Cost Efficiency of Dairy Farming in New Zealand: a stochastic frontier analysis

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Abstract

Historically NZ dairy farming has held a position as the lowest cost, non-subsidized producers of milk. Recently, this position has been eroded as a result of increases in labor and land costs, while other emerging countries, such as Argentina and Ukraine, have adopted lower cost production systems. This indicates a need to continually build competitiveness on efficient utilization of resources, both physical and financial.

Literature on the efficiency performance of dairy farming in NZ is dearth and the focus to date has been on technical efficiency, which only reveals how well farms utilize the physical production process. This paper contributes to the empirical literature by examining the cost efficiency of NZ dairy farms. Simplified translog stochastic cost frontiers are estimated using an unbalanced panel of 824 dairy farms, observed during 1999-2005. Average cost efficiency is estimated to be around 83% for the North Island dairy farms and 80% for the South Island. Analysis of the relationship between inefficiency and farm characteristics suggests capital intensity, livestock quality and farm size all have significant associations with cost efficiency.

Key words: stochastic cost frontier, NZ dairy farming, cost efficiency

JEL classification: D24 ·L79 ·Q12

Introduction

New Zealand is a world leader in producing and exporting dairy products. NZ dairy farming is well known for its low cost, high quality pasture based production systems and high levels of technological expertise. Recently, this position has been eroded as a result of increases in land and labor costs. While other emerging countries, such as Argentina and Ukraine, have adopted lower cost production systems. To keep pace with the increasing global demand and maintain a competitive edge, an investigation into on-farm efficiency would shed some light on the scope for profit improvement.

Efficiency studies of NZ dairy farms have typically involved non-parametric data envelope analysis (Jaforullah and Whiteman 1999, Jaforullah and Premachandra 2003, Rouse *et al.* 2009) and parametric stochastic frontier analysis (Jaforullah and Devlin 1996, Jaforullah and Premachandra 2003, Jiang and Sharp 2008). Average technical efficiency estimates range from 86% to 95%. Surveys of the empirical literature suggest stochastic frontier analysis is the most commonly used approach because of the non-negligible random factors involved in agricultural production (Battese 1992, Coelli 1995, Bravo-Ureta *et al.* 2007).

The above studies share two things in common: (1) they are based on relatively small cross sectional datasets pooled across regions; and (2) all analysis focus on technical efficiency. Technical efficiency evaluates how well farms utilize their physical resources and production technology. For a dairy farm with a profit maximizing business objective, correctly identifying the optimal input mix is also part of management practice. The success of achieving the best economic outcome hinges on both and can be measured by profit efficiency, which is the ratio of actual profit obtained to maximum profit attainable.

In the context of New Zealand dairying, the milk produced by about 97% of dairy farms is supplied to the Fonterra Co-operative, owned by farmer suppliers. The amount of milk each farm can supply is largely determined by the Fonterra shares they hold. Farmers are paid regularly, based on an estimate of returns from the milk. A final payment is made at the end of the season to reflect actual returns. This means in the short run, the output level is targeted and milk price is taken as given, the potential on the revenue side is limited. Therefore it seems appropriate to analyze efficiency in cost minimization.

Cost efficiency (CE) is the product of input-oriented technical and allocative efficiency. Input oriented technical efficiency measures the ability to produce a given level of output with minimum inputs. Allocative efficiency measures the ability to produce this output with the input bundle that costs the least under current market prices. Cost efficiency therefore measures the ability to produce a certain level of output at minimum cost. At the industrial level, long-run competitiveness in a generic commodity market like milk depends upon low cost production. At the farm level, CE evaluation is crucial in signalling profit potential and identifying areas for improvement.

The objective of this study is to evaluate the CE performance of NZ dairy farms, benchmarking a dairy farm’s production cost against a common estimated best practice frontier, and investigating farm characteristics affecting efficiency performance. The rest of the paper is structured as follows. Section 2 reviews the basic economic concepts underpinning CE analysis and limited empirical literature. Section 3 elaborates the empirical model and summarizes the data. Section 4 describes the estimation results and section 5 concludes with an overview of main findings.

Methodology and Literature

A cost function can be estimated using micro data on observed operating cost, input prices and output quantity. The general form of the cost frontier model can be written:

$$c_{it} \geq c(w_{1it}, w_{2it}, \cdots, w_{Kit}, y_{it}; \boldsymbol{\beta}) \quad i = 1,2,\cdots,N; t = 1,2,\cdots,T \qquad (1)$$

where: c_{it} is the observed cost of firm i in period t; w_{kit} is the k-th input price; y_{it} is the output volume and $\boldsymbol{\beta}$ is a vector of technological parameters depicting the relationship between input prices, output and minimum cost of production. The cost function $c(.)$ should satisfy the following properties for it to be seen as a cost minimizing solution: nonnegative, nondecreasing in input prices and output, homogeneous of degree one, and concave in input prices (Coelli *et al*. 2005, p23).

The above cost function is deterministic as it ignores statistical noise; such as measurement error and random shocks outside the control of the operator. Especially for agricultural production, this kind of random shocks can exhibit non-negligible effects on performance. As a result, a stochastic cost frontier can be written:

$$c_{it} \geq c(w_{1it}, w_{2it}, \cdots, w_{Kit}, y_{it}; \boldsymbol{\beta}) \exp\{v_{it}\} \qquad (2)$$

where v_{it} is an independently and identically distributed random error component reflecting statistical noise, usually assumed to follow the standard normal distribution with zero mean and constant variance σ_v^2. Actual cost can be greater than the stochastic minimum production cost due to inefficiency such that:

$$c_{it} = c(w_{1it}, w_{2it}, \cdots, w_{Kit}, y_{it}; \boldsymbol{\beta}) \exp\{v_{it} + u_{it}\} \qquad (3)$$

where u_{it} is a non-negative producer specific inefficiency error term that follows certain distributional assumptions. If the firm is 100% efficient, this inefficiency error term will be zero and the firm is operating on the stochastic cost frontier. The measurement of CE is provided by the ratio of stochastic frontier cost to actual cost:

$$CE_{it} = \frac{c(w_{1it}, w_{2it}, \cdots, w_{Kit}, y_{it}; \boldsymbol{\beta}) \exp\{v_{it}\}}{c(w_{1it}, w_{2it}, \cdots, w_{Kit}, y_{it}; \boldsymbol{\beta}) \exp\{v_{it}\} \exp\{u_{it}\}} = \exp\{-u_{it}\} \qquad (4)$$

Parameters of the stochastic cost frontier can be estimated consistently by maximum likelihood (ML) provided that v_{it} and u_{it} are distributed independently of each other and of the regressors. Producer specific CE can be estimated using Battese and Coelli (1988) point estimator:

$$CE_{it} = E[\exp(-u_{it}) | v_{it} + u_{it}] \qquad (5)$$

Empirical CE analysis is relatively limited because of difficulties with data. Cost frontier estimation requires data on the input prices paid by each firm, and there has to be variation in the price data. Early application of the stochastic cost frontier to dairy farming goes back to Dawson (1987b), based on a cross-section of 406 dairy farms in England and Wales. The cost frontier was implied by the Cobb-Douglas production function under the "dual property" and input prices were hypothesized to be invariant across farms. Another early application was Rieger and Bravo-

Ureta (1991), who used a cross-section of 511 New England dairy farms. In contrast to Dawson (1987b), Rieger and Bravo-Ureta (1991) estimated a Cobb-Douglas stochastic production frontier and recovered the corresponding cost frontier with the "dual property".

Following the reforms of the European Union Common Agricultural Policy, analysts predicted a reduction in milk prices paid to farms in Europe (Hennessy *et al*. 2005). This set the stage for panel data cost efficiency studies aimed at improving the survivability of dairy farms. Scottish dairy farms are found to have an average CE of 58% (Revoredo-Giha *et al*.2009), relative to other types of farms in an aggregate translog stochastic cost frontier. Spanish has a CE of 72% for extensive dairy farms located in Asturias and 81% for intensive farms (Alvarez *et al.* 2008), where production heterogeneity is imposed between the two. Canadian dairy farms have a CE score ranged between 84% and 92% (Hailu *et al.* 2005), obtained under a translog stochastic cost frontier with local concavity constraints. More sophisticated studies, such as Pierani and Rizzi (2003) who estimated a symmetric generalized McFadden cost function for a panel of Italian dairy farms, and Reinhard and Thijssen (2000) who developed a shadow cost system for Dutch dairying, have limited empirical application due to the complexity involved and the requirement for a long panel of observations.[1]

[1] Pierani and Rizzi (2003) utilized a balanced panel of 41 Indian dairy farms observed from 1980-1992. Reinhard and Thijssen (2000) used a panel of 434 Dutch dairy farms observed during the period 1985-1995 where each farm was observed on average 6 times. The complete shadow cost system could not be estimated because of too many parameters.

Data and Empirical Model

The dataset containing farm level financial and physical information for the period 1999-2005 was provided by DairyNZ. It was obtained from an annual survey undertaken by NZ Livestock Improvement Corporation and Dexcel using a random sampling procedure, stratified by region and herd size.

Farms with a missing regional code were dropped from the analysis. Not all sampled farms provided information in a form that could be used. For example, some observations did not separate out expenditure on fertiliser and feed. Such observations were considered to be recording errors and were not used in the analysis. The total number of observations in each year is summarized in table 1, and the proportion of sampled South Island farms is compared with the actual figures from national statistics. The number of observations available per farm varied from a low of one and a high of six. Table 1 reveals that South Island dairy farms were underrepresented in the sample dataset.

<Insert Table 1 about here>

The traditional farming area is in the North Island of NZ, which accounts for 66% of the national livestock nowadays. Climate in this region is subtropical, with consistent year-round rainfall of around 1,200mm and temperature averages approximately 14℃. These climatic conditions and fertile soils make it one of the most productive grass growing regions in the world. Since 1980s, the availability of modern technology, access to water, and relatively cheap land has made the South Island increasingly attractive for dairy farming. Climate is temperate, 600mm annual rainfall is relatively low and temperature averages 11.5℃. Irrigation is used extensively to improve production as the summers are hot and dry. Given diverse climate conditions and differences in the stage of development of North Island and South Island dairy farming, an independent variable cost frontier is estimated for each region.

Different algebraic forms give rise to different functional relationships. Cobb-Douglas (Bravo-Ureta and Rieger 1991, Ahmad and Bravo-Ureta 1996, Hadri and Whittaker 1999, Jaforullah and Premachandra 2003, Kompas and Che 2006) and translog (Dawson 1987a, Kumbhakar and Heshmati 1995, Jaforullah and Devlin 1996, Reinhard *et al.* 1999, Cuesta 2000, Hadley 2006, Moreira and Bravo-Ureta 2010) are the two most commonly applied functions in the technical efficiency analysis literature. It has been argued that rankings of farm technical efficiency estimates are generally robust to functional form choice (Maddala 1979, Good *et al.* 1993, Ahmad & Bravo-Ureta 1996). We considered both and the robustness of CE rankings with respect to functional form.

Variable cost expenditure measured in per cow terms was used as the dependent variable in the cost frontier, derived from the data by summing the total on-farm cash expenditure. Output was measured by the average milksolids produced per cow. The absence of input price information meant that we had to resort to using average input cost. The price for labour was obtained by dividing total payments to employed labour plus adjustments made for family labour, by the number of full time equivalent workers (FTEs). Feed price was derived by taking the ratio of all feed related expenses to the total tons of dry matter supplements made on farm and brought-in. Average fertilizer cost was obtained by dividing the total expenditure on fertilizer by the quantity of fertilizer purchased. Effective dairy land, in hectares, was used as a proxy for fixed capital.

The variables are further transformed to incorporate the linear homogeneous constraint on input prices, such that:

$$c = \ln\left(\frac{variable\ cost}{cow}\right) - \ln(fertilizer\ price)$$

$$y = \ln\left(\frac{milksolids}{cow}\right)$$

$$w1 = \ln(labour\ price) - \ln(fertilizer\ price)$$

$$w2 = \ln(feed\ price) - \ln(fertilizer\ price)$$

$$z = \ln(effective\ dairy\ hectares)$$

A linear time trend and its quadratic term were incorporated into the cost frontier to capture potential technical change. The resulting Cobb Douglas cost frontier is specified as:

$$c_{it} = \beta_o + \beta_y \cdot y_{it} + \beta_1 \cdot w1_{it} + \beta_2 \cdot w2_{it} + \beta_z \cdot z_{it} + \beta_t \cdot t + \beta_{tt} \cdot t^2 + v_{it} + u_{it} \tag{6}$$

The translog cost frontier with the usual symmetry constraint is:

$$\begin{aligned} c_{it} = \beta_o &+ \beta_y \cdot y_{it} + \beta_1 \cdot w1_{it} + \beta_2 \cdot w2_{it} + \beta_z \cdot z_{it} \\ &+ \beta_{yy} \cdot (y_{it})^2 + \beta_{11} \cdot (w1_{it})^2 + \beta_{22} \cdot (w2_{it})^2 + \beta_{zz} \cdot (z_{it})^2 + \beta_{12} \cdot (w1_{it} \cdot w2_{it}) \\ &+ \beta_{y1} \cdot (y_{it} \cdot w1_{it}) + \beta_{y2} \cdot (y_{it} \cdot w2_{it}) + \beta_{z1} \cdot (z_{it} \cdot w1_{it}) + \beta_{z2} \cdot (z_{it} \cdot w2_{it}) \\ &+ \beta_{yz} \cdot (y_{it} \cdot z_{it}) + \beta_t \cdot t + \beta_{tt} \cdot t^2 + v_{it} + u_{it} \end{aligned} \tag{7}$$

Following Kumbhakar *et al.* (1991) and Battese and Coelli (1995), the inefficiency error component u_{it}, is assumed to follow a truncated normal distribution with mean as a function of explanatory variables. These variables can be farm characteristics which might impact on management performance, and/or time variables to capture efficiency variation across time. This specification, as demonstrated in equation (8), allows the distribution of the inefficiency error term to vary between each observation.

$$u_{it} \sim N^{+}(\boldsymbol{Z}'_{it}\boldsymbol{\alpha}, \sigma_u^2) \qquad (8)$$

where $\boldsymbol{Z}_{it}$ is a vector involving capital intensity, livestock quality, a categorical variable for farm size and the linear time trend. $\boldsymbol{\alpha}$ is the associated vector of parameters to be estimated simultaneously with the parameters in the stochastic cost frontier by ML. Capital intensity is measured by the per cow expenditure on repair and maintenance plus depreciation. Livestock quality is measured by average livestock market value. A mutually exclusive categorical variable equals to 0 if the maximum number of milking cows is no more than 150, equals to 1 if no more than 250, 2 if no more than 500, and 3 if the herd size is greater than 500.

The descriptive statistics of the variables are provided in table 2. As can be seen from the means, standard deviations and ranges, there are considerable regional differences. South Island dairy farms are, on average, larger and more capital intensive with higher livestock values and productivity, compared with those in North Island; they also faced higher input costs.

<Insert Table 2 about here>

Results and Discussions

Maximum likelihood estimates of the parameters were obtained using the FRONTIER 4.1 program (Coelli 1996). Results for the Cobb-Douglas stochastic cost frontier are presented in table 3. As can be seen, all the estimated coefficients associated with output and input prices have positive signs and are highly significant, implying the cost function is well behaved. The null hypothesis that the one-sided inefficiency error term is insignificant can be rejected at the 1% level given the Kodde and Palm critical value of 17.755 with 7 degrees of freedom.

<Insert Table 3 about here>

For the North Island, the Cobb Douglas functional form is rejected in favour of the translog based on a Likelihood Ratio (LR) test.[2] For the South Island however, we cannot reject the null hypothesis that the underlying functional form is Cobb-Douglas, implying the cost function representing the South Island sample is more restrictive. Cobb Douglas is favoured for its simplicity but at the cost of imposing unrealistically restrictive assumptions on the functional relationships.[3] Although the translog model is much more flexible, the problem is that many estimated coefficients turn out to be insignificant due to the incorporation of second order parameters.

Motivated by Ahmad and Bravo-Ureta (1996) and Reinhard *et al.* (2000), who employ a simplified version of the translog, we used simplified translog cost frontiers containing only the significant parameters estimated during the experimentation with the data. Estimation results are presented in table 4.

[2] Results for the translog stochastic cost frontiers are attached in Appendix A.

[3] The own-price elasticities are assumed to be -1 and the cross-price elasticities are assumed to be equal to 0.

<Insert Table 4 about here>

Besides constraints imposed prior to estimation, a well behaved cost function should be cancave and nondecreasing in input prices,. Cancavity implies the conditional input demand functions cannot slope upwards, i.e. increasing an input price will not encourage its use. This was examined by checking the negative semi-definiteness of the hessian matrix at each data point. For both regional frontiers, the eigenvalues of the entire hessian matrix for each observation are negative; thus the cancavity property was satisfied at all sample data points. The monotonicity property was checked by examining the nonnegativity of the estimated conditional input demand. For the North Island frontier, only 18 observations were found to violate the monotonicity property with respect to feed price. No violations in the South Island frontier were found.

All the estimated coefficients associated with the time trend are significant in the simplified translog frontiers, implying the exhibition of non-linear technical change and efficiency variation across time.

In terms of modelling technical inefficiency, the North Island results show that more capital intensive farms or farms with higher value livestock are associated with higher inefficiency, therefore lower efficiency performance, ceteris paribus. Whereas the size of a farm is found to have a negative estimated coefficient: -0.0941, suggesting that larger farms tend to have a better CE score relative to those that are smaller, holding everything else constant. The same applies to South Island except that the quality of the livestock does not exhibit any significant association with inefficiency.

Mean CE estimates vary as shown in table 5. The average CE is about 83% for the North Island dairy farms and 80% for the South Island, relative to their own frontiers. Within the North Island, the Waikato region has the best average CE performance, with a mean efficiency score of 84.5% and one quarter of the sampled farms operated above 92%. The resulting implication is a 15.5% decrease in variable expenditure on average, if all the farms in the Waikato area become fully efficient.

<Insert Table 5 about here>

Robustness of the CE estimates with respect to functional forms were examined by the CE Spearman rank correlation coefficients presented in table 6. These correlations range from 0.67 to 0.98 for the different cost frontiers estimated for North Island dairy farms, suggesting the efficiency rankings do not differ a lot between the choice of different functions for this dataset. However, in terms of the South Island sample, the correlation coefficient is 0.86 between translog and the simplified translog, but only 0.27 between Cobb-Douglas and the simplified translog. The log likelihood function supports use of the simplified translog for the South Island cost frontier.

<Insert Table 6 about here>

Conclusion

To the best of our knowledge, this is the first cost efficiency study of NZ dairying. Utilizing an unbalanced panel of farms observed during 1999-2005, an independent simplified translog stochastic cost frontier was estimated for North Island and South Island, to account for technological differences between the two regions. The estimated cost functions were checked against regularity conditions and we found no violation of the cancavity property and only a few violations of the monotonicity properties, indicating the cost functions are reasonably well behaved.

The average cost efficiency is about 83% for North Island dairy farms, within which, Waikato ranked first, with a mean efficiency score of 84.5%; Bay of Plenty was second place (84.1%), followed by Taranaki (81.7%), Northland and Lower North (80.7%). For South Island dairy farms, the cost efficiency distribution is more dispersed, the mean efficiency score is 80% relative to their own frontier, 35% of the sampled farms scored above 92%.

Cost inefficiency was modelled as a truncated normal distribution with the mean as a function of farm characteristics, parameters were estimated simultaneously with those in the stochastic cost frontier by maximum likelihood. Results indicate a significant negative relationship between capital intensity, livestock quality and cost efficiency, and a positive relationship between herd size and efficiency performance.

A non-linear technical change effect was found to exist as well as improvements in on-farm efficiency performance over time as a result of experience accumulation. However, our results show that the rate of technical change decreased over the sample period. Bearing in mind future challenges from low cost producers, such as the Ukraine and Argentina, opportunities exist for gains in CE. Looking further into the future, with increased water scarcity, rising land costs and the prospect of agriculture entering the emissions trading scheme, NZ dairy farming is more likely to improve its competitiveness through the use of advanced technologies that economise on inputs and contribute to efficient management systems. The collection of more farm level data will contribute to an on-going research program that seeks to better understand how these challenges will impact the competitiveness of dairy farming. With the availability of more information, future research could separate out inputs such as nitrogen , energy and water. This would benefit the industry and policy makers in designing a competitive, and sustainable dairy farming protocol.

Tables and Figures

Table 1: Number of Observations by Year

Observations	1999	2000	2001	2002	2003	2004	2005	Total
Pool	187	190	245	180	193	202	203	1400
North	170	171	211	154	163	172	172	1213
South	17	19	34	26	30	30	31	187
Sample South %	9.1%	10%	13.9%	14.4%	15.5%	14.9%	15.3%	13.4%
Actual South %	14.1%	15.1%	15.2%	16.5%	17.3%	17.9%	18.4%	16.4%

Table 2: Summary Statistics of Variables

Variables	Region	Mean	Std. Dev.	Min	Max
variable cost/cow ($)	North	960	234	392	2211
	South	1159	316	667	2750
milksolids/cow (kgs)	North	312	50	140	559
	South	354	56	218	533
labor price ($/FTE)	North	32679	10006	10250	106282
	South	35643	9117	13315	70135
feed price ($/t.dm)	North	236	193	41	1840
	South	247	211	45	1500
fertilizer price ($/100 g)	North	14.35	7.80	3.04	85.62
	South	14.90	8.79	3.17	59.75
effective dairy hectares	North	90.53	49.86	20	570
	South	135.59	72.19	36	490
capital value/cow ($)	North	171	81	39	881
	South	221	108	48	756
Average livestock value ($)	North	1098	286	315	2866
	South	1171	344	353	2450
Size Categories	North	1.17	0.80	0	3
	South	1.78	0.85	0	3

Table 3: Cobb Douglas Stochastic Cost Frontier Estimates

	North		South	
β_0	-3.3414	***	-3.1885	***
β_y	0.3333	***	0.3189	**
β_1	0.6531	***	0.7152	***
β_2	0.1558	***	0.1252	***
β_z	-0.0479	**	-0.0025	
t	0.1414	***	-0.3164	***
β_{tt}	-0.0179	***	0.0134	
α_0	-1.3737	***	-1.6599	***
$\alpha_{capital\ intensity}$	0.2044	***	0.2789	***
$\alpha_{livestock\ quality}$	0.1479	***	0.0200	
$\alpha_{farm\ size}$	-0.1004	***	-0.1079	***
α_t	-0.2173	***	0.3311	**
α_{tt}	0.0245	***	-0.0144	
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.0392	***	0.0437	***
$\gamma = \frac{\sigma_u^2}{\sigma^2}$	0.0135	**	0.0000	
Log Likelihood	242.213		27.415	
LR test of the one-sided error	284.439		51.478	

*The estimated coefficient is significant at 10%

** significant at 5%

***significant at 1%

Table 4: Simplified Translog Stochastic Cost Frontier Estimates

	North		South	
β_0	21.8218	***	46.1100	***
β_y	-9.4632	***	-16.9705	***
β_1	1.7920	***	0.7122	***
β_2	-1.0360	***		
β_{yy}	0.8254	***	1.5369	***
β_{11}	-0.0699	***		
β_{22}	-0.0442	***		
β_{zz}	0.0526	***	0.0656	
β_{12}	0.0847	***		
β_{y2}	0.1376	***		
β_{z1}	-0.0658	***		
β_{z2}			0.0254	***
β_{yz}			-0.1276	*
β_t	0.0808	***	0.5016	*
β_{tt}	-0.0109	***	-0.0594	**
α_0	-1.7567	***	-0.5364	
$\alpha_{capital\ intensity}$	0.2133	***	0.3379	***
$\alpha_{livestock\ quality}$	0.1882	***	-0.0054	
$\alpha_{farm\ size}$	-0.0941	***	-0.0616	*
α_t	-0.1823	***	-0.5329	**
α_{tt}	0.0200	***	0.0633	**
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.0368	***	0.0396	***
$\gamma = \frac{\sigma_u^2}{\sigma^2}$	0.0039	**	0.0380	
Log Likelihood	284.759		37.716	
LR test of the one-sided error	298.131		49.095	

Table 5: Summary of Cost Efficiency Estimates

Region	Count	mean	min	max	p50	p75
Northland	179	0.8071	0.4654	1	0.8044	0.8806
Waikato	400	0.8449	0.4791	1	0.8505	0.9209
Bay of Plenty	230	0.8407	0.5816	1	0.8375	0.9163
Taranaki	240	0.8167	0.5354	1	0.8158	0.8731
Lower North	164	0.8065	0.5006	1	0.8097	0.8827
North Island	**1213**	**0.8278**	**0.4654**	**1**	**0.8302**	**0.9014**
South Island	**187**	**0.8034**	**0.3538**	**0.9954**	**0.8421**	**0.9676**

Table 6: Cost Efficiency Estimates Spearman Rank Correlation Coefficients

North Island frontier	Simplified TL	Translog	Cobb-Douglas
Simplified TL	1		
Translog	0.6708***	1	
Cobb-Douglas	0.9818***	0.7017***	1

South Island frontier	Simplified TL	Translog	Cobb-Douglas
Simplified TL	1		
Translog	0.8576***	1	
Cobb-Douglas	0.2732***	-0.1618**	1

References

Alvarez, A., J. del Corral, D. Solis, and J.A. Pérez. 2008. Does intensification improve the economic efficiency of dairy farms? *Journal of Dairy Science* 91: 3693-3698.

Battese, G.E. 1992. Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. *Agricultural Economics* 7: 185-208.

Ahmad, M., and B.E. Bravo-Ureta. 1996. Technical efficiency measures for dairy farms using panel data: a comparison of alternative model specifications. *The Journal of Productivity Analysis* 7: 399-415.

Battese, G.E., and T.J. Coelli. 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function models. *Journal of Econometrics* 38: 387-399.

Battese, G.E., and T.J. Coelli. 1995. A model for technical efficiency effects in a stochastic frontier production function for panel Data. *Empirical Economics* 20: 325-332.

Bravo-Ureta, B.E., and L. Rieger. 1991. Dairy farm efficiency measurement using stochastic frontiers and neoclassical duality. *American Journal of Agricultural Economics* 73: 421-428.

Bravo-Ureta, B.E., D. Solis, V.H. Moreira, J. Maripani, A. Thiam, and T. Rivas. 2007. Technical efficiency in faming: a meta-regression analysis. *Journal of Productivity Analysis* 27: 57-72.

Coelli, T.J. 1995. Recent developments in frontier modelling and efficiency measurement. *Australian Journal of Agricultural Economics* 39: 219-245.

Coelli, T.J. 1996. A guide to FRONTIER version 4.1: a computer program for stochastic frontier production and cost function estimation. CEPA Working Paper 7/96, School of Economics, University of New England, Armidale.

Coelli, T.J., D.S. Prasada Rao, C.J. O'Donnell, and G.E. Battese. 2005. *An Introduction to Efficiency and Productivity Analysis* (2nd ed.). New York: Springer Science + Business Media, LLC.

Cuesta, R.A. 2000. A production model with firm-specific temporal variation in technical inefficiency: with application to Spanish dairy farms. *Journal of Productivity Analysis* 13: 139-158.

Dawson, P.J. 1987a. Farm-specific technical efficiency in the England and Wales dairy sector. *European Review of Agricultural Economics* 14: 383-394.

Dawson, P.J. 1987b. Technical efficiency relative to a stochastic cost frontier for the England and Wales dairy sector. *Oxford Development Studies* 16: 45-55.

Good, D.H., M.I. Nadiri, L. Roller, and R.C. Sickles. 1993. Efficiency and productivity growth comparisons of European and U.S. air carriers: a first look at the data. *Journal of Productivity Analysis* 4: 115-125.

Hadley, D. 2006. Patterns in technical efficiency and technical change at the farm-level in England and Wales, 1982-2002. *Journal of Agricultural Economics* 57: 81-100.

Hadri, K., and J. Whittaker. 1999. Efficiency, environmental contaminants and farm size: testing for links using stochastic production frontiers. *Journal of Applied Economics* 2: 337-356.

Hailu, G., S. Jeffrey, and J. Unterschultz. 2005. Cost efficiency for Alberta and Ontario dairy farms: an interregional comparison. *Canadian Journal of Agricultural Economics* 53: 141-160.

Hennessy, T., L. Shalloo, and P. Dillon. 2005. The economic implications of complying with a limit on organic nitrogen in a decoupled policy environment – An Irish case. *Journal of Farm Management* 12: 297-311.

Jaforullah, M., and N.J. Devlin. 1996. Technical efficiency in the New Zealand dairy industry: a frontier production function approach. *New Zealand Economic Papers* 30: 1-17.

Jaforullah, M., and E. Premachandra. 2003. Sensitivity of technical efficiency estimates to estimation approaches: an investigation using New Zealand dairy industry data. Economics Discussion Papers No. 306, University of Otago, Dunedin, New Zealand.

Jaforullah, M., and J. Whiteman. 1999. Scale efficiency in the New Zealand dairy industry: a non-parametric approach. *The Australian Journal of Agricultural and Resource Economics* 43: 523-541.

Jiang, N., and B. Sharp. 2008. Technical Efficiency Analysis of New Zealand Dairy Farms: A Stochastic Production Frontier Approach. 13th New Zealand Agricultural and Resource Economics (NZARE) conference papers, Nelson.

Kompas, T., and T.N. Che. 2006. Technology choice and efficiency on Australian dairy farms. *The Australian Journal of Agricultural and Resource Economics* 50: 65-83.

Kumbhakar, S.C., S. Ghosh, and J.T. McGuckin. 1991. A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms. *Journal of Business and Economic Statistics* 9: 279-286.

Kumbhakar, S.C., and A. Heshmati. 1995. Efficiency measurement in Swedish dairy farms: an application of rotating panel data, 1976-88. *American Journal of Agricultural Economics* 77: 660-674.

Maddala, G.S. 1979. A note on the form of the production function and productivity. In: *Measurement of Agricultural Productivity*. National Research Council, Washington D.C. National Academy of Sciences, 00-00.

Moreira, V.H., and B.E. Bravo-Ureta. 2010. Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: a stochastic meta-frontier model. *Journal of Productivity Analysis* 33: 33-45.

Pierani, P., and P.L. Rizzi. 2003. Technology and efficiency in a panel of Italian dairy farms: an SGM restricted cost function approach. *Agricultural Economics* 29: 195-209.

Reinhard, S., C.A.K. Lovell, and G.J. Thijssen. 1999. Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms. *American Journal of Agricultural Economics* 81: 44-60.

Reinhard, S., C.A.K. Lovell, and G.J. Thijssen. 2000. Environmental efficiency with multiple environmentally detrimental variables: estimated with SFA and DEA. *European Journal of Operational Research* 121: 287-303.

Reinhard, S., and G.J. Thijssen. 2000. Nitrogen efficiency of Dutch dairy farms: a shadow cost system approach. *European Review of Agricultural Economics* 27: 167-186.

Revoredo-Giha, C.L., C.E. Milne, P.M.K. Leat, and W.J. Cho. 2009. Efficiency of Scottish farms: a stochastic cost frontier analysis. *Agricultural Economics Review* 10: 17-35.

Rieger, L., and B.E. Bravo-Ureta. 1991. Dairy farm efficiency measurement using stochastic frontiers and neoclassical duality. *American Journal of Agricultural Economics* 73: 421-428.

Rouse, P., L. Chen, and J.A. Harrison. 2009. Benchmarking the Performance of Dairy Farms using Data Envelopment Analysis. 2009 Performance Measurement Association (PMA) conference papers, University of Otago, Dunedin, New Zealand.

Appendix A: Translog Stochastic Cost Frontier Estimates

	Pool		North		South	
β_0	31.0431	***	19.7181	***	36.3027	***
β_y	-11.3623	***	-8.4187	***	-16.0275	***
β_1	1.0714	*	1.8163	***	1.6833	**
β_2	-0.5081		-1.0491	***	0.2734	
β_z	-0.7482		-0.5665		1.3187	
β_{yy}	0.9232	***	0.7033	***	1.7398	***
β_{11}	-0.0472	**	-0.0676	***	0.0069	
β_{22}	-0.0485	***	-0.0443	***	-0.0700	
β_{zz}	0.0739	***	0.0559	***	0.0904	***
β_{12}	0.0714	***	0.0852	***	0.0223	
β_{y1}	0.0737		-0.0114		-0.2440	
β_{y2}	0.0637		0.1422	**	0.0546	
β_{z1}	-0.0682	**	-0.0658	**	0.0447	
β_{z2}	0.0038		-0.0035		-0.0514	**
β_{yz}	0.0931		0.0986		-0.4220	**
β_t	0.1070	***	0.1718		0.3149	***
β_{tt}	-0.0145	***	-0.0285		-0.0325	***
α_0	-1.9262	***	-1.3357	***	-0.2436	
$\alpha_{capital\_cost}$	0.2455	***	0.1988	***	0.1197	***
α_{cow_price}	0.1831	***	0.1708	***	0.0444	
α_{size}	-0.0707	***	-0.1015	***	-0.0140	
α_t	-0.2096	***	-0.2586		-0.2915	**
α_{tt}	0.0236	***	0.0361	*	0.0304	**

	Pool		North		South	
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.0383	***	0.0372	***	0.0470	***
$\gamma = \sigma_u^2 / \sigma^2$	0.0252		0.3943		0.0000	
Log Likelihood	**297.526**		**287.405**		**33.839**	
LR test of the one-sided error	342.929		302.038		22.571	
df=7 P=0.01 critical value	17.755		17.755		17.755	
LR test of CD function	**85.838**		**90.384**		**12.848**	
df=10 p=0.01 critical value	23.21		23.21		23.21	
LR test of same technology	47.436					
df=25 p=0.01 critical value	44.31					

Appendix B: NZ Dairying Regional Map