Cost Efficiency of Dairy Farming in New Zealand: A Stochastic Frontier Analysis

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Research on the efficiency of dairy farming in New Zealand is limited and has focused predominantly on technical efficiency. We contribute to the literature on empirical analysis by examining cost efficiency of New Zealand dairy farms. We construct simplified translog stochastic cost frontiers based on an unbalanced panel of 824 farms. Average cost efficiency is estimated at 83 percent for dairy farms in the North Island and 80 percent for farms in the South Island. Our analysis of the relationship between inefficiency and farm characteristics suggests significant associations between cost efficiency and capital intensity, livestock quality, and farm size.

***Key Words**: cost efficiency, New Zealand dairy farming, stochastic frontier*

New Zealand (NZ) is a world leader in production and export of dairy products and its dairy farm industry is well known for low-cost, high-quality, pasture-based production systems and exceptional technological expertise. Recently, however, this position has eroded as a result of increases in land and labor costs in New Zealand as emerging countries such as Argentina and Ukraine have adopted lower-cost production systems. Efforts in New Zealand to keep pace with increasing global demand for dairy products and maintain a competitive edge can benefit from an investigation into on-farm efficiency to shed light on potential areas for profit improvement.

Prior studies of the efficiency of NZ dairy farms typically involved nonparametric data envelope analysis (Jaforullah and Whiteman 1999, Jaforullah and Premachandra 2003, Rouse, Chen, and Harrison 2009) and parametric stochastic frontier analysis (Jaforullah and Devlin 1996, Jaforullah and Premachandra 2003, Jiang and Sharp 2008). In those studies, the average technical efficiency estimates ranged from 86 percent to 95 percent. Surveys of the empirical literature (Battese 1992, Coelli 1995, Bravo-Ureta et al. 2007) suggest that stochastic frontier analysis is the most commonly used approach, perhaps because economists are particularly interested in the relationship between inputs and output. Of the 167 farm-level studies reviewed by Bravo-Ureta et al. (2007), 149 relied on parametric models.

In general, the studies of NZ dairy farms have been based on relatively small sets of cross-sectional country-level data and focused on technical efficiency, a measure of how well farms use physical resources and production technologies.

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However, for a dairy farmer with a profit-maximizing business objective, correctly identifying the optimal input mix is an important management practice. Achieving the best economic outcome hinges on both use of resources and technologies and on identifying the optimal input mix, and success can be measured by profit efficiency—the ratio of actual profit obtained to maximum profit attainable.

The milk produced by about 97 percent of NZ dairies is sold through Fonterra Cooperative, which is owned by farmer suppliers. The amount of milk each farm can supply is largely determined by the number of Fonterra shares held. Farmers are paid regularly based on an estimate of the cooperative's returns from the milk, and a final payment is made at the end of the season to reflect actual returns. Thus, in the short run, the output level is targeted, the milk price is taken as given, and the potential on the revenue side is limited. Therefore, an analysis of efficiency in terms of cost minimization is useful.

Cost efficiency is a product of input-oriented technical efficiency and allocative efficiency. Input-oriented technical efficiency represents the ability to produce a given level of output with minimum inputs. Allocative efficiency represents the ability to produce a given level of output with the input bundle that costs the least under market prices at the time. Cost efficiency therefore measures the ability to produce a given level of output for the smallest cost. At an industry level, long-run competitiveness in generic commodity markets depends on low-cost production. At the farm level, then, evaluations of cost-efficiency are crucial to signal the industry's profit potential and identify areas for improvement.

The objective of this study is to evaluate cost efficiency on the part of NZ dairy farms by comparing individual farms' production costs against a common, estimated benchmark of the best-practice frontier and investigating farm characteristics that affect efficiency.

Methodology

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

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

where c_{it} represents the observed costs of firm i in period t, w_{kit} is the kth input price, y_{it} is the output volume, and $\boldsymbol{\beta}$ is a vector of technological parameters depicting the relationship between the input prices, the output, and the minimum cost of production. To be a cost-minimizing solution, the cost function, $c(\cdot)$, must be nonnegative, nondecreasing in input prices and output, homogeneous of degree one, and concave in input prices (Coelli et al. 2005).

This cost function is deterministic because it ignores statistical noise such as measurement error and random shocks that are outside of the control of the operator. Random shocks can have non-negligible effects on agricultural production. A stochastic cost frontier model that incorporates statistical noise can be specified as

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

where v_{it} is an independently and identically distributed random error component that reflects statistical noise and usually is assumed to follow the standard normal distribution with a mean of 0 and constant variance, represented by σ_v^2. The actual cost can be greater than the stochastic minimum production cost due to inefficiency, in which case

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

where u_{it} is a non-negative producer-specific inefficiency error term that follows certain distributional assumptions. If a firm is 100 percent efficient, the inefficiency error term is 0 and the firm is operating on the stochastic cost frontier. Cost efficiency is measured by the ratio of the stochastic frontier cost to the actual cost:

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

The parameters of the stochastic cost frontier can be estimated consistently using maximum likelihood as long as v_{it} and u_{it} are homoskedastic and distributed independently of each other and of the regressors.[1] Producer-specific cost efficiency can be estimated using Battese and Coelli's (1988) point estimator:

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

Relatively few studies have involved empirical analysis of cost efficiency because of a lack of data that include the input prices paid by each firm and have variation in prices. Early applications of the stochastic cost frontier to dairy farming go back to Dawson (1987b), which was 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 as invariant across farms. Another early application was Bravo-Ureta and Rieger (1991), which involved a cross-section of 511 New England dairy farms. In contrast to Dawson (1987b), Bravo-Ureta and Rieger (1991)estimated a Cobb-Douglas stochastic production frontier and recovered the corresponding cost frontier with the dual property.

Following reforms associated with the European Union's Common Agricultural Policy, analysts predicted a reduction in milk prices paid to farmers in Europe (Hennessy, Shalloo, and Dillon 2005), and that potential pressure motivated some cost efficiency studies aimed at improving the survivability of dairy farms. Using an aggregate translog stochastic cost frontier, Revoredo-Giha et al. (2009) examined Scottish dairy farms and found that dairy farms had an average cost efficiency of 58 percent. Alvarez et al. (2008) imposed production heterogeneity and compared cost efficiency of dairy farms by scale, finding that extensive operations had an efficiency ratio of 72 percent while intensive operations had an efficiency ratio of 81 percent. Efficiency scores for Canadian dairy farms ranged from 84 percent to 92 percent (Hailu, Jeffrey, and Unterschultz 2005) when estimated using a translog stochastic cost frontier

[1] Heteroskedasticity in the one-sided inefficiency error term can be handled by the inefficiency effects model adopted in this study because the distribution of u now varies across farms and time (Kumbhakar and Lovell 2000). Neglecting heteroskedasticity in the noise component alone is not a serious problem; one will still obtain unbiased estimates of all parameters that describe the structure of the frontier.

Table 1. Number of Observations by Year

Sample	1999	2000	2001	2002	2003	2004	2005	Total
Pool	187	190	245	180	193	202	203	1,400
North	170	171	211	154	163	172	172	1,213
South	17	19	34	26	30	30	31	187
South Island								
Sample percent	9.1	10.0	13.9	14.4	15.5	14.9	15.3	13.4
Actual percent	14.1	15.1	15.2	16.5	17.3	17.9	18.4	16.4

with local concavity constraints. More sophisticated studies, such as Pierani and Rizzi (2003), which estimated a symmetric generalized McFadden cost function for a panel of Italian dairy farms, and Reinhard and Thijssen (2000), which developed a shadow cost system for Dutch dairying, have limited empirical application because of the complexity involved in computation and the need for a long panel of observations.[2]

Data and Empirical Model

The data set contains farm-level financial and physical information about NZ dairy farms for 1999 through 2005 provided by DairyNZ that was collected through an annual survey conducted by New Zealand Livestock Improvement Corporation and Dexcel using a random sampling procedure. The data set is stratified by region and herd size.

Some observations were dropped prior to the analysis because they lacked a regional code or provided information in a form that could not be used. For example, some farms did not separate the fertilizer and feed expenditures. 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. Observations per farm varied between one and six. Table 1 reveals that South Island dairy farms were moderately underrepresented proportionally in the data set, most likely because farms in the South Island generally are considerably larger than farms in the North Island.

The traditional dairy farming area of New Zealand is in the North Island. It accounted for 62 percent of the nation's livestock in 2013 statistics published by Livestock Improvement Corporation (DairyNZ 2013). The climate in the region is subtropical with consistent year-round rainfall of around 1,200 millimeters and temperatures that average approximately 14 degrees Centigrade. The climate conditions and fertile soils make it one of the most productive grass-growing regions in the world. The South Island's appeal as a site for dairy farming began increasing in the 1980s as access to modern technologies and to water and relatively cheap land on the island became available. Its climate is temperate with an average temperature of 11.5 degrees Centigrade and

[2] Pierani and Rizzi (2003) used a balanced panel of 41 Indian dairy farms observed from 1980 through 1992. Reinhard and Thijssen (2000) used a panel of 434 Dutch dairy farms observed from 1985 through 1995 in which each farm had been observed six times on average. Their complete shadow cost system could not be estimated because it involved too many parameters.

relatively low average annual rainfall of 600 millimeters. Irrigation is used extensively to improve production as the summers are hot and dry. Given the diverse climate conditions and different stages of development of dairy farming in the North and South Islands, we estimate an independent-variable cost frontier for each region.

Functional relationships vary according to the algebraic forms used. The two most commonly applied in technical efficiency analyses are Cobb-Douglas (e.g., Bravo-Ureta and Rieger 1991, Ahmad and Bravo-Ureta 1996, Hadri and Whittaker 1999, Jaforullah and Premachandra 2003, Kompas and Che 2006) and translog (e.g., Dawson 1987a, Kumbhakar and Heshmati 1995, Jaforullah and Devlin 1996, Reinhard, Lovell, and Thijssen 1999, Cuesta 2000, Hadley 2006, Moreira and Bravo-Ureta 2010). Ranking farms by technical efficiency estimates is generally considered to be robust with respect to functional form choice (Maddala 1979, Good et al. 1993, Ahmad and Bravo-Ureta 1996). We considered both Cobb-Douglas and translog forms when constructing our stochastic cost frontiers and tested the robustness of our cost efficiency rankings under several functional forms.

Our model used expenditure per cow, derived from the data by summing all on-farm cash expenditures, as the dependent variable in the cost frontier. Output was represented by average milk solids produced per cow. Because we had no farm-level input-price information, we used average input costs. The cost of labor per farm was obtained by combining total payments to employed labor and adjustments for family labor and then dividing that figure by the number of full-time-equivalent (FTE) workers. The price of feed was derived by dividing the farm's total feed-related expense by the total tons of dry matter supplement used (made on farm and brought in). The average fertilizer cost was obtained by dividing the farm's total expenditure on fertilizer by the quantity of fertilizer purchased. We used effective dairy land in hectares as a proxy for fixed capital.

Our average-input-cost approach may raise some concern about potential endogeneity. The relative quality of inputs used in dairy farming is likely to be affected by farmers' choices and reflected in prices. As noted in Mutter et al. (2013), if quality is cost-enhancing and is not included in the cost equations, a producer who uses relatively high-quality inputs may be incorrectly measured as less efficient than a producer who uses lesser-quality inputs. This bias would result in correlation between the cost variables and the error term in equation 3. Our use of milk solids instead of liters of milk reduces the concern because it controls for output quality. Nonetheless, in a case of uncontrolled endogeneity, consideration could be given to modifications of the Battese-Coelli estimator (Battese and Coelli 1988) proposed by Kutlu (2010) or the generalized method of moments procedure recommended in Tran and Tsionas (2012).

We further transformed the variables to incorporate the linear homogeneity constraint on input prices:

$$
\begin{aligned}
c &= \ln(\textit{variable cost} \,/\, \textit{cow}) - \ln(\textit{fertilizer price}),\\
y &= \ln(\textit{milk solids} \,/\, \textit{cow}),\\
w1 &= \ln(\textit{labor price}) - \ln(\textit{fertilizer price}),\\
w2 &= \ln(\textit{feed price}) - \ln(\textit{fertilizer price}), \text{ and}\\
z &= \ln(\textit{effective dairy hectares}).
\end{aligned}
$$

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

$$(6) \quad c_{it} = \beta_0 + \beta_y \times y_{it} + \beta_1 \times w1_{it} + \beta_2 \times w2_{it} + \beta_z \times z_{it} + \beta_t \times t + \beta_{tt} \times t^2 + v_{it} + u_{it}.$$

The translog cost frontier with the usual symmetry constraint is

$$(7) \quad c_{it} = \beta_0 + \beta_y \times y_{it} + \beta_1 \times w1_{it} + \beta_2 \times w2_{it} + \beta_z \times z_{it} + \beta_{yy} \times (y_{it})^2 + \beta_{11} \times (w1_{it})^2 + \beta_{22} \times (w2_{it})^2 + \beta_{zz} \times (z_{it})^2 + \beta_{12} \times (w1_{it} \times w2_{it}) + \beta_{y1} \times (y_{it} \times w1_{it}) + \beta_{y2} \times (y_{it} \times w2_{it}) + \beta_{z1} \times (z_{it} \times w1_{it}) + \beta_{z2} \times (z_{it} \times w2_{it}) + \beta_{yz} \times (y_{it} \times z_{it}) + \beta_t \times t + \beta_{tt} \times t^2 + v_{it} + u_{it}.$$

Following Kumbhakar, Ghosh, and McGuckin (1991) and Battese and Coelli (1995), we assume that the inefficiency error component, u_{it}, follows a truncated normal distribution in which the mean is a function of some explanatory variables. The variables can be farm characteristics that might have an impact on management performance and/or time variables to capture efficiency variation across time. The resulting specification, as demonstrated in equation 8, allows the distribution of the inefficiency error term to vary for each observation:

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

where $\mathbf{Z}_{it}$ is a vector of capital intensity, livestock quality, a categorical variable for farm size, and the linear time trend and $\boldsymbol{\alpha}$ is the associated vector of parameters to be estimated simultaneously with the parameters in the stochastic cost frontier using maximum likelihood. Capital intensity is measured by the per-cow expenditure on repairs and maintenance plus depreciation. Livestock quality is measured by average livestock market value. We include a mutually exclusive categorical variable, farm size, for herd size that takes a value of 0 for 150 cows or less, a value of 1 for 250 cows or less, a value of 2 for 500 cows or less, and a value of 3 for more than 500 cows.

Table 2 provides descriptive statistics of the variables. Considerable regional variation is evident in the means, standard deviations, and ranges. South Island dairy farms, on average, are larger, are more capital-intensive, and generate greater livestock values and productivity than farms in the North Island but also pay more for inputs.

Results and Discussion

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

Table 2. Summary Statistics of Variables

Variable	Region	Mean	Std. Dev.	Min.	Max.
Variable cost per cow (dollars)	North	960	234	392	2,211
	South	1,159	316	667	2,750
Milk solids per cow (kilograms)	North	312	50	140	559
	South	354	56	218	533
Labor price (dollars per FTE)	North	32,679	10,006	10,250	106,282
	South	35,643	9,117	13,315	70,135
Feed price (dollars per ton of dry matter)	North	236	193	41	1,840
	South	247	211	45	1,500
Fertilizer price (dollars per 100 grams)	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 per cow (dollars)	North	171	81	39	881
	South	221	108	48	756
Average livestock value (dollars)	North	1,098	286	315	2,866
	South	1,171	344	353	2,450
Size categories	North	1.17	0.80	0	3
	South	1.78	0.85	0	3

For the North Island, the Cobb-Douglas functional form is rejected in favor of the translog based on a likelihood-ratio test.[3] For the South Island, however, we cannot reject the null hypothesis that the underlying functional form is Cobb-Douglas, which implies that the cost function representing the South Island sample is more restrictive. Cobb-Douglas is favored for its simplicity but requires us to impose unrealistically restrictive assumptions on the functional relationships.[4] The translog model, on the other hand, is much more flexible but many of the resulting coefficients are insignificant because of incorporation of second-order parameters.

Motivated by Ahmad and Bravo-Ureta (1996) and Reinhard, Lovell, and Thijssen (2000), we performed a final set of estimations using a simplified translog model for both regions, which eliminated the coefficients that were jointly insignificant in a likelihood-ratio test. Those results are presented in Table 4.

In addition to the constraints imposed prior to estimation, a well-behaved cost function should be concave and nondecreasing in input prices and

[3] The results for the translog stochastic cost frontiers are presented in an appendix that is available from the authors.

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

Table 3. Cobb-Douglas Stochastic Cost Frontier Estimates

	North	South		North	South
β_0	–3.3414***	–3.1885***	α_0	–1.3737***	–1.6599***
β_y	0.3333***	0.3189**	$\alpha_{capital\ intensity}$	0.2044***	0.2789***
β_1	0.6531***	0.7152***	$\alpha_{livestock\ quality}$	0.1479***	0.0200
β_2	0.1558***	0.1252***	$\alpha_{farm\ size}$	–0.1004***	–0.1079***
β_z	–0.0479**	–0.0025	α_t	–0.2173***	0.3311**
t	0.1414***	–0.3164***	α_{tt}	0.0245***	–0.0144
β_{tt}	–0.0179***	0.0134			
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.0392***	0.0437***	$\Upsilon = \sigma_u^2 / \sigma^2$	0.0135**	0.0000

	North	South
Log likelihood	242.213	27.415
Likelihood ratio test of the one-sided error	284.439	51.478

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

output. Concavity implies that the conditional input demand functions cannot slope upward (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 of the regional (island) frontiers, the eigenvalues of the entire Hessian matrix are negative for each observation, and thus the concavity property is satisfied at all sample data points. For monotonicity, we examined the non-negativity of the estimates of the conditional input demand and the marginal cost. For the North Island frontier, less than 1.5 percent of the observations violate monotonicity with respect to feed price and less than 10 percent violate monotonicity with respect to output. For the South Island frontier, there is no violation of monotonicity with respect to input prices; 20 percent of the observations violate monotonicity for output. This relatively high incidence of violation of monotonicity against output may be related to our use of milk solids as the sole measure of on-farm output. However, other sources of dairy revenue are negligible, accounting for less than 10 percent of annual incomes on average.

All of the estimated coefficients associated with the time trend variables are significant. These results suggest that the cost frontiers are shifting out at a decreasing rate, which confirms an observed erosion of competitiveness, and inefficiencies are decreasing over time, meaning that dairy farmers were able to improve cost efficiency as they accumulated management experience.

In terms of cost inefficiency, the North Island results show that farms that are relatively capital-intensive or have higher-value livestock are associated, *ceteris paribus*, with lower efficiency ratings. Farm size has a negative estimated coefficient of –0.0941, indicating that larger farms tend to have better cost efficiency scores than smaller ones when holding everything else constant. The same applies to South Island dairies with one exception—livestock quality has no significant association with inefficiency.

Table 4. Simplified Translog Stochastic Cost Frontier Estimates

	North	South		North	South
β_0	21.8218***	46.1100***	α_0	−1.7567***	−0.5364
β_y	−9.4632***	−16.9705***	$\alpha_{capital\ intensity}$	0.2133***	0.3379***
β_1	1.7920***	0.7122***	$\alpha_{livestock\ quality}$	0.1882***	−0.0054
β_2	−1.0360***	—	$\alpha_{farm\ size}$	−0.0941***	−0.0616*
β_{yy}	0.8254***	1.5369***	α_t	−0.1823***	−0.5329**
β_{11}	−0.0699***	—	α_{tt}	0.0200***	0.0633**
β_{22}	−0.0442***	—			
β_{zz}	0.0526***	0.0656	$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.0368***	0.0396***
β_{12}	0.0847***	—	$\Upsilon = \sigma_u^2 / \sigma^2$	0.0039**	0.0380
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**			

	North	South
Log likelihood	284.759	37.716
Likelihood ratio test of the one-sided error	298.131	49.095

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level.

Table 5 summarizes the results of our cost efficiency estimates. North Island dairy farms are estimated to have an average cost efficiency of 83 percent relative to the North Island frontier, and South Island dairies are estimated to have an average cost efficiency of 80 percent relative to the South Island frontier.[5] Within the North Island, the Waikato region has the best average cost efficiency; the mean score is 84.5 percent and one-quarter of the sampled farms scored 93 percent or higher. This result indicates that the average annual expenditure on variable inputs in the region would decline 15.5 percent if all of the farms in the Waikato area became fully efficient.

We analyzed the robustness of the cost efficiency estimates for the Cobb-Douglas, translog, and simplified translog forms by calculating Spearman rank correlation coefficients, which are presented in Table 6. The North Island correlations range from 0.67 to 0.98, indicating that the choice of functional form has little effect on efficiency rankings for this data set. The range of

[5] This does not imply that South Island dairy farms were doing worse than North Island dairy farms in absolute terms. Efficiency is a relative concept and scores are relative to the estimated frontier, which represents the current best practice. Efficiency estimates obtained under separate frontiers (or reported in different studies) are not comparable with each other. In addition, there was no area code for the South Island farm observations so we could not analyze specific sub-regions like we did for the North Island.

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	1,213	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 of Spearman Rank Correlation Coefficients

	Simplified Translog	Translog	Cobb-Douglas
North Island Frontier			
Simplified Translog	1		
Translog	0.6708***	1	
Cobb-Douglas	0.9818***	0.7017***	1
South Island Frontier			
Simplified Translog	1		
Translog	0.8576***	1	
Cobb-Douglas	0.2732***	–0.1618**	1

the South Island correlations is significantly wider—0.86 for the translog / simplified translog models but only 0.27 for the Cobb-Douglas / simplified translog models. The log-likelihood function thus supports use of the simplified translog form for the South Island cost frontier.

Conclusion

To the best of our knowledge, this is the first study of the cost efficiency of dairying farming in New Zealand. Using an unbalanced panel of farms observed from 1999 through 2005, we estimated separate stochastic cost frontiers for the North Island and South Island. When we examined the properties of the estimated cost frontiers, we found no violation of the concavity property and relatively few violations of monotonicity, an indication that the cost functions are reasonably well-behaved.

The average cost efficiency for dairies in the North Island overall relative to its frontier is about 83 percent. Regionally, Waikato ranks highest with a mean efficiency score of 84.5 percent, followed by Bay of Plenty (84.1 percent), Taranaki (81.7 percent), and Northland and Lower North (80.7 percent). For South Island dairy farms, the cost efficiency distribution is more dispersed. The overall mean efficiency score is 80 percent relative to its frontier and 35 percent of the sampled farms have efficiency scores that exceed 92 percent.

The inefficiency error term was modeled as a truncated normal distribution with the mean as a function of farm characteristics. The parameters were estimated simultaneously with those in the stochastic cost frontier by maximum likelihood. The results identify significant negative relationships between cost efficiency and capital intensity and livestock quality and a positive relationship between cost efficiency and herd size.

Our results indicate that there are opportunities for NZ dairies to improve cost efficiency and thus competitiveness. Looking ahead, with increasing pressure on water supplies, rising land costs, and implementation of New Zealand's emission trading scheme, NZ dairy farmers will likely look to advanced technologies that economize on inputs and contribute to efficient management systems to improve their ability to compete globally. Collection of additional farm-level data will allow for an ongoing research program focused on understanding how these challenges will impact the competitiveness of New Zealand's dairy industry. Future studies also could separate the effects of individual inputs (such as nitrogen, energy, and water) as more detailed data sets become available. Such research would benefit not only the industry but also policymakers charged with designing a competitive and sustainable dairy farming protocol.

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