Efficiency measurement of New Zealand dairy farms

Xiaoqi Wei

A thesis submitted to
Auckland University of Technology
in partial fulfilment of the requirements for the degree of
Master of Business (MBus)

2014

Business School

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature: Xiaoqi Wei

Date: 31/07/2014

Abstract

Improving efficiency is important for New Zealand dairy farming to lift productivity and performance. This paper estimates technical efficiency performance of NZ dairy farms using both the stochastic frontier analysis (SFA) and data envelopment analysis (DEA), based on a sample of 315 New Zealand dairy farms in 2006-2007. The DEA model adopts two scale assumptions, which are the constant returns to scale (CRS) and variable returns to scale (VRS) respectively.

The objective of this research is to analysis the efficiency performance of New Zealand dairy farms utilizing these two approaches to see whether there are any substantial differences in the resulting efficiency estimates. The average technical efficiency is found to be 96 percent in SFA, 82 percent in CRS DEA and 86 percent in VRS DEA. The scale properties are analysed under the two methods. Under the SFA approach, the NZ dairy farms indicate constant returns to scale. Under the DEA approach, the NZ dairy farms show increasing and dominantly decreasing returns to scale. The NZ dairy farming’s potential for increasing production through efficiency improvement is also discussed.

Acknowledgements

I am very thankful to my supervisor Nan Jiang, whose critical thinking, empirical expertise and dedication guided me through the whole process and helped me improve. I am grateful to my parents, Ruiling Wei and Junling Liu, for their wisdom and support of my dreams. I would also like to express my gratitude to my supervisor Nan again, who gave me many valuable comments and suggestions, for her support, guidance, encouragement and motivation throughout my dissertation. Any errors and omissions are my sole responsibility.

Table of Contents

List of Tables

1. Introduction

Fonterra forecasts global demand in dairy markets will increase by at least 100 billion litres in 2020 (DairyNZ, 2013b). This extremely positive outlook is likely to generate milk supply. New Zealand dairy farms have long maintained a worldwide reputation for their technological expertise in advanced pasture-based dairy production systems. As the most influential exporter in global dairy markets, NZ accounts for over a third of the world's dairy market (DairyNZ, 2013b).

Domestically the New Zealand dairy industry plays a key role in economic performance. The New Zealand dairy industry exports were worth 13.7 billion dollars in 2012, which is approximately 29 percent of total exports and a 5 billion dollar contribution to GDP. This figure accounts for more than a third of the total primary sector production. Meanwhile there are 45,000 people directly employed in the dairy sector (DairyNZ, 2013c). In the 2012/13 season, 18.9 billion litres of milk were processed by NZ dairy firms, including 1.66 billion kilograms of milksolids; furthermore, the total number of herds increased to 11,891, which reflected the fifth continuous season of small rises. The average herd size was 402 in the 2012/13 season, reflecting an increase of 117 cows over the last 10 years and this number was tripled in the past 30 seasons; total dairy cows increased by 150,000 to 4.78 million over 10 years period (DairyNZ, 2013a).

The NZ dairy industry is well positioned as a low cost, high quality dairy producer. However, defending and enhancing the NZ dairy industry's global competitiveness requires consistent and sustained work, because of increased competition for resources (e.g. increasing labour and land costs in NZ), production systems (e.g. the adoption of lower cost production systems in Argentina and Ukraine) and high subsidies in other countries (e.g. the US allotted a total of $5.3 billion to dairy program subsidies from 1995-2012, and especially allocated 3.3 billion dollars to the Milk Income Loss Contract Payment Program (EWG Farm Subsidies, 2004)). In addition, efficiency and productivity evaluation of the sector's performance remains an important study area with high empirical significance.

Note that the efficiency concept refers to a production frontier. The theoretical definition of the production frontier represents the maximum quantity of output obtainable from given input bundles with current technology; if the firms in this industry operate on the frontier, they reflect full technical efficiency. The technical efficiency of dairy farms is a comparison of actual output with maximum output attainable given a certain input bundle, and is an important component in the pursuit of output growth on New Zealand dairy farms. Output growth can be obtained by changing the scale of operations or introducing new technology which leads to the production frontier shifting upward, as well as by operating more closely on the current production frontier (Coelli et al., 2005). NZ dairy farms are struggling to improve efficiency in dairy performance. For example, since 1990 the number of peak cows milked per time equivalent (FTE) labour unit has risen from 83 to 142, which reflects the growing herd size, the increased use of technology and labour-saving techniques (DairyNZ, 2013a).

The objective of this paper is to analysis the efficiency performance of New Zealand dairy farms utilising both the parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA) to see whether there are any substantial differences in the resulting efficiency estimates. Jaforullah and Whiteman (1999) addressed whether increasing dairy farm size can imporve the efficiency of NZ dairy production by utilising DEA, while Jaforullah and Devlin (1996) investigated the relationship between technical efficiency and farm size in the NZ dairy industry by using SFA.

The remainder of this thesis is organized as follows: Section 2 discusses the detailed specifications of the SFA and DEA models. Section 3 reviews the literature on SFA and DEA of dairy farms. Section 4 describes the data and the empirical models to be estimated. Section 5 reports and compares the results. Section 6 concludes.

2. Methodology

2.1 Stochastic frontier model

The stochastic frontier production function can be expressed as:

$$y_i = f(x_i;\ \beta) \cdot e^{(v_i - u_i)} \qquad \varepsilon_i = v_i - u_i \ \text{ and } \ i = 1, 2, 3 \ldots, n \tag{1}$$

where y_i denotes the scalar output of i^{th} sample farm $(i = 1,2,3, \ldots\ldots, n)$, x_i is a $(1 \times k)$ vector of inputs used by the i^{th} farm, and β is a $(k \times 1)$ vector of unknown parameters to be estimated. The first components v_i s, are two-sided symmetric random variables and are assumed to be independently and identically distributed (iid) with zero mean and constant variance σ_v^2 $(N\ (0, \sigma_v^2))$, which intends to capture the effects of statistical noise. The second error component u_is, are the one-sided non-negative random variables and are assumed to be independently and identically distributed (iid) and truncations (at zero) of the normal distribution with mean, μ, and variance, σ_u^2 $(N^+(\mu, \sigma_u^2))$, which is designed to represent the effects of inefficiency. The u_is and v_is are assumed to be uncorrelated with each other and are independent of the input vector x_i. The variance parameters of this model are presented as:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2, \qquad \gamma = \sigma_u^2/\sigma^2 \text{ and } 0 \le \gamma \le 1 \tag{2}$$

The common output-oriented measure of tehnical efficiency is computed as its observed output divided by its corresponding stochastic frontier outputs. The technical efficiency of the i^{th} farm, denoted by TE_i, can be given by:

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(x_i; \beta) \cdot e^{(v_i - u_i)}}{f(x_i; \beta) \cdot e^{v_i}} = e^{-u_i} = \exp(-u_i) \tag{3}$$

Estimation of the farm-specific efficiency e^{-u_i} relies on the decomposition of ε_i and can be obtained from the conditional expectation of expression of e^{-u_i}, given the values of ε_i (Battese & Coelli, 1988; Jondrow et al., 1982). TE_i can take a value between zero and one $(0 \le TE_i \le 1)$; a value of one means the farm operates on the production frontier and is fully technically efficient.

Using standard integrals computes the estimate of technical efficiency; given the probability density function of both ν_i and u_i, can be expressed as:

$$TE_i = E(e^{-u_i}|\varepsilon_i) = \left[\frac{1-\phi\{\sigma_{iu}^* - (\mu_i^*/\sigma_{iu}^*)\}}{1-\phi(-\mu_i^*/\sigma_{iu}^*)}\right] e^{(-\mu_i^* + \frac{1}{2}\sigma_{iu}^{*2})} \quad (4)$$

where the mean $\mu_i^* \equiv \frac{\mu\sigma_v^2 - \varepsilon_i\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$

and the variance $\sigma_{iv}^{*2} \equiv \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$

The function $\phi(\cdot)$ represents cumulative distribution function. Technical inefficiency can be estimated by $1 - \mathrm{E}(e^{-u_i}|\varepsilon_i = \nu_i - u_i)$. Applying the results from the equation the farm-specific efficiency e^{-u_i}, can calculate the average technical efficiency of the farms, $\overline{TE} = E(e^{-u_i})$, which is obtained as:

$$\overline{TE} = \left[\frac{1-\phi\{\sigma_u - (\mu/\sigma_u)\}}{1-\phi(-\mu/\sigma_u)}\right] e^{(-\mu + \frac{1}{2}\sigma_u^2)} \quad (5)$$

The SFA method has been widely used in agricultural application because it is capable of accounting for statistical noise (such as measurement error, omitted variables and weather) and can allow standard hypotheses tests to be performed (Coelli, 1995). More specifications and applications can be found in publications by Fried et al. (1993), Kumbhakar and Lovell (2000), and Coelli et al. (2005).

2.2 Data envelopment analysis

DEA utilises linear programming methods to establish a non-parametric frontier over the data. Efficiency estimates depend on solving separate linear programming (LP) problems for each farm. More treatments of this methodology are found in Färe, Grosskopf, & Lovell (1985), Färe, Grosskopf, & Lovell (1994), Seiford & Thrall (1990). Assuming that there are n decision making units (DMUs), each producing a single output by using m different inputs, the i^{th} DMU utilising x_{ki} units of the k^{th} inputs produce y_i units of output. The variable returns to scale (VRS) output-oriented DEA model for the i^{th} farm unit are expressed as:

$$\max_{\phi_i \lambda_i} \phi_i \tag{4}$$

subject to:

$$\sum_{j=1}^{n} \lambda_i \, y_i - \phi_i y_i - s = 0 \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j \, x_{kj} + e_k = x_{ki}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{6}$$

$\lambda_i \geq 0, s \geq 0, e_k \geq 0;$

$k = 1, \ldots, m$ inputs; $j = 1, \ldots, n$ DMUs;

where ϕ_i is the proportional increase in output that could be obtained by the i^{th} farm unit; given the input vector x_{ki}; s is the output slack; e_k is the k^{th} input slack; and λ_j is the weight of j^{th} farm unit, m and n are the number of inputs and farm units respectively. If the constraint (6) ($\sum_{j=1}^{n} \lambda_j = 1$) is eliminated, this is the constant returns to scale (CTS) output-oriented model.

The output-oriented DEA frontier attempts to maximize the proportional increase in output level while remaining within the envelopment space or efficient frontier. The proportional increase in output is achieved when the output slack, s, becomes zero. If $\phi_i = 1, \lambda_i = 1,$ and $\lambda_j = 0$ for $i \neq j$, the results indicate the i^{th} farm unit is efficient and lies on the frontier. If $\phi_i > 1$, $\lambda_i = 0$, and $\lambda_j \neq 0$ for $i \neq j$, the results show that the i^{th} farm unit is inefficient and lies outside the frontier. The frontier production level for the i^{th} farm, denoted by $\widehat{y_i}$, is shown as:

$$\widehat{y_i} = \sum_{j=1}^{n} \lambda_j \, y_j = \phi_i y_i \tag{7}$$

The output-oriented technical efficiency estimate of the i^{th} farm, TE_i, can be measured by:

$$TE_i = \frac{y_i}{\widehat{y_i}} = \frac{y_i}{\phi_i y_i} = \frac{1}{\phi_i} \tag{8}$$

the TE scores of farms in the output-oriented VRS DEA ($TE_{i,VRS}$) will be equal to or larger than those in the output-oriented CRS DEA ($TE_{i,CRS}$), since the VRS DEA envelops the data in a tighter way than the CRS DEA frontier. The scale efficiency (SE) for farm i can be measured by this relationship (Johnes, 1995; Favero & Papi, 1995; Bjurek, Hjalmarsson, & Førsund, 1990), denoted by SE_i, as:

$$SE_i = \frac{TE_{i,CRS}}{TE_{i,VRS}} \tag{9}$$

As can been seen, scale efficiency can be calculated by the ratio of technical efficiency estimated under constant returns to scale (CRS) to technical efficiency estimated under variable returns to scale (VRS), through the adoption of DEA technique. The nature of returns to scale can be measured utilising scale efficiency estimates for any decision making unit (Färe et al., 1994). The technical efficiency estimated under constant returns to scale (CRS) is the overall technical efficiency of a dairy farm, while the technical efficiency estimated under variable returns to scale (VRS) is the pure technical efficiency. When $SE_i = 1$ reveals scale efficiency, $SE_i < 1$ or $SE_i > 1$ indicates scale inefficiency due to either increasing or decreasing returns to scale which depend on inspecting the sum of the weights:

$$S = \sum_{j=1}^{n} \lambda_j \tag{10}$$

under the specification of CRS DEA (Banker, 1984). $S = 1$ indicates constant returns to scale (optimal scale); $S < 1$, shows increasing returns to scale (sub-optimal scale); $S > 1$, presents decreasing returns to scale (super-optimal scale) (Banker & Thrall, 1992; Førsund & Hernaes, 1994).

3. Literature review

Efficiency measurement in production has been carried out by researchers with an aim to explore the performance of farms, the effects of farm characteristics on productivity and a more profitable way to engage in production. To prevent waste of resources, efficiency is regarded as a significant basic economic concept for every sector in the economy.

The pioneering work of Farrell (1957) provided the possibility to measure the technical efficiency of a firm by estimating efficient production functions. Although many researchers used more careful measurements of inputs and outputs, they still failed to combine the measurements into any satisfactory measure of efficiency, partly due to pure neglect of the theoretical part. For example, using the average productivity of labor as an efficiency measurement is unsatisfactory, beacause this ignores the use of all other labor saving inputs. Farrell (1957) brings forth the importance of the efficiency of a firm as an estimate of productive efficiency and investigates how far a given firm can be expected to produce more outputs by simply increasing its efficiency without using more inputs. This effort provides the extensive platform for the development of efficiency measurement.

After Farrell (1957), several methods of efficiency and productivity analysis were developed (Bravo-Ureta & Pinheiro, 1993; Greene, 1993; Coelli, 1995; Cooper, Seiford, & Tone, 2000; Kumbhakar & Lovell, 2000; Coelli et al., 2005). Among these, the stochastic frontier production function was independently introduced by Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1997), while the DEA method was initiated by Charnes, Cooper, and Rhodes (1978). Many researchers have utilised and extended these two approaches, and especially in agricultural economics, the SFA has been widely adopted (Coelli & Battese, 1996; Cuesta, 2000; Bravo-Ureta et al., 2007). For example, Cuesta (2000) used parametric SFA based on a sample of 82 Spanish dairy farms. DEA is also commonly practised in the agricultual field (Dimara et al., 2005; Aldeseit, 2013; Skevas & Lansink, 2014). To illustrate this method, Skevas and Lansink (2014) utlised non-parametric DEA on a panel of Dutch arable farms. One can say that stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are two dominant approaches in empirical efficiency measurement. However, the SFA is mostly recommended for use in agricultural production probably due to its ability to account for measurement errors and other statistical noise (Coelli, 1995).

In particular, the SFA is a parametric method based on econometric techniques that is characterised by the composed error term comprising a non-negative random error due to inefficiency (e.g. a given input bundle used without maximum output produced) and a symmetric random error (good or bad but out of control by firms) due to statistical noise (such as measurement errors, omitted variables, or random shocks etc.). SFA assumes the existence of an underlying structure in the best-practice frontier and then draws a fit curve. Moreover, the SFA approach can identify observations which need intervention simultaneously with producer characteristics (e.g. size, ownership, location, etc.) which might be the sources of inefficiency. The error terms in SFA can have a significant effect on the shape and position of the estimated frontier. In summary, the main attractive merits of the SFA approach are that it copes with stochastic noise, allows for formal hypotheses testing and the construction of confidence intervals mostly within 6% to 11% limit (Hjalmarsson, Kumbhakar, & Hesmati, 1996).

Compared with the nonparametric approach, the main disadvantage of the parametric method is to provide an explicit functional form of production frontier for the underlying technology, which means it relies a priori on a hypothesized production function, which is susceptible to the effect of outliers and extreme points (Harris, 1993) and an explicit distributional assumption for the inefficiency term (e.g. half-normal, truncated normal, exponential etc.) (Schmidt & Sickles, 1984). In addition, production data are probably subject to high measurement errors which might distort the shape and position of a deterministic frontier, because farms are generally small family-owned operations and accurate records are not always collected (Coelli & Battese, 1996).

In contrast, DEA constructs a non-parametric piece-wise surface or frontier over the data by using a linear programming method, and then efficiency estimates are measured relative to this surface (Coelli et al., 2005). DEA is used to empirically measure the productive efficiency of various decision making units (DMUs) on the basis of multiple inputs and outputs (Zhang, Huang, & Yu, 2009). Benchmarking is a procedure for improving performance through identifying best practice and then building a benchmarking partnership between best practice (peers) and non-best practice firms, in order to eliminate less efficient practices. DEA identifies a frontier where the relative performance of all utilities in the sample can be compared, a best-practice benchmark selected and other best-practice benchmark partners from the data on inputs and outputs can be found. The rest of the non-best-practice or less efficient farms will identify their relative benchmark partners. As a result, the best-practice or efficient farms can be grouped, and the non-best-practice or less efficient farms can emulate and catch up with the better parctice or more efficient farms, and thus can eliminate the sources of inefficiency.

The obvious merit of non-parametric DEA is that is a deterministic method based on linear programming techniques in estimating efficiency to envelop the observed input-output data in a tight way that makes no explicit specification of the production functional form, and thus does not require specific structure in its shape. The assumption of the DEA approach does not take into account any possible effects of measurement errors or other noise upon the shape and positioning of the estimated frontier; all deviations from the best practice frontier are attributed to inefficiency.

The measure of technical efficiency in DEA can be separated into three components: a measure of scale efficiency, a measure of efficiency regarding input congestion, and a measure of pure technical or managerial efficiency (Färe, Grosskopf, & Lovell, 1985). This paper ultilises the methodology of Färe et al. (1985) to measure the technical efficiency and the scale efficiency of NZ dairy farms. Output-oriented technical efficiency measures under CRTS and VRTS are computed and then applied to the data on NZ dairy farms.

However, due to its non-parametric feature and all deviations from the frontier being attributed to inefficiencies, there are some disadvantages of DEA. Firstly, it is unlikely to build any statistical foundation and make any inference on estimates of DEA sensitivity and asymptotic propertites due to its non-parametric and non-statistical features. For sensistive issues, Ahn and Seriford (1993) found DEA was not senstive to variable selection and the aggregation and disaggregation of variables; for example, the omission of critical factors could have a significant influence on the results. For the asymptotic propertity problem, Banker (1996) used DEA to investigate statistical tests which were not sufficient to ultilise in an empirical research, since their asymptotic distribution and finite sample properties were not clear. Therefore, Simar and Wilson (2000a), Simar and Wilson (2000b) and Lothgren and Tambour (1999) have utilised bootstrap techniques to measure the statistical precision in the DEA approach; for example, Simar and Wilson (2000a) utilised bootstrapping in the DEA framework to allow for consistent estiation of the production frontier, corresponding efficency scores, standard errors and confidence intervals. Secondly, it is not easy to solve the problem that the measurement errors amd other non-measureable stochastic variables might have some effects on the results of pure technical inefficiency estimates; for example, it is difficult to separate the influences of uncontrollable environmental variables (e.g. weather) and measurement errors in the different managements of dairy farms (Jaforullah & Whiteman, 1999).

SFA using a parametric method can solve the above problems. This is because this method is based on the assumption that one part of the error term is due to inefficiency and another part of the error is attributed to stochastic factors, such as measurement errors and random shocks. The strength of the SFA method is that the causal factors are capable of being quantified, and hypotheses regarding differences in technical efficiency can be tested statistically; on the other hand, the non-parametric DEA does not allow statistical hypothesis testing, and thus can be regarded as a potential tool to improve overall technical efficiency for farm managements, but not to test behavioural hypotheses (Jaforullah & Whiteman, 1999).

The quality of data, the appropriate functional forms and the assumptions of the two methods determine the shape of the efficient frontier and the exsitence of random errors. Both methods are very sensitive to random errors in different ways. DEA is very sensitive to measurement errors and random errors because the existence of any random error may be regarded as a difference in efficiency measurement. By contrast, SFA is also sensitive to random errors due to its composed error term representing inefficiency and statistic noise. However, the SFA method has been criticized for potentially confounding estimated efficiency with specification errors (Cummins & Zi, 1998). For example, Cummins and Weiss (2013) found that the various distributional assumption (half-normal, truncated normal and exponential) methods have been criticized for confounding efficiency estimates with the choice of inappropriate probability distributions.

3.1 Efficiency literature on New Zealand dairy farms

There exist four studies in NZ that investigate the efficiency of dairy farms. A summary of empirical studies is shown in Table 1.

Table 1: Empirical studies of NZ on the efficiency of dairy farms

Studies	Method	Data	Mean Technical Efficiency	Output ($)	Inputs	Findings
Jaforullah and Devlin (1996)	SFA	264 dairy farms in the 1991/92 season	CRTS Translog TE: Half normal: 89.7% Truncated normal: 91.4% Exponential : 94.6%	Total farm revenue ($)	Labour (hrs per wk); Total dairy herd (cows no.); Animal health (%); Feed supplements and grazing ($); Fertilisers($); Assets (including the value of land and buildings, $)	1. NZ dairy farms operated close to their own production frontier. 2. TE is sensitive to distributional assumptions about technical inefficiency error term (e.g. half-normal, truncated normal and exponential). 3. Low correlation TE and farm size, TE and total herd size. 4. Farm size not influnece TE scores. 5. Constant returns to scale (CRTS) in NZ farms.
Jaforullah and Whiteman (1999)	DEA	Same as Jaforullah and Devlin (1996)	VRTS TE: 89% SE: 94%	Milksolids (kg), Milk-fat (kg), Milk protein (kg)	Same as Jaforullah and Devlin (1996)	1. IRTS (sub-optimal scale): 53%; DRTS (super-optimal scale): 28%; CTRS (optimal scale): 19%. 2. Overall TE: 83%; Pure technical inefficiency: 11%; technical inefficiency due to scale: 6%. 3. Different optimal farm sizes based on each farm's different input-output configuration.
Jaforullah and Premachandra (2003)	COLS SFA DEA	Same as Jaforullah and Devlin (1996)	CRTS: COLS: 57.3% SFA: 85.3% DEA: 80.7% VRTS Cobb-Douglas TE: COLS: 56.9% SFA: 85.5% DEA: 86%	Total farm revenue ($)	Same as Jaforullah and Devlin (1996)	1. The average TE of NZ dairy farms were sensitive to the choice of methodology. 2. NZ dairy industry operated close to or on the efficient production frontier in both SFA and DEA TE estimates due to clustering around the upper end of the TE distributions. 3. The DEA TE scores under both CRTS and VRTS assumptions exhibited greater variability than COLS and SFA. 4. The strongest correlated coefficients of the individual TE estimates-- SPF and COLS; the weakest correlated coefficients-- DEA and SFA.
Jiang and Sharp (2013)	SFA	824 dairy farms in the 1999-2005 season	North Island CE: 83% South Island CE: 80%	Milksolids (kg)/cow	Labour price ($/FTE); Feed price ($/t.dm); Fertiliser price ($/100g); Capital intensity (capital value/cow; $); Livestock quality (average livestock value; $); Farm size (size categories)	1. First cost efficiency study for the dairy sector in NZ. 2. CE had a negative relationship with capital intensity and livestock quality; positive relationship with farm size. 3. North Island: strongest correlated coefficients of CE—Cobb-Douglas and simplified translog (0.98); the weakest correlated coefficients-- simplified translog and translog (0.67). South Island: strongest correlated coefficients of CE-- simplified translog and translog (0.86); the weakest correlated coefficients--Cobb-Douglas and simplified translog (0.27).

Especially in Jaforullah and Devlin's study (1996), the results indicated that the technical efficiency level of NZ dairy farms ranged between 76 to 95 percent, with an average of 90 percent. Compared with Battese's and Coelli's (1988) results for Australian dairy farms (average TE in New South Wales: 0.77, in Victoria: 0.63 ranging between 54.8 to 92.7 percent), NZ dairy farms have less variable technical efficiency scores. In particular, 98 percent of NZ dairy farms operated at over 80 percent of technical efficiency level based on a half-normal translog stochastic production frontier.

Jaforullah and Whiteman (1999) investigated three different types of scale behaviour involved in estimating technical efficiency and scale efficiency; they are constant returns to scale (CRS), non-increasing returns to scale (NRS) and variable returns to scale (VRS). The results indicated the average pure technical efficiency; scale efficiency and overall technical efficiency were 89%, 94% and 83% respectively. Eliminating 11 percent of technical inefficiency and 6 percent of scale inefficiency, the NZ dairy farms decreased their inputs usage by 17 percent without affecting output. Although the DEA results supported an agricultural policy encouraging bigger farms that would have a beneficial influence on the efficiency of NZ dairy farming, the individual dairy farm level indicated different results. For example, 19 percent of farms were operating at their optimal scale. The DEA results for individual farms could be used to identify their optimal scale and their pure technical inefficiency, and thus determine which farms were already operating at their optimal scale or which farms increased their productivity of inputs by moving to their optimal scale.

Jaforullah and Premachandra (2003) utilised corrected ordinary least squares [1] (COLS), stochastic production frontier (SPF) and data envelopment analysis (DEA) to estimate technical efficiency. In particular, under CRTS, the COLS (statistical deterministic production frontier) obtained the lowest average TE (57.3%) while the SPF model yielded the highest average TE

[1] The corrected ordinary least squares (COLS) method by Lovell et al. (1994), involves two steps. The first step involves estimating consistent and unbiased slope parameters, and also estimating a consistent but biased intercept parameter by using OLS. In the second step, the biased OLS intercept is adjusted by shifting up so that the estimated frontier bounds the data from the above.

(85.3%). Under VRTS, the COLS still had the lowest mean TE (56.9%) and the highest mean TE (86%) for the DEA. In the three models, at least two of them were significantly different from one another for the average technical efficiencies in both the ANOVA test and Kruskal-Wallis test. The results indicated three models were consistent with their TE ranking of dairy farms, especially under the CRTS assumption. The correlated coefficients of the individual TE estimates from three models were significantly different from zero and were more than 0.5. They found that the average TE estimates were not significantly influenced by the two scale assumptions (CRTS and VRTS) for the NZ dairy industry.

Jiang and Sharp (2013) explored the cost efficiency of NZ dairy farms by estimating translog stochastic cost frontiers for the North Island and the South Island separately. Cost efficiency is the ratio of minimum cost to observed cost, and can be decomposed into technical and allocative efficiency components. Thus cost efficiency can be expressed as a product of technical and allocative efficiency. This paper used the input-oriented technical efficiency, which is to measure the ability of dairy farms to produce a given quantity of output using the least input bundles under current techonology. Allocative efficiency measures the ability to produce a given quantity of output by using the inputs mix which costs the least. The cost function that they constructed for NZ dairy farms is shown to be well behaved, given the concave property (discouraging the use of an input when its price increases) is satisfied at all sample data points, and only a few violate the monotonicity property (additional units of input used can not decrease output level). According to the correlated coefficients of cost efficiency estimates for the North Island, ranging from 0.67 to 0.98, the choice of these three functions (simplified translog, translog and Cobb-Douglas) should not make much difference to efficiency ranking; while for the South Island the simplified translog function prevails.

3.2 Efficiency literature in other countries

There exist four studies in other countries that explore the efficiency of dairy farms. Some empirical studies are summarized in Table 2.

Table 2: Empirical studies of other countries on the efficiency of dairy farms

Studies	Method	Data	Mean Technical Efficiency	Output (s)	Inputs	Findings
Theodoridis and Psychoudakis (2008)	Cobb-Douglas SFA and DEA (CRS and VRS)	165 Greek dairy farms in 2003/04 season	SFA: 0.812 CRS DEA: 0.634; VRS DEA: 0.685 SE: 0.927	Gross output (€)	Labour (hrs); Fixed cost (e.g. buildings, machinery and livestock for breeding and utilisation; €); Variable cost (e.g. fertilisers, fuel, herd labour, purchased feed, etc.; €)	1. Efficiency scores in both CRS and VRS DEA exhibit greater variability than the SFA scores. 2. The mean TE was sensitive to the choice of methodology. 3. The highest correlated coefficients of TE: CRS and VRS DEA (0.9034); the lowest correlation: SFA and VRS DEA (0.7991).
Theodoridis and Anwar (2011)	Translog SFA and DEA (CRS and VRS)	240 Bangladeshi farms in 2003/04 season	SFA: 0.818 CRS DEA: 0.774 VRS DEA: 0.819 SE: 0.946	Gross output (taka)	Land size (hectares); Labour (man-days); Contract paid (taka); Instant Paid (taka); Age of farmers (yrs); Education (yrs); Land degradation (binary); Extension service (binary)	1. The estimates of average TE in DEA indicated more variability than SFA frontier. 2. The highest correlated coefficients of TE: CRS and VRS DEA (0.8609); the lowest correlation: SFA and VRS DEA (0.5368). 3. SFA: also using stochastic inefficiency model; DEA: tobit model. 4. The determinants of efficiency measurements- human capital variables
Murova and Chidmi (2013)	Cobb-Douglas SFA and DEA	1215 US dairy farms in 2005	SFA: 0.724 DEA: 0.778	Total value of milk produced ($)	Land (acre); Labour (week hrs; including paid and unpaid labour); Feed (cwt; including purchased and home-grown); Age(years; the average age of cows in years); Mortality (%; no. of milk cows died per farm size in 2005); System (hrs; no. of hrs operating milking system); Dummy for states participating in the Federal Milk Marketing Orders(FMMO) program; Average Federal Milk Income Loss(FMIL) contract payments($); Region dummy for North-eastern region of the US; Region dummy for North-western region of the US; Region dummy for South-western region of the US	1. SFA: also using stochastic inefficiency model; DEA: logistic model. 2. The SFA TE scores indicated more variability than the DEA TE scores. 3. Investigate the impact of categorical variables on TE.

The results have varied across past studies. This could be because dairy or other industry efficiencies have varied systematically across countries or time, but also they could be different because of the nature of the data limitations.

In particular, Theodoridis and Psychoudakis (2008) found that the average TE scores of both CRS and VRS DEA model were smaller than SPF model, and the mean TE estimates in VRS DEA were larger than those obtained from CRS DEA. This might be because the DEA model attributes all deviations from the frontier to inefficiency, while the statistical noise in the SFA beyond the control of farmers has a significant effect on the output level. In terms of SFA, according to the general likelihood ratio test[1] result, the null hypothesis of the Cobb-Douglas functional form is appropriate could not be rejected; meanwhile, the half-normal[2] distribution was chosen for the distribution of inefficiency error term. The farming frontier exhibited increasing returns to scale as shown by an elasticity of scale for 1.1. For DEA, the VRS frontier envelops the data points more tightly than the CRS frontier. The estimated scale efficiency ranges from 0.298 to 1.000, CRS for 27 farms, IRS for 61 farms and DRS for 77 farms out of the total of 165 farms, indicating IRS and prevailing DRS in the data. These two different methodologies revealed highly positive significant spearman rank correlation coefficients for the technical efficiency estimates.

Theodoridis and Anwar (2011) found the average technical efficiency score in the SFA was 0.818, while those obtained from the CRS and VRS DEA were 0.774 and 0.819, respectively, which suggested an increase of production level about 18-23% under the current technology without affecting inputs used. The efficiency scores in the CRS DEA were expected to be lower than the SFA score, since all deviations from frontier in DEA were attributed to inefficiency, while the

[1] The generalized likelihood ratio test (LR) statistic, $\lambda = -2\{\log[\mathrm{Likelihood}(\mathrm{H}_0)] - \log[\mathrm{Likelihood}(\mathrm{H}_1)]\}$ has approximately Chi-square distribution with parameter equal to the number of restrictions under the null hypothesis, H_0 assumes H_0 is true. The LR is used to compare the fit of the Cobb-Douglas model and translog model. It is to test whether or not the Cobb-Douglas production function can be considered as an appropriate representation of the underlying production function.

[2] The half-normal model by Aigner, Lovell and Schmidt (1977) estimate ML under the assumptions $v_i \sim iidN\ (0, \sigma_v^2)$ which means v_i s are independently and identically distributed normal random variables with zero means and variances σ_v^2, and $u_i \sim iidN^+(0, \sigma_u^2)$ which means the u_is are independently and identically distributed half-normal random variables with scale parameter σ_u^2.

statistical noise of the SFA method out of the control of farmers could influence output. However, the efficiency score in VRS DEA was higher than the SFA model, because the VRS DEA frontier fitted data in a tighter way (Sharma, Leung, & Zaleski, 1997; Wadud, 2003), or there was the inclusion of the determinants (such as latent variables: education, experience and managerial ability) of technical efficiency in the SFA model (Kalaitzandonakes & Dunn, 1995). These results showed that the VRS DEA frontier enveloped the data in a tighter way than the CRS DEA frontier. In terms of the sources of inefficiency, they used the stochastic inefficiency effect model and the tobit model (in VRS and VRS DEA model estimates). They found that the human capital variables (e.g. the age of farmer and the level of education) were determinants of efficiency measurements and also had a significantly beneficial effect on efficiency.

Murova and Chidmi (2013) utilised the logistic regression in DEA, which is estimated by finding the probability of how efficient dairy farms are related to important variables, and it is also used to link efficiency to both policy and technical varibales. The SFA approach used the same variables as the logistic model to explain technical inefficiency in milk production. This paper estimated TE by ulitising logistic regression to investigate the effects of technical and policy variables on efficiency measurements. There were two federal milk policies to estimate TE: marketing policy and milk income loss policy. They found that the Federal milk marketing orders program had a significant negative effect on TE estimates in both approaches, while the milk income loss program had a positive influence in the SFA method and had no effect in the DEA method. In the DEA model, the mean TE scores are calculated for all explanatory variables and these variables are divided into categories, in order to compare each category's performance with the overall average efficiency of 0.778. Some categorical variables in graphs revealed some other views of their influences on technical efficiency. For example, farms in categories two and three of herd size variables were more efficient. They are farms obtained 100-1000 cows due to beyond the DEA average technical efficiency scores (0.778). The variables could be highly significant in explaining inefficiency. For instance, in the DEA-logit model, according to the highly negative significant coefficient for age of cows, the farms needed to increase mortality to decrease average age of cows to less than four years old, which would be more efficient for dairy farms. In the stochastic inefficiency effect model, the negative significant coefficient of equipment usage indicated that an increase in hours of equipment usage would be more efficient for dairy farms.

Both the SFA and DEA methods are also widely used in other industries and throughout the world. Wadud and White (2000) compared technical efficiency estimates obtained from these two methodologoes (SFA and DEA), based on farm-level survey data from 150 Bangladesh rice farmers in 1997. The average TE scores in VRS DEA (0.858) were higher than those obtained from the CRS DEA (0.789) and SFA (0.834). And DEA technical efficiency scores exhibited less variability than SFA technical efficiency scores. For scale efficiency, most of the farms exhibited DRTS, followed by CRTS. Specifically, in the SFA model, the farms exhibited decreasing returns to scale due to an elasticity of scale for 0.8908. In the DEA model, the average output level under the super-optimal scale[1] was higher than under the optimal scale[2], which in turn was higher than under the sub-optimal scale[3] for the farms. These two different methodologies exhibited highly positive significant spearman rank correlation coefficients for the technical efficiency estimates, particularly the strongest correlation of 0.8409 between the VRS and CRS DEA, and the weakest correlation of 0.7471 between the SFA and VRS DEA. They found the environmental degradation (e.g. soil degradation) in both methods had a negative and significant influnence on the efficiency of the farms, while the irrigation infranstructure (e.g. diesel-operated irrigation schemes) had a significantly positive effect on the efficiency of the farms.

Sharma, Leung, and Zaleski (1997) investigated the technical efficiency of Hawaiian swine producers by employing these two methods. The average technical effciency score in SFA (0.749) was greater than those obtained from the DEA approach (VRS: 0.726 and CRS: 0.644). The DEA

[1] The super-optimal scale is identified by the decreasing returns to scale input measures of technical efficiency, which also means the dairy farms are operating at above their optimal scale. This implies that farms can increase their technical efficiency by keeping decreasing their size (Jaforullah & Whiteman, 1998).
[2] The optimal scale is identified by the constant returns to scale input measures of technical efficiency (Jaforullah & Whiteman, 1998).
[3] The sub-optimal is identified by the increasing returns to scale input measures of technical efficiency, which also means the dairy farms are operating at below their optimal scale. This implies that farms can increase their technical efficiency by continuing to increase their size (Jaforullah & Whiteman, 1998).

TE scores showed more variability than the SFA TE scores. In terms of scale efficiency, under the SFA method, the farms exhibited constant returns to scale due to an elasticity of scale for 1.046. Under the DEA method, both increasing returns to scale and decreasing returns to scale were prevalent. They found that the average output at the optimal scale was greater than that at the super-optimal scale. They also found that a very wide range of outputs at the optimal scale overlapped a large part of the sub-optimal scale and the super-optimal scale. There were highly positive significant spearman rank correlation coefficients for the technical efficiency estimates between the two approaches. The strongest correlated coefficient of 0.883 was for TE estimates between SFA and CRS DEA, while the weakest correlation of 0.745 was for SFA and VRS DEA.

In summary, the choice of methods might not affect the TE results in the economic sectors. Other studies outside the agricultural sector also compared these two approaches and had similar findings. For example, Coelli and Perelman (1999) undertook a comparison of technical efficiency estimates based on a sample of European railways. They suggested that the choice of approach selection had no large effects on the technical efficiency results. Resti (1997) conducted a comparison of cost efficiency estimates by using Indian bank data. The study pointed out that there was not much difference between the two approaches; the efficiency scores showed a high variance, with the gap between the best and the worst banks in the sample indicating approximately 40-50 percentage points, and if the tails were eliminated, the difference between the third and the first quartile remained high.

However, some of the literature (Ferrier & Lovell, 1990; Bauer et al., 1998; Cummins & Zi, 1998) implied that the choice of methods might affect the TE results in the economic sectors. The efficiency estimates of both approaches had quite different distributions of efficiency measurement. Bauer et al. (1998) found SFA had a tendency towards a higher mean and a lower standard deviation than the DEA approach. Bravo-Ureta and Pinheiro (1993) pointed out that the choice between a non-parametric and a parametric specification in efficiency measurement for a developing country's agricltural studies was still uncertain.

In addition, Hjalmarsson et al. (1996) found DEA and SFA had both similar and dissimilar results depending on the inclusion of control variables in the inefficiency error term specification (e.g. type of production process (wet, dry, both), fuel type (coal, gas, oil), regions, locations, etc.) in the stochastic frontier, and the sequential or intertemporal specification in the DEA frontier. The squential frontier computed efficiency each year on the basis of all observations generated up to that year. If the data over many years was involved, the data for all the years was combined into one set and efficiency scores for the entire data set were calculated; this was an intertemporal frontier. They undertook a comparison of TE estimates, using data on 15 Colombian cement plants observed during 1968-1988. In the DEA model, the average efficiency scores of sequential frontier revealed a slight decrease, while the average efficiency scores of intertemporal frontier indicated U-shaped form, which showed a relatively faster rate of technical change during the first part of the period, compared with the last part of the period. In the stochastic inefficiency model, the inclusion of control variables were considered as determinants of technical inefficiency, for example, plants located in the urban areas indicated that they were more inefficient due to the positive coefficient of urban area variables. The plants exhibited constant returns to scale in the SFA model. In terms of scale properties of the DEA model, they found that the range of optimal scale values was very large and overlapped a large part of the sub-optimal and super-optimal output levels.

4. Data and empirical specification

The data presented in this study were obtained from *DairyNZ*, which is the single good industry body in the dairy industry and represents New Zealand's dairy farmers. Before 2006, an annual economic dairy survey was undertaken by the Livestock Improvement Corporation (LIC) and Dexcel. After 2005, the survey was published by *DairyNZ*, which owns and manages the *DairyBase*® on behalf of the dairy farmers of New Zealand. This dataset is sourced from *DairyBase*®, which is a web-based software tool to collect dairy farm business information and is available for all levy-paying NZ dairy farmers (DairyNZ, 2013).

This paper uses a sample of 315 owner-operator dairy farms from the year of 2006/07. Not all sampled farms can be used; for example, there are three farms in the sample indicating zero value observations for fertiliser expenditure. In the SFA model, the value of one can be used to replace the zero observations. Since these zero observations are not a significant proportion of the total number of sample observations, we assume they occur mainly owing to data entry error, rather than reflecting different output elasticities with respect to inputs for these farms (Battese, 1997). Both methods should use the same output and input variables in efficiency measurement. Therefore, the three farms with zero value for fertiliser expense are dropped from the analysis.

4.1 The variables

Dairy products can be produced by using a number of inputs, such as labour and capital. The output is considered as dairy revenues from selling milk or livestock. The choice of relevant variables relies on dairy product information, previous literature reviews and available data.

Many dairy outputs like milk fat, milk protein and milk solids are produced by NZ dairy farms. According to combined available data and the *DairyNZ* economic dairy survey, milksolids in kilograms (kgs) are regarded as a proxy for total output of the dairy farm, because milksolids are what NZ farmers get paid for. In this sample, on average, selling milksolids constitutes 91 percent of gross farm revenue. The use of similar output measures can be found in Rouse et al. (2009), Jiang and Sharp (2013) and Jiang (2011).

Inputs include cows, labour, capital, feed, fertiliser, and veterinary services:

- Cows are measured by the number of peak cows milked[1] in 2006/07;

[1] Peak cows milked: the cows that produce the most milk at any time during the year.

- Labour is measured by the total number of working hours per day, which is based on the number of full time equivalent (FTE) labour units, including paid FTEs[1], unpaid family labour[2] and unpaid family management[3];
- Capital is measured by the closing book value of dairy assets, which includes land and buildings; plant and machinery; livestock; farming shares; and other fixed assets;
- Feed is measured by expenditure on supplements purchased, made and cropped; run-off lease; owned runoff adjustments; weed and pest management; feed inventory adjustments; and total grazing;
- Fertiliser is measured by expenditure on all types of fertiliser, except nitrogen.
- Veterinary services are measured by expenditure on animal health, breeding and herd improvement.

4.2 Descriptive statistics

Table 3 shows the descriptive statistics of the variables in aggregate terms, which presents the means, stand deviations and ranges for each variable. The average milksolids of the sampled dairy farms is 119,982 kilograms with a standard deviation of 75,920, and ranges from 28,354 to 669,346. There is an average of 340 peak cows milked in 2006/07, ranging from 100 to 1,650. The average total working hours of labour per day which represents total FTEs[4], is 2.57, ranging from 0.87 to 9.44. The average closing book value of dairy assets is 4,860,801 NZ dollars, ranging from 263,250 to 39,457,619. The average feed expense is 89,951 NZ dollars, ranging from 6,494 to 454,671. The average expenditure on all types of fertiliser (except nitrogen) is 50,215 NZ dollars, ranging from 3,699 to 257,347. The average expenditure on animal health; breeding and herd improvement (veterinary services) is 31,599 NZ dollars, ranging from 2,897 to 173,839. The

[1] Paid FTEs refer to the number of full time equivalents employed. Note that the *DairyBase* asks for working hours. One FTE is 2400 hours.
[2] Unpaid family labour relates to the number of family unpaid FTE.
[3] Unpaid family management involves the number of family unpaid FTE's managing the operation, like milking or moving stock, etc.
[4] Total FTEs refers to the paid FTEs and unpaid FTEs (e.g. unpaid family labour and unpaid family management, details on p24).

choice of inputs selection is similar to Jaforullah and Devlin (1996), Jaforullah and Whiteman (1999), and Jaforullah and Premachandra (2003).

Table 3: Summary statistics of variables used in the efficiency analysis for 315 NZ dairy farms

Variable	Mean	Standard deviation	Minimum	Maximum
Milksolids (kg)	119,982.11	75,920.85	28,354	669,346
Cows (No.)	340	198.67	100	1,650
Labour (hours per day)	2.57	1.29	0.87	9.44
Capital (NZD)	4,860,801.18	3,302,789.69	263,250	39,457,619
Feed (NZD)	89,951.01	74,770.07	6,494	454,671
Fertiliser (NZD)	50,215.60	37,584.64	3,699	257,347
Veterinary Service (NZD)	31,599.19	20,939.03	2,897	173,839

4.3 SFA Empirical Specification

In SFA, different models are based on different algebraic forms. There are two most commonly functional forms (Cobb-Douglas and translog) utilised in the empirical literature. For Cobb-Douglas, studies include those by Jaforullah and Premachandra (2003), Theodoridis and Psychoudakis (2008), Coelli and Battese (1996), Sharma, Leung, and Zaleski (1997), and Murova and Chidmi (2013). For translog, studies can be found in Jaforullah and Devlin (1996), Theodoridis and Anwar (2011), Hjalmarsson, Kumbhakar, and Hesmati (1996), and Wadud and White (2000).

The most attractive characteristic of the Cobb-Douglas functional form is its simplicity, which uses linear regression in the logs of the inputs and thus can be easily used in the econometric estimation; however, it still has several restrictive properties; for instance, the elasticity of substitution is assumed to be unity and the returns to scale (i.e. the sum of the technological parameters) are assumed to be fixed across all farms in the sample (Coelli, 1995). The translog functional form does not impose those assumptions. It tends to compute a second-order differential approximation at a single point, but its major drawback is a multicollinearity problem (Cornwell, Schmidt, & Sickles, 1990).

The principle of parsimony maintains that one should choose the simplest functional form that “gets the job done adequacy” (Coelli et al. 2005, p.212). The most important objective of this paper is to compare the difference in TE estimates between SFA and DEA, specifically to estimate stochastic frontier based on the estimated technological parameters. The multicollinearity issue that results in insignificant estimated coefficients should be considered. Several studies suggested that technical efficiency estimates were robust to functional form choice (Maddala, 1979; Good et al., 1993; Ahmad & Bravo-Ureta, 1996). Therefore, the Cobb-Douglas production frontier is finally used.

The specified empirical stochastic frontier estimates in this study:

$$\ln(\text{milksolids}) = \beta_0 + \beta_1(\text{lncows}_\text{i}) + \beta_2(\text{lnlabour}_\text{i}) + \beta_3(\text{lncapital}_\text{i}) + \beta_4(\text{lnfeed}_\text{i}) + \beta_5(\text{lnfertiliser}_\text{i}) + \beta_6(\text{lnVS}_\text{i}) + v_i + u_i$$

Where: $i = 1, 2, \dots, N$ denotes dairy farms, $v_i \sim iidN\ (0, \sigma_v^2)$, and $u_i \sim iidN^+(\mu, \sigma_u^2)$.

5. Empirical results and discussion

5.1 Stochastic frontier results

The maximum likelihood estimates of the Cobb-Douglas SFA were obtained by using the FRONTIER 4.1 program (Coelli, 1996a); the results are reported in Table 4. This table presents the coefficients of the estimated variables, their standard errors, t-ratios and the estimated variance parameters. All input variables are measured in logarithmic form, output elasticities or “share parameters” are represented by the estimated coefficients. As can be seen, all of the estimated parameters associated with inputs indicate positive signs and most of them (the coefficients of cows, feed and veterinary service) are highly significant at the 1% of significance level and the coefficient of fertiliser is significant at the 10% of significance level; the exceptions are, labour and capital. Among all input variables, the number of cows has the largest influence with an elasticity equal to 0.7697, which means on average, a 1% increase in the number of cows in the herd results in an estimated increase of 0.7697% in milksolids sold.

The generalized likelihood ratio test (LR) is a statistical test used to compare the fit of the Cobb-Douglas model and the translog model. It is to test whether or not the Cobb-Douglas production function can be considered as an appropriate representation of the underlying production function. According to the likelihood ratio test result, the null hypothesis that the Cobb-Douglas functional form (LR= 24.26) was appropriate cannot be rejected at the 1% significance level, using a Chi-Square critical value of 23.21 with 10 degrees of freedom.

The estimated value of the variance parameter gamma (γ) is significantly different from zero (3.9413^{***}), which means there are high inefficiencies in production; 60.29 percent variation in production performance among farms can be attributed to inefficiency and the remaining 39.71 percent is due to statistical noise. This result is in accord with Wadud and White (2000), Sharma et al. (1997), Hjalmarsson et al. (1996), Coelli and Battese (1996), in which inefficiency plays a significant role in explaining production performance differences. The null hypothesis that the one-sided technical inefficiency error term (LR test is 3.034) is not significant can be rejected at the 5% siginificance level, using the Kodde and Palm critical value of 2.706 with 1 degree of freedom. The estimated value of σ^2 is also highly significant at the 1% significance level, which conforms with Sharma et al. (1997) and Hjalmarsson et al. (1996). This result argues that the traditional "average" production function cannot adequately represent the data.

The sum of estimated elasticities of output with respect to all inputs (scale elasticity) is 1.0092, indicating that dairy farms exhibit constant returns to scale. This result is consistent with Cabrera et al. (2010) and Kompas and Che (2006). Based on the likelihood ratio test, the null hypothesis that NZ dairy farms exhibit constant returns to scale (LR is 0.352) cannot be rejected, compared with a Chi-Square critical value of 2.706 with 1 degree of freedom at 10% level of significance. Further explanation of CRS is that changing productivity level relies on improvement of tehnology and efficiency, rather than the scale of the farm (Kompas and Che, 2006).

Table 4. Maximum-likelihood estimates of the Cobb-Douglas stochastic production frontier model

Name of Variables	Parameters	Coefficients	t-ratios
Stochastic frontier			
Constant	β_0	2.0888 (0.0984)	21.2191***
Cows	β_1	0.7697 (0.0378)	20.3727 ***
Labour	β_2	0.0189 (0.0290)	0.6539
Capital	β_3	0.0188 (0.0145)	1.2981
Feed	β_4	0.0843 (0.0140)	6.0125 ***
Fertiliser	β_5	0.0259 (0.0156)	1.6638 *
Veterinary Service	β_6	0.0916 (0.0221)	4.1423 ***
Variance Parameters			
Sigma-squared	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.0045 (0.0008)	5.3087 ***
Gamma	$\gamma = (\sigma_u^2/\sigma^2)$	0.6029 (0.1530)	3.9413 ***
log-likelihood		483.298	
LR test of the one-sided error		3.034	
LR test of CD vs. TL		24.26	

Note: *, **, and *** indicate the variables are significant at the 10%, 5%, and 1% level of significance, respectively.

The frequency distribution of the technical efficiency estimates from the stochastic frontier is reported in Table 5, indicating approximately 99.05% of the dairy farms obtained TE levels of 90% or higher. The average technical efficiency of the 315 NZ dairy farms is estimated to be 0.96 with a standard deviation of 0.0183 (in Table 6), which means, on average, farms can produce 96% of maximum attainable output levels and also can increase milksolids production sold by 4%

through using the current input quantities. However, Jaforullah and Devlin (1996) presented an 86.7 percent average technical efficiency score in their stochastic frontier studies. Jaforullah and Premachandra (2003) reported an 85 percent average techchnical efficiency. It is noteworthy that the average level of efficiency achieved from our result is comparable with the average efficiency level obtained from Jaforullah and Devlin (1996) and Jaforullah and Premachandra (2003), whose results indicate considerable production inefficiencies among the sample dairy farms in New Zealand, based on the stochastic production frontier. Thus, there is a potential for increasing the production of NZ milksolids using the same amount of inputs through improving efficiency.

5.2 DEA frontier results

The constant returns to scale (CRS) and variable returns to scale (VRS) output-oriented DEA frontier are estimated for the same farms using the same output and input variables through the adoption of the program, DEAP (Coelli, 1996b). The frequency distribution of technical efficiency estimates and their summary statistics are reported in Table 5 and Table 6 respectively.

The average technical efficiency estimates in DEA models are 0.8246 (under CRS) and 0.8598 (under VRS), and their standard deviations are 0.1078 and 0.1096 respectively. This is because VRS DEA envelops the data points more tightly than the CRS DEA. The results indicate there are considerable production inefficiencies among the sample dairy farms in New Zealand and inefficiency plays a significant role in explaining production performance differences. Thus farms can increase production using the same amount of inputs through improvements in efficiency. This is similar for the stochastic frontier analysis having production inefficiencies among the sample NZ dairy farms, which can be removed by improving efficiency. Under the CRS DEA, there are 34 fully technically efficient dairy farms, while under the VRS DEA model, 64 farms are fully technically efficient.

As expressed in equation (9), the scale efficiency is derived from the CRS technical efficiency scores divided by VRS technical efficiency scores, which range from 0.761 to 1, with a sample mean of 0.9599 and a standard deviation of 0.0451. Specifically, 50 farms are scale efficiency due to their scale efficiency scores being equal to one. In other words, the overall technical efficiency[1] (CRS) of a dairy farm is the product of its pure technical efficiency[2] (VRS) and its scale efficiency[3] (SE). The average overall technical efficiency (CRS) is estimated at 82.46 percent, the average pure technical efficiency (VRS) is 85.98 percent and the average scale efficiency (SE) is estimated at 95.99 percent. Therefore, the average overall technical inefficiency for the NZ dairy farms is estimated appropriately at 18 percent, which consists of 14 percent pure technical inefficiency and 4 percent scale inefficiency.

The scale properties of the sample farms are reported in Table 7. As can be seen, the results for the individual farms suggest that of the 315 NZ dairy farms, more than half (201 farms or 64%) are operating above their optimal scale. This implies that these dairy farms have increased their technical efficiency by continuing to decrease their size. 61 farms or 19 percent are operating below their optimal scale and thus can increase their technical efficiency by retaining increasing their size. The rest (53 farms or 17 percent) are operating at their optimal scale by keeping their constant size.

Therefore, there are only 53 farms exhibiting constant returns to scale, which makes up the smallest part of total dairy farms. This result is consistent with Hjalmarsson et al. (1996), Sharma et al. (1997) and Jaforullah and Whiteman (1999). Decreasing returns to scale dominate most of NZ dairy farms, and a few farms have increasing returns to scale. However, Jaforullah and Whiteman (1999) show opposite results between IRS and DRS DEA in NZ dairy farms, IRS shows 53%; and DRS shows 28%, and also, contrary to Hjalmarsson et al. (1996), IRS shows 78%; and DRS shows 14%.

[1] CRS efficiency scores indicate the overall technical efficiency scores in DEA model
[2] VRS efficiency scores indicate the pure technical efficiency scores in DEA model
[3] SE efficiency scores indicate the scale efficiency scores in DEA model

The average output level under the super-optimal scale (DRS) is larger than that under the optimal scale (CRS) and that under the sub-optimal scale (IRS); that is, consistent with results obtained by Wadud and White (2000). Output ranges between the minimum and maximum output level under these three scale behaviours. The range of optimal scale values is very large and overlaps a large part of the super-optimal scale and sub-optimal outputs. This result is in accordance with Wadud and White (2000), Hjalmarsson et al. (1996) and Sharma et al. (1997).

Table 5. Frequency distributions of technical efficiency scores from the stochastic frontier and technical and scale efficiency from the DEA models

Efficiency scores	**Stochastic Frontier**		**Data Envelopment Analysis**					
			CRS		**VRS**		**SE**	
	No. of farms	% of farms	No. of farms	% of farms	No. of farms	% of farms	No. of farms	% of farms
<0.60	0	0.00	5	1.59	3	0.95	0	0.00
0.60-0.70	0	0.00	35	11.11	24	7.62	0	0.00
0.70-0.80	0	0.00	92	29.21	72	22.86	2	0.63
0.80-0.90	3	0.95	103	32.70	95	30.16	26	8.25
0.90-1.00	312	99.05	46	14.84	57	18.10	237	75.24
1.00	0	0.00	34	10.79	64	20.32	50	15.87
Total	315	100.00	315	100.00	315	100.00	315	100.00

Table 6. Summary statistics of efficiency estimates from both the stochastic frontier and DEA model

Efficiency score	SFA	CRS	VRS	SE
Mean	0.9600	0.8246	0.8598	0.9599
Standard deviation	0.0183	0.1078	0.1096	0.0451
Minimum	0.8539	0.5390	0.5410	0.7610
Maximum	0.9882	1.0000	1.0000	1.0000
Skewness	-1.5316	-0.0406	-0.3124	-1.5697
Kurtosis	4.1309	-0.6725	-0.7963	2.6716

Note: SFA efficiency scores indicate the technical efficiency scores in SFA model
CRS efficiency scores indicate the overall technical efficiency scores in DEA model
VRS efficiency scores indicate the pure technical efficiency scores in DEA model
SE efficiency scores indicate the scale efficiency scores in DEA model

Table 7. Optimal, sub-optimal, and super-optimal outputs for the 315 NZ dairy farms

Scale	Number of farms	% of farms	Mean output	Output range
Optimal scale(CRS)	53	17%	100,505.64	44,500-290,996
Sub-optimal scale(IRS)	61	19%	62,192.00	28,354-95,012
Super-optimal scale(DRS)	201	64%	142,655.87	41,178-669,346

5.3 Comparison of the efficiency results

As can be seen, there are substantial differences in technical efficiencies estimated using these two methods. The estimated average technical efficiency score in SFA (0.96) is larger than those obtained from CRS (0.8246) and VRS DEA (0.8598). Furthermore, the different distributions of technical efficiency reveal that with the SFA model approximately 99 percent of the dairy farms obtained TE levels of 90 percent or higher. In DEA, the different distributions of technical efficiency show approximately 60 percent of the dairy farms obtained TE levels of 80 percent or higher. The TE scores from both the SFA and the DEA approaches are clustered around the upper end of the TE distributions, which implies that most farms are close to or fully technically efficient in the sample. However, no farms operate in a fully technically efficient manner in the SFA model. Because the stochastic frontier allows for statistical noise which is beyond the control of farms and has a significant effect on the output level. This result implies efficiency scores in both CRS and VRS DEA exhibit greater variability than the SFA scores.

These results are consistent with Theodoridis and Psychoudakis (2008), where the average TE scores from the SFA model (0.812) are greater than those from both the CRS (0.634) and the VRS DEA (0.685) models. They are also in line with Sharma et al. (1997), where the mean TE scores of SFA (0.749) were larger than those obtained from the DEA approach (VRS: 0.726 and CRS: 0.644). However, Wadud and White (2000) stated that the average TE scores in VRS DEA (0.858) were higher than obtained those from both the CRS DEA (0.789) and the SFA (0.834), indicating different TE estimates compared with our results; however, their results revealed efficiency estimates for both VRS and CRS DEA exhibited greater variability than stochastic frontier efficiency measures, which confirms our results.

The efficiency scores obtained from the stochastic frontier and DEA indicate the negative skews, which suggest they have an asymmetrical distribution with a long tail to the left. In particular, the skewness of the SFA model is less than negative one, which means its skewness is substantial and the distribution of TE is far from symmetrical. Meantime, both VRS and CRS DEA obtain negative kurtosis compared with the positive kurtosis in the SFA model, which means there is a longer and flatter tail of the distribution with the DEA model. This result also indicates efficiency estimates for both VRS and CRS DEA exhibit greater variability than stochastic frontier efficiency measures. This result is consistent with Jaforullah and Premachandra (2003).

The spearman rank correlated coefficients between the technical efficiency rankings of NZ dairy farms obtained from the SFA and DEA models are presented in Table 8. As can be seen, all correlative coefficients are positive and highly significant at the 1% significance level. The strongest correlation (0.9246) is captured between the TE estimates from the VRS and CRS DEA, while the weakest correlation (0.7760) is obtained between the TE estimates from the SFA and VRS DEA. Because the correlative coefficients are significantly different from zero and greater than 0.5, it can be concluded that SFA, VRS and CRS DEA are in accord with their technical efficiency ranking. This result is consistent with Jaforullah and Premachandra (2003), Theodoridis and Psychoudakis (2008), Theodoridis and Anwar (2011), and Wadud and White (2000). But Sharma et al. (1997) found the weakest correlated coefficient was SFA and VRS DEA, which was opposite to our results.

Under the stochastic method, the sum of estimated elasticities of output with respect to all inputs (scale elasticity) is 1.0092, indicating that dairy farms exhibit constant returns to scale. According to the likelihood ratio test, the hypothesis that NZ dairy farms exhibit constant returns to scale cannot be rejected. This result is consistent with Sharma et al. (1997),Cabrera et al. (2010), and Kompas and Che (2006).

Table 8. Spearman rank correlation matrix of technical efficiency ranking of 315 NZ dairy farms obtained from SFA and DEA models

	TE_{SFA}	TE_{CRS}	TE_{VRS}
TE_{SFA}	1.0000		
TE_{CRS}	0.8592^{***}	1.0000	
TE_{VRS}	0.7760^{***}	0.9246^{***}	1.0000

Note: *** indicates significance at 1% level

In the DEA analysis, the results for the individual farms suggest that, of the 315 NZ dairy farms, more than half are operating above their optimal scale. 19 percent of dairy farms are operating below their optimal scale and 17 percent of dairy farms are operating at their optimal scale. Decreasing returns to scale dominates most NZ dairy farms, and a few farms indicate increasing returns to scale. This result is consistent with Wadud and White (2000), and Sharma et al. (1997). Hjalmarsson et al. (1996) found the DEA revealed increasing returns to scale that contrasts with our results.

6. Conclusion

This study investigates the efficiency performance utilising both the parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA) for a sample of 315 New Zealand dairy farms in 2006-2007. In the stochastic method, the efficiency measures are estimated under the specifications of the Cobb-Douglas production frontier. Based on the likelihood ratio test, the hypothesis that Cobb-Douglas functional form was an appropriate representation of the underlying production function cannot be rejected at the 1% significance level. In the DEA method, the output-oriented frontiers are estimated under the specifications of two scale assumptions: constant returns to scale and variable returns to scale. Both methods are estimated for the same farms using the same output and input variables in order to estimate the technical efficiency in a sample of dairy farms.

There are substantial differences in technical efficiencies estimated from these two methods. The estimated average technical efficiency in the SFA model (0.96) is greater than those obtained from CRS (0.8246) and VRS DEA (0.8598). The average technical efficiency of the dairy farms is sensitive to the choice of the production frontier estimating method. The different distributions of technical efficiency show that using the SFA model, approximately 99 percent of the dairy farms obtained TE levels of 90 percent or higher. With DEA, approximately 60 percent of the dairy farms obtained TE levels 80 percent or higher. The TE scores obtained from both the SFA and the DEA approaches are clustered around the upper end of the TE distributions, which implies that most of the farms are close to or fully technically efficient in the sample. Because in the DEA model, all deviations of the data from the frontier are attributed to inefficiency, while the stochastic frontier allows for statistical noise which is beyond the control of farms and has a significant influence on the output level. These results imply that the DEA (both VRS and CRS) efficiency measures indicate greater variability than the stochastic efficiency estimates.

The average technical efficiency estimates in DEA models are 0.8246 (under CRS) and 0.8598 (under VRS). This is because VRS DEA envelops the data points more tightly than the CRS DEA. The results indicate there are considerable production inefficiencies among the sample NZ dairy farms.

According to spearman rank correlated coefficients obtained from SFA and DEA models, the correlative coefficients are positive and highly significant at the 1% significance level. The strongest correlation of 0.9246 is captured between the TE estimates from the VRS and CRS DEA, while the weakest correlation of 0.7760 is obtained between the TE estimates from the SFA and VRS DEA. This result conforms to Jaforullah and Premachandra (2003), Theodoridis and Psychoudakis (2008), Theodoridis and Anwar (2011), and Wadud and White (2000). However, Sharma et al. (1997) found the weakest correlated coefficient was SFA and VRS DEA, which contrasts with our results.

In terms of scale efficiency, the NZ dairy farms are characterized by constant returns to scale in the SFA approach due to 1.0092 of scale elasticity (the sum of estimated elasticities of output with respect to all inputs), which is consistent with Cabrera et al. (2010), and Kompas and Che (2006). Based on the likelihood ratio test, the hypothesis that NZ dairy farms exhibit constant returns to scale cannot be rejected.

The DEA analysis indicates that decreasing returns to scale is prevalent in NZ dairy farms, which conforms to Wadud and White (2000), Sharma et al. (1997), but contrasts with Jaforullah and Whiteman (1999) and Hjalmarsson et al. (1996). The results for the individual farms indicate that more than half the dairy farms are operating above their optimal scale, which implies that these dairy farms increase their technical efficiency by continuing to decrease their size. This indicates that smaller farms will face a larger number of competitors and thus make less profits. 19 percent of dairy farms are operating below their optimal scale, which suggests that they could increase their technical efficiency by continuing to increase in their size. 17 percent of dairy farms are operating at their optimal scale, which implies they are increasing their technical efficiency by keeping their size constant.

In the DEA method, the average output level under the super-optimal scale (DRS) is larger than that under the optimal scale (CRS) and that under the sub-optimal scale (IRS), which conforms to the findings of Wadud and White (2000). In terms of output range, the range of optimal scale values is very large and overlaps a large portion of the super-optimal scale and the sub-optimal outputs, which conforms to the findings of Wadud and White (2000), and Sharma et al. (1997).

The DEA results support an agricultural policy encouraging larger farms, which can have a beneficial effect on the efficiency of NZ dairy farms. A key consideration is the larger observed dairy herds in recent decades, presumably due to taking advantage of economies of scale. But at the individual dairy farm level, there are different results. For instance, 19 percent of farms were operating below their optimal scale, 64 percent of farms were operating above their optimal scale, and 17 percent of farms were operating at their optimal scale. These results are consistent with Sharma et al. (1997), while they contrast with those of Jaforullah and Whiteman (1999).

Based on the results obtained from this study, it can be seen that most of the farms are close to or fully technically efficient in the New Zealand dairy industry. However, the results obtained from both the SFA and the DEA indicate that there are substantial production inefficiencies in NZ dairy farms. On average, the sample of NZ dairy farms would increase their milksolids by 4-18% using the same amount of inputs through efficiency improvement.

This paper is limited to estimate the technical efficiency; for instance, the estimated parameter associated with labour is statistically insignificant at the conventional levels, due to data limitations for this analysis such as human capital information (e.g. the age of farmers and the level of education), which belongs to the factors of inefficiency. The human capital variables could be the determinants of efficiency measurement and could also have a significant effect on efficiency performance (Theodoridis & Anwar, 2011). Future research could involve human capital inputs such as a farmer's age and educational level. Farmer education should be a concern of policy makers.

In addition, the estimated parameter associated with capital is also statistically insignificant at the conventional levels, owing to the limitations in the data availbale for this analysis; for example, no information is available about the size and quality of the land, which is used to measure the capital value of a farm. A concern of policy makers about the economies of scale of dairy farms would have required much better information on land quantity and land quality. On the other hand, incorporating land with the capital value of other physical assets could be a serious drawback for obtaining better information on land quantity and quality.

Estimating the stochastic frontier based on the estimated technological parameters, the multicollinearity issue leads to insignificant estimated coefficients. Several studies suggested that technical efficiency estimates were robust to functional form choice (Maddala, 1979; Good et al., 1993; Ahmad & Bravo-Ureta, 1996). This paper finally uesd the Cobb-Douglas production frontier and thus it is a necessary procedure to assess the robustness of the estimates.

Moreover, this study lacks some environmental factors, which affect the technical efficiency estimate in NZ dairy farms. For example, considering weather and rainfall conditions on NZ dairy farms might impact on the use of feed and the estimates of technical efficiency because farms might depend less on a local irrigation system. As DairyNZ (2013) reported, the milksolids processed decreased by 1.6% in the year of 2007/08, due to a widespread summer and autumn drought. NZ dairy farmers have to change their production structure more environmentally in order to deal with uncertainties and challenges in a new environment, to which they might slowly adapt and apply technically efficient technology. It is worth noting for policy makers that environmental factors may have an impact on the technical efficiency of NZ dairy farms.

Jaforullah and Whiteman (1999) mentioned that the DEA has increasingly been used as a benchmarking tool in other industries and countries, like introducing benchmarking as a means of stimulating microeconomic reform for the Australian government, while the SFA currently cannot provide the same level of details on individual farms compared with the DEA on estimating farm efficiency.

Reference

Ahmad, M., & Bravo-Ureta, B. E. (1996). Technical efficiency measures for dairy farms using panel data: a comparison of alternative model specifications. *Journal of Productivity Analysis*, *7*(4), 399-415.

Ahn, T. S., & Seiford, L. M. (1993). Sensitivity of DEA to models and variable sets in a hypothesis test setting: The efficiency of university operations. In *Creative and innovative approaches to the science of management* (pp. 191-208). New York: Quorum Books.

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21-37.

Aldeseit, B. (2013). Measurement of Scale Efficiency

in Dairy Farms: Data Envelopment Analysis (DEA) Approach. *Journal of Agricultural Science*, *5*(9), p37.

Banker, R. D. (1984). Estimating most productive scale size using data envelopment analysis. *European Journal of Operational Research*, *17*(1), 35-44.

Banker, R. D. (1996). Hypothesis tests using data envelopment analysis. *Journal of Productivity Analysis*, *7*, 139-159.

Banker, R. D., & Thrall, R. M. (1992). Estimation of returns to scale using data envelopment analysis. *European Journal of Operational Research*, *62*(1), 74-84.

Battese, G. E. (1997). A note on the estimation of Cobb-Douglas production functions when some explanatory variables have zero values. *Journal of Agricultural Economics*, *48*, 250-252.

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*, *38*(3), 387-399.

Bauer, P. W., Berger, A. N., Ferrier, G. D., & Humphrey, D. B. (1998). Consistency conditions for regulatory analysis of financial institutions: a comparison of frontier efficiency methods. *Journal of Economics and Business, 50*(2), 85-114.

Bjurek, H., Hjalmarsson, L., & Førsund, F. R. (1990). Deterministic parametric and nonparametric estimation of efficiency in service production: A comparison. *Journal of Econometrics, 46*(1), 213-227.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1993). Efficiency analysis of developing country agriculture: a review of the frontier function literature. *Agricultural and Resource Economics Review*, *22*(1), 88-101.

Bravo-Ureta, B. E., Solís, D., López, V. H. M., Maripani, J. F., Thiam, A., & Rivas, T. (2007). Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis*, *27*(1), 57-72.

Cabrera, V. E., Solis, D., & Del Corral, J. (2010). Determinants of technical efficiency among dairy farms in Wisconsin. *Journal of Dairy Science*, *93*(1), 387-393.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429-444.

Coelli, T. J. (1995). Recent developments in frontier modelling and efficiency measurement. *Australian Journal of Agricultural and Resource Economics*, *39*(3), 219-245.

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

Coelli, T. J. (1996b) A guide to DEAP Version 2.1: A data envelopment analysis (Computer) program, *CEPA Working Paper 8/96*. Armidale: University of New England.

Coelli, T. J., & Battese, G. E. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural and Resource Economics*, *40*(2), 103-128.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd Edition). New York: Springer.

Coelli, T., & Perelman, S. (1999). A comparison of parametric and non-parametric distance functions: With application to European railways. *European Journal of Operational Research*, *117*(2), 326-339.

Cooper, W. W., Seiford, M. L. & Tone, K. (2000). Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software. Boston: Kluwer Academic Publishers.

Cornwell, C., Schmidt, P., & Sickles, R. C. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics*, *46*(1), 185-200.

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*(2), 139-158.

Cummins, J. D., & Weiss, M. A. (2013). Analyzing firm performance in the insurance industry using frontier efficiency and productivity methods. In *Handbook of insurance* (pp. 795-861). New York: Springer.

Cummins, J. D., & Zi, H. (1998). Comparison of frontier efficiency methods: An application to the U.S. life insurance industry. *Journal of Productivity Analysis*, *10*(2), 131-152.

DairyNZ (2013a). *DairyNZ Economic Survey 2012-13*. Last retrieved July 1st 2014 at: http://www.dairynz.co.nz/publications/dairy-industry/dairynz-economic-survey-2012-13/

DairyNZ (2013b). *Strategy for Sustainable Dairy Farming 2013-2020-Background supplement*. Last retrieved July 1st 2014 at http://www.dairynz.co.nz/publications/dairy-industry/strategy-for-sustainable-dairy-farming-2013-2020-background-supplement/

DairyNZ (2013c). *Strategy for Sustainable Dairy Farming 2013-2020*. Last retrieved July 1st 2014 at http://www.dairynz.co.nz/publications/dairy-industry/strategy-for-sustainable-dairy-farming-2013-2020/

Dimara, E., Pantzios, C. J., Skuras, D., & Tsekouras, K. (2005). The impacts of regulated notions of quality on farm efficiency: A DEA application. *European Journal of Operational Research*, *161*(2), 416-431.

EWG Farm Subsidies (2004). *The United States Dairy Program Subsidies*. Last retrieved July 1st 2014 at http://farm.ewg.org/progdetail.php?fips=00000&progcode=dairy

Färe, R., Grosskopf, S., & Lovell, C. K. (1985). *The measurement of efficiency of production* (Vol. 6). Springer.

Färe, R., Grosskopf, S., & Lovell, C. K. (1994). *Production frontiers*. Cambridge University Press.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*. Series A (General), 253-290.

Favero, C. A., & Papi, L. (1995). Technical efficiency and scale efficiency in the Italian banking sector: a non-parametric approach. *Applied Economics*, *27*(4), 385-395.

Ferrier, G. D., & Lovell, C. K. (1990). Measuring cost efficiency in banking: econometric and linear programming evidence. *Journal of Econometrics*, *46*(1), 229-245.

Førsund, F. R., & Hernaes, E. (1994). A comparative analysis of ferry transport in Norway. In Charnes, A., Cooper, W.W., Lewin, Y. A., & Seiford (Eds.), *Data Envelopment Analysis: Theory, Methodology, and Applications* (pp. 285-311). Netherlands: Springer.

Fried, H. O., Lovell, C. K., & Schmidt, S. S. (Eds.). (1993). *The measurement of productive efficiency and productivity growth*. New York: Oxford University Press.

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

Greene, W. H. (1993). The econometric approach to efficiency analysis. In Fried, H. O., Lovell, C. K., & Schmidt, S. S. (Eds.), *The measurement of productive efficiency: techniques and applications* (pp68-119). New York: Oxford University Press.

Harris, R. I. (1993). Measuring efficiency in New Zealand manufacturing in 1986/7 using a frontier production function approach. *New Zealand Economic Papers*, *27*(1), 57-79.

Hjalmarsson, L., Kumbhakar, S. C., & Heshmati, A. (1996). DEA, DFA and SFA: a comparison. *Journal of Productivity Analysis*, *7*, 303-327.

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

Jaforullah, M., & Premachandra, E. (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., & Whiteman, J. (1998). Scale Efficiency in the New Zealand Dairy Industry: a Non-parametric Approach. *Economics Discussion Papers No. 9810*, University of Otago, Dunedin, New Zealand.

Jaforullah, M., & Whiteman, J. (1999). Scale Efficiency in the New Zealand Dairy Industry: a Non-parametric Approach. *Australian Journal of Agricultural and Resource Economics*, *43*(4), 523-541.

Jiang, N. (2011). *Efficiency analysis of NZ dairy farming and the issue of climate change policy* (Doctoral thesis, University of Auckland, Auckland, New Zealand). Retrieved from https://researchspace.auckland.ac.nz/bitstream/handle/2292/10210/whole.pdf

Jiang, N., & Sharp, B. (2013). Cost Efficiency of Dairy Farming in New Zealand: a stochastic frontier analysis. In *New Zealand Association of Economists Annual Conference* (pp. 3-5), Wellington, New Zealand.

Johnes, G. (1995). Scale and technical efficiency in the production of economic research. *Applied Economics Letters*, *2*(1), 7-11

Jondrow, J., Lovell, C. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, *19*(2), 233-238.

Kalaitzandonakes, N. G., & Dunn, E. G. (1995). Technical efficiency, managerial ability and farmer education in Guatemalan corn production: a latent variable analysis. *Agricultural and Resource Economics Review*, *24*(1), 36-46.

Kompas, T., & Che, T. N. (2006). Technology choice and efficiency on Australian dairy farms. *Australian Journal of Agricultural and Resource Economics*, *50*(1), 65-83.

Kumbhakar, S. C., & Lovell, C. K. (2000). *Stochastic frontier analysis*. Cambridge University Press.

Lothgren, M., & Tambour, M. (1999). Bootstrapping the data envelopment analysis Malmquist productivity index. *Applied Economics*, *31*(4), 417-425.

Lovell, C. K., Travers, P., Richardson, S., & Wood, L. (1994). *Resources and functionings: a new view of inequality in Australia* (pp. 787-807). Springer Berlin Heidelberg.

Maddala, G. S. (1979). A note on the form of the production function and productivity. In: *Measurement of Agricultural Productivity* (pp. 309-457). National Research Council, Washington D.C.: National Academy of Sciences.

Meeusen W. & Broeck, J. (1997) Efficiency estimation from Cobb-Douglas production functions with composite error. *International Economic Review*, *18*, 435-444.

Murova, O., & Chidmi, B. (2013). Technical efficiency of US dairy farms and federal government programs. *Applied Economics*, *45*(7), 839-847.

Resti, A. (1997). Evaluating the cost-efficiency of the Italian banking system: what can be learned from the joint application of parametric and non-parametric techniques. *Journal of Banking and Finance*, *21*(2), 221-250.

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

Schmidt, P., & Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business and Economic Statistics*, *2*(4), 367-374.

Seiford, L. M., & Thrall, R. M. (1990). Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of Econometrics*, *46*(1), 7-38.

Sharma, K. R., Leung, P., & Zaleski, H. M. (1997). Productive efficiency of the swine industry in Hawaii: stochastic frontier vs. data envelopment analysis. *Journal of Productivity Analysis*, *8*(4), 447-459.

Simar, L., & Wilson, P. W. (2000a). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, *27*(6), 779-802.

Simar, L., & Wilson, P. W. (2000b). Statistical inference in nonparametric frontier models: The state of the art. *Journal of productivity analysis*, *13*(1), 49-78.

Skevas, T., & Lansink, A. O. (2014). Reducing Pesticide Use and Pesticide Impact by Productivity Growth: the Case of Dutch Arable Farming. *Journal of Agricultural Economics*, *65*(1), 191-211.

Theodoridis, A. M., & Anwar, M. M. (2011). A comparison of DEA and SFA methods: a case study of farm households in Bangladesh. *Journal of Developing Areas*, *45*(1), 95-110.

Theodoridis, A. M., & Psychoudakis, A. (2008). Efficiency measurement in Greek dairy farms: Stochastic frontier vs. data envelopment analysis. *International Journal of Economic Sciences and Applied Research*, *2*, 53-66.

Wadud, A., & White, B. (2000). Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics*, *32*(13), 1665-1673.

Wadud, M. A. (2003). Technical, allocative, and economic efficiency of farms in Bangladesh: A stochastic frontier and DEA approach. *Journal of Developing Areas*, *37*, 109-126.

Zhang, X., Huang, G. H., Lin, Q., & Yu, H. (2009). Petroleum-contaminated groundwater remediation systems design: A data envelopment analysis based approach. *Expert Systems with Applications*, *36*(3), 5666-5672.