The Australian Journal of
Agricultural and Resource Economics

AARES
AUSTRALASIAN AGRICULTURAL & RESOURCE ECONOMICS SOCIETY

Australian Journal of Agricultural and Resource Economics, 64, pp. 818–844

Droughts and farms' financial performance: a farm-level study in New Zealand*

Farnaz Pourzand, Ilan Noy and Yiğit Sağlam[†]

We quantify the impacts of droughts in New Zealand on the profitability of dairy, sheep and beef farms using a comprehensive administrative database of all farms in New Zealand. For dairy farms, we found that drought events have positive impacts on dairy farms' revenue and profit in the year of the drought. This effect is most likely attributable to drought-induced increases in the export price of milk solids, as New Zealand is the market maker in this global market and almost all domestic dairy production is exported. All of these quantified impacts, however, are not very large, suggesting that, at this point in time, droughts have a fairly moderate impact on New Zealand dairy and sheep–beef businesses.

Key words: dairy, drought, New Zealand, profitability, sheep/beef farming.

1. Introduction

In most places, agriculture is likely the sector worst affected by droughts. From a dairy, sheep or beef farmer's point of view, drought may lead to increasing expenditures on feed supplements for their livestock and consequently reduction in farm productivity and profitability, all due to reduced amounts of forage. As a consequence, farmers generate less income, diminishing their ability to service debt, 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 implications (Lawes and Kingwell 2012). Ultimately, these losses flow through into downstream production in other sectors, and thus, droughts can have a large adverse impact on the aggregate economy.

New Zealand has experienced several major droughts during the last few decades. The 2013 drought in particular 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

*We thank audiences at the 2018 New Zealand Association of Economics conference, the 2018 New Zealand Agricultural and Resource Economics Society conference, the 2019 Australian Agricultural and Resource Economics Society conference and the 2019 Western Economic Association International for very constructive comments on earlier versions of the paper. All errors are, of course, our own.

[†]Farnaz Pourzand is a PhD candidate, Ilan Noy is a Chair in the Economics of Disasters (email: ilan.noy@vuw.ac.nz), and Yiğit Sağlam is a Senior Lecturer with the School of Economics and Finance, Victoria University of Wellington, Wellington, New Zealand.

doi: 10.1111/1467-8489.12367

Industries (MPI), its impact on the economy was estimated to be at least $1.3 billion, and it affected 20,000 farmers. The 2013 drought was estimated to have caused GDP to drop by 0.6 per cent (Kamber *et al.* 2013). Some North Island regions received less than half of the expected summer rainfall, and this led to a decrease in the number of livestock in some regions.

There were other instances of local droughts. For example, in Northland, the worst drought happened in 2010 when record low rainfall levels were recorded between November 2009 and April 2010. This led to parched soils, a drastic reduction in pasture growth and reductions in farm productivity (NIWA 2017). In 2008, the Waikato region experienced the driest January in a century. Severe moisture deficits continued in that year until April/May.

A changing climate, with higher average temperatures, more extreme temperatures and changing rainfall patterns – in New Zealand, mainly drier in the north and east and wetter in the west and south – is expected to affect the frequency and intensity of droughts (NIWA 2015). Another report concluded that under the more extreme projections, New Zealand will become more arid by 2040. Moreover, this report projected most parts of New Zealand, except for the West Coast of the South Island, will be faced with prevailing drought conditions about 5–10 per cent more of the time, according to their mid-range projections. Their high-end projections include predictions of '>10 per cent' (NIWA 2011, pp. 28–29).

In this paper, we undertake an assessment of drought impacts for farms in New Zealand. Our focus is on dairy farming and sheep/beef farming. Dairy contributes 3.5 per cent to New Zealand's total GDP, and sheep/beef is the second largest agricultural sector (NZIER 2017). New Zealand is one of the largest milk producers in the world, with more than 4.9 million dairy cows producing 21.2 billion litres of milk annually (NZIER 2019). New Zealand also accounts for 5 per cent of world sheep meat production and supplies over half of the global lamb exports (NZIPIM 2019). The majority of dairy herds (72.3 per cent) are located in the North Island, with the greatest concentration (28.7 per cent) in the Waikato region (DairyNZ 2018). Most of the pasture land in these areas is not irrigated, and the Ministry for the Environment identified drought as one of the major constraints to pasture grazing in New Zealand (MfE 2001).

The majority of existing empirical literature analyses the effects of climate-extreme events on the agricultural sector at the national level or at similarly high levels of aggregation. These may therefore underestimate the negative local impacts of adverse events on the entities most affected. 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 determine the design of assistance policies for individual firms.

In this study, we combine administrative 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 analyse the impacts of droughts on farms' economic performance and their balance sheets. Our focus is on agricultural drought. Since there is no common definition of drought, for this study, agricultural drought is defined as follows:

> 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, p. 847)

The objectives of this work are to: (i) analyse the frequency, severity and spatial spread of droughts; (ii) investigate the effects of droughts on agricultural profitability and farms' business performance; and (iii) identify the most vulnerable agricultural subsectors 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.

We found that, on average, a recent drought increases revenue and profit from dairy farming, potentially implying that the losses in milk productions may have been compensated by increasing export milk prices. However, once we control for changes in milk prices, drought events have a small (and mostly statistically insignificant) negative impact.

Following that, we examine all other farm business performance indicators that might plausibly be affected by the negative shock, and that are available in the database for 3 years following drought events. These include interest coverage (IC), return on capital (ROC), business equity (BE) and debt-to-income (DI) ratio. If the drought had any impact on revenue or on expenses (e.g. for feed), then we would expect these variables to be affected.

This paper is structured as follows: 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 (Section 3), the empirical model used (Section 4) and a spatial and temporal description of the data (Section 5). The main findings are summarised in Section 6, and we conclude in Section 7.

2. Literature review

Some recent studies have focused on the relationship between climate-related risks, extreme weather and agriculture (e.g. Schlenker and Roberts 2009; Howitt, *et al.* 2014; Moore and Lobell 2014; Ali *et al.* 2017). The focus of most studies has been the impacts of changes in temperature and precipitation on agricultural production. For example, Schlenker and Roberts (2009) estimated the relationship between weather and yields for corn, soya beans and cotton in the United States. They found that there is a nonlinear relationship between yields and temperature in both the cross section of counties and the aggregate year-to-year time series.

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 showed that drought, during the monsoon period, has an adverse effect on the agricultural sector. Yet, loss of production also led to an increase in the prices of agricultural commodities. Shakoor *et al*. (2011) showed a significant negative impact of rising temperatures on agricultural production and a positive impact of rainfall. Similar results were reported in Barrios *et al*. (2008) on the relationship between rainfall and temperature and agricultural output using cross-country data from sub-Saharan Africa. However, Moore and Lobell (2014) found that agricultural profits could moderately increase under climate change if farmers implement adaptation measures, but could decrease in many regions if there is no adaptation.

There is also an extensive literature 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; Spinoni *et al*. 2014). Several studies investigated the spatial patterns of drought risk in order to assist agricultural–environmental management (Vicente-Serrano and López-Moreno 2005) or identify and quantify drought vulnerability (Shahid and Behrawan 2008; Cheng and Tao 2010).

A number of studies have been carried out to measure the impact of droughts on agricultural activities using input–output tables (Wilhite 1997; Wittwer and Griffith 2010; Howitt *et al*. 2014), farms' business performance using data from agricultural consulting firms (Lawes and Kingwell 2012; Kingwell and Xayavong 2017), farmers' consumption and income using household surveys (Garbero and Muttarak 2013) and farms' resilience to droughts using district-level production data (Birthal *et al*. 2015).

Some findings from this literature are worth noting here: first, it remains difficult to adequately characterise droughts and there is no consensus on their definition, identification and measurement. Secondly, the impacts of droughts on agricultural yield vary during its timing during the crop-growing cycle. Thirdly, farmers use various coping strategies, so distinguishing drought impact on production while accounting for adaptation is not a straightforward task.

Research on the impacts of climate-induced extreme risks on New Zealand agriculture dates back about 40 years to Maunder (1968, 1971a, 1971b). Below, we describe seven studies, six of which looked at the historical effects of dry periods on agriculture in all New Zealand, while the remaining one focused on the 1998–1999 drought in Canterbury alone. These studies applied different empirical methods and covered different historical periods, regions and agricultural subsectors. None of them uses the administrative micro-firm/farm-level data we use here.

Tweedie and Spencer (1981) focused on the econometric estimation of export supply functions over the period 1961–1978, but they also provided estimates of the effects of weather (measured in terms of days of soil moisture deficit – DSMD) on agricultural production. They separately estimated the shorter run effects and the long-run equilibrium impacts of climate on the number of animals and production of meat, milk and wool. The results showed that climate influenced the slaughter rate, the milk production per cow and the growth rate of wool. They note, though, that the impact on dairy production seemed low in relation to the effects of weather on other agricultural sectors.

Wallace and Evans (1985) examined the effect of annual climate variability (measured by standard deviations in DSMD) on expected farm outputs, inputs and profits, using a panel database from 1950 to 1979. They used separate series for positive and negative variations in DSMD in order to evaluate asymmetric reactions to dry and wet conditions. They observed that a deviation from normal DSMD in either direction negatively affected sheep farm output. Profitability differed between dry and wet years. In general, the effects on sheep and beef production from changes in DSMD were comparable to the findings in Tweedie and Spencer (1981). Wallace and Evans (1985) only examined regions with Class VI.[1] sheep farms; it is therefore expected that these farms were 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 1961–1998. They 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) presented 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, using a panel data set from the annual Livestock Improvement Corporation Dairy Statistics publications. To calculate the economy-wide implications of changes in milk solid 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 solid production per cow by 3–4 per cent. This was broadly consistent with the estimate of 2.6 per cent by Tweedie and Spencer (1981).

[1] According to Beef & Lamb New Zealand, 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 6 to 11 stock units per hectare on dryland farms and over 12 stock units per hectare on irrigated units, mainly in Canterbury and Otago. Class VI is the dominant farm class in the South Island.

In contrast, Kamber *et al.* (2013) investigated the economic impact of the 2013 drought using a macroeconomic model. An important contribution of this research was the weather data; they looked at alternative weather measures and showed that these indicators were consistent with the timing of recognised 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. Their findings indicate the 2013 drought reduced annual GDP for the full year by 0.3 per cent.

From this review of previous studies, it is quite apparent that data aggregated at the regional or national level will not represent the full picture of impacts of climatic disasters on rural farming with different agroecological characteristics. Any level of aggregation would inevitably hide heterogenous impacts that drought events may have.

3. Data sources and sample

3.1 Drought Index data set

There is no universal definition of drought, as it can be defined based on different perspectives – meteorological, hydrological, agricultural or socio-economic (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 the following: Rainfall deciles (Gibbs and Maher 1967); Hutchinson Drought Severity Index (Smith *et al.* 1993); Drought Severity Index (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 (Palmer 1965; Alley 1984; Dai *et al.* 2004); Potential Evaporation Deficit (PED) (Nagarajan 2010); Soil Moisture Deficit Index (Narasimhan and Srinivasan 2005; Tang and Piechota 2009); Drought Area Index (Bhalme and Mooley 1980); NOAA Drought Index (Strommen *et al.* 1980); and Integrated Agricultural Drought Index (Zhao *et al.* 2017).

Given the complexity of droughts, various sources of drought-related elements such as precipitation, vegetation growth condition, soil moisture and land surface temperature can be integrated to indicate the spatial extent and intensity of droughts (Meng *et al.* 2016). It is apparent that the aggregation of all drought-related factors depends on the availability of data. In this study, we utilise a new Drought Index (NZDI), developed by NIWA, 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: SPI; Soil Moisture Deficit (SMD); Soil Moisture Deficit Anomaly (SMDA); and Potential Evapotranspiration Deficit (PED).

Standardised Precipitation Index, 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).

Soil Moisture Deficit 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 may also be also defined as the difference between the current and historical soil moisture deficits (or difference from normal).

Potential Evapotranspiration Deficit is the difference between 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 nonzero values.

The daily data of the NZDI and its four components are available at the district level and are linked to our sample population by spatially joining the value of the drought index to each meshblock within each district.[2] 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. We note if the NZDI is equal to or higher than 1.75 (severe drought – SD), and if the NZDI is between 1.50 and 1.75 (drought – D). These are the thresholds identified by NIWA, which constructed the NZDI, based on international practice and the specific distribution of the NZDI. To analyse 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.

3.2 Agricultural, financial and productivity data, and other data sets

The main source of data is Statistics New Zealand's LBD,[3] which combines administrative and survey data for all businesses in New Zealand. We use

[2] Meshblocks are the smallest administrative unit used by Statistics New Zealand when collecting individual and business information. Their size varies by the population density across the country, with more densely populated areas having many more meshblocks. Overall, New Zealand is divided into 46,637 meshblocks in 2013.

[3] See Fabling and Sanderson (2016).

Table 1 Variables, data sets and sources

Variables	Spatial level	Data sets	Sources
Farm input	Farm level	Agricultural Production Survey/Census (APS/APC)	Stats NZ's Longitudinal Business Database
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

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

annual data for the period 2007–2016. Table 1 lists the data sets 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 designation available from Statistics New Zealand). Since we are not able to match the tax data to a specific geographical location for firms with multiple locations, we aggregate the data to the enterprise level (rather than per location). Multiple-location farms account for about 27 per cent of dairy farms and 18 per cent of sheep/beef firms. There are some enterprises which occupy meshblocks in more than one territorial authority or regional council. These account for about 11.9 per cent and 0.2 per cent of multilocation firms, respectively, recorded by a set of territorial authorities and regional council binary variables.

We use a map of all irrigated areas, data for which were collected in 2017 (Dark and Kashima 2017). To allocate an irrigated area (farm level) to a meshblock level, first, we calculate the centroid point of each irrigated area and then denote as irrigated any meshblock in which there is an 'irrigated' centroid (i.e. an irrigated farm).[4]

[4] 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 per cent) of our sample population. The majority of irrigated land was in Canterbury, followed by Otago and Marlborough regions, all located in the South Island.

3.3 Sample population

Our sample population consists of enterprises (firms) with the relevant agricultural industry code included in both the productivity data set and the APS/APC, and who have productive land.[5] 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 categorised dairy firms; or no more dairy cows, horses, pigs or hens than sheep/beef cattle if they are classified 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 available 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.[6] 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 droughts depending on its nature (direct or indirect) and the level of aggregation (farm, household, regional or economy-wide). A simple method to measure the effect of droughts is to calculate the deviation in crop yield in a drought year from its previous normal (Xiao-jun *et al.* 2012). In addition, linear and nonlinear mathematical programming models have been used to simulate the economic impacts of droughts (Jenkins *et al.* 2003; Booker *et al.* 2005; Dono and Mazzapicchio 2010; Peck and Adams 2010). Some studies have used macroeconometric VAR-type models to assess the damage from droughts at the national level (Kamber *et al* 2013) or at the disaggregated regional or crop level (Quiroga and Iglesias 2009; Birthal *et al.* 2015). Computable general equilibrium and input–output models have also been used to assess the welfare impacts of droughts (Pérez y Pérez and Barreiro-Hurlé 2009; Martin-Ortega and Berbel 2010).

We pursue an econometric approach to estimate the effect of drought on agricultural revenue, profitability and balance-sheet indicators. We estimate different specifications including a reduced-form linear and nonlinear 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:

[5] Dairy and sheep/beef are coded AA13 and AA12 ANSIC06 classifications in the productivity data set, respectively.

[6] We removed the enterprises who were inactive in the previous year (i.e. changed ownership or stopped farming).

Table 2 Farm business indicators

Abbreviation	Indicator	Definition
OP	Operating profit per hectare	(Total operating income – total operating costs)/total area farmed
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

$$y_{dit} = \alpha + \beta_1 DI_{\mathrm{d}t} + \beta_2 DI_{\mathrm{d}t-1} + \beta_3 DI_{\mathrm{d}t-2} + \beta_4 DI^2_{\mathrm{d}t} + \beta_5 DI^2_{\mathrm{d}t-1} + \beta_6 DI^2_{\mathrm{d}t-2} + \beta_4 X_{dit} + \gamma_i + \sigma_t + \varepsilon_{dit}, \tag{1}$$

where the dependent variables are sale of product per hectare, operating profit per hectare and balance-sheet variables (see Table 2).[7,8] The subscripts dit denote the district, enterprise and time, respectively. $DI_{\mathrm{d}t}$ and $DI^2_{\mathrm{d}t}$ represent the linear and quadratic functional forms of 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 whose impacts could carry beyond a 1-year period, we also examine first and second lags of drought days ($DI_{\mathrm{d}t-1}, DI_{\mathrm{d}t-2}, DI^2_{\mathrm{d}t-1}$ and $DI^2_{\mathrm{d}t-2}$). X_{dit} is the multifarm indicator variable. Time-invariant firm-specific characteristics such as land quality and slope can also influence agricultural productivity. Meanwhile, shocks and factors changing over time such as changes in prices can also matter. Therefore, we control for unobserved spatial and temporal heterogeneity using firm (γ_i) and year (σ_t) fixed effects. In some specifications, we include global milk price (P_t), instead of time fixed effects. Finally, ε_{dit} is the error term. 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).[9]

We also aim to evaluate the degree to which droughts affected various categories of farms, since the scope and magnitude of drought differ from irrigated to nonirrigated land as well as across farms of different sizes. We therefore stratify the sample based on irrigated land and farm size. Farms are categorised as small (<1,000 ha), medium (1,000–3,000 ha) and large (>3,000 ha).

[7]There are multifactor productivity data available in the data set, 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.

[8]We converted all observations below the 1st percentile and above the 99th percentile to these threshold values.

[9]We also used two-way 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. The index ranges from 0 to 2.5 (see Figure 1). A value of zero indicates that there were no drought-like conditions on the day or accumulated in the previous month for a particular location. The distribution is skewed towards the left (Figure 1a). The incidence of SD events, NZDI ≥ 1.75, was rare. Figure 1b recalculates the frequency distribution by focusing only on the extreme events where the NZDI is above a 1.5 threshold value.

To identify the most critical months for experiencing drought, in Figure 2, 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 SD event is observed in March, with approximately 27 per cent, followed by December and April.

Drought occurrence (in the number of days) across all regions in New Zealand is shown in Figure 3. Each drought intensity had a different spatial pattern during this time period. About half of the districts had experienced SD, and almost 85 per cent 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 north-west of the North Island experienced the longest spells of SD with a range of 94–135 days and high severity (NZDI ≥ 1.90). A significant portion of the North Island is covered of grassland populated by sheep, cattle and deer farms. Most of the pasturelands are not irrigated and thus depend on rainfall.

The percentage of districts hit by different drought intensity categories during the agricultural year is presented in Figure 4. In New Zealand, approximately 34 per cent of districts experienced SD at least once in the year 2012/13, whereas none of the districts had SD in the years 2008/09, 2011/12 and 2015/16. In 2012/13, drought occurred in about 52 per cent of the districts at least once, and only 2.5 per cent of districts were affected by SD. The percentage area covered by SD and drought intensity in 2010/11 is around 42 per cent and 30 per cent, respectively.

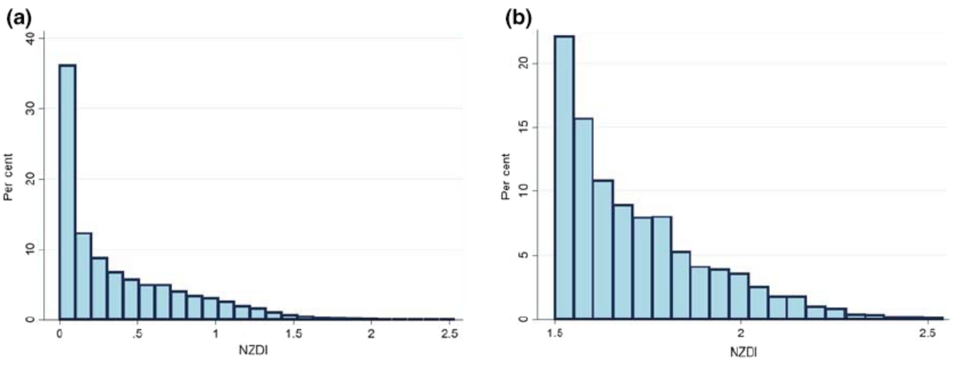

Figure 1 (a) Frequency distribution of New Zealand Drought Index; (b) frequency distribution of extreme events only (NZDI ≥ 1.5). [Colour figure can be viewed at wileyonlinelibrary.com]

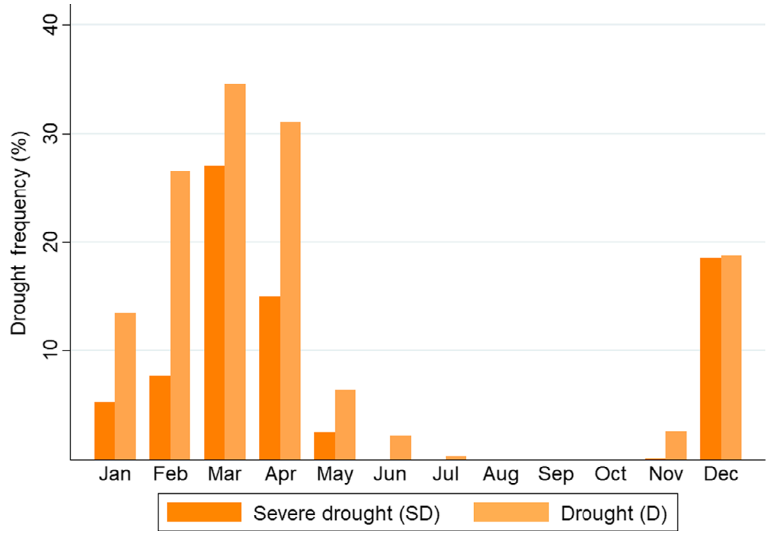

Figure 2 The frequency of drought intensities by month. [Colour figure can be viewed at wileyonlinelibrary.com]

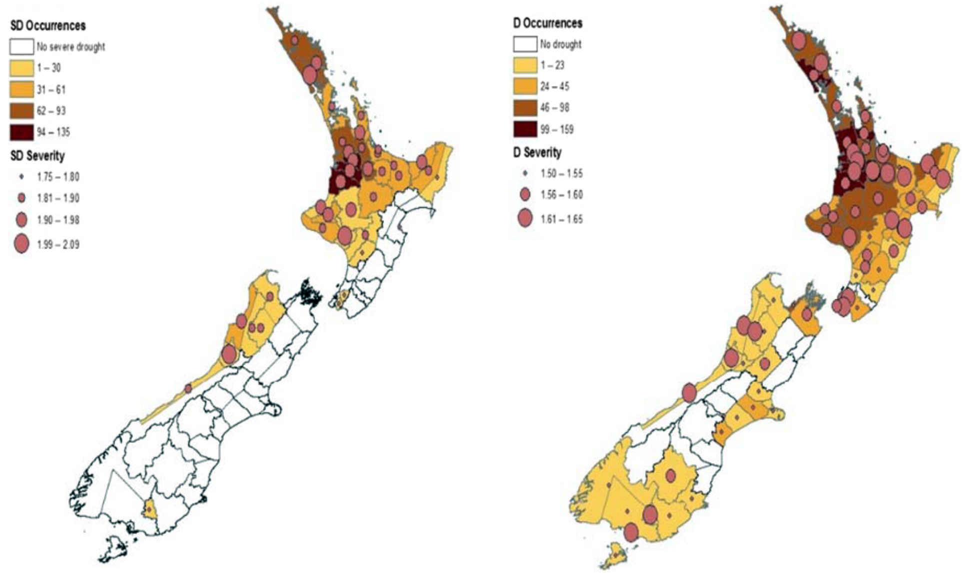

Figure 3 Event occurrence (in days) for severe drought (SD) and drought (D). [Colour figure can be viewed at wileyonlinelibrary.com]

6. Results and discussion

Table 3 provides summary statistics for the data. On average, dairy farms generate greater revenue and operating profit per hectare; consequently, their DI ratio (IC ratio) is smaller (higher) than the sheep/beef farms' average ratios. The average ratio of equity to total assets (BE) of the sheep/beef sector (58 per cent) is higher than that of the dairy sector (49 per cent).

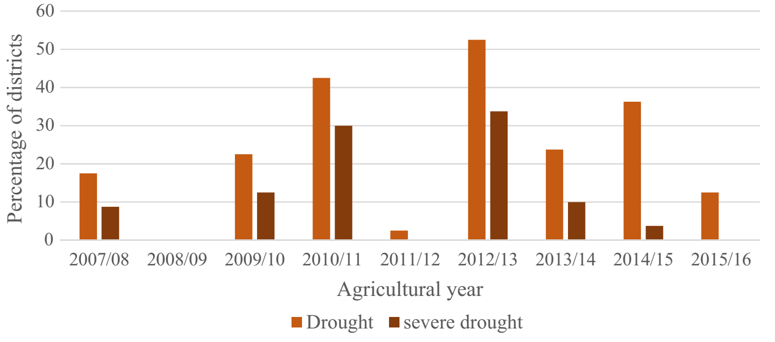

Figure 4 Frequency of districts experiencing drought conditions over time. [Colour figure can be viewed at wileyonlinelibrary.com]

Table 3 Descriptive statistics – by industry

Variable	Dairy sector			Sheep/beef sector		
	Mean	Standard deviation	Observation	Mean	Standard deviation	Observation
Sale of product per hectare	532.88	3717.54	16,218	267.34	1,825.82	42,471
Operating profit per hectare	381.81	2402.49	16,212	161.01	990.64	42,549
Return on capital	1.91	1.64	16,212	1.63	1.75	42,546
Business equity	0.49	0.38	16,209	0.58	0.48	41,952
Debt-to-income ratio	3.65	7.39	16,092	3.82	9.90	41,436
Interest coverage ratio	0.90	0.43	16,206	0.83	0.52	42,534
Multifarm	0.27	0.44	16,266	0.171	0.38	42,714
No. drought days (*t*)	27.51	18.10	4,869	22.92	17.85	9,714
Drought intensity (*t*)	1.65	0.32	4,869	1.51	0.50	9,714

Results in Tables 2 and 3, in Appendix S1, provide a comparison of performance between irrigated and nonirrigated firms. The average revenue and operating 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 debt. Irrigated dairy farms also generate a higher ROC compared with sheep/beef farms.[10]

[10] Descriptive statistics of variables for different farm sizes are shown in Tables 4 and 5 of Appendix S1. 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 maximisation, larger dairy 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 (60 per cent) than medium-size dairy farms (50 per cent) and large dairy farms (41 per cent); similarly for sheep/beef farms, small farms have the highest business equity (68 per cent), followed by medium farms with 61 per cent and large farms with 50 per cent.

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 IR10 tax form, which constitutes the source for the administrative data we use, changed in 2013. That change may have led to reduced reporting. But, there was also a very significant drought in the same year. 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 are higher than the rates of the drought-prone districts. Put differently, attrition seems to be orthogonal to drought conditions, so that this reduction is most likely not related to the effects of a drought. We also ran a cross-sectional regression with these data, and show that there is no statistically significant relationship between the dropout rate and the number of drought days at the district level (Table 6, Appendix S1).

We estimate Equation (1) for different output variables, that is sale per hectare, operating 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) includes the number of drought days, first and second lags of drought days and multiple-location farm indicator, while the second specification (model 2) also controls for unobserved temporal effects using year fixed effects; the third specification (model 3) includes global milk price (only for dairy farming). The fourth specification (model 4) includes quadratic terms of the number of drought days and its lags. We also run these full specifications for different subsamples, that is irrigated/nonirrigated and farm size categories.[11] The estimation results for each of the outcome (dependent) variables are discussed in detail in the following subsections.

6.1 Sale of product per hectare

Regression results of the impacts of drought on revenue (sale of product) are summarised in Table 4. Column (1) shows that coefficients of the number of drought day (t) are positive and statistically significant at 1 per cent, and the coefficients of the first and second lags are not statistically significant. *Prima facie*, drought seems to have a significant positive effect on the revenue of the dairy sector in NZ. This is likely a result of a revenue offset through higher milk prices, or the positive effects in the current year may be due to increased stock sales. However, this positive impact is no longer identifiable once we add year fixed effects, thereby controlling for any change in the global price (column 2). Cumulatively, over the 3 years, droughts have no statistically observable average negative effect on revenue of the dairy sector, as we

[11] We included multifarm and milk price variables into these additional regressions, but we are not reporting them in the result tables.

Table 4 Regression results for sale per hectare – by industry

	Dairy farming				Sheep/beef farming		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. drought days (t)	2.687*** (0.703)	0.348 (0.901)	−0.0773 (1.202)	1.202 (2.914)	1.150 (0.946)	2.028* (1.051)	−3.312 (2.385)
No. drought days (t−1)	2.948 (1.960)	0.370 (2.196)	2.466 (1.840)	1.953 (2.999)	0.722 (0.769)	0.448 (0.628)	−0.483 (1.433)
No. drought days (t−2)	−0.485 (1.643)	0.156 (1.869)	−1.155 (1.729)	−6.897 (6.792)	0.510 (1.063)	0.745 (1.092)	−4.719** (2.112)
No. drought days $(t)^2$	—	—	—	−0.0103 (0.0496)	—	—	0.126** (0.0542)
No. drought days $(t-1)^2$	—	—	—	−0.0366 (0.0508)	—	—	0.0271 (0.0229)
No. drought days $(t-2)^2$	—	—	—	0.129 (0.114)	—	—	0.106** (0.0409)
Multifarm	−84.13 (98.35)	−66.79 (105.2)	−77.60 (97.86)	−66.43 (104.5)	38.59 (61.88)	39.59 (62.05)	41.46 (75.96)
Global milk price	—	—	2.272** (0.904)	—	—	—	—
Year FE	No	Yes	No	Yes	No	Yes	Yes
Observations	13,401	13,401	13,401	13,401	33,963	33,963	33,963
R^2	0.201	0.203	0.202	0.203	0.423	0.424	0.429

Note: $^*P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$. All specifications include firm fixed effects. Clustered standard errors at district level in parentheses.

observe in columns 2–4. And if anything, there is a positive effect through higher milk prices (since NZ's Fonterra is by far the largest actor in the global dairy trade market).

As we control for global milk prices, in column (3), milk price itself has a positive and statistically significant impact on sales. When we use quadratic terms, in column (4), all the drought coefficients are insignificant, thus failing to uncover any significant nonlinear relationship between dairy revenue and the drought days.

Table 4 also shows results for sheep/beef farms (columns 5–7). Here, after controlling for year fixed effects, drought still has a positive/significant impact on farms' sales, though all lagged first- and second-year indicators show no statistical significance. The contrast between columns (5) and (6) suggests that for sheep/beef farming, the selling of stock during drought events might be a more significant phenomenon affecting farm sales.

Estimates of quadratic forms of the number of drought days with 95 per cent confidence intervals for sheep/beef farming (column 7) are displayed in Figure 5. We find some evidence of a nonlinear relationship between sheep/beef revenue and the number of drought days after very long droughts. For instance, if sheep/beef farmers experience 40 days of drought, their revenue will increase by 60 per cent as sheep/beef farmers have to sell their livestock.

To explicitly investigate the impacts of drought on the irrigated and nonirrigated farm, Table 7 in Appendix S1 presents the regression results for irrigated and nonirrigated samples separately. The signs of coefficients are consistent with our findings in the full-sample regressions. We note that the coefficients in the nonirrigated farms are more pronounced than for the

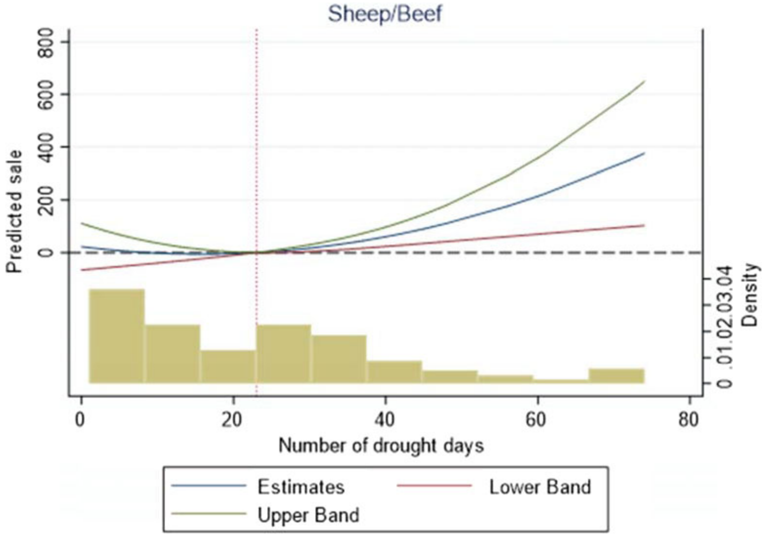

Figure 5 Nonlinear relationship between sale and the number of drought days for sheep/beef sector. [Colour figure can be viewed at wileyonlinelibrary.com]

irrigated farms. This is a consistent finding, as the nonirrigated farms who are affected by droughts sell their stock, while those with irrigation find it easier to continue as before.

The regression results of the impacts of droughts on revenue per hectare by farm size are shown in Table S6 in Appendix S1. The coefficients of the number of drought days and its first lag for small and medium dairy farms are positive and statistically significant, whereas for large farms, the coefficients are negative but statistically insignificant, and much smaller. Droughts have a more positive effect on small and medium dairy farms' revenue. We could not find any significant differences between sheep/beef farms' vulnerability to drought events across the different farm sizes.

6.2 Operating profit per hectare

Table 5 provides the estimated coefficients for the same specifications as in Table 4, but with operating profit per hectare as a dependent variable. These show very similar results. For dairy farming, the coefficient of the current year drought days (*t*) is positive and statistically significant for the specification that does not control for the global milk price (column 1). Once we include year fixed effects (column 2), global milk price (column 3) and the quadratic drought term (column 4), all of the drought results are statistically insignificant. Not surprisingly, the coefficient of milk price is positive and statistically significant at 1 per cent. The operating profit of sheep/beef farms is positively associated with the contemporaneous drought measure after controlling for year fixed effect and negatively associated with the first lag, similarly to what we observed for the sales measure in Table 4.

In Table 6, we differentiate between irrigated and nonirrigated farms. In columns (1)–(2), where we present the results for dairy farms, none of the drought coefficients (including the quadratic terms) are ever statistically significant. This suggests that except through the (positive) impact on milk prices, droughts do not pose a significant downside to profits. For sheep/beef farmers, in columns (3)–(4), we find some evidence of a positive effect on profits, probably through the sales of stock, but this result does not continue to hold when we add the quadratic terms, suggesting this is not a very significant impact. Table 7 reports the estimates of Table 5 regressions for different farm sizes. There is some evidence of positive coefficients of drought days in the current for medium-size farms, but again this result does not appear very robust, as it disappears once we include quadratic terms.

6.3 Balance-sheet indicators

Table 8 provides the estimation of the impact of droughts on balance-sheet indicators: returns on capital, equity, DI ratio and IC ratio. The ROC (column 1) shows a statistically significant and negative effect in the year of the drought, and for the first lag. The impact of drought event on the farm's

Table 5 Regression results for operating profit per hectare – by industry

	Dairy farming				Sheep/beef farming		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. drought days (t)	2.147*** (0.668)	0.262 (0.550)	−0.0660 (0.647)	1.259 (2.406)	0.332 (0.447)	0.891** (0.443)	−1.094 (1.126)
No. drought days (t−1)	2.353 (1.888)	0.634 (1.666)	1.966 (1.780)	1.719 (2.331)	0.152 (0.377)	−0.180 (0.319)	−0.429 (0.689)
No. drought days (t−2)	−0.257 (1.155)	−0.103 (1.452)	−0.796 (1.159)	−4.976 (5.251)	0.276 (0.437)	0.486 (0.372)	−0.610 (0.759)
No. drought days $(t)^2$	—	—	—	−0.0154 (0.0439)	—	—	0.0421* (0.0243)
No. drought days $(t-1)^2$	—	—	—	−0.0258 (0.0298)	—	—	0.00741 (0.0122)
No. drought days $(t-2)^2$	—	—	—	0.0893 (0.0885)	—	—	0.0208 (0.0128)
Multifarm	−77.33 (69.27)	−64.68 (74.55)	−72.10 (68.93)	−64.51 (74.03)	19.34 (36.68)	21.12 (36.68)	20.26 (36.71)
Global milk price	—	—	1.818*** (0.527)	—	—	—	—
Year FE	No	Yes	No	Yes	No	Yes	Yes
Observation	13,398	13,398	13,398	13,398	34,041	34,041	34,041
R^2	0.259	0.260	0.259	0.260	0.476	0.476	0.476

Note: *P < 0.1; **P < 0.05; ***P < 0.01. All specifications include firm fixed effects. Clustered standard errors at district level in parentheses.

Table 6 Regression results for operating profit per hectare – by irrigated/nonirrigated

	Dairy		Sheep/beef	
	(1)	(2)	(3)	(4)
Nonirrigated sample				
No. drought days (t)	0.481 (0.435)	−0.281 (1.733)	1.274** (0.535)	−0.889 (1.338)
No. drought days (t−1)	−1.040 (1.167)	−0.801 (2.112)	−0.0381 (0.410)	−0.0402 (0.970)
No. drought days (t−2)	0.774 (1.804)	−0.275 (3.689)	0.865** (0.425)	−0.0519 (0.570)
No. drought days $(t)^2$	—	0.015 (0.031)	—	0.0423 (0.0291)
No. drought days $(t-1)^2$	—	−0.004 (0.030)	—	0.00223 (0.0164)
No. drought days $(t-2)^2$	—	0.019 (0.056)	—	0.0162 (0.0128)
Year FE	Yes	Yes	Yes	Yes
Observations	9,054	9,054	21,585	21,585
R^2	0.481	0.188	0.490	0.490
Irrigated sample				
No. drought days (t)	0.00617 (1.113)	6.222 (8.689)	0.236 (0.677)	−0.509 (2.011)
No. drought days (t−1)	5.479 (6.583)	9.040 (8.086)	−0.580 (0.454)	−0.999 (0.895)
No. drought days (t−2)	−3.019 (2.951)	−18.12 (18.35)	−0.434 (0.886)	−0.683 (2.628)
No. drought days $(t)^2$	—	−0.126 (0.180)	—	0.0183 (0.0464)
No. drought days $(t-1)^2$	—	−0.0975 (0.0809)	—	0.0116 (0.0158)
No. drought days $(t-2)^2$	—	0.287 (0.305)	—	0.00637 (0.0384)
Year FE	Yes	Yes	Yes	Yes
Observations	4,344	4,344	12,456	12,456
R^2	0.300	0.301	0.450	0.450

Note: *P < 0.1; **P < 0.05; ***P < 0.01. All specifications include firm fixed effects and multifarm variable. Clustered standard errors at district level in parentheses.

BE is shown in column (2) and on IC ratio in column (4), with statistically significant negative results for all drought indicators. Only in column (3), where the impact of droughts on the DI ratio is estimated, we observe no negative impact. Overall, if farmers experience drought conditions over three consecutive years, we can conclude that they face significant financial strain.

In the second panel of Table 8, we present the effect of drought on balance-sheet indicators for the sheep and beef sector. Only returns on capital and IC ratio are negatively and significantly affected by drought events in the first lag, with no statistically significant effect beyond that. We do observe an increase in debt levels in the year after a drought, maybe suggesting farmers are borrowing to restock their herd.

Table S9 in Appendix S1 represents regression results of the same balance-sheet indicators for irrigated/nonirrigated samples by industry. Consistent

Table 7 Regression results for operating profit per hectare – by farm size

	Dairy		Sheep/beef	
	(2)	(3)	(5)	(6)
Small farms				
No. drought days (t)	−1.525 (2.673)	7.091 (7.446)	0.278 (0.527)	1.185 (1.474)
No. drought days (t−1)	4.612 (6.014)	3.255 (7.510)	−0.0809 (0.317)	−0.0130 (0.949)
No. drought days (t−2)	1.166 (5.828)	−16.80 (21.87)	0.213 (0.424)	0.0725 (1.283)
No. drought days $(t)^2$	—	−0.147 (0.126)	—	−0.0183 (0.0210)
No. drought days $(t-1)^2$	—	0.00758 (0.103)	—	−0.00291 (0.0178)
No. drought days $(t-2)^2$	—	0.333 (0.365)	—	0.00197 (0.0185)
Year FE	Yes	Yes	Yes	Yes
Observations	3,006	3,006	11,286	11,286
R^2	0.287	0.288	0.785	0.785
Medium farms				
No. drought days (t)	1.523* (0.821)	−1.432 (2.191)	0.522 (0.453)	1.356 (1.418)
No. drought days (t−1)	−1.503 (1.489)	0.0845 (2.712)	0.439 (1.198)	1.709 (2.220)
No. drought days (t−2)	−0.659 (0.695)	−2.585 (3.606)	0.344 (0.491)	2.458** (1.167)
No. drought days $(t)^2$	—	0.0613 (0.0404)	—	12.74 (50.03)
No. drought days $(t-1)^2$	—	−0.0278 (0.0475)	—	−0.0186 (0.0220)
No. drought days $(t-2)^2$	—	0.0334 (0.0628)	—	−0.0250 (0.0249)
Year FE	Yes	Yes	Yes	Yes
Observations	6,255	6,255	7,626	7,626
R^2	0.175	0.175	0.249	0.249
Large farms				
No. drought days (t)	−1.049 (0.845)	−1.478 (1.993)	1.691 (1.074)	−4.400* (2.300)
No. drought days (t−1)	0.178 (0.512)	1.100 (1.341)	−0.265 (0.766)	−1.473 (1.219)
No. drought days (t−2)	−0.312 (0.384)	1.535 (1.027)	0.915 (1.192)	−3.462** (1.594)
No. drought days $(t)^2$	—	0.00793 (0.0251)	—	0.131** (0.0580)
No. drought days $(t-1)^2$	—	−0.0171 (0.0208)	—	0.0315 (0.0243)
No. drought days $(t-2)^2$	—	−0.0379* (0.0212)	—	0.0838** (0.0347)
Year FE	Yes	Yes	Yes	Yes
Observations	4,137	4,137	15,132	15,132
R^2	0.427	0.427	0.227	0.228

Note: *P < 0.1; **P < 0.05; ***P < 0.01. All specifications include firm fixed effects and ultiform variable. Clustered standard errors at district level in parentheses.

Table 8 Regression results for balance-sheet indicators – by industry

Industry	(1) Return on capital	(2) Business equity	(3) Debt-to-income ratio	(4) Interest coverage ratio
Dairy farming				
No. drought days (t)	−0.00308*** (0.000580)	−0.000354** (0.000154)	0.00417 (0.00605)	−0.00100*** (0.000296)
No. drought days (t−1)	−0.00113* (0.000657)	−0.000374*** (0.000104)	0.00686 (0.00555)	−0.000681** (0.000331)
No. drought days (t−2)	−0.000410 (0.000686)	−0.000206* (0.000116)	0.00123 (0.00538)	−0.000508* (0.000274)
Observations	13,398	13,404	13,296	13,392
R^2	0.778	0.860	0.539	0.711
Sheep/beef farming				
No. drought days (t)	−0.000314 (0.000823)	0.0000987 (0.000184)	−0.00301 (0.00334)	−0.000640* (0.000370)
No. drought days (t−1)	−0.00322*** (0.00106)	−0.000304 (0.000193)	0.00593* (0.00313)	−0.00139*** (0.000437)
No. drought days (t–2)	−0.000286 (0.00113)	−0.0000737 (0.000138)	−0.00381 (0.00264)	−0.000203 (0.000466)
Observations	34,035	33,480	33,051	34,029
R^2	0.806	0.858	0.712	0.737

Note: *P < 0.1; **P < 0.05; ***P < 0.01. All specifications include firm and year fixed effects. Clustered standard errors at district level in parentheses.

with our prior findings, we conclude that the results for the nonirrigated and irrigated sample largely align with the results for the full sample, with somewhat larger point estimates for the dairy sector. There are fewer distinctions between nonirrigated/irrigated estimates for sheep and beef farms. Regression results of balance-sheet indicators by farm size categories are summarised in Table S10 in Appendix S1. We find few differences in terms of the impacts of droughts on balance-sheet indicators among small, medium and large farms. The regression results with quadratic terms of drought indicators for full, irrigated/nonirrigated and farm size samples for both dairy and sheep/beef industries are also shown in Tables 11–13 in Appendix S1.

6.4 Robustness checks – alternatives to the NZDI

We also estimated a set of regressions using alternative drought indicators to test whether our results are robust, since it is possible that the NZDI is simply not a reliable measure for agricultural drought risks. We apply two soil moisture-based drought indicators (PED and SMD) and a rainfall-based indicator (SPI). The regression results of revenue per hectare, operating profit per hectare and balance-sheet indicators for full, irrigated/nonirrigated and farm size samples for both dairy and sheep/beef industries are summarised in Tables 1–21 in Appendix S2.

Our results are generally very similar to the prior findings, with limited switching in the sign of coefficients or in their statistical significance. There is no consistently different pattern. Our results appear robust and there is not much evidence for any significant impacts of drought conditions on farm profitability of dairy and sheep/beef farming in New Zealand over the time period we investigated, once milk prices are controlled for.

In addition, we estimate the specifications of Table 5 with a drought intensity measure instead of the number of drought days. The results are consistent with our prior findings. When the treatment variable is measured differently, only the scale of the coefficients is different when compared to the results in Table 5. These results are available in Table 22 in Appendix S2.

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 operating profit, we also examined a set of balance-sheet indicators including ROC, BE, DI ratio and IC ratio.

We show that over the last 10 years, about half of the districts had experienced SDs, as measured by the NZDI, and almost 85 per cent 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, we found that current (same fiscal year) drought events have positive impacts on dairy farms' revenue and operating profit; this effect is most likely attributable to drought-induced increases in the global price of milk solids (the vast majority of milk in New Zealand is converted to milk powder and exported). Once we control for milk prices (or use year fixed effects), the drought measures show no impact on dairy farm revenue or operating profits. Overall, therefore, the experienced impact of droughts on farms' revenue and profit appears to be quite modest. The pasture-based dairy systems in NZ appear to have high levels of adaptive capacity (Lee *et al.* 2013). However, drought events do have some significant negative effect on balance-sheet indicators. We also found a nonlinear relationship between sheep/beef revenue and the number of drought days. This implies that during an extended period of drought conditions, sheep/beef revenue will increase as a result of selling their livestock.

In general, dairy farmers 'benefit' more from drought events when compared to sheep/beef farms, as the latter sector has less impact on global prices. The immediate impact of drought in the sheep and beef sector is moderated by increased selling of livestock that shows up later in worsening balance-sheet indicators. Lastly, our results do not demonstrate a very significant effect of irrigation as moderating the harmful balance-sheet effects of droughts.

Empirically, we are not able to describe what is leading to the increases in debt and servicing ratios, nor are we able to pin down evidence to convincingly show that the global price channel we hypothesise is the unique mechanism that can explain our findings. This limitation is common to nonstructural estimations, and in this case, these limitations are exacerbated because our tax record data are only available annually. We also do not have access to data from the corresponding lenders (mostly banks) to shed light on what are the reasons behind the changes in debt patterns, and what that debt is being used for.

All these suggest the need for more detailed data, or more structural modelling of farm operations, to shed more lights on the mechanisms that lead to the impacts we have identified in our nonstructural approach. For that, one would need to develop an analytical framework of farm production and farmer decision-making, and we leave that for future work.

Our results of the impacts of droughts point to two potentially interesting policy conundrums. First, it seems that the market concentration and the reliance of the New Zealand farming sector on one major source of revenue (dairy) are actually important in reducing the financial vulnerability of the sector to droughts. Had the sector been more diversified, with less price-setting market power, the adverse financial impact of droughts might have been larger. Second, resilience-building measures for the dairy and sheep and beef sectors should focus on ameliorating the longer-term deteriorations in balance sheets, rather than focus on short-term indicators of revenue and profit, as the latter seem not to be adversely affected that much.

Another policy implication, in our view, is that it might be that the NZDI, the New Zealand Drought Index, is not constructed to measure the actual impact of drought on farm operations. As such, it is not measuring 'agricultural drought'. More research resources should be directed, in our view, to develop an index that is potentially more helpful in measuring these 'dryness' shocks as they are experienced by the NZ farming sector. It might even be necessary to develop two indices, one for each of the sectors we examined.

Furthermore, 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, and the regional differences in the ways such new indices should be constructed, 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, 39.

Alley, W.M. (1984). The palmer drought severity index: limitations and assumptions, *Journal of Climate and Applied Meteorology* 23, 1,100–1,109.

American Meteorological Society (1997). Meteorological drought-policy statement, *Bulletin of the American Meteorological Society* 78, 847–849.

Barrios, S., Ouattara, B. and Strobl, E. (2008). The impact of climatic change on agricultural production: is it different for Africa?, *Food Policy* 33, 287–298.

Bhalme, H.N. and Mooley, D.A. (1980). Large-scale droughts/floods and monsoon circulation, *Monthly Weather Review* 108, 1,197–1,211.

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.

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, 1–15.

Cancelliere, A., Mauro, G.D., Bonaccorso, B. and Rossi, G. (2007). Drought forecasting using the standardized precipitation index, *Water Resources Management* 21, 801–819.

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, 1,117–1,130.

Dairy New Zealand (DairyNZ). (2018). Dairy statistics. Livestock Improvement Corporation Limited & DairyNZ Limited. Available from URL: https://www.lic.co.nz/documents/450/NZ_DAIRY_STATISTICS_2017-18-WEB-10_OCT.pdf [accessed 19 February 2020].

Dark, A., KC, B. and Kashima, A. (2017). National Irrigated Land Spatial Dataset: Summary of methodology, assumptions and results. Ministry for the Environment, C17042-1. Aqualinc Research Limited.

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, 361–370.

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, 109–131.

Fabling, R. and Sanderson, L. (2016). *A Rough Guide to New Zealand's Longitudinal Business Database* (2nd edn). Motu Economic and Public Policy Research Working Paper 16-03.

Forbes, R. (1998). The El Nino weather pattern and pastoral supply response forecasting. Paper presented to Annual Conference of the New Zealand Agricultural and Resource Society, Blenheim 4–5 July.

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, 1–18. https://doi.org/10.5751/es-05871-180427

Gibbs, W.J. and Maher, J.V. (1967). Rainfall deciles as drought indicators. Bureau of Meteorology Bulletin 48, Commonwealth of Australia, Melbourne.

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, 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, 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, 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.

Kingwell, R.S. and Xayavong, V. (2017). How drought affects the financial characteristics of Australian farm businesses, *Australian Journal of Agricultural and Resource Economics* 61, 344–366.

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, 94–101.

Lee, J.M., Clark, A.J. and Roche, J.R. (2013). Climate-change effects and adaptation options for temperate pasture-based dairy farming systems: a review, *Grass & Forage Science* 68, 485–503.

Livada, I. and Assimakopoulos, V.D. (2007). Spatial and temporal analysis of drought in Greece using the Standardized Precipitation Index (SPI), *Theoretical and Applied Climatology* 89, 143–153.

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, 3,990–3,997.

Maunder, W.J. (1968). Effect of significant climatic factors on agricultural production and incomes: a New Zealand example, *Monthly Weather Review* 96, 39–46.

Maunder, W.J. (1971a). Weather and Operational Decision-Making – the Challenge, in Quarterly Predictions. New Zealand Institute for Economic Research, September.

Maunder, W.J. (1971b). The economic consequences of drought: with particular reference to the 1969/70 drought in New Zealand. NZ Meteorological Service Technical Note 192.

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.

Ministry for the Environment (MfE). (2001). Managing Waterways on Farms: A guide to sustainable water and riparian management in rural New Zealand. Available from URL: https://www.mfe.govt.nz/sites/default/files/managing-waterways [accessed 10 December 2019].

Moore, F.C. and Lobell, D.B. (2014). Adaptation potential of European agriculture in response to climate change, *Nature Climate Change* 4, 610–614.

Nagarajan, R. (2010). *Drought Assessment*. Springer Science & Business Media, Dordrecht, The 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, 69–88.

New Zealand Institute of Economic Research (NZIER). (2017). NZIER report: Dairy trade's economic contribution to New Zealand. Feburary 2017. Dairy Companies Association of New Zealand (DCANZ). Available from URL: https://nzier.org.nz/static/media/filer_public/29/33/29336237-3350-40ce-9933-a5a59d25bd31/dairy_economic_contribution_update_final_21_february_2017.pdf [accessed 19 February 2020].

New Zealand Institute of Economic Research (NZIER). (2019). New Zealand Dairy Statistics, Ministry for Primary Industries. Available from URL: https://www.dairynz.co.nz/media/5792398/quickstats-about-dairyingnew-zealand-2019.pdf [accessed 19 February 2020].

New Zealand Institute of Primary Industry Management (NZIPIM). (2019). What does the future look like for New Zealand lamb?. Available from URL: https://www.nzipim.co.nz/BlogPost?Action=View&BlogPost_id=7 [accessed 12 January 2020].

NIWA. (2011). Scenarios of regional drought under climate change. Available from URL: https://www.niwa.co.nz/sites/niwa.co.nz/files/slmacc_drought_sldr093_june2011.pdf [accessed 1 January 2020]

NIWA. (2015). Are we experiencing more droughts? Available from URL: https://www.niwa.co.nz/news/are-we-experiencing-more-droughts [accessed 1 January 2020]

NIWA. (2017). Available from URL: https://www.niwa.co.nz/natural-hazards/hazards/droughts [accessed 1 January 2020]

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, 43–60.

Pérez y Pérez, L. and Barreiro-Hurlé, J. (2009). Assessing the socio-economic impacts of drought in the Ebro River Basin, *Spanish Journal of Agricultural Research* 7, 269–280.

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, 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, 91–100.

Schlenker, W. and Roberts, M.J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change, *Proceedings of the National Academy of Sciences* 106, 15,594–15,598.

Shahid, S. and Behrawan, H. (2008). Drought risk assessment in the western part of Bangladesh, *Natural Hazards* 46, 391–413.

Shakoor, U., Saboor, A., Ali, I. and Mohsin, A.Q. (2011). Impact of climate change on agriculture: empirical evidence from arid region, *Pakistan Journal of Agricultural Sciences* 48, 327–333.

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

Spinoni, J., Naumann, G., Carrao, H., Barbosa, P. and Vogt, J. (2014). World drought frequency, duration, and severity for 1951–2010, *International Journal of Climatology* 34, 2,792–2,804.

Strommen, N., Krumpe, P., Reid, M. and Steyaert, L. (1980). Early warning assessments of droughts used by the US agency for international development, in Pocinki, L.S., Greeley, R.S. and Slater, L. (eds), *Climate and Risk*. The MITRE Corporation, McLean, pp. 8–37.

Tait, A.B., Renwick, J.A. and Stroombergen, A.H. (2005). The economic implications of climate-induced variations in milk production, *NZ Journal of Agricultural Research* 48, 213–225.

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, 122–135.

Tweedie, A.J. and Spencer, G.H. (1981). Supply Behaviour in New Zealand's Export Industries. Reserve Bank of New Zealand Research Paper No. 31, Wellington.

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, 523–533.

Wallace, R. and Evans, L.T. (1985). Effects of climate on agricultural production and profit. Victoria University of Wellington Research Project on Economic Planning. Occasional Paper No. 84.

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, 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.

Wu, Z.Y., Lu, G.H., Wen, L. and Lin, C.A. (2011). Reconstructing and analyzing China's fifty-nine year (1951–2009) drought history using hydrological model simulation, *Hydrology and Earth System Sciences* 15, 2,881–2,894.

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, 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.

Supporting Information

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

Appendix S1. Further descriptive analysis and regression results.
Appendix S2. Robustness check.