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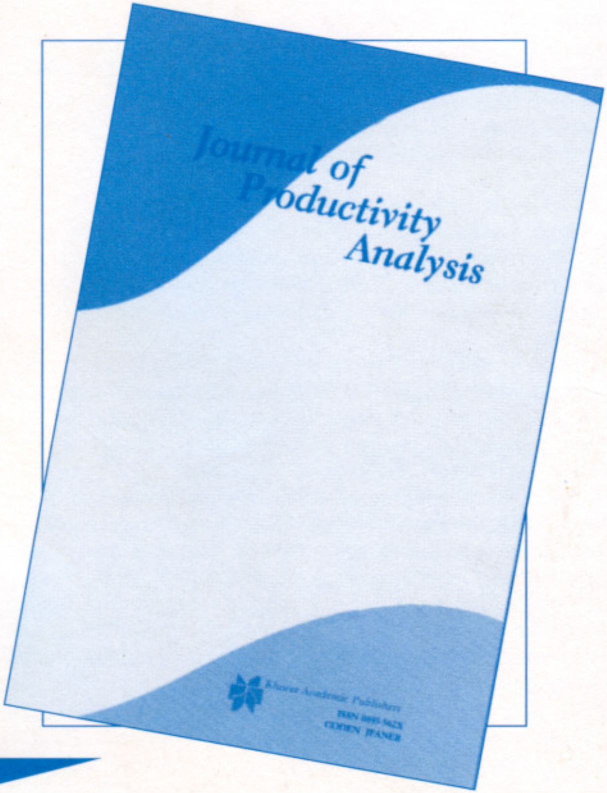

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Technical Efficiency Measures for Dairy Farms Using Panel Data: A Comparison of Alternative Model Specifications

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Abstract

This article examines the impact of fixed effects production functions vis-à-vis stochastic production frontiers on technical efficiency measures. An unbalanced panel consisting of 96 Vermont dairy farmers for the 1971–1984 period was used in the analysis. The models examined incorporated both time-variant and time-invariant technical efficiency. The major source of variation in efficiency levels across models stemmed from the assumption made concerning the distribution of the one-sided term in the stochastic frontiers. In general, the fixed effects technique was found superior to the stochastic production frontier methodology. Despite the fact that the results of various statistical tests revealed the superiority of some specifications over others, the overall conclusion of the study is that the efficiency analysis was fairly consistent throughout all the models considered.

Keywords: Production functions, stochastic frontiers, fixed effects, technical efficiency, panel data

1. Introduction

The reliance on production functions to analyze firm level efficiency dates back at least to an article published by Earl Heady (1946) almost 50 years ago. Since this early work, a great deal of progress has been made in efficiency measurement via production functions. Two specific methodologies that have been developed and used for this purpose, and which are the focus of this article, are the fixed effects model and the frontier production function. Both models have been used extensively in the empirical analysis of technical efficiency.

The fixed effects model was introduced by Hoch (1955) and extended by Hoch (1958, 1962) and Mundlak (1961, 1978). Although the fixed effects is a relatively old methodology, there has been continued interest in its use, as evidenced by the work of Hoch (1976), Dawson and Lingard (1982), Turvey and Lowenberg-DeBoer (1988), and Seale (1990), among others. The production frontier methodology was initiated by Farrell in a path-breaking article published in 1957. A decade later, Aigner and Chu (1968) introduced a deterministic parametric (Cobb–Douglas) frontier model which they estimated using mathematical programming techniques. A deficiency characterizing these deterministic models is their sensitivity to outliers. This deficiency was solved by Aigner, Lovell, and Schmidt (1977) and by Meeusen and van den Broeck (1977), who introduced the stochastic frontier model.

In the fixed effects model, which requires panel data for estimation, dummy variables are introduced to account for individual firm effects. By comparison, the stochastic production frontier model, initially developed for and primarily applied to cross-sectional data, assumes an error term that has two additive components: a symmetric component which accounts for pure random factors, and a one-sided component which captures the effects of inefficiency relative to the frontier.[1]

Initial refinements of the stochastic frontier model, made by Pitt and Lee (1981) and followed by Schmidt and Sickles (1984) and Battese and Coelli (1988), included the accommodation of balanced panel data assuming that technical efficiency was time invariant. These models have been further extended by Battese, Coelli, and Colby (1989), and Seale (1990) so as to handle unbalanced panel data. More recently, models that allow efficiency to vary over time for both balanced (Kumbhakar, 1990) and unbalanced panels (Battese and Coelli, 1992) have been introduced. The current state of the art in this area of work is the (one-step) estimation of the usual stochastic frontier parameters in conjunction with the parameters of variables introduced to explain efficiency (Kumbhakar, Ghosh, and McGuckin, 1991; Battese and Coelli, 1993).[2]

The firm-specific dummy variables in the fixed effects model were initially interpreted as a management index, but more recently some authors have argued that the firm effects can be construed as a measure of technical efficiency (Hoch, 1976; Russell and Young, 1983). Consequently, there is a clear link between the fixed effects model and the more recent stochastic frontier models for panel data. A crucial difference between these two approaches, however, is that the fixed effects model allows correlation between technical efficiency and the other explanatory variables, whereas the frontier model requires the explicit assumption that technical efficiency is uncorrelated with the other regressors. Moreover, Mundlak (1961) showed that the fixed effects approach leads to parameter estimates that are free of management bias, hence overcoming the omitted variable problem discussed by Griliches (1957). In addition, Hoch (1962) demonstrated that the fixed effects model mitigates and might even avoid the simultaneous equation bias associated with single-equation production function models.

The impact that the choice between the fixed effects and the frontier methodology has on efficiency requires examination. Therefore, the objective of this article is to compare the impact of fixed effects and stochastic production frontier models on technical efficiency measures. Several features of these models are also investigated. The specific hypotheses tested concern the following issues: (1) significance of firm effects; (2) returns to size; (3) functional form: Cobb–Douglas versus a simplified translog; (4) distribution of the one-sided error term in the stochastic production frontiers: half-normal versus truncated normal; (5) time-variant versus time-invariant technical efficiency; and (6) correlation between efficiency and other regressors (i.e., fixed effects versus stochastic frontier).

The remainder of this article is organized into five sections. Section 2 develops the methodological framework employed, and section 3 gives a brief discussion of the data and empirical model. Section 4 contains the efficiency analysis, and section 5 presents the results of the various statistical tests undertaken to evaluate the performance of the alternative specifications under study. The article ends with some concluding remarks.

2. Analytical framework

This section presents the key characteristics of the fixed effects and stochastic frontier methodology based on single-equation production models. The econometric estimation of single-equation production models has been justified by assuming that producers maximize the mathematical expectation of profits or that profits are maximized with respect to anticipated output instead of realized output. Given this assumption, the simultaneous-equation bias often associated with single-equation production models is avoided (Zellner, Kmenta, and Drèze, 1966; Hoch, 1958, 1962; Kumbhakar and Hjalmarsson, 1993). Moreover, in a Montecarlo evaluation of alternative estimators of efficiency, Gong and Sickles (1989) found that a single-equation model performed better than a multi-equation model.

The first model considered in this article is a fixed effects Cobb–Douglas production function, incorporating smooth technological change and time invariant technical efficiency, which can be written as

$$\ln Y_{it} = \alpha + \sum_i \gamma_i D_i + \sum_k b_k \ln X_{kit} + \zeta T + v_{it}, \tag{1}$$

where i, t and k are subscripts for firms, time and inputs, α, γ_i, b_k and ζ are parameters to be estimated, Y is output, D_i is a dummy variable having a value one for the ith farm and zero otherwise, X_k are inputs, T is a smooth time trend that accounts for technological change, and v_{it} is the usual disturbance term. Using dummy variables to model technological change, (1) can be rewritten as

$$\ln Y_{it} = \alpha + \sum_i \gamma_i D_i + \sum_k b_k \ln X_{kit} + \sum_t \zeta_t C_t + v_{it}, \tag{2}$$

where C_t is a dummy variable having a value of one for the tth time period and zero otherwise, and ζ_t are parameters to be estimated.

An alternative functional form used in this study is the simplified translog model

$$\ln Y_{it} = \alpha + \sum_i \gamma_i D_i + \sum_k b_k \ln X_{kit} + \sum_k \xi_k \ln X_{kit}\, T + \zeta T + \lambda T^2 + v_{it} \tag{3}$$

which assumes that inputs are separable from each other but not from time (Fan, 1991). This simplified form is estimated instead of the full translog model because the latter, as is often the case (e.g., Cornwell, Schmidt, and Sickles, 1990), presented major multicollinearity problems.

The measures of technical efficiency for each farm, using the models in equations (1) to (3), can be calculated as

$$TE_i = \frac{exp\ (\gamma_i)}{max\ [exp\ (\gamma_i)\ ]}, \tag{4}$$

where $max[exp(\gamma_i)]$ is the highest predicted value for the ith firm.

The assumption that technical efficiency is time invariant can be relaxed by allowing farm-specific effects to vary over time, as suggested by Mundlak (1978). To measure time-variant technical efficiency, (1) and (3) can be estimated in two steps (Cornwell, Schmidt, and Sickles, 1990; Kumbhakar and Hjalmarsson, 1993). In the first step, (1) and (3) are estimated to obtain consistent estimates of b_k, ξ_k, ζ, and λ. In the second step the residuals from the first step, $\hat{\varepsilon}_{it}$, which include farm-specific effects ($u_{it} = \gamma_i + \rho_i T$) as well as the usual error term (v_{it}), are regressed as

$$\hat{\varepsilon}_{it} = \sum_i \gamma_i D_i + \sum_i \rho_i D_i T + v_{it}, \tag{5}$$

where v_{it} is *iid* $N(0, \sigma^2{}_v)$. The expression $\hat{\gamma}_i + \hat{\rho}_i T$ obtained from the estimates of (5) yields the efficiency indicator $\hat{u}_{it}$ (Fecher and Pestieau, 1993). Technical efficiency at each data point is then calculated as

$$TE_{it} = \frac{exp\ (\hat{u}_{it})}{max\ [exp\ (\hat{u}_t)\ ]} \tag{6}$$

where $max[exp(\hat{u}_t)]$ is the highest predicted value in the tth period.

Now, consider the following three stochastic production frontier models: (1) a Cobb–Douglas (CD) with smooth technological change; (2) a CD with dummy variables to account for technological change; and (3) a simplified translog (STL) with smooth technological change. These models can be written, respectively, as

$$\ln Y_{it} = \alpha + \sum_k b_k \ln X_{kit} + \zeta T + v_{it} - u_{it}, \tag{7}$$

$$\ln Y_{it} = \alpha + \sum_k b_k \ln X_{kit} + \sum_t \zeta_t C_t + v_{it} - u_{it}, \tag{8}$$

and

$$\ln Y_{it} = \alpha + \sum_k b_k \ln X_{kit} + \sum_k \xi_k \ln X_{kit}\, T + \zeta T + \lambda T^2 + v_{it} - u_{it} \tag{9}$$

where u_{it} in (7), (8) and (9) is equal to

$$u_{it} = \eta_{it} u_i = e^{[-\eta(\tau(i)-T)]} u_i \qquad (i = 1, 2, \ldots, N). \tag{10}$$

The term v_{it} in (7), (8) and (9) is assumed to be independent and identically normally distributed with mean zero and constant variance [$v_{it} \sim N(0, \sigma_v^2)$], while u_{it} follows a non-negative truncation of a normal distribution with mean μ and constant variance [$\mu_{it} \sim |N(\mu, \sigma_u^2)|$], or a half-normal distribution [$\mu_{it} \sim |N(0, \sigma_u^2)|$]. Moreover, η "…is an unknown scalar parameter and $\tau(i)$ represents the set of (T_i) time periods among the T periods involved for which observations for the ith (farm) are obtained" (Battese and Coelli, 1992, p. 154). Technical efficiency increases, remains constant or decreases over time, when $\eta > 0$, $\eta = 0$ or $\eta < 0$, respectively.

Equations (7), (8) and (9) are estimated using the program "FRONTIER" written by Coelli (1992). This program first estimates maximum likelihood parameters of the model, and then uses these estimates to calculate technical efficiency ($\hat{TE}_{it}$) at each data point as

$$\hat{TE}_{it} = exp\,(-u_{it}). \tag{11}$$

3. Data and empirical model

The data for this study comes from 96 Vermont dairy farms participating in the New England Electronic Farm Accounts Program (ELFAC) from 1971 to 1984. The number of observations available per farm varies from a low of six to a high of 14. Pooling the 96 farms yields a total of 1072 observations.

In the production function models, output (Y) is the annual milk produced per farm measured in hundredweights, and the inputs are: (1) number of dairy cows (X_z); (2) total labor (X_l), including hired and family labor, measured in worker equivalents; (3) purchased dairy concentrate feed (X_f), measured in tons; (4) animal expenses (X_s), consisting of veterinary medicine, breeding, and animal supplies; (5) crop expenses (X_c), comprising fertilizer, seed, spray, lime, repairs, and maintenance on machinery and equipment, and gas and oil; and (6) other farm expenses (X_m), including electricity, hauling, miscellaneous expenses, and depreciation on buildings and equipment set at 3 and 15% of the stock value, respectively. In addition, the models incorporate either a smooth time trend (T) or time dummies (T_i, $i = 2,3,\ldots 14$) to account for technological change. Table 1 shows descriptive statistics for the dependent and independent variables and for milk production per cow (Y/X_z) for the 1971–1984 period, and separately for the first (1971) and last year (1984) included in the data set.

4. Efficiency analysis

This section presents the results of nine models which were estimated assuming that efficiency is time invariant, and eight models in which efficiency is assumed to be time variant. To simplify the exposition, the models are numbered as shown in Table 2.

4.1. Time-invariant technical efficiency

Six of the nine time-invariant efficiency models used a Cobb–Douglas specification (Model I to Model VI); the other three (Models VII, VIII and IX) are based on a simplified translog. Statistical results for the nine models, presented in Table 3, show quite similar parameter estimates. The function coefficients in all of these models were greater than one, indicating increasing returns to scale.[3] The function coefficients for the fixed effects

Table 1. Descriptive statistics for a sample of Vermont dairy farms.

Variable	Abbreviations	Mean	Standard deviation	Minimum	Maximum	No. of farms
Period: 1971–1984						
Milk (100 lbs.)	Y	8813.5	5045.0	268.6	33370.0	1072
Cows (Number)	X_z	64.7	32.4	17.3	217.4	1072
T. Labor (W. Eq.)	X_l	4.2	1.2	2.2	9.0	1072
Conc. Feed (Ton)	X_f	159.9	111.9	5.1	922.1	1072
Animal Exp. ($)	X_s	20.6	13.7	2.4	111.6	1072
Crop Exp. ($)	X_c	31.4	23.7	2.6	165.9	1072
Other Farm Exp.	X_m	37.6	25.9	7.3	336.2	1072
Milk/Cow (100 lbs)	Y/X_z	134.2	23.99	13.4	210.3	1072
Year: 1971						
Milk (100 lbs.)	Y	7755.2	4466.4	2509.0	31670.0	77
Cows (Number)	X_z	59.5	30.3	28.1	212.7	77
T. Labor (W. Eq.)	X_l	3.1	0.8	2.2	7.3	77
Conc. Feed (Ton)	X_f	139.7	103.9	37.3	746.5	77
Animal Exp. ($)	X_s	19.4	10.8	3.9	62.9	77
Crop Exp. ($)	X_c	28.8	21.8	3.8	137.7	77
Other Farm Exp. ($)	X_m	39.4	25.8	11.1	183.3	77
Milk/Cow (100 lbs)	Y/X_z	128.8	19.7	68.9	170.0	77
Year: 1984						
Milk (100 lbs)	Y	9624.1	5954.2	2813.00	31940.0	67
Cows (Number)	X_z	63.6	35.1	25.8	208.5	67
T. Labor (W. Eq.)	X_l	4.7	1.1	3.0	9.0	67
Con. Feed (Ton)	X_f	160.7	120.9	35.6	653.4	67
Animal Exp. ($)	X_s	23.3	17.5	5.0	87.2	67
Crop Exp. ($)	X_c	30.43	19.8	3.0	93.6	67
Other Farm Exp. ($)	X_m	43.7	27.6	13.7	167.7	67
Milk/Cow (100 lbs)	Y/X_z	148.0	29.3	89.0	202.1	67

models are greater than those for the stochastic frontier models, a result that is at variance with the findings of Mundlak (1961), Hoch (1962), Dawson and Lingard (1982), Turvey and Lowenberg–DeBoer (1988), and Seale (1990), but is in line with the findings reported by Hoch (1958, 1976). These results are consistent, however, with the notion that the effect of simultaneous-equation bias, which might be present in the stochastic frontier model where explicit farm effects are excluded, is to move the function coefficient towards constant returns to scale (Hoch, 1958, 1962).

To compute technical efficiency measures from the fixed effects models (Models I, II and VII), the estimates for the farm-specific dummies are converted into antilog values. Some of the antilog values are higher than one and some are less than one, while the antilog of the reference farm is equal to one. The farms with values greater than one are considered more efficient than the reference farm, and those with values less than one are considered less efficient. The antilogs are normalized by the highest antilog value (i.e., the most efficient farm in the panel) to obtain efficiency indexes that fall between zero and one.

Descriptive statistics for technical efficiency measures derived from Models I through IX are given in Table 4. The average technical efficiency for Models I and VII is about 0.77 with a minimum of 0.53 and a maximum of 1.00. This implies that shifting from the CD

Table 2. Major characteristics of models used in the analysis.

Model		Functional form	Estimator	Technological change	One-sided term
Time-invariant efficiency					
Model	I	CD	FE	SM	—
	II	CD	FE	DU	—
	III	CD	SF	SM	HN
	IV	CD	SF	SM	TN
	V	CD	SF	DU	HN
	VI	CD	SF	DU	TN
	VII	STL	FE	SM	—
	VIII	STL	SF	SM	TN
	IX	STL	SF	SM	HN
Time-variant efficiency					
Model	Ia	CD	FE	SM	—
	IIa[1.]	CD	FE	DU	—
	IIIa	CD	SF	SM	HN
	IVa	CD	SF	SM	TN
	Va	CD	SF	DU	HN
	VIa	CD	SF	DU	TN
	VIIa	STL	FE	SM	—
	VIIIa	STL	SF	SM	TN
	IXa	STL	SF	SM	HN

Functional Form	CD: Cobb–Douglas	STL: Simplified Translog
Frontier Specification	FE: Fixed Effects	SF: Stochastic Frontier
Technological Change	SM: Smooth	DU: Dummy
Efficiency Distribution	HN: Half-Normal	TN: Truncated Normal

[1.] This model is not estimated because the interaction between firm- and time-specific dummies creates an excessive number of parameters.

to the STL specification, while holding other factors constant, leads to the same average, minimum, and maximum technical efficiency measures. This result is compatible with the argument made by Good et al. (1993) and Maddala (1979) that technical efficiency measures do not depend on functional form. Model II, which uses time-specific dummy variables, also provides technical efficiency measures very close to Models I and VII.

Models III, V, and IX are stochastic production frontiers where the one-sided error term follows a half-normal distribution. By contrast, the one-sided error term in the other three stochastic frontier models (IV, VI and VIII), is assumed to follow a truncated normal distribution. Models III, V, and IX provide almost identical average (0.86) as well as minimum (0.60) and maximum (0.99) technical efficiency indices. In comparison, average technical efficiency for Models IV, VI, and VIII is 0.76, with a minimum of 0.55 and a maximum of 0.96.

The comparison between the fixed effects models (Models I, II, and VII) and the stochastic frontiers, where the one-sided error is truncated normal (Models IV, VI, and VIII), shows that both formulations yield very similar average technical efficiencies, a result that is in agreement with that of Hughes (1988). By contrast, the average technical efficiency measures using stochastic frontier models with a half-normal distribution for the one-

Table 3. Parameter estimates for the time-invariant technical efficiency models.

Variable/parameter	Model								
	I	II	III	IV	V	VI	VII	VIII	IX
Intercept	4.289[a]	4.293[a]	4.811[a]	4.784[a]	4.843[a]	4.814[a]	4.181[a]	4.631[a]	4.666[a]
X_z	0.774[a]	0.796[b]	0.679[a]	0.705[a]	0.690[a]	0.718[a]	0.808[a]	0.756[a]	0.735[a]
X_l	0.011	0.042[b]	0.014	0.015	0.038[b]	0.039[b]	0.021	0.004	0.001
X_f	0.175[a]	0.167[a]	0.198[a]	0.198[a]	0.191[a]	0.190[a]	0.239[a]	0.266[a]	0.263[a]
X_s	0.071[a]	0.060[a]	0.059[a]	0.071[a]	0.049[a]	0.062[a]	0.059[a]	0.056[a]	0.044[a]
X_c	0.031[a]	0.034[a]	0.036[a]	0.034[a]	0.040[a]	0.036[a]	−0.047[a]	−0.038[b]	−0.038[b]
X_m	0.053[a]	0.050[a]	0.057[a]	0.063[a]	0.056[a]	0.061[a]	0.041[c]	0.039[c]	0.033[c]
Time	0.010[a]	—	0.010[a]	0.010[a]	—	—	0.023[b]	0.029[a]	0.030[a]
T2	—	−0.012	—	—	−0.010	−0.012	—	—	—
T3	—	−0.064[a]	—	—	−0.060[a]	−0.059[a]	—	—	—
T4	—	−0.043[a]	—	—	−0.033[b]	−0.034[a]	—	—	—
T5	—	−0.019	—	—	−0.006	−0.008	—	—	—
T6	—	0.003	—	—	0.016	0.012	—	—	—
T7	—	−0.022	—	—	−0.009	−0.013	—	—	—
T8	—	0.027	—	—	0.038[b]	0.035[b]	—	—	—
T9	—	0.023	—	—	0.030[c]	0.029	—	—	—
T10	—	0.057[a]	—	—	0.067[a]	0.064[a]	—	—	—
T11	—	0.065[a]	—	—	0.077[a]	0.074[a]	—	—	—
T12	—	0.066[a]	—	—	0.078[a]	0.073[a]	—	—	—
T13	—	0.043[b]	—	—	0.055[a]	0.049[a]	—	—	—
T14	—	0.084[a]	—	—	0.095[a]	0.090[a]	—	—	—
T*T	—	—	—	—	—	—	0.001[b]	0.000[c]	0.000[c]
X_z*T	—	—	—	—	—	—	−0.005	−0.007[c]	−0.008[b]
X_l*T	—	—	—	—	—	—	−0.002	0.002	0.003
X_f*T	—	—	—	—	—	—	−0.008[a]	−0.009[a]	−0.009[a]
X_s*T	—	—	—	—	—	—	0.002	0.002	0.002
X_c*T	—	—	—	—	—	—	0.013[a]	0.012[a]	0.012[a]
X_m*T	—	—	—	—	—	—	−0.001	0.001	0.001
$\bar{R}^2$	0.96	0.96	—	—	—	—	0.96	—	—
LLF	—	—	806	817	828	840	—	843	831
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	—	—	0.043[a]	0.020[a]	0.044[a]	0.020[a]	—	0.019[a]	0.044[a]
μ	—	—	0	0.273[a]	0	0.276[a]	—	0.270[a]	0
η	—	—	0	0	0	0	—	0	0

[a]Significant at 1%.
[b]Significant at 5%.
[c]Significant at 10%.
LLF = Log Likelihood Function.

sided error term (Models III, V, and IX) are about 10 percentage points higher than the average technical efficiencies for the other six models.

4.2. *Time-variant technical efficiency*[4]

Time-variant technical efficiency measures are computed using eight of the nine alternative specifications discussed above.[5] Five of the models are based on the CD specification

Table 4. Descriptive statistics for time-invariant technical efficiency measures.

Model	Mean	Standard deviation	Minimum	Maximum
Cobb–Douglas (CD)				
Model I	0.767	0.082	0.531	1.000
Model II	0.762	0.084	0.518	1.000
Model III	0.861	0.076	0.600	0.990
Model IV	0.764	0.070	0.553	0.955
Model V	0.860	0.077	0.589	0.991
Model VI	0.762	0.071	0.541	0.955
Simplified Translog (STL)				
Model VII	0.769	0.084	0.531	1.000
Model VIII	0.766	0.071	0.551	0.956
Model IX	0.859	0.077	0.595	0.990

(Models Ia to VIa) and the other three are STL (Models VIIa to IXa).[6] Again, Table 2 presents a more complete description of the key features of each model, and Table 5 shows the parameter estimates.

To estimate time-variant technical efficiency indices for Models Ia and VIIa, the two-step procedure is adopted. In the first step, parameter estimates are obtained using the fixed effects technique, as was done for Models I and VII.[7] In the second step, the residuals from the first step are regressed on an overall constant, 95 farm-specific dummy variables, and the interaction between the farm-specific dummies and the time variable. Consequently, a total of 191 parameters are estimated in this second step. Of this total, only 73 in Model Ia and 62 in Model VIIa are significant at the 10% level or better. The adjusted R^2 for both models is about 0.60.[8]

The parameter estimates for the stochastic frontier models were also identical to the corresponding models where technical efficiency was assumed to be time invariant. However, the standard errors of most of the estimates for the stochastic models under time varying technical efficiency were higher than for the invariant case. Thus, higher standard errors resulted in nonsignificance of some of the parameter estimates.

The technical efficiency measures at each data point for the fixed effects models (Ia and VIIa) are calculated following the same procedure used in the time-invariant case. The average technical efficiency for Models Ia and VIIa is 0.76 with a maximum of 1.00, while the minimum for Model Ia is 0.47 and for Model VIIa is 0.50 (Table 6). Models IIIa, IVa, Va, VIa, VIIIa, and IXa are stochastic production frontiers. The index of technical efficiency measures for these models, as discussed earlier, is calculated as the antilog of the one-sided error term using equation (11). The results in Table 6 indicate that average technical efficiency for Models IIIa and Va is 0.86 with a minimum of 0.59 and a maximum of 0.99. The average technical efficiency for Models IVa and VIa is 0.76 with a maximum of 0.95. The minimums for Model IVa and VIa are 0.55 and 0.54, respectively. Model VIIIa, a STL specification, shows an average technical efficiency of 0.76 ranging from a minimum of 0.54 to a maximum of 0.96. Model IXa, also a STL, exhibits an average technical efficiency of 0.85 with a minimum of 0.59 and a maximum of 0.99. In general, the results in Table 6 reveal fairly stable annual average technical efficiency measures over the period under analysis.

Table 5. Parameter estimates for the time-variant technical efficiency models.

Variable/parameter	Model							
	Ia	IIIa	IVa	Va	VIa	VIIa	VIIIa	IXa
Intercept	4.289	4.812[a]	4.785[a]	4.844	4.814[a]	—	4.617[a]	4.660[a]
X_z	0.774[a]	0.678[a]	0.705[a]	0.690[a]	0.718[a]	0.808[a]	0.755[a]	0.732[a]
X_l	0.011	0.014	0.015	0.038[b]	0.038[b]	0.021	0.003	0.001
X_f	0.175[a]	0.199[a]	0.198[a]	0.191[a]	0.190[a]	0.239[a]	0.267[a]	0.265[a]
X_s	0.071[a]	0.060[a]	0.071[a]	0.010[a]	0.062[a]	0.059[a]	0.054[a]	0.044[a]
X_c	0.031[a]	0.037[a]	0.034[b]	0.040[a]	0.036[c]	−0.047[a]	−0.038[b]	−0.037[b]
X_m	0.053[a]	0.058[a]	0.063[a]	0.056[a]	0.061[b]	0.041[c]	0.039[b]	0.034[c]
Time	0.010[a]	0.010	0.010	—	—	0.023[b]	0.031[b]	0.031[a]
T2	—	—	—	−0.010	−0.011	—	—	—
T3	—	—	—	−0.060[a]	−0.059	—	—	—
T4	—	—	—	−0.034	−0.034	—	—	—
T5	—	—	—	−0.007	−0.008	—	—	—
T6	—	—	—	0.012	0.012	—	—	—
T7	—	—	—	−0.011	−0.013	—	—	—
T8	—	—	—	0.030[c]	0.035	—	—	—
T9	—	—	—	0.028	0.030	—	—	—
T10	—	—	—	0.065[a]	0.065	—	—	—
T11	—	—	—	0.075[a]	0.074	—	—	—
T12	—	—	—	0.075[a]	0.073	—	—	—
T13	—	—	—	0.051[c]	0.048	—	—	—
T14	—	—	—	0.092[a]	0.090	—	—	—
T*T	—	—	—	—	—	0.001[b]	0.000	0.000
X_z*T	—	—	—	—	—	0.005	−0.007	−0.008[c]
X_l*T	—	—	—	—	—	−.002	0.002	0.003
X_f*T	—	—	—	—	—	−0.008[a]	−0.009[b]	−0.009[a]
X_s*T	—	—	—	—	—	0.002	0.002	0.002
X_c*T	—	—	—	—	—	0.013[a]	0.012[a]	0.012[a]
X_m*T	—	—	—	—	—	−0.001	0.001	0.001
$\bar{R}^2$	0.96	0.96	—	—	—	0.96	—	—
LLF	—	806	817	828	840	—	843	831
$\sigma^2=\sigma_v^2+\sigma_u^2$	—	0.042[a]	0.020[a]	0.043[a]	0.020[b]	—	0.020[a]	0.047[a]
μ	—	0	0.273[b]	0	0.276[a]	—	0.277[a]	0
η	—	0.003	0.001	0.002	0.001	—	−0.004	−0.001

[a]Significant at 1%.
[b]Significant at 5%.
[c]Significant at 10%.
LLF = Log Likelihood Function.

4.3. *Technical efficiency comparisons*

To compare the rankings of technical efficiency measures resulting from all model specifications, Spearman rank correlation coefficients are calculated (Table 7). A total of 36 pairwise correlation coefficients among the various time-invariant technical efficiency

Table 6. Descriptive statistics of time-variant technical efficiency measures.

Year	Model Ia	Model IIIa	Model IVa	Model Va	Model VIa	Model VIIa	Model VIIIa	Model IXa
1971	0.762	0.869	0.763	0.868	0.761	0.757	0.773	0.870
1972	0.764	0.869	0.763	0.868	0.761	0.760	0.772	0.870
1973	0.762	0.870	0.763	0.869	0.761	0.760	0.771	0.870
1974	0.764	0.870	0.763	0.869	0.761	0.761	0.770	0.869
1975	0.762	0.870	0.763	0.869	0.761	0.760	0.770	0.866
1976	0.757	0.870	0.763	0.869	0.761	0.758	0.768	0.868
1977	0.752	0.871	0.763	0.869	0.761	0.757	0.768	0.867
1978	0.760	0.871	0.764	0.869	0.761	0.759	0.767	0.867
1979	0.781	0.871	0.764	0.870	0.762	0.767	0.766	0.866
1980	0.785	0.872	0.764	0.870	0.762	0.772	0.765	0.866
1981	0.747	0.872	0.764	0.870	0.762	0.767	0.764	0.865
1982	0.740	0.872	0.764	0.870	0.762	0.764	0.763	0.864
1983	0.770	0.873	0.764	0.870	0.762	0.778	0.762	0.864
1984	0.769	0.873	0.764	0.871	0.762	0.777	0.762	0.863
Mean	0.761	0.857	0.761	0.855	0.759	0.764	0.763	0.854
Standard deviation	0.090	0.077	0.071	0.078	0.072	0.089	0.072	0.078
Minimum	0.468	0.594	0.551	0.585	0.540	0.498	0.541	0.585
Maximum	1.000	0.990	0.955	0.991	0.956	1.000	0.959	0.991

indices are calculated, out of which 16 are equal to 0.99. The remaining 20 coefficients fall between the range of 0.91 to 0.98. These values indicate that all nine specifications provide almost the same technical efficiency rankings.

Spearman rank correlation coefficients for the time-variant technical efficiency models again show a strong association among the efficiency measures arising from the alternative specifications. The overall comparison of the magnitudes of these correlation coefficients shows a relatively weak association among the technical efficiency indices obtained from the fixed effects models (i.e., Ia and VIIa) and from the stochastic frontiers with a half normally distributed one-sided error term (i.e., IIIa, Va, and IXa). These correlations range from 0.85 to 0.88. By contrast, the association is much stronger among the technical efficiency indices of the stochastic frontier models (IIIa, IVa, Va, VIa, VIIIa, and IXa), where no correlation coefficient is less than 0.98.

The average efficiency indices reported in this article are within the bounds of those found in other studies of dairy farm efficiency. Using cross-sectional data sets for dairy farms in Northeastern United States, Bravo-Ureta (1986), Tauer and Belbase (1987), and Bravo-Ureta and Rieger (1991) estimated average efficiency indices equal to 82%, 69%, and 83%, respectively. Other cross-sectional studies of dairy operations have found average technical efficiency levels equal to 72% for farms in the continental United States (Kumbhakar, Ghosh, and McGuckin, 1991), 65% for Utah farms (Kumbhakar, Biswas, and Bailey, 1989), 77% for Ecuadorean farms, 81% for farms in England and Wales (Dawson, 1987), and 90% for farms located in central Argentina (Schilder and Bravo Ureta, 1993). More recently, Kumbhakar and Heshmati (1995), using panel data for a sample of Swedish farms, reported an average level of technical efficiency equal to 85%.

Table 7. Correlation coefficients for time-invariant and time-variant technical efficiency measures.

Time invariant	I	II	III	IV	V	VI	VII	VIII	IX
Model I	1.00								
Model II	0.99	1.00							
Model III	0.99	0.99	1.00						
Model IV	0.94	0.92	0.94	1.00					
Model V	0.99	0.98	0.99	0.97	1.00				
Model VI	0.94	0.91	0.93	0.99	0.96	1.00			
Model VII	0.99	0.97	0.99	0.96	0.99	0.97	1.00		
Model VIII	0.94	0.93	0.94	0.99	0.97	0.99	0.96	1.00	
Model IX	0.99	0.99	0.99	0.96	0.99	0.95	0.99	0.97	1.00
Time variant	**Ia**	**IIIa**	**IVa**	**Va**	**VIa**	**VIIa**	**VIIIa**	**IXa**	
Ia	1.00								
IIIa	0.86	1.00							
IVa	0.89	0.98	1.00						
Va	0.86	0.99	0.98	1.00					
VIa	0.89	0.97	0.99	0.98	1.00				
VIIa	0.98	0.87	0.90	0.88	0.90	1.00			
VIIIa	0.89	0.97	0.99	0.97	0.99	0.90	1.00		
IXa	0.85	0.99	0.96	0.98	0.96	0.87	0.97	1.00	

Note: All coefficients are significant at the 1% level.

5. Evaluation of models: some statistical tests

This section summarizes the results of statistical tests conducted to evaluate various hypotheses imbedded in the models estimated (Table 8). Based on the results of these tests, OLS estimates excluding farm-specific effects were rejected in favor of fixed effects and stochastic frontier models. The CD functional form was rejected for both fixed effects and stochastic frontier formulations in favor of the STL specification. However, the results discussed above imply that technical efficiency measures do not appear to be affected by the choice of functional form.

The stochastic frontier model incorporating a half normally distributed one-sided error was rejected when tested against the stochastic production frontier which assumed a truncated normal distribution. This test leads to the conclusion that the half-normal distribution for the efficiency component, which has a mean equal to zero, is too restrictive for the data being analyzed. Moreover, the efficiency analysis indicates that the assumption concerning the one-sided error does have important implications.

Likelihood ratio tests showed that technical efficiency does not vary over time for the stochastic frontier models. By contrast, statistical tests revealed that technical efficiency measures do vary over time for the fixed effects approach. To resolve these conflicting results, a Hausman (1978) specification test was performed to evaluate the performance of the stochastic frontier technique, which assumes independence between inputs and technical efficiency, vis-à-vis the fixed effects approach, where technical efficiency is allowed to be correlated with the other regressors. The stochastic frontier approach was strongly rejected against the fixed effects methodology. This result implies that the farm-

Table 8. Specification tests for alternative production models.

Model	Null hypothesis	F value	F crit.	χ^2 value	χ^2 crit.	Reject
Fixed effects models						
No farm-specific effects						
Model I	$b_i = 0$	8.7	1.32	—	—	Yes
Model II	$b_i = 0$	10.1	1.32	—	—	Yes
Model VII	$b_i = 0$	10.0	1.32	—	—	Yes
Constant returns to size						
Model I	$\Sigma b_k = 1$	488.2	3.84	—	—	Yes
Model II	$\Sigma b_k = 1$	493.5	3.84	—	—	Yes
Model VII	$\Sigma b_k = 1$ and $\Sigma \xi_k = 0$	239.0	3.00	—	—	Yes
Cobb–Douglas vs. modified translog						
Model I vs. VII	$\xi_k = \lambda = 0$	7.5	2.64	—	—	Yes
Time variant technical efficiency						
Model Ia 2nd step	$\rho_{it} = 0$	3.15	1.32	—	—	Yes
Model VIIa 2nd step	$\rho_{it} = 0$	2.86	1.32	—	—	Yes
Stochastic frontiers models						
OLS vs stochastic frontier						
Model IV	$\gamma = u = 0$	—	—	381.6	9.2	Yes
Model VI	$\gamma = u = 0$	—	—	402.6	9.2	Yes
Model VIII	$\gamma = u = 0$	—	—	398.1	9.2	Yes
Constant returns to size						
Model IV	$\Sigma b_k = 1$	—	—	16.3	6.6	Yes
Model VI	$\Sigma b_k = 1$	—	—	23.8	6.6	Yes
Model VIII	$\Sigma b_k = 1$ and $\Sigma \xi_k = 0$	—	—	96.8	9.2	Yes
Cobb–Douglas vs. modified translog						
Model VI vs. VIII	$\xi_k = \lambda = 0$	—	—	48.0	18.5	Yes
Half-normal vs. truncated normal distribution						
Model IX vs. VIII	$\mu = 0$	—	—	23.1	6.6	Yes
Time variant technical efficiency						
Model VIII vs. VIIIa	$\eta = 0$	—	—	0.1	6.6	No
Model IX vs. IXa	$\eta = 0$	—	—	0.1	6.6	No
Fixed effect vs. stochastic frontier models						
Model IV vs. I	$E(X'U) = 0$	—	—	84.3	18.5	Yes
Model VIII vs. VII	$E(X'U) = 0$	—	—	53.9	29.1	Yes

specific effects are indeed correlated with the inputs used in the model; thus, if this correlation is not accounted for, the parameter estimates are biased.

Given that the results of the statistical tests performed suggested that the preferred specification is the fixed effects time-variant model, Spearman rank correlations are computed between technical efficiency and herd size and input use per cow, based on Models Ia and VIIa. The results, presented in Table 9, show a negative and significant (at the 1% level) correlation between herd size and technical efficiency. This finding is consistent with those of Bravo-Ureta (1986), and Byrnes et al. (1987), but conflicts with the results obtained by Kumbhakar, Biswas, and Bailey (1989), and by Bravo-Ureta and Rieger (1991). The results show a significant positive relationship between concentrate feed per cow and other expenses per cow, while the association between technical efficiency and the per-cow level for the other three inputs (i.e., labor, animal expenses, and crop expenses) is generally weak.

6. Concluding comments

This article examined the impact of fixed effects production functions and of stochastic production frontiers on technical efficiency measures using an unbalanced panel consisting of 96 Vermont dairy farmers for the 1971–1984 period. The stochastic frontiers incorporated either a half-normal or a truncated normal distribution for the efficiency component. The Cobb–Douglas and a simplified translog functional forms were used, assuming either a smooth time trend or time-specific dummy variables to model technological change. These models incorporated both time-variant and time-invariant technical efficiency.

The fixed effects and truncated normal one-sided error term models yielded very close average technical efficiency measures—around 77%—for both the time-variant and time-invariant cases. In contrast, the half-normal one-sided error term models yielded average technical efficiency measures around 86%. These efficiency estimates are well within the bounds of those reported in other studies of dairy farms.

Various statistical hypothesis were also tested. The results of these tests lead to the following conclusions: (1) the farm-specific effects were significantly different from zero, which supports the fixed effects formulation; (2) the Cobb–Douglas functional form was rejected in favor of the simplified translog; (3) the one-sided error term in the stochastic frontier models followed a truncated normal distribution; (4) the stochastic frontier models revealed that technical efficiency is time invariant; (5) fixed effects models indicated technical efficiency was time variant; and (6) farm-specific effects were correlated with the inputs included in the production functions. Thus, the fixed effects technique was found superior to the stochastic production frontier methodology.

Although the stochastic frontier specification was rejected based on various statistical tests, the parameter estimates and efficiency rankings from these models are similar to those obtained from the fixed effects models. Moreover, the stochastic frontier assuming a truncated normal distribution for the efficiency term gave average technical efficiency measures, in both the time-variant and time-invariant models, very close to those obtained from the fixed effects models. Hence, our overall conclusion is that despite the fact that the statistical tests performed did indicate the superiority of some specifications over oth-

Table 9. Correlation coefficients between technical efficiency and herd size and per cow inputs.

Items	Technical efficiency	
	(Model VIIa)	(Model Ia)
Herd size	−0.20[a]	−0.23[a]
Feed per cow	0.45[a]	0.45[a]
Labor per cow	0.01	−0.02
Animal exp. per cow	0.08[b]	0.03
Crop exp. per cow	0.04	0.03
Other exp. per cow	0.20[a]	0.19[a]

[a]Significant at the 1% level.
[b]Significant at the 10% level.

ers, the efficiency analysis was fairly consistent throughout the models considered. An interesting implication is that the relatively old but simple fixed effects approach deserves serious consideration when examining technical efficiency with panel data.

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Notes

1. For recent reviews of methodological issues concerning frontier models see Bauer (1990), Lovell (1993), and Seiford and Thrall (1990). Reviews of applications of frontier methodology to agriculture are found in Battese (1992) and Bravo-Ureta and Pinheiro (1993).
2. Recent applications of frontier methodology to agriculture using panel data include Battese and Coelli (1992), Kalirajan (1991), and Kumbhakar and Hjalmarsson (1993).
3. The function coefficients for Models I through IX are, respectively: 1.11; 1.15; 1.04; 1.08; 1.06; 1.11; 1.11; 1.08; and 1.04. The last three function coefficients are for STL models, and are calculated at the mean of the data. The function coefficients for the time-variant technical efficiency models (Models Ia–IXa, discussed in the following subsection) are the same as those obtained for the corresponding time-invariant models.
4. The time-variant efficiency models were also estimated restricting the parameters associated with time to zero. In all cases the hypothesis that these parameters are equal to zero is strongly rejected, a result that is in contrast with the findings of Battese and Coelli (1992).
5. The fixed effects model with time-specific dummy variables (Model IIa) is not used to calculate time-variant technical efficiency, because the interaction between firm- and time-specific dummies creates too many parameters to be estimated.
6. The roman numeral coincides with the equivalent time-invariant technical efficiency model. The letter following the number is introduced to indicate that technical efficiency is time variant.
7. Recently, Fecher and Pestieau (1993) reported time varying technical efficiency estimates from a model that does not incorporate firm-specific dummy variables in the first step. The residuals from the first step were regressed on time and time squared to calculate technical efficiency indexes. The problem with Fecher and Pestieau's two-stage procedure is that efficiency is assumed to be correlated with the inputs used in the model, but this correlation is not accounted for in the first step. Thus, if efficiency is associated with the inputs, then the parameter estimates from the first step are biased. Consequently, biased parameters from the first stage could lead to biased efficiency estimates in the second step.
8. The parameter estimates for the second step are not presented due to space limitations.

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