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Further enquiries to:

The Administrator
School of Economics and Finance
Victoria University of Wellington
P O Box 600
Wellington 6140
New Zealand

Phone: +64 4 463 5353
Email: alice.fong@vuw.ac.nz

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Droughts and farms’ financial performance in New Zealand: A micro farm-level study

Farnaz Pourzand, Ilan Noy, Yiğit Sağlam
School of Economics and Finance
Victoria University of Wellington, New Zealand

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Note on Random Rounding: All counts presented in this study have had Statistics New Zealand confidentiality rules applied. This includes the random rounding of all counts to base 3. Therefore, the sample counts presented are not exact, and in some cases, aggregating sub-samples will not yield the exact population counts.

Abstract: We quantify the impacts of droughts in New Zealand on the profitability of dairy, and sheep and beef farms. Using a comprehensive administrative database of all businesses in New Zealand, we investigate the impact of droughts on farm revenue, profits, return on capital, business equity, debt to income ratio, and interest coverage ratio. Over the period we examine (2007-2016) about half of the districts experienced severe droughts, and almost 85% of districts were affected by more moderate droughts at least once. For dairy farms, there is a strong negative relationship between the occurrence of droughts two years earlier and farms’ revenue, profit and consequently their return on capital. More surprisingly, we found that current (same fiscal year) drought events have positive impacts on dairy farms’ revenue and profit; this effect is most likely attributable to drought-induced increases in the price of milk solids (New Zealand is the market maker in this global market). In general, dairy farmers ‘benefit’ more from drought events when compared to sheep/beef farms, whereas the latter sector has less impact on global prices. These findings are useful for shaping climate-change adaptation as there is a clear variation in the future climate-change projections of drought intensities and frequencies for different regions in New Zealand.

Keywords: Drought; profitability; dairy; sheep/beef farming; New Zealand

JEL: Q12, Q54

1. Introduction

Agriculture is likely the worst affected sector by droughts. From a dairy or sheep/beef farmer's point of view, drought have significant adverse effects, leading to larger expenditure on feed supplement for livestock due to lack of forge and consequently reduction in farm productivity and profitability. As consequence, farmers are able to generate less income, their ability to service debt is diminished, and they may find it more difficult to replace capital items (e.g. machinery) and invest in recovery (Edwards et al., 2009). If the farmers' capacity to finance their agricultural activities during recovery is limited, drought can have long term adverse consequences (Lawes and Kingwell, 2012). Ultimately, these losses flow through into downstream production and other sectors, and thus droughts can have a large impact on the aggregate economy.

New Zealand has experienced several major droughts during the last decades. The 2013 drought affected the whole of the North Island and the West Coast of the South Island, and was one of the most extreme on record in New Zealand. According to the Ministry for Primary Industries (MPI), its impact on the economy was estimated to be at least $1.3 billion, and it affected 20,000 farmers. Some North Island regions received less than half of the expected summer rainfall. This led to a decrease in the number of livestock in some regions, where Hawke's Bay and Manawatu-Wanganui experienced the most significant decreases (Agricultural Production Statistics: June 2013). The 2013 drought was estimated to have caused GDP to drop by 0.6% (Kamber et al., 2013). The worst drought in Northland in 2010 happened when record low rainfall levels were recorded between November 2009 and April 2010. Instead of receiving the 748mm of precipitation which fell during the previous year, only 253 mm fell during this period; this led to parched soils, a drastic reduction in pasture growth as well as reductions in farm productivity (NIWA, 2017). In 2008, Waikato experienced the driest January in a century. Severe moisture deficits continued in the North Island until April/May. The cost of the 2007-08 drought was estimated to reach $894 million for dairy farming and $345 million for sheep and beef farming.

A changing climate, with higher average temperatures, more extreme temperatures, and changed rainfall patterns (mainly, drier in the north and east and wetter in the west and south), is expected to affect the frequency and intensity of droughts for New Zealand (NIWA, 2015). A report from the National Institute of Water and Atmospheric (NIWA) concluded that under the more extreme projections, New Zealand will become more arid by 2040. Moreover, NIWA projected most parts of New Zealand, except for the West Coast of the South Island, will spend about 10 percent more of the year in drought conditions (NIWA, 2011).

In this paper, we undertake an assessment of drought risk for farms in New Zealand. Our focus is on dairy farming and sheep/beef farming, as dairy contributes approximately 45% to agricultural GDP, and sheep/beef is the second largest agricultural sector (Stats NZ, 2015). New Zealand is one of the largest milk producers in the world, with more than 4 million dairy cows producing over 15 billion liters of milk annually. New Zealand also accounts for %5 of world sheep meat production and supplies over half of the global lamb exports (NZIPIM, 2019). The majority of dairy herds (72.3%) are located in the North Island, with the greatest concentration (28.7%) in the Waikato region (DairyNZ, 2018). Most of the pasture land in these areas is not irrigated. The Ministry for the Environment (MfE, 2001) identified drought as one of the major constraints to pasture grazing in New Zealand.

The majority of existing empirical literature analyses the effects of climate-extreme events on the agricultural sector at the national level, which may underestimate the negative local impacts of adverse events. The micro-level analysis we pursue provides a more precise picture of the effects of droughts, and has a practical application as it provides inputs for evidence-based policy to assist farm enterprises.

In this study, we combine a farm-level panel data from Statistics New Zealand's Longitudinal Business Database (LBD) with a drought-conditions measurement tool (the New Zealand Drought Index) to analyze the impacts of droughts on farms' economic performance and their balance sheets. To the best of our knowledge, this is the first empirical analysis using micro enterprise-level data. It is noted that the main focus of this study is on agricultural drought. Since, there is no common definition of drought, for this study, agricultural drought is defined as:

> *"Agricultural drought links the diverse characteristics of meteorological droughts to agricultural impacts which focus on precipitation shortages, differences between actual and potential evapotranspiration, and soil moisture deficits" (American Meteorological Society, 1997).*

The objectives of this work are to (1) analyze frequency, severity, and spatial spread of droughts over the past ten years; (2) investigate the effects of agricultural droughts on agricultural profitability and farms' business performance; and (3) identify the most vulnerable agricultural sub-sectors in New Zealand. To address these objectives, we apply a fixed effect panel regression model using tax and productivity data at the firm level, coupled with the New Zealand Drought Index.

During 2007-2016, about 50% of districts in New Zealand experienced at least one severe drought. The northwest of the North Island (particularly Waikato region) is the most affected area. We found that, on average, a recent drought affects revenue and profit of dairy farming less adversely (and sometimes more positively) than sheep and beef farming, potentially implying that the losses in milk productions may be compensated by increasing milk prices. In contrast, earlier drought events can have significant negative impacts on farms' revenue and profit. Consequently, we examine the average farm's business indicators for the next two years including interest coverage (IC), return on capital (ROC), business equity (BE), and debt to income (DI) ratio.

This paper is structured as followed; section 2 provides an overview of the literature on assessing the risk from climate-extreme events to identify the gap in the research that we aim to fill. The following sections present data sources, the empirical model used, and a spatial and temporal description of the data. The main findings are summarised in section 6, and the last section concludes.

2. Literature Review

Some recent studies have focused on the relationship between climate-related risks, extreme weather, and agriculture (Ali et al., 2017; P. Birthal et al., 2014; Fuhrer et al., 2006; Howitt, Medellín-Azuara, MacEwan, Lund, and Sumner, 2014; Kumar et al., 2011). The focus of most of these studies has been the impacts of changes in temperature and precipitation on agricultural production at the national level. For example, Ali et al. (2017) investigated the impacts of maximum temperature, minimum temperature, rainfall, relative humidity, and sunshine on major crops in Pakistan (wheat, rice, maize, and sugarcane) using time series data for the period 1989-2015. Kumar et al., 2011 examined the effect of monsoon drought on the production, demand, and prices of seven major agricultural commodities – rice, sorghum, pearl millet, maize, pigeon pea, groundnut and cotton in India. Their results show drought during the monsoon period has an adverse effect on the agricultural sector. Yet, loss of production leads to an increase in the prices of agricultural commodities. Usman et al., (2011) showed a significant negative impact of rising temperatures on agricultural production and also found the positive impact of rainfall on production. Similar results have been reported from Barrios et al. (2008) on the relationship between rainfall and temperature and agricultural output using cross-country data. Their results suggest that climatic changes have had important effects on total agricultural output in Sub-Saharan Africa.

An extensive literature is focused on the climatological assessment of drought characteristics in terms of its frequency, duration, severity, and spatial extent to gain a better understanding of this phenomenon (Livada and Assimakopoulos, 2007; Wu et al., 2011; He et al., 2013; Spinoni et al., 2014). Several studies investigated the spatial patterns of drought risk in order to assist agricultural or environmental management (Vicente-Serrano and López-Moreno, 2005). Some other research aims to identify and quantify drought vulnerability (Cheng and Tao, 2010; Shahid and Behrawan, 2008). A number of studies have been carried out to measure the impact of droughts on agricultural production (Ferrari and Ozaki, 2014; Howitt et al., 2014; Wilhite, 1997; Wittwer and Griffith, 2010), farms' business performance (Lawes and Kingwell, 2012), farmers' consumption and income (Garbero and Muttarak, 2013) and also farms' resilience to droughts (Brithal et al, 2015).

Some findings from this literature are worth noting here: First of all, it remains difficult to adequately characterize droughts due to their complexity; so there is no consensus on their definition, identification, and measurement. Secondly, the impacts of droughts on agricultural yield vary during the crop- growing period. Thirdly, farmers use various coping strategies, so distinguishing drought impact on production volumes or values might not be a straightforward task.

Research on the impacts of climate-induced extreme risks on New Zealand agriculture dates back about 40 years to Maunder's work (1968, 1971a, 1971b). In the following paragraphs, we describe seven comprehensive studies, six of which look at the historical effects of dry periods on agriculture at a national level, while the remaining one focuses on the 1998-99 drought in Canterbury alone. These studies apply different empirical methods, cover different historical periods, regions and agricultural sub-sectors.

Tweedie and Spencer's study(1981) focus on the econometric estimation of export supply functions over the period 1961–1978, but they also provide estimates of the effects of climate (measured in terms of Days of Soil Moisture Deficit (DSMD)) on agricultural production. The longer run equilibrium impacts of climate and the shorter run effects are separately estimated on the number of animals and production of meat, milk, and wool, respectively. The results show that climate influences the slaughter rate, the milk production per cow, and the growth rate of wool. The authors note that the impact on dairy production seems low in relation to the effects of weather on other agricultural production.

Wallace and Evans (1985) examined the effect of annual climate variability (measured by standard deviations in DSMD) on expected farm outputs, inputs and profit using a panel database from 1950 to 1979. They use separate series for positive and negative variations in DSMD in order to evaluate asymmetric reactions to dry and wet conditions. They observe that a deviation from normal DSMD in either direction negatively affects sheep output. There is an exception for Southland where the impact of wet weather is considerably stronger, attributed to the mostly wetter soil in this area. Profitability differs between dry and wet years. In general, the effects of the sheep and beef production from changes in DSMD are comparable with Tweedie and Spencer (1981), although marginally lower than they estimated. Since Wallace and Evans (1985) took into account only the regions with Class VI[1] sheep farms, it is expected that these farms are better adapted to address climate variability on sheep and beef production than similar farms in other places.

Forbes (1998) estimated changes in agricultural output as a result of the climatic conditions with data covering the period 1961 to 1998. It used the MAF Pastoral Supply Response Model (PSRM) on Statistics NZ's agricultural time series, and found similar results to Tweedie and Spencer (1981) and Wallace and Evans (1985). However, Forbes (1998) presents a strong positive effect on the slaughter rates for adult animals. Tait et al (2005) looked at the effects of climate variability on dairy production in dairying regions using a panel dataset from annual Livestock Improvement Corporation Ltd Dairy Statistics publications and NIWA national climate dataset. To calculate the economy-wide implications of changes in milksolids production they incorporate the impacts of production into a general equilibrium model. The results showed negative economic effects. As Tait et al. (2005) state, they find that an adverse change of one standard deviation can cause a reduction in milk solids production per cow by 3–4%. This is broadly consistent with the estimate of 2.6% estimated by Tweedie and Spencer (1981).

Kamber et al (2013) investigated the economic impact of the 2013 drought using a macroeconomic model. An important contribution of this research is the climate data. Indicators used in previous studies are not always consistent with one another. Kamber et al (2013) provide alternative weather measures and show that these indicators are consistent with the timing of recognized droughts. Furthermore, since the effect of seasonal variation can be highly significant, they calculate the impact of drier-than-usual March quarters when the most damaging droughts usually take place. The findings indicate the 2013 drought reduced annual GDP for the full year by 0.3 percent.

[1] Class VI is defined as South Island Finishing Breeding: more extensive type of finishing farm, also encompassing some irrigation units and frequently with some cash cropping. Carrying capacity ranges from six to eleven stock units per hectare on dryland farms and over twelve stock units per hectare on irrigated units. Mainly in Canterbury and Otago. This is the dominant farm class in the South Island (Beef + Lamb New Zealand, 2017).

From this review of previous studies, it is quite apparent that understanding the effects of past weather extreme events on the agricultural sector at the farm level can be very informative, and that this work has only been done before with aggregated data - regionally or nationally, in New Zealand and elsewhere. Data aggregated at the regional or national level will not represent the real picture of impacts of climatic disasters on rural farming with different agroecological characteristics. Any level of aggregation will hide heterogenous impacts that drought events may have.

3. Data sources and sample

I. Drought Index dataset

There is no universal definition of drought as it can be defined based on different perspectives i.e.: meteorological, hydrological, agricultural and socioeconomic (American Meteorological Society, 1997). An agricultural drought, in New Zealand, is defined as a prolonged moisture deficit that has adverse impacts on agricultural production (NIWA, 2017). A large body of literature exists on the diverse range of drought indicators to measure and detect drought. These drought indicators have been developed based on the available climate and weather data. These include: Rainfall deciles (Gibbs and Maher 1967); Hutchinson Drought Severity Index (HDSI) (Smith et al., 1993); Drought Severity Index (DSI) (Phillips and McGregor, 1998); Standardised Precipitation Index (SPI) (Cancelliere et al., 2007; Hayes et al., 2011; Huo-Po et al., 2013); Palmer Drought Severity Index (PDSI) (Alley, 1984; Dai et al., 2004; Palmer, 1965); Potential Evaporation Deficit (PED) (Nagarajan, 2010); Soil Moisture Deficit Index (SMDI) (Narasimhan and Srinivasan, 2005; Tang and Piechota, 2009); Drought Area Index (DAI) (Bhalme and Mooley, 1980); NOAA Drought Index (NDI) (Strommen et al., 1980); and Integrated Agricultural Drought Index (IADI) (Zhao et al., 2017).

Given the complexity of drought, various sources of drought-related elements such as precipitation, vegetation growth condition, soil water, and land surface temperature should be integrated to indicate the spatial extent and intensity of droughts (Meng, Zhang, Su, Li, and Zhao, 2016). It is apparent that the aggregation of all drought-related factors depends on the availability of data. In this study, we apply a new New Zealand Drought Index (NZDI) developed by NIWA. The NZDI is used to identify the onset, duration, and intensity of drought conditions. The index has five categories: Dry, Very Dry, Extremely Dry, Drought, and Severe Drought (NIWA, 2017). The NZDI combines four commonly-used drought indicators: The Standardised Precipitation

Index (SPI); Soil Moisture Deficit (SMD); Soil Moisture Deficit Anomaly (SMDA); and Potential Evapotranspiration Deficit (PED).

SPI, as a universal drought indicator, is based solely on the accumulated precipitation for a given time period (e.g. for New Zealand, over the last 60 days), compared with the long-term average precipitation (30 years) for that period. This precipitation difference is "standardised" by dividing by the long-term standard deviation of precipitation for that period (NIWA, 2017).

SMD is measured based on daily rainfall (mm), outgoing daily potential evapotranspiration (PET, mm), and a fixed available water capacity (the amount of water in the soil 'reservoir' that plants can use) of 150 mm. SMDA is also defined as difference between the current and historical soil moisture deficits (or difference from normal).

PED is the difference between potential evapotranspiration (PET) and actual evapotranspiration (AET). As conditions get drier, there will be a difference between the amount of water that is actually evaporated and transpired (AET) compared to the amount of water that would be evaporated and transpired if all the water is available (PET). To some extent, PED is related to SMD. Once sufficient water is available, SMD is small and the PED is zero. Conversely, when SMD is increasing, PED will show non-zero values. Thus, similarly to SMD, PED only shows dryness (NIWA, 2017).

The data are supplied as the daily value of NZDI and its 4 components at the district level and are linked to our sample population by spatially joining the value of drought index to each Meshblock within each district. Our analysis uses the two highest categories of the index – 'drought' and 'severe drought'. Since our goal is to investigate the effects of extreme events, we build new distributions of NZDI for extreme drought categories by looking at certain threshold values. If NZDI is equal to or higher than 1.75, severe drought (SD) is defined, and drought (D) event can be defined if NZDI is between 1.50 and 1.75. These are the thresholds identified by NIWA, which constructed the NZDI, based on interntional practice and the distribution of the NZDI. To analyze the frequency, severity and spatial spread of droughts, the number of SD/D days, the average value of the index for SD/D events and standard deviation of the index are calculated for each district over the last 10 years.

II. Agricultural-Financial-productivity and other datasets

The main source of data for the dependent variables is Statistics New Zealand's Longitudinal Business Database (LBD)[2], which combines administrative and survey data for all businesses in

[2] See Fabling (2016) for an introduction to the LBD.

New Zealand. We use data for the periods between 2007 and 2016. Table 1 lists the datasets used in this study.

Financial (tax) data are available at the enterprise level in the LBD, while information from the Agricultural Production Survey/Census (APS /APC) is collected at the farm level with a different geographical location identified at the meshblock level (the most detailed spatial level available from StatisticsNZ). Since we are not able to match the tax data to specific geographical location for firms with multiple locations, we aggregate the data to the enterprise level (rather than per location). Multiple location enterprises account for 27.5% of the enterprises in the LBD dataset. There are some enterprises which occupy meshblocks in more than one territorial authority and regional council. These account for about 11.9% and 0.2% of multi-location firms, respectively, recorded by a set of territorial authorities and regional council binary variables.

We also use a map of all irrigated areas, data for which was collected in 2017 (Dark, K.C, and Kashima, 2017). To allocate an irrigated area (farm level) to a meshblock level, first, we calculate the centroids of irrigated area and then count the number of points in each meshblock using QGIS3.2. The irrigated land (meshblock) is recorded by generating binary variable. The irrigated land is linked to each firm by identification to an assigned meshblock. To check the consistency of the irrigated land variable over time, we compared also the irrigated land to information from the 2002 APS. In total, irrigated enterprises accounted for one-third (32%) of our sample population. The majority of irrigated land was in Canterbury, followed by Otago and Marlborough regions, all located in the South Island.

Table 1. datasets and sources

Data	Spatial level	Datasets	Sources
Farm input	Farm level	Agricultural Production Survey/Census (APS/APC)[3]	Statistics New Zealand's Longitudinal Business Database (LBD)
Financial variables	Enterprise level	IR10 (Tax-filed financial accounts)	
Firm age, location, and industry	Meshblock, territorial authorities, regional councils	Longitudinal Business Frame (LBF)	
Drought index	District level	New Zealand Drought Monitor	the National Institute of Water and Atmospheric (NIWA)
Land quality	Meshblock level	New Zealand's Land Resource Information system	Landcare Research
Irrigated land	Farm level	National Irrigated Land Spatial Dataset	Ministry for the Environment

3 We use data from the APS for the time periods between 2008-2011 and 2013-2016; and data from the APC for the 2007 and 2012 years.

III. Sample population

Our sample population consists of enterprises (firms) with the agricultural industry code of our interest[4] in both the productivity dataset and APS/APC who have any productive land. We place some restrictions on our sample. Firstly, dairy or sheep/beef farming must be the enterprises' primary activity. Secondly, their number of deer, pigs, horses or hens must not be more than the number of cows if the enterprises are categorized dairy firms; or no more dairy cows, horses, pigs, or hens than sheep/beef cattle if they are classed as sheep/beef firms. Thirdly, enterprises must not have more land allocated to forestry than to their major activity. In addition, since the drought indicators are provided at the district level, we also restrict our sample to single district/region enterprises.

Lastly, it is important to consider land conversions during our study time period. Farmers might have switched to dairy farming because of a significant increase in dairy prices during the period of our study, in particular in 2014, our sample is also restricted to those farmers who did not switch or convert their land to other actives.[5] After these restrictions, our sample contains 72,384 observations from 12,534 enterprises.

4. Empirical Method and variables

There are a number of methods for estimating the impact of drought depending on its nature (direct or indirect) and the level of aggregation (farm, household, regional or economy-wide). The simple form is measuring the effect of droughts as the negative deviation in crop yield in a drought year from its previous normal (Xiao-jun et al., 2012). In some literature, linear and non-linear mathematical programming models have been used to simulate economic impacts of droughts (Booker, Michelsen, and Ward, 2005; Dono and Mazzapicchio, 2010; Jenkins, Lund, and Howitt, 2003; Peck and Adams, 2010). Some studies have used macro-econometric models to assess the damage as a result of droughts at an aggregate national level (Kamber et al, 2013) or at a disaggregated regional or crop levels (P. S. Birthal, Negi, Khan, and Agarwal, 2015; Quiroga and Iglesias, 2009). Computable general equilibrium and input-output models have also been used to assess the welfare impacts of droughts (Martin-Ortega and Berbel, 2010; Pérez y Pérez and Barreiro Hurlé, 2009).

An econometric approach is followed here to estimate the effect of drought on agricultural revenue, profitability and balance sheet indicators. We estimate different specifications including

4 Dairy and sheep/beef are coded AA13 and AA12 ANSIC06 classifications in the productivity dataset, respectively.
5 We removed the enterprises who were inactive in the previous year (farms might have changed ownership or stopped farming).

a reduced-form linear model in a farm fixed-effect panel regression for dairy and sheep/beef farming over the period 2007-2016. The regression equation we estimate is:

$$y_{dit} = \alpha + \beta_1 DI_{dt} + \beta_2 DI_{dt-1} + \beta_3 DI_{dt-2} + \beta_4 X_{dit} + \gamma_i + \sigma_t + \varepsilon_{dit} \quad (1)$$

Where the dependent variables are: sale of product per hectare, profit per hectare, and balance sheet variables (see Table 2).[6] The subscripts *dit* denote the district, enterprise and time, respectively. DI_{dt} represents the number of days of drought (we count the number of drought days if NZDI ≥1.5 during the summer season from October to March in the same financial year). As drought is a prolonged weather event of which impacts could carry beyond a one-year period, we also examine first and second lags of drought days (DI_{dt-1} and DI_{dt-2}). X_{dit} is multi-farm variable. Time invariant firm specific characteristics such as land quality and slope can influence agricultural productivity. At the same time, we also need to control for shocks and factors changing over time such as changes in prices. Therefore, we control for unobserved spatial and temporal heterogeneity using firm (γ_i) and year fixed effect (σ_t); ε_{dit} is the error term. In some specifications, we include global milk price (P_t), instead of time fixed-effects. Furthermore, we assume that errors are correlated within districts but not across districts, and we cluster errors around district (the level in which the drought index is measured).[7]

One of our aims is to evaluate the degree to which droughts affected the various categories of farms. Since the scope and magnitude of drought differ from irrigated to non-irrigated land as well as across farms of different sizes, the sample is stratified based on irrigated land and farm size. Farms are categorized as small (<1000 ha), medium (1000-3000 ha) and large (>3000 ha).

Table 2. Farm business indicators

Abbreviation	**Indicator**	**Definition**
ROC	Return on capital	Net income /total business capital
DI	Debt to Income Ratio	Total liabilities/gross income
BE	Business equity	(Total assets-total liabilities)/total assets
IC	Interest Coverage Ratio	Net income/interest expense

[6] There is multi-factor productivity data available in the dataset, but since it is imputed, it cannot measure the impacts of droughts. The financial data are in real dollar values, obtained by deflating all monetary quantities by the Consumer Price Index (CPI) based on the year 2000.

[7] We also used two-ways clustering by district and year. The results were very similar to one-way clustering.

5. Analysis of Drought characteristics

Figure 1 depicts the frequency histogram of the New Zealand drought index, i.e. NZDI. The index ranges from zero to 2.5 (see Figure 1(a)). Values of zero indicate that there were no drought-like conditions on the day or accumulated in the previous month for the particular location. A zero index value reflects a normal day. The distribution is skewed toward the lower bound (NZDI<1). The incidence of severe drought events, NZDI≥1.75, was rare. Figure 1(b) represented the frequency distribution of extreme events where the NZDI is beyond the 1.5 threshold value.

To identify the most critical months for experiencing drought, in Figure2, we show the frequency of different drought intensity categories by months across the country during 2007-2016. As shown in Figure 2, Maximum frequency of severe drought (SD) event is observed in March, with approximately 27%, and followed by December and April.

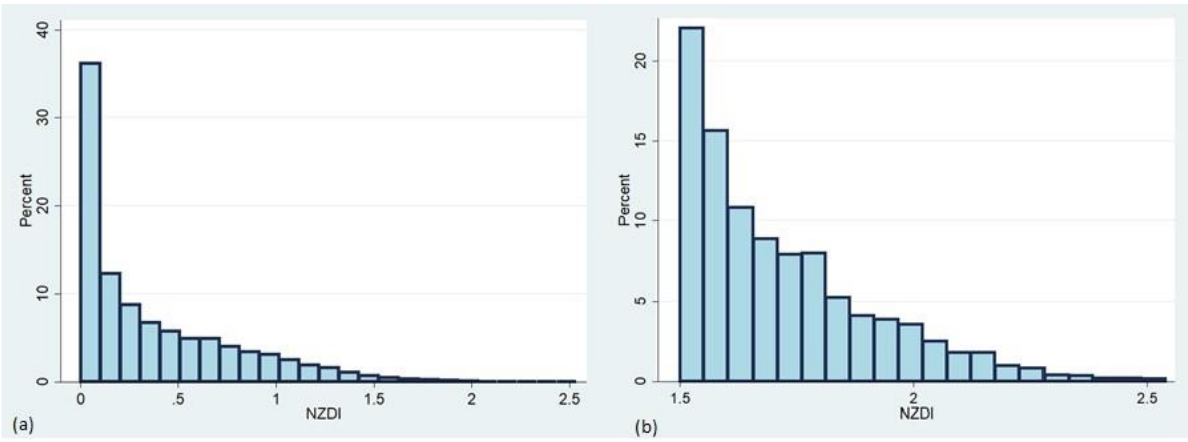

Figure 1. (a) Frequency distribution of New Zealand Drought Index; (b) Frequency distribution of extreme events (NZDI≥1.5)

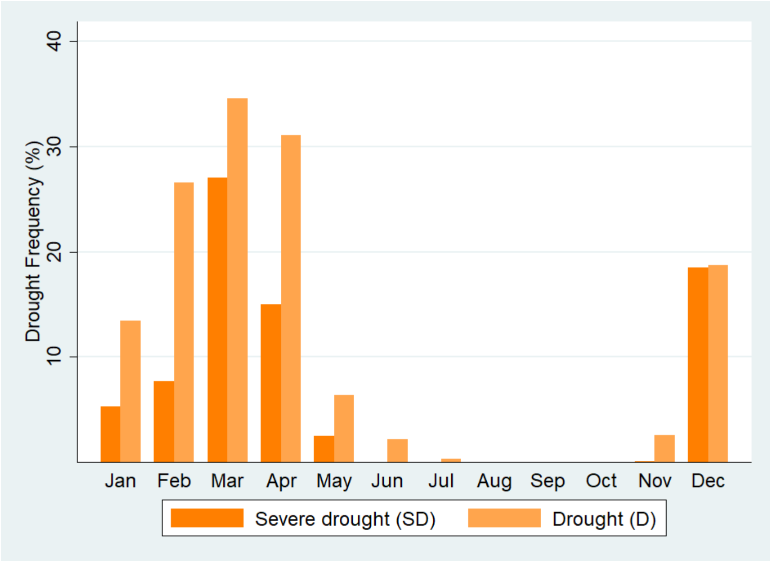

Figure 2. The frequency of drought intensities by month

Drought occurrence (in the number of days) across all regions in New Zealand is shown in Figure 3. Figure 3 illustrates the spatial distribution of drought occurrence and severity for intensity categories, during the years 2007 to 2016. Each drought intensity had a different spatial pattern. About half of the districts had experienced severe drought, and almost 85% of districts experienced a drought at least once. The North Island has experienced high-intensity droughts frequently, whereas some areas in the South Island have been free of droughts. The northwest of the North Island experienced the longest spells of severe drought with a range of 94-135 days and high severity (NZDI≥1.90). A significant portion of the North Island is covered of grassland populating by sheep, cattle, and deer farms. Most of the pasturelands there are not irrigated and depend on rainfall.

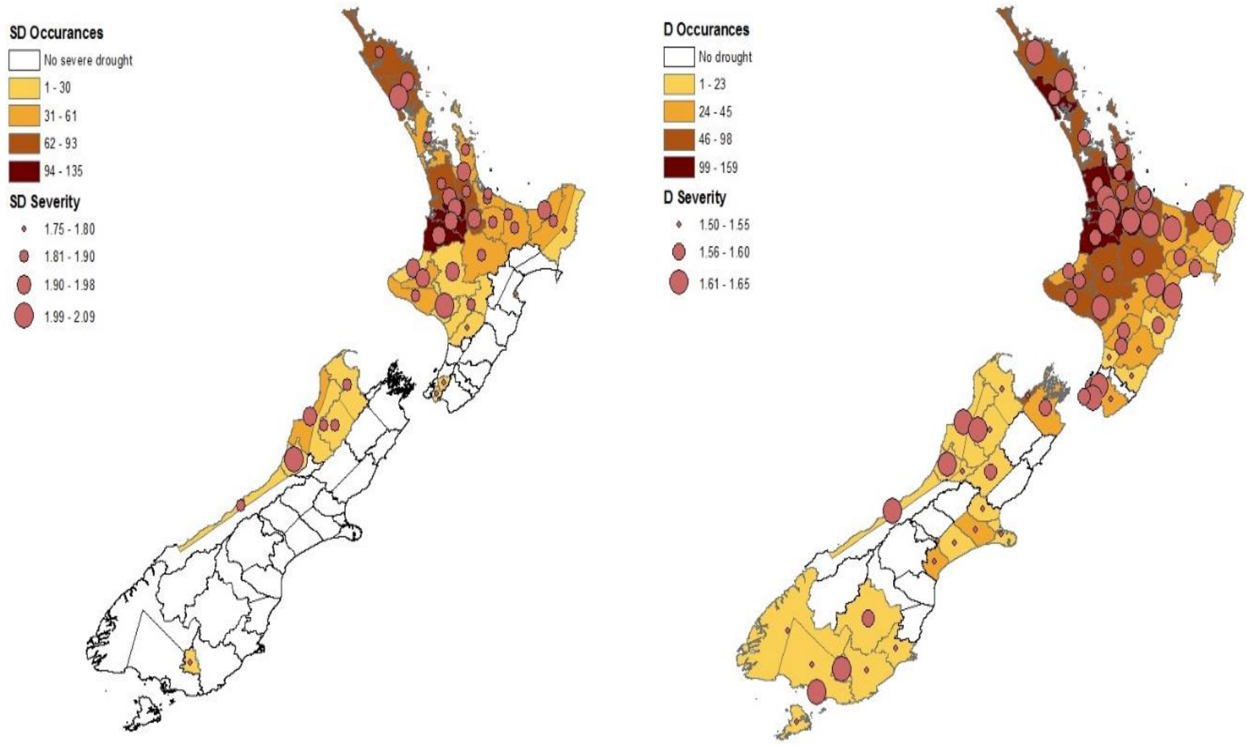

Figure 3. Drought occurrence (in days) for severe drought (SD) and drought (D)

The percentage of districts hit by different drought intensity categories during the agricultural year is presented in Figure 4. In New Zealand, approximately 34% of districts experienced severe drought (SD) at least once in the year 2012/13, whereas none of the districts had SD in 2008/09, 2011/12 and 2015/16 years. In 2012/13, drought (D) occurred in about 52% of the districts at least once, and only 2.5% of districts were affected by drought intensity (D). The percentage area covered by severe drought (SD) and drought (D) intensity in 2010/11 is around 42% and 30%, respectively. This figure shows that droughts occur somewhere in New Zealand almost every year.

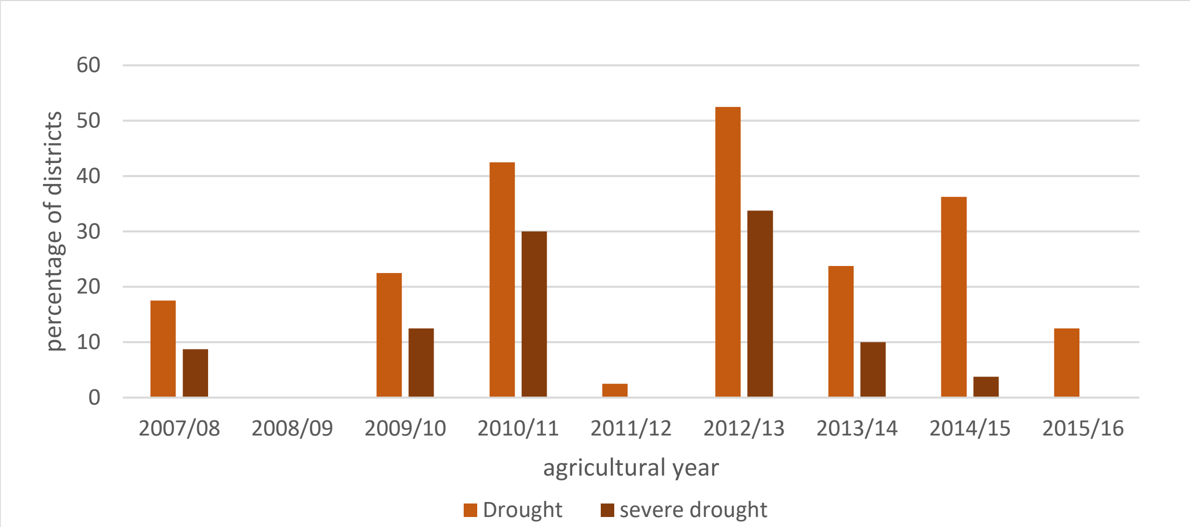

Figure 4. Frequency of districts experiencing drought conditions over time

6. Results and discussion

Table 3 summaries the means, standard deviations and the number of observations for each variable. On average, dairy farms generate greater revenue and profit, consequently, their debt to income ratio (interest coverage ratio) is smaller (higher) than the sheep/beef farms' average ratios. Business equity is similar across the two industries. The average ratio of equity to total assets (business equity) is 47% for the two sectors. Multiple-location farms account for about 27% of dairy farms and 18% of sheep/beef firms.

Results in Tables 2 and 3, in Appendix A, provide a comparison of performance between irrigated and not-irrigated firms. Average revenue and profit in irrigated farms are higher than those of unirrigated farms across industries. However, irrigated farms have a greater ratio of debt to income. Thus, irrigation alleviates forage availability constraints, but it increases the vulnerability of farms to financial risk due to an increase in costs. As a result, farmers are required to borrow capital to maintain their irrigation systems. As a difference across industries, irrigated dairy farms generate a higher return on capital compared with sheep/beef farms.

Descriptive statistics of variables for different farm sizes are shown in Tables 4 and 5 (Appendix A) for dairy and sheep/beef farming, respectively. As expected, since large farms have more resources and produce more than do smaller farms, larger farms earn more revenue and profit more. In terms of return on capital reflecting a farmer's efficiency where the objective is profit maximization, larger farms have a higher return on capital across industries. By contrast, small farming businesses tend to have higher debt to income ratio. When looking at business equity by farm category across industries, small dairy farms have higher business equity (58%)

than medium-size dairy farms (47%) and large dairy farms (37%) whereas for sheep/beef farms, medium farms have the highest business equity (51%), followed by large farms with 46% and small farms with 44%.

Table 3. Descriptive statistics –full sample by industry

variable	Dairy sector			Sheep/beef sector		
	Mean	Standard deviation	Observation	Mean	Standard deviation	Observation
Sale of product	928899.80	1181666	19986	377777.30	873467.2	52020
Gross profit	848073.10	1109901	19983	282909.20	461904	52128
Return on capital	4.48	5.43	19983	3.56	5.08	52125
Business equity	0.47	0.91	19971	0.47	7.41	51363
Debt to income ratio	4.77	35.55	19794	7.67	184.00	50586
Interest Coverage Ratio	2.01	0.53	19971	1.83	5.28	52107
Multi farm	0.27	0.44	20046	0.18	0.38	52338
#drought days(t)	8.00	15.79	20046	4.90	12.52	52338
#drought days(t-1)	3.13	10.98	17631	1.63	8.35	45639
#drought days(t-2)	3.45	10.34	16566	2.00	7.78	41853

Not all farms are observed every year, and we would like to verify that sample attrition is not due to the impact of droughts (leading farms to cease their operations). Specifically, we observe a decline in the number of observations in 2013. The format of IR10 tax form, which constitutes the source for the administrative data we use, changed in 2013. That change may have led to reduced reporting. To verify that these attritions are not related to drought conditions, we calculate the average attrition rate across districts for 2013. We find that the drop rates in some districts that are not affected by droughts is higher than the rates of the drought-prone districts. Attrition seems to be randomly distributed across districts, so that this reduction is most likely not related to the effects of a drought. We also ran a cross-sectional regression with this data, and the results show that there no statistically significant relationship between the dropout rate and the number of drought days at the district level (see appendix A Table 6).

We estimate the regression model (1) for different output variables; i.e. sale per hectare, profit per hectare and a set of balance-sheet indicators. Various specifications are considered for the estimation of outcome variables in our study. The first specification (model 1) only includes the number of drought days while the second specification (model 2) also includes first and second lags of drought days; the third specification (model 3) includes multiple-locations farm indicator and global milk price (only for dairy farming). The fourth specification (model 4) control for unobserved temporal effects using year fixed effects. We also run our full specifications for different sub-samples; i.e. irrigated/not-irrigated and farm size categories[8]. The estimation results for each of outcome variables are discussed in detail in the following subsections.

I. Sale of product per hectare

Regression results of the impacts of drought on revenue (sale of product) are summarised in Table 4. Column (2) shows that coefficients of the number of drought day (t) and its first lag are positive but not statistically significant, whereas the coefficient of the second lag is negative and statistically significant at 5%. The drought has no statistically observable average effect on revenue of dairy sector, though there is some evidence of a delayed negative effect.

These results can be explained if prices rise during a drought period because of decreases in the quantities produced. Essentially, there will be a revenue offset through higher milk prices, but a delayed adverse effect through reduced productivity of the dairy herd. So, it seems that on average dairy farmers do not lose much concurrently from drought events. Two years after the drought, the marginal revenue loss for an additional day of drought was $4.3 per hectare.

In column (3), after controlling for milk price, the magnitude of the coefficient of drought day (t) increases, though it stays statistically insignificant, while the magnitude of the coefficient of second lag decreases to $3.6 per hectare. Milk price itself has, unsurprisingly, also a positive but statistically insignificant impact. When we use, instead of the mild price, year fixed-effects effects, all the drought coefficients are no longer significant.

Table 4 also shows similar results for sheep/beef farms (columns 5-7); drought in the current and previous year has on average a positive impact on farms' revenue while drought lagged two years shows up negatively but with no statistical significance. When compared with the dairy sector, the magnitude of the effect of drought on revenue of sheep/beef sector is always smaller.

To explicitly bring out the impacts of drought on the irrigated and non-irrigated farm, Table 5 presents the regression results for irrigated and non-irrigated samples separately. The signs of coefficients are consistent with our findings in the full sample regressions. Drought events that occurred in the recent and previous year have positive impacts of farm's revenue. We note that the magnitudes of coefficients in the not-irrigated farms are always smaller than irrigated farms. This is a consistent finding, but the coefficients in the irrigated sample are never statistically significant.

The regression results of the impacts of droughts on revenue per hectare by farm size are shown in Table 6. The coefficients of the number of drought days and its first lag for small dairy

[8] We included multi-farm and milk price variables into the regressions of each of these categories. But we are not reporting them in these result tables.

farms are positive but statistically insignificant whereas for medium farms are statistically significant at 1% level, but much smaller. Droughts have a negative effect on large dairy farms' revenue. We could not find any differences between sheep/beef farms' vulnerability to drought events, across the different farm-size classifications.

Table 4. Regression results for sale per hectare - full sample by industry

	Dairy farming				Sheep/beef farming		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
#drought days(t)	4.063*	4.463	10.39	12.34	1.050	1.350	2.024**
	(2.240)	(2.829)	(12.21)	(14.56)	(0.894)	(0.992)	(0.795)
#drought days(t-1)		5.806	5.181	-3.986		0.569	0.940
		(4.656)	(4.787)	(9.172)		(1.173)	(1.166)
#drought days(t-2)		-4.313**	-3.549**	-5.405		-1.599	-0.933
		(1.743)	(1.658)	(8.409)		(1.144)	(0.900)
Multi-farm			-3589.2	-3527.9			39.57
			(4033.0)	(3966.2)			(55.51)
Global milk price			3.719				
			(6.884)				
Firm FE	yes	yes	yes	yes	yes	yes	yes
year FE	No	No	No	Yes	No	No	Yes
Observation	20046	16566	16566	16566	52338	41853	41853
R-squared	0.251	0.251	0.252	0.252	0.417	0.443	0.443

Note: All specifications include firm fixed effects. Clustered Standard errors at district level in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 5. Regression results for sale per hectare - irrigated/not irrigated sample

	Dairy farming			Sheep/beef farming		
Not irrigated sample	(1)	(2)	(3)	(4)	(5)	(6)
#drought days(t)	1.670***	1.806***	0.456	1.346	1.762	2.388**
	(0.531)	(0.502)	(0.905)	(1.140)	(1.272)	(0.909)
#drought days(t-1)		4.010	-1.012		0.984	1.485
		(3.639)	(2.086)		(1.336)	(1.427)
#drought days(t-2)		-2.728**	-0.440		-2.265*	-0.940
		(1.109)	(1.212)		(1.296)	(0.741)
year FE	No	No	Yes	No	No	Yes
Observations	13299	11127	11127	32667	26388	26388
R-squared	0.133	0.139	0.140	0.419	0.438	0.438
Irrigated sample						
#drought days(t)	11.86	13.41	24.13	0.0857	0.0586	0.999
	(9.441)	(12.59)	(32.62)	(0.856)	(0.719)	(1.08)
#drought days(t-1)		9.990	-1.207		-1.111	-1.137
		(14.08)	(23.17)		(0.725)	(0.86)
#drought days(t-2)		-10.22	-8.732		0.895	0.509
		(7.329)	(21.83)		(1.98)	(2.572)
year FE	No	No	Yes	No	No	Yes
Observations	6744	5439	5439	19668	15465	15465
R-squared	0.253	0.253	0.256	0.410	0.454	0.454

Note: All specifications include firm fixed effects. Clustered Standard errors at district level in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 6. Regression results for sale per hectare - farm size sample by industry

Farm category	Dairy farming			Sheep/beef farming		
Small farms	(1)	(2)	(3)	(4)	(5)	(6)
#drought days(t)	21.37	23.43	124.6	0.299	0.588	1.423*
	(17.46)	(22.42)	(148.1)	(0.631)	(0.535)	(0.730)
#drought days(t-1)		22.52	-65.41		-0.839*	-0.442
		(28.73)	(106.7)		(0.466)	(0.689)
#drought days(t-2)		-14.76	-26.68		0.0299	-0.738
		(11.72)	(70.24)		(1.126)	(1.486)
year FE	No	No	Yes	No	No	Yes
Observations	4593	3969	3969	18126	14733	14733
R-squared	0.253	0.253	0.261	0.737	0.751	0.751
Medium farms						
#drought days(t)	1.621***	1.738***	-0.110	1.270	1.627	1.962
	(0.520)	(0.559)	(1.314)	(1.493)	(2.020)	(1.193)
#drought days(t-1)		3.642	0.212		-0.522	-0.380
		(3.467)	(1.393)		(0.817)	(0.513)
#drought days(t-2)		-2.951**	-1.877		-1.271	0.749
		(1.184)	(1.791)		(1.667)	(1.100)
year FE	No	No	Yes	No	No	Yes
Observations	9471	7815	7815	11799	9501	9501
R-squared	0.137	0.146	0.147	0.259	0.25	0.251
Large farms						
#drought days(t)	-0.604*	-0.710*	-0.872	1.845	2.039	3.340
	(0.342)	(0.405)	(0.607)	(3.107)	(2.847)	(3.040)
#drought days(t-1)		0.393	-0.339		5.424	6.418
		(0.466)	(0.559)		(5.466)	(5.512)
#drought days(t-2)		0.0960	1.058		-5.472	-5.332
		(0.557)	(1.031)		(4.196)	(4.395)
year FE	No	No	Yes	No	No	Yes
Observations	5982	4779	4779	22410	17616	17616
R-squared	0.276	0.326	0.331	0.231	0.290	0.292

Note: All specifications include firm fixed effects. Clustered Standard errors at district level in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

II. Profit per hectare

Table 7 provides the estimated parameters for similar specifications to Table 4, but with profit per hectare as the dependent LHS variable. For dairy farming, the coefficient of the current year drought days (t) is positive but statistically insignificant; but the second lag of the drought indicator does have a significant negative impact on dairy profit (it decreases by $3.3 per hectare – column 2). According to model (3), when we incorporate milk price, the negative impact of drought in the year t-2 becomes smaller while the positive impact of first drought (t) becomes greater. The coefficient for the milk price is positive but statistically insignificant, as was the case with revenue. We also found that the sign of first lag of drought days becomes negative after controlling for the year fixed effect whereas the second lag losses its significance. The profit of sheep/beef farms is negatively impacted by both the first and second lags of droughts (though only the first lag is statistically significant).

According to column (2) of Table 7 in Appendix A (comparable to Table 6), one additional day of drought in the first year increases the dairy profit of not-irrigated and irrigated farms by $1.8 and $7.9 per hectare, respectively. As we expected farmers without irrigated land gain fewer benefits of drought-induced higher prices when compared to farmers with irrigated land. But the second lag drought variable has a significantly negative impact on dairy profit of not-irrigated farms, while that coefficient for irrigated farms is not statistically significant. In addition, there is little evidence for the importance of irrigation in changing profits after drought events among sheep/beef farmers.

Table 8 in Appendix A reports the estimates of regressions for different farm size. The coefficient of drought days in the first year is positive across all farm categories. However, the magnitudes of the coefficient for medium and large farms are smaller than the coefficient for small farms. Once more, we could not find any differences between sheep/beef farms across their different size classifications.

Table 7. Regression results for profit per hectare - full sample by industry

	Dairy farming				Sheep/beef farming		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
#drought days(t)	2.779	3.222	7.877	9.216	0.196	0.443	1.049**
	(1.788)	(2.274)	(9.807)	(11.69)	(0.436)	(0.539)	(0.461)
#drought days(t-1)		4.311	3.769	-3.024		-0.716**	-0.614**
		(3.855)	(4.003)	(7.587)		(0.271)	(0.265)
#drought days(t-2)		-3.338**	-2.762**	-4.262		-0.653	-0.0885
		(1.439)	(1.184)	(7.053)		(0.626)	(0.566)
Multi-farm			-2907.4	-2858.4			24.99
			(3242.2)	(3188.6)			(35.57)
Global milk price			2.877				
			(5.533)				
year FE	No	No	No	Yes	No	No	Yes
Observations	19980	16500	16500	16500	52128	41643	41643
R-squared	0.253	0.253	0.254	0.254	0.414	0.444	0.444

Note: All specifications include firm fixed effects. Clustered Standard errors at district level in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

III. Balance-sheet indicators

Table 8 provides the estimation of the impact of droughts on balance-sheet indicators: returns on capital, equity, debt to income ratio, and interest coverage ratio. In line with our previous findings on revenue and profit, the return on capital (column 1) shows a statistically significant and positive effect in the year of the drought, and a negative effect for the second lag. The impact of drought event on the farm’s business equity is shown in column (2) and on debt/income ratio in column (3), with no statistically significant results, but similar patterns in terms of the signs of the coefficients. The last, column (4), shows the coefficient for the drought measure as positive and statistically significant for the first two years, while the sign of the coefficient for the second lag is negative. The second part of Table 8 presents the effect of drought on balance-sheet indicators for sheep and beef sector. All farms' business indicators except debt to income are negatively affected by drought events in the current year, with no statistically significant effect beyond that.

Appendix A Table 9 represents regression results of the same balance-sheet indicators for irrigated/not irrigated samples by industry. Consistent with our prior findings, we found that the results for the non-irrigated sample largely align with the results for the full sample, with somewhat larger point estimates for the dairy sector. Results for the irrigated sample are largely statistically insignificant, and with smaller estimated effects. There are fewer distinctions between non-irrigated/irrigated estimates for sheep and beef farms.

Regression results of balance-sheet indicators by farm size categories are summarized in Appendix A Table 10. We found that there are not many differences in terms of the impacts of droughts on balance-sheet indicators among small, medium and large farms.

Table 8. Regression results for Balance-Sheet indicators

Industry	(1)	(2)	(3)	(4)
Dairy farming	Return on capital	Business equity	Debt to income ratio	Interest Coverage Ratio
#drought days(t)	0.00706**	0.000408	0.00785	0.000855*
	(0.00284)	(0.000273)	(0.0135)	(0.000473)
#drought days(t-1)	0.00550	0.000606	-0.0135	0.00228***
	(0.00332)	(0.000993)	(0.0197)	(0.000715)
#drought days(t-2)	-0.0119***	-0.000128	-0.0316	-0.000876**
	(0.00325)	(0.000726)	(0.0245)	(0.000392)
Observations	16500	16506	16344	16494
R-squared	0.726	0.469	0.584	0.590
Sheep/beef farming				
#drought days(t)	-0.00480***	-0.00215	-0.0245*	-0.00179***
	(0.0011)	(0.00534)	(0.0138)	(0.00055)
#drought days(t-1)	0.0023	0.00256	0.0161	0.000196
	(0.00146)	(0.00362)	(0.0172)	(0.00053)
#drought days(t-2)	-0.00115	0.00269	-0.0125	-0.00137
	(0.0029)	(0.00555)	(0.013)	(0.00215)
Observations	41640	40929	40290	41628
R-squared	0.761	0.224	0.36	0.136

Note: All specifications include firm fixed effects. Clustered Standard errors at district level in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

IV. Robustness check

We also run a set of regressions using alternative drought indicators to test whether our results are robust and NZDI is not simply an unreliable measure for agricultural drought risks. We apply two soil moisture-based drought indicators (the PED and SMD) and a rainfall-based indicator (SPI). The regression results of revenue per hectare, profit per hectare and balance-sheet indicators for full, irrigated/not irrigated and farm size samples for both dairy and sheep/beef industries are summarised in Tables 1-18 in Appendix B.

We found that our results are largely very similar to the prior findings, with limited switching in the sign of coefficients or in their statistical significance. However, there is no consistently different pattern. Our results appear robust and there is not much evidence on very significant impacts of drought conditions on farm profitability of dairy and sheep/beef farming in New Zealand over the time period we investigated (2007-2016).

7. Conclusion

This paper has examined the impacts of drought in New Zealand on the financial operations and profitability of dairy, and sheep and beef farms. Beyond revenues and profits, we also examined a set of balance sheet indicators including return on capital, business equity, debt to income ratio and interest coverage ratio.

We show that over the last ten years about half of the districts had experienced severe droughts, and almost 85% of districts were affected by more moderate droughts at least once. The North Island has experienced high-intensity droughts more frequently, whereas some areas in the South Island have been free of high-intensity droughts. Droughts occur somewhere in New Zealand almost every year, usually during peak summer, between December and March.

For dairy farming, there is a strong negative relationship between the occurrence of droughts two years earlier and farms revenue, profit and consequently their return on capital (ROC) ratio. More surprisingly, we found that current (same fiscal year) drought events have positive impacts on dairy farms' revenue and profit; and this effect is most likely attributable to drought-induced increases in the price of milk solids (the vast majority of milk in New Zealand is converted to milk powder, and much of it is exported).

In general, dairy farmers 'benefit' more from drought events when compared to sheep/beef farms, whereas the latter sector has less impact on global prices. However, the impact of drought in the sheep and beef sector is moderated by increased selling of livestock due to drought-induced food shortages, and therefore short-term increases in revenue. This is evidenced later with lagged increases in debt to income and interest servicing ratios. Lastly, our results do not demonstrate a very significant effect of irrigation as moderating the harmful balance-sheet effects of droughts.

Our results about the temporal dynamics of the impacts of droughts are potentially important for shaping policy. They suggest that resilience-building measures in the agricultural sector, such as the development of a drought index insurance schemes, should focus on ameliorating these longer-term deteriorations in balance-sheets rather than focus on short term indicators of revenue and profit.

Since there is a clear variation in drought characteristics for different regions, and since the future projections of drought intensities and frequencies, driven by climate change, are different for different regions in New Zealand, exploring the regional differences in the effects of droughts remains an important area for further research.

References

Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A., and Din, I. (2017). Climate Change and Its Impact on the Yield of Major Food Crops: Evidence from Pakistan. *Foods, 6*(6), 39.

Alley, W. M. (1984). The Palmer drought severity index: limitations and assumptions. *Journal of climate and applied meteorology, 23*(7), 1100-1109.

Bhalme, H. N., and Mooley, D. A. (1980). Large-scale droughts/floods and monsoon circulation. *Monthly Weather Review, 108*(8), 1197-1211.

Birthal, P., Negi, D. S., Kumar, S., Aggarwal, S., Suresh, A., and Khan, M. T. (2014). How Sensitive is Indian Agriculture to Climate Change? *Indian Journal of Agricultural Economics, 69*(4).

Birthal, P. S., Negi, D. S., Khan, M. T., and Agarwal, S. (2015). Is Indian agriculture becoming resilient to droughts? Evidence from rice production systems. *Food Policy, 56*, 1-12. doi:https://doi.org/10.1016/j.foodpol.2015.07.005

Booker, J. F., Michelsen, A. M., and Ward, F. A. (2005). Economic impact of alternative policy responses to prolonged and severe drought in the Rio Grande Basin. *Water Resources Research, 41*(2).

Cancelliere, A., Mauro, G. D., Bonaccorso, B., and Rossi, G. (2007). Drought forecasting using the Standardized Precipitation Index. *Water Resources Management, 21*(5), 801-819. doi:10.1007/s11269-006-9062-y

Cheng, J., and Tao, J.-p. (2010). Fuzzy comprehensive evaluation of drought vulnerability based on the analytic hierarchy process:—an empirical study from Xiaogan City in Hubei Province. *Agriculture and Agricultural Science Procedia, 1*, 126-135.

Dai, A., Trenberth, K. E., and Qian, T. (2004). A global dataset of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming. *Journal of Hydrometeorology, 5*(6), 1117-1130.

Dark, A., K.C, B., and Kashima, A. (2017). National Irrigated Land Spatial Dataset: Summary of methodology, assumptions and results. *Ministry for the Environment*.

Dono, G., and Mazzapicchio, G. (2010). Uncertain water supply in an irrigated Mediterranean area: An analysis of the possible economic impact of climate change on the farm sector. *Agricultural Systems, 103*(6), 361-370. doi:https://doi.org/10.1016/j.agsy.2010.03.005

Edwards, B., Gray, M., and Hunter, B. (2009). A sunburnt country: the economic and financial impact of drought on rural and regional families in Australia in an era of climate change. *Australian Journal of Labour Economics, 12*(1), 109.

Ferrari, G. T., and Ozaki, V. (2014). Missing data imputation of climate datasets: Implications to modeling extreme drought events. *Revista Brasileira de Meteorologia, 29*(1), 21-28.

Fuhrer, J., Beniston, M., Fischlin, A., Frei, C., Goyette, S., Jasper, K., and Pfister, C. (2006). Climate risks and their impact on agriculture and forests in Switzerland. In *Climate Variability, Predictability and Climate Risks* (pp. 79-102): Springer.

Garbero, A., and Muttarak, R. (2013). Impacts of the 2010 Droughts and Floods on Community Welfare in Rural Thailand: Differential Effects of Village Educational Attainment. *Ecology and Society, 18*(4). doi:10.5751/es-05871-180427

Hayes, M., Svoboda, M., Wall, N., and Widhalm, M. (2011). The Lincoln declaration on drought indices: universal meteorological drought index recommended. *Bulletin of the American Meteorological Society, 92*(4), 485-488.

Howitt, R., Medellín-Azuara, J., MacEwan, D., Lund, J. R., and Sumner, D. (2014). *Economic analysis of the 2014 drought for California agriculture*: Center for Watershed Sciences University of California, Davis, CA.

Huo-Po, C., Jian-Qi, S., and Xiao-Li, C. (2013). Future changes of drought and flood events in China under a global warming scenario. *Atmospheric and Oceanic Science Letters, 6*(1), 8-13.

Jenkins, M. W., Lund, J. R., and Howitt, R. E. (2003). Using economic loss functions to value urban water scarcity in California. *Journal (American Water Works Association), 95*(2), 58-70.

Kamber, G., McDonald, C., and Price, G. (2013). *Drying out: Investigating the economic effects of drought in New Zealand*. Retrieved from Reserve Bank of New Zealand Wellington:

Kumar, S. N., Aggarwal, P. K., Rani, S., Jain, S., Saxena, R., and Chauhan, N. (2011). Impact of climate change on crop productivity in Western Ghats, coastal and northeastern regions of India. *Current Science*, 332-341.

Lawes, R., and Kingwell, R. (2012). A longitudinal examination of business performance indicators for drought-affected farms. *Agricultural Systems, 106*(1), 94-101.

Martin-Ortega, J., and Berbel, J. (2010). Using multi-criteria analysis to explore non-market monetary values of water quality changes in the context of the Water Framework Directive. *Science of The Total Environment, 408*(19), 3990-3997. doi:https://doi.org/10.1016/j.scitotenv.2010.03.048

Meng, S., Zhang, C., Su, L., Li, Y., and Zhao, Z. (2016). Nitrogen uptake and metabolism of Populus simonii in response to PEG-induced drought stress. *Environmental and Experimental Botany, 123*, 78-87.

Nagarajan, R. (2010). Drought Indices. In *Drought Assessment* (pp. 160-204). Dordrecht: Springer Netherlands.

Narasimhan, B., and Srinivasan, R. (2005). Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology, 133*(1), 69-88. doi:https://doi.org/10.1016/j.agrformet.2005.07.012

NIWA. (2011). Scenarios of Regional Drought under Climate Change. https://www.niwa.co.nz/sites/niwa.co.nz/files/slmacc_drought_sldr093_june2011.pdf

NIWA. (2015). Are we experiencing more droughts? doi:https://www.niwa.co.nz/news/are-we-experiencing-more-droughts

NIWA. (2017). doi:https://www.niwa.co.nz/natural-hazards/hazards/droughts

Palmer, W. C. (1965). *Meteorological drought* (Vol. 30): US Department of Commerce, Weather Bureau Washington, DC.

Peck, D. E., and Adams, R. M. (2010). Farm-level impacts of prolonged drought: is a multiyear event more than the sum of its parts? *Australian Journal of Agricultural and Resource Economics, 54*(1), 43-60. doi:10.1111/j.1467-8489.2009.00478.x

Pérez y Pérez, L., and Barreiro Hurlé, J. (2009). Assessing the socio-economic impacts of drought in the Ebro River Basin.

Phillips, I. D., and McGregor, G. R. (1998). The utility of a drought index for assessing the drought hazard in Devon and Cornwall, South West England. *Meteorological Applications, 5*(4), 359-372.

Quiroga, S., and Iglesias, A. (2009). A comparison of the climate risks of cereal, citrus, grapevine and olive production in Spain. *Agricultural Systems, 101*(1), 91-100.

Shahid, S., and Behrawan, H. (2008). Drought risk assessment in the western part of Bangladesh. *Natural Hazards, 46*(3), 391-413. doi:10.1007/s11069-007-9191-5

Smith, D., Hutchinson, M., and McArthur, R. (1993). Australian climatic and agricultural drought: payments and policy. *Drought Network News, 5*(3), 11-12.

Strommen, N., Krumpe, P., Reid, M., and Steyaert, L. (1980). Early warning assessments of droughts used by the US agency for international development. *Climate and risk. The MITRE corporation, McLean*, 8-37.

Tang, C., and Piechota, T. C. (2009). Spatial and temporal soil moisture and drought variability in the Upper Colorado River Basin. *Journal of Hydrology, 379*(1), 122-135. doi:http://dx.doi.org/10.1016/j.jhydrol.2009.09.052

Vicente-Serrano, S. M., and López-Moreno, J. (2005). Hydrological response to different time scales of climatological drought: an evaluation of the Standardized Precipitation Index in a mountainous Mediterranean basin. *Hydrology and Earth System Sciences Discussions, 9*(5), 523-533.

Wilhite, D. A. (1997). Responding to drought: common threads from the past, visions for the future. *JAWRA Journal of the American Water Resources Association, 33*(5), 951-959.

Wittwer, G., and Griffith, M. (2010). *Closing the factory doors until better times: CGE modelling of drought using a theory of excess capacity.* Paper presented at the GTAP 13th annual conference, Penang, Malaysia.

Xiao-jun, W., Jian-yun, Z., Shahid, S., ElMahdi, A., Rui-min, H., Zhen-xin, B., and Ali, M. (2012). Water resources management strategy for adaptation to droughts in China. *Mitigation and adaptation strategies for global change, 17*(8), 923-937.

Zhao, H., Xu, Z., Zhao, J., and Huang, W. (2017). A drought rarity and evapotranspiration-based index as a suitable agricultural drought indicator. *Ecological Indicators, 82*, 530-538. doi:http://dx.doi.org/10.1016/j.ecolind.2017.07.024

All appendix tables are available at:

https://www.dropbox.com/s/q03nfck8xvkfzbi/First%20paper_23.04.19-APPENDIX.pdf?dl=0