quad ; \qquad [27]$$

the percentage change in output (holding all inputs and output composition constant) resulting from an incremental change in z_k. Similarly, for the heteroscedasticity models,

$$-\frac{\partial D_{O,i}}{\partial z_k} = \frac{\partial \ln y_{1,i}}{\partial z_k} = -\frac{\partial E[u_i]}{\partial z_k} = -\lambda_k \sigma_i \phi(0) \quad . \qquad [28]$$

The input distance functions require a slightly different estimation framework. Technical efficiency is measured as $E[\exp(u_i) \mid e_i]$., with $u > 0$. This implies that we can interpret the coefficients on the input distance functions in the same manner as the coefficients for the output distance function. As E[u] decreases, technical efficiency increases. Thus for the conditional mean models, if $z_k \notin X \cup Y$,

$$-\frac{\partial D_{I,i}}{\partial z_k} = \frac{\partial \ln x_{1,i}}{\partial z_k} = \frac{\partial E[u_i]}{\partial z_k} = \delta_k \left(1 - \Delta \frac{\phi(\Delta)}{\Phi(\Delta)} - \left(\frac{\phi(\Delta)}{\Phi(\Delta)} \right)^2 \right) \quad ; \qquad [29]$$

and for the heteroscedastic models,

$$-\frac{\partial D_{I,i}}{\partial z_k} = \frac{\partial \ln x_{1,i}}{\partial z_k} = \frac{\partial E[u_i]}{\partial z_k} = \lambda_k \sigma_i \phi(0) \quad . \qquad [30]$$

8. Output Distance Function Results

The estimation results for all the models are available from the authors. Here we summarize and discuss the major results of the various models with emphasis on efficiencies. Many of the production frontier parameters are statistically significant in all models. Summary statistics for all estimated efficiencies are shown in Table 3.

We calculate the estimated marginal effects of all the efficiency variables via the Wang formulas and the results are shown in Table 4. The presented marginal effects are the average of all the individual farm marginal effects The original econometrically estimated efficiency coefficients are not shown, but the computed Z values under the null hypothesis of $H_0=0$ for these coefficients are also shown in Table 4. In models with both mean and variance components, the first listed Z value is for the mean, the second is for the variance. Since the variables operator value of labor and management per cow, net farm income per cow from the previous year, operator age, operator education, and cows all enter the models as their natural logs, the marginal effects of these variables can be interpreted as elasticities. For example, in Model 4, the average marginal effect of an increase in net farm income per cow from the previous year is -0.0262, implying a 2.62 percent decrease in the expected value of u, or, equivalently, a 2.62 percent expansion in output due to increased efficiency.

In Model 1, all of the technical efficiency variables are significant except Milking Frequency and Survey 10 Years. The Model 1 results indicate that efficiency increases with management ability as measured by operators' own values of labor and management per cow. Efficiency decreases with age and increases with education, and participation in the *DFBS* for at least four years and seven years. Likewise, the negative sign on the coefficient for Cows indicates increasing efficiency with farm size. However, these results are not robust to changes in model specification. In Model 2, when Cows is excluded from the parameterization of μ, none of the efficiency variables is statistically significant. The average estimated technical efficiency under the Model 1 specification is 0.77, which is much lower than the average estimate of technical efficiency in Model 2 of 0.92. This shows that the presence of the Cows variable in the efficiency term tends to have a large impact on the production frontier, contributing to a larger downward shift in the production frontier for the farms in the sample than in Model 2.

When net farm income per cow from the previous year is used in place of operators' values of labor and management per cow in Models 4 and 5, we see a similar effect of the inclusion of Cows in the efficiency term. As in the previous models, efficiency tends to increase with education and decrease with operator age. The survey variables all have the expected negative sign, indicating increasing efficiency with extended participation in the *DFBS*, although not all are statistically significant.

The effects of the efficiency variables and their significance in the mean-variance models are quite similar to the results from the conditional mean models. In Model 6, efficiency increases with an increase in management ability as measured by operators' own values of their labor and management. However, in Model 7, when farm size, as measured by the natural log of the average number of cows in production is not included in the expressions for the variances of v and u, the results show an insignificant negative effect on farm efficiency. When the natural log of net farm income per cow from the previous year is used as a measure of management ability in Models 8 and 9, we see a consistently positive effect of management ability on farm efficiency. All four models show efficiency increasing with average operator education levels and decreasing efficiency with operator age, consistent with the results from the conditional mean models. The effects of the *DFBS* participation variables are slightly different from the results of the conditional mean models. Models 6 and 7 show that efficiency increases with participation in the *DFBS* for more than four years. Model 8 shows a significantly *negative* effect of participation in the *DFBS* for more than 6 years and a significantly positive effect of participation for more than 10 years. Model 9 shows a significantly positive effect of participation for more than 10 years only. Average estimated technical efficiencies are relatively high and consistent across the four models, ranging from 0.91 to 0.92. Returns to scale are significantly different from unity in Models 6, 7, and 9, but their magnitudes imply returns to scale that are basically constant.

The marginal effects for the operator value of labor and management per cow on efficiency are larger than those for net farm income per cow for the models where farm size is included as an efficiency variable. However, the marginal effects of net farm income per cow are more consistent than operators' own values of labor and management, as they show an increase in efficiency with increasing management ability regardless of specification. This suggests that net farm income per cow from the previous year may be a better measure of management ability than farmers' own subjective estimates.

9. Input Distance Function Results

Input distance functions were estimated for Models 1 – 3 and Models 6 – 9. Models 4 and 5 are not presented due to failed convergence[1]. Many of the input requirement function coefficients are statistically significant. The coefficients are much more stable across model specifications than coefficients for the output distance functions.

Summary statistics for the predicted technical efficiencies from each of the input distance function models are presented in Table 3. These models predict average technical efficiency ranging from 1.05 to 1.07, or between 93 percent – 95 percent efficient, slightly higher than the predicted efficiencies from the output distance function specifications, except for Model 3 at 1.45

For the conditional mean Models 1 and 2, only operator value of labor and management per cow and operator education are significant at 95 percent confidence.

However, these models predict that management ability when measured this way serves to decrease efficiency, in contrast to the output distance function models.

The heteroscedastic input-oriented Models 6 and 7 show similar results to the output distance models for age, education and survey participation. The model results diverge, however, with respect to the effects of farm size and management ability. Models 6 and 7 each show decreasing efficiency for higher levels of both management ability measures, as measured by operators' own values of labor and management. Model 6 predicts that efficiency may *decrease* with farm size; an interesting result given how strong the efficiency effects due to farm size are in the output distance function models. For the heteroscedastic Models 8 and 9, with net farm income per cow from the previous year used as a measure of management ability, the results are very similar to the results for Models 8 and 9 using the output distance function specifications.

In contrast to the output-oriented models, all specifications predict increasing returns to scale. The estimated elasticities of inputs with respect to output show, as expected, that milk output far outweighs the other output in terms of input use. Decomposition of these elasticities shows significant negative cross effects between the two outputs, indicating production jointness. An increase in one output leads to an increase in the marginal productivity of inputs used in the production of the other output. Given that the accrual receipts aggregated to form the "other" output largely consist of by-products of milk production, this result is expected.

With regard to both the input and output specifications, it seems that lagged values of net farm income per cow provides a better estimate of management ability than

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[1] Several alternative algorithms and many sets of starting values were tried.

operators' own values of their labor and management per cow. Net farm income per cow is a more objective measure and consistent with Stigler's conjecture that differences in management ability should be reflected in profits.

10. Cost Frontier Results

Cost frontiers were estimated for all model specifications, but none was found to be well behaved for either the concavity or monotonicity assumptions. To impose these assumptions on the estimation equations, we restrict the coefficients of all of the input price cross terms and the input price – output interaction to zero.[2] The resulting estimates preserve the concavity and monotonicity assumptions while still allowing scale economies to vary with output.

The input price coefficients showed some variation across model specifications, implying that the predicted cost frontier is dependent on the specification of the efficiency term. All specifications show increasing returns to scale, similar to the estimates provided by the input distance function models. The sign of the coefficient for the output interaction term is significantly negative in all specifications indicating the presence of output jointness, similar to the input distance functions.

Marginal cost efficiency effects were calculated via the Wang formulas. The marginal effects are shown in Table 6, and are the average of all the individual computed marginal effects. All marginal effects are calculated at the sample means of the data. Summary statistics for the computed cost efficiencies for each model specification are presented in Table 3**.** Here again, the results show that average efficiency scores (and hence the frontier) are dependent on the specification of the efficiency term. We use these estimated cost efficiencies with the estimated input-oriented technical efficiencies to derive an estimate of the degree of allocative efficiency of the farms. Models 1 and 2, and 6-9, show that the average farm is close to being fully allocatively efficient, while Model 3 predicts an average of 94 percent allocative efficiency. It should be noted that these allocative efficiency measures are only theoretically bounded. Some of the farms in the analysis show greater than 100 percent estimated allocative efficiency. This may be due to the fact that the translog function is not self-dual.

None of the efficiency term variables is statistically significant in Models 1 or 2. Models 4 and 5 show increasing efficiency with management ability as measured by net farm income per cow from the previous year, operator education, and farm size. Both models show that older farmers are less efficient then younger farmers with a positive sign for the coefficient on Age. The coefficient signs for the DFBS participation variables are consistent across both models. The heteroscedastic cost efficiency Models 6 – 9 show very similar results for the efficiency variables. Using net farm income per cow from the previous year to measure farmers' management ability in Models 8 and 9 shows significant efficiency gains with increasing management ability.

11. Revenue Frontier Results

Not surprisingly, given the jointness of the two outputs of the farms in our sample, the results from the revenue frontier functions resemble the results from the output distance function quite closely. All relevant model specifications show increasing revenue efficiency with management ability as measured by net farm income per cow from the previous year. The revenue efficiency effects for operators' own values of the

[2] These restrictions imply global satisfaction of the concavity and monotonicity assumptions.

labor and management per cow are mixed, indicating that net farm income per cow from the previous year may be the better measure of management ability.

Estimated revenue efficiencies for each model specification are presented in Table 3. The conditional mean Models 1 and 4, with farm size included in the efficiency term show lower average revenue efficiencies than the other specifications of 0.79 and 0.80, respectively. Just as with the output distance function models, Model 5 also shows a relatively low average level of revenue efficiency. Models 6 – 9 all show average revenue efficiency near 0.91.

Summing the first partial derivatives of the revenue function with respect to each input, show decreasing returns to scale for Models 1 and 4 and near constant or slightly increasing returns to scale for all other models, quite consistent with the estimates from the output distance functions.

12. Discussion

We have presented a large number of model specifications, but we are left to choose which is best. There are four criteria presented in the above results on which we must base our preferred model choice. First, we can choose which orientation (output or input) most likely describes the economic behavior of the farms in our sample. Second, we can choose which management ability indicator is likely to give the best estimates of the true management abilities of the dairy farm operators in our sample. Third, we can choose between the conditional mean or heteroscedastic specifications. Fourth, we can decide whether farm size, as measured by the average number of cows in production, should be included in the set of efficiency variables.

The choice of an output or input specification depends on whether one believes input or output choices are more likely to describe farmers' decision-making processes. The duality of the input distance function and the cost function suggests that if farmers choose inputs to minimize the cost of producing some target output, then an input distance function approach would be most appropriate, with allocative efficiency extracted from the estimated cost function. On the other hand, if farmers are believed to choose outputs to maximize revenue, then an output distance function would be more appropriate, with estimated allocative efficiency derived from estimated revenue efficiency. Revenue maximization is a reasonable assumption for firms that sell their outputs in competitive markets or have fixed inputs, while cost minimization assumes exogenously determined output levels, possibly due to regulation or some other constraint (Färe and Primont 1995). Given the farms in our data set, which sell milk on competitive markets and may deal with input fixities, the assumption of revenue maximization seems most appropriate. Thus, the output specifications may provide better insights into the technical and allocative efficiencies of the dairies in our sample.

The choice of the preferred measure of management ability is clearer. The efficiency effects of net farm income per cow from the previous year were more consistent across specifications, and were always statistically significant. This measure is also more objective than operators' own values of their labor and management in that it is directly linked to farm performance.

The model results support the choice of the heteroscedastic specifications over the conditional mean specifications. All of the heteroscedastic models show significant coefficients in the residual variance. The variance of v tends to increase with management ability (regardless of measure) and decrease with farm size and milking frequency across the several specifications. In addition, the conditional mean model coefficients are more volatile across the specifications, likely due to their greater flexibility relative to the heteroscedastic specifications and the correlation of farm size with the input and output levels, thus influencing the input and output elasticity estimates.

Finally, the inclusion of farm size, as measured by the average number of cows in production in the efficiency term seems justified given the significant results in each of the output oriented models. While there may be some problems with this measure with respect to endogeneity (it is possible that large farms achieve their size relative to their peers *because* they are efficient), its inclusion in the variance of the efficiency distribution is reasonable given the Tauer and Mishra (2006) observation that there exist greater variation in firm efficiencies among smaller U.S. dairies than larger ones.

13. Efficiency over Time

As discussed previously, we may expect some increase in efficiency for any particular farm over time due to learning effects. Through learning over time, farm operators may simply become better farmers and move their operations closer to the attainable frontier, although some of this learning may be counteracted by the empirical observation that farm efficiency decreases with farmer age, all else held constant. However, at least part of the management capacity that we hope to measure may not be influenced by such learning effects inasmuch as it may be influenced by idiosyncratic, inherent abilities of the farmers in our sample.

We will focus on the output distance function Model 8. Recall that for this model, our proxy for farmer management ability is net farm income per cow from the previous year with a total sample size of 2358 observations on 510 farms over 11 years. We created a data set consisting of all observed year over year changes in estimated technical efficiency for each farm. This method necessarily excludes the estimated technical efficiencies for farms that do not appear in our unbalanced panel in two consecutive years. The above methods create a data set of 1762 year over year changes in estimated technical efficiency. A summary of these data are presented in Table 8. Roughly 30 percent of all the observed year over year changes in estimated technical efficiency is less than 0.5 percent with 45 percent less than 1 percent.

14. Conclusions

We explored the role of management ability in explaining efficiency on a group of New York dairy farms using stochastic frontier estimation. We estimated input- and output-oriented technical efficiencies, cost efficiencies and revenue efficiencies using stochastic frontier functions. Using an unbalanced panel of individual farm data from 1993 – 2004, we defined 6 inputs, including operator labor, hired labor, purchased feed, livestock, capital, and crop inputs, and two outputs, including milk output and all other outputs. We defined the management input in two ways. First, farmers estimated their own values of labor and management. Second, the panel nature of the data set allows us to use the previous year's net farm income as a measure of farmer management ability. We transformed our management input variables to a per cow basis and included them as efficiency effect variables along with operator age, education, farm size, and years of participation in the panel. We estimated conditional mean and heteroscedastic efficiency term specifications for each frontier model.

We find that using lagged net farm income per cow may be a preferred measure of management ability than farmers' own estimates of the value of their labor and management per cow. We find that at the margin this measure of management ability increases input-oriented technical efficiency by 1.4 – 1.5 percent and cost efficiency by between 1.7 – 2.9 percent, depending on specification. Output-oriented technical efficiency and revenue efficiency increase at the margin by 1.8 – 3.0 percent and by 2.4 – 4.2 percent respectively. We also find efficiency increases with operator education, farm size, and extended participation in a farm management program and efficiency decreses with operator age.

Table 1: Summary Statistics for Inputs and Outputs

Variable	Mean	Std. Dev.	Min	Max
Milk Output	6538	8830	375	83724
Other Output	931	1277	-326	10180
Operator Labor Input	274	136	34	857
Hired Labor Input	631	850	0	8324
Purchased Feed Input	1800	2463	60	22460
Livestock Input	1538	2176	94	21539
Capital Input	1849	2161	174	17785
Crop Input	415	490	5	3919
Operator Value of Labor and Management per Cow	347	244	45	2080
Net Farm Income per Cow	928	1448	-1536	12227
N = 3375				

Table 2: Stochastic Frontier Model Descriptions

	Model 1	Model 2	Model 3	Model 4
N	3351	3351	3375	2358
Parameter	μ	μ	Time Invariant	μ
Operator Value of Labor and Management per Cow	X	X		
Net Farm Income from the Previous Year per Cow				X
Age	X	X		X
Education	X	X		X
Milking Frequency	X	X		X
DFBS Participation at least 4 years	X	X		X
DFBS Participation at least 7 years	X	X		X
DFBS Participation at least 10 years	X	X		X
Cows	X			X

	Model 5	Model 6		Model 7		Model 8		Model 9	
N	2358	3351		3351		2358		2358	
Parameter	μ	σ^2_u	σ^2_v	σ^2_u	σ^2_v	σ^2_v	σ^2_v	σ^2_u	σ^2_v
Operator Value of Labor and Management per Cow		X	X	X	X				
Net Farm Income from the Previous Year per Cow	X					X	X	X	X
Age	X	X	X	X	X	X	X	X	X
Education	X	X	X	X	X	X	X	X	X
Milking Frequency	X	X	X	X	X	X	X	X	X
DFBS Participation at least 4 years	X	X	X	X	X	X	X	X	X
DFBS Participation at least 7 years	X	X	X	X	X	X	X	X	X
DFBS Participation at least 10 years	X	X	X	X	X	X	X	X	X
Cows	X	X	X			X	X		

Table 3. Summarized Statistics for Estimated Efficiencies, Mean Values (Standard Deviation in Parenthesis)

Model	Output Distance Function	Input Distance Function	Cost	Allocative (Cost)	Revenue
1	0.77	1.07	1.08	1.01	0.79
	(0.14)	(0.05)	(0.08)		(0.13)
2	0.92	1.07	1.08	1.01	0.92
	(0.06)	(0.05)	(0.07)		(0.06)
3	0.87	1.45	1.54	1.06	0.88
	(0.08)	(0.12)	(0.14)		(0.07)
4	0.80		1.13		0.80
	(0.14)		(0.11)		(0.13)
5	0.81		1.33		0.82
	(0.05)		(0.09)		(0.07)
6	0.91	1.05	1.06	1.01	0.91
	(0.07)	(0.03)	(0.03)		(0.07)
7	0.91	1.07	1.09	1.02	0.91
	(0.05)	(0.03)	(0.05)		(0.05)
8	0.92	1.07	1.08	1.01	0.91
	(0.07)	(0.07)	(0.09)		(0.08)
9	0.92	1.07	1.09	1.01	0.91
	(0.07)	(0.07)	(0.09)		(0.08)

Table 4: Estimated Marginal Efficiency Effects, Output Distance Functions Models (Computed Z Values in Parenthesis; Mean or Mean and Variance)

	Operator Value of Labor and Management per Cow	Net Farm Income per Cow from the Previous Year	Age	Education	Cows
Model 1	-0.0696 (-10.97)		0.0480 (4.12)	-0.1172 (-7.63)	-0.2506 -(23.61)
Model 2	0.0172 (1.75)		0.0409 (1.63)	-0.0942 (-1.81)	
Model 4		-0.0262 (-26.75)	0.0382 (3.16)	-0.1341 (-8.66)	-0.1803 (-19.75)
Model 5		-0.0311 (-28.17)	0.0596 (4.27)	-0.1041 (-5.94)	
Model 6	-0.0355 (-6.31), (3.28)		0.0410 (3.45)(-1.80)	-0.0920 (-5.92)(0.38)	-0.0965 (-13.10)(1.73)
Model 7	0.0042 (0.94)(6.03)		0.0530 (4.17)(-1.67)	-0.1161 (-6.71)(0.79)	
Model 8		-0.0180 (-16.78)(4.36)	0.0316 (2.48)(-0.68)	-0.0847 (-5.03)(2.48)	-0.0526 (-8.93)(-1.20)
Model 9		-0.0179 (-17.79)(5.62)	0.0284 (2.42)(-0.67)	-0.0755 (-4.93)(2.59)	

	Milking Frequency	DFBS Participation at least 4 years	DFBS Participation at least 7 years	DFBS Participation at least 10 years
Model 1	-0.0025 (-0.39)	-0.0183 (-3.81)	-0.0210 (-3.35)	0.0059 (0.63)
Model 2	-0.0111 (-1.49)	-0.0105 (-1.43)	0.0101 (-1.08)	0.0191 (0.85)
Model 4	-0.0085 (-1.38)	-0.0040 (-0.82)	-0.0008 (-0.15)	-0.0236 (-2.96)
Model 5	-0.0123 (-0.54)	-0.0025 (-2.02)	-0.0410 (-0.41)	-0.0063 (-499)
Model 6	0.0017 (0.24)(-2.55)	-0.0137 (-2.84)(0.94)	-0.0102 (-1.44)(0.59)	0.0145 (1.51)(0.53)
Model 7	-0.0212 (-3.85)(-3.76)	-0.0067 (-4.11)(0.79)	0.0014 (-1.03)(0.81)	-0.0901 (0.14)(1.51)
Model 8	0.0000 (-0.01)(-2.75)	-0.0038 (-0.71)(2.00)	0.0119 (1.96)(-0.51)	-0.0230 (-2.47)(2.31)
Model 9	-0.0070 (-4.09)(-6.29)	0.0040 (-1.49)(1.62)	-0.0330 (0.74)(-0.13)	-0.0035 (-3.47)(3.25)

Table 5: Estimated Marginal Efficiency Effects Input Distance Functions Models (Computed Z Values in Parenthesis; Mean or Mean and Variance)

	Operator Value of Labor and Management per Cow	Net Farm Income from the Previous Year per Cow	Age	Education	Cows
Model 1	0.0098		0.0168	-0.0479	-0.0033
	(1.97)		(1.57)	(-1.91)	(-0.71)
Model 2	0.0306		0.0436	-0.1284	
	(2.26)		(1.82)	(-2.28)	
Model 6	0.0192		0.0177	-0.0841	0.0258
	(3.47)(-0.85)		(1.64)(-1.26)	(-4.35)(-1.40)	(3.73)(-6.87)
Model 7	0.0039		0.0276	-0.0944	
	(0.72)(3.85)		(2.36)(-1.25)	(-4.34)(-0.90)	
Model 8		-0.0145	0.0167	-0.0689	-0.0087
		(-8.60)(4.26)	(1.19)(-1.33)	(-3.65)(1.63)	(-1.84)(-4.97)
Model 9		-0.0142	0.0170	-0.0661	
		(-9.55)(5.00)	(1.29)(-1.55)	(-3.78)(1.25)	

	Milking Frequency	DFBS Participation at least 4 years	DFBS Participation at least 7 years	DFBS Participation at least 10 years
Model 1	-0.0028	-0.0049	-0.0033	0.0047
	(-0.68)	(-1.42)	(-0.78)	(0.77)
Model 2	-0.0127	-0.0081	0.0097	0.0924
	(-0.87)	(-1.61)	(-0.80)	(0.69)
Model 6	0.0052	-0.0136	0.0021	-0.0123
	(1.17)(-3.42)	(-2.83)(2.23)	(0.41)(-0.20)	(-1.52)(1.78)
Model 7	-0.0174	0.0003	-0.0067	-0.0162
	(1.45)(-5.74)	(-2.90)(2.15)	(0.05)(0.02)	(-0.69)(1.62)
Model 8	0.0009	-0.0080	0.0079	-0.0328
	(0.14)(-2.92)	(-1.43)(2.93)	(1.30)(-0.91)	(-3.38)(2.79)
Model 9	-0.0086	0.0063	-0.0298	-0.0073
	(-0.74)(-7.60)	(-1.67)(2.46)	(1.12)(-0.84)	(-3.61)(2.55)

Table 6: Estimated Marginal Efficiency Effects, Cost Frontier Models (Computed Z Values in Parenthesis; Mean or Mean and Variance)

	Operator Value of Labor and Management per Cow	Net Farm Income from the Previous Year per Cow	Age	Education	Cows
Model 1	-0.0012 (-0.32)		0.0386 (1.40)	-0.0810 (-1.48)	-0.0311 (-1.43)
Model 2	0.0099 (1.22)		0.0420 (1.33)	-0.0897 (-1,38)	
Model 4		-0.0204 (-13.83)	0.0352 (3,01)	-0.0909 (-5,32)	-0.0436 (-5.51)
Model56		-0.0289 (-27.30)	0.0490 (3.90))	-0.0887 (-5.38)	
Model 6	-0.0034 (-0.85)(0.78)		0.0307 (2.81)(-0.94)	-0.0675 (-4.07)(-1.91)	0.0160 (2.85)(-7.87)
Model 7	-0.0055 (-1.21)(6.10)		0.0452 (3.93)(-1.44)	-0.0967 (-5.65)(-0.62)	
Model 8		-0.0170 (-10.38)(4.62)	0.0247 (1.89)(-1.60)	-0.0798 (-4.37)(1.79)	-0.0072 (-1.54)(-5.40)
Model 9		-0.0169 (-11.18)(5.54)	0.0249 (2.00)(-1.72)	-0.0801 (-4.53)(1.46)	

	Milking Frequency	DFBS Participation at least 4 years	DFBS Participation at least 7 years	DFBS Participation at least 10 years
Model 1	-0.0082 (-0.79)	-0.0086 (-1.15)	-0.0074 (-0.84)	0.0136 (1.00)
Model 2	-0.0088 (-1.15)	-0.0081 (-1.11)	0.0082 -0.86)	0.0011 (0.73)
Model 4	-0.0103 (-1.50)	-0.0066 (-0.99)	0.0091 (1,30)	-0.0245 (-2.83)
Model 5	-0.0171 (2.30)	0.0007 (-1.95)	-0.0434 (0.09)	-0.0064 (-5.10)
Model 6	0.0025 (0.57)(-3.21)	-0.0085 (-1.58)(0.58)	-0.0035 (-0.60)(0.27)	-0.0194 (-2.03)(-0.24)
Model78	-0.0151 (0.56)(-5.99)	-0.0038 (-2.47)(0.84)	-0.0076 (-0.54)(0.54)	-0.0955 (-0.81)(1.95)
Model 8	-0.0009 (-0.16)(-3.05)	-0.0126 (-1.81)(3.09)	0.0141 (2.00)(-1.11)	-0.0434 (-4.30)(4.23)
Model 9	-0.0144 (-1.21)(-8.18)	0.0134 (-2.19)(2.58)	-0.0398 (1.97)(-1.20)	-0.0109 (-4.37)(4.21)

Table 7: Average Marginal Revenue Efficiency Effects Models (Computed Z Values in Parenthesis; Mean or Mean and Variance)

	Operator Value of Labor and Management per Cow	Net Farm Income per Cow from the Previous Year	Age	Education	Cows
Model 1	-0.0714 (-10.80)		0.0503 (4.10)	-0.1160 (-7.17)	-0.2285 (-21.72)
Model 2	0.0126 (1.57)		0.0378 (1.57)	-0.0948 (-1.73)	
Model 4		-0.0338 (-36.23)	0.0310 (2.64)	-0.1308 (-8.65)	-0.1578 (-18.40)
Model 5		-0.0415 (-39.86)	0.0479 (3.71)	-0.1015 (-6.25)	
Model 6	-0.0457 ((-7.45)(4.07)		0.0439 (3.57)(-3.25)	-0.1042 (-6.36)(-0.32)	-0.0951 (-13.84)(1.86)
Model 7	0.0020 (0.44)(6.18)		0.0625 (4.74)(-3.15)	-0.1323 (-7.54)(0.20)	
Model 8		-0.0239 (-21.53)(10.88)	0.0239 (2,14)(-1.07)	-0.0696 (-4.83)(2.00)	-0.0361 (-8.14)(0.54)
Model 9		-0.0249 (-22.12)(12.83)	0.0176 (1.60)(-0.73)	-0.0744 (-5.16)(1.59)	

	Milking Frequency	DFBS Participation at least 4 years	DFBS Participation at least 7 years	DFBS Participation at least 10 years
Model 1	-0.0012 (-0.18)	-0.0169 (-3.18)	-0.0316 (-4.59)	0.0134 (1.30)
Model 2	-0.0083 (-1.58)	-0.0272 (-1.23)	0.0254 (-1.47)	0.0173 (1.35)
Model 4	-0.0054 (-0.94)	-0.0191 (-3.74)	0.0024 (0.44)	-0.0128 (-1.63)
Model 5	-0.0309 (0.26)	0.0050 (-5.10)	-0.0154 (0.85)	-0.0061 (-1.96)
Model 6	0.0038 (0.57)(-3.16)	-0.0123 (-2.37)(0.53)	-0.0208 (-2.72)(0.90)	0.0214 (2.14)(0.45)
Model 7	-0.0167 (-4.15)(-3.98)	-0.0176 (-3.14)(-0.11)	0.0146 (-2.57)(0.80)	-0.0910 (1.62)(1.07)
Model 8	0.0018 (0.34)(-3.00)	-0.0117 (-2.42)(1.17)	0.0099 (1.94)(-1.30)	-0.0064 (-0.89)(3.46)
Model 9	-0.0171 (-4.47)(-5.52)	0.0086 (-3.57)(1,12)	-0.0063 (1.69)(-1.25)	0.0027 (-0.92)(3.13)

Table 8: Summary Statistics for Changes in Estimated Technical Efficiency over Time, Output Distance Function Model 8.

	Observations	Farms	Proportion with Changes less than: Percentage	Proportion
	1	90	0.50%	0.3059
	2	47	1.00%	0.4523
	3	40	2.50%	0.6430
	4	47	5.00%	0.7798
	5	45	10.00%	0.8978
	6	23	Residual	1.0000
	7	30	Mean	0.0029
	8	17	Std Dev	0.0604
	9	9	Min	-0.2885
	10	48	Max	0.3111
Total	1762	396		

References

Aigner, D., C. A. Knox Lovell, and P. Schmidt. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6(1): 21-37

Battese, G.E. and T.J. Coelli. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics.* 38(3): 387-399.

Battese, G.E. and T.J. Coelli. (1995). A model of technical efficiency effects in a stochastic frontier production function for panel data. *Empirical Economics.* 20(2): 325-332.

Battese, G. E., T. J. Coelli and T. C. Colby. (1989). Estimation of Frontier Production Functions and the Efficiencies of Indian Farms Using Panel Data from ICRISAT's Village Level Studies. *Journal of Quantitative Economics*, 5(2): 327-48

Beyers, L. (2001). Managerial ability and its influence on size economies in South African dairy production. *Department of Agricultural Economics Working Paper*, University of Pretoria, South Africa. 2001-09.

Charnes, A., W.W. Cooper, and E. Rhodes. (1978). Measuring the efficiency of decision-making units. *European Journal of Operations Research.* 2: 429-444.

Coelli, T., D.S.P. Rao, and G.E. Battese. (1998). *An Introduction to Efficiency and Productivity Analysis*. Boston, MA: Kluwer Academic Publishers.

Dawson, P.J. and L.J. Hubbard. (1987). Management and size economies in the England and Wales dairy sector. *Journal of Agricultural Economics* 38: 27-38.

Debreu, G. (1951). The coefficient of resource utilization. *Econometrica* 19(3): 273-292

Førsund, F., C. A. Knox Lovell, and P. Schmidt (1980). A survey of frontier production functions and their relationship to efficiency measurement. *Journal of Econometrics* 13(1): 5-25.

Färe, R., and D. Primont. (1995). *Multi-output Production and Duality: Theory and Applications*. Norwell, MA: Kluwer Academic Publishers.

Färe, R. and S. Grosskopf. (2004). *New Directions: Efficiency and Productivity*. Norwell, MA: Kluwer Academic Publishers.

Farrell, M.J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society* 120(3): 253-290.

Hadri, K. (1999). Estimation of doubly heteroscedastic frontier cost function. *Journal of Business and Economic Statistics* 17: 171-180.

Huang, C. J. and J-T Liu. (1994). Estimation of a non-neutral stochastic frontier production function. *Journal of Productivity Analysis*. 5(2):171-180.

von Hayek, F.A. (1945). The use of knowledge in society. *American Economic Review* 35: 519-530.

Knight, F.H. (1921). *Risk, Uncertainty, and Profit*. Boston, New York: Hougthon Mifflin Company.

Kumbhakar, S.C., S. Ghosh, and J. T. McGuckin. (1991). A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U. S. Dairy Farms. Journal of Business and Economic Statistics 9(3):279-286.

Kumbhakar, S.C. and C.A. Knox Lovell. (2000). *Stochastic Frontier Analysis.* Cambridge (England), New York: Cambridge University Press.

Leibenstein, H. (1966). Allocative vs. "X-efficiency." *The American Economic Review* 56(3): 392-415.

Nelson, R.R. and Winters S.G.. (1982). *An Evolutionary Theory of Economic Change.* Boston: Harvard University Press.

Schmidt, P. and R. C. Stickles. (1984). Production Frontiers and Panel Data. Journal of Business and Economic Statistics. 2:367-374.

Shephard, R.W. (1953). *Cost and Production Functions*. Princeton, NJ: Princeton University Press

Shephard, R.W. (1970). *Theory of cost and production functions.* Princeton, N.J.: Princeton University Press.

Simon, H.A. (1959). Theories of decision making in economics. *The American Economic Review* 49: 253-283.

Stefanou, S.E. and S. Saxena. (1988). Education experience and allocative efficiency: A dual approach. *American Journal of Agricultural Economics* 70(2): 338-345.

Stigler, G.J. (1976). The xistence of x-efficiency. *The American Economic Review.* 66(1):213-216.

Tauer, L.W. (1993). Short-run and long-run efficiencies of New York dairy farms. *Agricultural and Resource Economics Review*. 22(1): 1-9.

Tauer, L.W. and A.K. Mishra. (2006).Can the small dairy farm remain competitive in US agriculture? *Food Policy.* 31:458-468.

Wang H. (2002). Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis.* 18: 241-253.