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State-contingent analysis of farmers' response to weather variability: Irrigated dairy farming in the Murray Valley, Australia

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Abstract

The agricultural sector is commonly regarded as one of the most vulnerable to climate change. Current understanding of the impact of climate change on this sector relies on the underlying assumptions about farmers' possible responses to weather variability, including changes in crop choice, input combinations and land management practices.

Many previous analyses rely on the implicit (and restrictive) assumption that farmers operate under a fixed technology set across different states of nature. This assumption, represented through stochastic production or profit functions, is commonly made but seldom tested, and may understate farmers' responses to climate change if state-contingent production technologies are, in reality, more flexible.

The potential for farmers to adapt production technologies in response to unforeseen events is at the core of the state-contingent approach. Advanced in Chambers and Quiggin (2000), the theory contends that producers can manage uncertainty through the allocation of productive inputs to different states of nature. In this article we test the assumption that farmers' observed behaviour is consistent with the state-contingent production theory using farm-level data from Australia. More precisely, we estimate the milk production technology for a sample of irrigated dairy farms from the southern Murray–Darling Basin over the period from 2006-07 to 2009-10.

Keywords: dairy industry; Murray–Darling basin; state-contingent theory; weather variability

1. Introduction

Agricultural systems have evolved to manage natural variability in the environment through a range of evolutionary and human-induced adaptations. These adaptations have helped raise agricultural productivity, reduce the adverse effects of agriculture on the wider environment and deliver the capacity for maintaining agricultural supplies year round. A key feature of these adaptations has been a greater integration of production technologies, business structures and human resources in farming to manage uncertainty relating to the natural environment. However, since these developments have tended to diminish the forces of natural selection, through management to overcome the constraints of history and chance, the overall fitness of these systems under environmental change may be suboptimal (Cody 1974).

The agricultural sector is one of the most vulnerable to climate change. Climate change can lead to increased variability in seasonal conditions, which, in turn, can expose agricultural systems to conditions beyond their historical experience. Such variation may render certain established farming practices ecologically infeasible or commercially unviable in current geographic locations, thus increasing the risk of failure as extreme conditions become more frequent (Hennessy *et al.* 2007; Pittock and Wratt 2001).

Climate mitigation will help reduce the long term rate of climate change. However, the costs of climate change also depend on the efficiency with which production systems adapt to higher temperatures and changed patterns of precipitation (Garnaut 2010). The efficiency of adaptive responses will, in turn, be affected by the flexibility or otherwise of agricultural production technology. This will rest largely on the availability and dissemination of knowledge of possible changes in climate, and the effectiveness of farmers' responses to changes in the availability of critical inputs such as water (Adamson *et al.* 2009; Garnaut 2010).

For example, from 2002 to 2009, during the extended drought in Australia, irrigated farming systems in the Murray–Darling Basin that were designed to operate productively under intensive irrigation experienced difficulties in coping with severe water shortages (ABS 2010; Adamson *et al.* 2009; Ashton *et al.* 2010). As a result, many irrigated dairy farms in the Basin were forced to change pasture management practices, feeding regimes and husbandry methods (Mallawaarachchi and Foster 2009), and suffered significant deterioration of financial performance (Ashton *et al.* 2010).

These coping responses were assisted by the availability of flexible technologies incorporating varying levels of crop–livestock integration, pasture and fodder utilisation (Ashton and Oliver 2012a; Bell and Moore 2012), and irrigation water trading, which permits in-season adjustments to on-farm feed availability in response to variations in irrigation water allocations (National Water Commission 2010). The availability of these technological and institutional innovations has significantly enhanced the capacity of dairy farmers to adapt to environmental changes that exceeded their historical experience (Khan *et al.* 2010).

Farmers are best placed to observe changes in the states of nature that affect their farms. In 2006-07, nearly a two-third (65.6 per cent) of Australian agricultural businesses reported that they considered the climate affecting their enterprise has changed and 62.4 per cent reported that the perceived change in climate had an impact on their enterprise. Approximately half (49.5 per cent) of agricultural businesses reported a change in management practices on their enterprise in response to perceived changes in climate. Dairy cattle farming businesses were among the top four agricultural industries with nearly 75 per cent of businesses reporting that they considered the climate affecting their enterprise had changed (ABS 2008). In this context, it is instructive to examine how management practices adopted by dairy farmers have influenced their performance and, in particular, whether the farmers' behaviour resembles decision-making under increasing uncertainty.

Numerous studies have attempted to assess the impact of climate change on agriculture. The most prominent approach to the analysis is a stochastic production function approach in which climate enters as an exogenous shock. This method depends on the implicit (and restrictive) assumption that farmers operate under a fixed technology set across different states of nature, rather than adjusting input combinations to better suit changes in climatic and other states of nature affecting production choices as observed in the above discussion.

The commonly made, yet seldom-tested, assumption of fixed production technology is usually represented through stochastic production or profit functions, which could understate farmers' responses to climate change if production technologies are, in reality, more flexible. For example, using Bayesian methods to estimate state-contingent production frontiers for Philippine rice farmers, O'Donnell and Griffiths (2006) show that elasticities of expected output with respect to inputs vary significantly across states of nature. Moreover, their estimates indicate that farmers display significantly higher estimates of technical efficiency when measured under state-contingent analysis.

The potential for farmers to adapt production technologies in response to unforeseen events is at the core of the state-contingent approach. Extended and generalised in Chambers and Quiggin (2000), the theory is based on the premise that producers can manage uncertainty by changing the allocation of productive inputs under different states of nature. By considering uncertain events over mutually exclusive states (for example low, normal or high water availability in a growing season), greater flexibility is achieved to represent technology choice under uncertainty within the standard modern theory of production (Adamson *et al.* 2007). State-contingent treatment of uncertainty thus overcomes some difficulties in the traditional stochastic approach to production choice problems, because it allows for substitutability between state-contingent outputs (that is, outputs under different seasonal conditions that are derived using alternative production technologies).

The use of such state-allocable production technologies where inputs can be allocated between different states of nature permits substitution between state-contingent outputs (Chambers and Quiggin 2000). Therefore, it allows for production and decision maker uncertainty to be treated separately in decision analysis (O'Donnell and Griffiths 2006; Rasmussen 2011), and brings risk management into focus (Just 2003). This permits analysis of adaptation to increased climate variability and change.

In this article we test the assumption that farmers' observed behaviour in managing production uncertainty is consistent with state-contingent production theory using farm-level data for irrigated dairy producers in Australia. More precisely, we estimate the milk production technology parameters for a sample of irrigated dairy farms from the southern Murray–Darling Basin over the period from 2006-07 to 2009-10. Two states of nature (favourable and unfavourable) are defined, based on water allocation announcements in October of each year.

Major inputs in the production process include land, capital, fertilisers, labour, water, and purchased fodder. Some of these inputs, such as land and capital are determined prior to the realisation of the state of nature, but may nonetheless be allocated in ways that have differential benefits in different states of nature. For example, choosing water-efficient irrigation systems may reduce variability arising from stochastic water allocations. Other inputs, such as purchased fodder, are chosen after the state of nature is known. These inputs may be allocated primarily either to favourable states (amplifying the variability of returns) or to unfavourable states (mitigating variability).

The paper is structured as follows. In Section 2 we present a background to the study. A brief introduction to the state-contingent model is presented in Section 3 and the data, econometric model and estimation method are presented in Section 4, including an explanation of the specification of the production technology and the estimation method. The model results are examined in Section 5. We briefly conclude in Section 6 with some suggestions for further work.

2. Background

The Murray Valley is an important dairy production region in Australia, forming part of the Murray–Darling basin (MDB) in south-eastern Australia. Historically, the Murray Valley dairy industry has been developed as year-round pasture-based operations supported with irrigated pastures, with supplementary feeding of fodder and concentrates to account for seasonal variability. In 2010-11, the most recent season with favourable conditions for irrigation, the MDB accounted for 40 per cent of agricultural firms using irrigation, 61 per cent of all irrigated agricultural land, applying 68 per cent of available irrigation water. Pasture for grazing was the predominant irrigated land use, accounting for around 45 per cent of the irrigated land in the Basin in 2010-11 (ABS 2012).

The MDB experienced a period of sustained low rainfall from 2000-01 to 2008-09. In 2006-07, dam storage levels remained very low, reaching only 15 per cent of their capacity. Water allocations for irrigation dropped to historically low levels in some regions, although rainfall had improved slightly. In 2009-10, the MDB experienced above-average rainfall and water storage levels began to recover.

Weather variability directly affects production in rainfed systems and irrigation water availability for intensively irrigated systems such as the Murray Valley dairy industry. Farm costs have increased as farmers adapt to drier conditions. In particular, reliance on purchased feed has increased considerably. Murray Valley milk production fell from 3 billion litres per year in 2002, to 2 billion litres per year in 2009 in response to drought that affected irrigation water availability (Australian Dairy Industry 2014; Dharma *et al.* 2012).

Dairy production typically involves two calving periods (or batches), with a primary batch in spring, with peak milk production in the spring pasture growth season. Pasture-based systems are often managed to optimise rather than maximise milk production by carefully controlling input costs. Most producers use a combination of grazing, cut forage (hay and silage) and concentrate feeding, allowing flexibility in managing costs and nutritional requirements through substitution. However, the practice exposes dairy farms to an increased level of risk as forage and grain prices can rise sharply during dry conditions, particularly if irrigation water supplies are restricted.

Year-round pasture availability is advantageous for dairy farming. The Murray Valley dairy industry draws this advantage from the ability to raise feed under irrigation. Irrigation increases the flexibility for year-round feed supply using a combination of annual and perennial pastures that can be grazed, or cut for hay and silage, as conditions warrant.

In recent decades, as the opportunity cost of water for irrigation has increased through greater competition [including water trading], dairy farmers have opted to substitute purchased feed for farm-grown pastures. Purchase of hay, silage, and grains such as wheat and barley adds to the flexibility as it permits sourcing feed from different regions that may have different exposure to climate variability, and different opportunity costs for water and land. Some farmers have also opted to raise their dry cows and replacement stock at different properties away from the main dairy, allowing a further level of flexibility (Mallawaarachchi and Foster 2009).

Based on past experience farmers would then be able to differentiate between good and bad seasons with high and low productivity, respectively. In such assessments, the separation of high and low prospects would depend on the balance between marginal productivity and risk tolerance (Jones *et al.* 2013; Just 2003, 2008; Miller *et al.* 2013).

Risk-neutral producers will seek to maximise expected net returns by equalising the marginal cost of expected output across states of nature. This will yield a relatively risky net return. By contrast, risk-averse producers will seek lower variation in net returns across states of nature, provided the cost, in terms of expected net returns, is not too great. The trade-off may be measured using the concept of the production certainty premium, developed by Chambers and Quiggin (2000).

3. The state-contingent model

The origins of state-contingent production theory can be traced back to Arrow and Debreu (1954) and recent developments of this theory can be found in Chambers and Quiggin (2000). In essence, the state-contingent theory considers that outputs are conditional on the states of nature (each state representing a particular uncertain event) and that producers can manage uncertainty through the allocation of productive inputs to different states of nature. In other words, the state-contingent approach recognises that actions (input choices) can have different consequences in different states of nature. This is not a property of conventional stochastic production theory, in which the role that inputs play remains the same regardless of which state occurs, and hence does not permit substitutability between state-contingent outputs. In this paper, we test whether the production behaviour of dairy farmers from the MDB in Australia represents state-contingent production technologies, where the states are defined based on the expected level of water available for irrigation.

In the general state-contingent model (Quiggin and Chambers 2006), there are M distinct outputs, N distinct inputs, and S possible states of nature. Inputs $x \in \Re_{+}^{N}$ are committed before the state of nature is known and fixed *ex post*. State-contingent outputs $z \in \Re_{+}^{S \times M}$ are chosen *ex ante* but produced *ex post*. That is, if state s is realised, and the *ex ante* output choice is the matrix z, the observed output is $z_s \in \Re_{+}^{M}$, which corresponds to the M outputs produced in state s.

Inputs that are variable *ex post*, such as irrigation, may be regarded as negative state-contingent outputs, in which case we generalise to allow $z_s \in \Re^{M}$. We denote by $1_s \in \Re^{S}$ the unit vector with all entries equal to 1.

The formal structure may be considered as a two-period game with nature, with periods denoted 0 and 1. In period 0, the producer commits inputs $x \in \Re_{+}^{N}$. When nature reveals the state s, the individual produces the output z_s.

The technology of production determines the feasible strategies (x, z). In the current analysis, dairy farmers' choice of irrigation and the level of fodder substitution for pastures in low and high water availability seasons are treated as state-allocable production technologies that contribute to state-contingent outputs (here milk produced) in low and high seasons respectively.

The number of applications of the state-contingent theory has grown in recent years. The most notable applications are O'Donnell and Griffiths (2006), Chavas (2008), O'Donnell *et al.* (2010), Serra *et al.* (2010), and Nauges *et al.* (2011). The studies from Chavas (2008) and Serra *et al.*

(2010), which are based on aggregated data from the United States over a 50-year period, provide empirical support for an output-cubical technology (technology that does not permit substitutability between state-contingent outputs). However, Nauges *et al.* (2011), using farm-data from Finland, found that a state-contingent production model with identifiable state-allocable inputs is preferred to the more restrictive output-cubical state-contingent model.

The existence of a state-allocable production technology has a number of important implications for agricultural production under uncertainty and farmers' adaptation to changing conditions. If the production technology is state-allocable, producers can respond to information by reallocating inputs towards states of nature that appear more likely in the light of new information. By contrast, under an output-cubical model, producers can respond to information by changing only the scale of production (Chambers and Quiggin 2007). The state-contingent framework thus allows for greater flexibility and adaptability of farmers when facing uncertainty than the standard (output-cubical) production models.

3.1. The cost function and production certainty premiums

The state-contingent technology described above may be characterised by a cost function c(z,w,π), where $z \in \Re^S$ is the state-contingent output of interest (in this case, milk), w is a vector of (possibly state-contingent) input prices and π is a probability vector. The cost function is defined as

(1) $c(z,w,\pi) = \min E_\pi[wx: (x, z) \text{ is feasible}]$

For a given stochastic output z, and probabilities π, let $\bar{z} \in \Re^S$ denote the non-stochastic output vector with all elements equal to $E_\pi[z]$, and define the absolute production certainty premium as

(2) $\rho^a(z,w,\pi) = c(\bar{z},w,\pi) - c(z,w,\pi)$

and the relative production certainty premium

(3) $$\rho^r(z,w,\pi)=\frac{c(\bar{z},w,\pi)}{c(z,w,\pi)}.$$

For any μ, let

(4) $z^*(\mu) = \arg\min \{c(z,w,\pi): E_\pi[z]=\mu\}$.

Observe that $\rho^a(z^*,w,\pi) \geq 0$, $\rho^r(z^*,w,\pi) \geq 1$. Equality arises in the case where $z^*(\mu)$ is non-stochastic. That is, in the terminology of Chambers and Quiggin (2000), the technology is not inherently risky.

3.2. State-contingent inputs and risk premiums

As noted above, some inputs may be state-contingent. Risk-averse producers may increase the use of such inputs in unfavourable states of nature in order to reduce the variability of state-contingent output. For livestock enterprises, including the dairy farms studied here, the most important response to adverse seasonal conditions is the use of purchased fodder to supplement pasture.

Following the approach described above, state-contingent inputs may be treated as negative outputs. We may model the use of purchased fodder by way of a two-stage technology, in which the final state-contingent output is

(5) $z = f(\zeta,-\chi)$

where

ζ is milk output in the absence of purchased fodder; and

χ is the input of purchased fodder.

We will further simplify by assuming that $z = f(\zeta,\chi)$ takes the simple separable form

(6) $z_s = \zeta_s + g(\chi_s)$

where z_s denotes output in state s, χ_s is fodder input in state s, and $g(\chi_s)$ is a concave increasing function. We will make the specific assumption $g(\chi_s)= \psi\log(\chi_s)$ where log is the natural logarithm and ψ is a constant.

With this specification, minimising the expected cost of producing a given expected output $E_\pi[z]$ requires making the fodder input χ_s equal in all states.[1] However, risk-averse producers will tend to use more fodder (and other variable inputs) in unfavourable states. The resulting expected output, as a proportion of the maximal expected output achieved by setting all inputs equal may be measured as:

(7) $E[\log(\chi)]/\log(E[\chi])$

If fodder inputs are chosen to equalise state-contingent outputs, this is a version of the production certainty premium.

4. Empirical analysis

4.1. Specification of the production technology and estimation method

We propose to estimate a production technology of the form: $y = f(x, z)$ where y represents milk production per cow, x is a vector of production inputs, and z is a vector of variables to control for farm heterogeneity. We consider the following production inputs: purchased fodder; area used to produce hay and silage; area of irrigated pasture; labour; and the number of milking cows (as a proxy for capital). We consider all inputs on a per cow basis (based on the number of milking cows). We will test a number of functional forms (Cobb-Douglas, Translog, quadratic) and keep the one that best fits our data.

The chosen estimation method must address three potential issues: first, inputs may be endogenous if unobserved productivity shocks (or unobserved farm-specific effects) are

[1] This assumes that fodder prices are equal across states. If fodder prices are higher in unfavourable states, risk neutral producers would use less in those states.

correlated with both inputs and output; second, some farmers in some years do not have any irrigated pasture; finally, our dataset is an unbalanced panel so not all farms have been observed in all years. We propose the following two-stage estimation strategy: in the first stage potential endogenous inputs are regressed on a set of instrumental variables, and in the second stage their predicted values (instead of their observed values) are used in estimating the production function. We estimate the first stage using a Tobit model, as the potential endogenous inputs contain observations that take the value zero. In the second stage, a fixed-effect estimator is used to model the production technology, where the within transformation removes unobserved farmer specific effects and corrects the endogeneity bias due to the correlation of farmer specific effects with the independent variables. Finding appropriate instrumental variables is difficult, so we consider a number of possible options: the (median) regional price of milk; the (median) regional price of water allocations; the (median) regional price of fodder; summer rainfall; and regional dummies. We assume that the size of the area is exogenous over the four-year period covered by our data.

4.2. Description of data

This study uses farm-level data obtained from a short time series of irrigation surveys conducted on farm by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES). Four rounds of these annual survey data are available, beginning from the 2006-07 financial year (see Ashton and Oliver 2012b). The data cover only four years but encompass periods of lower-than-average rainfall (2006 to 2008) and periods with rainfall well above the long-term average (2009 and 2010). In 2006-07, water allocations dropped to their lowest levels in some regions.

The sample is an unbalanced panel of 408 observations, comprising 204 farms observed from 2006-07 to 2009-10. Descriptive statistics on the variables used as explanatory factors in the production function are shown in Table 1. More detailed information is given in the Appendix.

Table 1. Descriptive statistics on the potential explanatory variables

Variable	Unit	Mean	Std. dev.	25th perc.	50th perc.	75th perc.
Purchased fodder	quantity index/cow	789	546	375	699	1147
On-farm irrigated pasture	ha/cow	0.26	0.32	0	0.18	0.39
On-farm hay and silage	ha/cow	0.23	0.30	0	0.14	0.33
Family labour	weeks/cow	0.71	0.60	0.38	0.56	0.84
Hired labour	weeks/cow	0.09	0.14	0	0	0.17
Area operated	ha	255	257	93	165	324
Number of milking cows		219	162	110	160	300

In Table 2 we report annual averages for variables of interest. The average milk production per cow has remained quite stable over the four years, varying from 5 506 litres in 2007-08 to 5 738 litres in 2009-10. The quantity of fodder purchased has varied across the four years from a low of 640 (quantity index per cow) in 2006-07 to a high of 1 013 in 2008-09. The large variation in the quantity of fodder purchased is driven, among other factors, by water availability (through rainfall and water allocations) and the price of fodder.

Table 2. Time variation of variables of interest

		2006–07	2007–08	2008–09	2009–10
Milk production	l/cow	5 660	5 506	5 703	5 738
Purchased fodder	quantity index/cow	640	896	1 013	749
Farmers having irrigated pasture	%	66	69	63	80
Irrigated pasture (all farms)	ha/cow	0.29	0.18	0.23	0.34
Irrigated pasture (for farms having irrigated pasture)	ha/cow	0.44	0.26	0.37	0.42
Farmers growing fodder crops	%	38	38	35	35
On-farm hay and silage	ha/cow	0.23	0.22	0.21	0.26
Family labour	weeks/cow	0.77	0.66	0.67	0.70

Hired labour	weeks/cow	0.08	0.09	0.11	0.10
Area operated	ha	237	242	287	279
Number of milking cows	-	208	217	245	220
Winter rainfall	mm	146	196	159	237
Summer rainfall	mm	101	210	161	252
Index price of fodder	1 in 2010	1.04	1.34	1.15	1.00
Price of milk	c/l	31	47	40	34
Price of water allocations	AUD/Ml	343	335	297	164

Note: summer rainfall is total rainfall from 1 November until 31 March. Winter rainfall is total rainfall from 1 April until 31 October.

5. Estimation results

5.1. Estimation of the production technology

In the first stage we consider three potentially endogenous variables – fodder expenditure, area of irrigated pasture, and hired labour – and find evidence for endogeneity of the area under irrigated pasture only. Because some farms do not have any irrigated pasture in some years, we use a Tobit model. Estimation results are shown in Table A3 in Appendix. The likelihood-ratio test indicates the overall significance of the model. Our estimates indicate that higher water allocation prices, higher summer rainfall and larger area operated are associated with smaller areas of irrigated pasture (per cow). We also find significant differences across regions, with irrigated pasture (on a per cow basis) being lower in the Murray region and higher in the Loddon–Avoca region in comparison with the Goulburn region, all other things being equal.

In the second stage we use the predicted area under irrigated pasture in place of the observed value to estimate the production technology. We find that a quadratic functional form fits the data better than a Translog or Cobb-Douglas functional form, and that most of the interaction terms are not significant. The within estimation results are shown in Table 3, after excluding insignificant interaction terms from the model.

Table 3. Within estimation results – Milk production technology

Dependent variable: milk production per cow	**Coef.**	**Std. Err.**	**P>t**
Irrigated pasture (ha/cow)	0.07	0.05	0.11
Fodder purchase (qty/cow)	0.20	0.03	0.00
Hired labour (weeks/cow)	0.12	0.02	0.00
Family labour (weeks/cow)	0.17	0.04	0.00
Hay and silage (ha)	0.004	0.01	0.71
Number of milking cows	-0.27	0.07	0.00
Area operated (ha/cow)	0.16	0.04	0.00
Goulburn region (ref)	-	-	-
Loddon–Avoca region	-0.08	0.05	0.08
Murray region	-0.10	0.07	0.15
Fodder purchase x Hired labour	-0.05	0.02	0.01
Constant	0.76	0.16	0.00

All inputs have the expected positive sign. Our findings also indicate that production per cow is significantly lower in larger herds. Using the estimated coefficients from Table 3, we calculate the elasticities of milk production with respect to the main inputs. Milk production is found relatively inelastic to irrigated pasture (0.12), fodder purchase (0.15) and hired labour (0.10).

5.2. Test of a state-contingent production technology

We now test whether the observed dairy production system is better represented in a state-contingent framework as opposed to the standard 'output-cubical' technology estimated previously, the latter being a restricted form of the state-contingent production technology. We define two states of nature to reflect favourable and unfavourable conditions of water availability as at 1 October each year. Based on knowledge of the dairy industry, this date represents the beginning of the prime growing season after production decisions have been made and so fits into a state-contingent framework where a set of state-allocable inputs can be identified with available data.

The state variable is constructed at the farm level based on an 'effective water allocation level', which is calculated as the proportion of water covered by a farm's entitlements that is actually available for use. This calculation takes into account the suite of entitlements held by the farmer (available from ABARES survey data) and their relative water allocations (obtained from regional water authorities). For regulated surface water entitlements, water allocations vary from 0 per cent to 100 per cent of entitlement volume depending on the type of entitlement, region, and date (allocations generally increase throughout the year as inflows enter storages). We assume that groundwater entitlements have an effective 100 per cent allocation. The remaining entitlement categories, which comprise less than 2 per cent of total entitlement volumes, we assume to have an effective 100 per cent allocation, as detailed information is not available. We define farmers to be experiencing a favourable state when effective water allocations are equal to or greater than 30 per cent. The proportion of farmers in a favourable state in each region and in each year is given in Table 4.[2]

The determination of the number of states and the definition of the states is a crucial modelling choice in the estimation of state-contingent technology. A larger number of states allows for more flexible estimation, but also increases the number of parameters to be estimated, thereby reducing the precision of estimates and the power of hypothesis tests. Most published analyses using the state-contingent approach have allowed for either two or three states of nature. In the present paper, two states of nature are modelled, with the threshold set at an allocation of 30 per cent or more. The choice of two states of nature reflects the relatively small sample size (approximately 400 observations on 100 farms over four years). Our primary motivation for the relatively low choice of threshold was the need to have sufficiently many farms in both states of

[2] One caveat of our analysis which covers only four years is that a number of farms remain in the same state. More precisely 75 data points only are from farms observed in both states. The remaining observations are 233 from farms observed only in the unfavourable state, and 100 from farms observed only in the favourable state. Identification would be stronger if we had more farmers switching states but we do not think it is critical for two main reasons: first, we control for farm-specific unobserved effects when estimating the production technology and second, we do not believe there is a risk of selection bias. Such a bias would occur if the dairy farmers in our sample had selected the location of their farm based on expected water allocations, which we believe is highly unlikely.

nature in all regions. As shown in Table 4, even with this relatively low threshold, only a few farms in the Loddon–Avoca catchment experienced the favourable state.[3]

Table 4. Percentage of farmers in a favourable state (our sample)

Region	2006-07	2007-08	2008-09	2009-10
Goulburn	32	16	13	20
Loddon–Avoca	17	7	8	16
Murray	91	37	41	36

In Table 5, we report the mean values of the main variables of interest in each state of nature, along with the outcome of a *t*-test of mean equality. This test highlights some differences in input use between the states. However, output remains relatively similar between states. This is partly because many farmers are on commitment to deliver a specific volume of milk and hence strive to maintain output. Furthermore, dairy cows represent a significant capital asset to these farms and their production goal is to maintain dairy cow performance over a productive lifespan.

Table 5. Comparison of means between the two states

		Unfavourable state	Favourable state	Test of mean equality
Milk production per cow	litre	6 139	6 296	ns
Irrigated pasture	ha/cow	0.26	0.19	**
Purchased fodder	qty/cow	1 030	850	***
Fodder crops	ha/cow	0.10	0.12	ns
Hired labour	weeks/cow	1.04	0.91	ns

Note: 'ns' is for non-significant; ** and *** indicate a significant difference between the two means at the 5% and 1% level, respectively.

[3] We ran some sensitivity analyses by varying the threshold that distinguishes between favourable and unfavourable states. Instead of a 30 per cent threshold we re-estimated the model using a 20 per cent and a 40 per cent threshold. We find that the results (in particular in terms of elasticities of milk production to inputs) were not substantially different as a result of varying the threshold.

We then estimate the original two-stage model separately for the two states of nature and test whether the parameters are the same. The first-stage estimation results are shown in Table A4 in Appendix and the estimation of the production technology along with corresponding elasticities of milk production to inputs in Table 6.

The Fisher-test of equality of coefficients between the two states has a p-value of 0.036, which indicates rejection of the null hypothesis that the coefficients of the production technology are equal between the two states of nature at the 5 per cent level of significance. This finding thus confirms our initial hypothesis that the production technology is flexible and state-specific.

The elasticities of milk production with respect to fodder purchase, irrigated pasture, and hired labour in the two states of nature were computed for each observation in the sample. Milk production is found to be more elastic to fodder purchase and less elastic to irrigated pasture in favourable states of nature. The distributions of the output elasticities to fodder purchase and irrigated pasture are shown in Figures A1 and A2 in Appendix.

Table 6. State-contingent production technology: estimated coefficients and elasticities

Dependent variable: milk production per cow	**Unfavourable state**		**Favourable state**	
	Coef.	**P>t**	**Coef.**	**P>t**
Irrigated pasture (ha/cow)	0.09**	0.049	0.02	0.853
Fodder purchase (qty/cow)	0.18***	0.000	0.20***	0.000
Hired labour (weeks/cow)	0.08***	0.006	0.06	0.269
Hay and silage (ha/cow)	0.01	0.477	-0.01	0.633
Number of milking cows	-0.38***	0.000	-0.33***	0.001
Area operated (ha/cow)	0.06	0.341	0.17***	0.000
Family labour (weeks/cow)	0.08	0.119	0.16***	0.002
Fodder purchase x Hired labour	-0.04**	0.044	0.02	0.647
Estimated elasticities of milk production to:				
Fodder purchase (qty/cow)	0.15		0.18	
Irrigated pasture (ha/cow)	0.16		0.03	
Hired labour (weeks/cow)	0.04		0.06	

Note: *, ** , *** indicate significance at the 10, 5, and 1 per cent level, respectively.

5.3. The production certainty premium

The summary statistics presented in Table 5 show that farmers use state-allocable inputs to reduce the state-contingent variability of output. The difference in mean output between the favourable and unfavourable states is neither statistically significant nor large in relative magnitude (about 2.5 per cent). It may be conjectured that farmers value stable output because it helps them to meet contractual requirements. A similar idea, 'insurance milk' was proposed by Alston and Quilkey (1980), though the market conditions at the time, with fluid milk quotas playing a central role, were very different. Stabilisation of output is achieved by increasing the use of state-contingent inputs, most notably purchased fodder, in unfavourable states of nature. As shown in Table 5, the mean input of purchased fodder is approximately 20 per cent higher in the unfavourable state. The productivity of fodder, as measured by the elasticity of output with respect to fodder, is correspondingly lower, also by around 20 per cent (Table 6).

These observations indicate that farmers are willing to incur a production certainty premium in order to stabilise output. However, as we will show, the flexibility of the production technology means that this premium is quite modest. Since the marginal product of fodder is approximately inversely proportional to the input level, we may estimate the premium using the additively separable technology in (6), with $g(\chi) = \log(\chi)$. We have

$\mathrm{Log}(\chi_u) = 6.94$,

$\mathrm{Log}(\chi_f) = 6.75$,

$\mathrm{Log}(E[\chi]) = 6.879$,

$E[\log(\chi)] = 6.875$,

Where $\chi_u = 1030$ is input in the unfavourable state and $\chi_f = 850$ is input in the favourable state.

Computation of the ratio

$E[\log(\chi)]/\log(E[\chi])$

yields a value of 0.9995, which is close enough to 1 to be within the range of measurement error.

6. Conclusion

Using limited farm survey data our analysis demonstrates that the production technology adopted by irrigated dairy farmers in the Murray–Darling Basin represents a pattern consistent with state-contingent production. Over recent years, irrigators in this region have endured highly variable seasonal water allocations making them more vulnerable to production and market risks. However, despite significant variability in seasonal conditions, milk production levels in the region have been relatively stable. Farmers have used additional resources in unfavourable states to maintain output levels. The cost of stabilization turns out to be modest. This is a manifestation of the flat payoff function commonly found in agricultural decision problems (Anderson 1975, Pannell 2006). Our finding that output is quite stable across states also somehow echoes results presented in Crean *et al.* (2013). Using discrete programming models on simulated data from a representative farm of the Central West region of New South Wales, the authors find that decisions consistent with the state-contingent theory lead to a reduced variability in farm income across the three states (characterised as dry, average, and wet) compared to decisions modelled under the traditional expected utility framework.

The state-contingent technology estimated here is very flexible, approaching the polar case of a perfectly state-allocable technology. This finding contrasts with some previous estimates of state-contingent production technology which have been closer to the opposite pole of a stochastic production function (for example, Chavas 2008). Our finding that farmers use state-allocable inputs to manage their exposure to unfavourable conditions using flexible technologies has significant policy relevance in understanding adaptation to climate variability and change.

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Appendix

Data description

The data set contains detailed financial and physical information on irrigated farms in three industries (broadacre, dairy and horticulture) across 10 regions of the Murray–Darling Basin. In particular, the data set contains information on area allocated to pasture and other crops; crop, livestock, and milk production and sales; expenditure on inputs, including fertilisers, chemicals, fodder, and number of weeks worked by permanent and casual workers (hired labour) and by family members; and the volume and prices of water allocations purchased and sold by each farmer on the market. For our purposes, expenditure on fodder was converted into a quantity index using a national price index for fodder and feedstuff (ABARES 2011).

In addition, we restrict the data to farms whose main enterprise is dairy: those farms for which milk receipts represent at least 50 per cent of total cash receipts. We also restrict the data to farms located in the southern regions of Goulburn, Loddon–Avoca, and Murray. These regions contain the majority of dairy farms in the survey and historical information on water availability for these regions is easily accessible. The excluded regions are the Condamine–Balonne, which is farther north and in a different climate zone, and Eastern Mount Lofty Ranges, for which appropriate water use data is not available. We also remove farms for which milk production is zero or the number of milking cows is zero. The final sample is an unbalanced panel of 408 observations, comprising 204 farms observed over a four-year period from 2006-07 to 2009-10. The distribution of observations and the variation of the output variable, milk production per cow (litres), over the three regions and four years are shown in Tables A1 and A2 in Appendix, respectively.[4]

[4] Output (milk) is measured in litres since we do not have any information in the data to control for milk composition or milk quality.

Table A1. Number of dairy farms by region and by year (our sample)

Region	2006-07	2007-08	2008-09	2009-10	Total
Goulburn	38	32	40	35	145
Loddon–Avoca	18	15	25	32	90
Murray	47	46	44	36	173
Total	**103**	**93**	**109**	**103**	**408**

Table A2. (Weighted) average of milk production per cow (litres)

Region	2006-07	2007-08	2008-09	2009-10
Goulburn	5 242	4 834	5 435	5 447
Loddon–Avoca	5 244	5 933	5 885	5 314
Murray	6 091	6 108	5 969	6 327

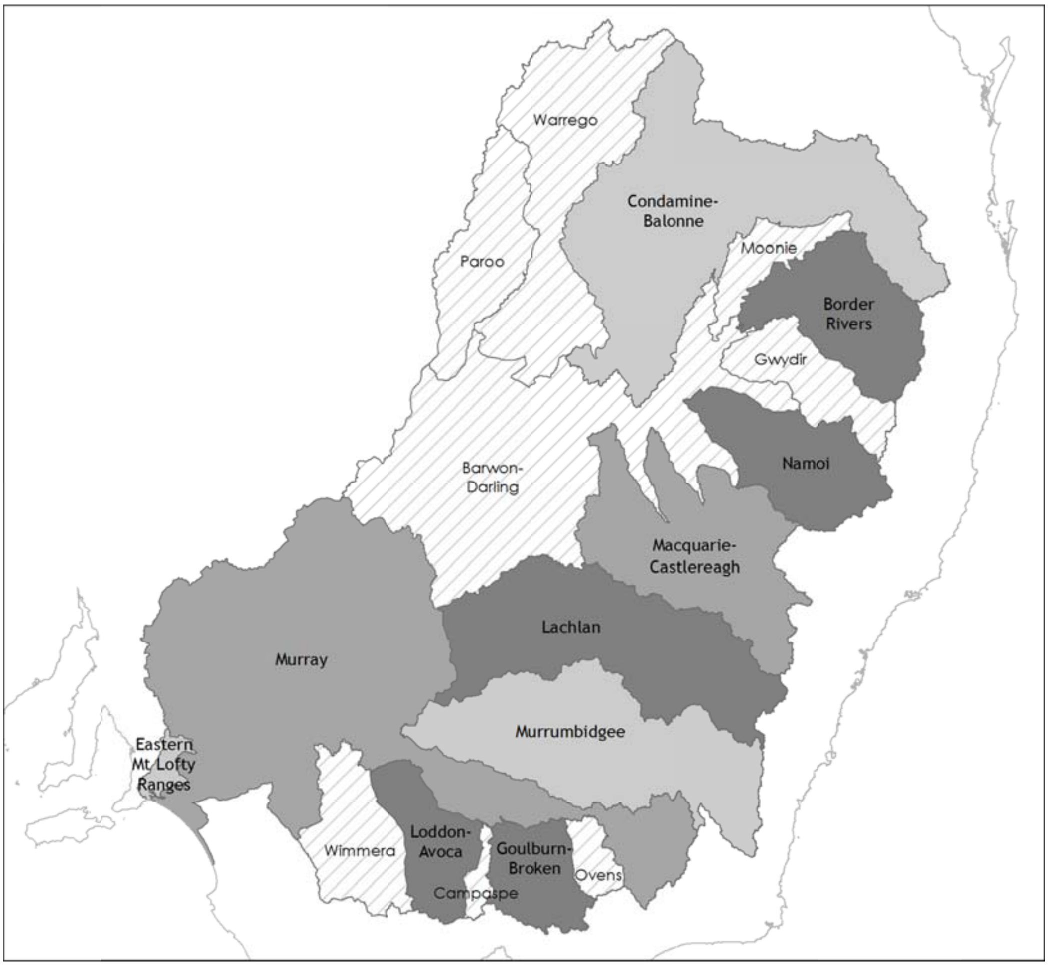
Table A3. Tobit estimation results

Dependent variable: irrigated pasture per cow (ha)	Coef.	Std. Err.	P>t
Price of water allocations	-1.49	0.41	0.00
Summer rainfall	-0.62	0.27	0.02
Goulburn region (ref)	-	-	-
Loddon–Avoca region	0.04	0.25	0.87
Murray region	-0.62	0.19	0.00
Area operated	-0.19	0.09	0.03
Constant	3.21	0.70	0.00
Number of observations	408		
Number of censored observations	134		
Likelihood-ratio test (p-value)	33.38	(0.000)	

Table A4. First-stage estimation results (Tobit model)

	Unfavourable state			Favourable state		
Dependent variable: irrigated pasture per cow (ha)	Coef.	Std. Err.	P>t	Coef.	Std. Err.	P>t
Price of water allocations	-1.42	0.41	0.000	-1.34	0.67	0.044
Summer rainfall	-0.35	0.37	0.348	-0.97	0.35	0.005
Goulburn region (ref)	-	-	-	-	-	-
Loddon–Avoca region	0.11	0.26	0.683	-0.04	0.66	0.950
Murray region	-0.57	0.22	0.009	-0.65	0.43	0.134
Area operated	-0.23	0.10	0.022	-0.11	0.13	0.384
Constant	2.92	0.78	0.000	3.23	1.01	0.001
Number of observations	277			131		
Number of censored observations	86			48		

Map 1. Regional coverage of the ABARES survey of irrigation farms in the MDB



Note: surveyed regions are shaded and their names are indicated in bold font

Figure 1. Distribution of estimated elasticities of output with respect to fodder purchase

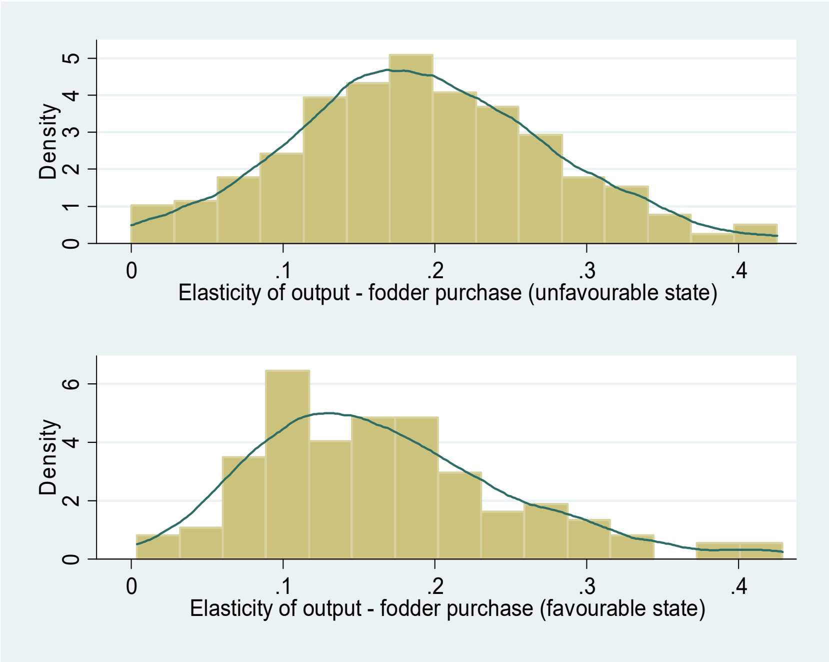


Figure 2. Distribution of estimated elasticities of output with respect to irrigated pasture