Exploring the Role of Managerial Ability in Influencing Dairy Farm Efficiency

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This paper explores the role of managerial ability in determining efficiency in New York dairy farms. Using an unbalanced panel of farm data from 1993 through 2004, we estimate output-oriented technical efficiencies using stochastic distance frontier functions. We find that both lagged net farm income and farmers' own estimates of the value of their labor and management as proxies for managerial ability impact measured efficiency. Efficiency increases with operator education, farm size, and extended participation in a farm management program, but decreases with operator age.

Key Words: dairy farms, distance function, management and efficiency, stochastic frontier analysis

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 (Seitz 1971, 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 for the inability of individuals to process the vast amounts of information necessary to behave optimally is presented in von 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 that any variation in output can be attributed to specific inputs, including managerial ability. The manager must decide, prior to 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 managerial ability. In an investigation of the effects of managerial ability on scale economies for dairy farms in England and Wales, Dawson and Hubbard (1987) define

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the managerial 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). Tauer (1993) regressed short-run and long-run technical and allocative efficiencies for a group of New York dairy farms on a set of variables including operator age and education, and Stefanou and Saxena (1988) found that 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, a possible missing input in efficiency measurement. We compute technical efficiencies for a sample of New York dairy farms using farm-level data. We insert two separate proxies for management, farmers' own estimates of the value of their management and labor, and net farm income per cow from the previous year. Farmers' own estimates of the value of their labor and management is a self-assessed value (measured in dollars) in response to a survey question. We assume that better managers will allot themselves a higher value for their management and labor services, while understanding that individual farmers may overstate or understate this value. The second—net farm income per cow from the previous year—measures managerial ability inasmuch as more efficient firms will be more profitable. Using the lagged values precludes any simultaneity bias in our estimates, and measuring net farm income on a per cow basis controls for farm size. We assume that managerial ability should not radically change from one year to the immediate next, thus better managers will have been more profitable in previous years than their peers. Operators' self-reported values of management are weakly positively correlated with lagged net farm income ($\rho = 0.26$). We treat both management indicators as substitute measurements for the same phenomenon. Since no perfect measure of managerial ability exists, we are left to rely on either a subjective measure or a metric of past success. Our results show that both have similar efficiency effects.

We estimate an output-oriented, heteroskedastic efficiency model [based on Hadri (1999)]. This approach allows for testing the impact of including management capacity on firm efficiencies, while at the same time controlling for other firm-specific characteristics. Coelli (2000) states that if the goal of the decision maker is to minimize cost, then an input distance function is appropriate. In contrast, if the goal is to maximize revenue, then an output distance function is more appropriate. The selection relates to the exogeneity of the inputs and outputs with econometric estimation. If inputs are exogeneous then an output distance function would be preferred, and if outputs are exogeneous then an input function would be preferred. 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. If inputs are fixed, or relatively so, then an output orientation is justified. Given that capital and crop input decisions are made far in advance of any milk production, and that herd sizes adjust slowly to changing conditions, an output distance function is the most appropriate choice for our data set.[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,

$$T = \{(\mathbf{x},\mathbf{y}) \mid \mathbf{x} \in \Re^{j}_{+}, \mathbf{y} \in \Re^{k}_{+}, \mathbf{x} \text{ can produce } \mathbf{y}\},$$

for **x** and **y** nonnegative ($j \times 1$) and ($k \times 1$) 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, where $D_O(\mathbf{x}, \mathbf{y})$ is the output distance function defined as

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

The output distance function seeks the largest possible radial expansion in outputs possible for a given input vector. The production frontier is then given by

$$(2) \qquad F = \{(\mathbf{x},\mathbf{y}) \mid D_O(\mathbf{x},\mathbf{y}) = 1\}.$$

[1] Other specifications were estimated including input-oriented technical efficiencies and conditional mean efficiency models. The results are available from the authors.

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

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

$$(3)\quad \ln D_{O,i} = \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln y_m \ln y_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln y_{m,i}.$$

The distance function requires homogeneity of degree one in outputs, which in turn requires

$$\sum_m \alpha_m = 1, \sum_n \beta_{mn} = 0, \text{ and } \sum_m \beta_{km} = 0.$$

This is accomplished by normalizing the function by an output. Using y_1 as the normalizing output, the distance function then becomes

$$(4)\quad \ln\left(\frac{D_{O,i}}{y_{1,i}}\right) = \alpha_0 + \sum_m \alpha_m \ln y^*_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln y^*_{m,i} \ln y^*_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln y^*_m,$$

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

$$(5)\ -\ln y_{1,i} = \alpha_0 + \sum_m \alpha_m \ln y^*_{m,i} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln y^*_m \ln y^*_{n,i} + \sum_k \alpha_k \ln x_{k,i} + \frac{1}{2}\sum_k \sum_l \beta_{kl} \ln x_k \ln x_{l,i} + \sum_k \sum_m \beta_{km} \ln x_{k,i} \ln y^*_m + v_i - u_i,$$

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 to be $v \sim N(0, \sigma_v^2)$. Defining $e_i \equiv v_i - u_i$, the estimated technical efficiency for the ith firm is $E[\exp(-u_i) \mid e_i]$.

The use of distance functions has become prevalent in measuring efficiency and productivity in agriculture. Newman and Matthews (2007) estimated an output distance function to measure the productivity of Ireland's agriculture. Brummer, Glauben, and Thijssen (2002) also used an output distance function to measure total factor productivity growth of dairy in three European countries and decomposed that growth into components. Karagiannis, Midmore, and Tzouvelekas (2004) used an input distance function for a similar decomposition of livestock farms in the United Kingdom.

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 summing inventory and accrual account data reported in the survey. The two outputs are "milk" and "other output." The inputs are operator labor input, hired labor input, purchased feed input, livestock input, capital input, and crop inputs. Price indexes taken from *Agricultural Prices* (USDA 2004) are used to deflate the accrual and inventtory accounts to constant dollars. Summary statistics are in Table 1.

The outputs aggregated to form our measure of "other output" consist largely of what may be considered by-products of milk production, such as livestock sales (cull cows and calves). Miscellaneous crop sales are also included, but to be included in the DFBS data set, milk receipts must constitute 90 percent or more of total receipts. Government payments, much of which are related to crop production in support of dairy operations, are also included in "other output."

Stochastic Frontier Methods

The final estimation equation for the output distance function is an adaptation of equation (5).

Table 1. Summary Statistics for Inputs and Outputs

Variable	Mean	St. Dev.	Min.	Max.
Milk output	6,538	8,830	213	122,857
Other output	931	1,277	-1,347	17,301
Operator labor input	274	136	12	1,033
Hired labor input	631	850	0	11,523
Purchased feed input	1,800	2,463	10	36,030
Livestock input	1,538	2,176	47	34,595
Capital input	1,849	2,161	118	19,567
Crop input	415	490	-86	5,252
Operator value of labor and management per cow	347	244	13	2,857
Net farm income per cow	928	1,448	-7,518	23,738
Operator age (years)	47	8	24	79
Operator education (years)	13	2	7	20
Cows (total number)	224	279	19	3,605
N = 3375				

Note: Inventory and accrual accounts, deflated by price index.

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

$$(6)\qquad \ln y_{1,i} = -TL(X_i, y_i^* \mid \alpha, \beta) + \sum_s \zeta_s D_{s,i} + \tau T - v_i + u_i,$$

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, T is a time trend, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ 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.

A distributional assumption is required for u in these equations. We assume a half-normal, zero-mean distribution with the variance of the efficiency term for the ith farm parameterized as

$$(7)\qquad \sigma_{u,i}^2 = \exp(\mathbf{z}_i^T \boldsymbol{\lambda}),$$

where $\mathbf{z}$ is a vector of exogenous variables (and a constant) and λ is a vector of parameters to be estimated. The stochastic distance function was estimated with equation (7) embedded into equation (6). Wang (2002) shows that the marginal effect of a change in an element of $\mathbf{z}$ on the expected value of u (and hence technical efficiency) is

$$(8)\qquad \frac{\partial E[u_i]}{\partial z_k} = \lambda_k \frac{\sigma_i}{2} \frac{\phi(0)}{\Phi(0)} = \lambda_k \sigma_i \phi(0),$$

where ϕ and Φ are the standard normal and cumulative standard normal probability density functions, respectively.

Technical Efficiency Variables

We define and use two measures of farmer managerial ability: farmers' 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 farmers 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, allowing us to test whether farms' participation in the business summary affects farm performance. Gallacher, Goetz, and Debertin (1994) previously found that participation in a farm business summary increased farm efficiency in Argentina agriculture. 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 as being at least four years in the sample period for years 1996 and later. The variable *DFBS participation at least 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 at least 10 years* indicates farms that participated for at least ten years in the sample period.[2]

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.

[2] A previous specification using a discrete, cumulative measure of years of participation in the survey yielded insignificant results, possibly from the unbalanced nature of the data. The more general specification presented above allows for the testing of the effects of survey participation among the three distinct groups.

A few words are required regarding interpretation of the λ parameters. Estimated technical efficiency is calculated as $E[\exp(-u_i)\,|\,e_i]$. 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

$$(9)\qquad -\frac{\partial D_{O,i}}{\partial z_k} = \frac{\partial \ln y_{1,i}}{\partial z_k} = -\frac{\partial E[u_i]}{\partial z_k} = -\lambda_k \sigma_i \phi(0)$$

is the percentage change in output (holding all inputs and output composition constant) resulting from an incremental change in z_k.

Results

The distance function estimates are summarized in Tables 2 and 3. Although the frontier components are listed separately from the efficiency components, both were estimated simultaneously. Results show that the farms in our sample are, on average, rather efficient. Model 1, which measures managerial ability using farmers' own estimates of their labor and management, calculates an average efficiency of 0.91 (standard deviation = 0.05). Model 2, using lagged net farm income per cow, calculates an average efficiency of 0.92 (standard deviation = 0.12). Both models are well-behaved, exhibiting positive production elasticities for all inputs (see Figure 1). Both models show calculated returns to scale close to unity. Both models contain statistically significant coefficients in the residual variance term, confirming our choice of heteroskedastic output distance function.

Both models show decreasing efficiency with operator age, and increasing efficiency with education levels and herd size. These results are all statistically significant at the one percent level. Milking frequency does not show any effect on efficiency in either model. The results are mixed for participation in the Dairy Farm Business Summary. Model 1 shows significant decreases in efficiency for participation of at least seven years, and significant increases in efficiency for participation of at least ten years. Model 2 exhibits significant increases in efficiency for participation of

Table 2. Output Distance Function Results Model 1

Number of observations	2358		
Log likelihood	2058.574		
PRODUCTION FUNCTION COMPONENT VARIABLE	Coefficient	Std. Err.	Z
Operator labor	0.0240	0.0643	0.37
Hired labor	0.0033	0.0415	0.08
Purchased feed	0.3715	0.0948	3.92
Livestock	0.2644	0.1040	2.54
Capital	0.0492	0.1188	0.41
Crops	0.1536	0.0646	2.38
(Operator labor) ^{2}	-0.0014	0.0120	-0.12
(Operator labor) × (Hired labor)	-0.0280	0.0081	-3.46
(Operator labor) × (Purchased feed)	-0.0482	0.0164	-2.95
(Operator labor) × (Livestock)	0.0432	0.0176	2.45
(Operator labor) × (Capital)	0.0201	0.0180	1.12
(Operator labor) × (Crops)	0.0156	0.0116	1.35
(Hired labor) ^{2}	0.0152	0.0054	2.80
(Hired labor) × (Purchased feed)	-0.0117	0.0073	-1.59
(Hired labor) × (Livestock)	0.0305	0.0106	2.88
(Hired labor) × (Capital)	-0.0025	0.0090	-0.28
(Hired labor) × (Crops)	0.0064	0.0056	1.14
(Purchased feed) ^{2}	0.1990	0.0255	7.82
(Purchased feed) × (Livestock)	-0.0321	0.0268	-1.20
(Purchased feed) × (Capital)	-0.0867	0.0265	-3.27
(Purchased feed) × (Crops)	-0.0461	0.0147	-3.14
(Livestock) ^{2}	-0.0973	0.0378	-2.58
(Livestock) × (Capital)	0.0589	0.0315	1.87
(Livestock) × (Crops)	0.0068	0.0167	0.41
(Capital) ^{2}	0.0486	0.0444	1.09
(Capital) × (Crops)	-0.0161	0.0164	-0.98
(Crops) ^{2}	0.0384	0.0074	5.17
Other output (normalized by milk output)	-0.1043	0.0256	-4.07
(Other output) ^{2}	-0.0127	0.0013	-9.50
(Other output) × (Operator labor)	0.0057	0.0047	1.22
(Other output) × (Hired labor)	-0.0001	0.0018	-0.08
(Other output) × (Purchased feed)	0.0111	0.0053	2.09
(Other output) × (Livestock)	-0.0096	0.0076	-1.26
(Other output) × (Capital)	-0.0107	0.0069	-1.55
(Other output) × (Crops)	0.0024	0.0037	0.65
Output dummy	0.0973	0.0440	2.21
Hired labor dummy	-0.0691	0.0530	-1.30
Time (1993 = 1)	0.0032	0.0009	3.58
Constant	1.8810	0.2581	7.29

cont'd.

Table 2. Output Distance Function Results Model 1 (cont'd.)

EFFICIENCY TERM VARIANCE COMPONENT VARIABLE	Coefficient	Std. Err.	Z
Net farm income per cow from the previous year	-0.4470	0.0266	-16.78
Age	0.7875	0.3172	2.48
Education	-2.1086	0.4191	-5.03
Cows	-1.3104	0.1468	-8.93
Milking frequency	-0.0012	0.1617	-0.01
DFBS participation at least 4 years	-0.0936	0.1314	-0.71
DFBS participation at least 7 years	0.2956	0.1508	1.96
DFBS participation at least 10 years	-0.5729	0.2323	-2.47
Net farm income dummy	-0.1136	0.2012	-0.56
Constant	4.1104	1.9085	2.15
RESIDUAL TERM VARIANCE VARIABLE	Coefficient	Std. Err.	Z
Net farm income per cow from the previous year	0.2528	0.0579	4.36
Age	-0.1763	0.2604	-0.68
Education	0.8380	0.3385	2.48
Cows	-0.0802	0.0671	-1.20
Milking frequency	-0.3051	0.1108	-2.75
DFBS participation at least 4 years	0.2206	0.1105	2.00
DFBS participation at least 7 years	-0.0536	0.1046	-0.51
DFBS participation at least 10 years	0.3320	0.1435	2.31
Net farm income dummy	0.2122	0.1323	1.60
Constant	-6.5444	1.4375	-4.55
	0.7875	0.3172	2.48

at least four years, and insignificant effects for additional participation in the survey.

Our measures of managerial ability are both statistically significant and lead to increases in efficiency. Both farmers' own estimates of the value of their labor and management (model 1) and lagged net farm income per cow (model 2) may indeed serve as proxy measures for managerial ability inasmuch as better managers can be expected to be more efficient. This supports our assertion that measured inefficiency may be due to the missing management input.

We plot the marginal effects for the four significant efficiency effect variables as calculated by equation (9) in Figure 2. Since the data enter the model as logs, we can interpret these marginal effects as elasticities. We can see that the marginal effects of both management variables are rather small in absolute magnitude. For the average farm, a one percent increase in managerial ability as measured by farmers' own values of their labor and management increases efficiency by 0.04 percent. However, increasing labor and management value per cow by one standard deviation of the data, or a 70 percent increase, results in an increase in efficiency of 2.8 percent. For lagged net farm income per cow, the average marginal effect is 0.02 percent, but increasing lagged net farm income per cow by one standard deviation, or 156 percent, increases efficiency by 3.12 percent. Both of these are significant increases in efficiency when the average efficiency is 91 or 92 percent.

Although we found constant returns to scale in the frontier component of the function, we found that increasing the size of the herd has significant

Table 3. Output Distance Function Results Model 2

Number of observations	3351		
Log likelihood	2534.067		
PRODUCTION FUNCTION COMPONENT VARIABLE	Coefficient	Std. Err.	Z
Operator labor	0.0138	0.0681	0.20
Hired labor	0.0408	0.0400	1.02
Purchased feed	0.2884	0.0910	3.17
Livestock	0.2636	0.1006	2.62
Capital	0.0346	0.1148	0.30
Crops	0.1345	0.0649	2.07
(Operator labor) ^{2}	0.0015	0.0120	0.12
(Operator labor) × *(Hired labor)*	-0.0320	0.0072	-4.45
(Operator labor) × *(Purchased feed)*	-0.0384	0.0149	-2.58
(Operator labor) × *(Livestock)*	0.0368	0.0167	2.21
(Operator labor) × *(Capital)*	0.0207	0.0173	1.20
(Operator labor) × *(Crops)*	0.0144	0.0111	1.30
(Hired labor) ^{2}	0.0201	0.0046	4.38
(Hired labor) × *(Purchased feed)*	-0.0066	0.0061	-1.09
(Hired labor) × *(Livestock)*	0.0165	0.0081	2.05
(Hired labor) × *(Capital)*	0.0007	0.0081	0.08
(Hired labor) × *(Crops)*	0.0067	0.0047	1.43
(Purchased feed) ^{2}	0.1700	0.0222	7.67
(Purchased feed) × *(Livestock)*	-0.0162	0.0235	-0.69
(Purchased feed) × *(Capital)*	-0.0652	0.0231	-2.82
(Purchased feed) × *(Crops)*	-0.0551	0.0131	-4.20
(Livestock) ^{2}	-0.1091	0.0342	-3.19
(Livestock) × *(Capital)*	0.0572	0.0283	2.02
(Livestock) × *(Crops)*	0.0168	0.0151	1.12
(Capital) ^{2}	0.0242	0.0396	0.61
(Capital) × *(Crops)*	-0.0103	0.0149	-0.69
(Crops) ^{2}	0.0343	0.0075	4.59
Other output (normalized by milk output)	-0.1015	0.0256	-3.96
(Other output) ^{2}	-0.0120	0.0013	-9.48
(Other output) × *(Operator labor)*	0.0108	0.0044	2.46
(Other output) × *(Hired labor)*	0.0018	0.0016	1.09
(Other output) × *(Purchased feed)*	0.0096	0.0048	2.02
(Other output) × *(Livestock)*	-0.0237	0.0066	-3.56
(Other output) × *(Capital)*	0.0003	0.0060	0.05
(Other output) × *(Crops)*	0.0015	0.0033	0.46
Output dummy	0.0338	0.0399	0.85
Hired labor dummy	-0.1097	0.0467	-2.35
Crops dummy	0.1667	0.1190	1.40
Time (1993 = 1)	0.0047	0.0007	6.37
Constant	2.2707	0.2799	8.11

cont'd.

Table 3. Output Distance Function Results Model 2 (cont'd.)

EFFICIENCY TERM VARIANCE COMPONENT VARIABLE	Coefficient	Std. Err.	Z
Operator value of labor and management per cow	-0.7622	0.1207	-6.31
Age	0.8804	0.2551	3.45
Education	-1.9774	0.3339	-5.92
Cows	-2.0753	0.1584	-13.10
Milking frequency	0.0361	0.1491	0.24
DFBS participation at least 4 years	-0.2953	0.1039	-2.84
DFBS participation at least 7 years	-0.2189	0.1516	-1.44
DFBS participation at least 10 years	0.3114	0.2062	1.51
Constant	7.8362	1.5439	5.08
RESIDUAL TERM VARIANCE VARIABLE	Coefficient	Std. Err.	Z
Operator value of labor and management per cow	0.2653	0.0809	3.28
Age	-0.3868	0.2151	-1.80
Education	0.1136	0.2999	0.38
Cows	0.1319	0.0764	1.73
Milking frequency	-0.2437	0.0956	-2.55
DFBS participation at least 4 years	0.0829	0.0881	0.94
DFBS participation at least 7 years	0.0571	0.0971	0.59
DFBS participation at least 10 years	0.0716	0.1357	0.53
Constant	-4.4794	1.2137	-3.69

impacts on efficiency. Increasing the size of the business one standard deviation in cow numbers, from 224 cows to 503 cows, essentially measures the farm as being efficient. These results support the finding of Tauer and Mishra (2006) that much of the higher production cost of the smaller dairy farm is due to inefficiency, with much less attributed to economies of size.

The other variables—education, age, and herd size—show small elasticity magnitudes, ranging from 0.05 percent to 0.1 percent in absolute value. These small marginal effects, when combined with the strong statistical significance we see in our model, are likely due to the high levels of efficiency calculated for our sample of New York dairy farms. Farms near the frontier benefit little from changes in these variables since they do not have much impact on efficiency improvement. Farms farther from the frontier, however, can improve their efficiency with increases in education and farm size, with marginal effects between 0.15 percent and 0.21 percent.

Conclusions

We explored the role of managerial ability in explaining efficiency in a group of New York dairy farms using stochastic frontier estimation. We estimated output-oriented stochastic frontier functions, using an unbalanced panel of individual farm data from 1993 to 2004. We used six inputs—operator labor, hired labor, purchased feed, livestock, capital, and crop inputs—and two outputs—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 allowed us to use the previous year's net farm income as a measure of farmer managerial 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.

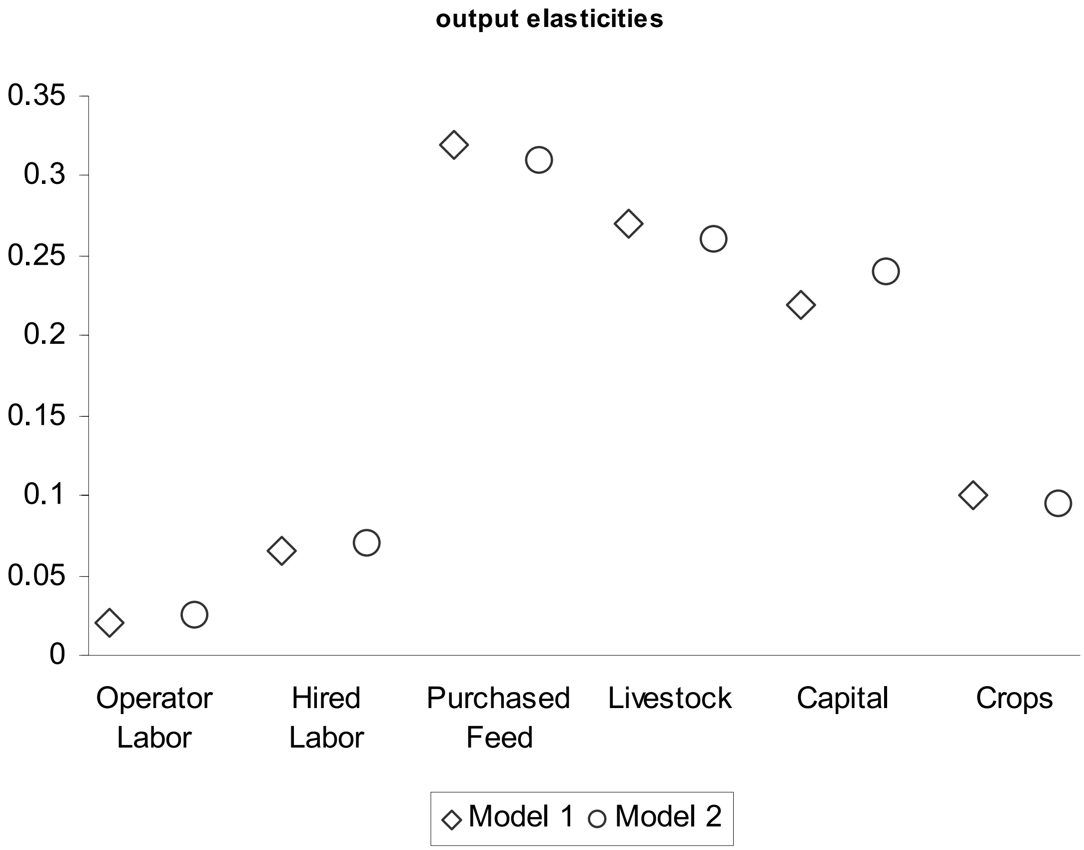

Figure 1. Production Elasticities

We find that both measures have statistically significant positive effects on efficiency while controlling for operator age and education, herd size, milking frequency, and participation in a farm management survey. The efficiency gains from increasing levels of our defined management abilities are significant for a standard deviation increase in these measured management inputs. Both measures show very similar results. It appears that measured inefficiency is influence by managerial ability. In addition, older and more educated farmers show higher efficiency, as do larger farms.

The measured efficiency effects for operator education, operator age, and farm size are in line with the established literature on the subject. Our models attempt two measures of managerial ability, and future research may focus on this area. Are there better measures of managerial ability? If so, are their effects on measured efficiency similar to the above results?

More work is necessary in explaining the determinants of managerial ability and how it relates to other characteristics like farmer education levels. If managerial ability influences farm efficiency, it would be helpful to know if it can be improved through education and outreach. We can measure efficiency until the cows come home, but until we can determine causation, corrections and remedies for greater efficiency are fleeting.

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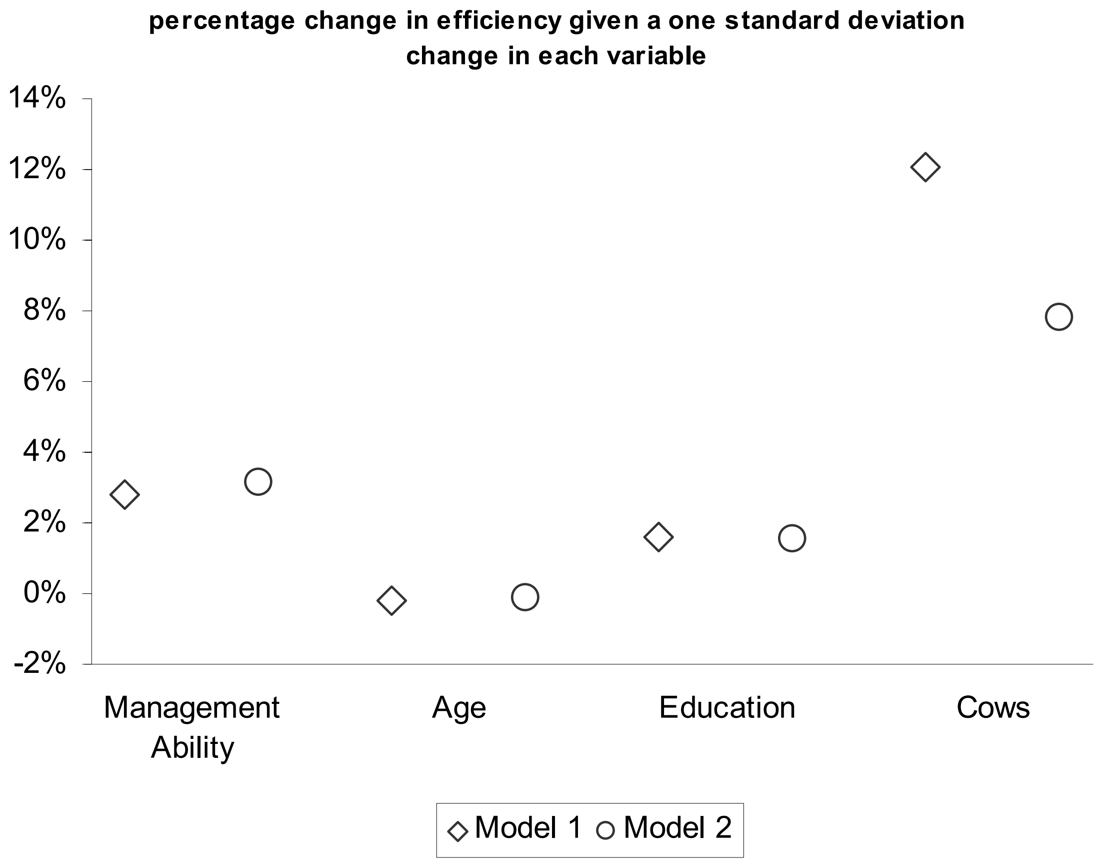

Figure 2. Average Effect of a One Standard Deviation Change

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