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Technical efficiency and technological gap of New Zealand dairy farms: a stochastic meta-frontier model

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Abstract The New Zealand North and South Island dairy farms differ in terms of climate, soil type and farming history. Using stochastic frontier models, an unbalanced panel of 1,294 dairy farms for the period between 1998/99 and 2006/07 is employed to test the hypothesis that the two regions share the same technology (The New Zealand dairy season runs from 1 June to 31 May each year). Results indicate heterogeneity in production technology across farms located in different islands. A meta-frontier model proposed by Battese et al. (J Product Anal 21:91–103, 2004) and O'Donnell et al. (Empir Econ 34:231–255, 2008) is therefore used to calculate the technological gap and compare on-farm technical efficiency.

Keywords Meta-frontier model · Stochastic production frontier · NZ dairy farming

JEL Classification D24 · L23 · Q12 · Q16

1 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 in the areas of breeding, pasture management, animal health and overall farm management. But to keep pace with the increasing global demand and maintaining a competitive edge among those often heavily subsidized dairy producers in other developed countries, productivity growth continues to be an important policy objective. On top of that, agriculture is scheduled to be included in NZ's emissions trading scheme (ETS) by 2015, further increasing the importance of efficient resource utilisation (Cooper et al. 2012).

Historically, the North Island of New Zealand, Taranaki and Waikato in particular, has been the main dairy farming area given its temperate climate, accounting for 64 % of the national dairy herd. Modern technology, access to water, and relatively cheap land has opened up sizable areas of the South Island to dairy farming. Farms located in the South Island are substantially larger than those in the North. Jaforullah and Devlin (1996) point out two potential contributing factors: (1) the conversion of sheep and beef farms, predominantly in the lower South Island, initiated by corporate companies in the late 1980s; and (2) the involvement of large, publicly listed companies investing in dairy farming in the South Island.

But be that as it may, a relationship between farm size and efficiency has not been established within the limited existing empirical literature. Investigations into NZ dairy farming efficiency were performed using both non-parametric data envelopment analysis (Jaforullah and Whiteman 1999; Jaforullah and Premachandra 2003; Rouse et al. 2009) and parametric stochastic frontier analysis(SFA; Jaforullah and Devlin 1996; Jaforullah and Premachandra 2003; Jiang and Sharp 2008). Average efficiency estimates range from 86 to 95 %. By incorporating a regional dummy into their stochastic production

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frontier (SPF), only (Jiang and Sharp 2008) found South Island dairy farms had slightly better efficiency performance than those located in the North Island.

Surveys of the empirical literature indicate SFA is the most widely adopted approach for dairy farming efficiency studies because of the non-negligible random factors involved in such agricultural production (Battese 1992; Coelli 1995; Bravo-Ureta et al. 2007). Previous NZ studies mentioned above were all based on relatively small cross sectional datasets pooled across regions. The question of whether recently developed South Island dairy farms share the same technology with historically established North Island farms arises. If the production technology is indeed heterogeneous, then using a single production frontier will inappropriately label such unobserved difference as inefficiency. There is also no exploration of farm operating factors contributing to better performance and the use of cross sectional data rules out the possibility of modelling technical change (TC) over time.

Procedures to determine whether technologies differ can be generally categorized into the Meta-Frontier (MF) model (Battese et al. 2004; O'Donnell et al. 2008) and the latent class model (Caudill 2003; Greene 2002; Orea and Kumbhakar 2004). Without utilizing pre-existing sample separation information, the latent class model controls production heterogeneity by parameterizing prior probabilities of class membership for each observation. And instead of being referenced against a unique technology, the efficiency measurement takes into account technologies from every class by using the estimated posterior class probabilities as weights. The MF model, on the other hand, handles technological difference through exploiting exogenous sample separation information. An application of this model is presented for dairy farms in three Southern cone countries (Moreira and Bravo-Ureta 2010).

The objective of this paper is to investigate technological differences between NZ North Island and South Island dairy farms using the stochastic MF model under a panel data framework. The rest of the paper is organized as follows: Sect. 2 explains the methodologies. Section 3 describes the data and empirical models. A discussion of the results follows in Sect. 4. Finally, the principle conclusions are drawn along with their policy implications in Sect. 5.

2 Methodological framework

To test the hypothesis that North and South Island farms have the same technology, three SPFs are estimated, two regional frontiers and one frontier based on the pooled sample, all under the assumption that farmers maximize expected profits with respect to anticipated output.[1] The SPF takes the following form:

$$y_{it} = f(X_{it};\beta)\cdot \exp\{v_{it}-u_{it}\} \quad i=1,2,\cdots,N \quad t=1,2,\cdots,T \tag{1}$$

where: y_{it} denotes the observed output produced by dairy farm i in year t; X_{it} denotes the $1 \times K$ vector of inputs and other explanatory variables associated with that farm; β represents the $K \times 1$unknown parameters to be estimated, which is common for all farms using the same production technology. The most commonly used mathematical production functions $f(\cdot)$in the literature (Battese 1992; Bravo-Ureta et al. 2007) are Cobb–Douglas (CD) and translog (TL).

The composite error term consists of the standard noise component v_{it} which is, as usual, assumed to be independently and identically distributed normal random variable with mean zero and constant variance, i.e. $iid \sim N(0, \sigma_v^2)$. The u_{it} is a one-sided, non-negative random variable representing technical inefficiency. Following Battese and Coelli (1995), we assume it is independently distributed such that

$$u_{it} \sim N^{+}(\gamma' Z_{it}, \sigma_u^2) \tag{2}$$

where: Z_{it} is a $1 \times Q$ vector of explanatory variables that may influence on-farm efficiency performance, γ is the associated vector of parameters to be estimated. Thus, the inefficiency effects in the frontier model have distributions that vary with Z_{it} so they are no longer identically distributed across farms and over time. If $Z_{it} = 1$for all t and $\gamma_2 = \cdots = \gamma_Q = 0$, this model collapses to the truncated normal stochastic frontier model with constant mode γ_1, which in turn collapses to the half normal stochastic frontier model with zero mode if $\gamma_1 = 0$. Each of these restrictions is testable.

Simultaneous estimation of the parameters in Eq. (1) and (2) can be obtained using the maximum likelihood method. The resulting farm specific technical efficiency (TE) relative to its own regional SPF is predicted as proposed in Battese and Coelli (1988):

$$TE_{it}^{j} = \frac{y_{it}^{j}}{f(X_{it}^{j};\beta^{j})\cdot \exp\{v_{it}^{j}\}} = E\left[\exp(-u_{it}^{j})\middle| v_{it}^{j}-u_{it}^{j}\right] \quad j = North, South \tag{3}$$

The same technology hypothesis can be tested by a likelihood ratio (LR) test upon the estimation of the two regional frontiers and the pooled sample frontier. If the null hypothesis that the stochastic frontier for the pooled data is rejected in favor of the separate regional frontiers, then the

[1] Given this assumption, the simultaneous-equation bias often associated single-equation production models is avoided (Zellner et al. 1966).

regional TE estimates will not be comparable with each other. One could adopt the MF framework to explore performance differences across North Island and South Island.

The meta-production function was first introduced by Hayami (1969) and Hayami and Ruttan (1970, 1971, p.82) as the envelope of commonly conceived neoclassical production functions. Battese and Rao (2002) operationalised the standard meta-production function in a SPF framework and Battese et al. (2004) refined this approach to make sure the MF envelops the separate SPFs for the different groups involved. A wider MF theoretical framework is established by O'Donnell et al. (2008) which invokes both parametric and non-parametric approaches.

The MF production function presents the potential technology available to the industry as a whole and is defined by Battese et al. (2004) as an overarching function of a given mathematical form that encompasses the deterministic components of the stochastic frontier production functions for the farms that operate under the different technologies involved. The MF production function can be expressed as

$$y_{it}^{*} = f(X_{it}; \beta^{*}) \tag{4}$$

Where β^{*} denotes the vector of parameters for the MF production function such that the predicted output from the MF is at least as large as the predicted value from the different regional frontiers constructed using all observations. The β^{*} parameters can be obtained by minimizing the sum of the logarithmic radial distance between the MF and the j-th regional frontier evaluated at the observed input vector (Moreira and Bravo-Ureta 2010).

The observed output for farm i in region j at year t can now be expressed as

$$y_{it}^{j} = \exp(-u_{it}^{j}) \times \frac{f(X_{it}^{j}; \beta^{j})}{f(X_{it}^{j}; \beta^{*})} \times f(X_{it}^{j}; \beta^{*}) \exp(v_{it}^{j}) \tag{5}$$

The first term on the right-hand side is the TE relative to the j-th regional stochastic frontier. The second term is called the technology gap ratio (TGR) by Battese and Rao (2002) and metatechnology ratio (MTR) by O'Donnell et al. (2008). It represents the difference between the best current technology, available to farms in region j, relative to the best technology available for the industry as a whole.[2] The product of farm specific regional TE and MTR gives the MF TE, denoted by TE_{it}^{*j}, which is the TE performance evaluated using the MF and is defined as the ratio of the observed output to the stochastic MF output:

$$TE_{it}^{*j} = \frac{y_{it}^{j}}{f(X_{it}^{j}; \beta^{*}) \exp(v_{it}^{j})} = TE_{it}^{j} \times MTR_{it}^{j} \tag{6}$$

3 Data and empirical models

The data for this study were provided by DairyNZ, formed in November 2007 after the merger of Dairy InSight and Dexcel. DairyNZ owns and manages *DairyBase*® on behalf of NZ dairy farmers, which is a web-based package for recording and reporting standardized dairy farm business information—both physical and financial. *DairyBase*® is available to all levy-paying New Zealand dairy farmers, participation is voluntary and therefore is likely to contain farms with above average performance.

Figure 1 shows the comparison of annual sample average per cow milksolids with the statistics published by NZ Livestock Improvement Corporation (LIC). The sample divergences from the national figures are relatively small and the patterns are systematic across both regions. The mean per cow milksolids production in the sample is higher than the national average in all years.

The total number of observations in each year is summarized in Table 1 below together with the actual proportion of South Island dairy farms. The number of observations available per farm varies from a low of one and a high of six. This study uses a sample of 1,294 owner-operator dairy farms between the 1998/99 season and the 2006/07 season; 1,042 farms are located in the North Island and 252 are located in the South Island. This is the first time a dataset of this nature and size has been available in NZ.

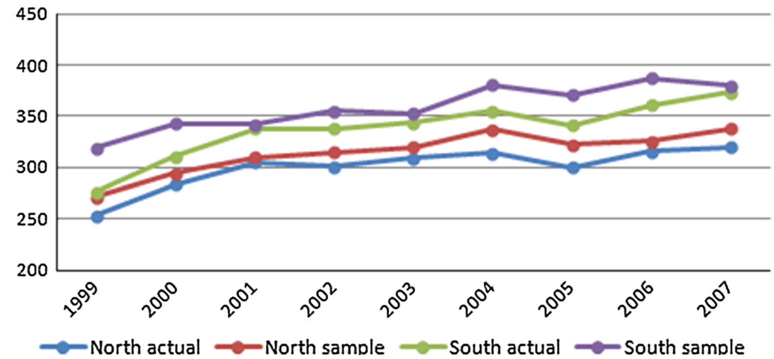
3.1 The variables

Dairy production involves the use of a variety of inputs. There is no consensus on what inputs should be included in a production frontier and how one should measure those inputs and output(s). Judgement on the relevant variables hinges on a combination of dairy production knowledge, review of past literature, a balancing between reality and simplicity, as well as compromises on data availability.

Upon examination of the variables and in consultation with DairyNZ, milksolids in kilograms (kgs) was retained as the measure of output. Milksolids are what farmers get paid for in NZ, and for this sample, on average, 91 % of gross farm revenue is derived from milk sales. Inputs that are considered to be imperative include livestock, labour, capital, veterinary services, feed, fertilizer and electricity. Livestock is evaluated by the number of maximum cows milked at any time during the year. Labour is measured in

[2] O'Donnell et al. (2008) pointed increases in the (technology gap) ratio imply decreases in the gap between the regional frontier and the meta-frontier, the use of MTR instead of TGR helps avoid the confusion.

Fig. 1 Annual average milksolids (kgs) per cow



total working hours. In line with similar studies (Jaforullah and Devlin 1996; Jaforullah and Whiteman 1999; Hallam and Machado 1996; Mbaga et al. 2003; Pierani and Rizzi 2003; Kompas and Che 2006), capital is approximated by the closing book value of dairy operating assets, which include: land and buildings evaluated at the current market rate, machinery and vehicles, etc.[3] Veterinary services, feed, fertilizer and electricity are all gauged by the corresponding expenditures. For farms with irrigation, irrigation expenses are included in electricity.

Since all inputs, except labour, are measured in value terms, Hadley (2006) pointed out the possibility of conflating TE with allocative efficiency; this can be avoided by making the assumption that all farmers face similar input prices.[4] The value of one is assigned for zero observations.[5] Expenses on veterinary services, feed, fertilizer and electricity were deflated using the relevant farm expenses price index published by Statistics NZ every quarter, so they are measured in 1998/99 constant dollars. All inputs and output were divided by the number of maximum cows milked and are therefore measured in per cow terms.[6]

Motivated by Reinhard and Thijssen (2000), Brümmer and Loy (2000), Kompas and Che (2006) and Hadley (2006), we examined the following operating factors which can potentially impact individual farm efficiency performance: farm size given by the number of maximum cows milked in logarithmic terms, dummies for shed technology, and intensity as measured by the number of maximum cows milked per hectare.

3.2 Descriptive statistics

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 differences among North and South Islands. South Island dairy farms have higher livestock productivity; on average, a cow produces 366 kgs of milksolids in a season, compared with only 315 kgs in the North Island. But they also consume more of every input with the exception of labour. The average farm located in the South Island is substantially larger and less intensive, a larger percentage employed rotary sheds and irrigation compared to the North Island.[7]

A trend towards bigger farms is evidenced in the data for both regions across the observed period, the average herd size increased by nearly 56 % (from 218 to 339) and output was nearly doubled (from 61 044 to 119 508 kgs milksolids). Milksolids production per cow rises 25 % in the

[3] Capital stock itself is distinct from the flow of capital services obtained from it, and it is the later that should represent 'capital' in production functions. But data dictate what we can do; there is no detailed information to reflect capital stock durability and composition. The use of the capital stock concept instead of the service flow concept may bias the estimation results if the capital service flow is a function of capital vintage as shown by Yotopoulos (1967). This is especially a concern with the expansion that has occurred in the South Island, as the use of capital stock places more weight on the more durable asset, such as irrigation and new land purchased. It would be particularly useful if more information on capital is collected in future surveys.

[4] This was a reasonable assumption to make in the NZ dairy inputs market.

[5] Four farms in the sample have zero value observations for electricity expenses, 2 farms have zero observations for feed expenses, and 33 have zero observations for fertilizer expenditure. Given that the "zero cases" are not a significant proportion in the sample, and they are perceived to be useful in the estimation of parameters which are common to all farmers, we adopted the approach of including "zero cases" by using the value of one. See Battese (1997) for a more detailed discussion on handling a significant proportion of "zero observations" when estimating agricultural production functions.

[6] This is similar to Mbaga et al. (2003), Saha and Jain (2004), and Hailu et al. (2005). The production unit is the 'cow' rather than the 'farm'. This specification implicitly assumes that the per-cow technology is invariant with respect to cows. It is also equivalent to impose CRTS on a production function with the 'farm' as the production unit and the 'cow' as an input on the right hand side. We acknowledge that for those who prefer to have the latter, the returns to scale (RTS) in this per-cow specification is not RTS in the usual sense, they might characterize changes in inputs per cow as changes in inputs mix. Therefore a researcher might want to consult on the production unit in practice before the specification of a production function.

[7] Irrigation data was not collected for season 2001/02 so the variable cannot be used in constructing the frontier.

Table 1 Number of observations by year

Observations	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Pool	216	208	268	211	208	223	218	202	318	2072
North	197	182	232	178	178	191	183	144	232	1,717
South	19	26	36	33	30	32	35	58	86	355
Sample south %	8.8	12.5	13.4	15.6	14.4	14.4	16.1	28.7	27.0	17.1
Actual south %	14.1	15.1	15.2	16.5	17.3	17.9	18.4	19.1	19.7	17.0

North Island and 19 % in the South Island respectively. Simultaneously, the average on-farm capital experienced dramatic growth (196 % in the North Island and 262 % in the South Island). In comparison, the change in labour is substantially smaller (14 % increase in the North and 40 % increase in the South). Capital expansion can be attributed to the surge of farmland price and escalation of on-farm capital investments, the later drives up the electricity bill for an average farm by 74 %.[8] But electricity expenses in per cow term is stabilized at around $23 over the sample period. An improvement in on-farm energy use can be implied when we consider this fact together with the livestock productivity growth mentioned before. The data also reveals more adoption of relatively advanced shed technology over time.

3.3 The empirical model

Different algebraic forms of $f(\cdot)$give rise to different models. CD and TL are the two most commonly applied production functions in empirical literature surveys (Battese 1992; Bravo-Ureta et al. 2007). Studies using CD include Battese and Coelli (1988), Bravo-Ureta and Rieger (1991), Ahmad and Bravo-Ureta (1996), Hadri and Whittaker (1999), Jaforullah and Premachandra (2003), and Kompas and Che (2006); and those using TL are: Dawson (1987), Kumbhakar and Heshmati (1995), Jaforullah and Devlin (1996), Reinhard et al. (1999), Cuesta (2000), Hadley (2006) and Moreira and Bravo-Ureta (2010).

Maddala (1979), Good et al. (1993) and Ahmad and Bravo-Ureta (1996) argued that TE measures were robust to functional form choice. CD is therefore used for its simplicity given the research objective of this study.[9]

The empirical SPF is described as the following:

$$\ln\left(\frac{millsolids}{cows}\right)_{it} = \beta_0 + \beta_1 \cdot \ln\left(\frac{labour}{cows}\right)_{it} + \beta_2 \cdot \ln\left(\frac{captial}{cows}\right)_{it} + \beta_3 \cdot \ln\left(\frac{veterinary}{cows}\right)_{it} + \beta_4 \cdot \ln\left(\frac{feed}{cows}\right)_{it} + \beta_5 \cdot \ln\left(\frac{fertilizer}{cows}\right)_{it} + \beta_6 \cdot \ln\left(\frac{electricity}{cows}\right)_{it} + \beta_7 \cdot time\,trend(t) + \beta_8 \cdot t^2 + v_{it} - u_{it}$$

where: $i = 1, 2,\ldots,N$ denotes farm; $t = 1, 2,\ldots, 9$ denotes year; $v_i \sim iidN(0, \sigma_v^2)$; and $u_{it} \sim N^+(\gamma_o + \gamma_1 \cdot \ln(cows_{it}) + \gamma_2 \cdot rotary_{it} + \gamma_3 \cdot other_{it} + \gamma_4 \cdot intensity_{it} + \gamma_5 \cdot t, \sigma_u^2)$.

Technological change often cause economic relationships, especially production functions, to change over time (Coelli et al. 2005, p213). This is usually accounted for by including time trends in the models. The nature of technological change is hypothesized to be smooth and time-varying and is captured by parameters β_7 and β_8, whereas changes in efficiency of the average farm through the period analysed is picked up by γ_5. Theγ's in the inefficiency effects model are estimated simultaneously with the β's in the production frontier by maximum likelihood method.

4 Empirical results and analysis

4.1 Production frontier estimates and specification tests

Upon estimation of the parameters with the *FRONTIER 4.1* program (Coelli 1996), Table 3 presents the results. In all three frontiers, the estimated parameters on inputs have positive signs and most of them are highly significant, implying the production function is well behaved. The null hypothesis that the one-sided technical inefficiency error term is insignificant can be rejected at the 1 % level given the corresponding Kodde and Palm critical value of 17.755 with 7 degrees of freedom.

The estimated coefficient on "labour" is significant at the 10 % level only in the North Island, and its magnitude is more than three times that of the South. The estimated coefficient on "electricity" in the North Island is more than twice of the electricity-output elasticity obtained for the

[8] The average dairy land price went up by 91 % over this sample period.

[9] The correlation coefficients of TE estimates obtained between CD and TL frontiers were in the range of 0.98 and 0.88 for this study.

Table 2 Descriptive statistics (2,072 observations for 1,294 farms)

Variables	Regions	Mean	Std. dev.	Min	Max
Peak cows milked	North	248	135	43	1,510
	South	399	220	55	1,650
Milksolids (kgs)/cow	North	315	57	84	1,382
	South	366	52	219	533
Labour (h)/cow	North	21.8	12.7	7.6	450.9
	South	21.1	9.2	9.2	85.7
Assets $/cow	North	10,323	4,757	1,208	79,339
	South	10,344	5,442	1,449	63,750
Veterinary $/cow	North	74	25	13	222
	South	80	28	20	211
Feed $/cow	North	166	92	0.006	808
	South	231	119	3.023	818
Fertilizer $/cow	North	114	50	0.002	438
	South	130	59	0.002	402
Electricity $/cow	North	21	8	0.002	92
	South	30	25	0.003	214
Intensity (cows/hectare)	North	2.71	0.52	0.62	4.95
	South	2.62	0.59	1.1	4.36
Irrigation = 0 if not irrigated					
1 if <30 % irrigated	North	0.07	0.36	0	2
2 if >30 % irrigated	South	0.6	0.92	0	2

		Herringbone	Rotary	Other	
Shed type (%)	North	89.63	9.26	1.11	100
	South	61.41	37.18	1.41	100

South. On the other hand, the parameter associated with "capital (assets)" in the South Island frontier is close to two times that of the North, and it also has a bigger fertilizer-output elasticity. It appears to be that labour and energy play relatively more important roles in dairy production for the North, and South Island dairy farming depends heavily on capital and fertilizer, this result is in accordance with what was observed before, viz. more dairy farms in the South Island use capital intensive irrigation and rotary shed technology than North Island.

The parameter estimates for time trends in the North Island SPF are significant at the 1 % level, implying the existence of a non-linear technological change effect that decreases with time:

$$\frac{\partial \ln y}{\partial t} = 0.0611 - 0.009 \cdot t \quad t = 1, 2, \cdots, 9$$

The increase in output y in the season of 1998/99 due to technological change, is estimated to be 5.21 %. This percentage change in output decreases at an annual rate of 0.9 %, which leaves us an average percentage change in milksolids produced per cow of 1.6 %, over the entire sample period under analysis. Whereas in the South Island frontier, only the parameter of the linear time trend has been estimated with statistical significance, suggests the nature of technological change is constant and negative.

In terms of the parameter estimates in the inefficiency effects model, the factors that appear to have statistically significant explanatory power on efficiency performance in North Island are: logarithms of herd size, farming intensity and dummy for other type of shed relative to herringbone. More efficient farms are bigger in herd size, more intensified, and employ herringbone shed over other unidentified type of shed technology. The case for South Island is different. Over time, the average farm was found to move closer to the current production frontier, as reflected in the parameter estimate associated with the time trend variable which is statistically significant at the 1 % level. This kind of improvement is not evident for the average North Island farm. Farming intensity is also negatively associated with efficiency in the South Island, as opposed to the positive relationship portrayed by the North Island frontier estimates.

Mean TE estimates vary between the regional frontiers. North Island dairy farms are shown to have a mean TE of 92 %, and the South Island dairy farms' average efficiency score is 82 %. This does not imply that South Island dairy farms have lower TE performance than the North as these

Table 3 Stochastic production frontier estimates

Variables	Parameters	Pooled	North	South
One	β_0	4.3798***	4.3069***	4.8827***
Labour/cow	β_1	0.0154	0.0189*	−0.0055
Assets/cow	β_2	0.0401***	0.0475***	0.0800***
Veterinary/cow	β_3	0.0898***	0.0883***	0.0786***
Feed/cow	β_4	0.0714***	0.0641***	0.0630***
Fertilizer/cow	β_5	0.0138***	0.0116***	0.0186***
Electricity/cow	β_6	0.0313***	0.0390***	0.0166**
$t = 1,\ldots, 9$	β_7	0.0538***	0.0611***	−0.0667**
t^2	β_8	−0.0036***	−0.0045***	0.0022
One	γ_0	2.0365***	2.6976***	0.5118***
ln(cows)	γ_1	−0.5421***	−0.4567***	−0.0018
Rotary shed	γ_2	−0.1896**	0.0661	−0.0081
Other shed	γ_3	0.2035	0.4435***	−0.0435
Intensity	γ_4	−0.2674***	−0.6075***	0.0329*
t	γ_5	−0.0082	−0.0009	−0.0710***
	$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.1597***	0.1379***	0.0183***
	σ_u^2/σ^2	0.9272***	0.9264***	0.8455***
	Mean TE	0.924	0.921	0.820
	LLF	1234.21	1065.02	288.36
	LR test of u	213.97	222.82	37.69

* Estimated coefficients significant at the 10 % level

** Significant at 5 %

*** Significant at 1 %

two scores are not comparable to each other unless the underlying production technology is the same. But if the technology is the same, then one should use the results from the pooled sample frontier.

The log likelihood function from the pooled data frontier is 1,234.21; the sum of the log likelihood functions of the two regional frontiers is 1,353.38; a LR test gives a test statistic around 238, compared with a critical value of 33 for χ^2_{17} at the 1 % significance level, we can easily reject the null in favour of the alternative hypothesis that North and South Island dairy farms employ different technologies.

The MF framework therefore should be adopted in order to compare efficiency performance across regions. One would obtain a biased production frontier and TE estimates if the regional technological differences are not taken into account.

Additionally, if the farming technology exhibits constant returns to scale (CRTS) then the technological parameters associated with all inputs will sum to one in both regional frontiers, i.e. $\sum_{k=1}^{6} \beta_k^j = 1 \quad for \quad \forall \quad j = north, south$. A CRTS in this specification means the milksolids produced by each cow will double if one doubles the inputs per cow. This restriction was imposed on the estimated regional frontiers and LR tests easily reject the null hypotheses. The estimated returns to scale are in fact less than one for both the North Island and South Island, implying decreasing returns to scale (DRTS). The output per cow responds at a lower rate to the rate of increase of per cow inputs, probably due to the biological production capacity constraint of the livestock.

4.2 MTR and TE analysis with the meta-frontier

As mentioned in the previous section, the MF technological parameters are obtained using linear programming with the *Shazam* software. Turn out they correspond to the parameter estimates for the South Island frontier, meaning the dairy production technology employed in the South Island is more advanced than the technology used in the North. The South Island production frontier defines the potential technology available for the whole dairy farming industry in NZ and it is above the North production frontier as depicted in Fig. 2, where point A illustrates a farm in the North Island.

The MTR, defined in Eq. (5), is therefore equal to 1 for every dairy farm in the South Island; the average MTR for farms in the North Island is about 75 % with a standard deviation of 11 %. These results imply that, for the North Island, the maximum output a dairy farm can produce using its inputs is, on average, only about 75 % of the maximum output that could be produced using the same inputs and the technology available in the South Island.

TE, relative to the MF as denoted by TE*, is estimated for each farm in the North Island sample according to Eq. (6), i.e. $TE_i^{*North} = TE_i^{North} \times MTR_i^{North}$. The South

Fig. 2 Illustration of estimated south and north frontiers

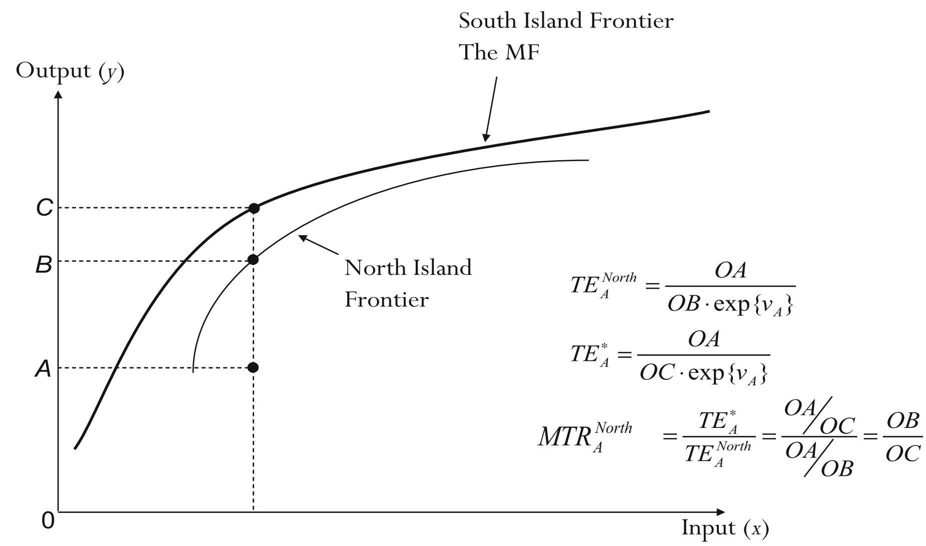


Table 4 Descriptive statistics and frequency distribution of TE and MTR estimates

Stats	TE_{north}	MTR_{north}	TE_{north}*	$TE_{south} = TE_{south}$*
Mean	0.9214	0.7540	0.6952	0.8196
Std. dev.	0.05381	0.1115	0.1129	0.1229
Min	0.4142	0.5311	0.2761	0.4444
Max	1	0.9790	0.9263	0.9841
Level				
(0.9–1.0)	1349 (78.6 %)	39 (2.3 %)	9 (0.5 %)	126 (35.5 %)
(0.8–0.9)	307 (17.9 %)	722 (42.1 %)	351 (20.4 %)	87 (24.5 %)
(0.7–0.8)	48 (2.8 %)	355 (20.7 %)	542 (31.6 %)	71 (20.0 %)
(0.6–0.7)	6 (0.3 %)	400 (23.3 %)	406 (23.6 %)	52 (14.6 %)
Below 0.6	7 (0.4 %)	201 (11.7 %)	409 (23.8 %)	19 (5.4 %)

Island farm specific TE estimate with reference to the MF is equivalent to that evaluated under the regional frontier. Table 4 summarizes the resulting efficiency and MTR estimates.

The North Island has an average TE* estimate of 70 % relative to the MF between 1999 and 2007; the most inefficient farm has a TE* score of only 28 %, whereas the most efficient farm is 93 %. The South Island's mean TE* is 82 %, substantially higher than the North, and its efficiency range is narrower, from a minimum of 44 % to a maximum of 98 %.[10]

If one compares the TE estimates relative to their own regional frontiers, the conclusion is contradictory to what we observed before and therefore misleading. The North Island's average dairy farm has a TE score of 92 % with reference to its regional frontier, higher than the South's average, and 79 % of the farms have an efficiency level >90 % as shown by the frequency distribution of the estimates in Table 4.

The sample mean statistics of the estimates for each year are shown in Fig. 3. It looks like in the North Island, the average MTR follows a steady increasing trend, from only 56 % in 1999 to 88 % in 2007, implying the technological gap between the regions substantially decreased over time. However, TE within the region changed slightly from 91 to 93 %. Thus the increase in efficiency with reference to the MF (i.e. TE*) mainly comes from regional technological change over time rather than improvements in individual on-farm efficiency relative to others in the same region. As for the South Island, a similar patterned rising trend in TE performance is noted with the exception of year 2005. The average TE is 60 % in 1999 and 92 % in 2007. In contrast to the North Island, this increase could be the result of better on-farm efficiency performance relative to regional

[10] Both the two-sample t test and the Wilcoxon rank-sum test reject the equality of mean TE scores between North Island and South Island at better than a 1 % significance level.

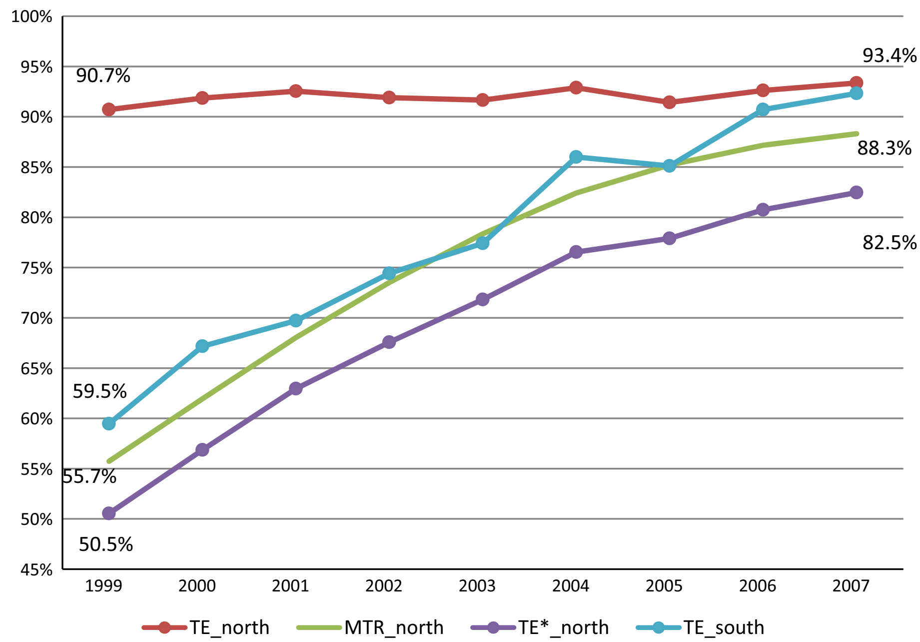


Fig. 3 Annual average TE and MTR estimates

Table 5 Sub-regional sample average TE and MTR

North Island region (1999–2007)	TE	MTR	TE*	Count
Northland	0.8928	0.7514	0.6708	267
Waikato	0.9305	0.7822	0.7290	617
Bay of Plenty	0.9286	0.7096	0.6594	298
Taranaki	0.9224	0.7465	0.6886	330
Lower North Island	0.9192	0.7486	0.6876	205
South Island region (2006–2007)		TE = TE*		Count
West Coast–Tasman		0.9006		43
Marlborough–Canterbury		0.9041		37
Otago–Southland		0.9349		64

peers when operators gain more experience in overall farm management.

Table 5 further breaks down the TE and MTR estimates over the sample period by each sub region within North Island and South Island. Because sub region specification for the South Island was not available in the dataset until the season 2005/06, the average TE and MTR estimates for South Island sub-regions are based on 2006–2007 only.[11]

Within the North Island, Waikato dairy farms have the highest regional TE estimate (93 %) and MTR (78 %) averaged over the entire sample period.[12] Bay of Plenty is in the second place in regional TE performance but in terms of technological distance from the MF, it is in the last place with only 71 % MTR. Taranaki sits in the third place in average sub-regional TE ranking (92 %), followed by Lower North Island and Northland. In the South Island, Otago–Southland has the highest TE score (93 %), Marlborough–Canterbury comes next and followed by West Coast–Tasman.

5 Conclusion and policy implications

In summary, North Island and South Island dairy farming do not share the same production technology as assumed in previous NZ dairy efficiency studies. What is in common is that the dairy farming production in both regions exhibits DRTS. North Island farmers use a more conventional dairy production system, in which labour and electricity have a larger and significant output elasticity compared to the South. Higher TE is associated with larger farm size, the employment of herringbone sheds over other unidentified sheds and more intensive farming. On the other hand, capital and fertilizer are relatively more important inputs in South Island dairying, farm size has a smaller and insignificant positive impact and intensity negatively affects individual farm efficiency performance.

Regarding the involvement of technology, a non-linear technological change effect which decreases over time is found for the North Island dairy farming, whereas for the South Island, a constant negative technological change effect has been estimated. One possible explanation for the inward shifting of the production frontier might be the rising farmland price. Holding everything else constant, the increase in farmland value will result in an increase in capital value, with no additional output. Ideally, a

[11] A New Zealand dairying regional map is attached in Appendix.

[12] Waikato also has the largest number of observations.

production frontier depicts the physical input output relationship, inability to separate the real price effect of land might bias the parameter estimates, especially those relate to technological change. Another possible explanation could be the continuous increasing trend in average farm size above the optimal scale. DairyNZ has confirmed both were working at the same time placing a downward pressure on the production frontier.

Upon the computation of the MF, South Island farming technology is found to be more advanced than the North and it defines the potential production technology available for the NZ dairy industry as a whole. Relative to the South Island MF, average TE over this sample period is estimated to be 70 % for the North Island and about 82 % for the South Island. Therefore, although the North Island dairy farms have been following the best farm management practices of their own regional counterparts (the mean TE is 92 % relative to the North Island frontier), the North Island, as a whole, is being left behind by the South dairy industry, whose technology is more up to date. The average gap between the two regional production frontiers, as denoted by the MTR, is estimated to be 75 %.

Results from modelling the inefficiency component suggest that policies aiming to promote the South Island dairy farming industry should focus on lifting individual farm TE performance, which could be achieved by encouraging the use of extension services. The average farm's milksolids produced per cow can be increased by up to 6 % in 2006/07 with reference to the most efficient farm if all the inefficiency in production was eliminated.[13] Policies that may impact North Island dairying should be designed with extra caution. Individual farm TE relative to their regional peers might be lifted through increased livestock, more intensive farming and the use of herringbone sheds. However, this improvement in TE would be rather limited due to constrained land space, more stringent environmental requirements, higher energy prices, and increased difficulty in finding experienced farm workers. The most prevalent objective, given the wide technological gap, is elevating the whole region's production frontier to catch up with their Southern mates, which suggests a movement towards a more capital intensive production system, such as wide application of irrigation, and other forms of technological progress induced by research and innovation.

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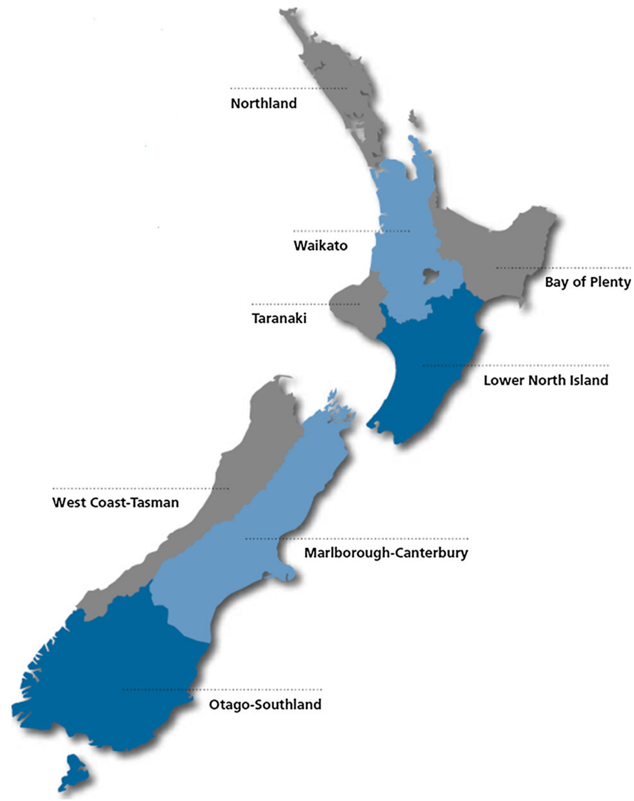
Appendix A: NZ dairying regional map



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[13] The average TE is 92.3 % in 2006/07 for South Island as shown by Fig. 3, and the most efficient farm was estimated to have a TE score of 98.4 %.

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