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Technical, allocative and economic efficiencies in swine production in Hawaii: a comparison of parametric and nonparametric approaches

Khem R. Sharma[a,*], PingSun Leung[a], Halina M. Zaleski[b]

[a] Department of Agricultural and Resource Economics, University of Hawaii at Manoa, 3050 Maile Way, Gilmore Hall 112, Honolulu, HI 96822, USA

[b] Department of Animal Sciences, University of Hawaii at Manoa, 1800 East–West Road, Henke Hall 106, Honolulu, HI 96822, USA

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Abstract

Technical, allocative and economic efficiency measures are derived for a sample of swine producers in Hawaii using the parametric stochastic efficiency decomposition technique and nonparametric data envelopment analysis (DEA). Efficiency measures obtained from the two frontier approaches are compared. Firm-specific factors affecting productive efficiencies are also analyzed. Finally, swine producers' potential for reducing cost through improved efficiency is also examined. Under the specification of variable returns to scale (VRS), the mean technical, allocative and economic efficiency indices are 75.9%, 75.8% and 57.1%, respectively, for the parametric approach and 75.9%, 80.3% and 60.3% for DEA; while for the constant returns to scale (CRS) they are 74.5%, 73.9% and 54.7%, respectively, for the parametric approach and 64.3%, 71.4% and 45.7% for DEA. Thus the results from both approaches reveal considerable inefficiencies in swine production in Hawaii. The removal of potential outliers increases the technical efficiencies in the parametric approach and allocative efficiencies in DEA, but, overall, contrary to popular belief, the results obtained from DEA are found to be more robust than those from the parametric approach. The estimated mean technical and economic efficiencies obtained from the parametric technique are higher than those from DEA for CRS models but quite similar for VRS models, while allocative efficiencies are generally higher in DEA. However, the efficiency rankings of the sample producers based on the two approaches are highly correlated, with the highest correlation being achieved for the technical efficiency rankings under CRS. Based on mean comparison and rank correlation analyses, the return to scale assumption is found to be crucial in assessing the similarities or differences in efficiency measures obtained from the two approaches. Analysis of the role of various firm-specific factors on productive efficiency shows that farm size has strong positive effects on efficiency levels. Similarly, farms producing market hogs are more efficient than those producing feeder pigs. Based on these results, by operating at the efficient frontier the sample swine producers would be able to reduce their production costs by 38–46% depending upon the method and returns to scale considered.

1. Introduction

Farrell's (Farrell, 1957) seminal article has led to the development of several techniques for the measurement of efficiency of production. These techniques can be broadly categorized into two approaches: parametric and nonparametric. The parametric stochastic frontier production function approach (Aigner et al., 1977; Meeusen and van den Broeck, 1977) and the nonparametric mathematical programming approach, commonly referred to as data envelopment

*Corresponding author. Tel.: +1-808-956-4976; fax: +1-808-956-2811; e-mail: khem@hawaii.edu

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analysis (DEA) (Charnes et al., 1978) are the two most popular techniques used in efficiency analyses.

Among many authors, Coelli (1995) presents the most recent review of various techniques used in efficiency measurement, including their limitations, strengths and applications in agricultural production. The main strengths of the stochastic frontier approach are that it deals with stochastic noise and permits statistical tests of hypotheses pertaining to production structure and the degree of inefficiency. The need for imposing an explicit parametric form for the underlying technology and an explicit distributional assumption for the inefficiency term are the main weaknesses of the parametric approach. The main advantages of the DEA approach are that it avoids parametric specification of technology as well as the distributional assumption for the inefficiency term. However, because DEA is deterministic and attributes all the deviations from the frontier to inefficiencies, a frontier estimated by DEA is likely to be sensitive to measurement errors or other noise in the data.

Given the different strengths and weaknesses of the parametric and nonparametric approaches, it is of interest to compare empirical performance of the two approaches using the same data set. However, relative to the total number of frontier studies found in the literature, very few studies compare the two approaches (for example, Ferrier and Lovell, 1990; Kalaitzandonakes and Dunn, 1995; Drake and Weyman-Jones, 1996; Hjalmarsson et al., 1996; Sharma et al., 1997a). The main objective of this paper is to estimate the technical, allocative and economic efficiency measures for a sample of swine producers in Hawaii using the parametric stochastic and nonparametric DEA approaches, and to compare the results obtained from the two approaches. The majority of studies aimed at comparing the two techniques have focused mostly on technical efficiency. Drake and Weyman-Jones (1996) and Ferrier and Lovell (1990) are the only studies comparing the two approaches in terms of technical, allocative and economic efficiency measures. Because DEA has not been applied frequently in agriculture (see Coelli, 1995), this paper also demonstrates its applicability in agriculture by using this technique in swine production. To our knowledge, Chavas and Aliber (1993) is the only study analyzing technical, allocative and economic efficiencies in agriculture using DEA.

This paper extends on an earlier paper in comparing stochastic and DEA frontier analyses of a sample of swine producers in Hawaii (Sharma et al., 1997a). The earlier paper primarily focused on the analysis of output-based technical efficiency. In this study, we apply the input-based approach to efficiency measurement and extend our analysis to allocative and overall economic efficiencies. The role of various firm-specific factors in productive efficiency not considered in our earlier paper is also examined here.

2. Analytical framework

2.1. Parametric approach

As in Bravo-Ureta and Evenson (1994) and Bravo-Ureta and Rieger (1991), the parametric technique used in this paper follows the Kopp and Diewert (1982) cost decomposition procedure to estimate technical, allocative and economic efficiencies.

The firm's technology is represented by a stochastic production frontier as follows:

$$Y_i = f(X_i;\beta) + \varepsilon_i \tag{1}$$

where Y_i denotes output of the ith firm; X_i is a vector of functions of actual input quantities used by the ith firm; β is a vector of parameters to be estimated; and ε_i is the composite error term (Aigner et al., 1977; Meeusen and van den Broeck, 1977) defined as

$$\varepsilon_i = v_i - u_i \tag{2}$$

where v_is are assumed to be independently and identically distributed $N(0, \sigma_v^2)$ random errors, independent of the u_is; and the u_is are nonnegative random variables, associated with technical inefficiency in production, which are assumed to be independently and identically distributed and truncations (at zero) of the normal distribution with mean, μ, and variance, $\sigma_u^2(|N(\mu, \sigma_u^2|)$. The maximum likelihood estimation of Eq. (1) provides estimators for β and variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$. Subtracting v_i from both sides of Eq. (1) yields

$$\tilde{Y}_i = Y_i - v_i = f(X_i;\beta) - u_i \tag{3}$$

where $\tilde{Y}_i$ is the observed output of the ith firm, adjusted for the stochastic noise captured by v_i.

Eq. (3) is the basis for deriving the technically efficient input vector and for analytically deriving the dual cost frontier of the production function represented by Eq. (1).

For a given level of output $\tilde{Y}_i$, the technically efficient input vector for the ith firm, X_i^t, is derived by simultaneously solving Eq. (3) and the input ratios $X_1/X_i = k_i(i > 1)$, where k_i is the ratio of observed inputs, X_1 and X_i. Assuming that the production function in Eq. (1) is self-dual (e.g., Cobb–Douglas), the dual cost frontier can be derived algebraically and written in a general form as follows:

$$C_i = h(W_i, \tilde{Y}_i; \alpha) \tag{4}$$

where C_i is the minimum cost of the ith firm associated with output $\tilde{Y}_i$, W_i is a vector of input prices for the ith firm, and α is a vector of parameters. The economically efficient input vector for the ith firm, X_i^e, is derived by applying Shephard's lemma and substituting the firm's input prices and output level into the resulting system of input demand equations:

$$\frac{\partial C_i}{\partial W_k} = X_k^e(W_i, \tilde{Y}_i; \psi) \quad k = 1, 2, \ldots, m \text{ inputs} \tag{5}$$

where ψ is a vector of parameters. The observed, technically efficient and economically efficient costs of production of the ith firm are equal to $W_i'X_i$, $W_i'X_i^t$ and $W_i'X_i^e$, respectively. These cost measures are used to compute technical (TE) and economic (EE) efficiency indices for the ith firm as follows:

$$\mathrm{TE}_i = \frac{W_i'X_i^t}{W_i'X_i} \tag{6}$$

$$\mathrm{EE}_i = \frac{W_i'X_i^e}{W_i'X_i} \tag{7}$$

Following Farrell (1957), the allocative efficiency (AE) index can be derived from Eqs. (6) and (7) as follows:

$$\mathrm{AE}_i = \frac{W_i'X_i^e}{W_i'X_i^t} \tag{8}$$

Thus the total cost or economic inefficiency of the ith firm $(W_i'X_i - W_i'X_i^e)$ can be decomposed into its technical $(W_i'X_i - W_i'X_i^t)$ and allocative $(W_i'X_i^t - W_i'X_i^e)$ components.

2.2. Nonparametric approach

Under the nonparametric approach, DEA (Charnes et al., 1978; Färe et al., 1985, 1994) is used to derive technical, scale, allocative and economic efficiency measures.

Consider the situation with n firms or decision making units (DMUs), each producing a single output by using m different inputs. Here, Y_i is the output produced and X_i is the $(m\times 1)$ vector of inputs used by the ith DMU. Y is the $(1\times n)$ vector of outputs and X is the $(m\times n)$ matrix of inputs of all n DMUs in the sample. W_i is the $(m\times 1)$ vector of input prices for the ith DMU.

The technical efficiency (TE) measure under constant returns to scale (CRS), also called the 'overall' TE measure, is obtained by solving the following DEA model:

$$\begin{aligned} &\min_{\theta_i^{\mathrm{CRS}}\lambda} \theta_i^{\mathrm{CRS}} \\ &\text{subject to} \quad Y_i \le Y\lambda \\ &\theta_i^{\mathrm{CRS}} X_i \ge X\lambda \\ &\lambda \ge 0 \end{aligned} \tag{9}$$

where θ_i^{CRS} is a TE measure of the ith DMU under CRS and λ is an $n\times 1$ vector of weights attached to each of the efficient DMUs. A separate linear programming (LP) problem is solved to obtain the TE score for each of the n DMUs in the sample. If $\theta^{\mathrm{CRS}}=1$, the DMU is on the frontier and is technically efficient under CRS. If $\theta^{\mathrm{CRS}}<1$, then the DMU lies below the frontier and is technically inefficient. Under CRS DEA, the technically efficient cost of production of the ith DMU is given by $W_i'(\theta_i^{\mathrm{CRS}}X_i)$.

In order to derive a measure of the total economic efficiency (EE) index, one can solve the following cost-minimizing DEA model (Färe et al., 1985, 1994)

$$\begin{aligned} &\min_{x_i^*\lambda} W_i'X_i^* \\ &\text{subject to} \quad Y_i \le Y\lambda \\ &X_i^* \ge X\lambda \\ &\lambda \ge 0 \end{aligned} \tag{10}$$

where X_i^* is the cost-minimizing or economically efficient input vector for the ith DMU, given its input price vector, W_i, and the output level, Y_i. The total or overall economic efficiency (EE) index for the ith firm is then computed as

$$EE_i = \frac{W_i'X_i^*}{W_i'X_i} \tag{11}$$

which is the ratio of the minimum cost to the observed cost and comparable to the economic efficiency index derived under the parametric approach Eq. (7). The allocative efficiency (AE) index, derived from Eqs. (9) and (11), is given by

$$\mathrm{AE}_i = \frac{\mathrm{EE}_i}{\theta_i^{\mathrm{CRS}}} = \frac{W_i'X_i^*}{W_i'(\theta_i^{\mathrm{CRS}}X_i)} \tag{12}$$

It should be noted that Eq. (10) also accounts for input slacks not captured by Eq. (9) above. Following Ferrier and Lovell (1990) this procedure attributes any input slacks to allocative inefficiency on the grounds that slack reflects an inappropriate input mix.[1]

The CRS or 'overall' ($\mathrm{TE_{CRS}}$) measure can be decomposed into its 'pure' TE and scale efficiency components by solving a variable returns to scale (VRS) DEA model, which is obtained by imposing the additional constraint, $\sum_{j=1}^{n}\lambda_j = 1$ on Eq. (9) (Banker et al., 1984). Let θ_i^{VRS} denote the TE index of the ith DMU under variable returns to scale ($\mathrm{TE_{VRS}}$), then the technically efficient cost of production of the ith DMU under VRS DEA is equal to $W_i'(\theta_i^{\mathrm{VRS}}X_i)$.

Because the VRS analysis is more flexible and envelops the data in a tighter way than the CRS analysis, the VRS TE measure (θ^{VRS}) is equal to or greater than the CRS measure (θ^{CRS}). This relationship is used to obtain a measure of scale efficiency (SE) of the ith DMU as[2]

$$\mathrm{SE}_i = \frac{\theta_i^{\mathrm{CRS}}}{\theta_i^{\mathrm{VRS}}} \tag{13}$$

where SE=1 indicates scale efficiency or CRS and SE <1 indicates scale inefficiency. Scale inefficiency is due to the presence of either increasing or decreasing returns to scale, which can be determined by solving a nonincreasing returns to scale (NIRS) DEA model which is obtained by substituting the VRS constraint $\sum_{j=1}^{n}\lambda_j = 1$ with $\sum_{j=1}^{n}\lambda_j \leq 1$. Let θ^{NIRS} represent the TE measure under nonincreasing returns to scale. If $\theta^{\mathrm{NIRS}}=\theta^{\mathrm{CRS}}$, there are increasing returns to scale, and if $\theta^{\mathrm{CRS}}<\theta^{\mathrm{NIRS}}$ there are decreasing returns to scale (Färe et al., 1994).

As in the parametric case, the total cost or economic inefficiency of the ith firm ($W_i'X_i - W_i'X_i^*$) can be decomposed into its 'pure' technical, ($W_i'X_i - W_i'\theta_i^{\mathrm{VRS}}X_i$), scale ($W_i'\theta_i^{\mathrm{VRS}}X_i - W_i'\theta_i^{\mathrm{CRS}}X_i$) and allocative ($W_i'\theta_i^{\mathrm{CRS}}X_i - W_i'X_i^*$) components.

2.3. Determining factors affecting efficiency

Analysis of the effects of firm-specific factors on productive efficiency has generated considerable debate in frontier studies. The most popular procedure is to first estimate efficiency scores and then to regress them against a set of firm-specific factors or to use nonparametric or analysis of variance (ANOVA) tests. While Kalirajan (1991) and Ray (1988) defend this two-step procedure, other authors (Kumbhakar et al., 1991; Battese and Coelli, 1995) challenge this approach by arguing that firm-specific factors should be incorporated directly in the estimation of the production frontier because such factors may have a direct impact on efficiency. Despite such criticism, the two-step procedure is still quite popular in investigating the relationship between efficiency and firm-specific variables.

Existing studies aiming to incorporate firm-specific effects directly into the frontier model are limited to the parametric approach (Kumbhakar et al., 1991; Battese and Coelli, 1995). Without prior assumptions on whether the firm-specific factors have a positive or negative impact on economic performance (see, for example, Ferrier and Lovell, 1990), the nonparametric DEA technique cannot easily incorporate firm-specific effects directly into the estimation of an efficient frontier. Because the two-step procedure is equally applicable to both approaches, we adopt this approach to analyze the role of firm-specific factors in the economic efficiency of swine producers in Hawaii.

[1] Some authors have treated slack as a source of technical inefficiency (see Ali and Seiford, 1993).

[2] Alternatively, SE can also be computed as $\mathrm{EE^{CRS}/EE^{VRS}}$, where $\mathrm{EE^{CRS}}$ is the total economic or cost efficiency measure under CRS and $\mathrm{EE^{VRS}}$ is the corresponding measure for VRS (Chavas and Aliber, 1993; Lund et al., 1993).

3. Data and empirical procedures

3.1. Data

Data were collected from a sample of 53 commercial swine producers in Hawaii during the fall of 1994. For the purpose of our study, farms with 10 or more sows are considered commercial producers. Of the total of 350 swine farms in Hawaii, about 60% raise swine commercially and the rest raise swine as a hobby, for family consumption and for cultural reasons. The sample included about one-third of all commercial swine producers in Hawaii. Information on the distribution of farms and sample producers by size and key characteristics can be found in Sharma et al. (1997a, b).

Hawaii's swine industry has experienced a continuous decline in recent years. The number of swine farms decreased from 650 in 1985 to about 350 in 1994 and the annual hog inventory decreased from 55 000 to 34 000 during this period. The market share of local production decreased from 45% in 1970 to 13.4% in 1994. This decline, which is attributed to high production costs, especially feed costs, price competition with imported hogs, limited land availability, rapid urbanization, and increasing environmental concerns, has posed serious challenges for the long-term survival of this industry.

The analysis of costs and returns of the sample producers showed a wide variation in profitability, with most of the sample producers, especially small and medium producers, earning a negative net return from swine production (Sharma et al., 1997b). This raises the question of the role of productive efficiency in profitability. We believe that the future of the swine producers in Hawaii will depend on their ability to enhance economic performance through improved productive efficiency.

3.2. Description of variables

Swine production features multiple outputs and inputs. For the purpose of efficiency analysis, output is aggregated into one category and inputs are aggregated into four categories, namely, feed, labor, other variable inputs and fixed input. Because hog prices vary by types of hogs produced and location of swine farms, the output variable is adjusted to account for such price differences. These output and input variables are described below.[3]

- Output (Y) represents a weighted output of live pigs produced (in tons) during 1994[4].
- Feed (X_1) represents the total quantity of swine concentrates and other grain-based feeds (in tons).
- Labor (X_2) represents the total amount of family labor and hired labor used in swine production (in person days).
- Other variable inputs (X_3) represent the total of all variable expenses, except feed and hired labor (in thousand dollars).
- Fixed input (X_4) represents total costs of fixed inputs including insurance, taxes and depreciation on pig housing, machinery and other equipment (in thousand dollars).

The input prices needed for deriving the dual cost frontier in the parametric approach and for solving the cost-minimizing DEA model in the nonparametric approach are defined below.

W_1 represents the price of feed computed as total feed expenses divided by X_1 (in dollars/ton). W_2 is the price of labor computed as the weighted average of the value of family labor assumed to be US\$ 6.94/h (Hawaii Agricultural Labor, 1994) and actual wage paid for hired labor (in dollars/person day). Because other variable and fixed inputs are expressed in values, the computation of their prices is far from satisfactory. The price of other variable inputs (W_3) is computed as total expenditures on all variable inputs except feed

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[3]Summary statistics of these variables can be found in Sharma et al. (1997a).

[4]The weighted average of the pigs produced on the ith farm, Y_i, is defined by

$$Y_i = \frac{\sum_{r=1}^{s} P_{ri} Q_{\mathrm{ri}}}{(\sum_{i=1}^{n} \bar{P}_i / n)}$$

where s denotes the number of different types of pigs, P_{ri} denotes the price received by the ith farm for pig type r, Q_{ri} denotes the live weight of pig type r for the ith farm, $\bar{P} = \sum_{r=1}^{s} P_{ri} \cdot Q_{ri}/Q_i$; $Q_i = \sum_{r=1}^{s} Q_{ri}$, and n denotes the number of farms in the sample. For our study s=5, where types of pigs produced were market pigs, roaster pigs, feeder pigs, suckling pigs and breeding stock. Because of the small share of culled breeding stock in total returns and the lack of systematic culling practice, culled breeding stock was not included in the output. It should be noted that defining the output variable this way may contaminate input-based technical and allocative inefficiencies with output or revenue-based allocative inefficiencies.

and hired labor divided by X_3. Similarly, the price of fixed input (W_4) is computed as total expenditures on fixed inputs divided by X_4. Similar to Ferrier and Lovell (1990), prices for other variable and fixed inputs equal US$ 1000 for all farms.

Various farm-specific factors are analyzed to assess their influence on productive efficiency. Size (Z_1) denotes the size of a farm, defined in terms of the number of sows. The farmer's education level is represented by two dummy variables, Z_2 and Z_3 where Z_2=1 for college education, 0 otherwise, and Z_3=1 for high school, 0 otherwise. Experience (Z_4) represents the farmer's experience measured in the number of years he/she has been engaged in swine production. The sample swine farmers are also differentiated in terms of the types of pigs produced (Z_5) and feeding regime (Z_6) where Z_5=1 for market hogs, 0 for feeder pigs, and Z_6=1 for garbage or mixed feeding, 0 for grain feeding. Finally, location (Z_7) is a dummy variable to differentiate farms located on Oahu from those on Neighbor Islands, with Z_7 being 1 for Oahu, 0 for Neighbor Islands.

3.3. Empirical models

Under the parametric approach, the Cobb–Douglas stochastic production frontier is specified as follows[5]

$$\ln Y_i = \beta_0 + \beta_1 \ln X_{i1} + \beta_2 \ln X_{i2} + \beta_3 \ln X_{i3} + \beta_4 \ln X_{i4} + \varepsilon_i \tag{14}$$

where i refers to the ith farm in the sample; Y is output and Xs are input variables, defined in the previous section; βs are parameters to be estimated; and ε_i is the composite error term, defined in Section 2.1. Note that the production frontier in Eq. (14) represents VRS technology and the corresponding frontier for CRS can be obtained by imposing the restriction that the sum of the output elasticities of inputs equals one (i.e., $\sum_{k=1}^{4} \beta_k = 1$).

The dual cost frontier of the production function in Eq. (14) can be derived as[6]

$$\ln C_i = \alpha_0 + \alpha_1 \ln W_{i1} + \alpha_2 \ln W_{i2} + \alpha_3 \ln W_{i3} + \alpha_4 \ln W_{i4} + \alpha_5 \ln \tilde{Y}_i \tag{15}$$

where i refers to the ith sample farm; C is the minimum cost of production; Ws are input prices, defined in the previous section; $\tilde{Y}$ is the output adjusted for stochastic noise v as in Eq. (3); and αs are parameters.

Under the nonparametric approach, CRS, VRS and NIRS input-reducing and CRS and VRS cost-minimizing DEA models as presented in Section 2.2 are estimated for the same number of farms and the same output and input variables as for the stochastic frontier.

To examine the role of relevant farm-specific factors in productive efficiency, the following equation is estimated:

$$\mathrm{EI}_i = \delta_0 + \delta_1 Z_{i1} + \delta_2 Z_{i2} + \delta_3 Z_{i3} + \delta_4 Z_{i4} + \delta_5 Z_{i5} + \delta_6 Z_{i6} + \delta_7 Z_{i7} + \omega_i \tag{16}$$

where i refers to the ith farm in the sample; EI is the total economic or cost inefficiency, measured in US$ 1000/ton of output produced;[7] Zs represent various farm-specific variables, as defined previously; δs are parameters to be estimated; and ω is a random error, assumed to be normally distributed. Because the dependent variable in Eq. (16) is a measure of inefficiency, variables with a negative (positive) coefficient will have a positive (negative) effect on efficiency levels.

4. Empirical results

4.1. Parametric frontier results

The maximum-likelihood (ML) estimates of the parameters of the stochastic production frontier were

[5] The Cobb–Douglas form is chosen because the methodology used here requires that the production function be self-dual. Despite its limitations, the Cobb–Douglas form is found to be an adequate representation of the data, given the specification of the more flexible translog form (see Sharma et al., 1997a). The production frontier was also estimated for a sample of 51 farms after eliminating the two farms associated with the highest and lowest technical and economic efficiency scores to assess the sensitivity of the two approaches to the possible outliers. It would also be interesting to analyze different sub-sets of data obtained by partitioning the sample farms based on their key characteristics (such as farm size, location, feed type, etc.) to further examine the robustness of the two approaches. However, because of a small sample, such analyses could not be carried out.

[6] See Sharma (1996) for mathematical details.

[7] The corresponding equations for technical, allocative, and scale efficiencies are obtained by replacing total economic or cost inefficiency (EI) in Eq. (16) with technical, allocative, and scale inefficiencies, again measured in US$ 1000/ton of output produced.

Table 1
Ordinary least squares (OLS) estimates of the average production function and ML estimates of stochastic production frontier for sample swine producers in Hawaii

Variable	OLS estimates		ML estimates	
	Coefficient	Standard error	Coefficient	Standard error
Intercept	−0.895	0.571	0.606	0.526
ln (Feed)	0.391[a]	0.069	0.365[a]	0.065
ln (labor)	0.286[a]	0.103	0.309[a]	0.088
ln (Other variable input)	0.286[a]	0.085	0.309[a]	0.078
ln (Fixed input)	0.084	0.087	0.063	0.082
$\bar{R}^2$	0.851	–	–	–
γ	–	–	0.867[a]	0.164
σ^2	–	–	0.897	0.790
μ	–	–	−1.763	2.241
Log likelihood	–	–	−33.146	–

[a] Significant at the 1% level.

obtained using the program, FRONTIER 4.1 (Coelli, 1994). These results are presented in Table 1. Also presented in Table 1 are the OLS results of the average production function for comparison. The ML results for the CRS model and for models without the two possible outliers are not presented due to space limitations.

As expected, the signs of the slope coefficients of the stochastic production frontier are positive. Except for the coefficient for fixed input, these estimated coefficients are highly significant. The estimate of the variance parameter, γ, is also significantly different from zero, which implies that the inefficiency effects are significant in determining the level and variability of output of swine producers in Hawaii.

The dual cost frontier derived from the stochastic production frontier, shown in Table 1, is as follows:[8]

$$\begin{aligned}\ln C_i = 1.836 &+ 0.349 \ln W_{i1} + 0.296 \ln W_{i2} \\ &+ 0.295 \ln W_{i3} + 0.060 \ln W_{i4} \\ &+ 0.956 \ln \tilde{Y}_i \qquad (17)\end{aligned}$$

The frequency distributions and summary statistics of the estimated technical, allocative and economic efficiency indices for the sample swine farms from the parametric approach are presented in Table 2. The estimated mean technical, allocative and economic efficiency indices are 75.9%, 75.8% and 57.1%, respectively, under VRS and 74.5%, 73.9% and 54.7% under CRS, indicating that there are considerable inefficiencies in swine production in Hawaii. The majority of producers fall within the ranges of 70–80%, 80–90% and 60–70% of technical, allocative and economic efficiency indices, respectively.

4.2. *DEA frontier results*

DEA models were estimated using the program, DEAP 2.0 (Coelli, 1996). The technical, allocative and economic efficiency measures estimated from the DEA approach and their frequency distributions are summarized in Table 2. The estimated mean TE measure for the sample swine producers is 75.9% for the VRS DEA model and 64.3% for the CRS DEA model. In terms of TE, 17 of the 53 farms investigated are fully efficient under the VRS model. Under the CRS model, only 10 farms are fully efficient. The mean allocative and economic efficiency measures estimated from the DEA frontier are 80.3% and 60.3%, respectively, for VRS, and 71.4% and 45.7% for CRS. Thus DEA analyses, especially CRS results, also reveal substantial inefficiencies in swine production in Hawaii.

The scale efficiency index for the swine producers varies from 43.2% to 100%, with a sample mean of 84.1%. In terms of scale efficiency, 13 farms exhibit CRS. Among the scale inefficient farms, 29

[8]The corresponding cost frontiers for the CRS model and for models without two potential outliers were also derived but are not presented here due to space limitations.

Table 2
Frequency distributions of technical (TE), allocative (AE), and economic (EE) efficiency measures from the parametric and DEA approaches

Efficiency (%)	Parametric approach			DEA		
	TE	AE	EE	TE	AE	EE
<40	1[a] (1)	0 (0)	5 (9)	3 (9)	0(2)	10(25)
40–50	2 (3)	2 (2)	10 (12)	4 (7)	4(3)	12(12)
50–60	3 (2)	6 (8)	12 (11)	5 (8)	2(6)	8(4)
60–70	4 (6)	9 (7)	18 (13)	12 (9)	7(11)	5(3)
70–80	21 (23)	11 (17)	7 (7)	4 (3)	6(14)	7(4)
80–90	19 (17)	19 (15)	1 (1)	5 (7)	20(12)	4(4)
90–100	3 (1)	6 (4)	0 (0)	3 (0)	11(4)	4(0)
100	0 (0)	0 (0)	0 (0)	17 (10)	3(1)	3(1)
Mean (%)	75.9 (74.5)	75.8 (73.9)	57.1 (54.7)	75.9 (64.3)	80.3(71.4)	60.3(45.7)
Minimum (%)	31.3 (29.4)	44.8 (41.3)	27.8 (25.3)	25.5 (14.3)	44.0(37.9)	21.0(11.7)
Maximum (%)	90.7 (90.1)	95.0 (95.4)	81.3 (80.7)	100.0 (100.0)	100.0(100.0)	100.0(100.0)
Standard deviation (%)	12.2 (12.8)	12.5 (13.3)	12.2 (13.1)	22.0 (24.6)	15.0(14.2)	21.4(20.7)

Figures in parentheses are the corresponding values for the CRS.
[a] Denotes the number of farms.

show increasing returns to scale and 11 show decreasing returns to scale. As expected, most of the large farms (>75 sows) are characterized by decreasing returns to scale, while the majority of small and medium sized farms ($\leq$75 sows) show increasing returns to scale.

The TE measures for the sample swine producers estimated here from the input-based DEA frontiers are quite comparable with those estimated from the output-based frontiers (Sharma et al., 1997a). Although, the mean scale efficiency from the output-based DEA frontier (89.2%) is higher than that from the input-based frontier (84.1%), this difference is not significant at the 0.05 level. However, the two frontiers differ considerably with respect to returns to scale properties. About 21% of sample farmers show decreasing returns to scale in input-based DEA analysis compared to 45% in output-based analysis.

4.3. Comparing parametric and DEA results

The two approaches used here to measure the technical, allocative and economic efficiency measures for the sample swine farms are based on different production frontiers. The parametric approach is based on a stochastic production frontier and nonparametric data envelopment analysis is based on a non-stochastic or deterministic frontier. It is expected that efficiency scores estimated from the DEA frontier would be less than those obtained from the stochastic frontier because the DEA attributes any deviation from the frontier to inefficiency.

The agreements or disagreements in the efficiency scores estimated from the two approaches are summarized in Table 3. Also presented in Table 3 are similar results obtained by eliminating two possible outliers associated with the highest and lowest technical and economic efficiency indices. Based on paired *t*-tests, on average, the technical and economic efficiencies under CRS are significantly higher in the parametric approach than in DEA, regardless of the presence or absence of the possible outliers, while for VRS models these results are similar for the two approaches except for a higher TE score in the parametric approach without the two outliers. On average, allocative efficiencies are higher in DEA than in the parametric approach, except for CRS models with all the observations in the sample where the allocative efficiency measure is higher under the parametric technique. Thus, for the data involved in this study the assumption on returns to scale is found to be critical in explaining the differences in efficiency measures derived from the two procedures. Although, because of its deterministic property, DEA is believed to be more sensitive to outliers and other noise in the data, comparing the results with and without the possible outliers we find DEA results to be more

Table 3
Mean comparison of TE, AE and EE measures and Spearman rank correlations of efficiency rankings of sample swine producers based on the parametric and DEA approaches

Efficiency	Sample mean		t-ratio[d]	Spearman rank correlation (ρ)
	Parametric	DEA		
TE_{CRS}	74.5 (80.5)	64.3 (66.5)	4.84 [a] (6.17[a])	0.891[a] (0.870[a])
TE_{VRS}	75.9 (84.2)	75.9 (77.5)	0.00 (2.82[a])	0.718[a] (0.695[a])
AE_{CRS}	73.9 (72.4)	71.4 (77.4)	1.70[c] (−3.10[a])	0.712[a] (0.690[a])
AE_{VRS}	75.8 (74.6)	80.2 (81.6)	−1.98 [b] (−3.08[a])	0.327[b] (0.383[a])
EE_{CRS}	54.7 (58.1)	45.7 (51.5)	5.14 [a] (2.96[a])	0.835[a] (0.671[a])
EE_{VRS}	57.1 (62.7)	60.4 (63.0)	−1.36 (−0.13)	0.558 [a] (0.361[a])

Subscripts CRS and VRS stand for constant and variable returns to scale, respectively.
Figures in parentheses are the results excluding the two potential outliers (i.e. n=51).
[a] Significant at the 1% level.
[b] Significant at the 5% level.
[c] Significant at the 10% level.
[d] Note that the t-ratio is based on the paired-difference t-test as the standard t-test is invalid because the individual efficiency scores from the two methods are not independent.

robust than those obtained from the parametric approach.[9]

To further examine the agreements between the parametric and nonparametric approaches, Spearman correlation coefficients between the efficiency rankings of the sample swine producers from the two approaches were also computed. These results are also presented in Table 3. All the TE, AE and EE rank correlations are positive and highly significant. The strongest correlation between the efficiency rankings from the two approaches is obtained for TE under CRS, while allocative efficiency under VRS shows the weakest correlation. The removal of the two outliers has little impact on efficiency rankings of the producers.

While the sample farms show both decreasing returns and increasing returns to scale in the DEA frontier, the null hypothesis of CRS is not rejected in the stochastic production frontier.[10] Furthermore, the VRS and CRS efficiency rankings of sample swine farms are more highly correlated in the parametric approach (ρ>0.98) than in nonparametric DEA (0.70<ρ<0.75).

Compared to previous studies applying the two approaches to the same data set, the estimated efficiencies presented here are more consistent with the expectation that efficiency scores derived from the parametric approach would be higher than those from nonparametric DEA. However, in terms of rank correlation of the various efficiency measures, the two approaches are found to be highly comparable. These results are quite consistent with the study of UK building societies by Drake and Weyman-Jones (1996). Based on the analysis of US banks, Ferrier and Lovell (1990) found higher technical but lower economic efficiency for the parametric method compared to DEA and insignificant rank correlations between the estimated efficiencies from the two approaches. Analyzing a sample of Guatemalan farmers, Kalaitzandonakes and Dunn (1995) reported a significantly higher level of mean TE under CRS DEA than under the stochastic frontier. These results contrast sharply with this study. These disagreements in

[9]The high degree of robustness of DEA can also be shown by comparing the numbers of technically, allocatively and economically fully efficient farms and the returns to scale properties with or without the two outliers. For example, the numbers of technically fully efficient farms under CRS and VRS in the original sample are 10 and 17, respectively, compared to 9 and 17 without the two outliers. Similarly, the numbers of allocatively and economically fully efficient farms for CRS and VRS models were 1 and 3, respectively, for the original sample compared to 1 and 4 without outliers. The estimates of scale efficiency (84.1% vs. 85.5%) and the distributions of farms by returns to scale property were also very similar for the two analyses.

[10]The likelihood test-statistic for the null hypothesis of CRS is equal to 0.29 compared to 3.84, the 95% critical value for the χ^2 distribution with one degree of freedom.

empirical studies in comparing the two approaches can be mainly attributed to differences in the characteristics of the data analyzed, choice of input and output variables, measurement and specification errors, and estimation procedures.

4.4. Factors affecting efficiency levels

The parameters in Eq. (16) were estimated using the OLS procedure for the parametric approach, while those for the DEA approach were estimated using the Shazam's tobit estimation procedure, because the values of the dependent variable are zero for some observations in the DEA. These results are presented in Table 4. Farm size has a negative and significant effect on inefficiency levels, which suggests that, on average, large farms operate at higher efficiency levels than small farms. Better performance among larger farms is attributable to significantly lower labor use per unit of output produced and a lower feed price on large farms than on smaller ones (Sharma et al., 1997b). Farms that produce market hogs are found to be more efficient than feeder pig producers and in most cases the associated coefficients are highly significant. Reasons for this difference include significantly lower labor use and lower feed price among market hog producers than feeder pig producers. The effect of the producer's experience on the efficiency of swine production is mostly positive but the effect is either moderate or insignificant. Except for allocative efficiency, the coefficients for education dummies show unexpected signs, although they are mostly insignificant. In most cases, garbage feeders seem less efficient than grain feeders, and farmers on Oahu seem more efficient than those on Neighbor Islands. However, the slope coefficients for these variables are mostly insignificant. Overall, both in terms of signs and significance levels of the coefficients, these results are quite similar for the two approaches.

4.5. Implications

Both approaches reveal considerable inefficiencies in swine production in Hawaii. Minimum or economically efficient costs and potential cost reductions at full efficiency levels by farm size are presented in Tables 5 and 6 for the parametric and DEA approaches, respectively.

According to the parametric results, the sample producers would be able to reduce their actual costs by 38% by operating at full technical and allocative efficiency levels. As shown in Table 5, large farms would reduce their costs by 34% and small and medium sized farms by 47% by operating at full

Table 4
Factors affecting productive inefficiencies (US$ 1000/ton of output produced) in swine production in Hawaii

Variable		Parametric approach[d]			DEA approach				
Name	Mean	TI	AI	EI	PTI	SI	OTI	AI	EI
Intercept	–	2.027[a]	1.021[a]	3.048[a]	0.907[c]	2.673[a]	2.082[a]	2.480[a]	3.091[a]
Size (Z_1)	76.50	−0.005[b]	−0.003[a]	−0.007[a]	−0.006[b]	−0.005[c]	−0.007[b]	−0.005[b]	−0.007[a]
College (Z_2)	0.24	0.952[b]	−0.092	0.859[c]	1.066[b]	0.199	1.090[b]	−0.487	0.829[c]
High school (Z_3)	0.53	0.279	−0.027	0.253	0.544	−0.019	0.537	−0.389	0.355
Experience (Z_4)	22.10	−0.018	−0.002	−0.020[c]	−0.026[b]	0.015	−0.019[c]	0.001	−0.020[b]
Market hogs (Z_5)	0.73	−0.806[b]	−0.160	−0.966[a]	−0.069	−2.226[a]	−0.961[a]	−0.128	−1.043[a]
Garbage fed (Z_6)	0.43	0.283	0.052	0.335	0.360	−0.029	0.247	−0.519	0.179
Oahu (Z_7)	0.53	−0.241	−0.051	−0.292	−0.109	−0.773[b]	−0.408	−0.126	−0.376
$\bar{R}^2$	–	0.23	0.18	0.34	–	–	–	–	–
Log-likelihood	–	–	–	–	−76.38	−40.15	−83.09	−21.77	−84.93

TI: Technical inefficiency, AI: Allocative inefficiency, EI: Economic inefficiency, PTI: Pure technical inefficiency, SI: Scale inefficiency, OTI: Overall technical inefficiency.
Standard errors are not provided due to space limitations.
[a] Significant at the 1% level.
[b] Significant at the 5% level.
[c] Significant at the 10% level.
[d] To be consistent with DEA, TI, AI, and EI for the parametric approach are based on the CRS specification.

Table 5
Minimum costs levels and potential cost reductions for sample swine producers by farm size (parametric approach)

Farm size[a]	Observed cost levels	Minimum cost levels	Potential cost reductions at full efficiency levels			
			Technical (US$ 1000)	Allocative	Total	(%)
Small (<25 sows)	48.23	24.47	12.27	11.49	23.76	49.3
Medium (25–75 sows)	81.04	40.55	25.73	14.76	40.49	50.0
Large (>75 sows)	320.27	208.62	63.33	48.32	111.65	34.9
All farms	157.52	96.25	35.40	25.87	61.27	38.9

The minimum cost levels and potential cost reductions are based on the CRS formulation to make the parametric results comparable with DEA results shown in Table 6. Moreover, in the parametric approach the VRS and CRS results are similar.
[a] Of the 53 farms analyzed, the numbers of small, medium and large farms are 19, 19 and 15, respectively.

Table 6
Minimum cost levels and potential cost reductions for sample swine producers by farm size (DEA approach)

Farm size	Minimum cost levels	Potential cost reductions at full efficiency levels				
		Pure technical (US$ 1000)	Scale	Allocative	Total	(%)
Small (<25 sows)	18.88	8.03	7.36	13.97	29.35	60.9
Medium (25–75 sows)	29.37	33.53	5.76	12.38	51.67	63.8
Large (>75 sows)	193.61	45.66	18.87	62.14	126.66	39.6
All farms	85.28	30.66	10.91	30.67	72.24	45.9

[a] Of the 53 farms analyzed, the numbers of small, medium and large farms are 19, 19 and 15, respectively.

efficiencies. Operating at the full TE level accounts for about 52%, 64% and 57% of the total cost reduction for small, medium and large farms, respectively. These results are quite similar under VRS and CRS specifications.

Based on DEA efficiency estimates, by reaching full efficiency levels, the sample producers would reduce their costs by 46% under CRS and 39% under VRS. As shown in Table 6, the CRS cost reductions for small, medium and large farms are estimated to be about 61%, 64% and 40%, respectively. These numbers are slightly smaller for the VRS DEA model. Operating at full pure technical and scale efficiency ('overall' TE) levels accounts for about 52%, 76% and 51% of the total cost reductions for small, medium, and large farms, respectively.

Based on these results, the total potential cost reduction for all commercial swine producers in Hawaii is estimated to be about US$ 5 million/year under the parametric technique and US$ 6–7 million/year under DEA.

5. Conclusions

This paper analyses technical, allocative and economic efficiency for a sample of swine producers in Hawaii using the parametric and nonparametric frontier approaches, and compares the efficiency estimates obtained from the two approaches. The parametric method is based on Kopp and Diewert's cost decomposition approach for estimating Farrell's efficiency measures where a Cobb–Douglas stochastic production frontier is estimated and the corresponding dual cost frontier is derived algebraically. The Kopp and Diewert's approach is useful when the input prices are inadequate to estimate a cost frontier econometrically. The nonparametric approach involves the estimation of various input-based data envelopment analysis (DEA) models. The effect of various factors on the efficiency levels is examined by estimating a regression model where various production inefficiencies (in US$ 1000/ton of output produced) are expressed as a function of various farm-specific factors.

The mean technical, allocative and economic efficiencies under variable returns to scale (VRS) are 75.9%, 75.8% and 57.1%, respectively, for the parametric approach and 75.9%, 80.3% and 60.3% for DEA. The corresponding measures for CRS are 74.5%, 73.9% and 54.7%, respectively, for the parametric approach and 64.3%, 71.4% and 45.7% for DEA. On average, the estimated technical and economic efficiencies are significantly higher in the parametric technique than in DEA for CRS models but quite similar for VRS models, while allocative efficiencies are generally higher in DEA than in the parametric method. However, the efficiency rankings of the sample producers based on the two approaches are positively and significantly correlated. Contrary to the expectation that DEA is more sensitive to outliers and other noise in the data, we find DEA results to be more robust than those obtained from the parametric approach. This interesting finding as well as the disagreements in existing studies comparing the two frontier approaches demonstrates the need for more empirical work to further examine the performance of the two approaches using the same data sets.

The results reveal substantial production inefficiencies for sample swine producers in Hawaii and hence considerable potential for enhancing profitability by reducing costs through improved efficiency. On average, by operating at full economic efficiency levels the sample producers would be able to reduce their cost by 38–46% depending upon the method employed and returns to scale assumption. These reductions in costs from improvements in efficiency are very important to enhance profitability of the sample producers, especially of medium and small producers who earn a negative net return from swine production. If all farms were fully efficient in production, Hawaii's swine industry would be able to save about US$ 5–7 million in production costs annually.

Analysis of various firm-specific factors shows that farm size has a positive and significant effect on efficiency levels, suggesting that cost inefficiency can be reduced by exploiting economies of size. The analysis also reveals that farms which raise hogs for market are more efficient than feeder pig producers. Results also show a positive relationship between a producer's experience and production efficiencies. However, the results do not support the hypothesis that education level has a positive impact on production performance.

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