Chapter 8
Inefficiency in Animal Production: A Parametric Approach

Emiliana Silva and Fátima Venâncio

Abstract A stochastic frontier approach (SFA) was estimated for three types of farms using Frontier Software. The groups of farms were created using cluster analysis and SPSS Statistical package for the Social Sciences. The Frontier Program allowed the estimation of efficiency (model I) and inefficiency models (model II). The efficiency in Faial (Azores) island farms was higher than 82%, and the most important inefficiency variables were subsidies, equipment amortization and small dimension.

Keywords Efficiency • Stochastic frontier production • Azores • Cluster

8.1 Introduction

The objectives of this chapter are (1) to estimate the technical efficiency (by stochastic frontier production) of the animal production farms of Faial (Azores, Portugal) and (2) to find the variables that influence the technical inefficiency.

In a first stage similar farms were obtained (clusters) since it was suspected that heterogeneity could affect the efficiency; in the next stage, a stochastic frontier production (efficiency and inefficiency models) was estimated for each cluster.

The output of the efficiency model was the income and the inputs were the area, the main variables and the fixed expenses. The variables considered as causing inefficiency were as follows: animal number (AN), subvention, beef sales, amortization, farm ownership type, economic dimension units (EDU) and the experience of the farmer (number of working years in the farm).

E. Silva (✉) • F. Venâncio
CEEAplA, Departamento de Ciências Agrárias, Universidade dos Açores, Rua Capitão João de Ávila, 9700-042 Angra do Heroísmo, Açores, Portugal
e-mail: emiliana@uac.pt; fvenancio@sapo.pt

A.B. Mendes et al. (eds.), *Efficiency Measures in the Agricultural Sector: With Applications*, DOI 10.1007/978-94-007-5739-4_8,

The Frontier version 4.1, developed by Coelli (1996), was selected to estimate the models. The stochastic frontier approach (SFA) is a parametric approach which was originally and independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) as referred by Battese and Coelli (1988). The SFA considers that an error term has two components: one to account for random effects and another to account for the technical inefficiency effects (Coelli 1995).

The efficiency model (model I) was proposed by Battese and Coelli (1992), and the u_{it} is the technical inefficiency variable which is defined by

$$u_{it} = \{\exp[-\eta(t - T)]\}\, u_i, \quad \text{with } i = 1, \ldots, N, \quad \text{and } t = 1, \ldots, T, \tag{8.1}$$

where η is an unknown parameter to be estimated and μ_i with $i = 1, 2, \ldots, N$, are independent and identically distributed non-negative random variables, which are assumed to account for technical inefficiency in production and obtained by truncations (at zero) of the normal distribution with unknown mean and unknown variance, σ^2.

This model specifies that the technical inefficiency effects for the sample in the earlier periods of the panel are a deterministic exponential function of the inefficiency effects for the corresponding firms in the last years of the panel (i.e., $u_{it} = u_i$, given the data for the ith firm is available in the period, T).

Given Eq. (8.1), the expectation of the mean technical efficiency is

$$\mathrm{TE} = \exp(-u_i) \tag{8.2}$$

and it is estimated considering the technical inefficiency effects (u_i).

Model I only permits to determine the technical efficiency in order to learn more about inefficiency. Battese and Coelli (1995) presented model II (inefficiency model) which permits to incorporate in model I the variable that could cause inefficiency in the firms. In this model the technical inefficiency effects are defined by

$$u_{it} = z_{it}\delta + w_{it}, \quad \text{and } i = 1, \ldots, N, \quad \text{and } t = 1, \ldots, T, \tag{8.3}$$

where z_{it} is $(1 \times M)$ vector of explanatory variables associated with technical inefficiency effects,

δ is $(M \times 1)$ vector of unknown parameters to be estimated and w_{it} are the unobservable random errors which are assumed to be independently distributed and obtained by truncation of normal distribution with unknown mean and variance, σ^2, such that u_{it} is non-negative ($w_{it} \geq -z_{it}\delta$).

Some examples of surveys using these models are Tauer and Mishra (2006), Hasnah Fleming and Coelli (2004), Lawson et al. (2004), Pascoe et al. (2001), Torres et al. (2002), Munzir and Heidhues (2002), Reinhard et al. (1999, 2000), Alvarez and Gonzalez (1999), Webster et al. (1998), Franco (2001) and Daryanto et al. (2002). In agriculture survey, we have Lawson et al. (2004), Venâncio and Silva (2004), Battese and Coelli (1988), Battese and Sumiter (1997), Brummer (2001) and Hallam and Machado (1996).

8.2 Materials and Methods

The FADN (Farm Agriculture Data Network) was used for Azores database (47 units) from 1996 to 1999. The data was analysed using current prices. The variables used in the cluster analysis were (1) income (subventions, milk and beef sales), (2) dimension and (3) variable expenses (rent equipments, conservation and reparations of equipment; fuel and oil; concentrate food and other specific expenses; fertilizers and general expenses).

The main characteristic of the farm cluster was as follows: (1) cluster A (smaller dimension, smaller number of animals, smaller incomes, subvention and beef sales' enormous importance), (2) cluster B (medium and larger dimension, smaller number of animals, mainly dairy production, medium income, smaller importance of earning subvention and beef sales, larger expenses of concentrate animals, higher investment) and (3) cluster C (medium and larger dimension, mainly dairy production, larger animal number, larger expenses in concentrate and fertilizers, larger incomes).

The efficiency and inefficiency models were applied to each cluster. In the efficiency model, it was necessary to group some expense variable to adequate the variable and observation number and to estimate SFA in translogarithmic and Cobb-Douglas functional forms. The inputs of production function are represented by four variables: (1) dimension (SAU), hectares; (2) expenses with animals per hectare (AN/HA); (3) expenses with equipment per hectare (EQ/HA); and (4) other expenses per hectare (OC/HA).

The variables' selection for the inefficiency models was based on previous works of Hallam and Machado (1996) and Puig-Junoy and Argilés (2000). These eight variables were as follows: (1) TIME *Trend*, (2) ANHA (animals per hectare), (3) SUBS (percent of subvention in income), (4) AS (percent of beef sales in income), (5) AM (amortization), (6) OW (ownership farm type *Dummy*) (OW = 1, rent, or OW = 0, not rent), (7) UDE (economic dimension unit) and (8) AG (experience age).

The next Figs. 8.1 and 8.2 present the steps followed in the methodology and the sequence of estimating the efficiency and inefficiency models.

The main procedures were (1) to define the specifications of each model using a statistic LR test, likelihood ratio tests; (2) to present the efficiency measures per cluster; (3) to define the final equations for both models (I and II) per cluster; and (4) to analyse the variables that caused inefficiency (Fig. 8.1).

Figure 8.2 shows the Frontier Software (Coelli 1996) step's procedure: (1) ordinary least squares (OLS) estimated the obtained function; all β estimators except the intercept were unbiased; (2) a two-phase grid search of γ was conducted, with the β parameters (except β_0) set to the OLS values and the β_0 and σ^2 parameters adjusted according to the corrected ordinary least squares formula presented in Coelli (1995). All other parameters (μ, α and δ's) were set to zero in this grid search; and (3) the values selected in the grid search were used as starting values in an iterative procedure to obtain the final maximum-likelihood estimates.

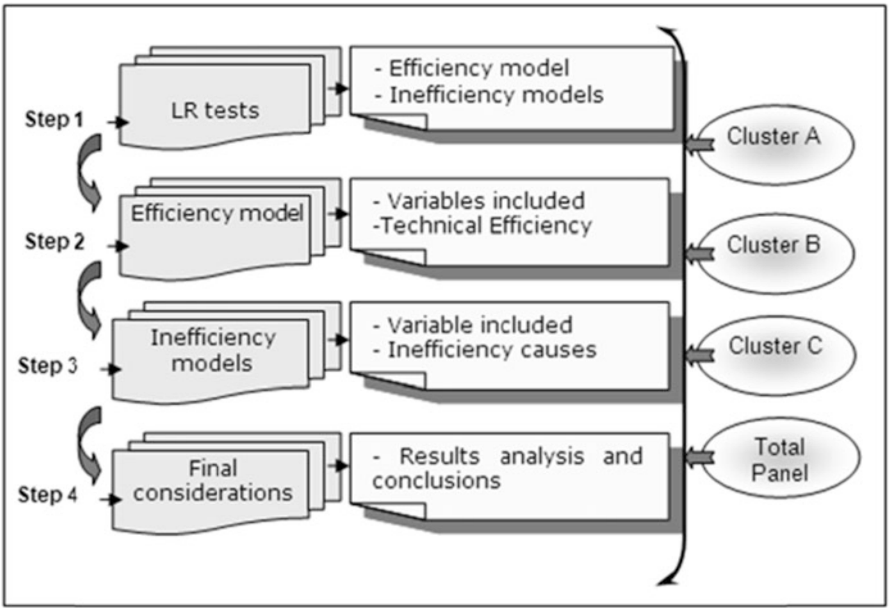

Fig. 8.1 The steps in the model applications

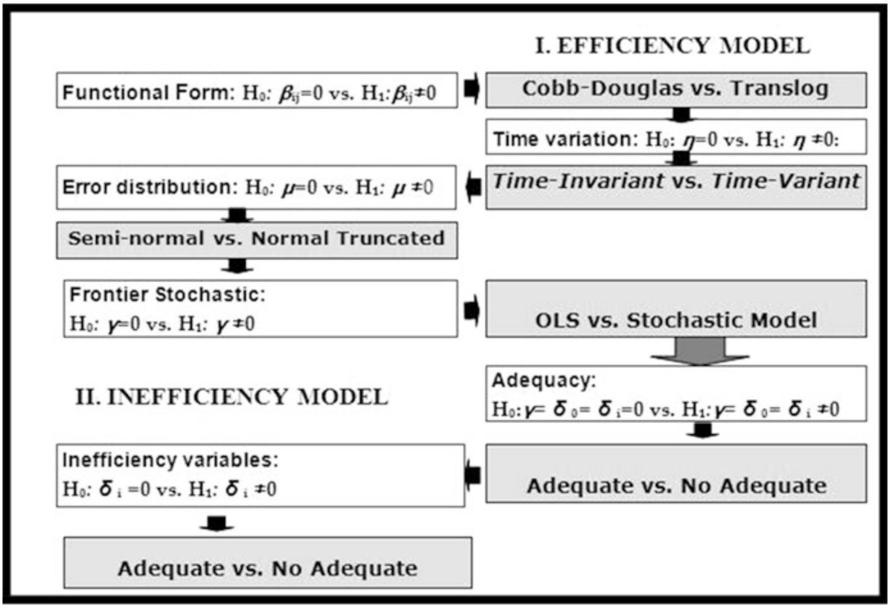

Fig. 8.2 LR tests and models I and II

The grid search value results were used in an interactive procedure to obtain LR test estimates. Critical chi-squared values were obtained by Kodde and Palm (1986) and used to test if the estimated γ and the variables explaining inefficiency jointly equalled 0.

The statistical tests were made according to the following: (a) the functional form that best adjust to the data, (b) the choice of the time-variant or time-invariant model, (c) the distribution of error model, (d) the adequate model to stochastic production according to the used data, (e) to adequate the inefficiency model to the data and (f) to adequate the inefficiency variable.

8.3 Results and Discussion

The following Tables 8.1, 8.2 and 8.3 and Figs. 8.3 and 8.4 show the main results for models (I and II) per cluster and by total panel.

Table 8.1 summarizes the results. In the efficiency model, the functional form is the translog, in cluster A and B, and Cobb-Douglas in cluster C and total panel. The time variation is variant only for the total panel. The error distribution is normal truncated to the total panel and semi-normal for all clusters. For all cases, there is a stochastic frontier. In the efficiency model, all cases have an adequate model, but in cluster A, the variables of inefficiency are not adequate.

Table 8.2 shows that the σ^2 parameter (variance of inefficiency term, u, and the residual term, ν) is significant for all the analysed groups. The defined γ has a value between 0 and 1: if there is inefficiency; if it is different from 0, then the error term expresses the traditional random variation that is uncontrolled by the farmer. There is variance between all different parameters of the model efficiency. The parameter γ (ratio of total model variance and the variance relative to the inefficiency firms) has lower values than cluster B but statistically significant. As a complementary analysis of this hypothesis test, the value γ was estimated to observe the existence or not of the stochastic frontier.

The γ values for clusters A, B and C were 0.766, 0.479 and 0.892, accordingly (Table 8.2). This value for cluster B though were relatively low (*between* 0 and 1) shows technical inefficiency in production processes and statistically significant at 5 and 1%, accordingly. Although this results revealed that only 47.9% of inefficiency of these farms were due to factors inherent of farms and the remaining were due to random and external factors of farms and not directly controlled, this result must be carefully considered because γ is relatively low.

The higher values of γ for clusters A and C confirm the results obtained by LR test, about the adequacy of model I to our survey data. As a consequence, the average production function (OLS) is less adequate to the frontier production

The η and μ values resulted from the specifications of statistic tests, and when they have zero values, the model adopted is *time-invariant* with semi-normal distribution; when they have a value different from zero, the model adopted is *time-variant* with error tem distribution truncated.

Table 8.1 Tests of hypotheses for coefficients of the technical efficiency variables in the stochastic frontier production function by cluster and total panel

		λ	Critical value (5%)	Decision
C	Model I			
l	H_0: $\beta_{ij}=0, i \le j = 1, 2, \ldots, 10$	71.38	18.31	Rejected H_0
u	H_0: $\eta = 0$	3.32	3.84	Accepted H_0
s	H_0: $\mu = 0$	0	3.84	Accepted H_0
t	H_0: $\gamma = 0$	13.82	7.05	Rejected H_0
e	Model II			
r	H_0: $\gamma = \delta_0 = \delta_i = 0, i = 1, \ldots, 8$	2, 271.58	16.27	Rejected H_0
A	H_0: $\delta_1 = \cdots = \delta_8 = 0$	13.76	15.51	Accepted H_0
C	Model I			
l	H_0: $\beta_{ij}=0, i \le j = 1, 2, \ldots, 10$	60.14	18.31	Rejected H_0
u	H_0: $\eta = 0$	−1.78	3.84	Accepted H_0
s	H_0: $\mu = 0$	−0.58	3.84	Accepted H_0
t	H_0: $\gamma = 0$	22.16	7.05	Rejected H_0
e	Model II			
r	H_0: $\gamma = \delta_0 = \delta_i = 0, i = 1, \ldots, 8$	2, 039.80	16.27	Rejected H_0
B	H_0: $\delta_1 = \cdots = \delta_8 = 0$	24.1	15.51	Rejected H_0
C	Model I			
l	H_0: $\beta_i = 0, i = 1, 2, 3, 4$	16.66	18.31	Accepted H_0
u	H_0: $\eta = 0$	0.24	3.84	Accepted H_0
s	H_0: $\mu = 0$	2.24	3.84	Accepted H_0
t	H_0: $\gamma = 0$	44.88	7.05	Rejected H_0
e	Model II			
r	H_0: $\gamma = \delta_0 = \delta_i = 0, i = 1, \ldots, 8$	996.82	16.27	Rejected H_0
C	H_0: $\delta_1 = \cdots = \delta_8 = 0$	15.72	15.51	Rejected H_0
T	Model I			
o	H_0: $\beta_i = 0, i = 1, 2, 3, 4$	1.4	18.31	Accepted H_0
t	H_0: $\eta = 0$	5.08	3.84	Rejected H_0
a	H_0: $\mu = 0$	7.96	3.84	Rejected H_0
l	H_0: $\gamma = 0$	15.72	7.05	Rejected H_0
	Model II			
	H_0: $\gamma = \delta_0 = \delta_i = 0, i = 1, \ldots, 8$	6, 100.46	16.27	Rejected H_0
	H_0: $\delta_1 = \cdots = \delta_8 = 0$	35.94	15.51	Rejected H_0

Table 8.2 Estimative of some parameters of SFA – model I

Parameter	Cluster A	Cluster B	Cluster C	Total panel
$\sigma^2 = \sigma_\mu^2 + \sigma_v^2$	0.091***	0.016***	0.043*	0.066***
$\gamma = \sigma_\mu^2/\sigma^2$	0.766***	0.479**	0.892***	0.391***
μ	0	0	0	0.321***
η	0	0	0	0.076***

***$(P < 0.01)$*; ** $(P < 0.05)$;* $P(P < 0.10)$*

Table 8.3 Maximum-likelihood estimates for parameters of the stochastic frontiers for the clusters and total panel

Variable	Parameter	Cluster A	Cluster B	Cluster C	Total panel
Constant	δ_0	−0.179	1.454	1.606**	1.271
Time Trend	δ_1	−0.031	−0.017	0.018	−0.055***
ln (AN/HA)	δ_2	−0.185	0.003	0.166	−0.241**
ln (SUBS)	δ_3	0.001	0.145***	0.204	0.045***
ln (AS)	δ_4	−0.109	−0.029	−0.147*	−0.058***
ln (AM)	δ_5	0.083	−0.051	0.205**	0.105***
OW Dummy	δ_6	−0.453***	−0.025	−0.082	−0.117**
ln (UDE)	δ_7	−0.009	−0.146	−0.688*	−0.201***
ln (AG)	δ_8	0.193	−0.106	−0.012	−0.196
	$\sigma^2 = \sigma_\mu^2 + \sigma_v^2$	0.032***	0.008***	0.014***	0.048***
	$\gamma = \sigma_\mu^2/\sigma^2$	0.216	0.999***	0.999***	0.038

***($P < 0.01$)*; ** ($P < 0.05$);* $P(P < 0.10)$*

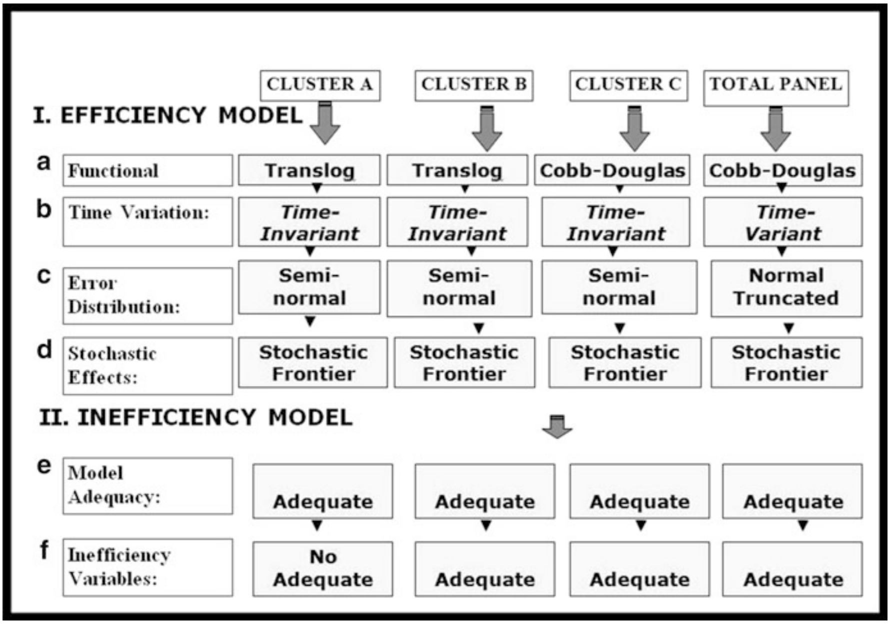

Fig. 8.3 Result models using the efficiency and inefficiency models

The three clusters for model I have similar values of efficiency intervals. They have more farms in the interval of 0.80–0.89 and superior to 0.90. Cluster A showed the efficiency lower values and that there are more farms in the groups inferior to 0.80. The difference between clusters B and C is at a lower level of efficiency for cluster C, which restrained the difference of the final values of both clusters.

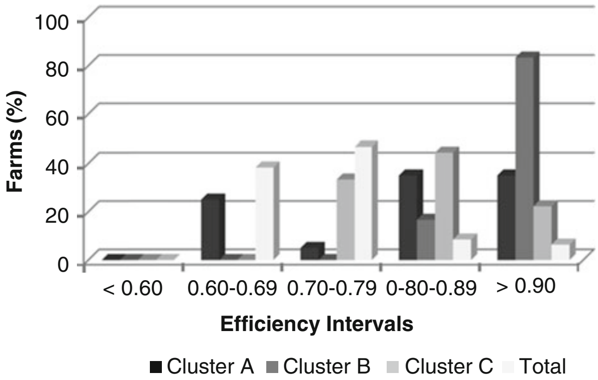

Fig. 8.4 Distribution of the technical efficiency clusters by using the efficiency interval

The average efficiencies for clusters A, B and C are 82.0, 93.2 and 85.1%, accordingly, and the most relevant efficiency intervals are superior to 80% (Fig. 8.4).

The results of inefficiency model – Model II – are shown in Table 8.3. The statistical variables are subvention, beef sales, amortization, ownership and economic dimension unit. Cluster A only has a significant inefficient variable (OW) with a negative signal, which contributes to decrease the inefficiency. The γ value shown for these eight variables, all together, explains only 21.6% of inefficiency. These results confirm the previous statistics tests about the adequate models to the selected variables (H_0: $\delta_1 = \cdots = \delta_8 = 0$). Cluster B only has a significant variable, SUBS. The parameter's positive signal shows its importance as an inefficiency factor. The γ value shows that 99.9% of the inefficiency is explained by inefficiency and the model is well adequate to the considered variables. Cluster C has AS and UDE, which were significant at a 10% significance level. Their parameter values have a negative signal and they contribute to decrease the inefficiency. The AM is significant at 5% level and contributes to the inefficiency level of this cluster. The γ value shows that 99.9% of the inefficiency is explained by these variables and the most adequate model.

The variables AN/HA and AG are not significant in this survey, and SUBS, AS, AM, OW and UDE are statistically significant y (Table 8.3). The Trend time has no significance (short period of time, 4 years).

8.4 Conclusions

The SFA model was more adequate than the traditional models of average production (OLS). This fact was demonstrated by the great adequacy of the models using the translog production function or Cobb-Douglas function.

To get a frontier in both models, with a different production function (translog and Cobb-Douglas) for each group of analysis, the input and output were the same for the three farm types; we verified that the stochastic frontier is sensible to the used data. When the variables are grouped in different ways, they result in a different frontier production and level of efficiency.

The levels of efficiency are constant and similar throughout time, and their values are 82, 93.2 and 85.1% accordingly for the clusters A, B and C.

The variables that cause inefficiency are subvention and equipment amortization. The variables with a major level of connection to efficient farms are lower rent fields, dimension and beef sales. The biggest farms seem more efficient, such as observed in Hallam and Machado (1996).

References

Aigner D, Lovell C, Scmidt P (1977) Formulation and estimation of stochastic frontier production function models. J Econ 6(1):21–37

Alvarez A, Gonzalez E (1999) Using cross-section data to adjust technical efficiency indexes estimated with panel data. Am J Econ 81:894–901

Battese G, Coelli T (1988) Prediction of firm-level technical efficiencies with a generalised frontier production function and panel data. J Econ 38:387–399

Battese G, Coelli T (1992) Frontier production functions. Technical efficiency and panel data: with application to paddy farmers in India. J Product Anal 3:153–169

Battese G, Coelli T (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir Econ 20:325–332

Battese G, Sumiter B (1997) Functional forms of stochastic frontier production function and models for technical inefficiency effects: a comparative study for wheat farmers in Pakistan. J Product Anal 8:395–414

Brummer B (2001) Estimating confidence intervals for technical efficiency: the case of private farms in Slovenia. Eur Rev Agric Econ 28(3):285–306

Coelli T (1995) Recent developments in frontier modelling and efficiency measurement. Aust J Agric Econ 39:219–245

Coelli T (1996) A guide to FRONTIER Version 4.1: a computer program for stochastic frontier production and cost function estimation, CEPA Working paper no. 96/07. Department of Econometrics, University of New England, Armidale

Daryanto H, Battese G, Fleming E (2002) Technical efficiencies of rice farmers under different irrigation systems and cropping seasons in West Java, University of New England, Asia Conference on Efficiency and Productivity Growth. Retrieved May 20, 2003 from http://www.sinica.edu.tw/~teps/A1-1.pdf

Franco F (2001) Eficiência Comparada Dos Serviços Hospitalares: O Método de Fronteira Estocástica, Tese de Mestrado, Universidade dos Açores

Hallam D, Machado F (1996) Efficiency analysis with panel data – a study of Portuguese dairy farms. Eur Rev Agric Resour Econ 23(1):79–93

Hasnah Fleming E, Coelli T (2004) Assessing the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra: a stochastic frontier analysis. Agric Syst 79(1):17–30

Kodde D, Palm F (1986) Wald criteria for jointly testing equality and inequality restrictions. Econometrica 54(5):1243–1248

Lawson L, Bruun J, Coelli T, Agger J, Lund M (2004) Relationships of efficiency to reproductive disorders in Danish milk production: a stochastic frontier analysis. J Dairy Sci 87:212–224

Meeusen W, van der Broeck J (1977) Efficiency estimation from Cobb-Douglas production functions with composed error. Int Econ Rev 18:435–444

Munzir A, Heidhues F (2002) Towards a technically efficient production in rural aquaculture, case study at Lake Maninjau. Indonesia, International Symposium Sustaining Food Security and Managing Natural Resources in Southeast Asia – Challenges for the 21st Century, Chiang Mai, Tailândia. Retrieved July 21, 2003 from http://www.uni-hohenheim.de/symposium2002/pa_full/Full-Pap-S3B-3_Munzir.pdf

Pascoe S, Hassaszahed P, Anderson J, Korsbrekke K (2001) Economic versus physical input measures in the analysis of technical efficiency in fisheries, XII Conference of the European Association of Fisheries Economists, Italia. http://www.eafe-fish.org/conferences/salerno/papers/paper04_seanpaschoe .doc. 2003-04-25

Puig-Junoy J, Argilés J (2000) Measuring and explaining farm inefficiency in a panel data set of mixed farms, Universidade Pompeu Fabra, Espanha. Retrieved March 21, 2003 from http://www.econ.upf.es/deehome/what/wpapers/postscripts/503.pdf

Reinhard S, Lovell K, Thijssen G (1999) Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farm. Am J Agric Econ 81:44–60

Reinhard S, Lovell K, Thijssen G (2000) Environmental efficiency with multiple environmentally detrimental variable: estimated SFA e DEA. Eur J Oper Res 121:287–303

Tauer L, Mishra A (2006) Dairy farm cost efficiency. J Dairy Sci 89:4937–4943

Torres J, Basch M, Vergara S (2002) Eficiência Técnica Y Escalas de Operación en Pesca Pelágica: Un Análisis de fronteras estocásticas, Universidade do Chile. Retrieved April 21, 2003 from http://www.ilades.cl/economia/Publicaciones/ser_inv/inv137.pdf

Venâncio F, Silva E (2004) A Eficiência de Explorações Agro-pecuárias dos Açores: uma abordagem paramétrica, Actas XIV Jornadas Luso – Espanholas de Gestão Científica

Webster R, Kennedy S, Johnson L (1998) Comparing techniques for measuring the efficiency and productivity of Australian private hospitals, Working papers (98/3) in econometrics and applied statistics, Australian Bureau of Statistics. Retrieved May 09, 2003 from http://www.abs.gov.au/websitedbs/D3110122.NSF/0/31f3a2cdb3dbbf85ca25671b001f1910/$FILE/13510_Nov98.pdf