Estimation of Firm-Varying, Input-Specific Efficiencies in Dairy Production

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Firm-varying production technologies were estimated using random coefficients regression methods for a sample of Massachusetts dairy farms. Results were compared to OLS Cobb-Douglas production function estimates. The random coefficients regression model was found to virtually eliminate conventionally measured firm technical inefficiencies by estimating individual firm technologies and ascribing remaining inefficiencies to specific inputs. Input-specific measures of firm inefficiencies showed hired labor, land, and machinery inputs to be used in excess of efficient levels. Livestock supplies were underutilized by all farms. Efficiencies of feed, crop materials, fuels, and utilities varied, although estimated means were closer to optimal levels.

Measurement of economic efficiency has been an important area of empirical research in production economics. During the last decade, several studies have been conducted to measure efficiency of Northeast dairy production (e.g., Bravo-Ureta and Rieger; Tauer and Belbase; Grisley and Mascarenhas). Development of neoclassical economic theory has provided means for identifying technical and allocative efficiencies. Technical efficiency typically is measured using estimated production functions; deviations from the frontier are assumed to represent technical inefficiencies. Econometric estimation methods have progressed from corrected least squares methods (Greene) to the stochastic frontier, composed error model used in recent studies (e.g., Bravo-Ureta and Rieger; Dawson and White). Inasmuch as output and input prices are rarely available in cross-sectional firm-level data, empirical measurement of allocative efficiency is seldom conducted.[1] Studies that do estimate firm-level allocative efficiency must make assumptions about input prices. For example, Bravo-Ureta and Rieger utilized state-level commodity prices to represent firm-level prices for input aggregates. The validity of such an approach given aggregation of inputs is questionable.

In this study, we present an alternative approach stipulating that production technology varies across firms. To allow individual firms to have their own production function, a random coefficients regression (RCR) model is used to estimate individual firm-varying production frontiers. Application of the RCR model also allows calculation of disaggregated input-specific estimates of inefficiencies directly from parameter estimates. Kopp presented measures of input-specific efficiencies. However, his measures relied upon assumptions about input prices and factor ratios. Unlike Kopp's measures, our approach estimates input-specific efficiencies "simultaneously" and does not rely upon input price or factor ratio assumptions. The measures presented in this paper are of economic or overall inefficiencies; technical and allocative inefficiencies are not separated. Such estimates are of interest, both from a research perspective as well as the more practical input allocation perspective of farm managers. The technique applied here represents a relatively new approach to estimation of production relationships. The ability to identify inputs that are overused or underused is important from the practical standpoint.

There are two reasons why the RCR model is appealing for production analysis. First, the exis-

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[1] Studies by Hopper, Sahota, Lau and Yotopoulos, and, more recently, Bravo-Ureta and Rieger, and Stefanou and Saxena are exceptions.

tence of a fixed-coefficient production function describing technology for all firms, such as the Cobb-Douglas form, is questionable (Fisher, Zellner). A common assumption in modeling production functions is one of constant coefficients, implying a stable production process being used by all firms as characterized in their output supply, input demand, and investment behavior. However, as noted in several studies of production efficiency (e.g., Yotopoulos and Lau), different farm sizes may have different technological structures. The conventional approach in the literature has been to arbitrarily classify farm sizes based on acreage or gross revenue. Use of the RCR model eliminates such ad hoc procedures and allows the researcher to measure production efficiency for individual farms regardless of size distribution. If in truth, industry technology cannot be described by a single production function, then the parameter vector for such a model does not have any meaningful physical interpretation (Swamy, Conway and von zur Muehlen). Existence conditions for varying-coefficients models are less restrictive than those of fixed-coefficient models (Narasimham, Swamy, and Reed; Zellner).

Second, fixed-coefficients model construction is based on prior information about data availability and parameter vectors. However, one cannot distinguish among the imposition of structure, determination of the parameter vector, and restrictions imposed by data. As a result, the model assumed by the analyst determines interpretation of the parameter vector that may have no relationship to reality. The RCR approach allows flexibility in functional form of estimated firm production functions. The functional form is flexible in that both production elasticities and elasticities of substitution vary across firms.

Dairy Production and Efficiency Analysis

There are substantial data requirements for complete analysis of both technical and allocative aspects of economic efficiency. Analysis of technical efficiency requires firm-level output and input data, while measurement of allocative efficiency requires price data as well. Cross-sectional data for dairy farms have been used to estimate primal and dual models of production. Dual applications to the dairy sector include Weaver and Lass, and Stefanou and Saxena. In both cases, detailed price data were available, allowing estimation of dual profit functions. Weaver and Lass utilized data from the 1974 U.S. Department of Agriculture (USDA) Cost of Production Survey, which was unusual for its detailed set of price data. Stefanou and Saxena combined Pennsylvania Farmers Association and Dairy Herd Improvement Association data to obtain necessary price information. Unfortunately, detailed price information usually is unavailable.

Estimation of the production function is an alternative to the dual approach. Zellner, Kmenta, and Dreze have shown that single-equation estimation of the production function is valid if farmers attempt to maximize expected profits. Griliches, in his classic article, estimated an agricultural production function in value form using aggregate cross-sectional data. Prices are assumed fixed over the time period for farmers, and changes in value of production due to changes in input costs are assumed to indicate production relationships. Tauer and Belbase, for example, estimated a Cobb-Douglas production function in value form for New York dairy farmers. Resulting parameter estimates are interpreted as production elasticities. However, evaluation of marginal products is difficult because prices are typically unknown or meaningless due to the level of aggregation. Bravo-Ureta and Rieger estimated a stochastic production frontier using the approach of Aigner, Lovell, and Schmidt, and Meeusen and van den Broeck. Technical efficiency was measured using the one-sided component of the composed error. Allocative efficiencies were measured by deriving the cost function dual to the estimated production frontier. They then used state-level prices in order to estimate allocative inefficiencies.

Efficiency analyses have focused primarily on technical efficiency using frontier production function methods.[2] Technical efficiencies of dairy farms in Maine and Vermont (Bravo-Ureta), Pennsylvania (Grisley and Mascarenhas), and New York (Tauer and Belbase) have been considered using frontier production techniques. Several dairy farm efficiency studies have focused on factors that may influence the level of technical efficiency. Grisley and Mascarenhas considered numerous farm characteristics, primarily ratios of fixed and variable factors of production. Tauer and Belbase concentrated on farm location and managerial indicators, such as record-keeping, DHIA membership, age, and education. Several factors were found to contribute to the level of technical efficiency; however, these studies all maintain the assumption of a common production technology.

[2] The pioneering work of Lau and Yotopoulos on technical and allocative efficiency is an exception. The recent work of Stefanou and Saxena focused on allocative efficiency and the effects of human capital.

As Stigler states in his discussion of Leibenstein's article on X-Efficiency, ". . . attention to X-inefficiency as the explanation is an act of concealment: it simply postulates the differences in technology among firms which should be explained" (p. 215). In this paper, we consider an alternative approach following Stigler's suggestion; firms are assumed to face different technologies. Measures of inefficiencies are then calculated from these individual firm technologies.

Empirical Model

In most empirical work, parameters of primal or dual functions are estimated using fixed-coefficient least squares procedures. Thus, researchers assume effects of exogenous variables are constant through time or across observation units for cross-sectional data. All firms are assumed to face the same technology. A plausible alternative would be to allow varying coefficients through time or across observational units. Such variations may be caused by differences in production structure, available resources, and a host of other farm-specific factors (i.e., management skill). We assume the following production function:

$$(1) \qquad Y_i = \prod_{k=1}^{K} X_{ik}^{\beta_{ik}},$$

where coefficients vary across firms ($i = 1, \ldots, n$):

$$(2) \qquad \beta_{ik} = \bar{\beta}_k + \epsilon_{ik}.$$

The β_{ik} are individual firm production coefficients defining the distribution of technology. Because $X_{i1} = 1$ for all $i = 1, \ldots, n$, β_{i1} are individual firm intercepts, and ϵ_{i1} assume roles of usual fixed-coefficient model random errors. This makes clear the distinction between traditional production function estimation and the approach taken here. If only the intercept in equation (1) were allowed to be random, the varying-coefficients model would be equivalent to the classical fixed-coefficient regression model (Narasimham, Swamy, and Reed). The model used here is more general, allowing all coefficients to be random.

Combining equations (1) and (2), the production function is written

$$(3) \qquad Y_i = \prod_{k=1}^{K} X_{ik}^{\bar{\beta}_k} X_{ik}^{\epsilon_{ik}}.$$

Equation (3) represents a general set of nonlinear equations that depend upon individual firm coefficient vectors. The form of the model used here is appealing in that the usual assumption of a fixed-coefficient model is relaxed, but not eliminated, as a possibility. If coefficient variances are zero (for $k = 2, \ldots, K$), then the fixed-coefficient Cobb-Douglas production function is appropriate.

As noted above, Stigler argued that technical inefficiencies may reflect differences in technology. We can illuminate Stigler's argument by rewriting equation (3) as follows:

$$(4) \qquad Y_i = \prod_{k=1}^{K} X_{ik}^{\bar{\beta}_k} \left[\prod_{k=1}^{K} X_{ik}^{\epsilon_{ik}} \right].$$

In this form, the model appears as the typical Cobb-Douglas production function. The first product of terms on the right-hand side includes fixed coefficients, $\bar{\beta}_k$, and terms in brackets represent usual fixed-coefficient model random errors. Estimation of (4) by fixed-coefficient methods and calculating technical inefficiencies from usual random errors may be inaccurate. The usual random errors may represent differences in technologies rather than technical inefficiencies.

Individual coefficients of equation (3) define individual farm technologies. Coefficients are interpreted as individual firm-varying production elasticities. First-order conditions for profit maximization specify that each input coefficient should equal the expenditure to revenue ratio:

$$(5) \qquad \beta_{ik}^* = \left(\frac{\partial Y_i}{\partial X_{ik}} \right)^* \cdot \frac{X_{ik}^*}{Y_i^*} = \frac{r_k X_{ik}^*}{p Y_i^*} = s_{ik}^*,$$

where asterisks denote optimal choices, r_k are input prices, and p is output price. All firms are assumed to face the same prices. Comparison of estimated individual coefficients ($\hat{\beta}_{ik}$) to actual input expenditure to revenue ratios (s_{ik}) indicates input efficiency. For example, the marginal product of an underutilized input will be greater than the input to output price ratio. As a result, the estimated coefficient will be greater than the actual expenditure to revenue ratio:

$$(6) \qquad \hat{\beta}_{ik} = \frac{\partial Y_i}{\partial X_{ik}} \cdot \frac{X_{ik}}{Y_i} > \frac{r_k X_{ik}}{p Y_i} = s_{ik}.$$

Similarly, if the input is overused, the marginal product would be less than the input to output price ratio. Ratios of estimated individual firm parameters with actual expenditure to revenue ratios give the following rules for judging firm-level individual input efficiencies:

$$\frac{s_{ik}}{\beta_{ik}} \begin{cases} > 1 & \textit{input is overused;} \\ = 1 & \textit{input is optimal;} \\ < 1 & \textit{input is underused.} \end{cases} \tag{7}$$

Individual firm coefficients may vary from optimal expenditure to revenue ratios for reasons of technical inefficiency or allocative inefficiencies. While the model allows estimation of individual input inefficiencies, we cannot distinguish the causes of inefficiencies. In fact, we capture economic inefficiency, which is the combination of technical and allocative inefficiency.

Several factors of production may be considered quasi-fixed inputs. Because farms report no expenditures on these inputs, estimation of efficiency for quasi-fixed inputs is not possible. However, we can estimate shadow values for quasi-fixed inputs as follows. Equation (1) can be expanded to include quasi-fixed inputs, say θ_{il}, and coefficients, α_{il}, which are also random. Given the functional form in (3), quasi-fixed input coefficients also represent production elasticities:

$$\hat{\alpha}_{il} = \frac{\partial\, Y_i}{\partial\, \theta_{il}} \cdot \frac{\theta_{il}}{Y_i}\,. \tag{8}$$

The shadow value of the lth quasi-fixed input for a profit-maximizing firm is determined as

$$\frac{\partial\, \pi_i}{\partial\, \theta_{il}} = \frac{\partial\, Y_i}{\partial\, \theta_{il}} \cdot p = \lambda_{il}\,. \tag{9}$$

The firm-varying shadow values can be calculated by multiplying estimated individual firm coefficients by value of output, and dividing by quasi-fixed input levels:

$$\hat{\alpha}_{il} \cdot \frac{p\, Y_i}{\theta_{il}} = \frac{\hat{\lambda}_{il}\, \theta_{il}}{p\, Y_i} \cdot \frac{p\, Y_i}{\theta_{il}} = \hat{\lambda}_{il}\,. \tag{10}$$

Swamy and Tinsley's stochastic coefficients model can be used to estimate the firm-varying production functions in (3). Following Swamy and Tinsley, varying-coefficient models may be written in matrix notation as

$$Y_t = X_t'\beta_t, \tag{11}$$

where

$$\beta_t - \bar{\beta} = \Phi(\beta_{t-1} - \bar{\beta}) + \epsilon_t. \tag{12}$$

An important special case of this model arises when the correlation matrix of varying coefficients, Φ, is a null matrix such that

$$\beta_t - \bar{\beta} = \epsilon_t. \tag{13}$$

The varying coefficients in equation (13) can be described as random variables drawn from a common distribution with mean $\bar{\beta}$. This departs from the time-varying stochastic coefficient specification in (12) because future values of varying coefficients are unpredictable from past values. This is a case where the regression slope is stochastic, but not autocorrelated. If the production structure is characterized by such behavior, the model is said to be generated under a random-coefficients procedure. The RCR model is often appropriate in analyzing cross-sectional data (Hildreth and Houck). In this study, a single time period is considered and the subscript for time can be dropped.[3] The error matrix ϵ is assumed to be a sequence of uncorrelated random variables with expected mean values of zero and constant variance-covariance matrix denoted Σ_ϵ with zero off-diagonal elements. Since Σ_ϵ and β are not known but must be estimated, the Swamy and Tinsley algorithm provides for a data-based iterative estimation procedure where Σ_ϵ initially is chosen arbitrarily with zero off-diagonal elements and Φ is restricted to a null matrix. Through several iterations, efficient and consistent estimates of Σ_ϵ and β are derived. Mean values, $\bar{\beta}$, which provide the lowest root mean square error, are selected and reported. Individual coefficient estimates are compared to actual expenditure/revenue ratios to determine firm-varying inefficiencies in input use.

Results

Empirical models were estimated using 1988 survey data for 33 Massachusetts dairy farms (Engel, Morzuch, and Lass). Variable-input expenditures were aggregated into eight accounts: (1) fuels and utilities; (2) crop production materials; (3) business and office expenses; (4) land expenses; (5) total purchased feeds; (6) hired labor; (7) livestock supplies; and (8) machinery services. In addition to variable-input expenditures, a set of quasi-fixed factors was included containing operator labor, unpaid labor, and number of cows. A preliminary investigation of multicollinearity was conducted by calculating variance inflation factors for each independent variable. Multicollinearity was not found to be of concern. Descriptive statistics for variables are presented in Table 1.

[3] The matrix of individual coefficients, β, is then N by K, where N is the sample number of farms and K is the number of explanatory variables plus a constant.

Table 1. Descriptive Statistics for Massachusetts Dairy Farms, 1988

	Means per Farm (N = 33)	Means per Cow (N = 33)
Gross Returns ($)	138,524.13	1817.18
	(131,578.22)[a]	(411.33)
Variable Inputs ($)		
Fuels and utilities	8,373.18	127.26
	(6431.53)	(54.23)
Crop production materials	13,118.88	135.68
	(19,752.56)	(91.51)
Business expenses	8,846.82	107.63
	(12,468.36)	(79.10)
Land expenses	11,346.03	163.58
	(13,762.25)	(16.91)
Purchased feeds	48,433.58	631.51
	(54,289.82)	(221.91)
Hired labor	21,857.26	225.57
	(33,963.42)	(224.71)
Livestock supplies	3,798.27	55.42
	(3,235.14)	(29.22)
Machinery services	24,311.01	212.32
	(18,361.75)	(177.19)
Quasi-Fixed Inputs		
Operator labor (hours)	3,585.37	76.56
	(1,330.17)	(55.16)
Unpaid labor (hours)	1698.01	38.72
	(2,556.98)	(60.99)
Herd size (number of cows)	77.58	77.58
	(87.02)	(87.02)

[a]Numbers in parentheses are standard deviations.

Farm Production Technology

A fixed-coefficients Cobb-Douglas production function was initially estimated by ordinary least squares (OLS) using data on a *per cow* basis. The model fit the data well, explaining about 72% of variation in output per cow. Independent variables in the model were collectively significant (F_{calc} = 4.93). White's test for heteroskedasticity resulted in a highly significant chi-square statistic. Coefficient estimates and t-statistics presented in Table 2 are OLS estimates using White's heteroskedasticity-consistent covariance matrix.

A random coefficients regression (RCR) model, in firm-varying Cobb-Douglas form, was estimated next using data on a *per cow* basis.[4] Estimated mean coefficients and asymptotic t-statistics for the mean coefficients are presented in Table 2. Coefficient estimates for individual farms were estimated using the mean vector ($\bar{\beta}$) and decomposition of the variance-covariance matrix (Σ_ϵ). OLS coefficient estimates and mean RCR estimates are comparable. OLS and mean RCR estimates all had the same signs, and magnitudes were similar.

There was variation in individual farm production technologies. Minimum and maximum values for individual farm coefficient estimates ($\hat{\beta}_{ik}$) are presented in Table 2. Coefficients for fuels and utilities, crop production materials, and business and office expenses varied from mean estimates by plus or minus 7% to 9%. Individual farm production coefficients for land and labor varied most from mean estimates. The maximum coefficient for land was 100% greater than the mean estimate, and the minimum coefficient for hired labor was nearly 70% lower than the mean coefficient estimate. Individual coefficients for machinery services also had significant variation, about 23% on either side of the mean estimate. Remaining individual farm coefficient estimates had little variation, about 2% or less.

Estimated fixed coefficients for quasi-fixed factors were also comparable to the mean estimates for the RCR model. Coefficients for operator labor and unpaid labor were statistically different from zero in both models. Comparison with previous studies is difficult since operator labor is often combined with other family labor (Tauer and Belbase) or aggregated into a single labor measure with family and hired labor (Bravo-Ureta and Rieger). It appears from the results that Massachusetts dairy farmers use unpaid labor beyond an economically efficient level. Estimated OLS and mean RCR parameters for unpaid labor were negative and statistically different from zero. Results suggest that there are opportunity costs of unpaid labor in terms of lower production, possibly due to training costs of children. These results suggest aggregating labor in production analyses can result in biased estimates of operator labor and/or hired labor production elasticities.

Efficiency Analysis

One objective of this study was to analyze farm-varying input-specific efficiency. An important aspect of the RCR model is its ability to ascribe farm inefficiencies to individual inputs. Frontier methods of efficiency analysis utilize estimates of random errors to calculate aggregate farm technical inefficiency. Estimates of technical efficiency typically employed in the literature do not capture input-specific inefficiencies. The stochastic frontier method of Aigner et al. is the prominent method for estimating both a one-sided error (technical efficiency) and a purely random two-sided error. Our approach is to estimate individual farm technologies and then calculate inefficiencies using these individual farm technologies. In this

[4] The Swamy and Tinsley estimator corrects for heteroskedasticity problems.

Table 2. Production Function Estimates, Massachusetts Dairy Farms, 1988[a]

Variable	Fixed-Coefficient Estimates (OLS)	Random-Coefficient Estimates		
		Means	Minimum	Maximum
Variable Inputs				
Fuels and utilities	0.0776	0.0832	0.0759	0.0892
	(1.35)[b]	(1.26)		
Crop materials	0.0505	0.0473	0.0436	0.0520
	(2.17)*	(2.56)*		
Business expenses	0.0869	0.0822	0.0756	0.0883
	(2.68)*	(2.25)*		
Land expenses	0.0139	0.0081	−0.0019	0.0162
	(0.49)	(0.24)		
Purchased feeds	0.2914	0.3308	0.3258	0.3352
	(3.67)*	(4.47)*		
Hired labor	0.0114	0.0100	0.0031	0.0167
	(1.31)	(0.99)		
Livestock supplies	0.1559	0.1563	0.1529	0.1591
	(2.95)*	(2.82)*		
Machinery expenses	0.0378	0.0324	0.0250	0.0398
	(0.94)	(0.87)		
Quasi-Fixed Inputs				
Operator labor	0.1798	0.1813	0.1793	0.1825
	(3.35)*	(2.08)*		
Unpaid labor	−0.2334	−0.2746	−0.2747	−0.2746
	(−5.67)*	(−5.03)*		
Number of cows	0.2943	0.0337	0.0297	0.0389
	(0.66)	(0.62)		
Intercept	3.5675	3.3490	3.3343	3.3635
	(6.94)	(5.33)*		

[a]Both fixed- and random-coefficient models were estimated in Cobb-Douglas form.
[b]The numbers in parentheses are t-ratios (OLS) and asymptotic t-ratios (RCR).
*Statistically different from zero at the 5% level or better.

way, aggregate inefficiency can be ascribed to individual inputs. To demonstrate, RCR results are compared to a corrected ordinary least squares (COLS) approach to measuring technical inefficiency (Greene).

COLS technical inefficiency measures were calculated using the regression results in Table 2.[5] The COLS method of measuring technical inefficiency indicated that Massachusetts dairy farmers in this sample were 78% efficient on average (Table 3). The minimum level of efficiency was 58%. The results are comparable to those reported by Bravo-Ureta, and Bravo-Ureta and Rieger for New England dairy farms, and Grisley and Mascarenhas for large Pennsylvania farms. Tauer and Belbase found New York dairy farms to be slightly less efficient using the same method.

In the RCR model, equation errors are not distinguished from errors of the constant term (β_{i0}). Thus, a "corrected" RCR model can be developed by shifting firm-level production functions using errors for the constant terms. This is analogous to the COLS approach. Results showed that virtually all errors considered to be technical inefficiencies in the COLS model are ascribed to individual inputs when individual farm technologies were estimated using the RCR model. This may mean that past estimates of technical efficiencies using COLS and other frontier methods were inappropriate because they did not account for differences in firm technologies. Previous estimates of technical inefficiency may have been measures of differences in farm technologies. These results support Stigler's argument.

Comparison of RCR estimated individual farm coefficient estimates with actual expenditure to revenue ratios allows us to identify inputs that are used inefficiently for each farm. Mean, minimum, and maximum values are presented in Table 3 for each variable input. As seen in Table 3, farmers have a wide range of efficiencies. On average, land and hired labor were managed least efficiently. All farms utilized excessive amounts of land, and a majority of farms used too much hired labor.[6] Machinery services were also used in ex-

[5] The composite-error methodology of Aigner, Lovell, and Schmidt was applied to the data; however, the one-sided error did not exist, making OLS results maximum-likelihood estimates.

[6] As one referee pointed out, excessive use of land and labor may

Table 3. Measures of Massachusetts Dairy Farm Inefficiency, 1988

Regression Model	Mean	Minimum	Maximum
Corrected Ordinary Least Squares			
Technical efficiency[a]	0.780 (0.096)[b]	0.583	1.000
Random Coefficients Regression			
Technical efficiency[c]	0.999 (0.001)	0.997	1.000
Input-specific efficiency			
Fuels and utilities	0.923 (0.522)	0.299	3.107
Crop materials	1.609 (1.109)	0.011	4.080
Business expenses	0.733 (0.468)	0.114	1.788
Land expenses	10.712 (11.265)	1.704	64.060
Purchased feeds	1.067 (0.348)	0.396	2.121
Hired labor	15.818 (22.335)	0.046	114.833
Livestock supplies	0.199 (0.104)	0.072	0.531
Machinery expenses	6.627 (4.344)	0.939	17.992
Shadow prices[d]			
Operator labor ($/hr.)	3.01 (1.28)	0.77	5.53
Unpaid labor ($/hr.)	−7.22 (3.31)	−13.65	−1.12
Number of cows ($/cow)	63.74 (16.54)	36.14	94.83

[a]Technical efficiency is measured by shifting the producting function using OLS errors.
[b]Numbers in parentheses are standard deviations from the means.
[c]Technical efficiency is measured by shifting the production functions using errors for the constant term.
[d]Shadow prices are measured as annual value for one unit of the quasi-fixed input.

cess of efficient levels. Only one farm had an efficiency measure value of unity or less for machinery services. Consistent underutilization of livestock supplies was also an important result. Livestock supplies include veterinary and breeding expenses. It appears that farmers could improve farm profitability by paying closer attention to herd health and breeding.

Variable inputs that farmers are more adept at managing include fuels and utilities, crop materials, business expenses, and purchased feeds. Means for these categories were relatively close to unity and variations in individual estimates were smaller. Purchased feeds, for example, was closest to the optimum value of unity and had limited variation. Farmers apparently are conscious of feed expenditures, possibly because farm management services commonly provide statistics on "concentrates fed."

Quasi-fixed input shadow prices are presented in Table 3. On average, operator labor was valued at about $3 per additional hour. Unpaid labor had a substantial negative shadow value. On average, unpaid labor cost the farm more than $7 for each additional hour. It must be noted that finding unpaid labor to be detrimental to production was unexpected, but not totally surprising. Among a host of reasons, this result could indicate costs associated with training children, excessive use of labor due to risk aversion, or farm operators overstating actual labor of unpaid family labor. The true value of unpaid labor is an empirical issue; the results of this study suggest there is a good deal of work needed in this area. Shadow values for cows were positive, but low. The average value for an additional cow was about $64 a year. The minimum shadow value for a cow was about $36 a year and the maximum value about $95 a year.

indicate risk aversion. Impacts of risk attitudes on efficiency is one direction for future research.

Summary and Conclusions

This study introduced another approach to the estimation of firm inefficiencies. Stigler suggested that measurement of technical inefficiencies may indicate differences in technology across firms. Traditional measures of technical inefficiency calculated from a fixed-coefficient estimation technique (corrected ordinary least squares) were compared to similar measures from the random coefficients regression model allowing firm-varying technology. In both cases, traditional measures of technical inefficiency were calculated by shifting the production frontier. Virtually all technical inefficiency, as measured traditionally by corrected ordinary least squares, was either ascribed to individual input use or eliminated by estimating firm-varying technologies. Thus, implications from past studies that technical inefficiencies can be represented by neutral shifts of the frontier production function are misleading.

Economic inefficiencies were also estimated using individual firm coefficients. Results of this study showed labor, land, and machinery use to be relatively inefficient on Massachusetts dairy farms. All farms used too much land, and all but one farm employed machinery beyond optimal levels. One input, livestock supplies, was underutilized by all dairy farmers. Variable inputs that were used more efficiently by Massachusetts dairy farmers were fuels and utilities, crop materials, and purchased feeds. Shadow values for the quasi-fixed inputs operator labor and dairy cows were lower than expected, and shadow values for unpaid labor were negative for all farms.

The methodology presented here has considerable promise in analysis of firm inefficiencies. By estimating firm-varying technologies, previously accepted measures of technical inefficiency can be explained by differences in technology and ascribed to specific input utilization. Firm-level analysis of input allocations can be used to guide farm decision making. For example, firms that over- or underutilize specific inputs can be identified from the results. The random coefficients regression model shows substantial flexibility in extending rigorous empirical modeling to the farm level.

References

Aigner, D.K., C.A.K. Lovell, and P.J. Schmidt. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6(1977):21–37.

Bravo-Ureta, B.E. "Nonparametric Measures of Technical Efficiency in Milk Production." *Journal of the Northeastern Agricultural Economics Council* 12(1983):69–76.

Bravo-Ureta, B.E., and L. Rieger. "Dairy Farm Efficiency Measurement Using Stochastic Frontiers and Neoclassical Duality." *American Journal of Agricultural Economics* 73(1991):421–28.

Dawson, P.J., and B. White. "The Post-Quota Performance of Dairy Farms in England and Wales." *Applied Economics* 22(1990):1399–1406.

Engel, N.E., B. Morzuch, and D. Lass. "Estimation of Farm Land Values in Massachusetts: Fiscal Year 1990." Department of Resource Economics, University of Massachusetts, Amherst, MA, 1989.

Fisher, F. "The Existence of Aggregate Production Functions." *Econometrica* 37(1969):553–77.

Greene, W.H. "Maximum Likelihood Estimation of Econometric Frontier Functions." *Journal of Econometrics* 13(1980):27–56.

Griliches, Z. "Estimates of the Aggregate Agricultural Production Function from Cross-Sectional Data." *Journal of Farm Economics* 45(1963):419–28.

Grisley, W., and J. Mascarenhas. "Operating Cost Efficiency on Pennsylvania Dairy Farms." *Northeastern Journal of Agricultural and Resource Economics* 14(1985):88–95.

Hildreth, C., and J.P. Houck. "Some Estimators for a Linear Model with Random Coefficients." *Journal of the American Statistical Association* 63(1968):584–95.

Hopper, W.D. "Allocation Efficiency in a Traditional Indian Agriculture." *Journal of Farm Economics* 47(1965):611–24.

Just, R.E., D. Zilberman, and E. Hochman. "Estimation of Multicrop Production Functions." *American Journal of Agricultural Economics* 65(1983):770–80.

Kopp, R.J. "The Measurement of Productive Efficiency: A Reconsideration." *Quarterly Journal of Economics* 96(1981):477–503.

Lau, L.J., and P.A. Yotopoulos. "A Test of Relative Efficiency and Application to Indian Agriculture." *American Economic Review* 61(1971):94–109.

Luh, Y.H., and S.E. Stefanou. "Dairy Supply and Factor Demand Response to Output Price Risk: An Econometric Assessment." *Northeastern Journal of Agricultural and Resource Economics* 18(1989):103–8.

Meeusen, W., and J. van den Broeck. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* 18(1977):435–44.

Narasimham, G.V.L., P.A.V.B. Swamy, and R.C. Reed. "Productivity Analysis of U.S. Manufacturing Using a Stochastic-Coefficients Production Function." *Journal of Business and Economic Statistics* 6(1988):339–49.

Sahota, G.S. "Efficiency of Resource Allocation in Indian Agriculture." *American Journal of Agricultural Economics* 50(1968):584–605.

Stefanou, S.E., and S. Saxena. "Education, Experience, and Allocative Efficiency: A Dual Approach." *American Journal of Agricultural Economics* 70(1988):338–45.

Stigler, G.J. "The Xistence of X-Efficiency." *American Economic Review* 66(1976):213–16.

Swamy, P.A.V.B., and P. Tinsley. "Linear Prediction and Estimation Methods for Regression Models with Stationary Stochastic Coefficients." *Journal of Econometrics* 12(1980):103–42.

Swamy, P.A.V.B., R. Conway, and P. von zur Muehlen. "The Foundations of Econometrics—Are There Any?" *Econometric Reviews* 4(1985):1–61.

Tauer, L.W., and K.P. Belbase. "Technical Efficiency of New York Dairy Farms." *Northeastern Journal of Agricultural and Resource Economics* 16(1987):10–16.

Weaver, R.D., and D.A. Lass. "Corner Solutions in Duality

Models: A Cross-Section Analysis of Dairy Production Decisions." *American Journal of Agricultural Economics* 71(1989):1025–40.

White, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48(1980):817–38.

Yotopoulos, P.A., and L.J. Lau. "A Test for Relative Economic Efficiency: Some Further Results." *American Economic Review* 63(1973):214–23.

Zellner, A. "On the Aggregation Problem: A New Approach to a Troublesome Problem." In *Economic Models, Estimation and Risk Programming: Essays in Honor of Gerhard Tintner,* edited by K.A. Fox, J.K. Sengupta, and G.V.L. Narasimham. New York: Springer-Verlag, 1969.

Zellner, A., J. Kmenta, and J. Dreze. "Specification and Estimation of Cobb-Douglas Production Function Models." *Econometrica* 34(1966):784–95.