

UNIVERSITY OF WAIKATO

**Hamilton
New Zealand**

**Cost Efficiency Analysis using Operating Profit Margin
for the New Zealand Dairy Industry**

Robbie Maris and Zack Dorner

Working Paper in Economics 4/21

May 2021

Robbie Maris

School of Accounting, Finance
and Economics
University of Waikato
Private Bag 3105
Hamilton, 3240
New Zealand

Email: robbiem8910@gmail.com

Zack Dorner

School of Accounting, Finance
and Economics
University of Waikato
Private Bag 3105
Hamilton, 3240
New Zealand

Email: zack.dorner@waikato.ac.nz

Abstract

Cost efficiency analysis has not been widely applied in the dairy industry, despite its role in driving profitability, resilience and debt serviceability in low subsidy export-oriented farming systems. We analyse cost efficiency using operating profit margin (a reliable, well-supported and easily interpretable parameter from the DuPont framework) for the first time on New Zealand dairy farms. We utilise a 10-year panel dataset, developed using sample and population data, to get a representative picture of the industry. We begin by grouping farms into quartiles of their long-run cost efficiency (10-year average) and perform non-parametric Games-Howell hypothesis testing to investigate differences in the groups. We then estimate a fixed effects panel regression model for each quartile to examine the factors correlated with cost efficiency over time within low to high performing groups. We find cost-efficient farms use less supplement and nitrogen fertiliser over the long run, milk price fluctuations disproportionately impact lower quartile groups, and farms may be able to reduce GHG emissions whilst maintaining strong cost efficiency. Our exercise demonstrates that analysing cost efficiency using operating profit margin can produce valuable insights for low subsidy export-oriented agricultural industries.

Keywords

cost efficiency

dairy industry

New Zealand

operating profit margin

panel data

JEL Classification

C12, C23, Q12

Acknowledgements

We thank the University of Waikato for providing funding for this research through their Summer Research Scholarship 2020/21 programme (project #51).

I. Introduction

The low subsidy, export-orientated agriculture sectors of Australasia must strive for efficiency to compete in international markets. Indeed, understanding the fundamentals of profitability is more important than ever, as Australasian farms are subject to stricter environmental standards, and heightened business risks such as price volatility and high levels of debt. Cost efficiency is the ability to produce a given level of revenue at the lowest cost (Jiang and Sharb, 2014). Cost efficiency has been identified as a crucial factor in achieving profitability and resilience on New Zealand dairy farms (Neal et al., 2018). Shadbolt et al. (2018) show that cost efficiency also improves a farms ability to service and reduce debt. Additionally, cost efficiency is a simple measure of farm performance, which can easily be calculated and interpreted by a farm manager. By building knowledge of drivers of cost efficiency across farms, managers can be supported to improve the profitability of their farms. However, there has been little research conducted on cost efficiency for New Zealand farms.

Thus, we conduct an analysis on drivers of cost efficiency for New Zealand dairy farms. This industry provides an excellent case study of how cost efficiency analysis can contribute to understanding competitiveness and profitability in a low subsidy, export-oriented agriculture sector. We take advantage of a novel, 10-year balanced panel data set for the dairy-focused region of Waikato and compare performance between and within low to high performing quartiles. The only other study of cost efficiency on New Zealand dairy farms that we are aware of is Jiang and Sharb (2014). They provide some useful insights, using an unbalanced panel data set, and a more complex stochastic cost frontier model. We build on their work by analysing cost efficiency with balanced panel data set and an easier cost-efficiency measure for farmers to understand and interpret.

In this study, we use operating profit margin (OPM) as a measure of farm cost efficiency. OPM was originally derived from the DuPont formulation (1) and is operating profit (OP) divided by operating revenue (OR). It is one of the three parameters in the decomposed DuPont formulation (1) which describes return on equity (RoE). The other two parameters are asset turnover, OR divided by total assets (A), and the leverage ratio, A divided by total equity (E). It is widely acknowledged that OPM measures cost efficiency, asset turnover measures revenue efficiency and the leverage ratio describes the leverage and solvency of a business (Doole and Te Rito, 2019).

$$\text{RoE} = \frac{\text{OP}}{\text{OR}} \cdot \frac{\text{OR}}{\text{A}} \cdot \frac{\text{A}}{\text{E}} \quad (1)$$

The DuPont formulation has been used extensively since its establishment in 1912 by the DuPont Corporation (Doole and Te Rito, 2019). The formulation is robust, globally applied and recognised as a useful tool for the dairy industry by pertinent stakeholders (Doole and Te Rito, 2019; Grashius, 2018). The formula for OPM is understandable and accessible to most farmers, rendering it a suitable and robust alternative to a stochastic cost frontier; which utilises

involved econometric formulations of cost functions (Jiang and Sharb, 2014).

At a basic level, OP can be decomposed into operating revenue (OR) less operating costs (OC). This leads to the simplification that OPM is equal to 1 less a cost ratio (OC/OR). This demonstrates that if operating costs increase for a fixed level of revenue, the cost ratio (OC/OR) increases. Subsequently, the value of OPM falls, demonstrating that the farm is less cost-efficient because they produce the same level of revenue with a higher cost (refer to the earlier definition of cost efficiency). Conversely, if operating costs fall, OPM will increase, demonstrating an increase in cost efficiency.

$$OPM = \frac{OP}{OR} = \frac{OR - OC}{OR} = 1 - \frac{OC}{OR} \quad (2)$$

The aim of this study is to comprehensively investigate factors correlated with cost efficiency through time over the long and short-run to produce valuable and interpretable insights for addressing challenges in dairy farming. We benchmark farms into quartiles, based on their long-term cost efficiency performance, and used Games-Howell tests to examine differences in farm variables between the groups. This indicates which farm variables are related to cost efficiency. Furthermore, we formulate a fixed effects (FE) panel regression model for each quartile to investigate the correlations between cost efficiency and pertinent farm variables (such as pasture and crop eaten, supplement costs and fertiliser costs) through time, whilst controlling for other relevant variables and farm-level effects.

2. Literature Review

2.1 Case study background

New Zealand has an export-orientated dairy industry, exporting 95% of domestic dairy production to international markets (Barry and Patullo, 2020). This accounts for over 20% of New Zealand exports and 3% of GDP, making dairy the largest export industry for New Zealand (Barry and Patullo, 2020). Moreover, the industry is worth NZD \$17 billion per annum (Ballingall and Pambudi, 2017). However, New Zealand makes up 3% of global production which categorises New Zealand as a price taker on the global market. In addition, the New Zealand dairy industry receives no subsidies from the government which increases exposure to market fluctuations and risk.

Meanwhile, the industry faces several other challenges including addressing environmental concerns, heightened price fluctuations and high levels of indebtedness. New Zealand dairy farmers are under increasing scrutiny around the environmental impacts of their farming practices. Farmers are developing action plans in concordance with The Action for Healthy Waterways and The Sustainable Dairying Water Accord (MFE & MPI, 2020). Moreover, the government has an interim target to reduce biogenic methane emissions by 10%, below 2017 levels, by 2030 (MFE, 2019). Recent modelling from the Climate Change

Commission (2021) indicates, absent any new technological innovation, herd sizes need to fall by 15% (below 2018 levels) by 2030 to meet those targets. Hence, possible decreases in milk production (as herd size falls or farmers decrease their system intensity to manage their environmental impacts) and increases in compliance costs - associated with these new environmental regulations - pose a risk to profitability.

Milk price and input price volatility present a threat to the stability of farm revenue and costs (Neal et al., 2018). This volatility greatly impacts the instability of farm profits and may necessitate the use of farm management strategies to mitigate against it (Neal & Roche, 2020). Finally, New Zealand farms have one of the highest levels of indebtedness worldwide (Doole and Te Rito, 2019). High debt levels on dairy farms can negatively impact productivity, resilience and profitability, as farms have less flexibility to respond to climatic, price and production shocks (Greig, 2010; Ma et al., 2020; Shadbolt et al., 2013). With these on-going pressures, and the need to compete internationally against subsidised agricultural sectors, it is important for the NZ dairy industry to continuously improve.

2.2 OPM definition

Within the dairy industry, OPM is given as (Doole & Te Rito, 2019):

$$OPM = \frac{\text{Dairy Operating Profit}}{\text{Dairy Gross Farm Revenue}} \quad (3)$$

For dairy OP, interest repayments are added, and unpaid family labour is subtracted (to compare across farms with varying levels of debt and allocations of labour resources). The literature is somewhat divided on the interpretation of OPM; however, one interpretation is more appropriate to the context of this paper. Predominantly, OPM is described and used as a financial measure of cost efficiency and operating efficiency (Beca, 2020; Doole & Te Rito, 2019; Grashuis, 2018; Ho et al., 2013; Pinochet-Chateau et al., 2005; Wolf et al., 2020). That is, the ability of a firm to minimise their costs of producing a given level of revenue. This definition is featured prominently in the literature for New Zealand dairy farms and is generally cited as a key driver of profitability (Beca, 2020; Doole & Te Rito, 2019; Ho et al., 2013). Alternatively, some authors have defined OPM as a measure of profitability itself (Hoppe, 2014; Langemeier, 2016; Langemeier & Yeager, 2018; Snider & Langemeier, 2009; Uzea et al., 2014). This strand of the literature focuses on dairy farms in the U.S. - which exhibit large systematic differences to farms in New Zealand. As a result, this study operates on the premise that OPM measures cost efficiency - which is a driver of profitability.

There are few studies in the literature which focus primarily on cost efficiency (Alvarez et al., 2008; Grashuis, 2018; Jiang & Sharb., 2014; Yeager, 2016). Only two studies that we are aware of are centred around OPM as the measure of cost efficiency (Grashuis, 2018; Wolf et al., 2020) and these studies are based on U.S. farms (Wolf et al., 2020) and U.S. farm

cooperatives (Grashuis, 2018). Research on cost efficiency for New Zealand farms has been limited to stochastic cost frontier analysis (Jiang & Sharb., 2014). Moreover, efficiency papers for New Zealand farms to date have predominantly focussed on technical efficiency (Ho et al., 2013; Ma et al., 2018). Our work addresses this gap by providing deeper insights into cost efficiency, using OPM as a novel measure for New Zealand farms.

2.3 OPM and benchmarking performance

OPM is a practical tool that can be used to benchmark farms by financial performance (Langemeier & Yeager, 2018). OPM has the benefit of being a transferable benchmark, both globally and cross-industry, due to its widespread use and the robustness of the DuPont formulation (Doole & Te Rito, 2019). Despite this, most longitudinal benchmarking studies have used incomplete panel data, which inhibits analysis on how OPM varies at the farm-level with time (Jiang & Sharb., 2014; Ma et al., 2018). However, a novel study of farms in Kansas, U.S., used a complete panel to investigate how OPM varies with time (Wolf et al., 2020). They find that using a single year to benchmark farms is inaccurate and misrepresentative of the true relative financial performance of farms. This is consistent with previous work (Langemeier, 2010, 2016; Mishra et al., 2012; Yeager et al., 2016) demonstrating that OPM is subject to external shocks and a central value ought to be taken to improve the accuracy of farm performance categorisation.

Wolf et al. (2020) use a five-year farm average of OPM for benchmarking purposes. They decompose variation in OPM over time into three effects: the firm effect, the industry effect and an error term. However, the error term was the largest effect, which suggests future models need to be refined to include more detail. We build on the work of Wolf et al. (2020) by benchmarking farms and developing a fixed effects model for OPM which uses a complete 10-year panel dataset and has a high degree of explanatory power. Furthermore, we perform robust Games-Howell hypothesis testing to investigate differences between the benchmarked groups. As far as we are aware, our work is the first time OPM and cost efficiency has been examined over time for New Zealand dairy farms, and even pasture-based dairy farming industries.

2.4 Factors impacting OPM

Snider and Langemeier (2009) find that OPM is positively correlated with farm size, which aligns with work done by Mishra et al. (2012). They also indicate that profitability is influenced by farm size. Both studies were done with U.S. farm data and directly contradict research by Beca (2020) who show that there was no relationship between farm size and profitability for Australian farms. However, Jiang and Sharb (2014) demonstrate that cost efficiency (using an alternative measure to OPM) increases with farm size and operator experience. However, U.S. farms operate on an intensive feedlot production system whilst New Zealand and Australian farms are predominantly pasture based.

Studies suggest that high OPMs may be associated with increased business risk within a dairy industry (Alvarez et al., 2008; Hedley and Kolver, 2016). Conversely, Pinochet-Chateau et al. (2005) show that farms with lower OPMs have greater financial risk measured by RoE - a generally accepted proxy for financial risk. This supports Gabriel and Baker's (1980) notion that farms can substitute between business and financial risk. Consequently, risk preferences and attitudes will likely have an impact on OPM. This is corroborated by Yeager (2016), who shows that farm inefficiencies will be inaccurately exacerbated if risk preferences are not accounted for. Yeager (2016) uses a non-parametric approach to efficiency and there are no studies to our knowledge that account for risk when analysing farm OPMs.

Generally, the literature agrees that OPM is positively correlated with profitability, measured by return on assets (RoA) or equity (RoE). This conclusion is expected, given the DuPont formulation formally relates these parameters (Beca, 2020; Grashuis, 2018; Ma et al., 2018; Mishra et al., 2012). Adopting a different approach, Fairfield and Yohan's (2001) find that OPM is uncorrelated with future profitability.

Ma et al. (2018) finds that OPM fell with intensification and RoA was unchanged, Shadbolt (2012) states that there was no correlation between OPM and intensity and Ho et al. (2013) find that RoA (inherently linked to OPM) increases with intensification. These studies focus on pasture-based dairy farms. Mishra et al. (2012) find positive correlations between OPM and operator education, farm size and diversification.

2.5 Risk attitude

Dairy farming has uncertainty and is risk prevalent in many areas (such as production, marketing and financing). Consequently, farmers and analysts are interested in the sources of risk, how such risk is managed and how farmers' risk preferences vary. Pinochet-Chateau et al. (2005) show that OPM is negatively correlated with risk exposure. Other authors have shown that financial performance (cost efficiency is one example) is a key tool in managing farm risk (Bardhan et al., 2006; Flaten et al., 2005). Consequently, we would expect financial performance measures (such as OPM) to be correlated with risk attitude. Therefore, we include an indicator of risk attitude in our analysis of OPM.

In agricultural literature, risk is often divided into two categories: financial risk and business risk. Financial risk relates to the capital structure of a farm and how it has been financed (Collins, 1985; Farina et al., 2013; Hardaker et al., 2004). Conversely, business risk can be defined as the aggregate remaining uncertainty relating to production, milk price, input prices and climate (Farina et al., 2013; Hardaker et al., 2004).

In the DuPont formulation for the RoE, the leverage and asset turnover ratios should incorporate the financial risk of the farm (as these ratios relate to the capital structure of the farm). Consequently, it appears reasonable to suggest that the variation in OPM would represent business risk. OPM incorporates farm revenues and farm costs, which are influenced

by the elements included in the business risk definition (production, prices, and climate). Further, there is support for using the standard deviation of outcome variables as an indicator of risk in agriculture (Sulewski et al., 2020). In banking, the standard deviation of OPM has been used as a measure of risk associated with businesses (Yu et al., 2019). Given the universality of the DuPont formulation (Doole & Te Rito, 2019), work by Yu et al. (2019) supports the use of the standard deviation of OPM as a measure of business risk in agriculture.

As far as we are aware, this is the first paper to analyse the relationship between risk preferences and OPM on dairy farms. However, future research can extend our work by calculating robust empirical risk aversion coefficients and modelling these in OPM models. Abdullahi (2003) and Saha (1997) present an excellent formulation for this type of analysis. An applied analysis of the dairy sector using such a method would merit a separate paper in itself.

3. Data

We source our data from Doole et al. (2021), who draw on sample and population data to develop a complete picture of the New Zealand dairy farming population. They take population data from the Livestock Improvement Corporation (LIC, a farmer-owned co-operative responsible for herd improvement and other production activities) for the 2018/19 season. They then build a picture of the population over 10 years by using a sample dataset from the more detailed industry dataset DairyBase, which is made representative by removing outliers and using a binary optimisation process for each year. The data are simulated for the entire population, at a farm level, over the 10 years for key economic farm variables while preserving population distributions in key variables in the LIC dataset. The milk price included is the observed milk price for farmers over the 10 years, and all input cost data are deflated using the Farm Expenses Price Index, generated by the government statisticians, Statistics New Zealand. Biophysical variables are estimated using a dynamic, simulation-based framework that models the biophysical interdependencies on the farm. This detailed model is calibrated using real data.

The dataset we use is the best dataset available to us of the New Zealand dairy farm population over time. It utilises two major dairy datasets and brings them together, leveraging the strengths of both. Dairybase is the most detailed dataset for New Zealand dairy farms, but comprises of a sample of self-selected dairy farmers submitting questionnaires and financial books. Therefore, the choice to submit farm data is correlated with aspects of the farm and its management (for example, financial astuteness). It is also a heavily restricted dataset, meaning only select individuals and organisations may analyse it. Conversely, our data characterises the entire population, using LIC population data and representative samples from the DairyBase data. This avoids the issues of self-selection and sampling biases. However, as the data are largely simulated over time, there is potential for some estimation error due to the original construction of the data. We believe the sophisticated, farm-level construction of the dataset from underlying observed data at a population level sufficiently ameliorates this concern.

Furthermore, it should not undermine our wider purpose in this paper to highlight the use of OPM in analysing farm performance. The fact that this is the best available dataset for New Zealand dairy farms over time is also a good argument for its use here, while highlighting the need for better collection and sharing of industry data in future.

We restrict the population to farms from the Waikato region, due to its large sample size (3745 farms) and diverse geographical nature. Previous studies have shown considerable regional heterogeneity across dairy farms in New Zealand, driven by climatic and topographical factors (Jiang & Sharb, 2014; Wales & Kolver, 2017). There are also some regional differences in regulations faced by farms. Not accounting for such heterogeneity may lead to regional effects dominating model parameters. By reducing the sample to the Waikato region, we can accurately model the region and make valid inferences with greater confidence.

During data cleaning, we remove 228, leaving us with 3517 farms. Farms are removed from the sample if they meet at least one of the criteria below:

- Farms that have zero milk solids or zero land because the farm has left the industry.
- Farms that have an OPM observation less than -1.0 , as these farms are assumed to be too cost-inefficient to continue production.

Consultation with dairy industry experts and analysis of DairyBase data demonstrates that the distribution of OPM does not fall below -1.0 . Therefore, we remove farms with OPM values lower than -1.0 , to ensure our data is representative.

We choose our model variables based on pertinent areas of farm management (cost variables, production yield, milk production, stocking rate, meat revenue) and variables of interest given current dairy trends (nitrogen leaching, total emissions). We include several control variables (cash operating surplus, pasture and crop eaten, leverage ratio) whose effects on cost efficiency and OPM are already known. The full list of variables is reported in Table 1 in the results section (which provides summary statistics and units for the variables).

Production yield is the ratio between a farms actual and potential milk production (kg MS/cow). The potential milk production term represents the output possible under a perfectly efficient environment, one where all farm inputs are utilised most efficiently (Ma et al., 2018). In this sense, the production yield is a partial productivity measure (as it only accounts for biophysical inputs and processes - see Doole et al. 2021).

$$\text{Production Yield} = \frac{\text{Milk solids per cow (kg } \frac{\text{MS}}{\text{cow}} \text{)}}{\text{Potential milk solids per cow (kg } \frac{\text{MS}}{\text{cow}} \text{)}} \quad (4)$$

4. Econometric methods

We initially categorise and benchmark farms by long-run cost efficiency performance. In line with Wolf et al. (2020), we divide farms into quartiles based on their long-run (10-year) mean OPM. Quartile 1 represents the least cost-efficient farms and quartile 4 represents the most cost-efficient farms. Wolf et al. (2020) find benchmarking farms in this way gives clearly defined and distinguishable characteristics within the groups. Thus, benchmarking by OPM is a useful way to investigate the factors associated with relative cost efficiency performance. Moreover, benchmarking farms into groups with similar characteristics provides greater depth for our FE analysis. For example, we can compare how cost efficiency varies with time between more efficient farms (farms in higher quartiles) and worse performing farms (farms in lower quartiles).

Following the benchmarking process, we perform a series of Games-Howell post-hoc tests on the data. The Games-Howell test is a pairwise comparison test that allows us to determine if there are significant differences in farm variables between quartiles. The test is based on the Welch correction with the t-test and the studentised range statistic (Shingala & Rajyaguru, 2015). It controls for and reduces the incidence of type I errors whilst maintaining a high degree of power (Sauder & DeMars, 2019). The Games-Howell test allows us to account for unequal variances between the cost efficiency quartiles and heteroskedasticity in the model errors (Sauder & DeMars, 2019; Shingala & Rajyaguru, 2015). We use the Games-Howell tests to determine if there are significant differences between the means of a farm variable based on quartile. As simple pairwise comparison tests, they do not control for other variables. Nonetheless, the results provide useful descriptive statistics for further modelling and suggestions as to which variables may be related to cost efficiency.

To develop our understanding of the relationships between cost efficiency and farm variables, we formulate FE panel regression models on OPM, including several key farm metrics and control variables as regressors. Hausman statistical tests informed the selection of FE modelling over a random-effects approach. We use a separate model for each quartile. In the models, the individual intercepts account for the unobservable characteristics (for each farm) that do not vary with time. We exclude regressors that remain near constant over time to avoid perturbation of the individual farm intercept terms. Consequently, neither stocking rate (cows per ha) or milk platform (ha) are included as regressors in the models. These variables had little variation over time and exhibited large levels of multicollinearity with the farm-level intercepts. We also exclude the standard deviation of OPM as it had a dominating and distorting effect on model estimates. These FE models allow us to examine cost efficiency relationships through time for each quartile and control for individual, farm-level variation. This is a useful progression from the Games-Howell tests, which only provides information on long-run differences in farm variables between cost efficiency quartiles.

We estimate the following fixed effects model:

$$OPM_{it} = \alpha_i + \beta_1 \mathbf{X}_{it} + \mu_{it} \quad (5)$$

OPM_{it} represents the OPM for individual i at time t , α_i is the time-independent intercept for each individual i , μ_{it} is an error term for individual i at time t , \mathbf{X}_{it} is a column vector of independent variables (regressors) and β_1 is a row vector of coefficients. We estimate a robust covariance matrix to account for autocorrelation and heteroskedasticity in the FE model errors (Torres-Reyna, 2010).

We find multicollinearity to be a serious issue in our initial FE models. To account for this, we examine a Pearson correlation matrix and consult with farm systems experts to identify culprit variables. Following this, we run the model omitting each culprit variable and regress the model residuals on the omitted variable, examining the coefficient. If this coefficient is insignificant at $\alpha = 0.1$, the removed variable is excluded from the FE models. If the coefficient is significant, the removed variable is not excluded from the FE model as it adds additional explanatory power. We repeat this process for each variable that is characterised as posing a serious multicollinearity risk to the FE models. Following this process, these variables are removed from the FE models:

- Nitrogen leaching (kg N/ha)
- Total emissions (kg GHG-e/ha)
- Supplement cost (\$/ha)
- Other fertiliser cost (\$/ha)

Nitrogen leaching is highly correlated with the nitrogen fertiliser term, supplement cost with the proportion of feed consisting of supplement, and total emissions with the nitrogen fertiliser, milk production and production yield terms. Moreover, the other fertiliser cost (\$/ha) variable is highly correlated with nitrogen fertiliser cost (\$/ha).

5. Empirical Results and Discussion

5.1 Summary statistics

Table 1 provides summary statistics for the variables included in our hypotheses testing and FE modelling. Units are included in the table for reference when reading the results and discussion. The statistics are summarised over the entire 10-year period across all farms. Consequently, each farm has ten observations (one for each year) contributing to the overall summary statistics.

Table 1. Summary statistics for farm variables in Games-Howell tests and FE models

Variable	Mean	Std dev	Count (N x 10)
Milk price (\$)	6.68	1.12	36620
Stocking rate (cows/ha)	2.86	0.33	36620
Production yield	0.82	0.08	36620
Standard deviation of OPM	0.12	0.03	36620
Proportion of feed consisting of supplement	24.68	8.81	36620
Milk production (kg MS/ha)	1047.32	187.34	36620
Nitrogen fertiliser cost (\$/ha)	188.25	71.40	36620
Pasture and crop eaten (kg DM/ha)	10628.37	1135.17	36620
Supplement cost (\$/ha)	1136.82	546.57	36620
Leverage ratio	2.03	2.09	36620
Cash operating surplus (\$/ha)	2595.19	1298.41	36620
Total emissions (kg CO ₂ -e/ha)	11397.34	1950.38	36620
Meat revenue (\$/ha)	621.79	435.95	36620
Overhead costs (\$/ha)	342.51	84.58	36620

5.2 Games-Howell tests

We report the results from the Games-Howell tests in Table 2. We present pairwise comparisons of means of farm variables for the quartile groups. For example, the value for stocking rate in the Q4-Q1 column is the mean stocking rate in quartile 4 minus the mean stocking rate in quartile 1.

We find no significant differences in stocking rate between quartiles. Furthermore, differences in milk production (kg MS/ha) are predominantly insignificant - except for the difference between Q4 and Q2 (-22.45 kg MS/ha) which is significant at $\alpha = 0.05$. These results suggest that there is no stocking rate or intensity effect on cost efficiency. This finding is in line with Beca's (2020) work on Australian farms, which is consistent with Australia and New Zealand farms being pasture-based. Our work builds on conclusions from Jiang and Sharp (2014) on cost efficiency for New Zealand farms. They find that herd size is positively correlated with cost efficiency, whilst controlling for farm size (effective hectares) and we find that stocking rate and milk production per hectare are uncorrelated with cost efficiency. However, they include a categorical variable for the traditionally continuous variable herd size. This may decrease the explanatory power of their model by confounding stocking rate and hectare effects, making it difficult to disentangle complicated regional effects that have a major influence on profitability.

Production yield exhibits significant differences between all quartile pairings (Table 2). We find that farms with a higher cost efficiency tended to have a lower production yield. This aligns with traditional economic thinking around diminishing marginal returns - as farms attempt to extract the final units of milk solids for each cow, the milking process becomes more intensive and costly. DairyNZ (2021) reinforce this idea, advocating a novel approach to milking in New Zealand: MaxT. This approach predetermines a specified time milking time, per cow (which has been optimised so that 80% of cows will finish milking in that duration).

While this process foregoes some final units of milk solids, it has been linked to improved milking efficiency and profitability (DairyNZ, n.d.).

We are surprised to find that farms with a lower standard deviation of OPM were in better quartiles. We expected the standard deviation to be higher for farms with larger average OPMs. As stated, in our literature review, standard deviation of OPM is an indicator of business risk appetite. An increase in the standard deviation of OPM is linked to less business risk aversion (as farmers are more willing to take on climatic, price and production uncertainty). As such, we expected these farmers to have a larger average payoff (in terms of cost efficiency) and risk-averse farmers to be less cost-efficient. However, our Games-Howell results show that farms with greater long-run cost efficiency may be exposed to less business risk.

This may have arisen due to differences in farm system intensity. More intensive farms expose themselves to higher business risk (as they have a greater reliance on supplement and market shocks have a greater impact on their profitability) and experience significant declines in RoE during bad years, driven by declines in OPM (Ho et al., 2013; Shadbolt, 2012). This could generate lower mean OPMs for those farms (which are exposed to more business risk). Our results in Table 2 provide mixed support for this explanation. Farms in the higher performing quartiles have lower levels of fertiliser and supplemental feed costs, which are two important aspects of farm intensity. However, they achieve this without having a lower stocking rate, which is also an indicator of intensity. Pasture and crop eaten seem to be a key driver of this ability to maintain milk production per hectare while reducing the intensity of some inputs (and thus their input costs). Therefore, it seems there are synergies between cost efficiency and reduced business risk.

As previously mentioned, nitrogen fertiliser cost, supplement cost and the proportion of feed consisting of supplement are all lower on average for more cost-efficient farms. The relationship between these inputs and cost efficiency depends on the production response a farmer can generate from their use. For example, if fertiliser expenditure increases but production remains unchanged, OPM will fall. Conversely, if production increases concurrently, OPM may also increase. Our findings suggest that, over the long run, farms purchasing more nitrogen fertiliser and supplement are less cost efficient.

A plausible explanation for this finding is that farms utilising more inputs generate a lower marginal production response and are consequently less cost efficient. Our work is consistent with Ma et al. (2018) who demonstrate that intensification of inputs does not provide a profit advantage and that there is a clear economical upper limit on the use of supplement. However, there may be sub-regional effects (within the Waikato region) which we have not been able to consider due to the unavailability of suitable data. Farms in certain areas may have a better natural environmental endowment for farming and thus require less inputs per hectare.

Table 2. Games-Howell test results comparing long-run farm variables between cost efficiency quartiles.

	Mean difference in OPM					
	Q4-Q1	Q4-Q2	Q4-Q3	Q3-Q1	Q3-Q2	Q2-Q1
Stocking rate	0.02 (0.011)	-0.02 (0.011)	-0.01 (0.011)	0.03 (0.011)	-0.02 (0.011)	0.04** (0.011)
Production yield	-0.05*** (0.003)	-0.04*** (0.003)	-0.03*** (0.003)	-0.02*** (0.003)	-0.01** (0.003)	-0.01* (0.003)
Std deviation of OPM	-0.07*** (0.001)	-0.03*** (<0.0001)	-0.02*** (<0.0001)	-0.05*** (0.001)	-0.01*** (<0.0001)	-0.04*** (0.001)
Prop of feed that is supplement	-8.19*** (0.28)	-6.42*** (0.26)	-4.11*** (0.26)	-4.08*** (0.29)	-2.31*** (0.27)	-1.77*** (0.29)
Milk production	-0.68 (6.11)	-22.45** (6.04)	-15.31 (5.96)	14.64 (6.24)	-7.14 (6.17)	21.77* (6.31)
Nitrogen fertiliser cost	-57.73*** (2.22)	-35.45*** (2.03)	-21.18*** (1.92)	-36.55*** (2.27)	-14.28*** (2.09)	-22.28*** (2.36)
Pasture and crop eaten	764.17*** (37.12)	415.74*** (36.70)	272.36*** (35.68)	491.81*** (36.71)	143.38** (35.28)	348.43*** (36.73)
Supplement cost	-432.85*** (17.20)	-344.00*** (15.59)	-216.17*** (15.06)	-216.68*** (18.24)	-127.84*** (16.73)	-88.85*** (18.69)
Leverage ratio	-0.35*** (0.04)	-0.27*** (0.05)	-0.10 (0.05)	-0.26*** (0.04)	-0.17* (0.05)	-0.08 (0.05)
Cash operating surplus	1591.29*** (19.51)	917.35*** (18.74)	505.46*** (19.24)	1085.83*** (17.54)	411.89*** (16.67)	673.94*** (17.34)
Total GHG emissions	-510.90*** (63.04)	-493.03*** (62.67)	-248.20** (63.27)	-262.71** (65.39)	-244.82** (65.03)	-17.88 (64.81)

*Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.; Q4 is the best and Q1 the worst*

Our pasture and crop eaten findings consolidate this assertion, as we find that better farms have greater pasture and crop eaten. Neal and Roche (2020) support this, as they find higher profitability was related to greater pasture and crop eaten. This could suggest that better farms are in superior locations for pasture growth, which would reduce the requirements for supplement and fertiliser. Alternatively, better farms may optimise and use more home-grown feed (pasture and crop eaten) and use fertiliser and supplement more efficiently to generate a greater production response. In fairness, it is likely a combination of the two. It would be useful to disentangle these effects in future research to see how much of the variation in cost efficiency depends on sub-regional effects rather than the efficient use of inputs and home-grown feed. Our individual fixed-effects model intercepts control for such sub-regional heterogeneity.

We find significant differences in financial leverage between quartiles - with more cost-efficient farms having a smaller leverage ratio. This finding is consistent with Javed et al. (2015) and Getu et al. (2007) who demonstrate that cost efficiency and financial performance are lower for firms with greater leverage. Furthermore, relatively cost-efficient farms have more scope to pay down debt (Shadbolt et al., 2018). Thus, increasing cost efficiency probably contributes to a decreased leverage ratio (rather than lower leverage ratios driving improved

cost efficiency). We performed an additional Games-Howell test on the asset value (\$/ha) for farms in each quartile and there were no significant differences. This implies that the difference in leverage ratios is due to better farms having more equity (supporting the notion that better farms can better pay down debt). On a related note, cash operating surplus tended to be greater for farms with a higher average OPM. This finding is expected, as cash operating surplus and OPM are both dependent on operating profit by mathematical calculation.

Apart from the difference between Q2 and Q1, there are significant decreases in GHG emissions when moving up a quartile. Our results suggest that some farmers may be able to begin to low their GHG emissions, whilst maintaining a strong level of cost efficiency. Indeed, the lower fertiliser use of the higher quartile farms should help lower nitrogen leaching levels and nitrous oxide emissions; the lower greenhouse gas emissions of the higher quartile farms is in fact mostly driven by lower nitrous oxide and not methane emissions. This is an important finding, considering the environmental actions farmers have already started taking and the active research and innovation around reducing agricultural GHG emissions (MFE, 2019; MFE & MPI, 2020).

5.3 Fixed Effects models

Our FE panel regression results by quartile are reported in Table 3. The significance and size of some coefficients are heterogeneous across quartiles. Our FE results demonstrate which variables drive variation in cost efficiency over time.

Milk price is a significant coefficient for all models and accounts for a large proportion of variation in cost efficiency over time. Milk price is a fundamental component of the farm operating revenue term in OPM. Therefore, we expect milk price variation to impact cost efficiency through time. As Beca (2020) and Jiang and Sharb (2014) state, New Zealand dairy farms are price takers and are subject to considerable milk price fluctuations. These fluctuations have a substantial impact on cost efficiency. Our results suggest that a \$1 increase in milk price is correlated with an average 12.5% increase in OPM for farms in Q1. Farms in higher quartiles exhibit smaller coefficients. Based on the standard errors, the differences between the coefficients appear significant, although we cannot say for sure.

Our results imply that the most cost-efficient farms have cost efficiencies that are less subject to milk price variation. This aligns with our findings from the Games-Howell tests, suggesting that farms in lower quartiles had higher business risk - which incorporates exposure to milk price risk.

Moreover, we suggest that the best farms have greater adaptability to pricing conditions. That is, when the milk price is favourable, the best farms will increase their system intensity, bring in more supplement and their operating expenses will increase (subduing the increased revenue effect in the OPM formula). This assertion is in line with Doole's (2014) work, which shows that the relative profitability of different production systems varies with milk and input prices. At high milk prices, more intensive systems (systems which utilise more supplement) become more profitable. Conversely, at low milk prices, less intensive systems become relatively more profitable.

Table 3. Coefficients and standard errors for quartile FE panel models

	OPM			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Milk price	0.125*** (0.005)	0.103*** (0.001)	0.093*** (0.001)	0.087*** (0.002)
Milk production	-0.0001 (0.0002)	0.0004*** (0.0001)	0.0003*** (0.00004)	0.0004*** (0.00004)
Proportion of feed that is supplement	0.001 (0.003)	-0.002*** (0.001)	-0.002*** (0.001)	-0.005*** (0.001)
Production yield	0.464** (0.190)	0.382*** (0.052)	0.394*** (0.053)	0.232*** (0.076)
Leverage ratio	0.001** (0.0004)	0.0001*** (0.00002)	-0.00003 (0.0001)	-0.00005 (0.0001)
Pasture and crop eaten	0.00000 (0.00002)	0.00002*** (0.00000)	0.00001** (0.00000)	-0.00001** (0.00000)
Nitrogen fertiliser costs	0.002*** (0.0002)	0.001*** (0.0001)	0.001*** (0.0001)	0.0003** (0.0001)
Overhead costs	0.0005 (0.0004)	-0.0001 (0.0001)	-0.0001 (0.0001)	0.0001 (0.0001)
Meat revenue	-0.001*** (0.0001)	-0.001*** (0.00004)	-0.0004*** (0.00003)	-0.0005*** (0.00003)
Cash operating surplus	-0.00003*** (0.00001)	-0.00003*** (0.00000)	-0.00002*** (0.00000)	-0.00002*** (0.00000)
Observations	9,160	9,150	9,160	9,150
Adjusted R ²	0.899	0.945	0.946	0.941
F Statistic	8,286.107*** (df = 10; 8234)	7,000.810*** (df = 10; 8225)	16,016.030*** (df = 10; 8234)	14,765.000*** (df = 10; 8225)

*Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.; Q4 is the best and Q1 the worst*

Milk production per hectare is significantly correlated with OPM over time for all models (except Q1). An increase in milk production by 100 kg MS/ha is associated with a 4%, 4% and 3% increase in OPM (for quartiles 2, 3 and 4). Our results imply relatively low performing farms are already at a production level where they have stopped seeing increasing returns to scale (whilst farms in higher quartiles have scope to increase production while increasing cost efficiency). Hence, for farms in Q1, improving cost efficiency does not require greater milk production. These farms should focus their attention to decreasing the cost of their current production levels or reduce their production to a more efficient level. Conversely, the best farms (in Q4) may experience even higher cost efficiency if they increase their milk production at the margin - perhaps because they are already producing milk in a highly productive and efficient manner.

The proportion of feed consisting of supplement is insignificant for the Q1 model - however, it is significant for the Q2, Q3 and Q4 models. The coefficients are all negative. Our results suggest that a 10% increase in the proportion of feed consisting of supplement is associated with a decrease in OPM of 2% for farms in Q2 and Q3, and 5% for farms in Q4.

These results indicate that farms above Q1 will experience decreases in cost efficiency as the proportion of feed consisting of supplement rises. This could be because these farms have already achieved a good balance between feed deficits and supplementary feed use. As a result, any additional supplement would substitute pasture or crop consumption - resulting in no net gain in milk production and an increase in operating costs (McCahon et al., 2019). Ma et al. (2018) corroborates this by demonstrating that there is a clear upper limit on the ability of supplement to improve farm efficiency. It appears that on average, most farms in the Waikato have reached or surpassed that upper bound and are experiencing decreasing returns to supplement use.

Production yield exhibits a statistically significant positive correlation with OPM for all models. For example, a 10% increase in production yield is correlated with an increase in OPM of 4.64% for farms in Q1, 3.82% for farms in Q2, 3.94% for farms in Q3 and 2.32% in Q4. This suggests that in the short-run, farms in any quartile could improve their cost efficiency by increasing their production yield. However, we find that over the long run, farms with a higher cost efficiency also have lower production yield (Table 3). This may imply that pursuing production yield is a good short-term strategy, but a poor long-term strategy. Similar to the findings for milk price, production yield has a much greater impact on poorly performing farms. Future research could address the mechanism driving these findings and elaborate on why the effect of certain variables taper off as farms improve their relative performance.

The pasture and crop eaten relationship with OPM is positive and significant for Q2 and Q3, whereas it is insignificant for Q1 and negative for Q4. The Q2 and Q3 results align with our Games-Howell tests and supports Beca (2020) and Shadbolt (2016) who demonstrate that pasture harvest is fundamental in cost minimisation. The negative association between pasture and crop eaten and cost efficiency for the best farms seems unusual. However, we might assume that better farms have well-rounded managerial skills that enable them to leverage several of the many interdependencies on a farm, rather than just pasture harvest and pasture eaten. It also indicates that pasture and crop eaten is a good classification tool across quartiles, but not necessarily within them.

The financial leverage coefficient is significant for Q1 and Q2 and insignificant for the other two models. However, the significant associations are relatively weak: an increase in the leverage ratio by 1 is correlated with a subtle increase in OPM of 0.1% for Q1 farms and 0.01% for Q2 farms. Given that the mean financial leverage ratio is 1.77 in Q2, this relationship does not appear to be economically significant.

The coefficients for nitrogen fertiliser costs are positive and significant for all models. A \$100 increase in nitrogen fertiliser costs per hectare was associated with a 20% increase in OPM for farms in Q1, a 10% increase for farms in Q2 and Q3, and a 3% increase for farms in Q4. This suggests that applying more nitrogen fertiliser may be a way to improve cost efficiency. However, our results suggest that above average farms will not experience the same magnitude of increase to cost efficiency if they increase nitrogen fertiliser use. Contrastingly,

our Games-Howell results show that farms in higher cost-efficiency quartiles have lower nitrogen fertiliser application on average over a ten-year period. Hence, within benchmarked quartiles, farms may improve their cost efficiency by increasing nitrogen fertiliser application. However, over the long run, it may be better to pursue a lower nitrogen fertiliser application rate to move up the cost-efficiency distribution of farms. Farmers would also be aware of the environmental implications of nitrogen fertiliser application

Overhead costs, meat revenue and cash operating surplus were included in the model as control variables. This was to account for differences in the expenses required to keep the farm running (overheads) and to control for changes in stock levels. Interestingly, meat revenue had a significant negative coefficient for all models. A plausible scenario is, controlling for all other variables (input costs and intensities included), farms that have greater meat revenue would have a smaller herd size than in the previous year, generate less operating revenue and have a lower OPM. Furthermore, greater meat revenue may be an indicator of poor animal health or productivity. If this is the case, our results are not unexpected as farms with less productive and healthy animals should have lower cost efficiency (due to higher health costs and lower milk productivity). Cash operating surplus has a significant negative coefficient for all models. This is an unusual observation as we would expect cash operating surplus and cost efficiency to be positively correlated, based on the discussion in the Games-Howell test results.

6. Conclusions

We address pertinent gaps in the academic literature by investigating cost efficiency for dairy farms in the Waikato region, New Zealand. In doing so we demonstrate how OPM can be usefully applied to analyse farm performance and provide insights that can be easily interpreted by everyone from farmers to academics. Some key findings are cost-efficient farms use less supplement and nitrogen fertiliser over the long run, milk price fluctuations disproportionately impact lower quartile groups, and farms may be able to lower their GHG emissions whilst maintaining strong cost efficiency. These findings deepen the understanding of cost efficiency and its relationships with farm variables on New Zealand dairy farms.

Future research could investigate the spatial distributions of farms within the quartiles and examine the relationship between cost efficiency and farm-specific characteristics (such as age of operator and education level). Furthermore, there is scope to investigate whether cost-efficient farms have more productive and better managers or environmental endowment advantages over other farms. Also, there is considerable heterogeneity in model parameters and statistical significance between the benchmarked quartiles. There is a need to establish what causes these effects to better understand the farm system and cost efficiency. Finally, while we use the best dataset available to us, there would be considerable value in improving data collection and reporting capabilities for the New Zealand dairy industry, and agricultural industries more broadly.

7. References

- Abdullahi, A. O. (2003). Estimating risk aversion coefficients for dry land wheat, irrigated corn and dairy producers in Kansas. *Applied Economics*, 35(7), 825-834. <https://doi.org/10.1080/0003648032000050612>
- Alvarez, A., Corral, J. D., Solis, D., & Perez, J. A. (2008). Does intensification improve the economic efficiency of dairy farms? *Journal of Dairy Science*, 91(9), 3693-3698. <https://doi.org/10.3168/jds.2008-1123>
- Ballingall, J., & Pambudi, D. (2017). Dairy trade's economic contribution to New Zealand. New Zealand Institute of Economic Research.
- Barry, P., & Pattullo, H. (2020). The dairy sector in New Zealand: Extending the boundaries. TBD Advisory.
- Beca, D. (2020). Evaluating the loss of profitability and declining milk production in the Australian dairy industry. *Australasian Agribusiness Perspectives*, 23(9), 136-164
- Climate Change Commission (CCC). (2021). *2021 Draft advice for consultation*. <https://www.climatecommission.govt.nz/get-involved/our-advice-and-evidence/>
- Collins, R. A. (1985). Expected utility, debt-equity structure, and risk balancing. *American Journal of Agricultural Economics*, 67(3), 627-629. <https://doi.org/10.2307/1241085>
- DairyNZ (2021). *Busting common MaxT myths*. <https://www.dairynz.co.nz/milking/milking-efficiently/milking-duration/busting-common-maxt-myths/>
- Department of Primary Industries (DPI). (n.d.). *Plant nutrients in the soil*. <https://www.dpi.nsw.gov.au/agriculture/soils/improvement/plant-nutrients#:~:text=Soil%20is%20a%20major%20source,are%20calcium%2C%20magnesium%20and%20sulfur.>
- Doole, G. J. (2014). Economic feasibility of supplementary feeding on dairy farms in the Waikato region of New Zealand. *New Zealand Journal of Agricultural Research*, 57(2), 90-99. <https://doi.org/10.1080/00288233.2013.870915>
- Doole, G. J., Alvaro, R. J., Leslie, J. E., Chapman, D. F., Pinxterhuis, I. J. B., & Kemp, P. D. (2021). Economic assessment of plantain (*Plantago lanceolata*) uptake in the New Zealand dairy sector. *Agricultural Systems*, 187.
- Doole, G. J., & Te Rito, R. (2019). Assessing the competitiveness and resilience of the New Zealand dairy sector. DairyNZ. Hamilton.
- Fairfield, P. M., & Yohn, T. L. (2001). Using asset turnover and profit margin to forecast changes in profitability. *Review of Accounting Studies*, 6(4), 371-385.

- Farina, S. R., Alford, A., Garcia, S. C., & Fulkerson, W. J. (2013). An integrated assessment of business risk for pasture-based dairy farm systems intensification. *Agricultural Systems*, 115, 10-20. <https://doi.org/10.1016/j.agsy.2012.10.003>
- Gabriel, S. C., & Baker, C. B. (1980). Concepts of business and financial risk. *American Journal of Agricultural Economics*, 62(3), 560-564. <https://doi.org/10.2307/1240215>
- Getu, H., Jeffrey, S. R., & Goddard, E. W. (2007). Economic performance and financial leverage of agribusiness marketing co-operatives in Canada. *Cooperative Firms in Global Markets*, 10, 47-77.
- Grashuis, J. (2018). A quantile regression analysis of farmer cooperative performance. *Agricultural Finance Review*, 78(1), 65-82. <https://doi.org/10.1108/AFR-05-2017-0031>
- Greig, B. J. (2010). New Zealand dairy farm debt [Conference paper]. South Island Dairy Event.
- Hardaker, J. B., Huirne, R. B. M., Anderson, J. R., & Lien, G. (2004). *Coping with Risk in Agriculture*. CABI Publishing, Wallingford, United Kingdom.
- Hedley, P. and E. Kolver (2006). Achieving high performance from a range of farm systems in Southland. South Island Dairy Event.
- Ho, C. K. M., Newman, M., Dalley, D. E., Little, S., & Wales, W. J. (2013). Performance, return and risk of different dairy systems in Australia and New Zealand. *Animal Production Science*, 53(9), 894-906. <https://doi.org/10.1071/AN12287>
- Hoppe, R. A. (2014). *Structure and finances of U.S. farms: Family farm report, 2014 edition* [Economic Information Bulletin Number 132]. U.S. Department of Agriculture (USDA), Economic Research Service.
- Javed, Z. H., Rao, H. H., Akram, B., & Nazir, M. F. (2015). Effect of financial leverage on performance of the firms: Empirical evidence from Pakistan. *SPOUDAI Journal of Economics and Business*, 65(1-2).
- Jiang, N., & Sharb, B. (2014). Cost efficiency of dairy farming in New Zealand: A stochastic frontier analysis. *Agricultural and Resource Economics Review*, 43(3). <https://doi.org/10.22004/ag.econ.189784>
- Langemeier, M. (2016, April 1). Measuring farm profitability. *Farmdoc Daily*, 63(6), Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign
- Langemeier, M. (2010). Persistence in financial performance. *Journal of International Farm Management*, 5(2), 1-15.
- Langemeier, M., & Yeager, E. (2018, August 24). Operating profit margin benchmarks. *Farmdoc Daily*, 159(8), Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

- Ma, W., Bicknell, K., & Renwick, A. (2018). Feed use intensification and technical efficiency of dairy farms in New Zealand. *Agricultural and Resource Economics*, 63(1), 20-38.
- Ma, W., Renwick, A., & Bickell, K. (2018). Higher Intensity, Higher Profit? Empirical Evidence from Dairy Farming in New Zealand. *Journal of Agricultural Economics*, 69(3), 739-755. <https://doi.org/10.1111/1477-9552.12261>
- Ma, W., Renwick, A., & Zhou, X. (2020). Short communication: The relationship between farm debt and dairy productivity and profitability in New Zealand. *Journal of Dairy Science*, 103(9), 8251-8256. <https://doi.org/10.3168/jds.2019-17506>
- Macdonald, K. A., J. W. Penno, J. A. Lancaster, A. M. Bryant, J. M. Kidd, and J. R. Roche. (2017). Production and economic responses to intensification of pasture-based dairy production systems. *Journal of Dairy Science* 100(8):6602-6619. <https://doi.org/10.3168/jds.2016-12497>
- McCahon, K., Neal, M., & Roche, J. R. (2019). Effects of removing imported feed. *Technical Series December 2019*, DairyNZ, Hamilton, New Zealand.
- MFE. (2019, November 25). *About New Zealand's emissions reduction targets*. <https://www.mfe.govt.nz/climate-change/climate-change-and-government/emissions-reduction-targets/about-our-emissions>
- MFE & MPI. (2020, July). *Action for Healthy Waterways - Information for Farmers*. <https://www.mfe.govt.nz/sites/default/files/media/Fresh%20water/action-for-healthy-waterways-information-for-dairy-farmers.pdf>
- Mishra, A. K., Harris, M. J., Erickson, K. W., Hallahan, C., & Detre, J. D. (2012). Drivers of agricultural profitability in the USA: An application of the Du Pont expansion method. *Agricultural Finance Review*, 72(3), 325-340.
- Neal, M., Roche, J. R., & Shaloo, L. (2018). Profitable and resilient pasture-based dairy farm businesses: The New Zealand experience [Conference paper]. Pasture Summit, New Zealand.
- Neal, M., & Roche, J. R. (2020). Profitable and resilient pasture-based dairy farm businesses in New Zealand. *Animal Production Science*, 60(1), 169-174. <https://doi.org/10.1071/AN18572>
- Pinochet-Chateau, R., Shadbold, N. M., Holmes, C., & Lopez-Villalobos, N. (2005). *Drivers of risk in New Zealand Dairy systems* [Paper presentation]. IFMA 15th Congress, Campinas, Brazil.
- Saha, A. (1997). Risk preference estimation in the nonlinear mean standard deviation approach. *Economic Inquiry*, 25, 770-782.
- Saiyut, P., Bunyasiri, R. Sirisupluxana, P., & Mahathanaseth, I. (2018). The impact of age structure on technical efficiency in Thai agriculture. *Kasetsart Journal of Social Sciences*, 40, 539-545. [10.1016/j.kjss.2017.12.015](https://doi.org/10.1016/j.kjss.2017.12.015)
- Sauder D. C., & DeMars C. E. (2019). An updated recommendation for multiple comparisons. *Advances in Methods and Practices in Psychological Science*. 26-44. [doi:10.1177/2515245918808784](https://doi.org/10.1177/2515245918808784)

- Shadbolt, N. (2012) Competitive strategy analysis of NZ pastoral dairy farming systems. *International Journal of Agricultural Management*, 1, 19–27.
- Shadbolt, N., Olubode-Awosola, F., & Rutsito, B. (2013). Resilience, to ‘bounce without breaking’ in New Zealand dairy farm businesses [Paper presentation]. 19th International Farm Management Congress, Warsaw, Poland.
- Shingala, M. C., & Rajyaguru, A. (2015). Comparison of post hoc tests for unequal variance. *International Journal of New Technologies in Science and Engineering*, 2(5), 22-33.
- Snider, L., & Langemeier, M. (2009). *A long-term analysis of changes in farm size and financial performance* [Paper presentation]. Southern Agricultural Economics Annual Meeting, Atlanta, Georgia.
- Sulewski, P., Was, A., Kobus, P., Pogodzinska, K., Syzmanska, M., & Sosulski, T. (2020). Farmers’ attitudes towards risk—An empirical study from Poland. *Agronomy*, 10, 1555. <https://doi.org/10.3390/agronomy10101555>
- Torres-Reyna, O. (2010). *Getting started in fixed/random effects models using R*. Princeton, Data and Statistical Services.
- Uzea, N., Poon, K., Sparling, D., & Weersink, A. (2014). Farm support payments and risk balancing: Implications for financial riskiness of Canadian farms. *Canadian Journal of Agricultural Economics*, 62(4). <https://doi.org/10.1111/cjag.12043>
- Wales, W. J., & Kolver, E. S. (2017). Challenges of feeding dairy cows in Australia and New Zealand. *Animal Production Science*, 57(7), 1366-1383. <https://doi.org/10.1071/AN16828>
- Westpac. (2020, October 12). *Weekly economic commentary: Agri exports doing well, but what are the risks?*
https://westpaciq.westpac.com.au/wibiqauthoring/_uploads/file/New_Zealand/2020/October_2020/12.10.20_Weekly_Economic_Commentary_-_Westpac_NZ.pdf
- Wolf, C. A., Black, R. J., & Stephenson, M. W. (2020). Benchmarking upper Midwest dairy farm profitability. *Agricultural Finance Review*, 80(5), 733-744. <https://doi.org/10.1108/AFR-02-2020-0022>
- Yeager, E. A., & Langemeier, M. R. (2016). Economic efficiency adjusted for risk preferences. *Applied Economics*, 49(16), 1627-2636. <https://doi.org/10.1080/00036846.2016.1223819>
- Yu, F., Liang, Q., & Wang, W. (2019). State ownership and banks’ information rents: Evidence from China. *Financial Review*, 55(2). <https://doi.org/10.1111/fire.12197>
- Wales, W. J., & Kolver, E. S. (2017). Challenges of feeding dairy cows in Australia and New Zealand. *Animal Production Science*, 57(7), 1366-1383. <https://doi.org/10.1071/AN16828>