Droughts, deluges, and (river) diversions: Valuing market-based water reallocation

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Job Market Paper

Abstract

This paper studies a water market used by irrigated farms inhabiting a connected river network in Australia's southern Murray-Darling Basin during a period of substantial environmental change (2007–2015). It uses new panel data to estimate shadow values of water for each farm from production functions identified with regulatory variation in river diversion caps. The estimates imply that observed water trades increased irrigated agricultural output by approximately 4–6%. Without this reallocation, output is the same as under an 8–11% uniform reduction in water resources, roughly the median reduction predicted for this region under 1°C of global warming. The value of the water market is increasing and highly convex in water scarcity, with realized gains an order-of-magnitude greater during drought, concentrated in regions with stricter diversion limits and among farms with less rainfall. This suggests that retrospective analyses may understate the future value of trade in a changing climate and that a water market is an important institutional adaptation to climate change.

JEL Classifications: D24, D51, F14, L51, Q15, Q54
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> "Nothing is more useful than water, but it will purchase scarcely anything; scarcely anything can be had in exchange for it."
>
> Adam Smith (1776)

1 Introduction

Climate change will continue to amplify water scarcity and variability. Rising temperatures directly alter the hydrological cycle (Oki and Kanae, 2006), intensifying droughts (Prudhomme *et al.*, 2014) and deluges (Sobel *et al.*, 2016). Climate models predict substantial declines in water resources for irrigation (Elliott *et al.*, 2014) and greater uncertainty over future river inflows (Schewe *et al.*, 2014). How this scarcity will interact with water misallocation is not well understood. Water regulators typically allocate water through non-market mechanisms, such as quotas based on landholdings, records of past usage, political influence, or historical priority.[1] When water is scarce, these allocation rules can imply that some users access water at zero marginal price until their quotas bind, while users without rights face an infinite price.

Despite the long-recognized possibility that "a continuous market in water rights" (Dales, 1968, p. 801) may improve efficiency, "the utility of water markets" remains "one of the most polarizing areas of water management" (Allan *et al.*, 2017, p. 397). Much of this controversy over water trading arises from a tension between neoclassical models, in which the opportunity to trade cannot deteriorate welfare, and the practical realities of a river system, where trading opportunities may be costly, uncertain, or manipulable. River flow constraints (Israel and Lund, 1995), noncompetitive conduct (Ansink and Houba, 2012), and liquidity constraints (Donna and Espin-Sánchez, 2018) can each dampen or reverse the gains from trade that are implied in competitive, frictionless models. Evidence from several nascent water markets has led some economists to conclude that "the reality of water markets falls short of their potential" (Regnacq *et al.*, 2016, p. 1274).

This paper contributes to the debate over water markets' role in climate adaptation by estimating the value of trade in annual water diversion rights, without assuming that water is valuable or that trade is efficient. It focuses on a set of irrigated farms trading in a connected river network in Australia's southern Murray-Darling Basin (sMDB), where rainfall is highly variable and environmental regulation has capped water diversions since the

[1] These institutions often reflect the view that water is an inalienable human right and should not be "treated as a commodity," and, in some places, histories of relative abundance due to expanding dam capacity. Olmstead (2010), Ostrom (2011), and Barbier (2019) provide longer historical discussions.

mid-1990s. Irrigated agriculture accounts for more than 70% of all water withdrawals globally, making this industry the single largest user of water in the global economy. As the water market "routinely described as the world's best" (Hughes *et al.*, 2016, p. 4), the sMDB mechanism is a key case study for the adoption of water markets worldwide. It is the largest water market in the world by trading volume and the most valuable, with 7,700 gigaliters or A$22.7 (US$15.3) billion of water entitlements on issue.[2] How valuable is observed market-based water reallocation, relative to fixed water rights? Does the market help farms adapt to evolving water scarcity and other climate and productivity shocks? How do farms respond to water market access through other economic decisions, such as demand for labor or long-run land use, and how do these forms of adaptation alter estimated gains from water trading?

Recovering the value of water trade in a river network with unobserved constraints on trade raises at least two major empirical challenges. First, agents' true valuations of river diversions cannot be inferred from market prices without explicitly modeling information at the time of trading, market structure, transaction costs, and the curvature of utility to extrapolate total values from marginal values. Second, hydrological flow constraints make it difficult to predict or even to characterize the set of feasible trades on a river network (Israel and Lund, 1995). Interconnected tributaries make the decentralized water market a multilateral bargaining game (Saleth *et al.*, 1991) for which the appropriate equilibrium concept is not obvious. Moreover, both valuations and trading opportunities depend on evolving water scarcity and other environmental conditions.

This paper's approach to address these challenges takes advantage of new data on water rights, trades, and agricultural production in the sMDB. It values the water market by (i) estimating irrigated agricultural production functions and then (ii) comparing producer surplus at observed pre- and post-trade water allocations. The assumption that allocative efficiency can be measured using physical input-output data differs from revealed-preference analyses of water markets which use only water trade data (e.g., Regnacq *et al.*, 2016; Hagerty, 2019) and delivers a distribution of trader valuations without assuming that water-trading behavior reveals value, that trading constraints take a specific form, or that the water market is competitive. The study of observed, rather than predicted, market-based reallocation means that the market's estimated value does not rely on a specification of river flow constraints or an equilibrium concept to predict trades. Although these are necessary ingredients for most calibrated models used to value water trade (e.g., Gupta *et al.*, 2018), they are unnecessary here because the data matches producers to rainfall, water rights, and

[2]Valued at average 2018 transaction prices for permanent rights; see Wakerman-Powell *et al.* (2019).

water trades.

First, I estimate production functions—which map irrigation volumes into agricultural output—with new producer-level panel survey data on irrigation and physical output obtained from the Australian Department of Agriculture and local environmental conditions from the Australian Bureau of Meteorology. Productivity differs arbitrarily across farms and crop types, and evolves stochastically as in Olley and Pakes (1996) and Ackerberg *et al.* (2015). Farms anticipate future productivity improvements, taking into account how crop choices and land investments will affect their future production possibilities. Production differs across crop types and depends on water (through irrigation, rainfall, and evapotranspiration) as well as land, labor, and materials. Water scarcity evolves over the growing season: farms first commit to planting decisions and then irrigate in response to within-year rainfall and water price shocks.

A significant concern in estimating the value of water in production is that (unobservably) more productive farms will likely use higher volumes of water, resulting in omitted variable bias (Marschak and Andrews, 1944). Unobserved productivity may also persist over time and exacerbate this endogeneity problem. The empirical strategy combines a standard technique to control for time-varying productivity by inverting static materials demand (Levinsohn and Petrin, 2003; Ackerberg *et al.*, 2015) with a water-rights-based instrument to identify irrigation-output elasticities.[3] Water-sharing rules (or "diversion formulas") evolve nonlinearly across regions and years in the sMDB, which provides a source of variation in irrigation decisions at the farm level. The assumption is that the differential incidence of these allocation rules across farms with different initial water rights is uncorrelated with the annual innovation in farm-level productivity, which I motivate through the mechanical nature of these rules under Schedule E of the 2007 Water Act. The use of this regulatory instrument differs from some recent work that identifies production functions by relying on instruments constructed from endogenous variables, such as lagged input decisions (Ackerberg *et al.*, 2015) or prices (De Loecker *et al.*, 2016; Doraszelski and Jaumandreu, 2018).

In addition to the water rights instrument, the empirical strategy requires that unobserved productivity is multiplicatively separable in production or "Hicks (1932)-neutral."

[3]An alternative method is to estimate the water-yield relationship with an experiment. However, such agronomic experiments are costly, particularly at the scale necessary for generalization (Young and Loomis, 2014, p. 154). Zwart and Bastiaanssen (2004) review more than eighty crop irrigation field experiments, concluding that "the lesson learnt here is that [yield-evapotranspiration] functions are only locally valid and cannot be used in macro-scale planning of agricultural water management." Moreover, output elasticities with respect to irrigation "derived from field experiments are very short run and for single crops, [so] the findings of those experimental studies would be of limited value for long-run policy decisions" (Scheierling and Tréguer, 2018).

While this assumption allows total factor productivities to differ flexibly across farms, crops, and time, it rules out unobserved forms of water-augmenting or water-saving technology. I show that the estimated relationship between irrigation and output is relatively stable under several alternative specifications that allow production functions to differ by period and irrigation efficiency to evolve over time or differ with farm-level irrigation equipment.[4]

Second, I take water trading data—linked to farms but not used to estimate the production functions—as a measure of "realized" market-based water reallocation. This data allows the use of the physical production functions to evaluate profits at observed pre-trade water endowments and post-trade water inputs. The advantage of this model-free approach to measuring reallocation is that it does not require specifying the set of feasible trades or an equilibrium concept for the water market. Therefore, I do not need to model the river flow network, the agents' information at the time of trading, or the search and bargaining protocol of the brokered bilateral market. The disadvantage is that this calculation only recovers the realized value of the market mechanism relative to pre-trade property rights.

The main empirical results indicate that water trading increased irrigated output for the farms in the data by 4–6%, averaged over the sample period 2007–2015. Put differently, output without the water market is the same as it is under an 8–11% uniform reduction in water resources. Given that government climate models predict sMDB surface water resources declining by 11 percent by 2030 in the median scenario under a 1°C temperature rise, this makes the cost of water misallocation comparable to the cost of water scarcity predicted to arise from short-run climate change. The value of trade arises primarily from productivity differentials and land-use decisions across farms.

This average value conceals an increasing and highly convex relationship between water scarcity and the value of an annual water market. Water market access for water-scarce regions and farms creates net gains from trade ranging 8–12% of the value of irrigated agricultural production; in contrast, during years of relative abundance or in regions that receive large water endowments, the realized value of water trading is, in many cases, indistinguishable from 0%. Water scarcity amplifies both the extent of misallocation and its social cost. This result implies that retrospective analyses of the historical value of water trading may understate its prospective benefits unless the historical data includes scarcity and vari-

[4] Appendix B derives a model that allows for unobserved differences in water-augmenting technology across farms, using a control function approach similar to Doraszelski and Jaumandreu (2018). Specifically, it introduces the auxiliary assumption that farms irrigate to maximize static profits under costless water market access. This relationship can then be inverted to control for unobserved water-augmenting productivity. However, the assumption of common water market access is troubling given the presence of unobserved flow constraints on trade. Given that the focus of this paper is to estimate the gains from trade without using revealed preference, I do not take this approach in the main text.

ability comparable to that predicted by climate models. It also implies that climate change may strengthen Dales' (1968) original case for market-based water reallocation and weaken the rationale for the non-market approaches that dominate water resource management in most places outside of Australia.

Next, I study how water market access affects dynamic land-use decisions. To do this, I augment the benchmark model with forward-looking crop choices, consistent with—but not captured by—the production functions. Farms produce with the same technology as the benchmark model and form beliefs about future productivity, prices, and environmental shocks based on current values. The dynamic model of crop adjustment is estimated in two steps. The first step recovers land policy functions and the law governing the evolution of prices and environmental states directly from the productivity estimates and the data. This lets me forward-simulate static profits and obtain each farm i's expected value function, up to unobserved crop-switching costs. The second step then estimates switching costs to rationalize the observed land choices over time as in Bajari *et al.* (2007) and recovers expected value functions with a fixed point contraction.

Like the benchmark model, this augmented model is robust to evolving constraints on trade and does not simulate water prices or calculate general equilibrium water market allocations. Instead, the water allocation under the market is obtained by estimating (partial equilibrium) irrigation policy functions designed to admit a range of possible forms of water market access. A long-run value of water market access is then calculated as the difference between the expected value of the sequence of water market allocations and a sequence of autarky allocations recovered from the distribution of observed permanent rights. Under autarky, farms reduce land allocations to perennials and save land investment costs; however, this adaptation channel lowers the costs of misallocation under autarky by only about one-tenth. Relative to a fixed regime of water rights, long-run water market access induces greater investment in orchards, vineyards, and other perennial crops. The long-run gains of the market for perennial irrigators are approximately 8% of output, with approximately one-fifth of this value arising from greater investment in perennial land relative to autarky.

Related literature. This paper builds on insights from several sets of papers. The results substantiate conjectures that the gains from trade in water rights may be substantial (Dales, 1968; Burness and Quirk, 1979; Libecap, 2011). They corroborate anecdotal accounts (Grafton *et al.*, 2016) and regional-scale Australian computable general equilibrium analyses of the Millennium Drought (Wittwer and Griffith, 2011). This paper's analysis of farm-level water values and trading decisions also complements ongoing regional modeling by the Australian Department of Agriculture to predict water prices under alternative climate futures (Gupta *et al.*, 2018).

The gains from trade found in the Australian context also provide a counterpoint to the recent collection of empirical papers on water markets mentioned earlier, which have led some to conclude that water markets have not realized their potential. This view reflects findings of limited or negative realized gains from trade in places such as California, Chile, and Spain, attributed to transaction costs (Regnacq *et al.*, 2016), local protectionism (Hagerty, 2019; Edwards *et al.*, 2018), noncompetitive conduct (Hantke-Domas, 2017), or liquidity constraints (Donna and Espin-Sánchez, 2018). In contrast to these case studies, this paper shows that a well-developed, advanced market mechanism can reallocate water swiftly and create value when water is scarce yet have a value close to zero in periods of abundance.[5]

The findings that connect the market's value for agricultural producers to changing climate conditions also relate to other work on climate shocks and agricultural markets. Particularly relevant are studies that incorporate irrigation technology (Schlenker *et al.*, 2005; Hornbeck and Keskin, 2014; García Suárez *et al.*, 2019) and agricultural trade (Costinot *et al.*, 2016) into the economics of climate change. The recognition that water markets may provide valuable flexibility to accommodate climate shocks is widespread (e.g., Greenstone, 2008; Debaere *et al.*, 2014; Anderson, 2015). This paper extends these arguments by demonstrating empirically that a water market can serve as a form of *institutional adaptation* to climate change.

More generally, this paper's focus on the efficient allocation of water rights across farms fits within the study of factor misallocation across firms (Caselli and Feyrer, 2007; Hsieh and Klenow, 2009; Adamopoulos and Restuccia, 2014; Asker *et al.*, 2014; Hsieh *et al.*, forthcoming), and, in environmental economics, the design and performance of environmental markets (Anderson and Libecap, 2014).[6] Most closely related is ongoing research in industrial organization focused on the relationship between factor misallocation and market structure, such as studies of deregulation and the efficient assignment of power plants to meet electricity demand in the U.S. (Cicala, 2019), employment law and the allocation of

[5]This paper's focus on trade, given a well-defined set of water rights, also makes it related to but distinct from recent work examining the redefinition (or "adjudication") of historical water rights in the western United States. These event studies of the Snake River Basin (Browne, 2017), the Rio Grande Valley (Debaere and Li, 2017), and the Mojave Desert (Ayres *et al.*, 2019) infer a value of water rights from the differential evolution of land values and agricultural output over time on parcels of land with and without adjudication. In the sMDB, a similar lower bound on the "economic value" of water rights is directly observable as the volume of entitlements on issue multiplied by the average entitlement transaction price, though a welfare interpretation of this number ($15.3 billion in 2018) requires a theory of the social value of the Australian government's aggregate diversion limits ("[t]he price signals that the government gets from the [water] market are 'false,' in the sense that they are largely echoes of its own arbitrary decision about the supply of rights," Dales, 1968, p. 804).

[6]For example, analyses of permit trading in cap-and-trade mechanisms for lead (Kerr and Maré, 1998), sulfur dioxide (Carlson *et al.*, 2000), nitrogen oxide (Fowlie *et al.*, 2012), and carbon dioxide (Borenstein *et al.*, 2018).

workers across French firms (Garicano *et al.*, 2016), and price collusion and global oil extraction (Asker *et al.*, 2019). In connecting factor market institutions to firm-level input-output data, these papers rely on production functions (Marschak and Andrews, 1944; Mundlak, 1961; Griliches and Mairesse, 1998). This paper contributes to the literature on using control function methods for estimating production functions (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg *et al.*, 2015) where unobserved input price variation typically poses a threat to the identification of these models. It overcomes this challenge by using a regulatory source of variation to identify the model.

Outline. The remainder of this paper is organized as follows. Section 2 describes irrigated agricultural production, the institutional background, and the data used. Section 3 then introduces an econometric model of water-based agricultural production in a regulated river system. Sections 4 and 5 describe the main empirical strategy, its key restrictions, and parameter estimates and robustness. Section 6 analyzes the realized gains from trade. Section 7 augments the model to include forward-looking land use and crop choices. Section 8 concludes.

2 Irrigated farms and water trading

This section describes the role of water in agricultural production in the river network and the regulatory and market institutions that dictate river diversions. These production possibilities determine the value of reallocating water across farms, seasons, and years, within the constraints imposed by the natural and regulatory environments. Section 2.1 introduces the data sources used, then Section 2.2 and 2.3 describe the agricultural production process as well as differences across operation types. Section 2.4 outlines the institutions that regulate water rights, river diversions, and trade. Sections 2.5 and 2.6 discuss patterns of water trading in the data indicating the potential sources of gains from trade.

2.1 Data sources

I use four data sources from 2007–2015, taking observations for each of nine Australian fiscal years. First, the primary dataset is new data on water trading from the 2006-7 to 2014-15 annual waves of a rotating panel survey conducted by the Australian Department of Agriculture.[7] The survey collects characteristics, input choices, and production levels from irrigated

[7] Hughes (2011) uses an earlier version of this data to estimate short-run marginal products of water for Department of Agriculture research purposes; this is the first academic study using this data outside of the Australian Department of Agriculture. The survey is conducted by its division of agricultural economists, the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), which collects a rotating random subsample of farms each year. Each data point entails an on-site visit by an analyst lasting four to six

farms, linked with records of water trades and water rights owned. Second, I augment this farm-level input-output data with spatial environmental data, including farm-level rainfall and regional evapotranspiration, measured by the Australian Bureau of Meteorology. Third, I obtain regulatory records of regional water allocation caps from state governments, which I match to farms by region and year.[8] Fourth, I draw on administrative, transaction-level water market price data from the Murray-Darling Basin Authority (MDBA), which regulates the water market, as well as from state governments and private brokers.[9]

2.2 Irrigation, rainfall shocks, and technology

I focus on four inputs in production used by all farms in the sample: land, irrigation, rainfall, and other flexible factors (labor and materials).[10]

Land and scale of operation. The average irrigated farm surveyed produces annual output valued at approximately 700,000 AUD, irrigates 299.7 hectares (ha.), and operates a total area of 569.5 ha. Size varies by operation type, as discussed below, and the size distribution is skewed, with the median farm irrigating 104 hectares of crops or pasture with a total area operated of 190.5 ha. In terms of revenue, these farms are small firms relative to broader industrial classifications; in terms of area operated, these are large farms, with the median farm corresponding to the 75%ile farm size in the U.S. agricultural industry. Farm managers average 50.9 years old.

Irrigation volumes. Irrigation inputs are recorded in megaliters (ML) at the farm-crop-year level. Water costs are significant for farm operations and, in many years, trading accounts for a substantial fraction of water used. The average farm diverts 685 ML for irrigation (Table 1), or roughly the annual consumption of nearly 4,000 average Australian

hours. See Ashton and Oliver (2014, pp. 35–36) for more details on the survey construction.

[8] I use records of total water entitlements and annual allocations, from the New South Wales Office of Water, Victorian Water Register, and the South Australian Department of Environment, Water and Natural Resources, collated by Hughes *et al.* (2016, pp. 45–46).

[9] Market-level records of the price, volume, date, and origin- and destination-region for every water trade between 2008–2015, comprising 80,599 trades after I omit outliers. I obtain these records from the Murray-Darling Basin Authority and the now-defunct National Water Commission. For 2007, which predates federal reporting requirements, I compile price data from various state government registries and a private broker.

[10] The primary capital input here is land (and, for dairy farms, dairy cows). The ABARES survey does record a measure of farm-level financial capital, which sums the value of land owned, equipment, water rights, livestock, and other capital, which averages 3.8 million AUD per farm (s.d., 3.5m). I do not use this financial measure for data quality concerns, because it includes two forms of capital I already account for directly in physical units (land and dairy cows), farms may rent machinery and equipment owned by others, and the approach that I use to assign inputs recorded at the farm level to crop types relies upon static first-order conditions inappropriate for dynamic fixed factors. The inclusion of this financial variable in the production function does not substantively affect results; the coefficient estimated is, in most cases, close to zero. Note that, for counterfactuals that hold capital fixed, the omission of this form of capital from the production function is without loss if it enters multiplicatively separably in production, because the Hicks-neutral productivity shock introduced in Section 3 will capture capital's entire contribution to production.

households (ABS, 2016). River water is the primary source of irrigation for these farms.[11] Valued at average market prices—235 AUD/ML over all years—this implies total irrigation costs equal to 13.8% of revenue from 2007–2015. The average volume of water reallocation, discussed at greater length below, is 17.6% of the average farm's irrigation.

Farms adjust irrigation between years in response to changing economic and environmental conditions. These adjustment possibilities differ across farm types, as I discuss below. Over all farms, the average within-farm standard deviation in irrigation from 2007–15 is 245.8 ML or 32.7% of the mean. Across farms, irrigation levels vary substantially, with an interquartile range more than twice the median, in part reflecting the dispersion in farm sizes discussed above. The scale of operation (area of land irrigated) and farm type (discussed below) can explain about two-thirds of the dispersion in irrigation levels across farms; i.e., the R^2 of a log-linear regression of water on land and farm type dummies is 0.680. Rainfall and farm type predict some, but not most ($R^2 = 0.171$), of the variation in water application rates (ML/ha.).

Rainfall. The total water available for a given crop over the growing cycle also depends on precipitation and evapotranspiration. I obtain both of these data from the Australian Bureau of Meteorology (BoM). Annual rainfall data is matched to each farm with georeferenced data by ABARES analysts. Evapotranspiration is model-derived by the BoM based on soil data and daily rainfall and temperatures (Frost *et al.*, 2016). I construct region-year measures of evapotranspiration, as discussed in Appendix C.

Natural water availability varies substantially across both space and time. Rainfall, reported in Table 2, averages 417 millimeters (mm) but ranges over more than an order of magnitude from 112.2 to 1,950.8 mm. In particular, average yearly rainfall rises to three to four times its drought levels once the drought abates (2010–2012), then diminishes again after 2013. The dispersion (standard deviation) in annual average rainfall across years (169 mm) is comparable to its spatial dispersion across farms within each year (136 mm).

Labor and materials. In addition to land and water, the main remaining variable costs to irrigators are labor and materials. Labor is measured in weeks and includes owner-operator labor, other family labor, and hired labor. Wages, which average 684.19 AUD/week, exhibit moderate variation across farm-years, with a standard deviation of about one-fifth the mean. Materials consist of all fertilizer, electricity, fuel, pesticides, seed, and packing costs that are used by the farm. I exclude services. These expenses, reported in Table A1, comprise 20.4% and 22.3% of all revenue, respectively, or 24.2% and 19.4% for the median farm-year. In

[11] Groundwater accounts for a small share of irrigation in the southern MDB, due to limited volume and salinity (Turral *et al.*, 2005). This is in contrast to many other settings, such as the western United States, where substantial groundwater reserves are essential aspects of irrigated agriculture and water regulation.

estimation, I require that farms have nonzero materials inputs, which holds for 99.6% of farms in the original sample.

2.3 Farm and crop types

Irrigation plays different roles in distinct types of agricultural production. The major irrigators in the sMDB fall into three categories or "operation types": (1) *perennial farms*, primarily growing perennial irrigated crops on orchards or vineyards, (2) *annual farms*, specializing in yearly crops, such as wheat and rice, and (3) *dairy farms*, which grow annual pasture and also some annual crops. In the medium run, farms specialize: 86.8% of farms operate in only one of these three categories.

Within each operation type, farms grow multiple crops. I group crops (e.g., wheat, rice) into four major crop-types: (i) perennial irrigated, (ii) annual irrigated, (iii) annual nonirrigated, and (iv) annual pasture. Irrigation inputs and dynamic adjustment margins differ substantially across these groupings.

This classification of crops into types reflects several aspects of agricultural production (Hughes, 2011). First, adjustment over time differs by crop-type. Perennial irrigators are primarily single-product firms that grow only perennial crops, such as fruits and wine grapes, on orchards and vineyards. These operators have the least flexibility in the short- and medium-run of the three types of irrigators considered. Trees and vines take five to ten years to mature and require continuous water input to keep vines and trees alive (Ashton and van Dijk, 2017). In contrast, annual crops and pasture are replanted and sown at the beginning of each year. The hectares allocated to grow irrigated crops, nonirrigated crops, and irrigated pasture changes on 95.0%, 97.8%, 92.7% of farms from one year to the next, in contrast to 44.3% of perennial operations.

Second, water-intensity varies substantially across crop-types, as shown in Table 2. Most obviously, nonirrigated annual crops require zero irrigation. This creates an important margin of adjustment for annual crop operations, which may plant both irrigated and nonirrigated annual crop-types. Farms often switch land between irrigated and nonirrigated crops, and about half of annual farms grow both irrigated and nonirrigated crops in a given year. Irrigation inputs are very similar across perennial and annual irrigated crops, 5.52 and 5.65 megaliters per hectare on average, but are more than pasture inputs (2.15 ML/ha).

Third, dairy farmers primarily irrigate annual pastures used to feed dairy cows. The average dairy operation surveyed has 511.8 milk cows on hand, with an average within-farm standard deviation in the nine-year sample of 11.6% of the mean, implying moderate adjustments in herd size. I distinguish "annual irrigated pasture" from "annual irrigated crops" both because water application rates differ and because dairy farms growing pasture have an additional outside option to purchase feed directly, which I also observe and include in the production function.

Consistent with these differences in production, Table 2 shows that revenue per hectare differs substantially across the four crop-types, with perennial crops generating higher average revenues per hectare (approximately 12,000 AUD/ha) compared with annual irrigated crops and pasture (8,000 and 6,500 AUD/ha) and with nonirrigated annual crops (400 AUD/ha).

2.4 River regulation and trade

River water in the sMDB is regulated at federal, state, and regional levels. Federal regulation under the 2007 Water Act restricts total diversions for non-environmental purposes to sustain minimum river flows and the integrity of environmental assets. Regional "allocations" (diversion limits) in each year are then determined by state laws and intricate interstate water-sharing agreements according to formulas described below. Appropriative water rights, or "entitlements," are owned by farms, indexed by region, and denominated in proportional shares of the annual regional allocation. Farm-level diversions are metered, and account for 80–90% of all river diversions in the MDB depending on the year.[12]

The total volume of allocations varies in each year according to fixed, regional diversion formulas mandated by Schedule E of the Water Act. Inputs into these formulas include the prior year's dam storage levels, the winter's snowmelt, and expected river inflows calculated from inflow models calibrated with historical climate data. Figure 2A draws realized allocation paths for each region. Realized allocations averaged 65.2% of the volume of issued entitlements over the sample period 2007–2015, with allocations in some regions falling to nearly zero in the worst drought year (2008), and rising slightly above 100% at the end of the drought in 2011.

Water trading requires a legal framework that allows for exchange. A prerequisite is the unbundling of water rights from land; appropriative rights replaced riparian rights in Australia at the end of the 19th century, but individual users could not hold water entitlements until the 1980s (Waye and Son, 2010). Local allocation trade dates to the early 1990s, while permanent entitlement trading rarely occurred outside of local irrigation districts until the federal 2007 Water Act outlawed local prohibitions on permanent trade. Water trades occur

[12]The initial allocation of these rights varies across different regions within the MDB, but generally reflects historical usage (NWC, 2011). The Australian government also owns rights, purchased through the Restoring the Balance Program, a large-scale reverse auction operated by the Commonwealth Environmental Water Office. See Grafton and Wheeler (2018) for details.

bilaterally between farms, with trades typically brokered through water exchange intermediaries. The Australian Competition and Consumer Commission (ACCC), which regulates these intermediaries, reported ad valorem commission rates for nine intermediaries in the range of 1–4% (ACCC, 2010, Appendix 1).

A river network's hydrological connectivity then determines the physical constraints on water trading at a given moment in time. These hydrological flow constraints are a function of infrastructure as well as evolving environmental conditions (MBDA, 2013). The interconnected river system in the sMDB enables reallocation of annual water diversion volumes within flow constraints, which depend on both artificial and natural river flows. River water originates in the Snowy Mountains Scheme, a collection of reservoirs and dams with 22,000 gigaliters of storage capacity. These dams allow river operators to channel water throughout the southern connected zone, subject to the river network's minimum and maximum flow constraints. For this reason, irrigators do not pay conveyance costs to trade water during my sample period; when flow constraints bind, river operators prohibit trade.

In particular, Schedule D of the Murray-Darling Basin Agreement under the Australian Government, 2007 Water Act specifies baseline rules for allowable trades in the sMDB river network based on hydrological constraints, complemented by additional transfer rules specified by the MDBA, state regulators, and local irrigation operators. Water cannot typically be transferred upstream, whereas downstream transfers are limited by upstream dam capacity and channel flow capacity, and large transfers may risk high transmission losses and/or environmental damage. In particular, interregional trading restrictions arise from the location of storages and westward direction of river flow in the map of Figure 1.[13] Flow constraints on interregional trade are automatically triggered as temporary bans when net trade balances reach certain thresholds:[14]

[13]Five major flow constraints are commonly cited by water traders. First, water cannot be transferred upstream into the Murrumbidgee in New South Wales. Second, although storage capacity in the Murrumbidgee (e.g., Burrinjuck Dam in Figure 1) allows the net export of water from Murrumbidgee, net export volumes are ordinarily restricted to 100 GL (NSWDI, 2019), due to concerns with transmission losses. This limit was lifted between 2007–2010. Third, water flows downstream from the Goulburn region in Victoria, so Schedule D requires net trade flow into the Goulburn to be nonnegative. Fourth, while water storage infrastructure (including reservoirs such as Lake Eildon in Figure 1) also allows the Goulburn to sustain a water trade surplus, from 2011, the Victorian government has limited net exports out of the Goulburn to 200 GL, due to concerns with storage spills. Fifth, prior to reaching South Australia, water must pass through the Barmah-Millewa forest on the Victoria/NSW border, the narrowest point of the Murray River. River flow through the Barmah Choke cannot exceed 7,000–10,000 ML/day (MBDA, 2019) without spilling over the banks and onto the surrounding floodplain. This constraint severely limits the delivery of irrigation water to South Australia, and is implemented similarly to the interregional accounts: trade downstream from the Choke requires sufficient matching trade capacity available in the opposite direction ("back trade"). Loch *et al.* (2018) find that river flow constraints on water delivery "appear to have impacted up to 15% of trades in 2015/16" (p. 567).

[14]Constraints bind automatically at either threshold, but are only relaxed after 15 GL of buffer has been restored, meaning that they frequently bind for extended periods of time. For example, between August–September 2015, the 100 IVT limit restriction on flows out of Murrumbidgee was hit. Hughes *et al.* (2016, Figure

> Over time, the MDBA adjusts these accounts via river operation decisions (that is, by physically releasing water from different storages).... As the account balances depend on river operation decisions, the actual volumes of trade that are permitted in any given month or year can vary significantly. (Hughes *et al.*, 2016, p. 32)

These constraints affect trade directly. As the state government of Victoria advises,

> People can seize trade opportunities quickly. If you plan to trade water to the Victorian Murray, you or your broker need to keep an eye on the limits that apply to you. Even when limits are reached, new trade opportunities can reopen during the season if the inter-valley trade balance decreases. (VDEPI, 2014).

In sum, realized constraints on trade depend on natural inflows, diversions for irrigation, and environmental diversions for conservation, as well as other river operation objectives (such as the need to avoid evaporation or storage losses) and state government priorities.

2.5 Water market prices

The most immediate fact in the southern Murray-Darling water market is a clear correlation between annual prices and changing diversion limits (Figure 2B). Water allocation prices fluctuate across years by more than an order of magnitude, peaking at the height of the Millennium Drought at 623.60 AUD/ML in 2008 and bottoming at 22.68 AUD/ML in 2012. Rainfall, superimposed in Figure 3A, and regional water allocations (Figure 2A) exhibit the inverse pattern, peaking at the end of the drought between 2011–2012.

In addition to annual water price fluctuations, interannual water price volatility is also substantial. The standard deviation of average daily water prices across the sMDB, obtained with administrative data on every water market transaction from 2008–2016, exceeds 70% of the mean in an average year. Figure 4 plots daily water spot prices for two illustrative years. The high-frequency nature of this daily market implies that even farms with the flexibility to adjust planting decisions at the start of each year face substantial water price uncertainty.

Although water prices are less dispersed across the river network than across time; however, moderate interregional daily price dispersion exists, with a coefficient of variation of 12% for a median day. Restricting water price comparisons to trades within a region eliminates about half of this dispersion, with the median daily within-region standard deviation of water prices ranging 5–7% of the mean (Table A3).

2.6 Farm-level water-trading patterns

Water trading is an endogenous decision, but it is useful to understand in a strictly statistical sense how the decision to trade correlates with observables. Together with evolving

33) show a considerable divergence between Murrumbidgee and Murray allocation prices that coincides with this restriction, and convergence after it is relaxed.

water scarcity, water trade participation and volumes vary substantially across years. Most striking is the evident co-movement between annual scarcity and reallocation. Figure 3B shows water trade volumes over time against rainfall. Farms trade the largest fraction of their water inputs at the height of the drought: net water purchases comprise 28.7% of irrigation in 2008–9, compared with 12.6% in 2010–15. Trade volumes also closely track water market participation. While nearly half (48%) of the farms in the sample trade annual water allocations in at least one year, participation in each year ranges from 18% to 66% of farms, falling to its lowest level when the drought abates in 2011.

Geography and farm type also predict trade, with farms in the Murrumbidgee region of New South Wales (NSW) substantially more likely to sell and less likely to buy annual water allocations than their counterparts in other regions (Table A4). In contrast, farms in South Australia are much more likely to buy. These patterns corroborate interregional trade flow data that shows South Australia and Victoria are net importers and the Murrumbidgee is a net exporter during the period considered (Hughes *et al.*, 2016, p. 15). Relative to dairy farms and annual croppers, perennial operators are less likely to purchase, and more likely to sell, water allocations, though the pattern reverses for permanent trades (Table A4, columns 3–4).

Time-varying rainfall remains a significant predictor for farm water trading, even after controlling for these permanent differences across years, regions, and operation types. Table 3 shows results from a linear probability model of the indicator for trade regressed against rainfall and water endowments. In particular, farms with relatively less rainfall within a given year are significantly more likely to buy annual water allocations (panel A, column 1). This correlation remains significant for farms with relatively lower rainfall given region (column 2), region-by-year (column 3), and farm fixed effects (column 4), indicating that rainfall shocks are important to explain the differential evolution of trading decisions across farms over time.

Taken together, these correlations indicate that farm-level annual water trading responds to changing environmental conditions and water endowments. These correlations motivate the model below, which (1) controls for rainfall directly in the production function, (2) distinguishes between crop types, and (3) allows unobserved productivity to evolve over time and differentially across farms, given that a farm's operation type, year, rainfall, and permanent characteristics cannot fully explain residual differences in output or water-trading.

3 A model of irrigated agricultural production

To value the water trade flows described above, this section specifies an econometric model of irrigated agricultural production. Farms combine land, irrigation, rainfall, labor, and materials to produce output. Section 3.1 defines each crop type's annual production technology. Given the evolving, intra-annual uncertainty over water prices and environmental shocks in the sMDB water market, Section 3.2 describes planting, growing, and harvest seasons and defines the timing of input choices within the year. Section 3.3 discusses the model's remaining economic restrictions.

3.1 Production

Production cycles occur in each year, indexed by $t \in \{0, 1, 2, \dots\}$, reflecting the annual nature of agricultural production. Farms, indexed by i, inhabit the river basin. I abstract from issues of entry or exit.[15] Each farm i specializes in annual, perennial, or dairy operations, and produces crop-types $c \in \mathcal{C}_i$, where

$$\mathcal{C}_i = \begin{cases} \{\text{irrigated perennial}, \emptyset\} & \text{if } i \text{ is a perennial operation} \\ \{\text{irrigated annual crops}, \text{nonirrigated annual crops}, \emptyset\} & \text{if } i \text{ is an annual crop operation} \\ \{\text{irrigated annual crops}, \text{nonirrigated annual crops}, \text{irrigated pasture}, \emptyset\} & \text{otherwise,} \end{cases}$$

as discussed in Section 2.3.

In year t, farm i allocates hectares of land, denoted by K_{ict}, to crop-types $c \in \mathcal{C}_i$. Given these planting decisions, farms choose irrigation volumes, W_{ict}, and other inputs, X_{ict}. The vector X_{ict} includes labor, X^L_{ict}, and total materials, X^M_{ict}, for all farms, as well as feed, X^F_{ict}, and cows, X^D_{ict}, for dairy farms. Rainfall and evapotranspiration, $E_{it} = (E^R_{it}, E^V_{it})$, are also observed. I assume that E_{it} enters production as net rainwater, defined in the same units as irrigation (ML) as

$$R_{ict} = (E^R_{it} - E^V_{it})K_{ict}, \tag{1}$$

which is the volume of rainwater, net of evapotranspiration, incident to the cropland.

I study aggregate physical output for each crop-type c, defined as $Q_{ict} = \sum_{c_k \in c} P_{c_k 0} Q_{ic_k t}$, from $Q_{ic_k t}$ (tonnes) and $P_{c_k 0}$ (AUD/tonnes) measured for crops c_k in each type c as described in Appendix C. Output for crop-type c on farm i in year t is given by

$$\begin{aligned} Q_{ict} &= e^{\omega_{ict} + \varepsilon_{ict}} F_c(W_{ict}, X_{ict}, K_{ict}, R_{ict}) \\ &\equiv e^{\omega_{ict} + \varepsilon_{ict}} \left(\alpha_c (W_{ict} + \vartheta_c R_{ict})^{\frac{\sigma_c - 1}{\sigma_c}} + (1 - \alpha_c) K_{ict}^{\frac{\sigma_c - 1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_c - 1}\beta_{cW}} \prod_{j \in \{L, M\}} (X^j_{ict})^{\beta_{cj}}, \end{aligned} \tag{2}$$

where ω_{ict} is unobserved productivity and ε_{ict} is measurement error. The specific form of the production function F_c in the second line of (2) is not important for identification.[16] The

[15] The ABARES survey is a random rotating panel, so it is not possible to determine if a farm not surveyed previously that enters the data is an "entrant" or if a farm that ceases to be surveyed has "exited." While some farms change crop choices or owners, fewer convert to non-farmland.

[16] That is, given any functional form, the assumptions in Section 4 will identify F_c. Section 5.4 discusses how the results differ under alternative specifications for F_c.

nested, constant elasticity of substitution (CES) form is chosen to allow the irrigation-output elasticity—crucial to the value of water—to vary flexibly across farms that use different irrigation, rainfall, or land inputs.[17] Note that (2) makes two assumptions to specialize the more general nested CES structure. First, rainwater is taken as a perfect substitute for irrigation, up to the conversion coefficient ϑ_c; second, the elasticity of substitution between labor, materials, and the water-land aggregate, $\mathbb{W}_{ict} \equiv \alpha_c (W_{ict} + \theta_c R_{ict})^{\frac{\sigma_c - 1}{\sigma_c}} + (1 - \alpha_c) K_{ict}^{\frac{\sigma_c - 1}{\sigma_c}}$, is taken as unity.

Crop-type details. The production parameters for irrigated crops in (2) are the distributional share $\alpha_c \in [0, 1]$ of water relative to land, the conversion rate ϑ_c of rainwater to irrigation, the elasticity of substitution $\sigma_c \in [0, \infty)$ between water and land, and the output elasticities β_{cj} of water, labor, and materials, or $\theta_c = (\alpha_c, \vartheta_c, \sigma_c, \beta_{cW}, \beta_{cL}, \beta_{cM})$ for irrigated crops, and $\theta_c = (\alpha_c, \sigma_c, \beta_{cW}, \beta_{cL}, \beta_{cM})$ for nonirrigated crops.

In addition to irrigated pasture, milk production on dairy farms also depends on purchased feed and the number of dairy cows. Given that milk production is limited by the number of cows and the pasture/feed required to maintain them, I impose a zero elasticity of substitution between these two factors, extending (2) to

$$F_c = \min \left\{ \left((1 - \alpha_F) \mathbb{W}_{ict}^{(\sigma_F - 1)/\sigma_F} + \alpha_F (X_{ict}^F)^{(\sigma_F - 1)/\sigma_F} \right)^{\frac{\sigma_F}{\sigma_F - 1}}, \frac{\alpha_D X_{ict}^D}{1 - \alpha_D} \right\}^{\beta_{cW}} \prod_{j \in \{L, M\}} (X_{ict}^j)^{\beta_{cj}} \quad (3)$$

for $c =$ dairy. To recover the Leontief form in (3) from the data, I assume that cows are not overfed in equilibrium, i.e.,

$$\left((1 - \alpha_F) \mathbb{W}_{ict}^{(\sigma_F - 1)/\sigma_F} + \alpha_F (X_{ict}^F)^{(\sigma_F - 1)/\sigma_F} \right)^{\frac{\sigma_F}{\sigma_F - 1}} \leq \frac{\alpha_D}{1 - \alpha_D} X_{ict}^D, \quad (4)$$

for all i, t, and $c =$ dairy, which is plausible given that herd size is predetermined by the time pasture is irrigated and feed purchased. This avoids estimation of the feed conversion ratio $(1 - \alpha_D)/\alpha_D$, although it can be recovered directly from the ratio of X_{ict}^D to the pasture/feed composite if (4) holds with equality. Consequently, the production parameters to estimate for $c =$ dairy are $\theta_c = (\alpha_c, \vartheta_c, \sigma_c, \alpha_F, \sigma_F, \beta_{cW}, \beta_{cL}, \beta_{cM})$.

Hicks-neutrality. The main restriction in (2) is that the unobservable ω_{ict} is multiplicatively separable from F_c, or "Hicks (1932)-neutral."[18] Through this unobserved term, total

[17] An implicit restriction in (2) is that output depends only on the total volume of irrigation applied throughout the year. This restriction reflects the annual resolution of the production data. In practice, the timing of irrigation throughout the season affects crop yields (Flinn and Musgrave, 1967). For total irrigation volume to be a sufficient statistic for output, the assumption in this setting is that for a given farm, conditional on crop choices, the intra-seasonal irrigation timing is optimal. This reflects the sophisticated irrigation scheduling schemes used by most farms (Ashton and Oliver, 2014). However, it rules out intra-seasonal gains from water trading that allow producers to better time water inputs (Beare *et al.*, 1998).

[18] The aggregation Q_{ict} from $\{Q_{ic_k t}\}_{c_k \in c}$ makes F_c defined in (2) a representation of the convex hull of the

factor productivity differs arbitrarily across farms and crop-types, allowing the marginal product of water to differ across otherwise identical farms in each year. Hicks-neutrality rules out unobserved differences in irrigation efficiency at the farm level, which may be a crucial aspect of the response to water scarcity. The inclusion of rainfall in the production function controls directly for one source of farm-year-specific differences in the marginal value of irrigation. For robustness, I also consider other forms of F_c that include differences in irrigation efficiency that take a known form, e.g., by allowing α_c or v_c to depend on t or other observed farm characteristics such as the value of the farm's irrigation equipment.

An alternative solution is to take one of the hypotheses this paper seeks to test—whether farms optimize irrigation levels given observed water market prices—as an auxiliary model assumption. Then it is conceptually straightforward to extend the procedure below to relax Hicks-neutrality and introduce unobserved water-augmenting technology estimated from the optimal irrigation moments (Doraszelski and Jaumandreu, 2018; Berry and Haile, 2018). Some aspects of this exercise are nontrivial, so I derive identification and construct an estimator for this alternative model in Appendix B. Because the focus of this paper is to study the efficacy of the water market without imposing assumptions on water market participation, search costs or trading constraints, I do not take this approach in the main text.

3.2 Timing of agricultural calendar

An important feature of the water market is within-year water price and rainfall uncertainty that resolves after planting decisions but before irrigation choices. I incorporate this feature with a growing season of length $b \in [0, 1]$. Farms plant at $t-1$, commit to irrigation at $t-b$, and then harvest output given by (2) at t. This timing over planting, growing, and harvest seasons, summarized in Figure 6, is based on my conversations with irrigators in the sMDB.

In each year, the agricultural calendar starts with the planting season, approximately April to June. At $t-1$, farms plant the season's crops by allocating land K_{ict} to each $c \in \mathcal{C}_i$. Dairy farms may also adjust their herd size, X^D_{ict}. The farm's information at $t-1$ includes its productivity at $t-1$, its "predetermined" inputs K_{ict} and X^D_{ict}, and all of its past decisions, prices, and water endowments. I denote this information set as

$$\mathcal{F}_{i,t-1} = (\{\omega_{ic\tau}, W_{ic\tau}, R_{ic\tau}, X_{ic\tau}, K_{ic\tau}, K_{ic,\tau+1}, P_{ic\tau}\}_c, \rho_{i,\tau+1}, \overline{W}_{r\tau}, P^W_{i\tau}, P^L_{i\tau})_{\tau \leq t-1}. \quad (5)$$

production possibilities frontiers of each of the crops c_k that farm i might consider growing. The assumption that F_c does not depend on c_k means that crop-switching within a given c can affect the curvature of F_c only through input combinations, so that all misspecification will be transmitted through ω_{ict}. One concern is that changing final crop price ratios will lead to different crop mixes to attain the same F_c (Diewert, 1978).

At $t-b$, the planting season (approximately June–October), farms observe

$$\mathcal{F}_{i,t-b} = (\mathcal{F}_{i,t-1}, E_{it}, P^W_{it}, \overline{W}_{rt}, \{\omega_{ic,t-b}\}_c),$$

decide water inputs W_{ict}, and, if $c =$ dairy, purchase feed, X^F_{ict}. Finally, farms learn their final productivity ω_{ict} and crop prices P_{ict} for each c, as well as wages $P^L_{X,it}$, then finalize labor X^L_{ict} and annual materials X^M_{ict} decisions and harvest crops Q_{ict} with some measurement error ε_{ict} (November–March). The cycle then begins anew.

The estimator below is not sensitive to every detail of this timing and information structure. Irrigation can occur at any time $t-b$ for $b \in [0,1]$; for example, farms can commit to irrigation alongside planting or make this decision at the same time as hiring labor and/or finalizing materials. Moreover, although it is natural to suppose that $\overline{W}_{rt}, E_{it} \in \mathcal{F}_{i,t-b}$ given that I use $\overline{W}_{rt}$ and E_{it} as instruments for time-$(t-b)$ irrigation decisions, my approach also yields consistent estimates if farms instead have some common prior over $\overline{W}_{rt}$ and E_{it} at $t-b$, provided that such beliefs correlate with realized levels. The water price that i faces, P^W_{it}, may be unobserved to either the econometrician, the farm, or both. The empirical strategy primarily requires that (i) land decisions are predetermined, $K_{ict} \in \mathcal{F}_{i,t-1}$; (ii) irrigation responds to $\overline{W}_{rt}$ and is not chosen strictly after the final time-t materials decision based on new information not known at t; and (iii) labor and materials decisions are made with knowledge of time-t prices and productivity.

3.3 Other economic assumptions

The main focus of this paper is water trading and the role of irrigation in production. I impose the following restrictions on the remaining economic environment, necessary both for the empirical strategy and for valuing water reallocation, which requires interpreting the physical output given by (2) in economic terms.

Market structure. Agricultural producers are small; agricultural commodities exhibit minimal differentiation relative to many other consumer goods; and trade is relatively free across countries (Mundlak, 2001). Australia exports about two-thirds of its agricultural output. I therefore assume that farms take crop prices P_{ict} as given for each c.

Labor and materials. Labor is mobile, agricultural wages do not differ substantially across farms (coefficient of variation of 0.207 across farm-years), and other inputs such as seed, fertilizer, and electricity are relatively undifferentiated and likely to be supplied competitively. I therefore assume farms take wages and materials prices $P_{X,it}$ as given. I observe expenditures on materials rather than physical quantities, and assume that in each year, materials prices do not differ across farms. Observed wages can and do vary across farms, but the empirical strategy below requires that materials or labor costs do not differ unobservably across firms.

I also suppose that labor and materials are set to maximize annual profits, as in Levinsohn and Petrin (2003), or, equivalently, to minimize the costs of producing expected output (Doraszelski and Jaumandreu, 2019). This rules out all dynamic aspects of these factors, such as labor adjustment costs that depend on past levels, or current materials inputs that affect next year's productivity. The assumption on labor can be relaxed (Ackerberg *et al.*, 2015), but delivers three main advantages in my setting: (i) increased precision, because the labor elasticity can be estimated in a first stage; (ii) a microfoundation for using elasticity-weighted revenue shares to apportion labor (observed at the farm level) to crop-types; and (iii) a closed-form representation for the response of labor demand to water reallocation.

The assumption on materials, however, is crucial to my empirical strategy. It means that static materials demand under the timing of Section 3.2 admits a nonparametric demand function for materials,

$$X_{ict}^{M} = \chi_{ct}\left(W_{ict}, R_{ict}, K_{ict}, X_{ict}^{L}, X_{ict}^{F}, P_{ict}, \omega_{ict}\right), \tag{6}$$

which I use, under the additional statistical assumptions below, to control for productivity's persistence over time. Note that neither water prices nor wages appear in χ_{ct}; this is because water and labor are set before intermediate materials, and only the levels of irrigation and labor inputs are output-relevant. Farms may face different water prices or employ different water trading strategies and water market access may differ unobservably across farms and over time. This is important given that actual water prices evolve over the course of the season and differ across the river network (Section 2.5) and that it is difficult to rationalize the large fraction of farms who do not trade in a given year (Section 2.6) with a continuous model of water demand. While (6) requires optimal materials, it does not require that farms optimize annual irrigation volumes. The time-t materials choice takes as given the irrigation decisions at $t-b$, but does not restrict the form that these irrigation decisions take.

4 Empirical strategy

The empirical strategy to identify and estimate the multifactor production function in Section 3 must account for the dynamic dependence of irrigation, labor, materials, and land decisions on productivity. First, Section 4.1 introduces statistical assumptions that allow me to control for the expected component of productivity by inverting a static materials demand function. This control function is conditioned on other current inputs, which both avoids the problem of functional dependence (Ackerberg *et al.*, 2015) and allows water prices, constraints on water trading, and market access to vary unobservably across farms. Second, I assume that regional water-sharing rules, interacted with a farm's predetermined water rights, are orthogonal to the innovation in productivity from $t-1$ to t as described in Section 4.2. This exclusion restriction shares with other dynamic methods the virtue of allowing the instrument to be correlated with past levels of productivity or permanent differences across farms or regions. The restriction differs from other models that use lagged decisions (Ackerberg *et al.*, 2015) or prices (Doraszelski and Jaumandreu, 2018) to identify flexible factors. Section 4.3 discusses how the water rights instrument weakens some of the key restrictions on water market structure and irrigation decisions that are implicit in the use of endogenous objects (such as past decisions or prices) as instruments. Section 4.4 describes the first-order conditions used for the remaining two flexible factors and Section 4.5 specifies the estimating equations.

4.1 Assumptions

The following allows observed materials to be used as a proxy for unobserved productivity:

Assumption A1. *Materials demand χ_{ct}, given in (6), is strictly increasing in ω_{ict} for all c and t.*

Assumption A1 is both an economic restriction—that firms make static, optimal materials decisions that differ only through the arguments of (6)—and a statistical restriction that unobserved productivity is scalar and continuously distributed. The strict monotonicity of materials demand in productivity follows from static optimality if firms take materials and final goods prices as given and F_c is everywhere strictly increasing in X^M_{ict} (as in the nested CES form (2) when $\beta_{cM} > 0$).

The estimator below identifies the production function using instruments orthogonal to the productivity innovation, defined for each i, c, and t as

$$\xi_{ict} = \omega_{ict} - \mathbb{E}[\omega_{ict}|\mathcal{F}_{i,t-1}]. \tag{7}$$

Given that $\mathcal{F}_{i,t-1}$ as defined in (5) is large and contains information that cannot be observed in any finite panel, any study of (7) requires some restriction on the dependence of ω_{ict} on $\mathcal{F}_{i,t-1}$. In particular, to guarantee the existence of the Markov decomposition

$$\begin{aligned} \omega_{ict} &= \mathbb{E}[\omega_{ict}|\mathcal{F}_{i,t-1}] + \xi_{ict} \\ &\equiv \psi_{ct}(\omega_{ic,t-1}) + \xi_{ict}, \end{aligned} \tag{8}$$

which allows (7) to be recovered from the path of $(\omega_{ict})_t$ with ψ_{ct}, I assume the following.

Assumption A2 (Markov)**.** *Productivity* $(\omega_{ict})_{t\geq 0}$ *evolves as an exogenous, first-order Markov process for each* i*,* c*, and* t*.*

Assumption A2 allows for a wide family of productivity processes. In particular, it makes no distributional assumption on the cross-sectional productivity innovation, ξ_{ict}. Its key restrictions are twofold. First, although farms anticipate future productivity and make long-run decisions given these beliefs, they cannot influence the evolution of productivity over time. For example, a farm's past irrigation levels, materials inputs, and labor decisions cannot affect its current or future productivity. Second, A2 rules out higher-order productivity processes, such as forms of soil depletion that unfold over several years. This first-order restriction is nontrivial because of A1: although any finite-order Markov process admits a first-order representation in an appropriately extended state space, such an extension is inconsistent with A1's single-index restriction.

4.2 Water rights instrument

Even when the anticipated component of productivity ψ_{ct} is known (or controlled for as in Section 4.5), the flexible factors W_{ict} and X_{ict} will depend upon $\xi_{ic,t-b}$ and ξ_{ict}, which will bias a production function estimated without instruments. The timing of agricultural input decisions given in Section 3.2 suggests several potential sources of variation in water inputs, though some of these (e.g., water prices) are likely endogenous. I use

$$Z^W_{ict} = \begin{cases} \rho_{i,t-1}\overline{W}_{rt} & \text{if } c = \text{annual irrigated crops, pasture, or perennial crops} \\ E^R_{it} & \text{if } c = \text{annual nonirrigated crops.} \end{cases} \tag{9}$$

For irrigated crops, the instrument for water is the interaction of annual regional allocations with that farm's previous year's water endowments. The interaction between allocations and previous endowments increases the variation from the region-year to the farm-year, allowing the treatment intensity to increase with a predetermined measure of an irrigation operation's size. For nonirrigated crops, the instrument for water is farm-specific rainfall, which provides exogenous variation in (rain)water applied to the crops conditional on the predetermined land decision K_{ict}.

The exclusion restriction for (9) is that water allocation rules $\overline{W}_{rt}$ satisfy

$$\mathbb{E}[\rho_{i,t-1}\overline{W}_{rt}\xi_{ict}|\mathcal{F}_{i,t-b}] = 0 \tag{10}$$

for each i, c, and t. This assumption is satisfied if a farm's productivity innovation is conditionally independent of the differential incidence of river diversion caps on farms with different predetermined water rights. The justification for this assumption is the mechanical nature of diversion formulas.[19] The primary threat is that the current and historical environmental conditions that determine allocation caps directly affect productivity, and do so differentially across large and small irrigation operations. To some extent, this concern is mitigated by controlling for regional rainfall, evapotranspiration, and soil moisture.

Furthermore, the assumption rules out the possibility that $\overline{W}_{rt}$ affects other, unobserved farm decisions, such as crop-mix choices. If these decisions are transmitted through ξ_{ict}, then (10) will not hold. However, note that $\overline{W}_{rt}$ may be correlated with either $\omega_{ic,t-1}$ or even $\mathbb{E}[\omega_{ict}|\omega_{ic,t-1}]$ without violating (10), since this information is contained in $\mathcal{F}_{i,t-b}$.

Another concern is that river extraction caps may be determined by political processes that react to productivity shocks at the farm level within the year. Although water market institutions reflect agricultural interests to an important extent, both the rule-based legislation implied by Schedule E and my conversations with river operators at MDBA suggest that regulatory agencies follow rigid water-sharing formulas rather than responding directly to agricultural industry interest groups.

4.3 Discussion of identifying variation

Identifying a production function requires variation in each flexible input that is both *consistent* with the restriction that demand for materials χ_{ct} is common across all farms growing c at t and *exogenous*. While a perfect control for ω_{ict} solves the endogeneity problem in (2) for static inputs (Olley and Pakes, 1996), perfectly controlling for ω_{ict} raises functional dependence issues, which is why Ackerberg *et al.* (2015) build moments based on the productivity innovation ξ_{ict} that control only for expected productivity $\psi_{ct}(\omega_{ic,t-1})$. However, moments based on the productivity innovation require stronger identifying assumptions—or better instruments—to avoid reintroducing the prospect of endogeneity. In this sense, while Olley and Pakes (1996) solved the endogeneity problem but introduced concerns of consistency, Ackerberg *et al.* (2015) obtain variation consistent with the model at the expense, potentially, of reintroducing an endogeneity problem.

First, note that functional dependence is not a concern despite the use of a common materials demand function. This is because, like Ackerberg *et al.* (2015), materials demand in (6) depends on other flexible inputs, so these other flexible inputs may differ arbitrarily across firms, provided that they are not chosen strictly after the final time-t materials decision with new information not known at t. Here, W_{ict} may vary across otherwise identical farms due

[19] While it would be ideal to use the direct and exogenous shifters of the nonlinear quantity schemes directly, quantity-setting models themselves are confidential.

to water allocations, rainfall, water prices, and any unobserved constraints on trade realized between planting and irrigation decisions (as described in the agricultural calendar in Section 3.2). Such variation affects output *only* through W_{ict}, does not influence the optimal choice of X^M_{ict} conditional on W_{ict}, and is therefore consistent with the control function.[20,21]

Second, and more importantly, the water rights instrument given by (9) provides observed variation in irrigation outside of the model, which opens the possibility for weakening some of the standard assumptions used to identify production functions (Griliches and Mairesse, 1998). Crucially, the water rights instrument replaces the Ackerberg *et al.* (2015) ("ACF") assumption,

$$\mathbb{E}[\xi_{ict}|\mathcal{F}_{i,t-1}] = 0, \tag{11}$$

with the alternative exclusion restriction used in this paper,

$$\mathbb{E}[\mathbf{Z}'_{ict}\xi_{ict}] = 0, \tag{12}$$

where $\mathbf{Z}_{ict} = (1, \zeta_c(Z^W_{ict}, K_{ict}, \widehat{\Phi}_{ic,t-1}))$, and $\widehat{\Phi}_{ic,t-1} = \ln Q_{ic,t-1} - \varepsilon_{ic,t-1}$ is a control for time-$(t-1)$ productivity defined below in Section 4.5. Equation (12) is not nested in the ACF moments because $\overline{W}_{rt}, E_{it} \notin \mathcal{F}_{i,t-1}$. However, the existence of an instrument in (10) allows the ACF assumption to be strictly weakened, in the sense that if (10) holds, then (11) implies (12). In particular, by using (12), it is not necessary to assume that

$$\mathbb{E}[W_{ic,t-1}\xi_{ict}] = 0, \tag{13}$$

which is implied by (11) and commonly used to justify the use of lagged inputs.

Lagged inputs are commonly used as instruments because they live in $\mathcal{F}_{i,t-1}$, and therefore are excluded by (13) under the ACF moments, and because observed input choices are highly correlated over time (Ackerberg *et al.*, 2007, p. 4223). While this argument is econometrically valid, its economic justification is less clear. The restriction $\mathbb{E}[\xi_{ict}|\mathcal{F}_{i,t-1}] = 0$ is both a statistical assumption on the process ξ_{ict} and an economic restriction on $\mathcal{F}_{i,t-1}$, which includes all economic decisions and equilibrium objects prior to t. This exclusion restriction is especially problematic given that identification also requires a source of variation in inputs across firms, but that many of the natural sources of variation cited by Ackerberg *et al.* (2015) as potential solutions to functional dependence, such as unobserved adjustment costs or autocorrelated firm-level input prices, seem likely to violate (11).

[20] In contrast, this variation will affect materials demand through water inputs, and is therefore inconsistent with a Levinsohn and Petrin (2003) unconditional control function that does not depend on current inputs, unless all such variation is observed and included in the control function.

[21] The argument for the variation that identifies the labor elasticity in this model is similar. Observed wages $P^L_{X,it}$ vary across farms, but affect output, and enter into χ_{ct}, only through labor inputs X^L_{ict}. This wage variation precludes collinearity by creating the possibility that two otherwise identical farms, each choosing materials according to (6), use different labor inputs at the same $(\omega_{ict}, W_{ict}, R_{ict}, K_{ict}, P_{ict})$.

To see this issue, consider (13). Suppose, for example, irrigation involves unobserved adjustment costs. If adjusting irrigation is costly, then a farm's irrigation at $t-1$ should depend on its beliefs about the distribution of productivity t—which suggests $\mathbb{E}[W_{ic,t-1}\xi_{ict}] \neq 0$.[22] The ACF moments therefore restrict the extent to which irrigation decisions are forward-looking (or restrict the distribution of ξ_{ict}). Alternatively, suppose that $W_{ic,t-1}$ is correlated with W_{ict} through autocorrelated input prices. Then (13) implies that the distribution of ξ_{ict} cannot affect water prices at $t-1$. Either water prices at $t-1$ do not depend on beliefs over t, or water prices at t are independent of productivity. Either restriction is problematic in a setting where water prices depend on forward-looking water storage decisions and ξ_{ict} is a source of the gains from trade.

In contrast to instruments constructed from endogenous variables such as lagged input decisions or prices, the water rights instrument is constructed from regulatory variation outside of the model. In particular, this allows irrigation $W_{ic,t-1}$ to depend on i's unobserved beliefs over the distribution of ξ_{ict} in unobserved ways. Serially correlated, unobservable, and endogenous trading constraints may shift or constrain W_{ict}, as long as $\rho_{i,t-1}\overline{W}_{rt}$ remains relevant to the irrigation decision. Irrigation can entail adjustment costs and this dynamic choice can depend on the variance of ξ_{ict}. Although the distribution of productivity must evolve exogenously, water prices and water market outcomes may be endogenous and depend on current or future distributions of ξ_{ict}; just not allocation rules, $\overline{W}_{rt}$, or predetermined rights $\rho_{i,t-1}$. This is still a strong assumption, but relies primarily on variation generated by the underlying institutions, rather than restrictions on equilibrium decisions.

4.4 Identification of other flexible factors

Finally, I recover relationships between output, labor, and materials, and infer the unobserved assignment of labor and materials to crops for multi-crop farms, using first-order conditions implied by the continuously differentiable production function and the facts that labor and materials are static factors selected optimally at t.

Materials and labor. Materials' contribution to output is not separately identified from the control using only moments constructed from $\mathbb{E}[\varepsilon_{ict}] = 0$ and $\mathbb{E}[\xi_{ict}|\mathcal{F}_{i,t-1}] = 0$. This functional dependence problem results in collinearity even when the only two flexible inputs are labor and materials (Gandhi *et al.*, 2016). To identify materials' contribution to F_c separately from χ_{ct}, I use the fact that (2) and the assumption of static optimality implies

[22] Controlling for $\hat{\omega}_{ic,t-1}$ does not alleviate these concerns; there is no reason why $W_{ic,t-1}$ should not depend on higher moments of the distribution of $\omega_{ict}|\omega_{ic,t-1}$. Note that this concern is only avoided for the predetermined input K_{ict} by assumption in (12); the moment implies that investment only depends on the *level* of current productivity; Griliches and Mairesse (1998) discuss this restriction.

that β_{cM} is identified from the first-order conditions,

$$\mathbb{E}[\varepsilon_{ict}|\mathcal{F}_{it}] = \mathbb{E}[\ln \beta_{cj} - \ln(P^{j}_{X,it} X^{j}_{ict}) + \ln(P_{ict} Q_{ict})|\mathcal{F}_{it}] = 0 \quad (14)$$

for $j = M$. This contrasts with Ackerberg *et al.* (2015), who do not estimate β_{cM}, and instead assume that output is Leontief in materials and a "value-added" production function that does not depend on materials, and that materials are never the limiting factor for production. In addition, while the farm-specific wages that I observe are possible instruments for X^{L}_{ict}, I recover β_{cL} using (14) for $j = L$, because (14) is more efficient and does not require assuming that $\mathbb{E}[P^{L}_{X,it} \xi_{ict}] = 0$.

Multi-crop farms. Irrigation volumes, land allocations, and physical output are observed at the crop level, but labor, materials, and water rights only at the farm level. Apportioning labor, materials and water rights to crop type is not a problem for the 65.5% of farms growing only a single crop type. To address this for the remaining 34.5% of farms, I apportion farm-level labor and materials inputs to crop types using elasticity-weighted realized revenue shares.[23] This imputation is implied by profit-maximization if labor and materials are uniquely assigned to crops and measurement error ε_{ict} does not depend on c for a given i and t.

4.5 Estimation procedure

The primitives for each c are the production technology θ_c, productivity distribution $\{\omega_{ict}\}$, and Markov transition operator ψ_{ct}. The algorithm proceeds in two steps, after recovering labor and materials elasticities from first-order conditions. As in Olley and Pakes (1996), I never recover χ^{-1}_{ct} directly; rather, in a first stage, I estimate the sum $\ln F_c(\cdot) + \omega_{ict} = \Phi_{ict}$,

$$\Phi_{ict} = \Phi_{ct}\left(X^{M}_{ict}; W_{ict}, R_{ict}, K_{ict}, X^{L}_{ict}, P_{ict}\right), \quad (15)$$

to eliminate the measurement error ε_{ict}. I estimate (15) by regressing $\ln Q_{ict}$ on transformations of

$$t, X^{M}_{ict}, W_{ict}, R_{ict}, K_{ict}, X^{L}_{ict}, \text{ and } P_{ict},$$

to obtain $\widehat{\Phi}_{ict}$ and the implied measurement error $\hat{\varepsilon}_{ict}$. I approximate this nonparametric regression with a cubic polynomial; polynomial splines (i.e. with $k > 0$ knots) as in Chen and Pouzo (2012) yield similar results.

[23] These elasticities are estimated by c using the revenue shares of single-product firms. If the elasticities do not differ across c, the unweighted revenue share can be used directly (e.g., De Loecker and Collard-Wexler, 2015). An alternative to using input maximization is to estimate F_c for single-crop farms, adjust for selection into single-cropping, then proceed as in De Loecker *et al.* (2016).

The second stage estimates the remaining parameters of the production function and the evolution of productivity, (θ_c, ψ_c), using

$$\mathbb{E}\left[\left(q_{ict} - f_{ict} - \psi_c(\widehat{\Phi}_{ic,t-1} - f_{ic,t-1})\right) \otimes \mathbf{Z}'_{ict}\right] = 0, \tag{16}$$

where lowercase letters denote natural logs, and f_{ict} to denote f_c evaluated at i's observed inputs in year t. I then estimate (16) using two-step generalized method of moments with an algorithm inspired by Ackerberg *et al.* (2015, Appendix A4) to concentrate out ψ_{ct} as described in Appendix A.1.

5 Estimates

I now report the estimated production function parameters, distribution of productivities, and curvature of production with respect to water. I then show that estimated productivity is statistically significant predictor of annual water-trading behavior, argue that the implied shadow values of water seem reasonable relative to existing evidence on agricultural water demand, and consider robustness to various alternative specifications.

5.1 Production technologies

Benchmark estimates of the main production function parameters are reported in Table 4. The main estimates in the first row of Table 4 show that water plays a significant role in the production of crops for irrigated farms in the southern Murray-Darling Basin, with average implied irrigation-output elasticities of 0.277, 0.210, and 0.087 for irrigated perennial crops, annual crops, and pasture, respectively. Irrigation elasticities $\frac{\partial \hat{f}_c}{\partial w}$ evaluated at observed input combinations differ meaningfully across farms; the interdecile range of elasticities for perennial operations, for example, is $[0.124, 0.381]$. That $\frac{\partial \hat{f}_c}{\partial w}$ differs across input combinations reflects the flexibility of the nested CES functional form in (2). In particular, allowing rainwater to substitute for irrigation plays an important role in these elasticity estimates. Tables A11—A13 show that restricting rainfall's presence in the production function to total factor productivity (i.e., $\vartheta_c \equiv 0$) inflates the estimated $\frac{\partial \hat{f}_c}{\partial w}$ by more than one-third.

The estimated elasticities of output with respect to the irrigation-land-rainwater composite, $\hat{\beta}_{cW}$, also differ across c—0.625 for perennial operations, 0.484 for annual irrigated, and 0.727 for irrigated pasture. This suggests that the technical differences in these operations (discussed in Section 2.3) translate into meaningful differences in the irrigation-output relationship for each crop type. For each c, the estimated distributional parameters α_c lie strictly in $(0, 1)$.

Labor and materials also play significant roles in production: $\hat{\beta}_{cL} + \hat{\beta}_{cM}$ ranges from 0.25 (for $c =$ dairy) to 0.66 (for annual crops). The relative importance of these two factors differs by operation, with output in perennial operations being roughly one-and-a-half times more elastic to labor than annual operations, consistent with the higher labor inputs required to maintain more sophisticated irrigation operation schemes. The estimates of the role of labor in production are in line with existing agricultural production function estimates. For example, the review in Mundlak (2001) finds output elasticities with respect to labor ranging from 0.25 to 0.45.

The returns to scale for dairy are close to unity but for perennial and annual operations, where $\sum_j \hat{\beta}_{cj} = 1.164$ and 1.142, exceeds one. This may reflect unobserved constraints on large-scale expansion (e.g., total landholdings) that prevent farms from growing the size of their operations to profit from increasing returns from scale.

The distributions of estimated productivities for each crop type, $\hat{\omega}_{ict} = \widehat{\Phi}_{ict} - \hat{f}_{ict}$, are reported in Table 5. In this setting, where productivities are used to infer the (in)efficient allocation of resources by agents without knowledge of ε_{ict}, the distinction between $\hat{\omega}_{ict}$ and the traditional Solow (1956)-residual $\hat{\omega}_{ict} + \varepsilon_{ict} = q_{ict} - \hat{f}_{ict}$ is crucial: the latter is a more appropriate primitive to measure welfare-relevant dispersion in shadow water prices.

For each c, the estimated $\{\hat{\omega}_{ict}\}$ lie within a narrow range, with standard deviations of 0.44, 0.50, and 0.70 for irrigated perennial, annual, and dairy types considerably below their respective means. In contrast, over all i, the standard deviation of farm-level productivity $\{\hat{\omega}_{it}\}$ is 2.71, where $\hat{\omega}_{it} \equiv \ln \sum_c e^{\hat{\omega}_{ict}} \frac{P_{ict} Q_{ict}}{\sum_c P_{ict} Q_{ict}}$. Finally, productivity persists across farms over time, with estimated persistence significantly above zero but also below one. Across irrigated crop types, productivity is most persistent for perennials—autocorrelation of $\hat{\varrho}_c = 0.639$, compared with $\hat{\varrho}_c \in \{0.504, 0.384\}$ for annual and dairy—consistent with the discussion in Section 2.3 that perennial operations have relatively fewer options for annual adjustment in production possibilities.

5.2 Productivity predicts trade

Given that estimated productivities did not use data on water trading, it is possible to test whether productivity predicts water trade by regressing an indicator for buying (selling) water allocations on the estimated productivities and other controls.

Panels A and B of Table 6 show that more productive farms buy annual water allocations and less productive farms sell water, consistent with economic intuition. These regressions include the same controls as the descriptive regressions from Table 3. The positive relationship between net trade and estimated productivity survives controls for year, region, region-by-year, and farm-type fixed effects, suggesting that the estimated differences in unobserved technology matter for interpreting water-trading behavior. A one-standard-deviation increase in $\hat{\omega}_{it}$ from its mean increases the conditional probability that i buys annual water allocations in year t by 0.104–0.141 across specifications, or 32–44% of the mean, and decreases the probability of sale by 0.065–0.101, or 33–52% of the mean. Table 7 shows that water trading also positively correlates with the productivity innovation at t, conditional on $\hat{\omega}_{i,t-1}$, with a one-standard-deviation increase in $\hat{\xi}_{it}$ increasing the probability that i buys annual allocations at t by 8–12% and decreasing the sale probability by 0–9%.

Perhaps surprisingly, the productivity estimates do not predict permanent trading, which I measure as the sign of $\rho_{it} - \rho_{i,t-1}$ for farms observed at least twice. Panels C and D of Table 6 show no statistically significant relationship between a farm's estimated productivity and either its decision to buy or to sell permanent rights. There are a variety of explanations for this result. Statistical insignificance could reflect sparse data, given that permanent trades are imputed from lags and fewer farms trade permanent rights than annual allocations. It may also suggest that in the presence of a liquid annual market, initial endowments do not affect real output (Coase, 1960).

5.3 Water shadow values

Crucial to the value of water reallocation is the derived shadow value of water in production. Using the estimated production functions, farm-crop-type-specific productivities, and realized crop prices, I define each farm i's "shadow value" function for water at t and crop c as

$$\hat{\lambda}_{ict}(W, X_{ict}, K_{ict}, R_{ict}) = P_{ict} e^{\omega_{ict}} \mathbb{E}[e^{\varepsilon_{ict}}] \frac{\partial F_c(W, X_{ict}, K_{ict}, R_{ict})}{\partial W}, \tag{17}$$

which is purged of measurement error ε_{ict}. The rest of this paper omits the constant $\mathbb{E}[e^{\varepsilon_{ict}}]$ in notation where relevant. Equation (17) captures the marginal effect of an additional megaliter of irrigation on expected time-t revenue. If variable irrigation costs do not differ across farms and water at t does not affect i's profits in years $s > t$, then (17) also measures the relative value of marginal river diversions to farm i at t.[24]

Figure 7 plots $\hat{\lambda}_{ict}(W; \cdot)$ for each c, with bands showing the interquartile and interdecile ranges of the function $\hat{\lambda}_{ict}$ over i and t. The figures show substantial dispersion across farms within each c (through ω_{ict}, P_{ict}, R_{ict}, and other inputs) and rapidly diminishing marginal returns in W. This convexity of production in water scarcity will affect the value of trade, which is a function of both $\partial F_c / \partial W$ and $\partial^2 F_c / \partial W^2$.

[24] In the context of the model of Section 3, the restriction that water at t does not affect i's profits for years $s > t$ only rules out current water inputs from affecting future input costs, since the production function in (2) is already restricted to depend only on current inputs, and Assumption A2 precludes $(W_{ict})_t$ from affecting ω.

Table 8 and Figure 8 report the distribution of shadow values (17) evaluated at observed inputs, $\hat{\lambda}_{ict}(W_{ict}, X_{ict}, K_{ict}, R_{ict})$. Most variation in shadow values occurs between farm types. Perennial operations, such as vineyards or orchards, have the highest estimated values, with the median marginal value of water for perennial farms close to the 90$^{\text{th}}$-percentile market-clearing water price. Irrigated annual crops and pasture have much higher values than nonirrigated crops but values that are significantly less than perennials.

How economically reasonable are these estimated shadow values? The dispersion across operation types and years may not be surprising given the wide range of demand elasticities for irrigation documented by agricultural economists (Scheierling *et al.*, 2006). The relatively higher estimated values for perennials, in particular, align with earlier estimates for the sMDB (Bell *et al.*, 2007; Hughes, 2011). The estimates for annual irrigated and pasture operations are also comparable to county-level estimates from García Suárez *et al.* (2019), who find marginal values of irrigation in the midwestern United States averaging \$196/acre or about \$205 AUD/ML.[25]

At observed input levels, the last column of Table 8 shows that shadow values for irrigated farms are similar to average observed water transaction prices discussed in Section 2.5 but not used in estimation. Furthermore, the average estimated shadow value of (rain)water for nonirrigated annual crops is less than the average market price of water, potentially rationalizing the decision of farms not to irrigate this land. While it is not possible to draw conclusions from this comparison without imposing additional structure on water market access and participation, given that this water price data is not used in estimation and that the shadow values of water are not calibrated to equalize the marginal products of water across farms, the comparison suggests the estimated production technologies are not unreasonable.

5.4 Robustness

The benchmark production function allows for arbitrary Hicks-neutral productivity, but constrains the parameters (θ_c, ψ_c) to be constant across t. Given the substantial changes in environmental conditions and aggregate water market prices over 2007–2015, Tables A6, A7, and A8 test the stability of the production function parameters over time. First, I consider differential irrigation efficiency across farms by replacing W_{ict} in (2) with $\exp(\zeta_{ict})W_{ict}$. I study common water-augmenting technical change across farms, which takes the form

[25] García Suárez *et al.* (2019) estimate a county-level biomass yield function in the United States from 1960–2007 and its elasticity with respect to a county's fraction of irrigated land. They find marginal values of irrigation averaging \$196/acre in 2007 USD, or 821.40 2015 AUD/ha. Even with identical crops grown, this number is not directly comparable to my estimates without a measure of the irrigation application rate. I recover \$205 AUD/ML using approximate average application rates for Nebraska, Texas, and Arkansas of 4 ML/ha.

$\zeta_{ict} = \zeta_t$. I also consider irrigation efficiency that differs with observed irrigation equipment, $\zeta_{ict} = \zeta_{\text{irrig}}\mathbf{1}\{i \text{ has irrigation equipment at } t\}$, an observable described in Appendix A.2. In addition, I partition the data into two periods (2007–2011 and 2012–2015) and estimate the entire production function (θ, ψ) separately for each period.

A separate concern is that the shape of the production function given by (2) may unduly constrain the substitution possibilities between factors. Table A9 and A10 test the sensitivity of results to the elasticity of substitution between water and land. The vast literature on agricultural production functions in general (Mundlak, 2001) provides limited guidance for the specification of irrigation in these functions (Scheierling *et al.*, 2014). I focus on two functional forms commonly used in agricultural economics that do not impose a constant elasticity of substitution between water and land: translog (García Suárez *et al.*, 2019) and quadratic (Shoengold and Zilberman, 2007) forms. The irrigation elasticity estimates are less precise, given that both forms double the dimension of θ_c, but not dissimilar from the main results. In particular, they imply similar shadow water value distributions. Table A9 also contains results from two important special cases of (2). First, Cobb-Douglas, where $\sigma_c = 1$ (Mundlak *et al.*, 2012); second, a Leontief relationship where $\sigma \to 0$.[26]

Finally, given the particular importance of rainfall for the value of water, Tables A11, A12, and A13 show the sensitivity of (θ_c, ψ_c) to the specification of rainfall and evapotranspiration, considering cases in which rainfall does not substitute directly for irrigation ($\vartheta_c = 0$) and is a perfect substitute ($\vartheta_c = 1$), in contrast to the benchmark estimated ϑ_c.

6 Valuing the water market

I now apply the estimates of Section 5—which used irrigation volumes and crop yields at the farm level to recover production technologie—to the water trading data not used in estimation. I focus on three main results from the market-based water reallocation from the initial pre-trade endowments described in Section 6.1. First, water trading reduces dispersion in estimated shadow water values across farms, although considerable dispersion remains (Section 6.2). Second, and most importantly, integrating over the observed trade flows, the efficiency gains from this reallocation are substantial (Section 6.3). Third, this value is concentrated in water-scarce years and water-scarce regions (Section 6.4).

[26] Although the latter case is commonly used in agricultural settings (Berck and Helfand, 1990), if $\sigma_c = 0$, then F_c is not smooth and not identified without additional assumptions; hence, I assume that farms never over-irrigate in equilibrium, which lets me recover β_{cW} using W_{ict} as a sufficient statistic for $\min\{W_{ict}, \frac{\alpha_c}{1-\alpha_c}K_{ict}\}$.

6.1 Pre-trade water allocations

The central exercise of this paper is to contrast observed irrigation under the water market with alternative distributions of water endowments. I construct three "pre-trade" allocations:

1. Input levels without annual allocation trades, $W_{ict}^{a,\text{annual}} = W_{ict} - \Delta_{ict}^{\text{annual}}$. Allocation trades are observed as net purchases $\Delta_{it}^{\text{annual}}$ at the farm level. I allocate trade volumes for farms growing more than one irrigated crop in proportion to realized water application rates, so that $\Delta_{ict}^{\text{annual}} = \frac{W_{ict}}{\sum_{c'} W_{ic't}} \Delta_{it}^{\text{annual}}$. The results are insensitive to allowing each water-trading farm i to allocate trade volumes optimally across c.

2. Input levels without permanent trades, $W_{ict}^{a,\text{permanent}} = W_{ict} - \Delta_{ict}^{\text{permanent}}$. Entitlements are denominated as proportional shares, so I construct realized volumes in megaliters using allocations $\overline{W}_{rt}$ as $\Delta_{it}^{\text{permanent}} \equiv (\rho_{it} - \rho_{i,t-1})\mathbf{1}_{i \in r}\overline{W}_{rt}$, again downscaled to c for multicrop farms in proportion to realized water application rates.

3. Input levels without annual or permanent trades: $W_{ict}^{a,\text{total}} = W_{ict} - (\Delta_{ict}^{\text{annual}} + \Delta_{ict}^{\text{permanent}})$.

These reallocations involve 13.3%, 5.0%, and 14.4% of total irrigation volumes, respectively.

The results in the next three sections analyze the value of the market mechanism as it operates in the world relative to these pre-trade endowments. Although pre-trade rights were determined for a variety of historical reasons, many of which predate trade in the permanent market (Turral *et al.*, 2005), it is possible that the distribution of pre-trade endowments would have been different had agents not anticipated the introduction of the water market. The measured gains from annual trading are potentially less likely to be confounded by this issue, given that some of the value of annual trading may arise from misallocation that even a first-best allocation of permanent water rights at $t-1$ cannot eliminate.

6.2 Marginal values and trade

Water trades that reduce misallocation shift resources from lower to higher-value farms. If market-based water allocation increases agricultural output, then water buyers should have higher pre-trade shadow values for water than the sellers with whom they trade. Although the data does not match buyers with sellers, Figure 10 reports the distributions of farm-level pre-trade shadow values conditioned on net annual allocation trade balances. The values are constructed with pre-trade endowments and de-meaned by average annual estimated shadow values for comparability across years. Panel A shows that water-buying farms have pre-trade shadow values that are more dispersed and on average greater than water-selling farms; Panel B shows that the first distribution stochastically dominates the second. Consequently, on average, the market reallocates water resources to more marginally productive farms, though the considerable overlap of these two distributions indicates the presence of residual constraints on trade.

In an efficient water market without trading frictions, shadow values should converge across traders with nonzero post-trade endowments. Figure 11 shows that the total effect of water trading on the distribution of estimated shadow values across all farms is small. A more apparent effect is evident during the drought (2007–2009, Figure 11), but substantial dispersion in shadow values remains. Given that only about half of farms trade water in any given year, Table 9 quantifies these effects for water-trading farms only using ordinal dispersion measures as in Syverson (2004). The estimates show that water trading reduces the interquartile range of the distribution of shadow values for water-trading farms in each year except 2007. However, none of these declines are statistically significant at a 10%-level except for 2011.

6.3 Total gains from trade

The marginal analysis above indicates that water market trade flows conform to some of the economic predictions that arise from efficient trade. Measuring the cost of pre-trade misallocation requires an infra-marginal calculation to integrate the distribution of shadow value functions over the set of observed trades. Using (2), I define farm i's expected profits at the time of harvest t, conditional on water inputs $W_{it} \equiv \{W_{ict}\}_c$, as

$$\Pi_{it}(W_{it}) = \max_{X_{it}} \sum_c P_{ict} e^{\omega_{ict}} F_c(W_{ict}, X_{ict}, K_{ict}, R_{ict}) - P_{X,it} \cdot X_{ict} - \Gamma^W_{it}(W_{it}), \tag{18}$$

which is revenue minus the costs of labor and materials, $P_{X,it} \cdot X_{ict}$, and irrigation, $\Gamma^W_{it}(W_{it}) = P^W_{it} \sum_c W_{ict}$, where P^W_{it} denotes the average price in i's region in year t.[27] The social value of producing in year t using equilibrium water inputs rather than pre-trade water endowments—what I call the "realized gains from trade"—is then

$$\text{GFT}^{(k)}_t = \sum_i \Pi_{it}(W_{it}) - \sum_i \Pi_{it}(W^{a,k}_{it}) \tag{19}$$

[27] Assuming this form of irrigation costs requires that (a) W and $W^{a,k}$ entail the same total conveyance costs and (b) variable irrigation costs differ across farms only through water prices. The former seems to be a reasonable approximation for the marginal reallocations considered given the discussion of conveyance costs in Section 2.4 (Note that any fixed irrigation costs incurred by farms both in equilibrium and k-autarky vanish from (19)). When the market clears in the observed sample ($\sum_i W_{it} = \sum_i W^a_{it}$) and P^W_{it} does not differ across i, then P^W_{it} also vanishes from the calculation of the gains from trade in (19). Because the ABARES survey is not an administrative dataset and does not contain all water traders, this means I account for trade surpluses and deficits at market prices. This makes (19) a lower bound on the gains from trade in years where $\sum_i W_{it} > \sum_i W^a_{it}$, and an upper bound in years where $\sum_i W_{it} < \sum W^a_{it}$.

for $k \in \{\text{annual}, \text{permanent}, \text{both}\}$. Note that using (18) to evaluate the gains from trade also strengthens the assumption of Section 3 that farms take crop prices as given to the assumption that the water market does not affect final crop prices. This rules out general equilibrium effects, such as countercyclical increases in the prices of water-intensive crops during water-scarce years, which will arise to the extent that sMDB agricultural output influences Australian or world prices.

Table 10 reports the total gains from trade, $\text{GFT}^{(k)} = \sum_t \delta^t \text{GFT}_t^{(k)}$, under each regime k, taking $\delta = 1 - \bar{r} = 0.957$ from the real market interest rate $\bar{r}$ faced by Australian farms from 2007–15.[28] The total gains from trade equal 6.2% of total irrigated output from 2007–2015, with most of the value from annual trading (5.7%) relative to permanent trades. Confidence intervals for the total gains, [3.3%, 7.8%] at the 90% level, clearly bound these gains from zero.[29] This is notable because nothing in the model prevents the estimated gains from trade from falling below zero. The net benefits of the market are concentrated in the years during the drought (2007–2009), in South Australia, and for perennial and annual irrigation operations rather than dairy farms (Table A15). In years in which water is abundant, 2011–2013, zero gains from trade cannot be rejected and the lower bounds of the 90% confidence intervals lie strictly below zero.

How does this benchmark estimate of the realized gains from the water market compare with water scarcity from expected climate change? Consider a uniform reduction in water resource availability across all farms that would reduce output by $\text{GFT}^{(k)}$. This number, -11.8% for $k = \text{both}$, is the *equivalent (uniform water) variation* of a price change that eliminates the market. For comparison, the most recent climate models run by the Australian government for the southern MDB predict median declines of surface water availability of 11 percent by 2030 (MDBA, 2019). Average annual rainfall and river runoff in the sMDB is expected to decline between [0, 9%] and [2, 22%], respectively, for 1°C of global warming, with estimates for 2°C "roughly twice as large" (CSIRO, 2012, pp. 31). Declining surface water availability is, of course, only one aspect of climate change, which alters higher moments of river inflow and rainfall distributions, as well as a range of other agronomically relevant variables such as temperature.

[28]Table A14 shows results for $\delta = 1$ as well as results that constrain labor and materials adjustment or hold both of these inputs fixed.

[29]Constructed as the 5%-95%-ile interval block-bootstrapped at the farm level. The confidence interval reflects both parametric uncertainty, with (θ, ψ) re-estimated for each draw, and uncertainty over realized trades.

6.4 Water scarcity and the value of water market access

A vital question in the context of climate change is whether regions receiving particularly low water allocations in a given year (relative to other years) realize greater gains from water market access. Here, I focus only on the annual allocation market, given that most of the trading occurs in this market and that these trades are likely to be most responsive to evolving water scarcity within the year.

Table 11 is the basis for this paper's claim that the value of a water market is increasing and convex in water scarcity. Taking regional water allocations $\overline{W}_{rt}$ as a proxy for water scarcity, Panel A stratifies (19) into within-region annual quantiles of realized allocations. The value of water trading is substantial for water-scarce quantiles, but declines dramatically for regions receiving more abundant annual surface water endowments.

Similarly, it is possible to test whether farms with below-median rainfall E^R_{it} have larger estimated gains from annual water trading. The gains from trade for below-median-rainfall farms (9.9%) is more than twice that of above-median rainfall farms (3.4%). Stratifying by quartile shows that the gains from trade for farms in the bottom rainfall quartile are 14.9%, compared with 7.5, 4.6, and 1.7% for the second, third, and fourth quartiles.

Across space, a similar pattern emerges. Panel C considers the value of trade for spatial differences in water scarcity, stratifying farms within each year by quartile of that year's rainfall. Gains from the annual market are 8.4% for farms with rainfall below that year's median, compared with only 3.5% for farms receiving above-median rainfall in that year. The within-farm differences in rainfall over time (Panel D) are similar, with gains of 9.6% for below-median within-farm rainfall versus 2.8% for above-median within-farm rainfall.

7 Forward-looking land investments and water market access

The benchmark empirical strategy allows unobserved productivity to differ across farms, crops, and years. It identifies the productivity distribution in the presence of dynamic decisions over land, crops, and other fixed factors, and recovers the efficiency of annual water reallocation holding these decisions fixed. But climate change will occur over long time horizons and create permanent changes for agricultural producers, and institutions for water management are infrequently revised. Permanent water market access alters the expected allocation of water resources across farms, which should influence forward-looking land-use decisions, such as investments in water-intensive crops such as orchards.

This section contrasts the long-run value of a water market with permanent water autarky. Section 7.1 augments the model of Sections 3–4 by specifying land-use costs and extending the informational assumption made on productivity to the process governing the evolution of prices and environmental shocks. Section 7.2 derives an estimator for land costs from the dynamic program that characterizes land-use decisions. Section 7.3 discusses the parameter estimates, and Section 7.4 recovers value functions and future land investments to study the long-run value of the sMDB mechanism.

7.1 Water market access and forward-looking land use

Under the water market, farm i's profits at the time of harvest t can be written as

$$\Pi(K_{it}, \omega_{it}, \mu_{it}) = \Pi_{it}\left(\mathcal{W}(K_{it}, \omega_{it}, \mu_{it})\right), \tag{20}$$

which is (18) evaluated at an irrigation function $\mathcal{W}(K_{it}, \omega_{it}, \mu_{it})$ that depends on land $K_{it} = \{K_{ict}\}_{c\in\mathcal{C}_i}$, productivity $\omega_{it} = \{\omega_{ict}\}_{c\in\mathcal{C}_i}$, and a farm state vector

$$\mu_{it} = (\rho_{i0}, \overline{W}_{rt}, P^W_{it}, E_{it}, P^X_{it}, \{P_{ict}\}_{c\in\mathcal{C}_i}, \mathcal{C}_i).$$

The farm state vector μ_{it} includes water market conditions—i-specific water rights, allocations, and water prices—as well as rainfall, evapotranspiration, wages, crop prices at t, and i's permanent operation type. Similarly, profits at an autarky allocation W^a_{it} are a function of $(K^a_{it}, \omega_{it}, \mu_{it})$,

$$\Pi^a(K^a_{it}, \omega_{it}, \mu_{it}) = \Pi_{it}(W^a_{it}) \tag{21}$$

for each i and t. The production function and productivity estimates from Section 5 suffice to calculate (20) and (21) for any given $\mathcal{W}$, W^a, and (K, K^a, μ). For example, the value of the water market in Section 6 for each farm i is the difference between (20) and (21), letting $\mathcal{W}$ equal observed irrigation and taking $K^a_{it} = K_{it}$ for all i and t.

This section endogenizes land-use trajectories with and without the water market, $(K_{it})_{t\geq 0}$ and $(K^a_{it})_{t\geq 0}$ respectively, as optimal forward-looking decisions given by functions κ and κ^a of i's current state,

$$s_{it} = (K_{it}, \omega_{it}, \mu_{it}).$$

Under the water market, i's land decisions κ maximize its expected value V,

$$V(s_{i0}; \kappa; \gamma) = \mathbb{E}_{i0}\left[\sum_{t=0}^{\infty} \delta^t \left[\Pi(\kappa^t(s_{i0}), \omega_{it}, \mu_{it}) - \Gamma\left(\kappa^t(s_{i0}), \kappa^{t-1}(s_{i0}); \gamma\right)\right]\right], \tag{22}$$

given investment costs, $\Gamma(K_{it}, K_{i,t-1}; \gamma)$, parametrized by γ. The value V^a for operation i under autarky is defined as (22) evaluated at Π^a rather than Π. Then the infinite-horizon value of the water market is given by

$$\text{GFT}_\infty = \sum_i V(s_{i0}; \kappa; \gamma) - V^a(s_{i0}; \kappa^a; \gamma). \tag{23}$$

This long-run value of the market is consistent with the earlier gains-from-trade measure (19), which is the special case of (23) where $\kappa^a = \kappa$, and μ does not evolve over time. Evaluating the more general version of (23) requires the irrigation policy $\mathcal{W}$ defined above, as well as land investment costs Γ and the evolution of the farm state vector μ.

Land investment costs. Land investment costs differ by i's operation type, as well as random fixed costs drawn by i in each t at the time of planting decisions. All farms adjusting land under cultivation incur quadratic adjustment costs that differ with the direction of adjustment and by the crop types discussed in Section 2.3. Perennials adjust land relatively infrequently (with 44% of farm-years making nonzero adjustments) and incur fixed costs for nonzero adjustment. Annual and dairy farms do not incur fixed costs (more than 95% of these farms adjust land in each year). Total costs then take the form of a piecewise polynomial of degree two; for a vector of land adjustments $x_c = K_{ict} - K_{ic,t-1}$ over c,

$$\Gamma(x;\gamma) = \sum_c \mathbf{1}(x_c > 0)\left[\tilde{\gamma}_{c1} + \gamma_{c2}x_c + \gamma_{c3}x_c^2\right] + \mathbf{1}(x_c < 0)\left[\tilde{\gamma}_{c4} + \gamma_{c5}x_c + \gamma_{c6}x_c^2\right] \tag{24}$$

The vector γ includes adjustment cost parameters, γ_{cj} for $j \in \{2,3,5,6\}$, which differ by c, but are otherwise common to all i and t, as well as the distributional parameters for the random fixed costs $\tilde{\gamma}_{c1}$ and $\tilde{\gamma}_{c4}$. Each perennial operation i draws an investment fixed cost, $\tilde{\gamma}_{c1} \sim \mathcal{N}(\overline{\gamma}_{i1}, \gamma_{\sigma 1}^2)$, and divestment fixed cost, $\tilde{\gamma}_{c4} \sim \mathcal{N}(\overline{\gamma}_{i4}, \gamma_{\sigma 4}^2)$, for $c =$ perennial in each t. These costs are drawn at $t-1$, prior to the decision K_{it}. The value function $V(s_{i,t-1};\kappa;\gamma)$ given in (22) is defined in expectation over these cost shocks and κ is the stochastic decision rule prior to the realization of $\tilde{\gamma}$. Only perennials incur fixed costs, so $\tilde{\gamma}_{c1} = \tilde{\gamma}_{c4} = 0$ for $c \neq$ perennial. The parameters necessary to calculate the expectation of (24) are then $\gamma = (\{\{\gamma_{cj}\}_{j\in\{2,3,5,6\}}\}_c, \{\overline{\gamma}_{i1}\}_i, \{\overline{\gamma}_{i4}\}_i, \gamma_{\sigma 1}^2, \gamma_{\sigma 4}^2)$.

In addition, I only consider reallocation of existing land under agriculture to alternative crop types, and restrict land allocations to lie within the maximum land irrigated over all years t, $\sum_c K_{ict} \leq \max_t \sum_c K_{ict}$ for each i. Modeling the rural real estate market lies outside the scope of this paper; at the farm level, the opportunities for expansion onto contiguous parcels are likely to be highly dependent upon endogenous arrival of neighbors willing to trade.

Evolution of states. The conditional expectation in (22) depends on the evolution of the farm state vector. To ensure that farm i's beliefs about its state μ_{it} at $t-1$ can be written as a function of observables at $t-1$, I assume:

Assumption A3 (Markov state)**.** *For every i and t, the conditional distribution of μ_{it} at $t-1$ is given by $H(\mu_{it}|\mu_{i,t-1})$.*

Assumption A3 is a natural extension of the information structure that farms have been assumed to hold about their productivity (Assumption A2) to the market prices and environmental shocks that they face. It allows me to recover state transitions directly from the data, up to unobservable water market access. Economically, Assumption A3 means that farmers in the sMDB treat last year's crop and water prices as sufficient statistics for predicting current prices and do not expect the law governing the conditional price distribution to shift over time. This assumption will not be satisfied if, for example, some farms have private information about wages or crop prices, form beliefs over longer-run averages, do not update their beliefs in each year, or anticipate longer-run structural changes in markets for labor or agricultural goods.

The policy rule κ for observed land decisions under water market access then solves the following dynamic stochastic program:

$$\kappa(s_{i,t-1}) = \arg\max_{K} \ \mathbb{E}_{i,t-1}\left[\Pi(K, \omega_{it}, \mu_{it}) - \Gamma(K, K_{i,t-1}; \tilde{\gamma}) + \delta V(K; \kappa; \gamma)\right]. \tag{25}$$

Note that κ is a random variable that depends on the distribution of $\tilde{\gamma}$. Integrating the values attained by κ over the distribution of cost shocks gives the value function (22). The empirical strategy below relies on (25) to estimate γ from the function κ implied by the observed path $(K_{it})_{t\geq 0}$, then uses a version of (25) with Π^a constructed from the initial distribution of water property rights to obtain land allocations under autarky to calculate (23).

7.2 Estimation

Estimating the dynamic gains from trade requires θ, ω, and ψ estimated in Section 5, as well as three new primitives: irrigation policies $\mathcal{W}$, the distribution H of state transitions, and investment cost parameters γ. I recover $\mathcal{W}$ and H directly from the data. To estimate γ, I follow Hotz *et al.* (1994), Bajari *et al.* (2007), and Pakes *et al.* (2007) to forward-simulate value functions given (a) a land policy function recovered from observed data and (b) alternative policies. The estimator for γ then rationalizes each irrigator's land use and investment strategy relative to paths not taken. Appendix A.3 describes the procedure in detail. The approach involves three steps.

Step 1. Recover irrigation $\mathcal{W}$ and state transitions H. Irrigation policy functions are necessary to infer irrigation inputs under alternative states s. I estimate irrigation functions for each c as functions of the observed components of s, by regressing water irrigated on state variables. The estimating equations,

$$W_{ict} = \mathcal{W}_c(s_{it}) + \vartheta_{ict}, \tag{26}$$

for each c, are based on flexible polynomial approximations $\mathcal{W}_c$. Two restrictions of (26) are worth highlighting. First, the specification of $\mathcal{W} = (\mathcal{W}_c)_c$ requires that dynamic aspects of irrigation decisions arise only through s and do not, for example, depend on past irrigation levels. Second, given that s_{it} includes water market access through P^W_{it}, in practice, I estimate (26) by including region fixed effects and summary statistics of the water price distribution of regional water transactions (mean and variance). The irrigation policy estimator is consistent if the unobserved component of irrigation decisions (including water market access), ϑ_{it}, is uncorrelated with the observable components of s_{it} used to estimate (26).

To recover the state transitions given by $H(\mu_{it}|\mu_{i,t-1})$, I estimate a linear model $\mu_{it} = M\mu_{i,t-1} + v_{it}$. The estimates of $\hat{M}$ are given in Table A18. Then I define $\hat{H}(\mu|\mu_-)$ as the law of

$$\mu = \hat{M}\mu_- + \hat{v}, \tag{27}$$

using draws of $\hat{v}$ from the joint empirical distribution of residuals, $\{\mu_{it} - \hat{M}\mu_{i,t-1}\}_{i,t}$.

Step 2. Recover land decisions. To extend observed land decisions to future states s, I estimate policy functions that differ by operation type and depend flexibly on s. The dynamic program (25) implies that optimal land use decisions $\kappa : s \mapsto \{K_c\}_{c\in\mathcal{C}_i}$ are functions of $s = (K_-, \omega, \mu)$ and differ across i only by operation type, as

$$\kappa(s) = \begin{cases} \kappa_{\text{perennial}}(s) & \text{if } s \text{ is perennial} \\ \kappa_{\text{annual}}(s) & \text{if } s \text{ is annual} \\ \kappa_{\text{dairy}}(s) & \text{otherwise.} \end{cases}$$

The land use decision for all perennial operations can be written as

$$\kappa_{\text{perennial}}(s) = \begin{cases} K_- + \overline{\kappa}(s) & \text{with probability } p_+(s) \\ K_- - \overline{\kappa}(s) & \text{with probability } p_-(s) \\ K_- & \text{else.} \end{cases}$$

I estimate the adjustment probabilities $p_\pm(s)$ with a probit model, first for the unconditional probability of $\{K_{ict} \neq K_{ic,t-1}\}$, and then for the conditional probability of investment, $\{K_{ict} > K_{ic,t-1}\}$, given $\{K_{ict} \neq K_{ic,t-1}\}$. Denoting these predictions with $\hat{p}_1$ and $\hat{p}_2$, respectively, the investment and divestment probabilities are $p_+(s) = \hat{p}_1\hat{p}_2$ and $p_-(s) = \hat{p}_1(1-\hat{p}_2)$. In principle, $p_\pm(s)$ should be a very flexible function of s; however, the data limits the power of these regressions and I estimate a linear probit model in $\ln(s)$. I estimate the adjustment width $\overline{\kappa}(s)$ by fitting the observed $|K_{ict} - K_{ic,t-1}|$ to transformations of

$$K_{ic,t-1}, \hat{\omega}_{ic,t-1}, E_{i,t-1}, W_{ic,t-1}, \text{ and } P_{ic,t-1}, \text{ for } c = \text{perennial}$$

and region fixed effects, specifically using a quadratic polynomial in $\ln(s)$ for all perennial i and t such that $K_{ict} \neq K_{ic,t-1}$. Annual and dairy operations make decisions jointly over more than one $c \in \mathcal{C}_i$. All annual operations share a policy function $\kappa_{\text{annual}}(s)$ obtained from regressing $\{K_{ict}\}_{c\in\mathcal{C}_i}$ on a quadratic polynomial in natural logarithms of

$$K_{ic,t-1}, \hat{\omega}_{ic,t-1}, E_{i,t-1}, W_{i,t-1}, \text{ and } P_{ic,t-1}, \text{ for } c \in \mathcal{C}_i.$$

Dairy operations use a function $\kappa_{\text{dairy}}(s)$ that predicts $\{K_{ict}\}_{c\in\mathcal{C}_i}$ from these observables as well as the number of cows, X^D_{ict}.

Step 3. Estimate switching costs. To search for a γ that rationalizes (25), I recover (22) by forward-simulating expected profits in each period with κ, F, ω, and $\mathcal{W}$ using ψ and H. Assumption A3 allows the expectation in (22) to be approximated by numerical integrating payoffs over $\prod_{t=1}^{T} d\hat{H}(\mu_{it}|\mu_{i0})$, simulating $\hat{H}$ with (27).

By revealed preference, the optimality of κ implies that

$$V(s;\kappa;\gamma^\star) \geq V(s;\kappa';\gamma^\star)$$

at the true parameter $\gamma^\star$ for any κ' and all initial conditions s. The Bajari *et al.* (2007) estimator searches over parameters γ to minimize profitable deviations from the optimal policy:

$$Q(\gamma) = \sum_i \sum_{\ell=1}^{L} \mathbf{1}\left\{V(s_{i0};\kappa;\gamma) < V(s_{i0};\kappa_\ell;\gamma)\right\} \|V(s_{i0};\kappa_\ell;\gamma) - V(s_{i0};\kappa;\gamma)\|, \quad (28)$$

using a sufficiently rich set of L alternative policies $\{\kappa_\ell\}_{\ell=1}^{L}$. In practice, I construct alternative policies by perturbing the policy functions with $\vartheta_\ell \in [0.75, 1.25]$, so that $\kappa_\ell = \vartheta_\ell \kappa(s)$, first along equilibrium investment choices, and then by adjusting investment (then, divestment) probabilities. I take $\|x\| = \mathbf{1}_{x>0} \ln(1+x)$ to penalize profitable deviations in proportion to the natural logarithm of the deviation's value.

To efficiently recover i-specific mean switching costs for perennials, I also use the additional moments implied by the optimal land rule in (25),

$$p_+(s) = \mathbb{P}_{\tilde{\gamma}}\left(V(s;\kappa_+;\gamma) - \tilde{\gamma}_{ic1} \geq \max\{V(s;\kappa_-;\gamma) - \tilde{\gamma}_{ic4}, V(s;\kappa_0;\gamma)\}\right)$$

and similarly for divestment,[30] where value functions conditional on investment, divestment, or doing nothing are denoted by $V(s;\kappa_j;\gamma)$ for $j \in \{+,-,0\}$.[31] These value functions $V(s;\kappa_+;\gamma)$, $V(s;\kappa_-;\gamma)$, and $V(s;\kappa_0;\gamma)$ are constructed alongside $V(s;\kappa;\gamma)$ during the forward-simulation by perturbing the initial land condition with $\overline{\kappa}(s_{i0})$ and $-\overline{\kappa}(s_{i0})$. Because $\tilde{\gamma}_{i1}$ and $\tilde{\gamma}_{i4}$ are Gaussian, $\mathbb{P}_{\tilde{\gamma}}(k)$ admits an exact functional form.[32] I also fix $\gamma_{\sigma 1} = \gamma_{\sigma 4} = 10^5$.

[30] $p_-(s) = \mathbb{P}_{\tilde{\gamma}}\left(V(s;\kappa_-;\gamma) - \tilde{\gamma}_{c4} \geq \max\{V(s;\kappa_+;\gamma) - \tilde{\gamma}_{c1}, V(s;\kappa_0;\gamma)\}\right)$.

[31] E.g., $V(s_{i,t-1};\kappa_+;\gamma) \equiv \mathbb{E}_{i,t-1}\left[\Pi(K_{i,t-1} + \overline{\kappa}(s_{i,t-1}), \omega_{it}, \mu_{it}) - \Gamma(K_{i,t-1} + \overline{\kappa}(s_{i,t-1}), K_{i,t-1}, \gamma) + \delta V(s_{it};\kappa;\gamma)\right]$.

[32] To further simplify the order statistic and make $\mathbb{P}_{\tilde{\gamma}}$ linear in $\overline{\gamma}_{i1}$ and $\overline{\gamma}_{i4}$, I also assume a zero probability for both divestment and investment being preferred to doing nothing; i.e., that $\{V(s;\kappa_+;\gamma) - \tilde{\gamma}_{i1} \geq V(s;\kappa_0;\gamma)\}$ implies $\{V(s;\kappa_+;\gamma) - \tilde{\gamma}_{i1} \geq V(s;\kappa_-;\gamma) - \tilde{\gamma}_{i4}\}$, and $\{V(s;\kappa_-;\gamma) - \tilde{\gamma}_{i4} \geq V(s;\kappa_0;\gamma)\}$ implies $\{V(s;\kappa_-;\gamma) - \tilde{\gamma}_{i4} \geq V(s;\kappa_+;\gamma) - \tilde{\gamma}_{i1}\}$. In practice, this restriction on the joint probability on the investment and divestment cost draws is not so restrictive, given the low probabilities of either investing or divesting.

For a candidate value of γ_c, the estimator first inverts $p_+(s)$ and $p_-(s)$ for each i to recover $\{(\overline{\gamma}_{i1}, \overline{\gamma}_{i4})\}_i$, and then minimizes (28). The estimator $\hat{\gamma} \in \arg\min_\gamma Q(\gamma)$ is then consistent for $\gamma^\star$ under additional regularity conditions to ensure that $\gamma^\star$ is the unique solution to $\min_\gamma Q(\gamma)$ (Bajari *et al.*, 2007, Assumption S2).

Computational details. Appendix A.3 contains details on the algorithm and its implementation. Note that the expected value function's linearity in the parameters γ (conditional on κ) significantly reduces algorithmic complexity. While per-period payoffs require the calculation of the expectation of various transformations of multivariate random variables, using the joint empirical probability distribution in the data retains linearity of payoffs across states of the world and means that, as in Bajari *et al.* (2007), it is sufficient to simulate trajectories of observables once along each of L paths of perturbed policy functions, $\{\kappa_\ell\}$, and then compute (28) over all of the perturbed policy functions for each candidate γ.

Relation to previous methods. The model of dynamic investment is similar to Ryan (2012), with an important difference: the dynamic land choices depend on unobserved, persistent differences in productivity. Dynamic models typically rule out agent-specific unobservables that persist over time because they preclude the estimation of policy functions "directly from the data" by making the state variables in the dynamic policy function correlated with unobservables that enter the same function. Here, because ω is estimated previously in Section 4 from the observed physical output, inputs, and prices, I can estimate dynamic policy functions that depend directly on ω. Note that without this production function estimation step, any persistence in ω would bias the approach taken above: investment at t depends on both K_{it} and productivity ω_{it}, but K_{it} will be correlated with ω_{it} through $\omega_{i,t-1}$, so a nonparametric regression of $K_{i,t+1}$ on K_{it} and μ_{it} cannot recover unbiased estimates of the true policy function $K_{i,t+1} = \kappa(K_{it}, \omega_{it}, \mu_{it})$.

7.3 Estimated primitives

The estimated irrigation policies increase in land, crop price, and productivity and decrease in rainfall and the average water price (Table A16). These estimates are relatively insensitive to the specific polynomial approximation (Table A17). The estimated adjustment probabilities for perennials (Table A19) are noisy, but show that adjustment is more likely for farms with greater land investments, higher average water prices, and higher crop prices. The adjustment bandwidth, $\overline{\kappa}(\cdot)$, increases in farm size and productivity, and diminishes in irrigation inputs. Annual farms' irrigated land inputs in $\kappa_{\text{annual}}(\cdot)$ increase in past land inputs and irrigation, but diminish in productivity. Dairy farms' area of irrigated pasture in $\kappa_{\text{dairy}}(\cdot)$ increases in past inputs, productivity, and dairy cows.

Table 12 contains the dynamic investment cost parameters. The distribution of means of the investment fixed cost distribution is moderately dispersed; the median is approximately A$1.5 million, with an interquartile range of A$833,000 to A$3.3 million. Divestment costs are smaller; the median cost is −A$850,000; the negative cost captures the value of the land's alternative use. Average costs are large, to rationalize the fact that perennial operations do not frequently adjust their operation size. Variable costs are much smaller relative to fixed costs, and convex—linear investment cost of $\hat{\gamma}_{c2}$ = A$88/ha for c = perennial and quadratic cost of γ_{c3} =A$312/ha. Divestment also exhibits increasing marginal costs, with $\hat{\gamma}_{c6}$ = A$55.

7.4 Long-run value of trade

While the value of the market can be recovered from V, the value V^a cannot be recovered from the estimated policy functions κ, which only capture land-use decisions in the presence of the water market. These value functions depend on a high-dimensional state s; to focus on land, I embed the dependence of V on s_{i0} by recovering i-specific value functions, and take as profits in each period $\widetilde{\Pi}_i(K_{it})$, defined as the expected profits over the paths of (ω_{it}, μ_{it}) expected to arise from (ω_{i0}, μ_{i0}). This allows me to recover value functions V_i for each i using a fixed point operator on a five-hectare discretized grid, via the contraction

$$V(s_{i0};\kappa;\gamma) = V_i(K_{i0}) = \max_K \mathbb{E}_{i0}\left[\widetilde{\Pi}_i(K) - \Gamma(K, K_{i0};\gamma) + \delta V_i(K)\right] \tag{29}$$

under the water market. For each iteration of the contraction (29), it is necessary to integrate over the distribution of $\tilde{\gamma}$ in the calculation of $\arg\max_K$, unlike the value function given in (25), which could be calculated using only on expected fixed costs of switching and the policy rule κ. The Gaussian distributional assumption makes numerical calculation of (29) straightforward.

Autarky endowments are constructed from $\rho_{i0}\overline{W}_{rt}$. To ensure that the total volume of water diverted across i in each year t is the same under both mechanisms in every state of the world, I calculate $\overline{W}_{rt}(s_t)$ by each year t by apportioning total irrigation under the market mechanism, $\overline{W}_t = \sum_i \mathcal{W}(s_{it})$, to regions using average historical shares over all years t in the data, $\frac{1}{T}\sum_t \frac{\overline{W}_{rt}}{\sum_r \overline{W}_{rt}}$. I then allocate $\rho_{i0}\overline{W}_{rt}$ across c for each i in proportion to $\frac{W_{ict}}{\sum_c W_{ict}}$ as before. These autarky allocations give $V_i^a(K_{i0})$ using (29), replacing $\widetilde{\Pi}_i$ with $\widetilde{\Pi}_i^a$.

Long-run gains from trade. Table 13 reports GFT_∞ from (23), taking the data from 2007–2015 as initial conditions and evaluating (23) for perennial operations only. The estimated long-run expected value of the market is 8.2% of total net output. This value moderately exceeds the annual gains calculated in the benchmark model (5.8% for perennials), implying that in the long run, land investments improve the dynamic efficiency of the land allocation relative to the observed initial land allocation in 2007–2015. That these investments amplify the longer-run gains from water market access implies that their value exceeds the adaptation under autarky that the benchmark calculation did not take into account.[33]

How does (23) differ from a short-run value of market-based water reallocation? The benchmark calculations did not assume dynamically efficient land-use; the opportunity to alter land-use investments affects the value of agricultural production under (i) autarky and (ii) the existing water market.

First, farms adapt to water misallocation under autarky. This adaptation channel was not considered when land was taken as a fixed characteristic, and an estimate of the long-run gains-from-trade calculated along the efficient water-market land trajectory will overstate the market's actual value. The second row of Table 13 reports the following decomposition:

$$\sum_i V(s_i^*;\kappa;\cdot) - V^a(s_i^a;\kappa^a;\cdot) = \sum_i \underbrace{V(s_i^*;\kappa;\cdot) - V^a(s_i^*;\kappa;\cdot)}_{\text{static allocative efficiency A}} - \underbrace{\left[V^a(s_i^a;\kappa^a;\cdot) - V^a(s_i^*;\kappa;\cdot)\right]}_{\text{value of adaptation}}. \tag{23A}$$

Evaluating (23) holding land use fixed to its efficient trajectory under the water market, the gains from trade are 9.0%, relative to 8.2%. Failing to take into account this adaptation channel would therefore overstate the market's estimated long-run value by about 10%. The opportunity for adaptation under autarky matters, but does not considerably dampen the water market's estimated value.

Second, water market access alters farms' land-use relative to autarky. Table 13 shows that irrigated perennial land increases by 4.6% with the introduction of the water market. The value of this investment, relative to a gains-from-trade estimate holding land fixed along its autarky path, can be recovered from the decomposition

$$\sum_i V(s_i^*;\kappa;\cdot) - V^a(s_i^a;\kappa^a;\cdot) = \sum_i \underbrace{V(s_i^*;\kappa;\cdot) - V(s_i^a;\kappa^a;\cdot)}_{\text{value of investment}} + \underbrace{V(s_i^a;\kappa^a;\cdot) - V^a(s_i^a;\kappa^a;\cdot)}_{\text{static allocative efficiency B}}, \tag{23B}$$

Equation (23B) separates the value of more efficient dynamic land use from allocative efficiency holding land fixed to its pre-market level. Table 13 shows that this dynamic investment channel creates value equal to 1.8% of output, relative to "static gains" calculated along the autarky path of land use, 6.3%. In this sense, measuring the value of *introducing* a water market—holding pre-market land-use decisions fixed—misses approximately one-fifth of the market's total value.

[33] Note that it is not possible to sign the difference ex-ante between (23) and the NPDV of (19). While the static measure of allocative efficiency in (23A) overstates (23) because $V^a(s_i^a;\kappa^a;\gamma) \geq V^a(s_i^*;\kappa;\gamma)$, it is not directly comparable because investment costs vanish from (19). The optimality of s_i^a does not imply (19) overestimates (23), because $\Pi^a(K,\cdot) - \Gamma(K,\cdot;\gamma) \leq \max_{K^a}\left[\Pi^a(K^a,\cdot) - \Gamma(K^a,\cdot;\gamma)\right]$ need not imply that $\Pi^a(K,\cdot) \leq \Pi^a(K^a,\cdot)$.

8 Conclusion

Climate change has renewed calls for water markets to allocate resources more efficiently and to forestall increasing scarcity. But how important is allocative efficiency in a changing climate? If the value of water differs greatly across competing uses and is relatively uncorrelated with current property rights, water markets may be crucial in the response to climate change; otherwise, water trading may be closer to rearranging deck chairs on the Titanic.

This paper used physical input-output data—not theories of water demand or assumptions about water market access—to identify shadow water values and recover the value of trade from observed market-based reallocation. This "primal" approach avoids using revealed preference from observed trades. Such analyses can deliver many critical, policy-relevant insights, including but not limited to the prediction of equilibrium water market prices (e.g., Gupta *et al.*, 2018). In contrast, the model presented here neither requires that farms trade or irrigate optimally, nor relies on a specific form of water market access, transaction costs, or trading constraints. This allows the paper to (a) value water trading without assuming that it cannot be bad, in contrast to revealed preference methods; and (b) test whether the market reallocates water efficiently, in contrast to simulations that typically assume efficient reallocation subject to a specification of river flow constraints.

The estimates imply that water trading under the Australian sMDB mechanism increased producer surplus by 4–6% of irrigated agricultural GDP between 2007–2015 for surveyed farms and that these gains increase with water scarcity. Viewed in terms of factor misallocation, more efficient water allocation across irrigated farms increased the industry's total factor productivity (TFP) by approximately one-half percent per year from 2007–2015, for an industry with annual TFP growth of 1–2% from 1970–present. Alternatively, reverting to pre-trade endowments reduces output by the same amount as an 11.8% uniform decline in water resources from observed levels, in a region where climate forecasts project median reductions in surface water of 11% from 1°C of warming. In this sense, the value of the Australian mechanism is potentially on the same order of magnitude as the water scarcity predicted to arise from short-run climate change. Dynamic reallocation of land (e.g., to high-value orchards and vineyards) further amplifies a water market's value.

These results raise a range of questions for future work. The focus on agricultural users while holding diversion caps fixed avoids the vital question of environmental protection, the other primary value of river water in the Murray-Darling (Grafton *et al.*, 2011). Whether general equilibrium forces (such as wages and crop prices) adjust countercyclically to mitigate the losses associated with the misallocation of water is an interesting question with a long lineage (Samuelson, 1948). In addition, water market access should affect equilibrium investment in irrigation technology (Acemoglu, 2007), which could further increase water markets' social value (Dales, 1968, p. 794). The ownership of water rights may also provide considerable insurance value for risk-averse farms (Bontems and Nauges, 2019), a value that measures of unweighted producer surplus will not capture. Finally, dams and other water storage technologies allow the conservation of river water between years, creating water stocks that affect equilibria in annual and permanent markets and serve an essential role in the management of future drought risk (Hughes *et al.*, 2013). Understanding the value of the intertemporal water trade enabled by these forms of infrastructure will be particularly crucial in a world where water resources are less evenly-distributed across time.

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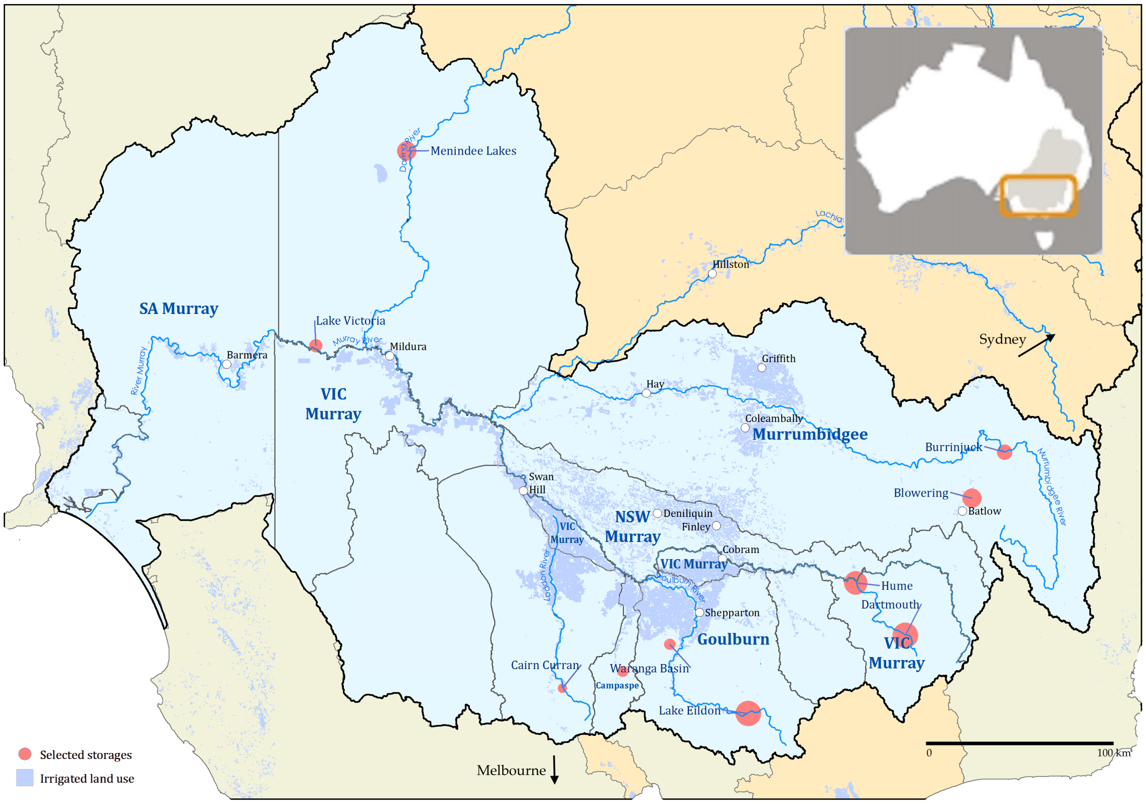


FIGURE 1. MAP OF THE SOUTHERN MURRAY-DARLING BASIN (SMDB)

River network, regions, irrigation areas, and dams in the southern Murray-Darling Basin.

Source: Australian Department of Agriculture.

TABLE 1. WATER RIGHTS, TRADING, AND PRICES

	$N \times T$	mean	s.d.	Q.10	Q.25	Q.50	Q.75	Q.90
total irrigation, ML	2,032	684.65	1,385.21	17.01	68.45	211.05	650	1,589.80
permanent rights, nominal ML	2,032	881.82	1,253.49	72	156	406.50	1,091.15	2,257.10
permanent rights, realized ML	2,032	515.90	794.42	31.91	81.49	233.39	609.70	1,259.38
buy annual water, $\{0,1\}$	2,032	0.32	0.47	0	0	0	1	1
annual volume bought, ML	2,032	93.49	296.12	0	0	0	35	235.40
sell annual water, $\{0,1\}$	2,032	0.20	0.40	0	0	0	0	1
annual volume sold, ML	2,032	26.40	87.60	0	0	0	0	80
buy permanent rights, $\{0,1\}$	954	0.23	0.42	0	0	0	0	1
permanent volume bought, realized ML	954	45.16	184.62	0	0	0	0	77.62
sell permanent rights, $\{0,1\}$	954	0.29	0.46	0	0	0	1	1
permanent volume sold, realized ML	954	60.28	235.62	0	0	0	7.32	129.32
net buyer, $\{0,1\}$	2,032	0.42	0.49	0	0	0	1	1
net volume bought, ML	2,032	120.98	341.03	0	0	0	78.25	333.94
net seller, $\{0,1\}$	2,032	0.31	0.46	0	0	0	1	1
net volume sold, ML	2,032	54.70	184.90	0	0	0	27.15	149.82
annual regional water price, AUD/ML	44	235.01	198.37	24.55	55.05	160.26	338.74	621.91

Farm-level irrigation, water rights, and trading from 2007–2015. Volumes denominated in megaliters (ML). Nominal permanent rights calculated as i's share of the total entitlement volume on issue, ρ_{it}. Realized permanent rights reported as $\rho_{it}\overline{W}_{rt}$. Number of observations falls for permanent rights because they are only defined for farms observed at least twice and each farm observation after the first.

Source: ABARES Survey of Irrigated Farms.

Table 2. Yields, Irrigation, and Rainfall

A. Yields ('1000 AUD/ha)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2007–15
Perennial	9.586	10.061	11.198	10.106	10.245	10.105	14.453	14.085	14.578	10.874
Annual (irrigated)	14.556	15.933	9.901	7.108	6.801	2.155	5.892	4.937	6.174	8.937
Annual (nonirrigated)	0.318	0.547	0.463	0.436	0.664	0.508	0.370	0.503	0.570	0.510
Pasture	5.608	10.383	11.665	9.723	6.999	5.542	3.748	5.205	9.864	7.767

B. Irrigation (ML/ha)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2007–15
Perennial	5.801	4.932	4.527	4.252	3.967	5.452	6.849	5.720	5.763	5.109
Annual (irrigated)	3.950	2.867	3.140	3.784	5.093	5.937	3.990	8.466	6.384	4.497
Annual (nonirrigated)	0	0	0	0	0	0	0	0	0	0
Pasture	2.511	2.124	1.897	1.969	2.020	2.127	2.208	3.141	2.985	2.275

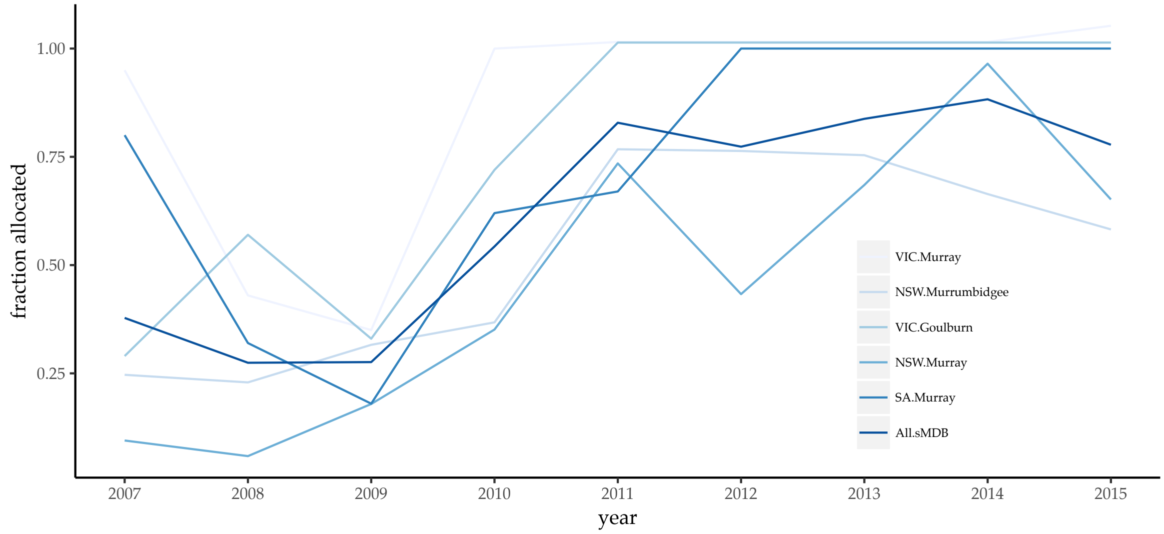
C. Rainfall and Evapotranspiration (mm)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2007–15
Rainfall	221.85	333.66	294.06	447.38	773.52	537.75	257.20	373.14	400.52	417.80
	(47.76)	(174.02)	(121.30)	(149.98)	(153.25)	(175.27)	(110.20)	(127.61)	(161.64)	(219.10)
Evapotr.	139.77	148.50	143.21	204.57	264.66	218.52	154.73	204.21	172.42	184.93
	(19.01)	(4.24)	(10.70)	(6.86)	(16.32)	(10.57)	(23.39)	(16.82)	(5.33)	(44.19)

The unit of observation is (i, c, t) for Panels A and B, (i, t) for Panel C rainfall, and (r, t) for Panel C evapotranspiration. Appendix C describes the definition of each crop type.

Source: ABARES Survey of Irrigated Farms; Australian Bureau of Meteorology.

A. Regional Water-Sharing Rules



B. Annual Water Prices

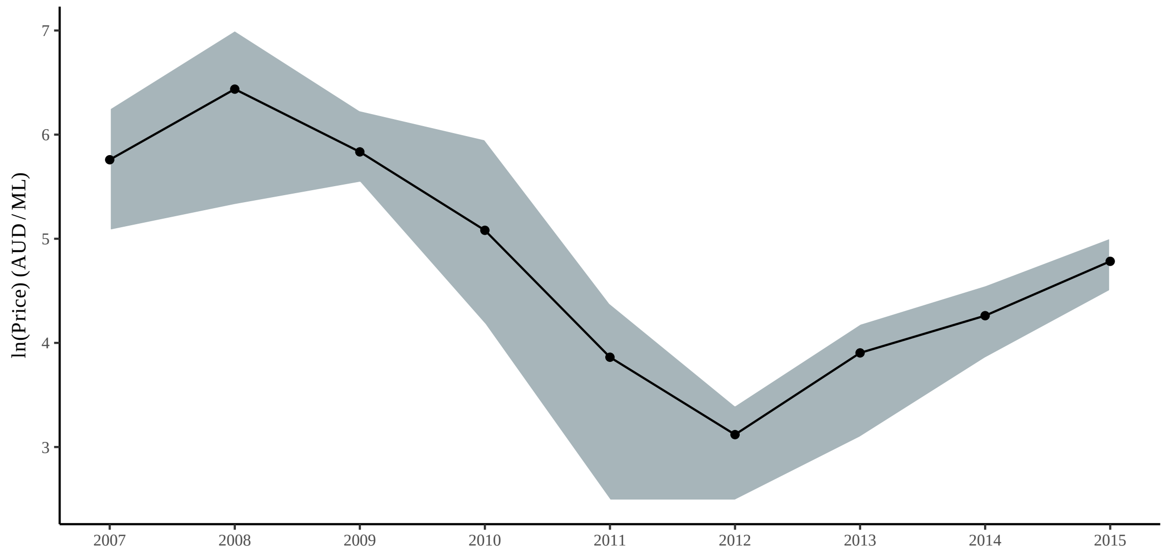


FIGURE 2. REGIONAL WATER ALLOCATIONS AND MARKET PRICES

A. Regional water allocations by year as percentages of entitlement volume on issue in 2007. Tabulated in Table A2.

B. Average annual sMDB-wide water allocation prices, ln(AUD/ML). Blue bands show [5-%,95%] intervals of transaction-volume-weighted price distribution of all trades within each year (2008–2015) and minimum and maximum annual regional average prices for 2007. Table A3 contains additional details on within-year water price variation.

Source: A. NSW, VIC, and South Australia state government regulatory records. B. MDBA administrative transaction-level allocation water trade data (2008–2015); state registries and a private water broker (2007).

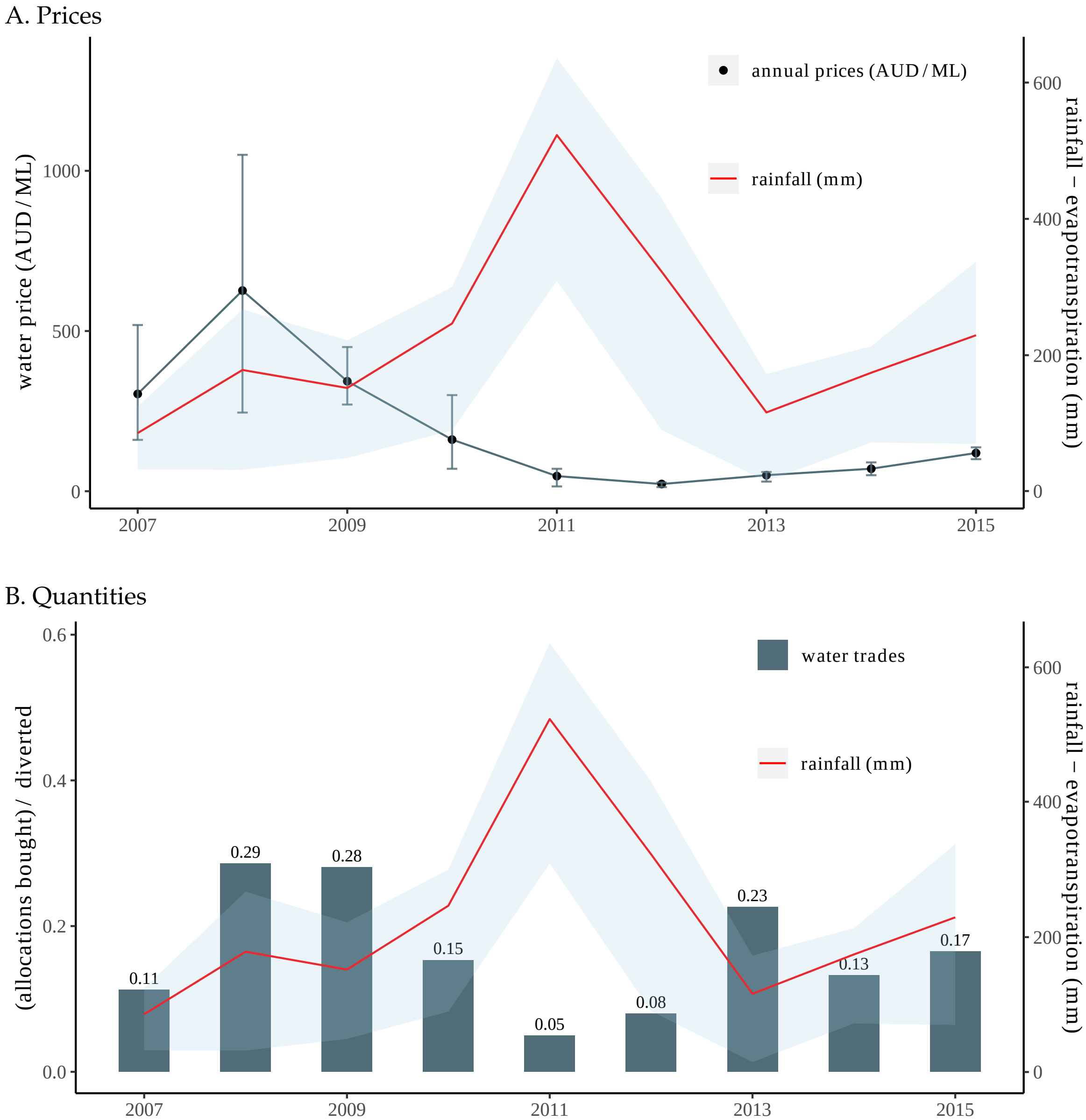


FIGURE 3. WATER MARKET OUTCOMES AND RAINFALL, 2007–2015

Panel A. Average annual allocation water prices (whiskers: interdecile interval of transaction price distribution) and mean (red) and interdecile interval (ribbon) of farm-level rainfall minus evapotranspiration.

Panel B. Fraction of total irrigation volumes bought on the annual water market in each year *t* (blue bars) and the same rainfall series.

Source: ABARES Survey of Irrigated Farms; MDBA, state government registries, and private water broker.

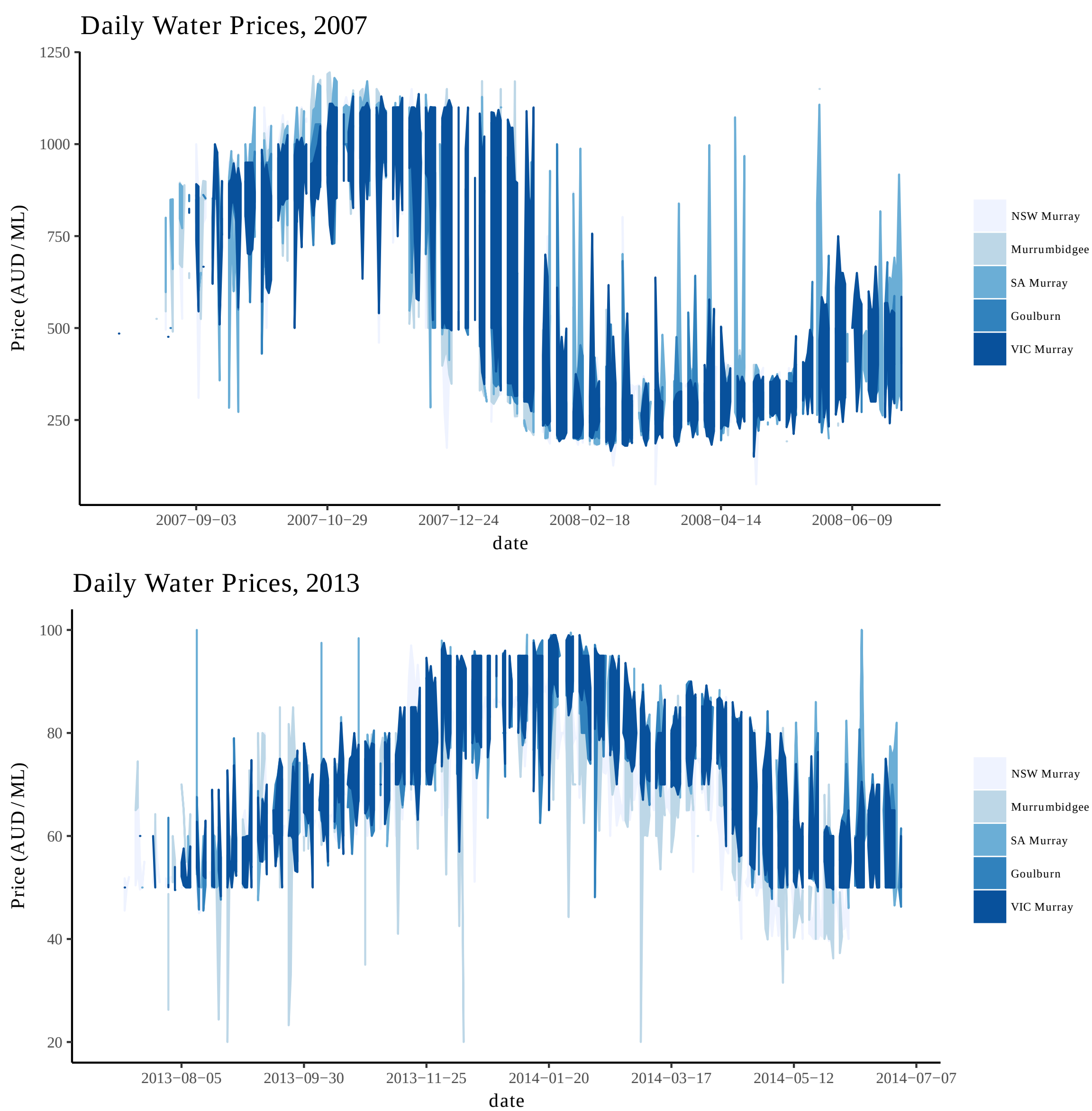


FIGURE 4. EXAMPLES OF INTRA-ANNUAL WATER PRICE DISPERSION

[5%,95%]-tile intervals of daily water prices (AUD/ML) and cumulative volume traded (ML). Note that the scale of the y-axes differ between figures. Figures for all years 2008–2015 in the Online Appendix.

Source: MDBA administrative transaction-level water price data.

TABLE 3. ANNUAL WATER TRADING DECISIONS AND RAINFALL

A. Annual purchases

	Dependent variable:			
	Buy, $\mathbf{1}(\Delta_{it} > 0)$			
	(1)	(2)	(3)	(4)
ln(net_rainfall$_{it}$)	−0.105***	−0.063***	−0.053***	−0.126***
	(0.017)	(0.019)	(0.020)	(0.036)
ln(water_endowment$_{it}$)	−0.003	0.017*	0.021**	−0.067**
	(0.010)	(0.010)	(0.010)	(0.028)
Year FEs	✓	✓	✓	✓
Region FEs		✓	✓	
Region×Year FEs			✓	
Farm FEs				✓
Observations	2,032	2,032	2,032	2,032
Adjusted R^2	0.122	0.142	0.191	0.401

B. Annual sales

	Dependent variable:			
	Sell, $\mathbf{1}(\Delta_{it} < 0)$			
	(1)	(2)	(3)	(4)
ln(net_rainfall$_{it}$)	0.023	−0.041**	−0.051***	0.035
	(0.016)	(0.017)	(0.019)	(0.024)
ln(water_endowment$_{it}$)	0.051***	0.028***	0.026***	0.045**
	(0.008)	(0.008)	(0.009)	(0.021)
Year FEs	✓	✓	✓	✓
Region FEs		✓	✓	
Region×Year FEs			✓	
Farm FEs				✓
Observations	2,032	2,032	2,032	2,032
Adjusted R^2	0.074	0.132	0.172	0.468

The unit of observation is the farm-year. Regressions of the indicator for trading annual water rights on net rainfall (annual rainfall minus evapotranspiration), realized permanent water endowments, and fixed effects denoted by checkmarks. Every regression includes crop-type fixed effects. Table A5 reports results for permanent trading.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses. Nonzero coefficients significant at *10%, **5% and ***1% levels.

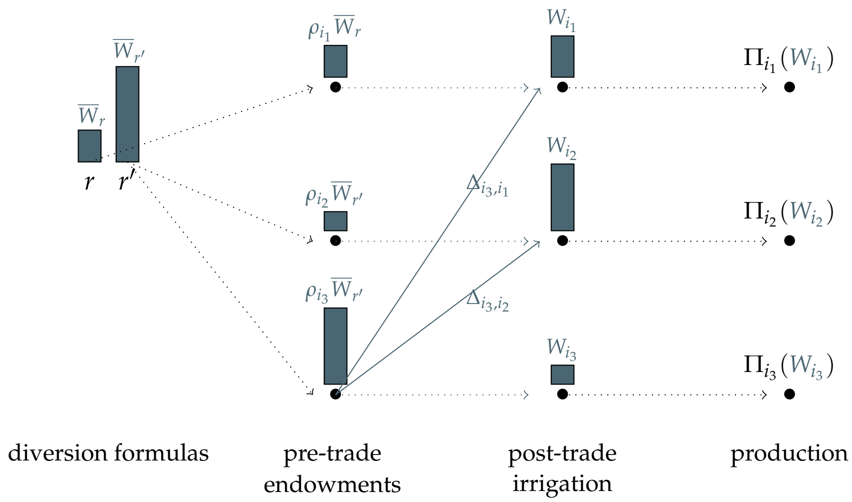


Figure 5. Example of Water Allocations and Trade

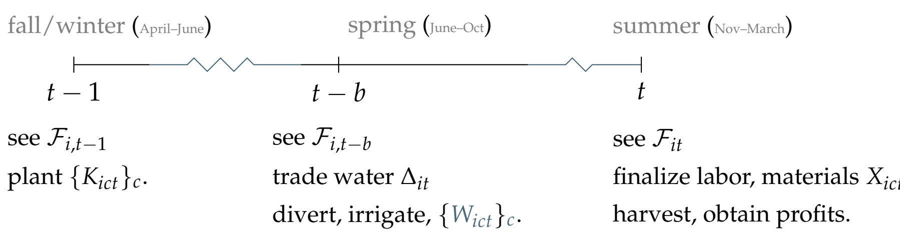


Figure 6. Agricultural Calendar

TABLE 4. PRODUCTION FUNCTION ESTIMATES

	Perennial (1)	Annual irrigated (2)	Annual nonirrigated (3)	Dairy (4)
Irrigation				
Average irrigation-output elasticity $\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.277***	0.210***	0.359***	0.087**
	(0.054)	(0.041)	(0.081)	(0.038)
Interquartile range of $\frac{\partial f_c}{\partial w}$ across i, t	[0.231, 0.354]	[0.149, 0.278]	[0.341, 0.388]	[0.043, 0.118]
10-90%-ile range	[0.124, 0.381]	[0.075, 0.321]	[0.305, 0.405]	[0.024, 0.152]
Water-land aggregator				
Scale coefficient, β_{cW}	0.625***	0.484***	0.549***	0.727***
	(0.135)	(0.080)	(0.067)	(0.157)
Irrigation share, α_c	0.575***	0.468***	—	0.125
	(0.053)	(0.045)		(0.095)
Land share, $1-\alpha_c$	0.425***	0.532***	0.450***	
	(0.053)	(0.045)	(0.131)	
Rainwater coefficient, ϑ_c			0.550***	
			(0.131)	
Elasticity of substitution, σ_c	1.744***	1.964***	2.014	
	(0.363)	(0.412)	(1.639)	
Other factors				
Labor elasticity, β_{cL}	0.348***	0.233***	0.233***	0.149***
	(0.016)	(0.013)	(0.013)	(0.007)
Materials elasticity, β_{cM}	0.191***	0.425***	0.425***	0.113***
	(0.009)	(0.016)	(0.016)	(0.004)
Feed share, α_F				0.875***
				(0.095)
Pasture-feed elasticity of substitution, σ_F				0.540
				(5.852)
Returns to scale, $\sum_j \beta_{cj}$	1.164***	1.142***	1.207***	0.988***
	(0.137)	(0.086)	(0.070)	(0.158)
J-statistic	0.206***	0.255***	2.664	1.161***
Adjusted R^2	0.816	0.748	0.793	0.866
Observations	493	170	210	256

Results from the GMM procedure described in Section 4 using the nested CES production function given by (2). Each column contains separately estimated production functions for each type. For irrigated/nonirrigated annual crops, first-stage labor and materials elasticities are estimated pooling across both crop-types. Instruments are regional water allocations interacted with previous period's water rights for irrigated c and rainfall for nonirrigated c as described in Section 4.2. Mean, interquartile, and interdecile ranges of $\{\frac{\partial f_c}{\partial w}\}$ calculated at observed inputs over all i, t. Adjusted R^2 reports the fit of the first-stage polynomial $\widehat{\Phi}_{ict} = \omega_{ict} + f_{ict}$ on q_{ict}.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses. Nonzero coefficients significant at *10%, **5% and ***1% levels.

TABLE 5. PRODUCTIVITY ESTIMATES

	Perennial (1)	Annual irrigated (2)	Annual nonirrigated (3)	Dairy (4)
Median productivity	7.828	3.617	1.655	6.366
	(1.006)	(1.470)	(9.782)	(1.582)
Interquartile interval	[7.55, 8.08]	[3.21, 3.99]	[1.13, 2.07]	[6.20, 6.59]
range	0.523	0.779	0.945	0.387
	(0.179)	(0.136)	(0.111)	(0.097)
Interdecile interval	[7.30, 8.33]	[2.77, 4.43]	[0.71, 2.47]	[6.01, 6.84]
range	1.028	1.656	1.763	0.829
	(0.301)	(0.195)	(0.153)	(0.153)
Persistence, $\hat{\varrho}_c$	0.639	0.504	0.640	0.384
	(0.062)	(0.091)	(0.055)	(0.180)
Growth rate	0.067	0.064	0.184	−0.103
	(0.018)	(0.059)	(0.044)	(0.037)
Observations	493	170	210	256

Estimated productivities $\{\hat{\omega}_{ict}\}$, denominated in natural logarithms of AUD and recovered as $\hat{\Phi}_{ict} - \hat{f}_{ict}$, using production function estimates $\hat{F}_c$ reported in Table 4.

Persistence is defined as the coefficient $\hat{\varrho}_c$ in the regression $\hat{\omega}_{ict} = \varrho_{0c} + \varrho_c \hat{\omega}_{ic,t-1} + \varepsilon_{ict}$. Growth rate is annual and defined as $\frac{1}{NT}\sum_{i,t}(\hat{\omega}_{ict} - \hat{\omega}_{ic,t-1})$

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

TABLE 6. WATER TRADING DECISIONS AND ESTIMATED PRODUCTIVITY

	Dependent variable:			
	A. Buy annual allocations			
	(1)	(2)	(3)	(4)
Productivity, $\hat{\omega}_{it}$	0.062***	0.057***	0.045***	0.051**
	(0.013)	(0.012)	(0.011)	(0.021)
	B. Sell annual allocations			
	(1)	(2)	(3)	(4)
Productivity, $\hat{\omega}_{it}$	−0.044***	−0.035***	−0.029***	−0.036*
	(0.010)	(0.010)	(0.010)	(0.021)
	C. Buy permanent rights			
	(1)	(2)	(3)	(4)
Productivity, $\hat{\omega}_{it}$	−0.009	−0.008	−0.002	−0.014
	(0.008)	(0.009)	(0.008)	(0.022)
	D. Sell permanent rights			
	(1)	(2)	(3)	(4)
Productivity, $\hat{\omega}_{it}$	0.010	0.009	0.005	0.026
	(0.010)	(0.010)	(0.011)	(0.030)
Rainfall	✓	✓	✓	✓
Endowment	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Region FEs		✓	✓	
Region×Year FEs			✓	
Farm FEs				✓
Observations	2,032	2,032	2,032	2,032

The unit of observation is the farm-year. Regressions of binary indicators of trading water on estimated farm productivity and the same controls as Table 3 (natural logarithms of net rainfall and realized permanent water endowments, plus fixed effects). Every regression includes crop-type fixed effects. Productivity defined for multicrop farms as output-weighted mean: $\hat{\omega}_{it} \equiv \ln(\sum_c \exp(\hat{\omega}_{ict}) P_{ict} Q_{ict})$.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses. Nonzero coefficients significant at *10%, **5% and ***1% levels.

TABLE 7. WATER TRADING DECISIONS AND ANNUAL PRODUCTIVITY SHOCKS

	Dependent variable:			
	A. Buy annual allocations			
	(1)	(2)	(3)	(4)
Productivity innovation, $\hat{\xi}_{it}$	0.126***	0.120***	0.089***	0.136***
	(0.027)	(0.027)	(0.026)	(0.039)
Lagged productivity, $\widehat{\omega}_{i,t-1}$	0.054***	0.051***	0.042***	0.030
	(0.016)	(0.016)	(0.015)	(0.030)
	B. Sell annual allocations			
	(1)	(2)	(3)	(4)
Productivity innovation, $\hat{\xi}_{it}$	−0.041	−0.019	0.006	−0.040
	(0.029)	(0.028)	(0.029)	(0.036)
Lagged productivity, $\widehat{\omega}_{i,t-1}$	−0.041***	−0.027**	−0.022*	−0.039
	(0.013)	(0.013)	(0.013)	(0.033)
	C. Buy permanent rights			
	(1)	(2)	(3)	(4)
Productivity innovation, $\hat{\xi}_{it}$	−0.027	−0.026	−0.020	−0.042
	(0.024)	(0.024)	(0.025)	(0.033)
Lagged productivity, $\widehat{\omega}_{i,t-1}$	−0.0003	0.0002	0.006	0.002
	(0.007)	(0.008)	(0.008)	(0.018)
	D. Sell permanent rights			
	(1)	(2)	(3)	(4)
Productivity innovation, $\hat{\xi}_{it}$	0.040	0.039	0.036	0.078**
	(0.027)	(0.028)	(0.027)	(0.039)
Lagged productivity, $\widehat{\omega}_{i,t-1}$	0.007	0.006	−0.001	0.023
	(0.011)	(0.011)	(0.011)	(0.036)
Rainfall	✓	✓	✓	✓
Endowment	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Region FEs		✓	✓	
Farm FEs				✓
Observations	954	954	954	954
Adjusted R^2	0.182	0.195	0.256	0.438

Version of Table 6 replacing $\hat{\omega}_{it}$ with $\hat{\omega}_{i,t-1}$ and $\hat{\xi}_{it}$.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses. Nonzero coefficients significant at *10%, **5% and ***1% levels.

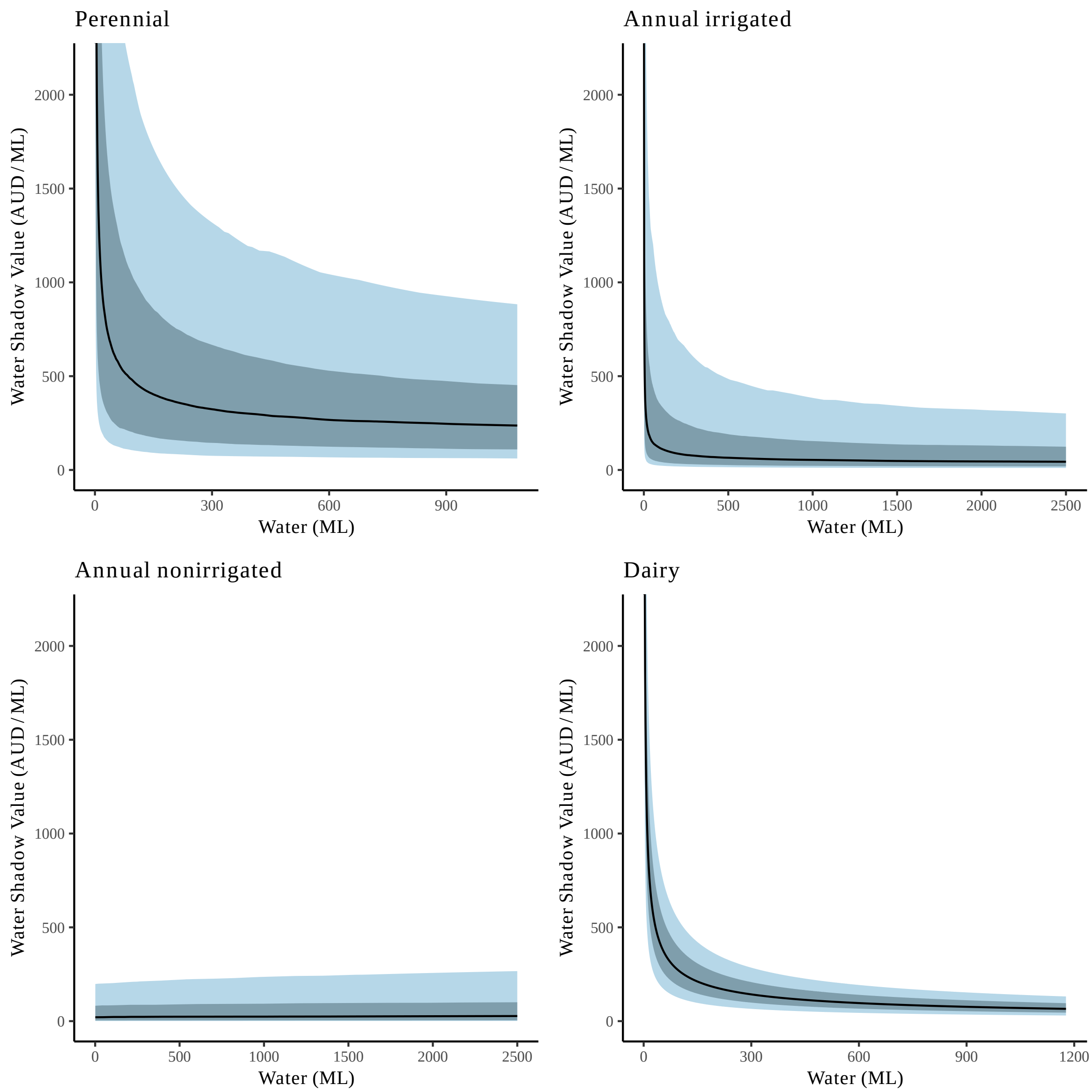


FIGURE 7. CURVATURE OF SHADOW VALUE FUNCTIONS

Plots of the estimated shadow value functions given by (17) with interdecile range (light blue band), interquartile range (dark blue), and median values (black line) across farm-years. Note that x-axes differ across figures as they are bounded by the 97.5%-ile volume of irrigation for each irrigated c.

Table 8. Water Shadow Values at Observed Inputs

	Perennial (1)	Annual irrigated (2)	Annual nonirrigated (3)	Dairy (4)	Water market (5)
Median shadow value (AUD/ML)	467.55	87.87	42.77	129.20	160.26
	(89.573)	(18.070)	(9.214)	(67.524)	(198.37)
Interquartile interval	[334.79, 666.43]	[50.06, 178.19]	[25.94, 63.59]	[55.91, 291.11]	[55.05, 338.74]
Range	331.633	128.129	37.641	235.205	289.81
	(77.407)	(94.311)	(8.478)	(79.382)	
Interdecile interval	[239.17, 1001.33]	[38.04, 721.42]	[17.48, 87.06]	[31.95, 587.85]	[24.55, 621.91]
Range	762.163	683.382	69.580	555.904	578.91
	(182.971)	(181.177)	(19.606)	(199.677)	
Observations	493	170	210	256	2,032

Water shadow water values pooled over 2007–2015, in columns (1)–(4); regional water allocation prices distributed over farms in column (5). Shadow values obtained by evaluating (17) at observed input levels, using the estimated production functions (Table 4) and productivities (Table 5).

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

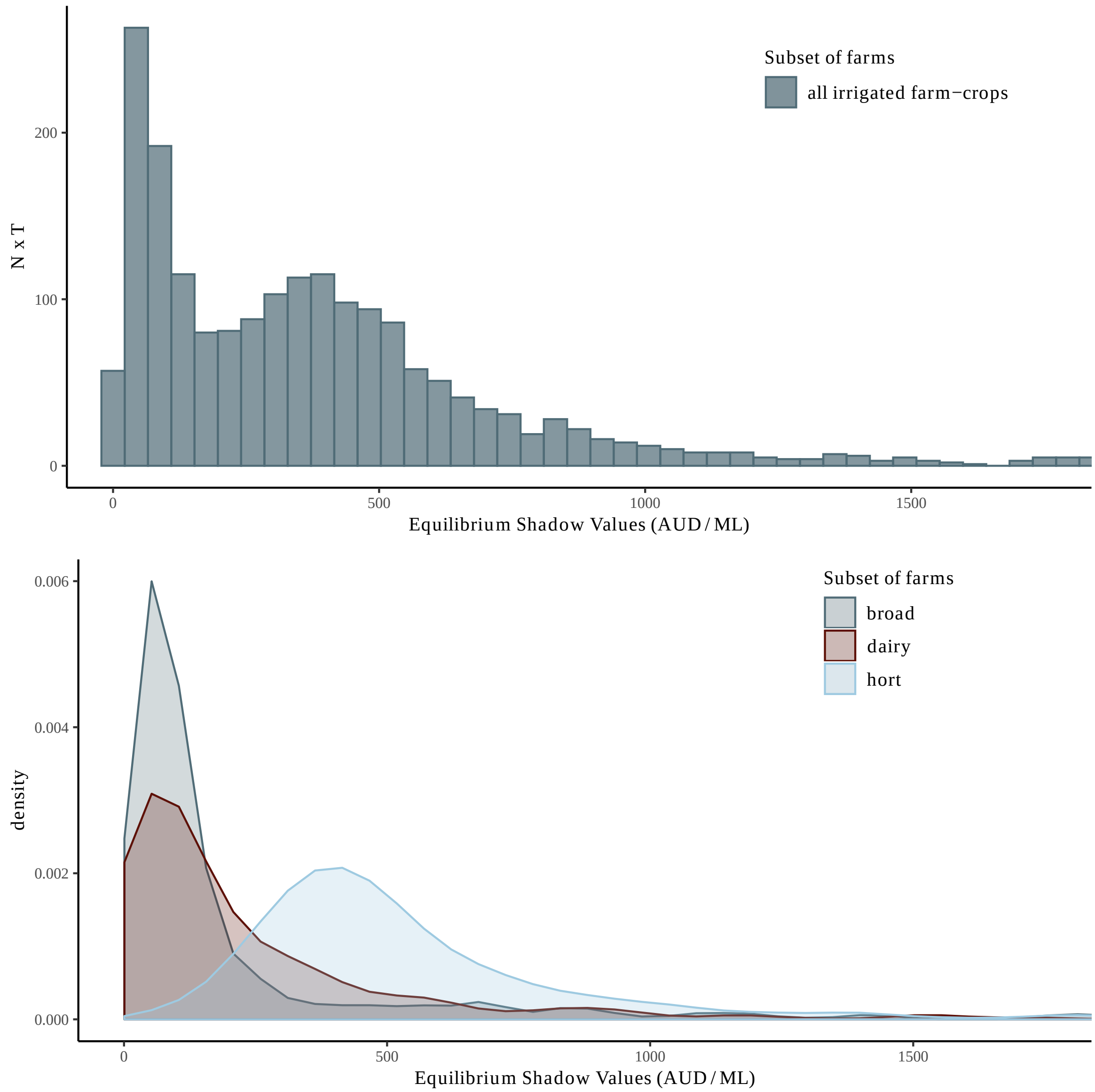


FIGURE 8. WATER SHADOW VALUES AT OBSERVED INPUTS

Pooled histogram (top) and conditional densities (bottom) of estimated farm-crop-level shadow water values obtained from evaluating (17) at observed inputs. The x-axis range is 0 to the 97.5%-tile observation. Nonparametric densities obtained using a Gaussian kernel estimator with a Silverman (1986) optimal bandwidth.

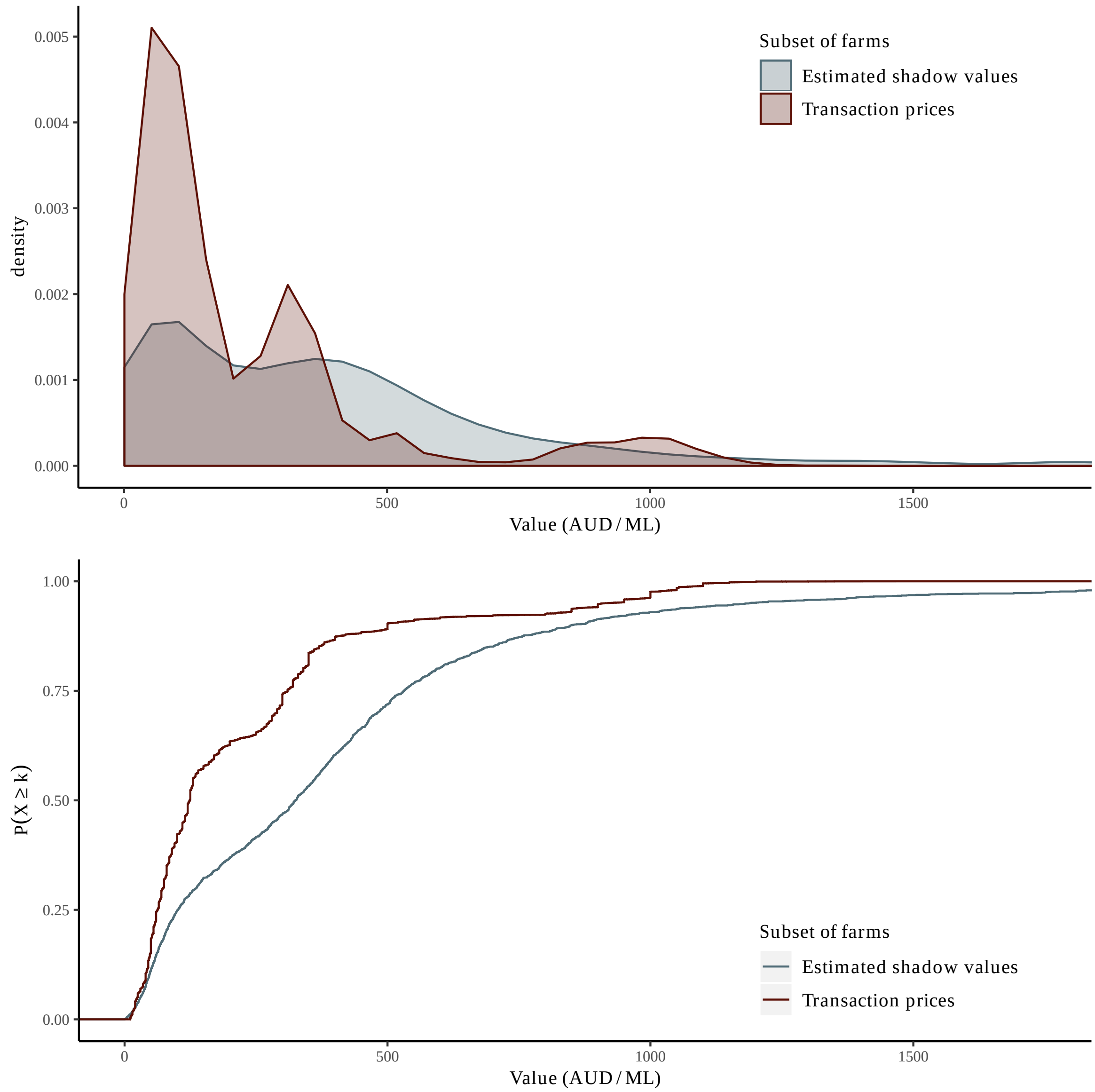


FIGURE 9. POST-TRADE SHADOW VALUE DISTRIBUTION V. TRANSACTION PRICES

Conditional probability densities (top) and CDF (bottom) of farm-crop-level shadow water values at observed inputs (blue) and transaction prices (red), both from 2008–2015; 2007 predates water-price-transaction-level reporting. The *x*-axis range is 0 to the 97.5%-ile shadow value observation. Nonparametric densities obtained using a Gaussian kernel estimator with a Silverman (1986) optimal bandwidth.

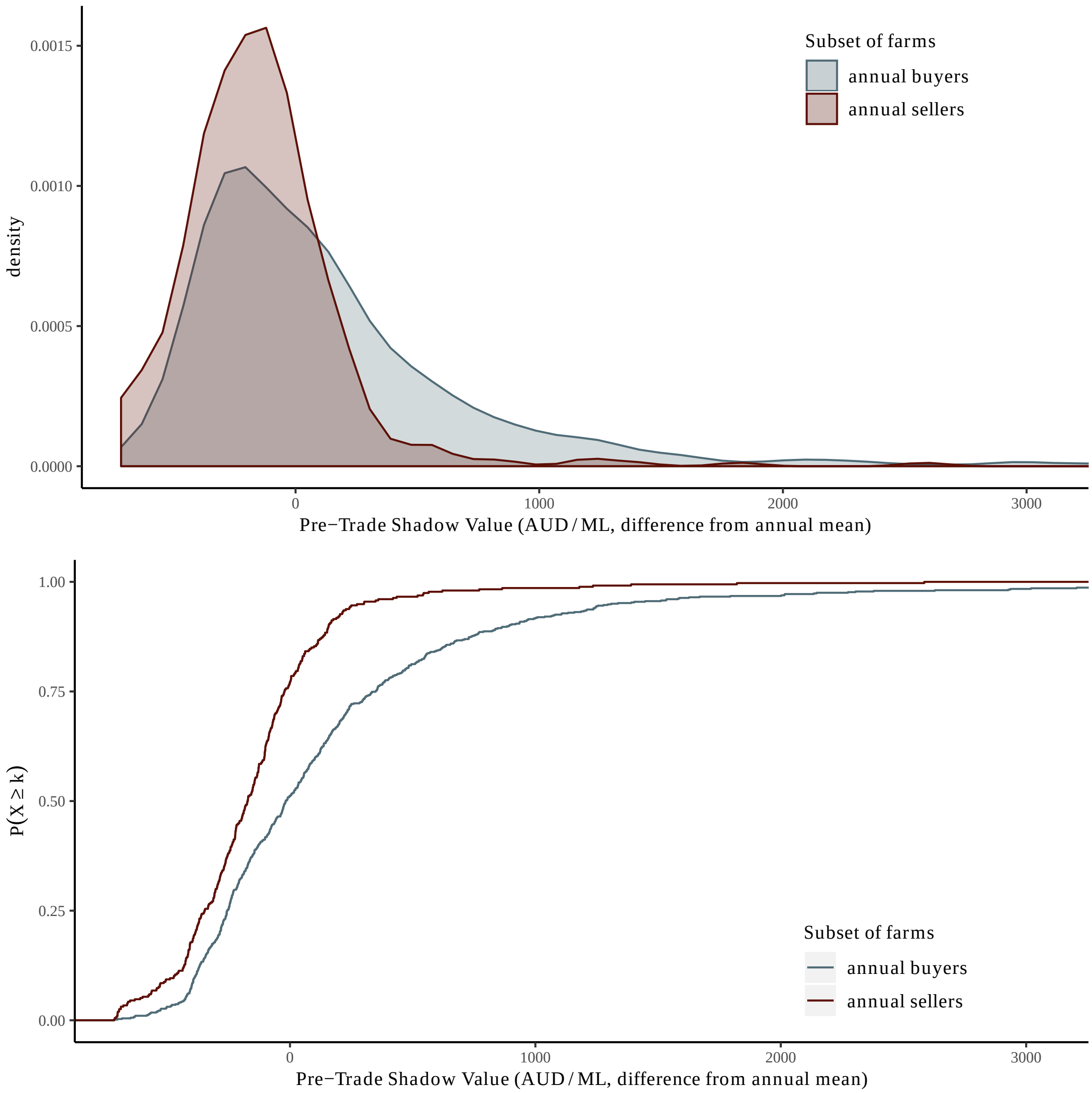
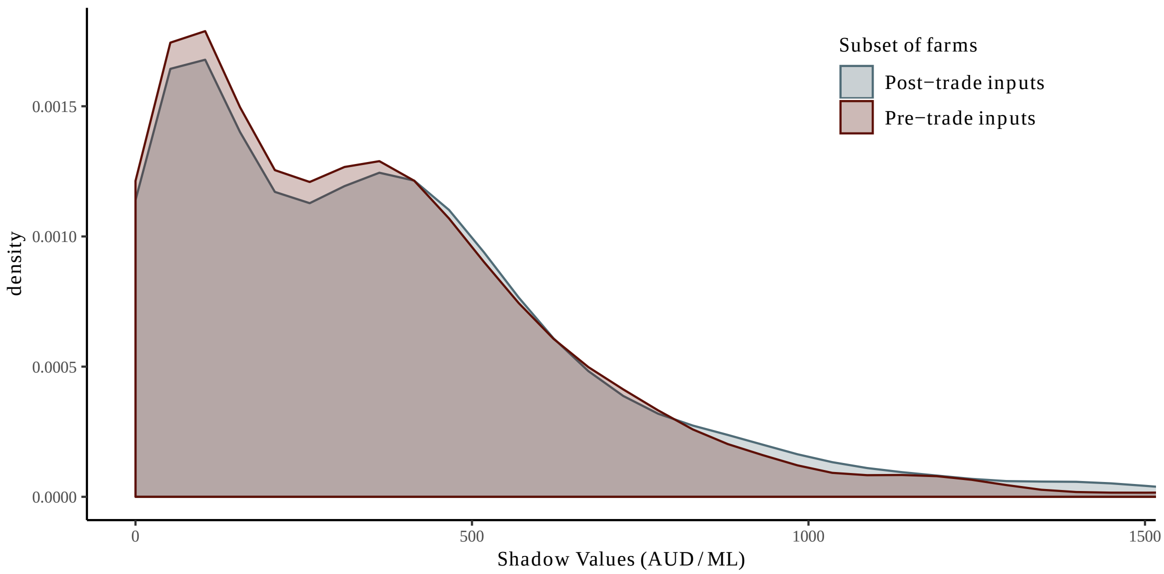


FIGURE 10. PRE-TRADE SHADOW VALUES

Conditional probability densities (top) and CDF (bottom) of farm-crop-level shadow water values, centered at the annual average, and evaluated at pre-annual-trade endowments for annual buyers (blue) and annual sellers (red). Nonparametric densities obtained using a Gaussian kernel estimator with a Silverman (1986) optimal bandwidth.

A. All years



B. Drought only (2007–2010)

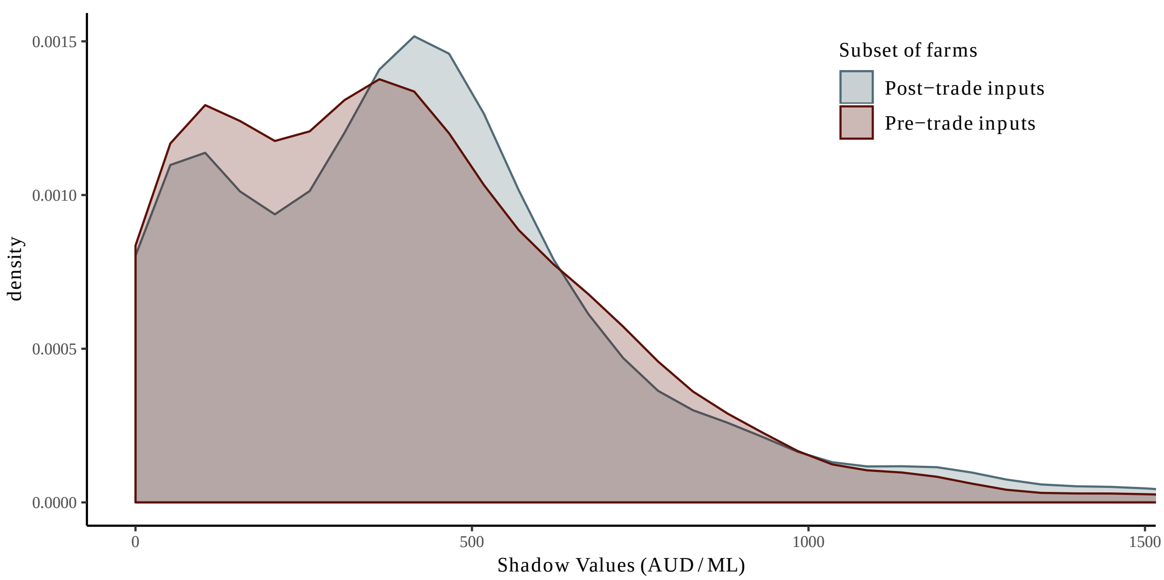


FIGURE 11. EFFECT OF TRADE ON SHADOW PRICE DISPERSION

Nonparametric densities of estimated farm-crop-level shadow water prices evaluated at observed inputs (blue) and pre-trade inputs (red), for 2007–2015 (top) and 2007–2010 (bottom). The x-axis range is 0 to 97.5%-tile observation. Nonparametric densities obtained using a Gaussian kernel estimator with a Silverman (1986) optimal bandwidth.

TABLE 9. MISALLOCATION AND WATER TRADING

	Interquartile shadow value range		
	Pre-trade	Post-trade	Difference
All	680.72***	641.52***	−39.19
	(150.47)	(151.38)	(24.90)
Years			
2007	640.28***	655.43***	15.15
	(187.00)	(174.04)	(47.83)
2008	765.02***	761.05***	−3.97
	(183.64)	(235.98)	(118.19)
2009	1207.85***	1025.99***	−181.86
	(252.27)	(276.22)	(129.52)
2010	540.46***	501.57***	−38.89
	(200.75)	(182.05)	(89.14)
2011	494.09***	368.86***	−125.23*
	(165.65)	(129.96)	(71.02)
2012	410.73***	365.49***	−45.24
	(134.26)	(109.16)	(48.49)
2013	400.17**	314.50*	−85.67
	(181.72)	(166.26)	(75.91)
2014	634.26***	614.65***	−19.61
	(192.21)	(178.34)	(66.02)
2015	797.76**	760.77***	−36.98
	(337.10)	(256.68)	(133.65)

	Interdecile shadow value range		
	Pre-trade	Post-trade	Difference
All	1579.37***	1567.63***	−11.73
	(355.39)	(354.17)	(70.05)
Years			
2007	1389.61***	1386.38***	−3.23
	(400.46)	(342.70)	(127.37)
2008	1627.09***	1676.32***	49.23
	(434.88)	(481.10)	(175.35)
2009	2467.01***	2055.77***	−411.24
	(613.19)	(708.76)	(402.34)
2010	1506.80***	1454.92**	−51.88
	(511.18)	(568.48)	(271.85)
2011	953.59**	847.60**	−105.99
	(393.62)	(351.46)	(119.82)
2012	749.38**	736.71***	−12.67
	(300.03)	(223.85)	(122.50)
2013	900.02**	844.67***	−55.35
	(349.17)	(306.67)	(114.26)
2014	1155.24**	1158.33***	3.09
	(540.53)	(421.65)	(203.07)
2015	1851.29*	1725.91***	−125.38
	(1003.65)	(578.99)	(619.77)

Restricted to water-trading farms only. Interquartile range of estimated shadow values evaluated at pre-trade endowments, post-trade observed inputs, and the difference between the two. Standard errors block-bootstrapped at the farm level (700 iterations) in parentheses. Nonzero coefficients significant at *10%, **5% and ***1% levels.

TABLE 10. REALIZED GAINS FROM WATER TRADING

	Gains from trade			Reallocation	
	%	%, traders	AUD/ML	realloc (%)	traders (%)
Both	0.062	0.093	414.98	0.144	0.62
	[0.034, 0.093]	[0.050, 0.135]	[202.98, 658.61]	[0.128, 0.161]	[0.60, 0.64]
Annual	0.057	0.101	412.47	0.133	0.50
	[0.033, 0.078]	[0.058, 0.133]	[208.46, 596.30]	[0.118, 0.149]	[0.48, 0.52]
Permanent	0.009	0.041	178.30	0.050	0.24
	[−0.011, 0.034]	[−0.054, 0.140]	[−192.15, 808.47]	[0.034, 0.069]	[0.21, 0.26]

Estimated gains from observed water trading, 2007–2015, from pre-trade endowments described in Section 6.1. Gains from trade defined as discounted sum of (19) over t, reported as the fraction of total irrigated profits (column 1), total irrigated profits of only water-trading farms (column 2), and total trade volume (column 3). Columns 4 and 5 show trade volumes divided by total irrigation volumes and the proportion of farm-years with nonzero trade balances.

Confidence intervals report [5%,95%]-ile range of 700 draws block-bootstrapped at the farm level.

TABLE 11. WATER SCARCITY AND THE GAINS FROM ANNUAL TRADE

	Gains from trade			Reallocation	
	%	%, traders	AUD/ML	realloc (%)	traders (%)
All (annual market)	0.057	0.101	412.47	0.133	0.50
	[0.033, 0.078]	[0.058, 0.133]	[208.46, 596.30]	[0.118, 0.149]	[0.48, 0.52]
A. Regional water allocations					
Below median	0.084	0.140	750.38	0.163	0.57
	[0.048, 0.129]	[0.077, 0.193]	[394.91, 1196.13]	[0.141, 0.186]	[0.54, 0.60]
Above median	0.038	0.070	243.29	0.122	0.43
	[0.011, 0.054]	[0.020, 0.100]	[67.12, 354.08]	[0.103, 0.141]	[0.40, 0.46]
Q1	0.104	0.185	870.86	0.187	0.63
	[0.045, 0.155]	[0.084, 0.230]	[369.18, 1244.34]	[0.156, 0.221]	[0.60, 0.67]
Q2	0.064	0.099	608.30	0.143	0.50
	[0.019, 0.136]	[0.031, 0.194]	[165.10, 1468.99]	[0.119, 0.169]	[0.46, 0.54]
Q3	0.046	0.069	223.62	0.134	0.56
	[0.010, 0.078]	[0.015, 0.117]	[42.35, 365.32]	[0.106, 0.163]	[0.51, 0.61]
Q4	0.034	0.071	258.31	0.114	0.37
	[0.004, 0.052]	[0.010, 0.103]	[35.74, 389.02]	[0.092, 0.138]	[0.33, 0.41]
B. Rainfall					
Below median	0.099	0.147	513.72	0.150	0.59
	[0.050, 0.129]	[0.079, 0.194]	[281.37, 786.94]	[0.125, 0.178]	[0.56, 0.61]
Above median	0.034	0.067	313.68	0.120	0.41
	[0.012, 0.055]	[0.023, 0.100]	[86.79, 499.40]	[0.102, 0.138]	[0.38, 0.44]
Q1	0.149	0.204	784.00	0.179	0.59
	[0.086, 0.204]	[0.121, 0.270]	[444.68, 1116.45]	[0.142, 0.222]	[0.56, 0.63]
Q2	0.075	0.117	390.26	0.139	0.58
	[0.023, 0.112]	[0.037, 0.179]	[123.10, 764.89]	[0.111, 0.170]	[0.54, 0.61]
Q3	0.046	0.071	347.48	0.171	0.57
	[0.010, 0.079]	[0.014, 0.108]	[52.04, 573.98]	[0.144, 0.196]	[0.54, 0.62]
Q4	0.017	0.054	226.56	0.068	0.24
	[0.005, 0.034]	[0.018, 0.106]	[64.27, 480.80]	[0.051, 0.087]	[0.20, 0.28]

Estimated gains from observed annual water trading, for all farms 2007–2015 and then subsets specified by row. See Table 10 for additional details.

Panel A stratifies the data by $\overline{W}_{rt}$ quartile, calculated across years within each region; B stratifies the data by rainfall quartile calculated over all farm-years. Continued on next page.

Confidence intervals report [5%,95%]-ile range of 700 draws block-bootstrapped at the farm level.

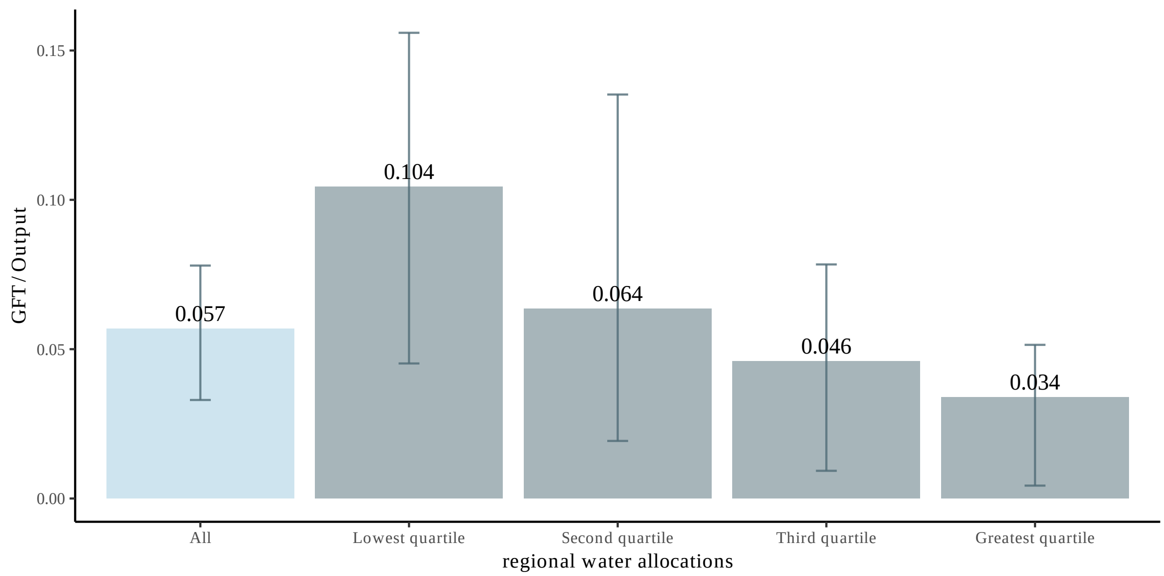
TABLE 11 (CONT'D). WATER SCARCITY AND THE GAINS FROM ANNUAL TRADE

	Gains from trade			Reallocation	
	%	%, traders	AUD/ML	realloc (%)	traders (%)
All (annual market)	0.057	0.101	412.47	0.133	0.50
	[0.033, 0.078]	[0.058, 0.133]	[208.46, 596.30]	[0.118, 0.149]	[0.48, 0.52]
C. Within-year rainfall					
Below median	0.084	0.131	459.87	0.130	0.56
	[0.042, 0.103]	[0.067, 0.156]	[212.09, 571.39]	[0.110, 0.154]	[0.54, 0.59]
Above median	0.035	0.070	344.92	0.138	0.44
	[0.014, 0.066]	[0.027, 0.130]	[124.76, 726.93]	[0.117, 0.158]	[0.41, 0.47]
Q1	0.077	0.145	477.32	0.121	0.55
	[0.042, 0.124]	[0.079, 0.202]	[259.36, 702.95]	[0.088, 0.161]	[0.51, 0.59]
Q2	0.089	0.123	448.75	0.137	0.58
	[0.027, 0.106]	[0.040, 0.147]	[109.16, 591.88]	[0.114, 0.162]	[0.54, 0.62]
Q3	0.030	0.062	306.42	0.132	0.45
	[−0.002, 0.063]	[−0.004, 0.110]	[−20.47, 582.54]	[0.106, 0.160]	[0.42, 0.50]
Q4	0.042	0.080	394.93	0.145	0.42
	[0.013, 0.090]	[0.032, 0.180]	[123.71, 1146.04]	[0.110, 0.181]	[0.38, 0.46]
D. Within-farm rainfall					
Below median	0.096	0.153	639.72	0.167	0.61
	[0.055, 0.141]	[0.077, 0.190]	[305.25, 879.00]	[0.140, 0.198]	[0.58, 0.65]
Above median	0.028	0.060	295.12	0.104	0.39
	[−0.006, 0.039]	[−0.013, 0.083]	[−53.54, 446.01]	[0.084, 0.125]	[0.36, 0.42]
Q1	0.125	0.162	675.53	0.162	0.62
	[0.060, 0.156]	[0.081, 0.203]	[303.78, 940.94]	[0.134, 0.194]	[0.58, 0.66]
Q2	0.042	0.118	492.54	0.192	0.60
	[0.015, 0.119]	[0.025, 0.178]	[100.63, 961.64]	[0.142, 0.242]	[0.54, 0.66]
Q3	0.017	0.028	194.90	0.107	0.50
	[−0.047, 0.033]	[−0.087, 0.057]	[−604.76, 372.99]	[0.075, 0.139]	[0.44, 0.55]
Q4	0.033	0.082	337.80	0.103	0.34
	[0.004, 0.054]	[0.012, 0.118]	[37.36, 636.73]	[0.079, 0.128]	[0.31, 0.37]

Continuation of previous table. Panels C and D stratify the data by rainfall quartile calculated for each year over all farms (Panel C) and for each farm over all years (Panel D).

Confidence intervals report [5%,95%]-ile range of 700 draws block-bootstrapped at the farm level.

A. Regional Water Scarcity, $\overline{W}_{rt}$



B. Farm-Level Rainfall, E^R_{it}

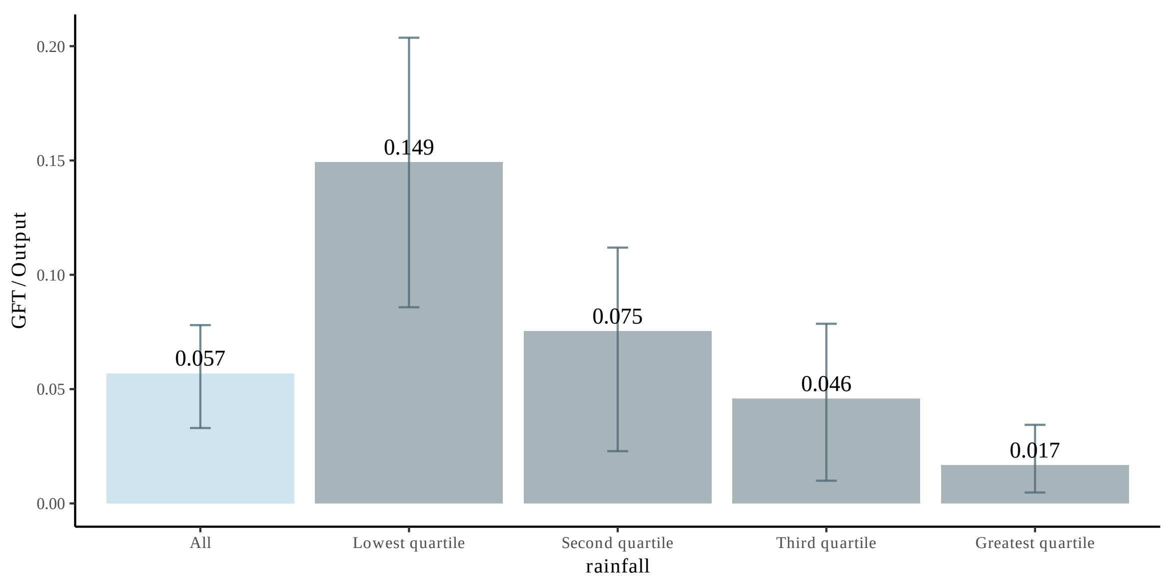
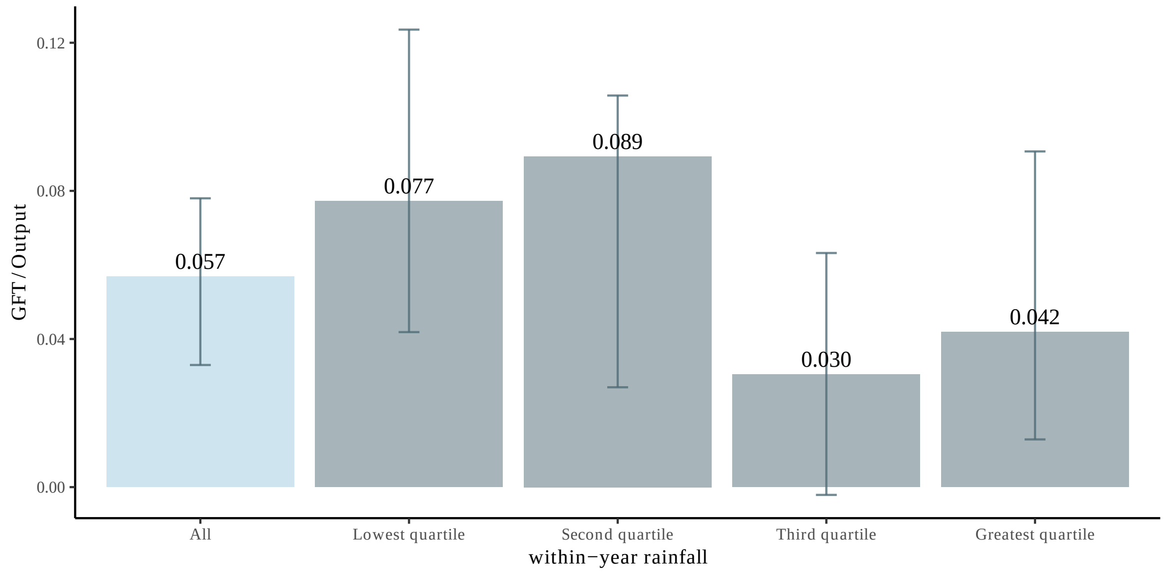


FIGURE 12. WATER SCARCITY AND THE GAINS FROM ANNUAL TRADE

Visual depiction of column (1) from Table 11.

Whiskers denote [5%,95%]-ile range of 700 draws block-bootstrapped at the farm level.

C. Within-Year Differences in Farm-Level Rainfall Across Farms, E_{it}^{R}



D. Within-Farm Differences in Rainfall Across Years, E_{it}^{R}

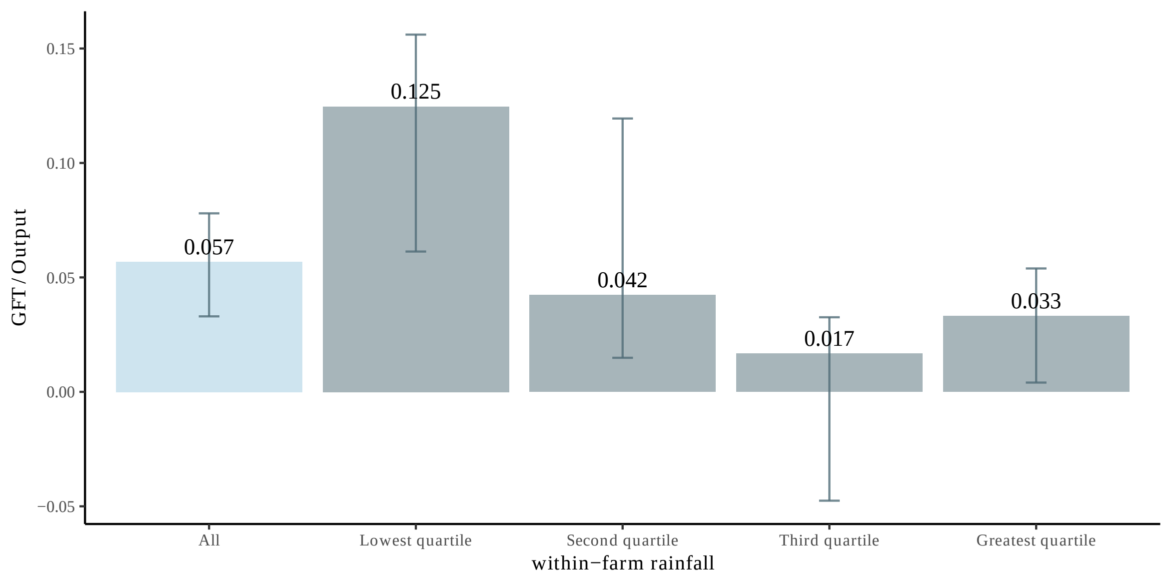


FIGURE 12 (CONT'D). WATER SCARCITY AND THE GAINS FROM ANNUAL TRADE

Whiskers denote [5%,95%]-ile range over 700 draws block-bootstrapped at the farm level.

TABLE 12. DYNAMIC PARAMETERS

	Operation type		
	Perennial	Annual	Dairy
Fixed investment cost parameters			
Median $\hat{\gamma}_{i1}$	$1,535,305.00$		
Q1	$833,641.00$		
Q3	$3,326,805.00$		
Fixed divestment cost parameters			
Median $\hat{\gamma}_{i4}$	$-850,368.20$		
Q1	$-2,390,432.00$		
Q3	$-357,217.30$		
Variable cost parameters			
Linear investment cost, $\hat{\gamma}_{c2}$	88.02	47.53	141.99
Quadratic investment cost, $\hat{\gamma}_{c3}$	312.89	-0.14	105.35
Linear divestment cost, $\hat{\gamma}_{c5}$	-97.96	329.58	156.01
Quadratic divestment cost, $\hat{\gamma}_{c6}$	54.63	0.003	-0.23

Estimated cost parameters for the land cost function (24).

TABLE 13. LONG-RUN VALUE OF WATER MARKET ACCESS

	Equilibrium outcome	
	GFT/Output	Perennial land
Dynamic gains from trade		
$\sum_i V(s_i^*) - V^a(s_i^a)$	0.082	0.044
Decomposition A.		
Static gains: $\sum_i V(s^*) - V^a(s_i^*)$	0.090	0
Dynamic adaptation channel: $\sum_i V^a(s_i^*) - V^a(s_i^a)$	−0.009	−0.044
Decomposition B.		
Static gains: $\sum_i V(s_i^a) - V^a(s_i^a)$	0.063	0
Dynamic investment channel: $\sum_i V(s_i^*) - V(s_i^a)$	0.018	0.046

Perennial operations only. Gains from trade divided by $\sum_i V(s_i^*)$. Estimated long-run gains from trade, GFT_∞ in equation (23), in the first row, with decompositions (23A) and (23B) in the successive rows. Column 2 contains average differences in investment, e.g., $\lim_{t\to\infty}(\sum_i K_{it} - K_{it}^a)/\sum_i K_{it}$.

A Estimation details

A.1 Concentration algorithm

I concentrate out ψ_c with the following procedure of Ackerberg *et al.* (2015, Appendix A4). For a candidate $\tilde{\theta}_c$, construct the residuals with (15) as

$$\hat{\omega}_{ict} = \hat{\Phi}_{ict} - \tilde{f}_c(W_{ict}, X_{ict}, K_{ict}, R_{ict}) \tag{30}$$

and

$$\hat{\omega}_{ic,t-1} = \hat{\Phi}_{ic,t-1} - \tilde{f}_c(W_{ic,t-1}, X_{ic,t-1}, K_{ic,t-1}, R_{ic,t-1}) \tag{31}$$

and regress (30) against (31). The coefficients of this regression give the transition function ψ_{ct}. The residual of this regression,

$$\tilde{\tilde{\xi}}_{ict} \equiv \omega_{ict} - \hat{\psi}_{ct}(\omega_{ic,t-1}) + \varepsilon_{ict}$$

is then stacked over t as $m_{ic} = (\tilde{\tilde{\xi}}_{ic1} \dots \tilde{\tilde{\xi}}_{icT})'$ to form the instrumental variables estimator

$$(\hat{\theta}_c, \hat{\psi}_c) \in \arg \min_{(\tilde{\theta}_c, \tilde{\psi}_c)} \left[\sum_i \mathbf{Z}'_{ic} m_{ic}(\tilde{\theta}_c, \tilde{\psi}_c)\right]' \widehat{\Xi} \left[\sum_i \mathbf{Z}'_{ic} m_{ic}(\tilde{\theta}_c, \tilde{\psi}_c)\right], \tag{32}$$

The estimator (32) is consistent for (θ_c, ψ_c) under that standard rank assumption that the inverse of $\mathbb{E}\left[\mathbf{Z}'_{ic} \frac{\partial m_{ic}}{\partial(\theta_c, \psi_c)}\right]$ exists for each c and every i. I recover the weight matrix $\widehat{\Xi}$ using a two-step procedure that first estimates (32) with $\widehat{\Xi} = I$ to obtain $(\check{\theta}_c, \check{\psi}_c)$ as above, then lets $\check{u}_{ic} = q_{ic} - \check{f}_c - \check{\psi}_{ic}$ and re-estimates (32) with $\widehat{\Xi} = \left[\sum_i \mathbf{Z}'_{ic} \check{u}_{ic} \check{u}'_{ic} \mathbf{Z}_{ic}\right]^{-1}$.

To recover $\{\hat{\omega}_{ict}\}$ for farm-years not in the main estimation sample, i.e., all (i, t) such that i first appears in the sample in year t (see Appendix C), I re-estimate the polynomial series Φ_{ict} over all farms and use the coefficients of $F_c(\cdot)$ from the estimation sample to recover $\hat{\omega}_{ict} = \widehat{\Phi}_{ict} - \hat{f}_c(\cdot)$.

A.2 Common water-augmenting technical change

Exogenous water-augmenting technical change that is common across farms and takes a known form can be included directly in the production function. I denote water-augmenting technical change by ζ_{ict} and consider the augmented production function

$$F_c(\cdot, \zeta_{ict}) = \left[\alpha_c \left(e^{\zeta_{ict}} W_{ict} + \vartheta_c R_{ict}\right)^{\frac{\sigma_c - 1}{\sigma_c}} + (1-\alpha_c) K_{ict}^{\frac{\sigma_c - 1}{\sigma_c}}\right]^{\frac{\sigma_c}{\sigma_c - 1}\beta_{cW}} \prod_j X_{ict}^{j})^{\beta_{cj}}. \tag{2'}$$

I consider irrigation-specific technical change that varies across two observables. First, over time, using the panel structure of the data; second, over observed irrigation equipment, using a measure of farm-specific irrigation capital contained in the data.

Technical change over time. I let water-augmenting technical change depend only on c and t, defined as

$$\zeta_{ict} = \mathbf{1}_{t \in T_0} + \zeta_{c1} \mathbf{1}_{t \in T_1} + \zeta_{c2} \mathbf{1}_{t \in T_2} \tag{33}$$

where $\{T_\tau\}$ is a partition of 2007–2015 into three periods of equal length. This requires no revision of χ_{ct} in (6), which already depends on t.

Observable irrigation equipment The data includes a direct value of irrigation equipment owned by the farm, K^I_{it}. All farms have land equipped for irrigation, primarily using flood-and-furrow methods; 46.9% of farms report some additional irrigation equipment of nonzero value. Relative to a farm's total capital, the value of this irrigation equipment is small—\$47,629 for an average farm with irrigation equipment—comprising 0.55% of non-land accounting capital for the median farm that does have nonzero irrigation equipment and 1.69% of non-land capital for the 75%-ile such farm. If irrigation equipment adoption decisions are exogenous,[34] then it is straightforward to allow the 47% of farms with nonzero irrigation equipment to have different water-augmenting technology, so that

$$\zeta_{ict} = 1 + \zeta_c \mathbf{1}\{K^I_{it} > 0\}. \tag{34}$$

Then I estimate F_c, now including ζ, as before, adding an indicator for irrigation equipment, $\mathbf{1}\{K^I_{it} > 0\}$ to the information set $\mathcal{F}_{i,t-1}$ in the exclusion restriction (10), and extending the functions for materials demand and the productivity control to include $\mathbf{1}\{K^I_{it} > 0\}$ as an argument in (6) and (15).

A.3 Details of dynamic estimation

First step. To recover the autocorrelation coefficients $\hat{M}$ in Table A18 used to simulate $\hat{H}$ via (27), I estimate the following first-order autoregression

$$\begin{bmatrix} \overline{W}_{rt} \\ P^W_{rt} \\ E_{it} \\ P^X_{it} \\ (P_{ict})_c \end{bmatrix} = M \begin{bmatrix} \overline{W}_{r,t-1} \\ P^W_{r,t-1} \\ E_{i,t-1} \\ P^X_{i,t-1} \\ (P_{ic,t-1})_c \end{bmatrix} + v_{it}$$

over all i and t, using a diagonal matrix M.

Second step. I construct $L = 90$ alternative policy functions κ_ℓ by perturbing the outcome of the realized policy function, as discussed in the text.

I initialize the algorithm taking each μ_{it} observed in the data for each i and t as an initial condition $\mu_{i_t 0}$; I abuse notation by taking $i = i_t$ in what follows. From these initial conditions, the algorithm simulates paths of $\mu_t \equiv \{\mu_{it}\}_i$ as in (27).

The full forward simulation runs $T = 50$ periods.

I draw $K = 500$ sequences of states, $\{(\{\mu^k_{it}\}_i)^T_{t\geq 0}\}^K_{k=1}$. For each k, I calculate the discounted sequence of payoffs for the k^{th} sequence using κ (and L perturbed κ_ℓ). Expected profits are obtained numerically for each i by averaging over all states $k = 1, \dots K$ profits, $\sum_t \delta^t \Pi$, associated with the policy κ and each policy κ_ℓ, respectively.

Each sequence also corresponds to an $L \times K$ matrix of alternative land adjustments. Each alternative adjustment path corresponds to a discounted sum of switching costs, translated into an expected discounted sum of switching costs by averaging over all sequences of states of the world. To preserve linearity, I form a basis $\mathbf{x}_{ik}$ that corresponds to the terms of Γ; specifically, for each state of the world k,

$$x_{i1k} = \sum_t \delta^t (K^k_{it} - K^k_{i,t-1})^+, \quad x_{i2k} = \sum_t \delta^t (K^k_{it} - K^k_{i,t-1})^+ (K^k_{it} - K^k_{i,t-1}), \quad \text{etc.}$$

which admits a representation of expected discounted land-switching costs as the linear function

$$\mathbb{E}_{i0}\left[\sum_t \delta^t \Gamma(\kappa^t_\ell, \kappa^{t-1}_\ell; \gamma)\right] = \gamma' \frac{1}{K} \sum_k \mathbf{x}^{(\ell)}_{ik}$$

for each ℓ and each c. Note that the appropriate γ_{i1} and γ_{i4} to use in this linear function are not the unconditional means $\overline{\gamma}_{i1}$ and $\overline{\gamma}_{i4}$, but the conditional means from the truncated normal distributions for which $\tilde{\gamma}_{i1} \leq V(s_{i0}; \kappa_+; \gamma) - V(s_{i0}; \kappa_0; \gamma)$, and similarly for divestment costs.

[34]This is partially motivated by the fact that during my period, the government ran a large-scale subsidy program irrigation technology, which complicates modeling the adoption decision. However, note that survey evidence finds a positive association between irrigation technology upgrades and a long-term plan to trade water allocations on the market (GBCMA, 2017, p. 57; Tables 42–43).

The estimator for γ is still not linear because (28) is a nonlinear objective function. As discussed, I calculate the objective in (28) by first recovering the i-specific means, then maximizing.To solve (28), I use the Nelder and Mead (1955) nonlinear optimization method implemented in `optim` in R.

Fixed point. I discretize the grid of K_{ict} for $c =$ perennial from $\{5, 10, \ldots, 500\}$, given that the maximum observed perennial land irrigated is 497 ha. I also restrict maximum jump sizes to 20 hectares. First, I run the contraction to calculate $V(s_i; \kappa; \cdot) = V_i$ under the water market. I then recover land paths $(K_{it})_{t\geq 0}$ by solving the Bellman equation given V_i. Then I use $\mathcal{W}$ under $(K_{it})_{t\geq 0}$ to calculate total long-run water use under the market mechanism. This allows me to construct stationary profits $\widetilde{\Pi}^a$ using the autarky allocations that sum to this total long-run water use. This allows the construction of $V^a(s_i; \kappa; \cdot)$ in (23A). More importantly, it allows me to solve for $V_i^a = V^a(s_i; \kappa^a; \cdot)$ with a second contraction mapping, which implies $V^a(s_i; \kappa^a; \cdot)$. Finally, I recover $(K_{it}^a)_{t\geq 0}$ by forward-simulating optimal autarky land use with V_i^a, which allows me to calculate the decomposition (23B).

B Nonparametric water-augmenting technological change

There are two steps. First, introduce a first-order condition that overidentifies the model of Section 4. Second, take this first-order condition and also make the model once again exactly-identified by introducing nonparametric technological change at the (i, c, t) level.

B.1 Water trading and price data in estimation

The estimator of Section 4 does not use water price data. In a first-best calculation, water inputs maximize interim expected profits. An immediate question is: how does imposing this optimality assumption in estimation affect the production functions? If observed inputs are set optimally, it is more efficient to include additional moments.

Information at the time of trade. To calculate the expectation $\mathbb{E}_{i,t-b}$, I assume that i draws productivity, wages, and crop prices at t conditional on their $t-1$ values. In other words, I assume that the joint distribution of productivity, wages, and crop prices is first-order Markov and that no new information arises in $[t-1, t-b]$. Let $\mathcal{F}_{it} = (P_{it}^W, E_{ict}, P_{ict}, P_{X,it}^L, \omega_{it})$ denote the payoff-relevant exogenous variables known by i at time t. Interim information at $t-b$ is given by

$$\mathcal{F}_{i,t-b} = (P_{it}^W, E_{ict}, P_{ic,t-1}, P_{X,i,t-1}^L).$$

That is, time-t water prices and rainfall are known at $t-b$, as discussed in Section 3.2, but no new information arrives about productivity, crop prices, or wages. The assumption is that $\mathcal{F}_{it}$ evolves from $\mathcal{F}_{i,t-b}$ for each i according to a first-order Markov process:

Assumption B1 (Interim information set)**.** *The interim, conditional distribution of $\mathcal{F}_{it}$ at $t-b$ is given by*

$$H(\mathcal{F}_{it}|\mathcal{F}_{i,t-b}), \tag{35}$$

that is, it does not depend on i, t, or $(\mathcal{F}_{i,t-s})$ for $s > 1$, except through $\mathcal{F}_{i,t-b}$.

Assumption B1 lets me recover the conditional distribution H of crop prices, wages, and productivity directly from the multivariate empirical distribution of

$$(P_{ict}, P_{X,it}^L, \hat{\omega}_{ict} | P_{it}^W, E_{it}, P_{i,c,t-1}, P_{X,i,t-1}^L, \hat{\omega}_{ic,t-1})$$

observed in (or, in the case of $\hat{\omega}_{ict}$, estimated from) the data. Then the interim expected shadow value of water can be written as

$$\mathbb{E}_{t-b}\left[P_{ict} e^{\omega_{ict}} \frac{\partial F_c}{\partial W}\right] = \Lambda_{ict}(W) \cdot \mu_{ict}(W, \mathcal{F}_{i,t-b}) \tag{36}$$

where the known component of the shadow value at $t-b$,

$$\Lambda_{ict}(W) = \frac{\alpha_c \beta_{cW} W^{-1/\sigma_c}}{[A_{ict}(W)]^{\frac{\sigma_c}{\sigma_c - 1 - \sigma_c \beta_{cW}}}},$$

is obtained with the derivative of (2), denoting $A_{ict}(W) \equiv (\alpha_c (W + \vartheta_c R_{ict})^{(\sigma_c - 1)/\sigma_c} + (1-\alpha_c) K_{ict}^{(\sigma_c-1)/\sigma_c})^{\sigma_c/(\sigma_c-1)}$, and the expected component due to random crop prices, labor, and productivity is defined given H and its support $\mathcal{H}$ as

$$\mu_{ict}(W, \mathcal{F}_{i,t-b}) = \int_{\mathcal{H}} \left[P_c e^{\omega} \prod_j X^*_{c,j}(W, P_c, P^L_X, \omega; \cdot)^{\beta_{cj}} \right] dH(P_c, P^L_X, \omega | \mathcal{F}_{i,t-b}). \tag{37}$$

With the estimated H, (36) then gives the interim expected shadow price of water relevant to the optimal irrigation decision.[35]

The decomposition (36) further simplifies when labor and materials are multiplicatively separable in the production function as in (2). After taking natural logarithms, optimal labor and materials solve the linear system of equations

$$\ln X^*_c(W, P_{ict}, P^L_{X,it}, \omega_{ict}; \cdot) = \begin{bmatrix} x^L_{ict} \\ x^{\mathcal{F}}_{ict} \end{bmatrix} = \begin{bmatrix} \beta_{cL} - 1 & \beta_{cM} \\ \beta_{cL} & \beta_{cM} - 1 \end{bmatrix}^{-1} \begin{bmatrix} p^L_{X,it} - c_{ict} \\ \ln 1 - c_{ict} \end{bmatrix}$$

where $c_{ict} = \omega_{ict} + p_{ict} + \beta_{cW} \ln A_{ict}$. Then $\ln \mu_{ict} = d_{ict} + b_{ict} \ln A_{ict}(W)$, where

$$d_{ict} = - \begin{bmatrix} \beta_{cL} \\ \beta_{cM} \end{bmatrix}' \begin{bmatrix} \beta_{cL} - 1 & \beta_{cM} \\ \beta_{cL} & \beta_{cM} - 1 \end{bmatrix}^{-1} \begin{bmatrix} \ln \beta_{cL} + \omega_{ict} + p_{ict} - p^L_{X,it} \\ \ln \beta_{cM} + \omega_{ict} + p_{ict} - \ln 1 \end{bmatrix}$$

$$\text{and} \quad b_{ict} = - \begin{bmatrix} \beta_{cL} \\ \beta_{cM} \end{bmatrix}' \begin{bmatrix} \beta_{cL} - 1 & \beta_{cM} \\ \beta_{cL} & \beta_{cM} - 1 \end{bmatrix}^{-1} \begin{bmatrix} \beta_{cW} \\ \beta_{cW} \end{bmatrix},$$

so that I can simulate $D_{ict} = e^{d_{ict}}$ separately from $\Lambda_{ict}(W)[A_{ict}(W)]^{b_{ict}}$.

Without transaction costs, if irrigation is set to interim first-best levels, given a market water price P^W_{it}—which in the data I take to be the average price of i's region in year t—then it is possible to model irrigation with the following assumption.

Assumption Z1 (Optimal irrigation)**.** *For all i, c, and t,*

$$\mathbb{E}_{i,t-b} \left[P_{ict} e^{\omega_{ict} + \varepsilon_{ict}} \frac{\partial F_c(W_{ict}, \cdot)}{\partial W_{ict}} \right] \leq P^W_{it}, \tag{38}$$

with equality if $W_{ict} > 0$.

The set of moments given previously by (16) become

$$\mathbb{E} \left[\left(\begin{matrix} q_{ict} - f_{ict} - \psi_c(\widehat{\Phi}_{ic,t-1} - f_{ic,t-1}) \\ \frac{\partial f_{ict}}{\partial w_{ict}} - p^W_{it} + \widehat{\Phi}_{ict} - f_{ict} - \psi_c \left(\frac{\partial f_{ic,t-1}}{\partial w_{ic,t-1}} - p^W_{i,t-1} + \widehat{\Phi}_{ic,t-1} - f_{ic,t-1} \right) \end{matrix} \right) \otimes \mathbf{Z}_{ict} \right] = 0, \tag{16$'$}$$

where $\frac{\partial f_{ict}}{\partial w_{ict}} = \ln \mu_{ict} + \lambda_{ict}(W_{ict})$ is the interim ex-ante shadow value.

[35] Calculating the integral in (37) once for every i, c, and t is computationally intensive, but (37) is also a function of W and in principle the expectation must be calculated for every value of W. The multiplicative separability of labor and materials in the production function (2) allows the derivation of $\mathbf{x}^*_c$ as a linear form in w_{ict}, giving the decomposition

$$\ln \mu_{ict}(W, \mathcal{F}_{i,t-b}) = d_{i,t-b} + b_{ict} \Lambda_{ict}(W),$$

which enables the evaluation of (36) at any W after a single evaluation of the integral in (37).

B.2 Nonparametric water-augmenting technology

If farms do make annual irrigation decisions with respect to the water price using (35) and (38), then a natural extension of the benchmark model of Section 3 is one that allows for an additional unobservable—"water-augmenting productivity"—recovered by jointly inverting the materials and irrigation optimality conditions to control for both unobserved productivities in the spirit of Ackerberg *et al.* (2007, §2.4.3) and Doraszelski and Jaumandreu (2018).

If Assumptions B1 and Z1 do hold, then this extension improves the fit of the model, and allows us to study water-augmenting productivity, a primitive that is relevant to water-trading as well as potentially of independent interest. It also delivers a calculation of the realized gains from trade under the hypothesis that the market is (interim ex-ante) efficient.

Overview of solution. The additional complication introduced by this extension is that materials demand χ_{ct}, used previously to control for ω_{ict}, now also depends on the unobserved ζ_{ict}. This requires extending Assumption A1 to restrict the conditional dependence of (X^M_{ict}, W_{ict}) on $(\omega_{ict}, \zeta_{ict})$. Given that the baseline model imposes the strongest possible restriction—that $\zeta_{ict} = 0$ for all i, c and t—this extension is a generalization of the model of Section 3.

The algorithm I use inverts irrigation demand $\mathcal{W}_{ct}(\cdot)$ to recover ζ_{ict} conditional on ω_{ict}, then inverts materials demand evaluated at $\exp(\zeta_{ict})W_{ict}$ to control for ω. The first step of this algorithm is the same as in Section 4, except that it uses a revised Φ^{ζ}_{ict} that inverts the composition of materials demand and (inverted) irrigation demand to control for ω. The step now includes a nested fixed point algorithm that, for each candidate $\tilde{f}_c$, recovers the unobserved water-augmenting change $\{\zeta\}$ to rationalize the observed irrigation decisions, and then proceeds to estimate $\mathbb{E}[\xi_{ict} + \varepsilon_{ict}|\mathcal{F}_{i,t-1}] = 0$ as before, replacing the observed value of W_{ict} with the technology-adjusted $e^{\zeta_{ict}}W_{ict}$. The algorithm is computationally intensive but attractive because it is clearly admits the model of Sections 4 as a special case.

Detailed assumptions. I assume that both ζ_{ict} and ω_{ict} are known at $t-b$, so that the time-$(t-b)$ information set is

$$\mathcal{F}_{i,t-b} = (P^W_{it}, E_{it}, P_{ic,t-1}, P^L_{X,i,t-1}, \omega_{ict}, \zeta_{ict}).$$

Irrigation demand equals

$$\begin{aligned} W_{ict} &= \mathcal{W}_{ct}(K_{ict}, \mathcal{F}_{i,t-b}) \\ &= \mathcal{W}_{ct}(K_{ict}, P^W_{it}, E_{it}, P_{ic,t-1}, P^L_{X,i,t-1}, \omega_{ict}, \zeta_{ict}). \end{aligned} \tag{39}$$

If $\mathcal{W}^{\zeta}_c(\cdot)$ is strictly monotonic in ζ_{ict}, it can be inverted obtain

$$\zeta_{ict} = (\mathcal{W}_{ct})^{-1}(W_{ict}; K_{ict}, \mathcal{F}_{i,t-b}). \tag{40}$$

The nonparametric demand function for intermediate inputs is unchanged from (6) after adjusting W_{ict} by its water-augmenting productivity:

$$\begin{aligned} X^M_{ict} &= \chi_{ct}\left(\exp(\zeta_{ict})W_{ict}, R_{ict}, K_{ict}, X^L_{ict}, X^F_{ict}, P_{ict}, \omega_{ict}\right) \\ &= \chi_{ct}\left(\exp\left((\mathcal{W}_{ct})^{-1}(W_{ict}; K_{ict}, \mathcal{F}_{i,t-b})\right) W_{ict}, R_{ict}, K_{ict}, X^L_{ict}, X^F_{ict}, P_{ict}, \omega_{ict}\right), \end{aligned} \tag{6$'$}$$

or the composition of χ_{ct} and $(\mathcal{W}_{ct})^{-1}$, given by

$$X^M_{ict} = \chi^{\zeta}_{ct}(W_{ict}, R_{ict}, K_{ict}, X^L_{ict}, X^F_{ict}, P_{ict}, \mathcal{F}_{i,t-b}, \omega_{ict}), \tag{41}$$

which differs from (6) only through the presence of $\mathcal{F}_{i,t-b}$. To use the two-step procedure similar to that of Section 4, I modify Assumption A1 to ensure that (40) exists and that (41) is strictly increasing in ω_{ict}:

Assumption Z1. *For all c and t, materials demand χ^{ζ}_{ct}, given in (41), is strictly increasing in ω_{ict}, and irrigation demand $\mathcal{W}_{ct}$, given in (39), is strictly increasing in ζ_{ict}.*

In language similar to Section 4, the key control function assumption is then that

$$\chi_{ct}(\exp((\mathcal{W})^{-1}_{ct}(\omega;\dots))W_{ict},\cdots,\omega)$$

remains strictly monotone in ω.

The only restriction that I impose on water-augmenting productivity is that it contain no useful information about Hicks-neutral productivity. I restate Assumption A2 as

Assumption Z2. *Productivity $(\omega_{ict})_{t\geq 0}$ evolves as an exogenous first-order Markov process that is conditionally independent from $(\zeta_{ict})_{t\geq 0}$ given $(\omega_{ic,t-1})_{t\geq 0}$, for each i, c, and t.*

Assumption Z2 is a convenient simplification to avoid needing to condition on $(\zeta_{ics})_{s\leq t}$ in the prediction $\psi_{ct}(\omega_{ic,t-1}) = \mathbb{E}[\omega_{ict}|\mathcal{F}_{i,t-1}]$. As mentioned previously, Assumption Z2 does not otherwise restrict water-augmenting productivity. In particular, it may evolve arbitrarily over time, in contrast to the first-order restriction on $(\omega_{ict})_{t\geq 0}$. This is because $(\zeta_{ict})_{t\geq 0}$ is never estimated, but recovered from (40) for every i, c, and t and candidate parameter value from the static optimality condition in Assumption Z1, and affects output only through $e^{\zeta_{ict}}W_{ict}$. Expectations about its evolution will affect the dynamic input decisions K_{ict}, but these are outside of the model.[36]

Algorithm. The first step recovers a slightly modified (15),

$$f^{\zeta}_{ict} + \omega_{ict} = \Phi^{\zeta}_{c}\left(X^{M}_{ict}; W_{ict}, R_{ict}, K^{D}_{ict}, X^{L}_{ict}, P_{ict}, \mathcal{F}_{i,t-b}\right). \tag{15$'$}$$

exactly as before, where f^{ζ}_{ict} denotes $f_c(\cdot;\zeta_{ict})$ evaluated at observed inputs. Equation (16) still holds, but now (16) is calculated as

$$\mathbb{E}\left[\left(q_{ict} - f^{\zeta}_{ict} - \psi_c(\widehat{\Phi}^{\zeta}_{ic,t-1} - f^{\zeta}_{ic,t-1})\right) \otimes \mathbf{Z}^{\zeta}_{ict}\right] = 0, \tag{16$'$}$$

with ζ_{ict} recovered from (36) as the solution to

$$\zeta = p^{W}_{it} - \Phi^{\zeta}_{ict} + f_c(\cdot;\zeta) - d_{ict} - \lambda_{ict}(W_{ict},\zeta) - b_{ict}\ln A_{ict}(e^{\zeta}W_{ict})$$

since $\Phi^{\zeta}_{ict} - f_c(\cdot;\zeta_{ict}) = \omega_{ict}$.

Because Z^{W}_{ict} and P^{W}_{it} appear in (15$'$) through $\mathcal{F}_{i,t-b}$, they can no longer be used as instruments for W_{ict}. Hence I use their lagged counterparts, setting

$$\mathbf{Z}^{\zeta}_{ict} = (1, \zeta_c(Z^{W}_{ic,t-1}, P^{L}_{X,it}, K_{ict}, E_{ict}))',$$

and then estimating two-step GMM as in (32).

[36]This is in contrast to Doraszelski and Jaumandreu (2018). In their setting, firms also choose an unobservable temporary labor share. To identify labor-augmenting productivity ζ_{ict} in the presence of this unobservable choice, they assume ζ is first-order Markov so that the time-t labor-augmenting productivity anticipated at $t-1$ can be estimated as a function of $\zeta_{ic,t-1}$.

C Details of data construction

1. Sample restrictions

1.1 Geographic restrictions. The survey collected data from the following regions from 2007–2015 in the southern Murray Darling Basin: Victoria Murray, Victoria Goulburn, South Australia Murray, New South Wales Murrumbidgee, and New South Wales Murray. (Survey regions outside of these five sMDB regions were discontinued after 2011 due to funding cuts.) Australian fiscal years run 1 July to 30 June; throughout, "2007" refers to 1 July 2006 to 30 June 2007, et cetera.

1.2 The rotating survey design means not all farms are observed more than once. I restrict estimation of (θ, ψ) to farms observed in at least two years. Counterfactuals are calculated with data from all farms.

2. Variable definitions

2.1 Output, Q_{ict}, is computed for each crop type c as the weighted sum of physical production Q_{ic_kt} over all crops $c_k \in c$,

$$Q_{ict} = \sum_{c_k \in c} P_{c_k 0} Q_{ic_k t}$$

weighted by baseline average prices, $P_{c_k 0} \equiv \sum_i Y_{ic_k 2007} / \sum_i Q^{\text{sold}}_{ic_k,2007}$, where $Y_{ic_k 2007}$ is the recorded revenue (AUD) farm i received in 2007 for $Q^{\text{sold}}_{ic_k,2007}$ tonnes of crop c_k sold. The categories are:

For $c =$ annual irrigated, $c_k \in \{$rice, oilseeds, cotton, pulse, vegetables, cereal, coarse grains$\}$.

For $c =$ annual nonirrigated, $c_k \in \{$rice, oilseeds, cotton, pulse, vegetables, cereal, coarse grains$\}$.

For $c =$ horticulture, $c_k \in \{$pome fruits, citrus fruits, stone fruits, vine fruits, wine$\}$.

For $c =$ dairy, c_k corresponds to milk production (liters).

2.2 Crop prices. I define crop-type prices as the weighted sum of the value of c_k in year t, $P_{c_k t} \equiv \sum_i Y_{ic_k t} / \sum_i Q^{\text{sold}}_{ic_k t}$ in year t for crop c_k, divided by output,

$$P_{ict} = \frac{\sum_{c_k \in c} P_{c_k t} Q_{ic_k t}}{\sum_{c_k \in c} P_{c_k 0} Q_{ic_k t}}.$$

2.3 Irrigation volumes and extent of land planted are recorded at the resolution $W_{ic_k t}$ and $K_{ic_k t}$, so $W_{ict} \equiv \sum_{c_k \in c} W_{ic_k t}$ and $K_{ict} \equiv \sum_{c_k \in c} K_{ic_k t}$. Irrigation and land for dairy is the sum of irrigation and land used for pasture to grow feed.

Other inputs

2.4 Materials, X^M_{ict}, are calculated as the sum of i's year-t expenditure on crop and pasture chemicals, fertilizer, seed, electricity, fuel, packing materials, and packing charges. The survey also records expenses for repairs and maintenance, administrative costs, motor vehicle expenses, handling and market expenses, and other services.

2.5 Labor, X^L_{ict}, is measured in total weeks worked, both by hired labor and family labor.

2.6 The wage, $P^L_{X,it}$, is the sum of i's hired labor costs and imputed family labor costs in year t (AUD), divided by the total labor weeks worked on farm i in year t.

Environmental variables

3.1 Rainfall is collected by the BoM, interpolated to a grid of 0.05 degree resolution. Rainfall is matched to farms by ABARES analysts with GIS codes. Winter rainfall is April–October and summer rainfall is November–March.

3.2 Evapotranspiration. The BoM Australian Water Resource Assessment Landscape (AWRA-L) model (Frost *et al.*, 2016) recovers implied evapotranspiration from rainfall, temperature, and soil conditions using an adaptation of the Penman (1948) equations to agriculture (Van Dijk and Bruijnzeel, 2001). I take the unweighted average over all grid cells in each Water Resource Plan Area (WRPA) surface water polygon, corresponding to the legal boundaries specified in the 2007 Water Act for NSW Murray, NSW Murrumbidgee, Victoria Murray, Victoria Goulburn, and South Australia Murray.

Other prices

4. Average farm interest rate data collected by ABARES. Real interest rate calculated by deflating the average nominal rate (0.0714) with the Australian Bureau of Statistics consumer price index.

A Supplementary Tables and Figures (Not For Publication)

Table A1. Output, Land, Labor, Materials

	$N \times T$	mean	s.d.	Q.10	Q.25	Q.50	Q.75	Q.90
price-weighted quantity	2,032	977.44	1,428.54	42.62	117.77	407.37	1,263.19	2,627.17
revenue	2,032	682.90	995.83	42.72	115.81	345.01	910.68	1,712.91
crop price index	2,032	0.88	0.30	0.42	0.66	0.94	1.11	1.23
irrigated land, hectares	2,032	299.72	522.37	11.40	25	104	360	780.90
land operated, hectares	2,032	569.45	1,148.44	16.20	40	190.50	607	1,360
labor, weeks	2,032	179.75	285.32	42.60	68.58	114	190	329
materials	2,032	158.65	249.45	12.51	29.10	75.63	183.19	383.92

Farm-level input-output data. Units are in thousands of 2015 Australian dollars.

Source: ABARES Survey of Irrigated Farms.

Table A2. Regional Water-Sharing Rules

	2007	2008	2009	2010	2011	2012	2013	2014	2015
NSW Murray	0.095	0.059	0.179	0.351	0.735	0.433	0.685	0.965	0.652
NSW Murrumbidgee	0.247	0.229	0.316	0.368	0.767	0.764		0.664	0.582
SA Murray	0.800	0.320	0.180	0.620	0.670	1	1	1	1
VIC Goulburn	0.290	0.570	0.330	0.720	1.014	1.014	1.014	1.014	1.014
VIC Murray	0.950	0.430	0.350	1.000	1.015	1.015	1.015	1.015	1.053

Data underlying Figure 2. Total water allocated in each region and each year, as a fraction of total entitlements on issue at baseline, 2007.

Source: NSW, VIC, and South Australia state government regulatory records.

Table A3. Intraday Water Price Dispersion

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Days	Volume
VIC Murray	0	0.043	0.076	0.124	0.140	2.471	1,908	2,217,989
NSW Murray	0	0.019	0.058	0.123	0.147	1.311	1,907	2,569,916
SA Murray	0	0.018	0.051	0.127	0.114	3.347	643	706,268
Murrumbidgee	0	0.032	0.073	0.173	0.173	2.552	1,211	2,283,161
Goulburn	0	0.029	0.058	0.117	0.116	4.217	1,681	1,650,034
All regions	0	0.068	0.126	0.213	0.239	4.345	2,459	9,427,368

Transaction-level water price data from the annual allocation market. Summary of the daily volume-weighted coefficients of variation for water prices, over all days with at least two trades (2008–2015). The last two columns report the number of days with at least two trades and total volume of traded water (ML), respectively.

Source: MDBA administrative transaction-level water price data.

TABLE A4. WATER TRADING AND FIXED CHARACTERISTICS

	Annual Rights		Permanent Rights	
	Buy, $\mathbf{1}(\Delta_{it} > 0)$	Sell, $\mathbf{1}(\Delta_{it} < 0)$	Buy, $\mathbf{1}(\rho_{it} > \rho_{i,t-1})$	Sell, $\mathbf{1}(\rho_{it} < \rho_{i,t-1})$
	(1)	(2)	(3)	(4)
$\ln(\text{net\_rainfall}_{it})$	-0.069^{***}	-0.049^{***}	-0.001	-0.013
	(0.016)	(0.014)	(0.019)	(0.022)
$\mathbf{1}(c = \text{annual\_nonirrig})$	-0.321^{***}	0.180^{***}	-0.034	0.010
	(0.039)	(0.033)	(0.040)	(0.046)
$\mathbf{1}(c = \text{pasture})$	-0.011	0.039	0.053	-0.036
	(0.036)	(0.030)	(0.037)	(0.043)
$\mathbf{1}(c = \text{perennial})$	-0.106^{***}	0.159^{***}	-0.006	-0.063^{*}
	(0.028)	(0.024)	(0.030)	(0.035)
$\mathbf{1}(t = 2008)$	0.225^{***}	0.022		
	(0.036)	(0.031)		
$\mathbf{1}(t = 2009)$	0.188^{***}	0.058^{*}	-0.102^{***}	-0.338^{***}
	(0.037)	(0.032)	(0.035)	(0.041)
$\mathbf{1}(t = 2010)$	0.118^{***}	-0.031	-0.177^{***}	-0.419^{***}
	(0.041)	(0.035)	(0.035)	(0.041)
$\mathbf{1}(t = 2011)$	-0.028	-0.056	-0.150^{***}	-0.392^{***}
	(0.049)	(0.042)	(0.043)	(0.050)
$\mathbf{1}(t = 2012)$	-0.021	-0.080^{**}	-0.176^{***}	-0.380^{***}
	(0.043)	(0.037)	(0.038)	(0.044)
$\mathbf{1}(t = 2013)$	0.109^{**}	0.004	-0.200^{***}	-0.480^{***}
	(0.052)	(0.045)	(0.046)	(0.053)
$\mathbf{1}(t = 2014)$	0.192^{***}	0.053	-0.101^{**}	-0.296^{***}
	(0.043)	(0.037)	(0.043)	(0.050)
$\mathbf{1}(t = 2015)$	0.061	0.087^{**}	-0.185^{***}	-0.420^{***}
	(0.041)	(0.035)	(0.038)	(0.044)
$\mathbf{1}(i \in r = \text{NSW Murrumbidgee})$	-0.101^{***}	0.150^{***}	0.005	0.023
	(0.034)	(0.029)	(0.034)	(0.039)
$\mathbf{1}(i \in r = \text{SA Murray})$	0.091^{**}	-0.209^{***}	0.009	0.013
	(0.036)	(0.031)	(0.039)	(0.046)
$\mathbf{1}(i \in r = \text{VIC Goulburn})$	0.065^{*}	-0.082^{**}	-0.065^{*}	0.053
	(0.037)	(0.032)	(0.038)	(0.044)
$\mathbf{1}(i \in r = \text{VIC Murray})$	-0.004	-0.057^{*}	-0.022	0.006
	(0.039)	(0.034)	(0.040)	(0.047)
Constant	0.661^{***}	0.359^{***}	0.243^{**}	0.578^{***}
	(0.071)	(0.061)	(0.096)	(0.112)
Mean of dep. var.	0.319	0.196	0.094	0.154
Observations	2,032	2,032	954	954
R^2	0.143	0.136	0.055	0.158

Unit of observation is the farm-year. OLS regression of an indicator variable for farm i
(1) buying water allocations in year t,
(2) selling water allocations in year t,
(3) increasing water entitlements owned from $t-1$ to t
(4) reducing water entitlements owned from $t-1$ to t.
Crop-types assigned by year t for multicrop farms as $c \in \arg\max_{c:K_{ict}>0} W_{ict}$. Omitted factors are $\mathbf{1}\{c = \text{annual irrigated}\}$, $\mathbf{1}\{t = 2007\}$, and $\mathbf{1}\{i \in \text{NSW Murray}\}$. Conventional standard errors in parentheses; nonzero coefficients significant at *10%, **5% and ***1% levels.

TABLE A5. PERMANENT WATER TRADING DECISIONS AND RAINFALL

A. Increase in permanent rights held

	Dependent variable:			
	Buy, $\mathbf{1}(\rho_{it} > \rho_{i,t-1})$			
	(1)	(2)	(3)	(4)
$\ln(\text{net\_rainfall}_{it})$	-0.009	0.010	0.027	0.004
	(0.014)	(0.023)	(0.026)	(0.034)
$\ln(\text{water\_endowment}_{it})$	0.030***	0.030***	0.031***	0.072*
	(0.009)	(0.009)	(0.010)	(0.037)
Year FEs	✓	✓	✓	✓
Region FEs		✓	✓	
Region×Year FEs			✓	
Farm FEs				✓
Observations	954	954	954	954
Adjusted R^2	0.059	0.058	0.059	0.036

B. Decrease in permanent rights held

	Dependent variable:			
	Sell, $\mathbf{1}(\rho_{it} < \rho_{i,t-1})$			
	(1)	(2)	(3)	(4)
$\ln(\text{net\_rainfall}_{it})$	-0.005	-0.007	-0.040	0.010
	(0.016)	(0.026)	(0.028)	(0.051)
$\ln(\text{water\_endowment}_{it})$	0.002	0.006	0.002	-0.142***
	(0.009)	(0.010)	(0.010)	(0.045)
Year FEs	✓	✓	✓	✓
Region FEs		✓	✓	
Region×Year FEs			✓	
Farm FEs				✓
Observations	954	954	954	954
Adjusted R^2	0.149	0.147	0.238	0.188

Version of Table 3 for permanent rights. The unit of observation is the farm-year. Regressions of the indicator of trading permanent water rights on farm-level characteristics: net rainfall (annual rainfall minus evapotranspiration), realized permanent water endowments, and crop prices.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses. Nonzero coefficients significant at *10%, **5% and ***1% levels.

TABLE A6. SENSITIVITY TO TECHNICAL CHANGE: PERENNIAL IRRIGATED

	(1)	(2)	(3)	(4)	(5)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.277	0.300	0.265	0.282	0.290
	(0.061)	(0.131)	(0.056)	(0.074)	(0.052)
$\frac{\partial f_c}{\partial w}$_10	0.124	0.137	0.116	0.127	0.182
	(0.038)	(0.048)	(0.036)	(0.045)	(0.044)
$\frac{\partial f_c}{\partial w}$_25	0.231	0.249	0.222	0.227	0.247
	(0.057)	(0.088)	(0.052)	(0.069)	(0.046)
$\frac{\partial f_c}{\partial w}$_75	0.354	0.380	0.340	0.359	0.359
	(0.074)	(0.182)	(0.071)	(0.091)	(0.063)
$\frac{\partial f_c}{\partial w}$_90	0.381	0.408	0.362	0.382	0.389
	(0.078)	(0.243)	(0.072)	(0.096)	(0.068)
Returns to scale, $\sum_j \beta_{cj}$	1.164	1.160	1.166	1.201	1.106
	(0.146)	(0.060)	(0.056)	(0.111)	(0.197)
λ_{ict}_median	467.55	507.62	447.50	470.57	473.11
	(99.76)	(215.73)	(93.13)	(126.64)	(84.26)
λ_{ict}_IQ	331.63	370.04	321.67	357.17	344.84
	(84.53)	(203.86)	(76.20)	(100.32)	(111.79)
λ_{ict}_90_10	762.16	818.47	713.25	841.22	881.51
	(195.99)	(407.35)	(179.49)	(247.92)	(219.87)
Productivity persistence, ρ_c	0.639	0.611	0.629	0.635	0.587
	(0.064)	(0.049)	(0.044)	(0.083)	(0.106)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	0.067	0.050	0.060	0.041	0.097
	(0.017)	(0.031)	(0.016)	(0.031)	(0.060)
J-statistic	0.206	0.349	0.325	0.154	0.248
Adjusted R^2	0.816	0.816	0.816	0.798	0.831
$N \times T$	493	493	493	298	189

(1) Original estimates.

(2) ζ_{ict} as a function of observed irrigation equipment as in (34).

(3) Common ζ_{ict} over time as in (33).

(4) Restricts estimation sample to 2007–2011.

(5) Restricts estimation sample to 2012–2015.

Standard errors block-bootstrapped at the farm level (500 iterations) in parentheses..

TABLE A7. SENSITIVITY TO TECHNICAL CHANGE: ANNUAL IRRIGATED

	(1)	(2)	(3)	(4)	(5)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.234	0.173	0.193	0.167	0.347
	(0.044)	(0.039)	(0.035)	(0.039)	(0.081)
$\frac{\partial f_c}{\partial w}$_10	0.089	0.068	0.082	0.053	0.192
	(0.035)	(0.025)	(0.023)	(0.020)	(0.063)
$\frac{\partial f_c}{\partial w}$_25	0.170	0.129	0.144	0.107	0.286
	(0.044)	(0.032)	(0.031)	(0.029)	(0.070)
$\frac{\partial f_c}{\partial w}$_75	0.309	0.226	0.249	0.228	0.430
	(0.054)	(0.050)	(0.044)	(0.051)	(0.099)
$\frac{\partial f_c}{\partial w}$_90	0.353	0.254	0.285	0.258	0.463
	(0.058)	(0.061)	(0.050)	(0.059)	(0.106)
Returns to scale, $\sum_j \beta_{cj}$	1.124	1.123	1.131	1.244	1.157
	(0.088)	(0.082)	(0.080)	(0.122)	(0.172)
λ_{ict}_median	100.84	74.25	82.44	72.53	127.25
	(19.05)	(17.18)	(15.54)	(45.67)	(28.97)
λ_{ict}_IQ	143.73	111.84	126.43	392.07	78.15
	(94.26)	(92.43)	(87.85)	(146.87)	(24.16)
λ_{ict}_90_10	774.29	599.81	675.39	712.12	234.45
	(195.47)	(170.78)	(157.38)	(242.92)	(163.33)
Productivity persistence, ρ_c	0.524	0.497	0.506	0.522	0.767
	(0.090)	(0.091)	(0.089)	(0.105)	(0.141)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	0.081	0.061	0.073	-0.151	-0.012
	(0.063)	(0.055)	(0.056)	(0.159)	(0.072)
J-statistic	0.191	0.218	0.217	0.360	0.651
Adjusted R^2	0.748	0.748	0.748	0.539	NaN
$N \times T$	170	170	170	90	74

(1) Original estimates.

(2) ζ_{ict} as a function of observed irrigation equipment as in (34).

(3) Common ζ_{ict} over time as in (33).

(4) Restricts estimation sample to 2007–2011.

(5) Restricts estimation sample to 2012–2015.

Standard errors block-bootstrapped at the farm level (500 iterations) in parentheses..

TABLE A8. SENSITIVITY TO TECHNICAL CHANGE: DAIRY

	(1)	(2)	(3)	(4)	(5)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.087	0.069	0.051	0.091	0.174
	(0.035)	(0.048)	(0.091)	(0.037)	(0.069)
$\frac{\partial f_c}{\partial w}$_10	0.024	0.016	0.015	0.056	0.088
	(0.020)	(0.022)	(0.021)	(0.019)	(0.037)
$\frac{\partial f_c}{\partial w}$_25	0.043	0.027	0.023	0.074	0.126
	(0.027)	(0.029)	(0.030)	(0.028)	(0.051)
$\frac{\partial f_c}{\partial w}$_75	0.118	0.083	0.063	0.111	0.227
	(0.046)	(0.058)	(0.090)	(0.048)	(0.090)
$\frac{\partial f_c}{\partial w}$_90	0.152	0.137	0.092	0.120	0.256
	(0.059)	(0.085)	(0.203)	(0.060)	(0.097)
Returns to scale, $\sum_j \beta_{cj}$	0.988	1.032	0.998	1.074	0.958
	(0.158)	(0.150)	(0.132)	(0.165)	(0.208)
λ_{ict}_median	129.20	85.32	68.93	217.62	224.15
	(64.45)	(73.42)	(81.34)	(85.86)	(90.14)
λ_{ict}_IQ	235.21	48.81	34.97	175.25	111.41
	(78.02)	(84.57)	(216.72)	(82.20)	(48.94)
λ_{ict}_90_10	555.90	125.88	90.74	366.57	225.15
	(196.25)	(211.51)	(720.66)	(196.36)	(102.85)
Productivity persistence, ρ_c	0.384	0.399	0.371	0.352	0.359
	(0.178)	(0.179)	(0.161)	(0.200)	(0.290)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	-0.103	-0.076	-0.089	-0.092	-0.021
	(0.035)	(0.033)	(0.030)	(0.090)	(0.031)
J-statistic	1.161	0.646	0.687	0.639	1.102
Adjusted R^2	0.866	0.866	0.866	0.913	NaN
$N \times T$	256	256	256	151	104

(1) Original estimates.

(2) ζ_{ict} as a function of observed irrigation equipment as in (34).

(3) Common ζ_{ict} over time as in (33).

(4) Restricts estimation sample to 2007–2011.

(5) Restricts estimation sample to 2012–2015.

Standard errors block-bootstrapped at the farm level (500 iterations) in parentheses..

TABLE A9. SENSITIVITY TO FUNCTIONAL FORM: PERENNIAL IRRIGATED

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.277	0.214	0.177	0.348	0.206	0.270
	(0.037)	(0.146)	(0.159)	(0.149)	(0.358)	(0.357)
$\frac{\partial f_c}{\partial w}$_10	0.126	0.033	0.177	0.150	0.123	0.090
	(0.026)	(0.175)	(0.159)	(0.105)	(0.331)	(0.259)
$\frac{\partial f_c}{\partial w}$_25	0.232	0.091	0.177	0.284	0.158	0.204
	(0.034)	(0.188)	(0.159)	(0.140)	(0.328)	(0.226)
$\frac{\partial f_c}{\partial w}$_75	0.352	0.331	0.177	0.453	0.254	0.359
	(0.046)	(0.138)	(0.159)	(0.184)	(0.408)	(0.237)
$\frac{\partial f_c}{\partial w}$_90	0.378	0.439	0.177	0.480	0.302	0.412
	(0.049)	(0.104)	(0.159)	(0.194)	(0.450)	(0.252)
Returns to scale, $\sum_j \beta_{cj}$	1.174	0.753	1.158	1.006	1.325	1.419
	(0.054)	(0.147)	(0.068)	(0.122)	(0.902)	(0.317)
λ_{ict}_median	467.87	307.78	295.72	582.84	354.24	459.74
	(63.57)	(261.58)	(261.16)	(250.73)	(586.98)	(359.83)
λ_{ict}_IQ	331.71	367.60	262.71	421.58	356.44	373.59
	(61.16)	(189.58)	(254.78)	(206.08)	(493.29)	(244.00)
λ_{ict}_90_10	760.99	678.88	711.42	951.41	858.91	955.68
	(146.34)	(577.21)	(668.12)	(491.95)	(1257.37)	(637.25)
Productivity persistence, ρ_c	0.619	0.602	0.601	0.617	0.591	0.729
	(0.054)	(0.087)	(0.069)	(0.064)	(0.083)	(0.049)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	0.058	0.064	0.059	0.059	0.057	0.059
	(0.017)	(0.019)	(0.017)	(0.017)	(0.019)	(0.017)
J-statistic	0.328	0.218	0.609	0.315	0.559	2.876
Adjusted R^2	0.816	0.816	0.816	0.816	0.816	0.816
$N \times T$	493	493	493	493	493	493

(1) Nested CES: original estimates of (2) in Table 4.

(2) Leontief ($\sigma_c \to 0$) without overwatering.

(3) Cobb-Douglas ($\sigma_c = 1$) with separable rain: $f_c = \theta_{cW} w_{ict} + \theta_{cK} k_{ict} + \sum_j \beta_{cj} x^j_{ict}$.

(4) Cobb-Douglas ($\sigma_c = 1$) with rain as a perfect substitute: $f_c = \theta_{cW} \ln(W_{ict} + \vartheta_c R_{ict}) + \theta_{cK} k_{ict} + \sum_j \beta_{cj} x^j_{ict}$.

(5) Translog: $f_c = \sum_{\ell+m+n\leq 2} \theta_{c,\ell mn} w^\ell_{ict} \ln(E^R_{ict} - E^V_{ict})^m \ln k^n_{ict}$.

(6) Quadratic: $F_c = \sum_{\ell+m+n\leq 2} \theta_{c,\ell mn} W^\ell_{ict} (E^R_{ict} - E^V_{ict})^m K^n_{ict}$.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

TABLE A10. SENSITIVITY TO FUNCTIONAL FORM: ANNUAL IRRIGATED

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.213	0.233	0.113	0.180	0.542	0.622
	(0.034)	(0.112)	(0.179)	(0.172)	(0.892)	(0.448)
$\frac{\partial f_c}{\partial w}$_10	0.083	0.070	0.113	0.040	0.453	0.259
	(0.025)	(0.137)	(0.179)	(0.163)	(0.809)	(0.454)
$\frac{\partial f_c}{\partial w}$_25	0.158	0.158	0.113	0.101	0.485	0.527
	(0.033)	(0.134)	(0.179)	(0.174)	(0.835)	(0.367)
$\frac{\partial f_c}{\partial w}$_75	0.280	0.317	0.113	0.252	0.582	0.794
	(0.043)	(0.107)	(0.179)	(0.185)	(0.941)	(0.272)
$\frac{\partial f_c}{\partial w}$_90	0.318	0.385	0.113	0.341	0.638	0.868
	(0.047)	(0.095)	(0.179)	(0.189)	(1.033)	(0.250)
Returns to scale, $\sum_j \beta_{cj}$	1.144	0.891	1.209	0.861	1.021	1.350
	(0.080)	(0.118)	(0.083)	(0.156)	(1.552)	(0.485)
λ_{ict}_median	92.45	96.58	50.92	66.68	237.59	269.63
	(15.52)	(52.88)	(75.80)	(72.55)	(407.70)	(136.79)
λ_{ict}_IQ	133.84	143.24	127.09	120.87	600.74	466.81
	(89.14)	(197.01)	(218.71)	(194.09)	(1139.29)	(428.16)
λ_{ict}_90_10	707.85	697.03	486.43	487.93	2650.07	2598.34
	(163.86)	(523.37)	(695.65)	(632.67)	(3513.66)	(1311.19)
Productivity persistence, ρ_c	0.500	0.508	0.541	0.544	0.438	0.714
	(0.089)	(0.099)	(0.097)	(0.095)	(0.151)	(0.111)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	0.064	0.067	0.075	0.064	0.054	0.053
	(0.056)	(0.059)	(0.055)	(0.056)	(0.075)	(0.084)
J-statistic	0.262	0.459	0.781	0.705	0.459	1.106
Adjusted R^2	0.748	0.748	0.748	0.748	0.748	0.748
$N \times T$	170	170	170	170	170	170

(1) Nested CES: original estimates of (2) in Table 4.

(2) Leontief ($\sigma_c \to 0$) without overwatering.

(3) Cobb-Douglas ($\sigma_c = 1$) with separable rain: $f_c = \theta_{cW} w_{ict} + \theta_{cK} k_{ict} + \sum_j \beta_{cj} x^j_{ict}$.

(4) Cobb-Douglas ($\sigma_c = 1$) with rain as a perfect substitute: $f_c = \theta_{cW} \ln(W_{ict} + \vartheta_c R_{ict}) + \theta_{cK} k_{ict} + \sum_j \beta_{cj} x^j_{ict}$.

(5) Translog: $f_c = \sum_{\ell+m+n \leq 2} \theta_{c,\ell mn} w^{\ell}_{ict} \ln(E^R_{ict} - E^V_{ict})^m \ln k^n_{ict}$.

(6) Quadratic: $F_c = \sum_{\ell+m+n \leq 2} \theta_{c,\ell mn} W^{\ell}_{ict} (E^R_{ict} - E^V_{ict})^m K^n_{ict}$.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

TABLE A11. SENSITIVITY TO RAINFALL SPECIFICATION: PERENNIAL IRRIGATED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.277	0.390	0.364	0.328	0.275	0.285	0.195	0.294
	(0.054)	(0.054)	(0.065)	(0.062)	(0.065)	(0.071)	(0.069)	(0.061)
$\frac{\partial f_c}{\partial w}$_10	0.124	0.342	0.319	0.197	0.165	0.135	0.093	0.125
	(0.034)	(0.052)	(0.060)	(0.046)	(0.048)	(0.039)	(0.039)	(0.036)
$\frac{\partial f_c}{\partial w}$_25	0.231	0.382	0.357	0.306	0.257	0.244	0.167	0.238
	(0.050)	(0.055)	(0.066)	(0.059)	(0.062)	(0.062)	(0.060)	(0.055)
$\frac{\partial f_c}{\partial w}$_75	0.354	0.414	0.387	0.389	0.326	0.358	0.245	0.380
	(0.067)	(0.057)	(0.069)	(0.073)	(0.076)	(0.089)	(0.087)	(0.076)
$\frac{\partial f_c}{\partial w}$_90	0.381	0.424	0.397	0.408	0.342	0.382	0.261	0.411
	(0.070)	(0.057)	(0.068)	(0.076)	(0.079)	(0.094)	(0.091)	(0.080)
Returns to scale, $\sum_j \beta_{cj}$	1.164	1.152	1.140	1.156	1.148	1.172	1.163	1.165
	(0.137)	(0.141)	(0.117)	(0.251)	(0.244)	(0.227)	(0.242)	(0.164)
λ_{ict}_median	467.55	648.10	604.60	549.80	461.01	481.22	329.59	494.78
	(89.57)	(93.70)	(112.33)	(104.92)	(108.81)	(117.35)	(113.12)	(101.53)
λ_{ict}_IQ	331.63	578.60	539.05	412.37	345.03	354.34	243.60	346.28
	(77.41)	(128.41)	(136.61)	(100.75)	(103.29)	(98.95)	(98.19)	(85.33)
λ_{ict}_90_10	762.16	1476.06	1377.04	945.77	794.45	784.15	536.33	798.93
	(182.97)	(288.29)	(311.28)	(239.07)	(241.76)	(226.34)	(219.33)	(200.83)
Productivity persistence, ρ_c	0.639	0.567	0.577	0.607	0.625	0.617	0.647	0.618
	(0.062)	(0.069)	(0.076)	(0.082)	(0.083)	(0.076)	(0.079)	(0.065)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	0.067	0.053	0.054	0.058	0.060	0.058	0.068	0.060
	(0.018)	(0.016)	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
J-statistic	0.206	0.240	0.238	0.233	0.175	0.277	0.140	0.317
Adjusted R^2	0.816	0.816	0.816	0.816	0.816	0.816	0.816	0.816
$N \times T$	493	493	493	493	493	493	493	493

Odd columns control for summer and winter rainfall separately rather than total annual rainfall.

(1) Original estimates.

(2), (3) Imposes $\vartheta_c = 0$.

(4), (5) Imposes $\vartheta_c = \frac{1}{2}$.

(6), (7) Imposes $\vartheta_c = 1$.

(8) Estimates $\hat{\vartheta}_c$.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

TABLE A12. SENSITIVITY TO RAINFALL SPECIFICATION: ANNUAL IRRIGATED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.210	0.335	0.312	0.263	0.235	0.240	0.243	0.211
	(0.041)	(0.047)	(0.068)	(0.034)	(0.044)	(0.029)	(0.037)	(0.038)
$\frac{\partial f_c}{\partial w}$_10	0.075	0.264	0.246	0.134	0.119	0.095	0.097	0.076
	(0.029)	(0.048)	(0.063)	(0.031)	(0.033)	(0.024)	(0.024)	(0.032)
$\frac{\partial f_c}{\partial w}$_25	0.149	0.307	0.286	0.211	0.188	0.176	0.182	0.150
	(0.038)	(0.047)	(0.067)	(0.034)	(0.039)	(0.029)	(0.032)	(0.039)
$\frac{\partial f_c}{\partial w}$_75	0.278	0.373	0.347	0.328	0.294	0.315	0.317	0.280
	(0.052)	(0.048)	(0.073)	(0.042)	(0.054)	(0.038)	(0.048)	(0.044)
$\frac{\partial f_c}{\partial w}$_90	0.321	0.389	0.362	0.360	0.323	0.357	0.358	0.323
	(0.057)	(0.049)	(0.072)	(0.045)	(0.059)	(0.043)	(0.055)	(0.048)
Returns to scale, $\sum_j \beta_{cj}$	1.142	1.173	1.137	1.161	1.145	1.152	1.154	1.161
	(0.086)	(0.088)	(0.088)	(0.084)	(0.086)	(0.083)	(0.086)	(0.082)
λ_{ict}_median	87.87	150.40	139.99	112.96	101.32	103.61	105.34	88.58
	(18.07)	(26.90)	(34.19)	(17.96)	(19.94)	(14.92)	(16.67)	(17.28)
λ_{ict}_IQ	128.13	315.98	295.43	186.59	165.96	150.24	155.06	127.30
	(94.31)	(132.68)	(130.73)	(125.26)	(113.26)	(105.50)	(97.62)	(94.63)
λ_{ict}_90_10	683.38	1393.43	1297.19	1054.82	941.40	806.63	817.95	685.25
	(181.18)	(343.16)	(361.58)	(215.05)	(208.07)	(171.24)	(167.44)	(182.63)
Productivity persistence, ρ_c	0.504	0.494	0.498	0.493	0.508	0.505	0.510	0.509
	(0.091)	(0.095)	(0.094)	(0.093)	(0.094)	(0.092)	(0.092)	(0.090)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	0.064	0.055	0.089	0.045	0.083	0.070	0.078	0.063
	(0.059)	(0.057)	(0.061)	(0.059)	(0.061)	(0.060)	(0.061)	(0.059)
J-statistic	0.255	0.508	0.185	0.523	0.154	0.318	0.152	0.349
Adjusted R^2	0.748	0.748	0.748	0.748	0.748	0.748	0.748	0.748
$N \times T$	170	170	170	170	170	170	170	170

See Table A11 for list of specifications.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

TABLE A13. SENSITIVITY TO RAINFALL SPECIFICATION: DAIRY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{E}[\frac{\partial f_c}{\partial w}]$	0.087	0.329	0.044	0.018	0.049	0.055	0.083	0.057
	(0.038)	(0.127)	(0.108)	(0.044)	(0.049)	(0.029)	(0.031)	(0.034)
$\frac{\partial f_c}{\partial w}$_10	0.024	0.272	0.010	0.001	0.009	0.003	0.006	0.034
	(0.021)	(0.120)	(0.102)	(0.025)	(0.029)	(0.011)	(0.013)	(0.019)
$\frac{\partial f_c}{\partial w}$_25	0.043	0.299	0.017	0.003	0.018	0.009	0.018	0.045
	(0.029)	(0.126)	(0.107)	(0.034)	(0.039)	(0.017)	(0.020)	(0.025)
$\frac{\partial f_c}{\partial w}$_75	0.118	0.358	0.052	0.020	0.065	0.079	0.120	0.069
	(0.049)	(0.134)	(0.114)	(0.058)	(0.064)	(0.043)	(0.044)	(0.044)
$\frac{\partial f_c}{\partial w}$_90	0.152	0.386	0.084	0.034	0.092	0.124	0.178	0.078
	(0.063)	(0.136)	(0.118)	(0.070)	(0.074)	(0.059)	(0.059)	(0.058)
Returns to scale, $\sum_j \beta_{cj}$	0.988	1.025	0.994	0.991	0.990	0.975	1.003	1.012
	(0.158)	(0.103)	(0.108)	(0.095)	(0.107)	(0.117)	(0.141)	(0.147)
λ_{ict}_median	129.20	599.09	52.30	15.70	64.63	54.60	97.34	99.89
	(67.52)	(242.57)	(203.75)	(80.25)	(91.43)	(47.99)	(53.70)	(60.11)
λ_{ict}_IQ	235.21	556.05	31.27	46.12	133.32	153.34	237.67	130.45
	(79.38)	(236.43)	(201.80)	(96.61)	(102.42)	(78.94)	(77.75)	(51.22)
λ_{ict}_90_10	555.90	1088.86	80.47	137.92	341.93	371.90	549.53	288.70
	(199.68)	(436.06)	(375.71)	(230.51)	(233.87)	(179.64)	(184.91)	(119.19)
Productivity persistence, ρ_c	0.384	0.412	0.431	0.391	0.399	0.379	0.390	0.381
	(0.180)	(0.123)	(0.131)	(0.147)	(0.156)	(0.165)	(0.179)	(0.171)
$\mathbb{E}[\omega_{ict} - \omega_{ic,t-1}]$	−0.103	−0.075	−0.097	−0.088	−0.115	−0.098	−0.129	−0.092
	(0.037)	(0.024)	(0.036)	(0.027)	(0.038)	(0.030)	(0.039)	(0.029)
J-statistic	1.161	2.060	0.638	0.923	0.914	1.218	1.371	1.052
Adjusted R^2	0.866	0.866	0.866	0.866	0.866	0.866	0.866	0.866
$N \times T$	256	256	256	256	256	256	256	256

See Table A11 for list of specifications.

Standard errors block-bootstrapped at the farm level (1000 iterations) in parentheses..

TABLE A14. REALIZED GAINS FROM WATER TRADING: SENSITIVITY TO PROFIT FUNCTION

	(1)	(2)	(3)	(4)	(5)
GFT/output	0.062	0.058	0.052	0.044	0.048
	[0.034, 0.093]	[0.032, 0.088]	[0.028, 0.071]	[0.021, 0.059]	[0.020, 0.060]
GFT/ML	414.98	481.08	287.58	210.15	171.50
	[202.98, 658.61]	[235.31, 763.50]	[156.36, 400.78]	[101.07, 281.54]	[72.50, 223.91]

Estimated gains from observed water trading, 2007–2015, relative to pre-trade endowments net of both annual and permanent trades, reported as proportion of total irrigated profits under the market.
(1) Baseline estimate: optimal labor, materials.
(2) No discounting ($\delta = 1$).
(3) Optimal labor, materials constrained to $X^*_{ict} \leq 5X_{ict}$.
(4) Optimal labor, materials constrained to $X^*_{ict} \leq 2X_{ict}$.
(5) Labor, materials held fixed at observed levels.

Confidence intervals report [5%,95%]-ile range of 700 draws block-bootstrapped at the farm level.

TABLE A15. REALIZED GAINS FROM TRADE — ADDITIONAL RESULTS

	Gains from trade			Reallocation	
	%	%, traders	AUD/ML	realloc (%)	traders (%)
All	0.062	0.093	414.98	0.144	0.62
	[0.034, 0.093]	[0.050, 0.135]	[202.98, 658.61]	[0.128, 0.161]	[0.60, 0.64]
Years					
2007	0.052	0.091	284.66	0.105	0.48
	[−0.002, 0.091]	[−0.006, 0.179]	[−17.65, 728.57]	[0.081, 0.131]	[0.44, 0.52]
2008	0.042	0.109	391.25	0.255	0.81
	[−0.045, 0.156]	[−0.053, 0.184]	[−245.22, 842.22]	[0.195, 0.327]	[0.78, 0.86]
2009	0.194	0.214	1164.24	0.308	0.76
	[0.099, 0.270]	[0.109, 0.299]	[602.14, 2011.97]	[0.253, 0.363]	[0.71, 0.81]
2010	0.158	0.185	1456.48	0.200	0.64
	[0.052, 0.300]	[0.065, 0.342]	[416.99, 2801.09]	[0.138, 0.266]	[0.58, 0.70]
2011	−0.002	−0.005	−22.58	0.095	0.45
	[−0.027, 0.014]	[−0.062, 0.034]	[−230.22, 167.22]	[0.067, 0.141]	[0.39, 0.51]
2012	−0.003	−0.005	−19.79	0.092	0.51
	[−0.049, 0.032]	[−0.080, 0.052]	[−294.30, 185.35]	[0.075, 0.121]	[0.45, 0.57]
2013	0.007	0.009	27.05	0.227	0.74
	[−0.061, 0.080]	[−0.083, 0.110]	[−268.71, 309.25]	[0.171, 0.282]	[0.65, 0.81]
2014	0.073	0.089	394.91	0.132	0.73
	[0.012, 0.106]	[0.015, 0.129]	[56.04, 634.53]	[0.105, 0.161]	[0.67, 0.79]
2015	0.014	0.022	79.67	0.158	0.64
	[−0.025, 0.040]	[−0.041, 0.063]	[−162.02, 223.38]	[0.119, 0.198]	[0.59, 0.69]
B. Regions					
VIC.Goulburn	0.073	0.101	647.58	0.209	0.60
	[0.027, 0.098]	[0.048, 0.147]	[250.08, 1120.52]	[0.171, 0.253]	[0.55, 0.66]
NSW.Murrumbidgee	0.063	0.092	324.04	0.095	0.60
	[−0.033, 0.165]	[−0.050, 0.220]	[−155.07, 981.56]	[0.074, 0.118]	[0.55, 0.64]
SA.Murray	0.108	0.145	677.49	0.220	0.68
	[0.032, 0.204]	[0.040, 0.260]	[210.36, 1130.80]	[0.176, 0.280]	[0.63, 0.71]
VIC.Murray	0.022	0.034	244.56	0.143	0.60
	[−0.001, 0.059]	[−0.001, 0.095]	[−5.54, 794.02]	[0.120, 0.188]	[0.54, 0.67]
NSW.Murray	0.056	0.103	316.94	0.179	0.62
	[0.014, 0.090]	[0.022, 0.136]	[54.22, 379.81]	[0.143, 0.216]	[0.57, 0.68]
C. Crop types					
Perennial irrigated	0.058	0.080	544.04	0.169	0.64
	[0.019, 0.098]	[0.026, 0.132]	[172.69, 985.93]	[0.147, 0.202]	[0.61, 0.67]
Annual irrigated	0.087	0.150	505.73	0.107	0.54
	[0.044, 0.185]	[0.075, 0.274]	[174.74, 1116.41]	[0.087, 0.127]	[0.50, 0.58]
Dairy	0.032	0.047	188.84	0.223	0.65
	[−0.011, 0.037]	[−0.016, 0.056]	[−61.27, 220.23]	[0.187, 0.260]	[0.60, 0.69]

Supplement to Table 11. Estimated gains from all water trading for all farms 2007–2015 and then subsets specified by row. Gains from trade defined as discounted sum of (19) over t, reported as the fraction of total irrigated profits (column 1), total irrigated profits of only water-trading farms (column 2), and total trade volume (column 3). Columns 4 and 5 show trade volumes divided by total irrigation volumes and the proportion of farm-years with nonzero trade balances.

Confidence intervals report [5%,95%]-ile range of 700 draws block-bootstrapped at the farm level.

TABLE A16. IRRIGATION POLICY FUNCTION

	crop type		
	(1)	(2)	(3)
land, K_{ict}	0.981	0.903	0.421
interquartile	0.060	0.106	0.122
interdecile	0.216	0.483	0.443
productivity, $\hat{\omega}_{ict}$	0.180	0.529	−0.257
interquartile	0.234	0.202	0.221
interdecile	0.754	0.918	0.751
crop price, P_{ict}	0.324	0.464	0
interquartile	0.169	0.857	0
interdecile	0.950	3.314	0
dairy cows, X^D_{ict}	0	0	0.442
interquartile	0	0	0.122
interdecile	0	0	0.474
rainfall, E^R_{it}	−0.303	−0.179	−0.271
interquartile	0.179	0.350	0.085
interdecile	0.845	1.518	0.437
water price, P^W_{rt}	−0.174	−0.161	−0.257
interquartile	0.053	0.358	0.152
interdecile	0.251	1.360	0.675
Region FEs	✓	✓	✓
Observations	1,000	464	475
R^2	0.848	0.833	0.648
Adjusted R^2	0.842	0.817	0.616

Summary statistics of local elasticities of estimated function $\mathcal{W}$: average, interquartile, and interdecile range across i, c, t of the local elasticity of irrigation at observed s_{it} with respect to land, productivity, and μ_{it}, indicated by row. Estimated separately for each c, using a fully saturated translog specification:
(1) perennial irrigated
(2) annual irrigated
(3) pasture.

TABLE A17. IRRIGATION POLICY ESTIMATES — SENSITIVITY TO POLYNOMIAL APPROXIMATION

A. Perennial irrigated

	specification				
	(1)	(2)	(3)	(4)	(5)
land, K_{ict}	0.996	0.981	0.947	1.002	0.972
interquartile	0	0.060	0.073	0.112	0.212
interdecile	0	0.216	0.442	0.734	1.212
productivity, $\hat{\omega}_{ict}$	0.285	0.180	0.129	−0.032	0.103
interquartile	0	0.234	0.349	0.203	0.585
interdecile	0	0.754	1.272	1.123	2.528
crop price, P_{ict}	0.385	0.324	0.086	−0.035	−0.213
interquartile	0	0.169	0.779	0.477	1.246
interdecile	0	0.950	3.657	2.823	4.985
rainfall, E^R_{it}	−0.412	−0.303	−0.318	−0.115	0.029
interquartile	0.065	0.179	0.255	0.168	0.474
interdecile	0.253	0.845	1.032	1.208	3.198
water price, P^W_{rt}	−0.223	−0.174	−0.023	−0.124	0.062
interquartile	0	0.053	0.215	0.150	0.478
interdecile	0	0.251	1.123	0.876	2.404
Region FEs	✓	✓	✓	✓	✓
Crop-specific estimates	✓	✓	✓	✓	✓
Observations	1,000	1,000	1,000	1,000	1,000
R^2	0.816	0.848	0.876	0.918	0.965
Adjusted R^2	0.814	0.842	0.859	0.911	0.953

B. Annual irrigated

	specification				
	(1)	(2)	(3)	(4)	(5)
land, K_{ict}	0.950	0.903	0.874	0.779	0.864
interquartile	0	0.106	0.148	0.217	0.465
interdecile	0	0.483	1.020	1.341	2.637
productivity, $\hat{\omega}_{ict}$	0.564	0.529	0.365	0.266	0.070
interquartile	0	0.202	0.622	0.390	0.651
interdecile	0	0.918	2.921	1.875	3.723
crop price, P_{ict}	0.558	0.464	−0.130	−0.182	−0.636
interquartile	0	0.857	2.507	0.965	2.187
interdecile	0	3.314	12.838	4.742	11.253
rainfall, E^R_{it}	−0.130	−0.179	−0.231	−0.218	−0.199
interquartile	0.021	0.350	0.687	0.570	1.250
interdecile	0.076	1.518	3.522	2.980	4.450
water price, P^W_{rt}	−0.260	−0.161	−0.066	−0.460	−0.161
interquartile	0	0.358	0.845	0.298	0.739
interdecile	0	1.360	4.288	1.996	5.181
Region FEs	✓	✓	✓	✓	✓
Crop-specific estimates	✓	✓	✓	✓	✓
Observations	464	464	464	464	464
R^2	0.789	0.833	0.896	0.801	0.950
Adjusted R^2	0.784	0.817	0.859	0.764	0.882

Summary statistics of local elasticities of estimated function $\mathcal{W}$: average, interquartile, and interdecile range across i, c, t of the local elasticity of irrigation at observed s_{it} with respect to land, productivity, and μ_{it}, indicated by row. Each polynomial estimated separately by c.
(1) log-linear
(2) translog, second-degree
(3) translog, third-degree
(4) quadratic, levels
(5) cubic, levels.

TABLE A17 (CONT'D). IRRIGATION POLICY ESTIMATES — SENSITIVITY TO POLYNOMIAL APPROXIMATION

C. Dairy

	specification				
	(1)	(2)	(3)	(4)	(5)
land, K_{ict}	0.466	0.421	0.302	0.231	0.277
interquartile	0	0.122	0.259	0.148	0.655
interdecile	0	0.443	1.257	0.702	2.403
productivity, $\hat{\omega}_{ict}$	−0.333	−0.257	−0.482	−0.161	−0.377
interquartile	0	0.221	0.633	0.230	0.658
interdecile	0	0.751	2.900	1.471	4.206
K_moo	0.404	0.442	0.497	0.532	0.482
interquartile	0	0.122	0.389	0.301	0.778
interdecile	0	0.474	2.108	1.295	3.629
rainfall, E^R_{it}	−0.319	−0.271	−0.359	−0.251	0.124
interquartile	0.086	0.085	0.310	0.322	1.414
interdecile	0.174	0.437	1.891	1.667	5.871
water price, P^W_{rt}	−0.291	−0.257	−0.309	−0.231	−0.106
interquartile	0	0.152	0.668	0.106	0.633
interdecile	0	0.675	1.982	1.230	3.425
Region FEs	✓	✓	✓	✓	✓
Crop-specific estimates	✓	✓	✓	✓	✓
Observations	475	475	475	475	475
R^2	0.602	0.648	0.746	0.725	0.900
Adjusted R^2	0.595	0.616	0.661	0.676	0.775

Table A17, continued.

TABLE A18. PERSISTENCE OF FARM STATES

	Current value, $s_{i(c)t}$				
	P^W_{it}	$E^R_{it} - E^V_{it}$	$P^L_{X,it}$	P_{ict}	$\hat{\omega}_{ict}$
	(1)	(2)	(3)	(4)	(5)
Lagged value, $s_{i,t-1}$	0.562***	0.617***	0.879***		
	(0.025)	(0.025)	(0.017)		
$s_{ic,t-1}\mathbf{1}\{c = \text{annual\_irr}\}$				0.714***	0.352***
				(0.041)	(0.038)
$s_{ic,t-1}\mathbf{1}\{c = \text{annual\_nonirr}\}$				0.384***	0.646***
				(0.046)	(0.035)
$s_{ic,t-1}\mathbf{1}\{c = \text{dairy}\}$				−0.167	0.235*
				(0.269)	(0.124)
$s_{ic,t-1}\mathbf{1}\{c = \text{perennial}\}$				0.355***	0.600***
				(0.043)	(0.047)
Observations	1,028	1,028	1,028	1,274	1,274
Adjusted R^2	0.332	0.370	0.724	0.642	0.896
Residual Std. Error	160.197	160.263	70.537	0.177	0.413

Columns (1)–(3) are regressions at the farm-year level; columns (4) and (5) are at farm-crop-type level.

Uncorrected standard errors.

TABLE A19. PERENNIAL ADJUSTMENT PROBIT

	specification							
	$\mathbf{1}(K_{ict} \neq K_{ic,t-1})$				$\mathbf{1}(K_{ict} > K_{ic,t-1} \mid K_{ict} \neq K_{ic,t-1})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
land, $K_{ic,t-1}$	0.186***	0.187***	0.240***	0.250***	−0.054	−0.049	−0.101	−0.086
	(0.058)	(0.059)	(0.062)	(0.063)	(0.110)	(0.112)	(0.116)	(0.118)
productivity, $\hat{\omega}_{ic,t-1}$	−0.041	−0.012	0.100	0.158	−0.072	0.027	−0.065	0.077
	(0.149)	(0.160)	(0.159)	(0.170)	(0.259)	(0.274)	(0.271)	(0.288)
crop price, $P_{ic,t-1}$	0.664	0.770*	1.333***	1.407***	0.260	−0.048	0.151	0.029
	(0.428)	(0.433)	(0.480)	(0.491)	(0.797)	(0.836)	(0.925)	(0.958)
rainfall, $E^R_{i,t-1}$	−0.151	−0.343*	0.340	0.327	0.071	0.245	0.130	0.320
	(0.170)	(0.196)	(0.216)	(0.292)	(0.282)	(0.340)	(0.366)	(0.482)
water intensity, $W_{ic,t-1}/K_{ic,t-1}$	−0.139	−0.099	0.001	0.016	0.245	0.297	0.302	0.363
	(0.130)	(0.132)	(0.141)	(0.142)	(0.223)	(0.228)	(0.249)	(0.258)
water price, $P^W_{r,t-1}$	0.221**	0.260**	0.349	0.245	0.011	0.045	−0.038	0.137
	(0.100)	(0.109)	(0.260)	(0.301)	(0.159)	(0.180)	(0.396)	(0.468)
allocation rule, $\overline{W}_{r,t-1}$	0.119	0.293*	−0.163	−0.119	−0.118	−0.122	0.006	0.162
	(0.136)	(0.172)	(0.156)	(0.213)	(0.194)	(0.302)	(0.219)	(0.389)
Region FEs		✓		✓		✓		✓
Year FEs			✓	✓			✓	✓
Mean empirical $p_{\pm}(s)$	0.316	0.316	0.316	0.316	0.477	0.477	0.477	0.477
Mean predicted $\hat{p}_{\pm}(s)$	0.316	0.316	0.316	0.316	0.477	0.478	0.477	0.478
Q0 predicted $\hat{p}_{\pm}(s)$	0.041	0.032	0.007	0.007	0.320	0.140	0.000	0.000
Q10 predicted $\hat{p}_{\pm}(s)$	0.157	0.139	0.110	0.103	0.388	0.347	0.338	0.300
Q25 predicted $\hat{p}_{\pm}(s)$	0.234	0.220	0.183	0.175	0.430	0.430	0.388	0.402
Q75 predicted $\hat{p}_{\pm}(s)$	0.391	0.403	0.424	0.436	0.522	0.544	0.548	0.576
Q90 predicted $\hat{p}_{\pm}(s)$	0.467	0.491	0.585	0.583	0.573	0.585	0.673	0.698
Q100 predicted $\hat{p}_{\pm}(s)$	0.609	0.632	0.850	0.864	0.621	0.655	0.836	0.881
Observations	484	484	484	484	153	153	153	153
Log Likelihood	−287.116	−282.291	−266.614	−264.227	−104.464	−102.016	−98.985	−96.804
Akaike Inf. Crit.	590.231	588.582	563.227	566.455	224.927	228.031	227.970	231.608

Definition of adjustment as 1 ha or greater and at least 1% total.

TABLE A20. PERENNIAL ADJUSTMENT BANDWIDTH

	specification for κ				
	(1)	(2)	(3)	(4)	(5)
land, $K_{ic,t-1}$	−0.003	0.062	1.005	0.037	1.029
interquartile	0	0.056	0.418	0.131	0.539
interdecile	0	0.214	1.853	0.552	2.117
water, $W_{ic,t-1}$	−0.062	−0.131	−0.097	−0.124	−0.127
interquartile	0	0.034	0.285	0.190	0.285
interdecile	0	0.138	1.297	0.531	1.871
productivity, $\hat{\omega}_{ic,t-1}$	−0.011	0.036	−0.431	0.073	0.334
interquartile	0	0.104	0.772	0.156	0.594
interdecile	0	0.384	3.420	0.675	3.065
Region FEs	✓	✓	✓	✓	✓
Observations	153	153	153	153	153
R^2	0.100	0.218	0.744	0.291	0.806
Adjusted R^2	0.056	0.138	0.718	0.145	0.765

Summary statistics of local elasticities of estimated function $\kappa_{\text{perennial}}$: average, interquartile, and interdecile range across i, t of the local elasticity of K_{ict} at observed $s_{i,t-1}$, with respect to land, productivity, and $\mu_{i,t-1}$, indicated by row. Preferred estimates are in column (2). Estimated from an ordinary least squares regression of $|k_{ict} - k_{ic,t-1}|$ (for logarithms; $|K_{ict} - K_{ic,t-1}|$ for levels) over all $c =$ perennial such that $K_{ict} \neq K_{ic,t-1}$, on the following transformations of $s_{i,t-1}$:
(1) logarithms (linear)
(2) logarithms (quadratic)
(3) levels (quadratic)
(4) logarithms (cubic)
(5) levels (cubic).

TABLE A21. LAND POLICY FUNCTION — ANNUAL FARMS

A. Annual irrigated crops

	specification for κ				
	(1)	(2)	(3)	(4)	(5)
land, $K_{ic,t-1}$	0.607	0.408	0.234	0.495	0.156
interquartile	0	0.148	0.112	0.194	0.163
interdecile	0	0.641	0.389	0.679	0.918
water, $W_{ic,t-1}$	0.189	0.343	0.228	0.428	0.342
interquartile	0	0.165	0.159	0.198	0.310
interdecile	0	0.548	0.425	0.758	0.898
productivity, $\hat{\omega}_{ic,t-1}$	−0.167	−0.132	−0.236	−0.109	−0.338
interquartile	0	0.043	0.120	0.201	0.176
interdecile	0	0.183	0.763	0.968	1.250
Region FEs	✓	✓	✓	✓	✓
Observations	172	172	172	172	172
R^2	0.707	0.735	0.421	0.757	0.455
Adjusted R^2	0.695	0.712	0.370	0.714	0.357

B. Pasture for dairy cows

	specification for κ				
	(1)	(2)	(3)	(4)	(5)
land, $K_{ic,t-1}$	0.149	0.081	−0.159	0.065	0.090
interquartile	0	0.261	0.065	0.249	0.275
interdecile	0	0.867	0.366	1.090	1.155
water, $W_{ic,t-1}$	0.069	0.077	0.120	0.020	0.137
interquartile	0	0.108	0.121	0.160	0.274
interdecile	0	0.436	0.494	0.979	1.218
productivity, $\hat{\omega}_{ic,t-1}$	0.109	0.159	0.260	0.222	0.148
interquartile	0	0.224	0.249	0.391	0.535
interdecile	0	0.863	0.787	1.847	2.356
dairy cows, X^D_{ict}	0.051	0.052	0.156	0.080	−0.223
interquartile	0	0.207	0.227	0.238	0.688
interdecile	0	0.728	1.040	1.577	2.561
Region FEs	✓	✓	✓	✓	✓
Observations	257	257	257	257	257
R^2	0.587	0.654	0.445	0.709	0.543
Adjusted R^2	0.571	0.617	0.385	0.625	0.413

Summary statistics of local elasticities of estimated function κ_{annual}: average, interquartile, and interdecile range across i, t of the local elasticity of K_{ict} at observed $s_{i,t-1}$, with respect to land, productivity, and $\mu_{i,t-1}$, indicated by row. Preferred estimates are in column (2). Polynomial approximation for κ_{annual}:
(1) logarithms (linear)
(2) logarithms (quadratic)
(3) levels (quadratic)
(4) logarithms (cubic)
(5) levels (cubic).

TABLE A22. SUMMARY OF NOTATION

	Farm inputs	units
Q_{ict}	physical output	tonnes
W_{ict}	irrigation volumes	megaliters (ML)
E^R_{it}	rainfall	millimeters (mm)
E^V_{it}	evapotranspiration	mm
X^L_{ict}	labor	weeks
X^F_{ict}	feed	deflated tonnes
X^M_{ict}	materials	AUD
X^D_{ict}	number of dairy cows	$\mathbb{Z}_+$
K_{ict}	land	hectares
P_{ict}	final crop price	AUD/tonne
$P^L_{X,it}$	realized wage	AUD/week
	Water market	
$\overline{W}_{rt}$	regional water allocation path	ML
P^W_{it}	water prices	AUD/ML
ρ_{it}	permanent water rights	$[0, 1]$
	Primitives	
F_c	production technology	
θ_c	production parameters	
ω_{ict}	productivity	
ε_{ict}	measurement error	
ψ_{ct}	Markov transition operator	

Summary of the notation used in the text: i indexes farm, c indexes crop type (irrigated annual, nonirrigated annual, irrigated pasture, or irrigated perennial), t indexes year.