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Feed use intensification and technical efficiency of dairy farms in New Zealand*

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In recent years, the traditionally pasture-based dairy farms in New Zealand have become more intensive by using higher proportions of supplementary feed. This trend has been attributed to a range of factors, such as productivity enhancement, overcoming pasture deficits and the improvement of body condition scores. However, there is a lack of knowledge as to how feed use intensification affects the technical efficiency of dairy farms in New Zealand. This paper addresses the research gap by estimating the impact of feed use intensification on the technical efficiency of New Zealand dairy farms, using a fixed effects stochastic production frontier model and a balanced panel of 257 farms from 2010 to 2013. The empirical results show that technical efficiency on New Zealand dairy farms is positively and significantly influenced by feed use intensification, herd size and milking frequency.

Key words: dairy farms, intensification, New Zealand, stochastic production frontier, technical efficiency.

1. Introduction

Although the global dairy industry has traditionally been heavily pasture dependent, in recent decades, there has been a worldwide trend towards intensifying dairy production through additional supplementary feed (Alvarez *et al*. 2008; Cabrera *et al*. 2010; Foote *et al*. 2015).[1] This trend may influence the social, economic and environmental performance of dairy farms because intensification requires changes in management practices. When considering the wider impact of feed use intensification on dairy farms, it is important to understand the link between this form of intensification and technical efficiency because of the implications for dairy productivity and competitiveness between countries and regions. In particular, understanding the nexus between feed use intensification and efficiency can provide dairy industry stakeholders with information to help improve farm management practices and enhance the productivity and competitiveness of dairy farms.

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[1] Dairy intensification can be defined as an increase in outputs per unit area by increasing external inputs such as supplementary feed (Foote *et al*. 2015).

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New Zealand is the world's largest exporter of dairy products, and the eighth largest milk producer worldwide.[2] Dairy farming dominates agriculture in New Zealand, with export sales of processed milk and manufactured dairy products of 12.2 billion NZ$ in 2015/16. Driven by increases in global demand and price over the past decades, New Zealand dairy farming has expanded dramatically. For example, the total effective land used for dairy production increased by approximately 45 per cent from 1995 to 2015 (reaching around 1.75 million hectares in 2015), while dairy cattle numbers more than doubled from 2.44 million to nearly 5.00 million between 1990 and 2015. In addition, the use of supplementary feed has been increasing in both absolute and relative terms in New Zealand. According to the Ministry of Primary Industries, non-pasture supplements made up approximately four per cent of an average dairy cows diet in 1990/91, and nearly 20 per cent in 2014/15 (MPI, 2017). In 2014/15, it was estimated that silage, palm kernel extract (PKE) and winter crops were the top supplements in New Zealand. A number of possible reasons have been identified for this trend, including productivity enhancement, overcoming pasture deficits and the improvement of body condition scores. Greig (2012) found that the development of irrigation based pastoral systems (especially in the South Island), changes in relative feed and milk prices, increased farmland values, personal preference and changing climate conditions are all potential determinants of the level of supplementary feed used on New Zealand dairy farms.

Extant studies have confirmed that the implementation of more intensive production systems contributes to an increase in dairy production (Hedley *et al*. 2006; Yates *et al*. 2010; Mounsey 2015; Ma *et al*. 2018). Considering that higher farm production could be achieved by means of better technology, higher levels of input use, and/or higher technical efficiency, it is possible that dairy farmers achieve high farm outputs (e.g. milksolids) simply by using more inputs rather than efficient usage of their inputs. A more thorough knowledge about the relationship between feed use intensification and technical efficiency would allow dairy farmers to adjust their farming practices sustainably. However, to the best of our knowledge, the question of whether the use of supplementary feed can boost technical efficiency on dairy farms in New Zealand is currently unanswered.

This study fills the gap by estimating the impact of feed use intensification on the technical efficiency of dairy farms in New Zealand. We use a fixed effects stochastic production frontier model on a balanced panel dataset to jointly estimate the stochastic frontier function and the inefficiency function. An important advantage of using panel data in an empirical study is that the effects of differences across individuals (individual farm-specific effects) can be distinguished from the effects changing over time within the individuals (Wang and Ho 2010).

[2] Other main milk producing countries include the United States, India, China, Brazil, Germany, Russia and France.

The data used in the empirical analysis represent a sample of 257 dairy farms that were part of the DairyNZ database from 2010 to 2013 (1,028 observations). The surveyed farms are located in both the North and South Islands, covering the main dairy producing regions in New Zealand. In the present study, we test the hypothesis that feed use intensification leads to higher levels of technical efficiency for the predominantly pasture-based farming systems in New Zealand. Efficiency may be enhanced by feed use intensification, but feed use intensification also has important implications for outcomes such as 'naturalness', animal welfare and environmental impact – all of which have been linked to consumer preferences to varying degrees and are therefore important for any country seeking either to differentiate food products by attributes, or when considering concepts such as 'limits to growth' in the design of their farming systems.

Given the important status of New Zealand milk production and supply in the world and the fact that dairy farmers in the country have significantly increased their use of supplementary feed in recent years (Mounsey 2015), it is critical to identify the potential role of extra supplementary feed use in improving the technical efficiency of dairy farms. This can deliver significant insights into strategies that enhance dairy performance and competitiveness.

The rest of the paper is structured as follows: Section 2 outlines the existing literature on technical efficiency of dairy farms with particular reference to the impact of feed use intensification. Section 3 describes the econometric framework used in the study. The data and descriptive statistics are presented in section 4, and the empirical results are reported and discussed in Section 5. The final section concludes.

2. Literature review

A number of studies have analysed the technical efficiency of dairy farms in different regions of the world. The earlier studies focused on estimating technical efficiency scores for dairy farms, and the extent to which the technical efficiency estimates were influenced by the specifications of the empirical models. Examples include Battese and Coelli (1988), Jaforullah and Devlin (1996), Jaforullah and Whiteman (1999), Jaforullah and Premachandra (2003), Karagiannis *et al.* (2002) and Abdulai and Tietje (2007). Later studies have extended the estimation of technical efficiency scores to considering the potential sources of inefficiency. These studies include those by Hardi and Whittaker (1999), Hadley (2006), Kompas and Che (2006), Cabrera *et al.* (2010) and Jiang and Sharp (2015). Table A1 in the Appendix S1 provides an overview of the empirical studies that have been reviewed for the current study. However, relatively few empirical studies have measured the impact of feed use intensification on technical efficiency. Because the objective of this study is to determine the relationship between higher levels of supplementary feed and technical efficiency on New Zealand dairy farms, we focus our attention on the findings from the studies that have previously explored this relationship. These studies provide empirical evidence on the size and significance of the relationship between feed use intensification and technical efficiency on dairy farms, and therefore inform our model specification and hypothesis development.

In an early contribution to the literature on dairy cow feed consumption and technical efficiency, Hallam and Machado (1996) explored the determinants of technical efficiency in a second-stage regression that included feed per cow and land per cow as explanatory variables to represent farming intensity. This study compared the performance of four stochastic production frontier models estimated with panel data collected from Portuguese dairy farms between 1989 and 1992, and found that increasing levels of feed have a positive impact on efficiency that is small in magnitude and only weakly significant. The relationship between land per cow and technical efficiency was not statistically significant. While this study suggests a positive relationship between feed intensification and technical efficiency, differences in farming systems between Portugal and New Zealand lead us to doubt the transferability of these results to a New Zealand context. In addition, it is unclear whether the feed variable includes pasture as well as purchased or self-procured non-pasture feeds.

With survey data from 1996, 1998 and 2000, Kompas and Che (2006) used a model proposed by Battese and Coelli (1995) to simultaneously estimate technical efficiency scores and the determinants of technical efficiency for dairy farms in Victoria and New South Wales. These authors included the average amount of concentrate fed to the cows (kg/head) as an indicator of feed use intensification in their inefficiency model. Their results suggest that feed intensification had a statistically significant, but extremely small impact on technical efficiency for farms in Australia. Other significant determinants of technical efficiency were dairy shed technology and the proportion of land under irrigation. While the farming systems in Australia can be expected to be far more similar to New Zealand systems than those in Portugal, the supplementary feed under consideration in the current study is more varied than just concentrate. From the descriptive statistics provided by the authors, it also appears that supplementary feed represents a higher proportion of the cows' nutritional intake in Australia then New Zealand. With those caveats in mind, the results of this study also indicate that we can anticipate a positive and significant relationship between feed use intensification and technical efficiency in our study.

Using a dataset from a cross-section of 273 dairy farms in the United States, Cabrera *et al.* (2010) investigated the determinants of technical efficiency among dairy farms in Wisconsin. These authors included two measures of farming intensity in their inefficiency model: the ratio of purchased feed to herd size, and a dummy variable associated with the use of a total mixed ration (TMR) feeding system. Their results suggested that purchased feed has a small but significant impact on technical efficiency. The coefficient on the TMR dummy was much larger in magnitude, but less significant statistically. Taken together, these results suggest that feed delivery, as well as feed volume, may influence technical efficiency.

Alvarez *et al.* (2008) used cluster analysis to classify farms in their sample by level of farming intensity, and then estimated independent stochastic cost frontiers for each group. Data were sourced from 224 dairy farms in Northern Spain from 1999 to 2007. Their results suggest that intensive farms were closer to their cost frontier than extensive ones, but that the cost frontier for the intensive group was above the frontier for the extensive group. So, while they may be closer to their frontier, the intensive farmers are higher cost producers per unit of output than the extensive farmers. Although these authors were looking more generally at farm intensification (rather than feed use intensification) and cost efficiency (as opposed to technical efficiency), their results are broadly consistent with the conclusion that more intensive farms are more efficient.

We are aware of only two studies in the published literature (Rouse *et al.* 2009; Jiang and Sharp 2015) that examine the determinants of technical efficiency for New Zealand dairy farms. Neither of these studies considered the impact of feed use intensification on technical efficiency. Rouse *et al.* (2009) estimated an average technical efficiency of 91 per cent and found that annual rainfall and herd size had a positive and significant effect on technical efficiency. Jiang and Sharp (2015) used panel data from 1,294 dairy farms to show that herd size, shed type (i.e. rotary) and irrigation intensity were all positively linked to technical efficiency. Given that both pasture growth and silage production are positively associated with rainfall and irrigation, the results of these studies are suggestive of a positive relationship between feed and technical efficiency in New Zealand. Whether the association between feed and efficiency is significant within the context of a wider range of supplementary feed is an empirical question that, until this study, had not been addressed.

As reported above and summarised in Table A1 in the Appendix S1, technical efficiency has been the focus of attention for several studies in dairy farming countries. Some studies have investigated the role of feed use intensification in determining the technical efficiency of dairy farms (Hallam and Machado 1996; Kompas and Che 2006; Alvarez *et al.* 2008; Cabrera *et al.* 2010), but there is a lack of empirical evidence as to how feed use intensification affects technical efficiency for the traditionally pasture-based dairy farms in New Zealand. The present study contributes to the literature by analysing the impact of supplementary feed use intensification on technical efficiency of dairy farms in New Zealand.

3. Econometric framework

3.1 Estimation issues and model selection

To assess the technical efficiency of dairy farms, previous studies have used both nonparametric methods such as data envelop analysis (e.g. Cloutier and

Rowley 1993; Fraser and Cordina 1999; Jaforullah and Whiteman 1999; Fraser and Graham 2005; Stokes *et al.* 2007; Rouse *et al.* 2009) and parametric method such as stochastic frontier analysis (e.g. Hardi and Whittaker 1999; Abdulai and Tietje 2007; Alvarez *et al.* 2008; Cabrera *et al.* 2010; Jiang and Sharp 2015; Dong *et al.* 2016; Latruffe *et al.* 2017). Both of these approaches have well-recognised advantages and disadvantages. While the nonparametric estimates are sensitive to measurement errors and attribute all deviations from the frontier to inefficiencies, they are free of assumptions regarding functional form for the frontier. The strength of the parametric approaches is that they explicitly consider stochastic noise in the data generation process and allow for the estimation of elasticities and the unified statistical testing of hypotheses on the production process and the determinants of inefficiency.

Given the inherently stochastic nature of pasture-based dairy production and the primary objective of identifying the impact of supplementary feed use on technical efficiency, we chose to adopt a stochastic frontier approach for the current study. This choice is entirely consistent with the results of a meta-regression analyses by Bravo-Ureta *et al.* (2007) and Mareth *et al.* (2017) which highlight the predominance of studies using a stochastic frontier approach to estimate technical efficiency for dairy farms.

The early stochastic frontier models for panel data do not distinguish between unobserved individual heterogeneity and inefficiency. This lack of specificity forces all time-invariant heterogeneity into the estimated inefficiency term (Aigner *et al.* 1977). Although the true fixed effects stochastic frontier model proposed by Greene (2005) can help overcome the issues facing early stochastic frontier models, the estimation of Greene's (2005) model may still be biased by the incidental parameters problem. Fortunately, a number of approaches have been proposed to address this issue (Wang and Ho 2010; Chen *et al.* 2014; Colombi *et al.* 2014). For example, Wang and Ho (2010) proposed a fixed effects panel stochastic frontier model that is immune to the incidental parameters problem, because the first-difference and within-transformation are analytically performed on this model so as to remove the fixed individual effects. The primary advantage of this model is that the term representing the individual farm's fixed effects is dropped from the estimation equation, and thus the incidental parameters problem is avoided altogether. Therefore, the fixed effects panel stochastic frontier model suggested by Wang and Ho (2010) is employed in the present study to estimate the impact of feed use intensification on the technical efficiency of dairy farms, and simultaneously identify which factors help explain observed differences in efficiency levels between farms.[3]

[3] The fixed-effects panel stochastic frontier model can be estimated using the STATA commands 'sf_fixeff' suggested in Kumbhakar *et al.* (2015).

3.2 Fixed effects panel stochastic frontier model

Following Wang and Ho (2010), we specify the following fixed effects panel stochastic frontier model:

$$\ln(Y_{it}) = \alpha_i + \beta \ln X_{it} + \varepsilon_{it}, \tag{1}$$

$$\varepsilon_{it} = v_{it} - u_{it}, \tag{2}$$

$$v_{it} \sim N(0, \sigma_v^2), \tag{3}$$

$$u_{it} = h_{it} \cdot u_i^*, \tag{4}$$

$$h_{it} = f(Z_{it}\delta), \tag{5}$$

$$u_i^* \sim N^+\left(\mu, \sigma_u^2\right), i = 1, 2, 3, \ldots, N; t = 1, 2, 3, \ldots, T, \tag{6}$$

where ln represents natural logarithm; Y_{it} is dairy output (e.g. milksolids) produced by farm operator i in year t; α_i is individual farm i's fixed effects; X_{it} is a vector of production inputs (e.g. labour, feed, land and herd size) used by farm operator i in year t; β is a vector of unknown parameters to be estimated; ε_{it} is the error term, which is composed of v_{it}, a zero-mean random error and u_{it}, a stochastic variable measuring inefficiency; h_{it} is a positive function of a vector of non-stochastic inefficiency determinants (Z_{it}) such as supplementary feed use, farm size, milking frequency and dairy breed. In Equation (6), the notation '+' indicates that realised values of the random variable u_i^* are positive because the underlying distribution is truncated from below at zero. The random variable u_i^* is assumed independent of v_{it} for all t, and both u_i^* and v_{it} are independent of $\{X_{it}, Z_{it}\}$.

The fixed effects stochastic frontier model specified above exhibits the 'scaling property'. That is, conditional on Z_{it}, the one-sided error term is comprised of a scaling function h_{it} multiplied by a one-sided error distributed independently of Z_{it} (Wang and Ho 2010). With this property, the shape of the underlying distribution of the inefficiency term is the same for all individuals, but the scale of the distribution is stretched or shrunk by observation-specific factors, Z_{it}. The time-invariant specification of u_i^* allows the inefficiency u_{it} to be correlated over time for a given farm.

In estimating the fixed effects stochastic frontier model, the stochastic inefficiency term (u_{it}) can be assumed to follow either a half-normal or a truncated-normal distribution (Kumbhakar *et al.* 2015). Model selection tests support the specification of a half-normal distribution for u_{it}.

The technical efficiency (TE_{it}) of the i-th farm in the t-th observation year can be defined as the ratio of observed production (conditional on its levels of factor inputs and farm effects) to the expected efficient production if the farm utilised its level of inputs most efficiently:

$$\mathrm{TE}_{it} = \frac{Y_{it}}{Y^{*}_{it}} = \frac{E(Y_{it}|u_{it}, X_{it})}{E(Y_{it}|u_{it} = 0, X_{it})} = \exp(-u_{it}), \tag{7}$$

where Y_{it} refers to the observed farm output, and Y^{*}_{it} is the maximum feasible farm output. Because Y_{it} is always $\leq Y^{*}_{it}$, TE_{it} is bounded between zero and one. TE_{it} achieves its upper bound when a dairy farm is producing the output at a maximum feasible level (i.e. $Y_{it} = Y^{*}_{it}$), given the certain levels of input quantities.

3.3 Functional form and variables for the production function

With respect to estimating Equation (1), both the Cobb-Douglas and the translog functional forms have been widely used in the empirical literature. Studies using the Cobb-Douglas form include Battese and Coelli (1988), Hadley (2006), Kompas and Che (2006), Cabrera *et al*. (2010), Jiang and Sharp (2015) and Latruffe *et al*. (2017), and those that applied the translog functional form include Jaforullah and Devlin (1996), Hadley (2006), Abdulai and Tietje (2007), Alvarez *et al*. (2008). To identify an appropriate functional form for our analysis, both the Cobb-Douglas and the translog functional form were estimated for preliminary comparison. The results, which are not presented here but are available on request, show that the coefficients on the quadratic and interaction terms in the translog form are not statistically significant. Moreover, a likelihood ratio test confirms that the Cobb-Douglas functional form is preferred over the translog functional form. Thus, the following Cobb-Douglas production function is used in the present study:

$$\begin{aligned} Ln(Y_{it}) = \beta_0 &+ \beta_1 Ln(Labour)_{it} + \beta_2 Ln(Stock)_{it} + \beta_3 Ln(Feed)_{it} \\ &+ \beta_4 Ln(Overhead)_{it} + \beta_5 Ln(Other)_{it} + \beta_6 Ln(Farm)_{it} \\ &+ \beta_7 Ln(Herd)_{it} + \beta_8 Year_{it} + \varepsilon_{it}, \end{aligned} \tag{8}$$

where the dependent variable $Ln(Y_{it})$ is the log-transformed quantity of farm output (e.g. milksolids). $Ln(Labour)_{it}$, $Ln(Stock)_{it}$, $Ln(Feed)_{it}$, $Ln(Overhead)_{it}$, and $Ln(Other)_{it}$ refer to log-transformed labour expense, stock expense, feed expenses, overhead expenses and other expenses for the i-th farm in the t-th observation year, respectively. The original values of input expenses were deflated to a base year of 2013 by the farm expenses price index for dairy farms released by Statistics New Zealand. $Ln(Farm)_{it}$ and $Ln(Herd)_{it}$ refer to log-transformed values of farm size and herd size, respectively. $Year_{it}$ is used to control for time effects and/or technological change. β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7 and β_8 are parameters to be estimated. The error term ε_{it}, has been elaborated by the Equations/specifications (2)–(6).

3.4 Technology heterogeneity and endogeneity

Random shocks, which are observed by farmers but not econometricians, may affect both farm input choices and dairy productivity. Optimising farmers may adjust input levels in response to productivity shocks that they observe, but which are unobserved to the statistician, resulting in a simultaneity problem in the estimation of the production frontier (Shee and Stefanou 2014). Ignoring such endogeneity issues altogether could result in biased parameter estimates and incorrect statistical inference. However, we suggest that endogeneity issues are not of major importance in the present study for two reasons. Firstly, the estimation utilises a relatively short panel and the fixed effects stochastic frontier model enables us to control for medium to longer-term investments by farmers associated with unobservable factors, such as shed investments or management approaches (which typically require major farm capital changes). Thus, the only possible endogeneity concerns are related to short-term changes available to farmers of which there are relatively few in dairy farming systems (due to the need to maintain a viable herd much like a perennial crop). Secondly, the focus of this study is on technical efficiency rather than on considering deep or structural aspects of the technology. Given that endogeneity affects the beta estimates but not the predictive validity of the output variable, the endogeneity issues are less important for considering technical inefficiency.

Another issue we need to account for is the potential for production technology differences among dairy farms under different production systems. In particular, if farms under different production systems operate under different production frontiers, the parameter estimates produced with pooled data will be biased. Differences in production technology are often formally tested with a likelihood ratio test as mentioned in Kumbhakar *et al.* (2015). Unfortunately, because some dairy farms in our sample 'swap' around between the five production systems through time, the panels of data are not balanced for the more general specification, which consists of five subsets of data. As a result, the likelihood ratio test fails to return a valid result for this overall dataset. Because our subsequent empirical estimation requires the pooled model, we retain this specification for estimation purposes.

4. Data and descriptive statistics

The empirical analysis was conducted using a balanced panel of 257 New Zealand dairy farms observed over the period 2010–13. The dairy farm business data were collected from dairy farms throughout the main dairy production areas in New Zealand through the DairyBase® database. DairyBase® is a web-based package that records and reports standardised physical and financial information of dairy farms, which is owned and managed by DairyNZ on behalf of the dairy farmers in New Zealand. The farms within the database cover the main dairy-producing areas in New Zealand.[4] Data are entered into the database by accredited providers.

The farm output variable is defined as total milksolids produced (kg). Based on the literature and the data provided by DairyBase® (2006), inputs are aggregated into seven categories (labour expenses, stock expenses, feed expenses, overhead expenses, other expenses, farm size and herd size). Table A2 in the Appendix S1 provides a more detailed description of the selected variables.

We combine the available data (DairyBase® 2006) with evidence from the existing empirical literature (e.g. Kompas and Che 2006; Abdulai and Tietje 2007; Cabrera *et al.* 2010; Jiang and Sharp 2015; Dong *et al.* 2016) to identify a set of explanatory variables for technical inefficiency. Specifically, variables representing supplementary feed use intensification, farm size, herd size, farm location, milking frequency and shed type were selected and included in the inefficiency model.

Table 1 presents descriptive statistics for the selected variables. Both output and inputs display a significant amount of variation. For example, milksolids production was 163,511 kg on average, but ranged from 26,566 to 655,458 kg. Feed was the major expense on farms, at an average of NZ $215,361 per farm. The average effective milking area for farms in the sample was 148 ha. Among the variables that are expected to affect technical inefficiency, Table 1 shows that more than 90 per cent of dairy farms chose to milk cows twice a day, and around 78.6 per cent of farms were located in the North Island. With respect to feed use intensification, most of the farms reported operating at a 'moderate' level of feed intensification.

The last column of the table presents the fraction of the variance of each variable that can be attributed to variation between different farms in the sample. The figures indicate the majority of the variation for the variables under consideration is between the farms, relative to within the farm. This high degree of between variation is consistent with our *a priori* expectation of intrinsic heterogeneity among the farms or farmers that is most appropriately captured by panel data techniques. Fortunately, there is still enough variation in the data within each farm to make estimation possible.

Table 2 reports the output and inputs over the 4-year panel period. It shows that milksolids production was generally increasing from 2010 to 2013, with a slight reduction in 2012. Among the six production inputs, labour expenses, stock expenses, feed expenses, overhead expenses, farm size and herd size were steadily increasing in different scales over the 4-year panel period. The descriptive statistics presented in Table 2 suggest that increases in input use are correlated with an increase in milksolids production, but it does not provide any information on whether these inputs contribute to overall

[4] More specifically, the database covers three regions in the South Island (West Coast-Tasman, Marlborough-Canterbury, and Otago-Southland) and five regions in the North Island (Northland, Waikato, Bay of Plenty, Taranaki and Lower North Island).

Table 1 Summary statistics of the employed variables (n = 1,028)

Variable	Mean	SD	Min.	Max.	Between variation
Milksolids (1,000 kg)	163.511	105.891	26.566	655.458	0.962
Labour expenses (1,000 NZ$)	152.459	90.855	2.080	660.131	0.929
Stock expenses (1,000 NZ$)	84.646	54.482	12.918	333.182	0.921
Feed expenses (1,000 NZ$)	215.361	201.033	4.086	1,424.327	0.903
Overhead expenses (1,000 NZ$)	93.515	70.891	3.994	515.727	0.950
Other expenses (1,000 NZ$)	181.838	145.604	15.051	979.744	0.947
Farm size (hectares)	148.400	78.151	43.000	559.500	0.963
Herd size (number)	429.250	249.929	130	1,551	0.971
Year (ordinal)	1.500	1.119	0	3	—
Feed intensification (ordinal)	2.936	1.038	1	5	—
Farm location (dummy)	0.786	0.410	0	1	—
Milking frequency (dummy)	0.912	0.283	0	1	—
Shed type (dummy)	0.206	0.405	0	1	—

Table 2 Output and inputs allocation by years

Variables	2010	2011	2012	2013
Output				
Milksolids (1,000 kg)	149.142	165.273	162.427	177.200
Inputs				
Labour expenses (1,000 NZ$)	139.491	150.976	156.912	162.456
Stock expenses (1,000 NZ$)	77.154	81.345	86.488	93.598
feed expenses (1,000 NZ$)	180.294	196.751	223.199	261.199
Overhead expenses (1,000 NZ$)	90.514	91.420	93.451	98.674
Other expenses (1,000 NZ$)	170.127	185.506	175.335	196.383
Farm size (hectares)	143.365	146.203	150.529	153.496
Herd size (numbers)	413.545	422.265	435.865	445.315

levels of productive efficiency and this is the purpose of the empirical part of this study.

5. Results and discussions

5.1 Production frontier

Table 3 presents the maximum likelihood parameter estimates for the production frontier model. Following Hadley (2006), a time variable was included in the production frontier model to capture the movement of the frontier over time and in the technical inefficiency model to pick up the change in efficiency of the average farm in each of the samples through the period analysed. Since all input variables and the dependent variable are expressed in logarithmic forms, the estimated coefficients of the input variables reflect the output elasticities (Kumbhakar *et al.* 2015). The results show that all output elasticities have the expected positive sign, suggesting that the increased use of the inputs increases milksolids production. These results are

Table 3 Estimation of milk production and technical efficiency in New Zealand

Variable	Coefficient	z-value
Production frontier model		
Labour expenses (ln)	0.030 (0.016)*	1.89
Stock expenses (ln)	0.087 (0.022)***	3.98
Feed expenses (ln)	0.018 (0.012)	1.52
Overhead expenses (ln)	0.014 (0.014)	0.97
Other expenses (ln)	0.080 (0.014)***	5.62
Farm size (ln)	0.368 (0.087)***	4.21
Herd size (ln)	0.254 (0.104)**	2.44
Year (ordinal)	0.033 (0.005)***	6.63
Inefficiency model		
Feed intensification (ordinal)	−0.068 (0.039)*	−1.74
Farm size (hectares)	0.005 (0.002)**	2.26
Herd size (numbers)	−0.003 (0.001)**	−2.46
Farm location (dummy)	0.121 (0.290)	0.42
Milking frequency (dummy)	−0.128 (0.075)*	−1.71
Shed type (dummy)	−0.041 (0.041)	−0.99
Year (ordinal)	0.051 (0.026)*	1.92
vsigmas	−5.307 (0.055)***	—
usigmas	−1.319 (0.747)*	—
Observations	1,028	
Number of groups	257	

Note: ***P < 0.01; **P < 0.05, *P < 0.10; Standard errors are reported in parentheses.

largely consistent with those reported in previous studies (Hardi and Whittaker 1999; Karagiannis *et al.* 2002; Kompas and Che 2006; Abdulai and Tietje 2007; Cabrera *et al.* 2010; Jiang and Sharp 2015; Dong *et al.* 2016).

Of the input variables, farm size has the highest impact on dairy production with an elasticity equal to 0.368. That is, a 10 per cent increase in effective area of farmland results in an estimated increase in milksolids production by 3.68 per cent. The second highest elasticity is for herd size. The positive and significant coefficient of herd size variable suggests that a 10 per cent increase in herd size increases dairy production by 2.54 per cent. The coefficient of stock expense, which is statistically significant at 1 per cent significance level, is 0.087. This suggests that a 10 per cent increase in stock expense increases milksolids production by 0.87 per cent. The positive and statistically significant coefficients for labour and other expenses indicate that 10 per cent increases in these variables will increase milksolids production by 0.30 and 0.80 per cent, respectively. Finally, the year variable, which is included to account for time effects and/or technological change, has a positive and statistically significant coefficient. The finding confirms the presence of technological progress over time for dairy production.

5.2 Determinants of technical efficiency

The empirical results presented in the lower part of Table 3 show the factors that influence technical inefficiency. Due to the inverse relationship between technical inefficiency and technical efficiency, the interpretation of the estimated parameters is performed with respect to their effect on technical efficiency.

An important objective of this study is to analyse the relationship between supplementary feed use intensification and technical efficiency. The coefficient on the feed intensification variable is negative and significant at the 10 per cent level, suggesting that intensifying dairy production with the use of supplementary feed has a positive and significant impact on the technical efficiency of dairy farms in New Zealand. The finding that feed use intensification improves technical efficiency is consistent with the findings by Kompas and Che (2006) for Australia, Abdulai and Tietje (2007) for Germany, Alvarez *et al.* (2008) for Spain and Cabrera *et al.* (2010) for the United States. It is plausible that dairy farmers investing more in supplementary feed are motivated to follow more effective farming practices to increase milksolids production.

The coefficient of the farm size variable is positive and statistically significant, suggesting that large farms are less technically efficient than small farms. This may reflect the rapid expansion that has occurred in the New Zealand dairy sector, which has involved both the expansion of existing farms and the conversion of farmland from other uses. Because highly productive farmland is limited, industry expansion generally involves marginal land, resulting in lower technical efficiency for the larger farms. The negative relationship between efficiency and farm size could also reflect the added complexity of managing a larger set of resources, which is consistent with the results of Abdulai and Tietje (2007), who discovered a positive relationship between farm size and technical inefficiency for Germany. By contrast, Kompas and Che (2006) and Jiang and Sharp (2015) found no significant relationship between farm size and technical efficiency in Australia and New Zealand, respectively. Consistent with previous studies by Kompas and Che (2006) for Australia, and Jiang and Sharp (2015) for New Zealand, technical efficiency tends to increase with increasing herd size. The findings that the technical efficiency is lower for larger farms but higher for larger herds suggest that technical efficiency is higher for more intensive farming systems. The results in Table 3 indicate that relative to other milking strategies (e.g. milking once a day), twice a day milking increases technical efficiency by 0.128 at the margin. Our finding contradicts the results of Cabrera *et al.* (2010) for the United States, who found that twice a day milking significantly decreased technical efficiency among dairy farms in Wisconsin.

5.3 Technical efficiency scores

The technical efficiency of a given farm is the ratio of observed production to the expected efficient production if the farm utilised its level of inputs most efficiently (Kumbhakar *et al.* 2015; Koirala *et al.* 2016). Using Equation (7), we found a mean technical efficiency score of approximately 0.788, with standard deviation of 0.078. The technical efficiency score for dairy farmers in the sample ranged from 0.407 to 0.969 across all farms (Table 4). This finding

Table 4 Summary of technical efficiency

Summary statistics	Technical efficiency
Mean	0.788
SD	0.078
Min.	0.407
Max.	0.969

suggests that, from a technical standpoint, using the current level of inputs and the existing technologies farmers could increase milksolids production by 21.2 per cent (on average) by using their inputs more efficiently. Our findings suggest a lower level of technical efficiency than the results of Jaforullah and Whiteman (1999) who recorded an average technical efficiency of 89 per cent and Rouse *et al*. (2009) who found a technical efficiency score of 91 per cent in their analysis on dairy farms in New Zealand. However, it should be noted that both Jaforullah and Whiteman (1999) and Rouse *et al*. (2009) used cross-sectional data in their analysis which may explain some of the difference. The results we obtained with our panel dataset are more consistent with those reported by Jiang and Sharp (2015).

Our results indicate that only 10.8 per cent of the dairy farmers in our dataset achieved a technical efficiency score below 70 per cent (Table 5). The majority of the farms (84 per cent) achieved technical efficiency scores between 70 and 90 per cent. The remaining 4.96 per cent of the farms obtained technical efficiency scores above 90 per cent. The results in Table 5 suggest that a large proportion of New Zealand dairy farmers are technically efficient.

Previous studies have noted that farm efficiency differs by region due to differences in soil quality, geographical climate, attitude and farming practices (Kompas and Che 2006; Dong *et al*. 2016). A recent study by Jiang and Sharp (2015) found that the mean technical efficiency for dairy farms in the South Island (81.96 per cent) was higher than that for farms in the North Island (69.52 per cent). To investigate this further, we disaggregated our technical efficiency scores by farm location. The results presented in Table 6 show that on average dairy farmers in the South Island are slightly

Table 5 Distribution of technical efficiency (TE) of dairy farmers in New Zealand

TE interval	Frequency	Farms in TE interval (%)
$0.40 < TE \leq 0.60$	27	2.63
$0.60 < TE \leq 0.70$	84	8.17
$0.70 < TE \leq 0.80$	417	40.56
$0.80 < TE \leq 0.90$	449	43.68
$0.90 < TE \leq 1.00$	51	4.96
Total	1,028	100

Table 6 Distribution of technical efficiency (TE) of dairy farmers in New Zealand by farm location

Category	Sample size	Mean	SD	Min.	Max.
North Island	808	0.777	0.076	0.407	0.928
South Island	220	0.830	0.074	0.551	0.969

Table 7 Distribution of technical efficiency (TE) of dairy farmers in New Zealand by production systems

Supplementary feed use	Technical efficiency score	Marginal increase in TE	95% Confidence interval	
System 1	0.742	—	0.723	0.760
System 2	0.754	0.012	0.745	0.764
System 3	0.793	0.039	0.786	0.800
System 4	0.825	0.032	0.817	0.833
System 5	0.833	0.008	0.825	0.842

more technically efficient than their counterparts in the North Island, with technical efficiency scores 0.830 and 0.777, respectively.

The main objective of this study was to develop a better understanding of the relationship between feed use intensification and technical efficiency on New Zealand's traditionally pasture-based dairy farms. To achieve this end, the technical efficiency scores were disaggregated by farming systems (Table 7). The results indicate that producers who use more supplementary feed are more efficient, on average, than those who use less. Producers who import between 20 and 30 per cent of their total feed (System 4), for example, are approximately 3 per cent more technically efficient than those who produce under system 3 (importing 10–20 per cent of their total feed). The results also indicate that there are 'diminishing returns' to supplementary feed with respect to technical efficiency, particularly for the most supplementary feed-intensive farms.

Earlier work on the relationship between supplementary feed and profitability by Ma *et al.* (2018) indicates that there is no significant profit advantage associated with additional supplements. The 'diminishing returns' relationship discovered here indicates that, strictly from a technical perspective, the efficiency advantage associated with supplementary feed is limited. Taken together, the two observations strongly suggest that there is a logical 'upper limit' to the use of supplementary feed from an economic perspective. This result has important implications for outdoor systems where there is a strong positive correlation between environmental nitrogen pollution and an increased consumption of supplements in pasture-based dairy farming systems (Kebreab *et al.* 2001).

6. Conclusions

While many New Zealand dairy farmers have been intensifying their production through the use of supplementary feed, little is known about how these changes affect the technical efficiency of dairy farms. The present study contributes to the literature by employing a fixed effects stochastic production frontier model to examine the impact of feed use intensification on technical efficiency for dairy farms in New Zealand. The empirical analysis was based on a balanced panel of 257 farms observed over the 4-year period 2010–13.

Our results indicate that supplementary feed has a positive and significant impact on the technical efficiency of dairy farms in New Zealand. Farm size, herd size and milking frequency also have significant effects on the technical efficiency of dairy farms in New Zealand. The empirical results also include estimates of output elasticities, providing an indication of the relative responsiveness of milk production to changes in inputs. Output is most responsive to an increase in farm size, with an output elasticity of 0.368. This is not surprising, as land is generally considered to be the most limiting factor of production for dairy farmers in New Zealand. Other important determinants of output include herd size, labour expenses, stock expenses and other expenses (e.g. fertilizer, vehicle, fuel, repairs and maintenance). The average level of technical efficiency in the sample was 78.8 per cent, which suggests that, on average, farms in the sample could increase milksolids production by 21.2 per cent using their current input quantities. The disaggregated analysis revealed that dairy farmers in the South Island tend to be more technically efficient than their counterparts in the North Island, which could reflect the relatively modern facilities of the recently established South Island farms.

This paper provides empirical insights into how feed use intensification influences farm performance in New Zealand. Although context specific, the results discussed here are relevant to other developed countries such as the United States, Germany, Australia, France and the UK that are all global leaders in dairy production who strive to farm sustainably in the face of increasingly stringent environmental and animal welfare standards. The results also have implications for emerging economies such as China and Brazil, whose rapid growth and development are being supported in part by an expanding dairy sector.

In addition to production enhancement, it might be assumed that dairy farmers use additional supplementary feed to increase farm business profit. However, it should be noted that whilst higher technical efficiency associated with current intensification strategies directly contributes to the improvement of dairy productivity, it does not necessarily improve profitability. The impact on profitability will depend on the relative prices of inputs used and outputs produced. This suggests that analysing the impact of supplementary feed use on profit efficiency could be a promising area for future work. Intensification might also be associated with negative environmental effects.

Another future avenue for research is to study the effect of supplementary feed use on the environmental externalities produced by the New Zealand dairy industry. Finally, there are a range of farmer specific demographic factors that are likely to influence technical efficiency on dairy farms. Unfortunately, we do not have the data to support such an extension of the analysis, and those effects will be controlled for with our fixed effects specification.

References

Abdulai, A. and Tietje, H. (2007). Estimating technical efficiency under unobserved heterogeneity with stochastic frontier models: application to northern German dairy farms, *European Review of Agricultural Economics* 34, 393–416.

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

Alvarez, A., del Corral, J., Solís, D. and Pérez, J.A. (2008). Does intensification improve the economic efficiency of dairy farms?, *Journal of Dairy Science* 91, 3,693–3,698.

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

Battese, G.E. and Coelli, T.J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data, *Empirical Economics* 20, 325–332.

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

Cabrera, V.E., Solís, D. and del Corral, J. (2010). Determinants of technical efficiency among dairy farms in Wisconsin, *Journal of Dairy Science* 93, 387–393.

Chen, Y.Y., Schmidt, P. and Wang, H.J. (2014). Consistent estimation of the fixed effects stochastic frontier model, *Journal of Econometrics* 181, 65–76.

Cloutier, L.M. and Rowley, R. (1993). Relative technical efficiency: data envelopment analysis and Quebec's dairy farms, *Canadian Journal of Agricultural Economics* 41, 169–176.

Colombi, R., Kumbhakar, S.C., Martini, G. and Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency, *Journal of Productivity Analysis* 42, 123–136.

DairyBase® (2006). *DairyBase® Report Description Handbook*. DairyNZ, Hamilton.

DairyNZ (2015). *DairyNZ Economic Survey 2013–2014*. DairyNZ, Hamilton.

Dong, F., Hennessy, D.A., Jensen, H.H. and Volpe, R.J. (2016). Technical efficiency, herd size, and exit intentions in U.S. dairy farms, *Agricultural Economics* 47, 533–545.

Foote, K.J., Joy, M.K. and Death, R.G. (2015). New Zealand dairy farming: milking our environment for all its worth, *Environmental Management* 56, 709–720.

Fraser, I. and Cordina, D. (1999). An application of data envelopment analysis to irrigated dairy farms in Northern Victoria, Australia, *Agricultural Systems* 59, 267–282.

Fraser, I. and Graham, M. (2005). Efficiency measurement of Australian dairy farms: national and regional performance data envelopment analysis, *Australasian Agribusiness Review* 13, 1–15.

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model, *Journal of Econometrics* 126, 269–303.

Greig, B. (2012). *Changing New Zealand dairy farm systems*, in South Island Dairy Event (SIDE) Conference, June 25–27. 2012 Dunedin, pp. 217–228.

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

Hallam, D. and Machado, F. (1996). Efficiency analysis with panel data: a study of Portuguese dairy farms, *European Review of Agricultural Economics* 23, 79–93.
Hardi, K. and Whittaker, J. (1999). Efficiency, environmental contaminants and farm size: testing for links using stochastic production frontiers, *Journal of Applied Economics*, II, 337–356.
Hedley, P., Kolver, E.S., Glassey, C., Thorrold, B., Van Bysterveldt, A., Roche, J. and Macdonald, K. (2006). *Achieving high performance from a range of farm system*, in South Island Dairy Event. Hamilton.
Jaforullah, M. and Devlin, N.J. (1996). Technical efficiency in the New Zealand dairy industry: a frontier production function approach, *New Zealand Economic Papers* 30, 1–17.
Jaforullah, M. and Premachandra, E. (2003). *Sensitivity of Technical Efficiency Estimates to Estimation Approaches: An Investigation Using New Zealand Dairy Industry Data (Economics Discussion Papers Series No. 306)*. University of Otago, Dunedin.
Jaforullah, M. and Whiteman, J. (1999). Scale efficiency in the New Zealand dairy industry: a non-parametric approach, *The Australian Journal of Agricultural and Resource Economics* 43, 523–541.
Jiang, N. and Sharp, B. (2015). Technical efficiency and technological gap of New Zealand dairy farms: a stochastic meta-frontier model, *Journal of Productivity Analysis* 44, 39–49.
Karagiannis, G., Midmore, P. and Tzouvelekas, V. (2002). Separating technical change from time-varying technical inefficiency in the absence of distributional assumptions, *Journal of Productivity Analysis* 18, 23–38.
Kebreab, E., France, J., Beever, D.E. and Castillo, A.R. (2001). Nitrogen pollution by dairy cows and its mitigation by dietary manipulation, *Nutrient Cycling in Agroecosystems* 60, 275–285.
Koirala, K.H., Mishra, A. and Mohanty, S. (2016). Impact of land ownership on productivity and efficiency of rice farmers: the case of the Philippines, *Land Use Policy* 50, 371–378.
Kompas, T. and Che, T.N. (2006). Technology choice and efficiency on Australian dairy farms, *Australian Journal of Agricultural and Resource Economics* 50, 65–83.
Kumbhakar, S.C., Biswas, B. and Bailey, D. (1989). A study of economic efficiency of Utah dairy farmers: a system approach, *The Review of Economics and Statistics* 71, 595–604.
Kumbhakar, S.C., Wang, H. and Horncastle, A.P. (2015). *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*. Cambridge University Press, Cambridge.
Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y. and Moreira, V.H. (2017). Subsidies and technical efficiency in agriculture: evidence from European dairy farms, *American Journal of Agricultural Economics* 99, 783–799.
Ma, W., Renwick, A. and Bicknell, K. (2018). Higher intensity, higher profit? Empirical evidence from dairy farming in New Zealand, *Journal of Agricultural Economics* 1–17.
Mareth, T., Thomé, A.M.T., Scavarda, L.F. and Oliveira, F.L.C. (2017). Technical efficiency in dairy farms: research framework, literature classification and research agenda, *International Journal of Productivity and Performance Management* 66, 380–404.
Moreira, V.H. and Bravo-Ureta, B.E. (2010). Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: a stochastic meta-frontier model, *Journal of Productivity Analysis* 33, 33–45.
Mounsey, Z. (2015). *Analysis of Production Systems in the New Zealand Dairy Industry*. DairyNZ Report, Hamilton.
MPI (2017). Feed Use in the NZ Dairy Industry, *Ministry for Primary Industries (MPI) Technical Paper 2017/53* (June 2016).
Rouse, P., Chen, L. and Harrison, J.A. (2009). *Benchmarking the performance of dairy farms using data envelopment analysis*, 2009 Performance Measurement Association (PMA) Conference Papers, The University of Otago, Dunedin, 2,009 pp.
Shee, A. and Stefanou, S.E. (2014). Endogeneity corrected stochastic production frontier and technical efficiency, *American Journal of Agricultural Economics* 97, 939–952.

Stokes, J.R., Tozer, P.R. and Hyde, J. (2007). Identifying efficient dairy producers using data envelopment analysis, *Journal of Dairy Science* 90, 2,555–2,562.

Wang, H.J. and Ho, C.W. (2010). Estimating fixed-effect panel stochastic frontier models by model transformation, *Journal of Econometrics* 157, 286–296.

Yates, L., Dotterer, J. and McDermott, A. (2010). *The consequences of variability in pasture growth and milk price on dairy farm profitability*, Proceedings of the 4th Australasian Dairy Science Symposium, 2010, Christchurch, pp. 244–248.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Table A1: Studies on technical efficiency of dairy farms. Table A2: Definition of variables. Table A3: The characteristics of five dairy production systems in New Zealand.