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Droughts, Deluges, and (River) Diversions: Valuing Market-Based Water Reallocation†

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This paper develops and applies a method to value water trading on a river network. The framework relies on regulatory variation in diversion caps to identify production functions for irrigated farms, then uses the estimated shadow values to assess the market's reallocation. I apply this framework to the largest water market in human history, located in southeastern Australia. Observed water trading increased output by 4–6 percent from 2007 to 2015, equivalent to avoiding an 8–12 percent uniform decline in water resources. Reallocation and average surplus both increase substantially during drought, implying that water markets can be most valuable when climatic variability is most severe. (*JEL* D23, D24, Q12, Q15, Q25, Q54)

Water is necessary for human life and most forms of economic activity, but uncommonly allocated through markets. Even as water scarcity and variability intensifies across the world, it is likely that less than 1 percent of the freshwater withdrawn worldwide is traded each year.[1] Economists have sought to explain these institutions through two unique aspects of water resources. First, many existing water allocation schemes were designed by hydrologists and engineers in past eras. Entrenched political interests can impede reform, even despite large changes in the underlying

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[1] Instead, water regulators typically allocate water through nonmarket mechanisms, such as quotas based on landholdings, records of past usage, or historical priority. See, e.g., Coman (1911); Libecap (2011); and Barbier (2019). For the 1 percent, see the calculation in online Appendix B.4.

environment. Second, while water markets can improve efficiency under ideal conditions, the practical realities of a river system mean that trading opportunities in an actual river network may be costly, uncertain, or manipulable. Flow constraints, noncompetitive conduct, and liquidity constraints can each dampen, or even reverse, the gains from trade that are implied in competitive, frictionless models.[2]

This paper contributes a new approach to estimate the value of market-based water reallocation in a way that is sensitive to these evolving hydrological constraints on trade, without assuming that water is valuable or that trade is efficient. The framework takes advantage of new data on water rights, trades, and agricultural production in the largest water market in human history, located in southeastern Australia. I value the water market in two steps: (i) estimate a model of irrigated agricultural production to recover the distribution of water value functions; (ii) compare welfare (producer surplus) under observed pre- and posttrade water allocations. The estimates allow me to value reallocation within the annual market across a range of environmental conditions, and show how this value depends on hydrological variability.

I apply this empirical framework to study irrigated farms trading water in a connected river network in southeastern Australia, where rainfall is highly variable and environmental regulation has capped water diversions since the mid-1990s. This water market is the world's largest by trading volume and the most valuable, with 7,700 gigaliters or AU\$22.7 (US\$15.3) billion of water entitlements on issue (Wakerman Powell et al. 2019). Moreover, the irrigated agricultural industry is the single largest user of water in the global economy, accounting for more than 70 percent of all water withdrawals. In this context, I ask the following questions: 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 does water reallocation, and the estimated value of trade, depend on natural sources of variability?

I find that water trading increased irrigated output for the farms in the data by 4–6 percent, averaged over the sample period 2007–2015. Put differently, without water reallocation through the annual market, output would fall by the same amount as if farms faced a uniform reduction in water resources of 8–12 percent. By comparison, government climate models for this region predict surface water resources to decline by 11 percent in the median year under a 1°C increase in temperature by 2030. These average gains conceal 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 7–11 percent of output; 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, statistically indistinguishable from 0 percent.

Obtaining these estimates of the value of trade involves at least two major empirical challenges, which are compounded by some of the unique aspects of a river network mentioned above. First, agents' true valuations of river diversions cannot

[2]Flow constraints, which evolve rapidly with precipitation and other river inflows, affect the timing and location of delivery because water is heavy and incompressible, and cannot be quickly transported large distances or elevations (Chong and Sunding 2006, p. 243). The fixed costs of irrigation capacity give rise to concerns about market power (Burness and Quirk 1979). For earlier discussions of water market imperfections, see Ciriacy-Wantrup (1967); Young (1986); and Colby (1990).

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 (Livingston 1995). Interconnected tributaries make the decentralized water market a multilateral bargaining game (Saleth, Braden, and Eheart 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 two-step approach—recover production functions for irrigated farms, then use the estimated shadow values to assess the market's reallocation—is designed to address these challenges. The first step, to estimate production functions that map irrigation volumes into agricultural output, relies on new producer-level panel survey data on irrigation, physical output, and local rainfall. The empirical framework allows productivity to differ arbitrarily across farms and crop types, and evolve stochastically as in Olley and Pakes (1996) and Ackerberg, Caves, and Frazer (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 plant crops, then irrigate in response to within-year rainfall and water price shocks.

A significant concern in identifying 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 panel-data technique to control for time-varying productivity by inverting static materials demand (Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 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 river basin that I analyze, which provides a source of variation in farm-level irrigation decisions. The empirical strategy controls for each farm's expected productivity for each crop type, and the identifying assumption is therefore that a farm's annual innovation in productivity is conditionally independent from its region's water allocations, which I motivate through the mechanical nature of these rules.

The second step takes water trading data—linked to farms but not used to estimate the production functions—to value the water market. The physical production functions, together with optimal materials and labor demand schedules, allow the evaluation of profits at observed pretrade water endowments and posttrade water inputs. This delivers a direct measure of the value of "realized" market-based water reallocation for the years that my data include. The advantage of this approach to

[3] An alternative method is to estimate the water-yield relationship with an experiment. Zwart and Bastiaanssen (2004, p.123) review more than eighty such agronomic 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."

measuring reallocation is that it does not require specifying the set of feasible trades or an equilibrium concept for the water market. Therefore, the researcher does 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 annual trades for each farm under the market mechanism relative to the initial distribution of water rights.

The value of the empirical contributions obtained using this approach arise from three interrelated aspects of water that differentiate this resource from other goods. First, as mentioned above, water markets are rarely used. One simple explanation for the continued use of fixed allocation rules is that water transfers' practical difficulties make the gains from water trading universally small. The paper's findings reject this explanation. While such frictions may have prevented water markets from delivering benefits in the past, the estimates show that modern water infrastructure can enable markets to create substantial value despite constraints. In particular, the gains from trade that I find in the Australian context provide a counterpoint to a recent collection of empirical papers on water markets, 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, Dinar, and Hanak 2016), local protectionism (Hagerty 2019), 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.

Second, water is naturally variable, and there is broad consensus that climate change will intensify this variability.[4] This paper finds that the gains from trade increase substantially during drought and for places experiencing relative water scarcity, implying that water markets can help economies adapt to natural water variability. Many have suggested that water markets may provide valuable flexibility to accommodate climate shocks (e.g., Debaere et al. 2014; Anderson 2015). This paper is the first to demonstrate empirically that water trading can substantially increase agricultural output in the presence of such climatic variability. This finding also implies that retrospective analyses of water trading may understate its prospective benefits, unless the historical data include variability comparable to that predicted by climate models. For policymakers considering the value of transitioning to water markets, the results imply that a river basin's current (and future) hydrological variability should be critical aspects of such assessments.

Third, water flows downstream and is very heavy, making the set of feasible trades on a river network a complicated function of evolving hydrological conditions. Conventional approaches to value water markets address this difficulty through various assumptions about these markets' contractual, informational, and competitive features. Differences in these assumptions have led to conflicting results and conflicting guidance on water markets. This paper's final empirical contribution

[4]Rising temperatures accelerate the hydrological cycle (Oki and Kanae 2006), intensifying droughts and deluges. Climate models predict large declines in water resources for irrigation (Elliott et al. 2014) and greater uncertainty over future river inflows (Schewe et al. 2014).

is in developing and applying a new framework to value water markets that is more robust to these differences. The key point is that the gains from trade are not generally identified without data on agricultural production linked to trade flows. Without such data, depending on a researcher's identifying assumptions, the same observed water allocation that differs from some ideal first best may lead to a finding of substantial water misallocation (and tremendous prospective gains from trade) or, alternatively, of large transaction costs or frictions that rationalize the absence of trade (and negligible gains from trade). This paper overcomes this potentially severe identification issue through data on the joint distribution of water trades and production decisions, as well as a model of agricultural production consistent with a variety of potential water market outcomes.

Broadly speaking, the existing literature has taken three approaches to learn about the value of water markets, and this paper's approach has advantages relative to each. The first and most common approach calculates the prospective value of trading from a profit-maximizing water allocation across competing uses (Flinn and Guise 1970).[5] This paper follows much of this work in assuming that agricultural data contain information about the distribution of water values. The key differences lie in the new model to identify and estimate irrigated agricultural production functions, which imposes fewer restrictions on the unobserved differences across farms, and in the counterfactual analysis, which contrasts pre- and posttrade water allocations within an existing water market, rather than assuming that water trading will maximize agricultural profits.

A second approach focuses on trade flows in actual water markets (Colby 1990). More recent versions of these studies identify water demand and transaction costs from equilibrium trading conditions and revealed preference, then simulate an equilibrium with lower transaction costs or fewer trading constraints.[6] This paper shares with these studies the concern that trading barriers and constraints may confound earlier research designs, and like these papers, the empirical strategy requires data on water reallocation from an actual water market. The key differences are that, by relying on a model of agricultural production, it does not need to assume that trade flows are an equilibrium outcome to identify preferences or transaction costs. This sacrifices an opportunity to learn about the sources of trading frictions, but avoids ruling out a range of unobserved trading constraints and forms of water market conduct.

A final approach consists of applying hedonic methods to compare places with and without tradable water property rights.[7] These research designs can be informative about the value of well-defined water rights in general, but typically cannot separately identify the value of securing property rights from the value of trading. In contrast,

[5] These studies often calibrate regional water value functions from crop data and other sources (Vaux and Howitt 1984; Dinar and Letey 1991), then solve for water market allocations under a fixed set of hydrological constraints (Sunding et al. 2002; Peterson et al. 2005; Gupta, Hughes, and Wakerman Powell 2018).

[6] These simulations use various approaches to identify demand from transaction data, such as calibrating water demand with external estimates (Edwards et al. 2018), imposing general equilibrium conditions to infer variable trade costs from price differentials (Regnacq, Dinar, and Hanak 2016; Hagerty 2019), or using auxiliary financial data to proxy for liquidity constraints (Donna and Espin-Sánchez 2018).

[7] Recent work examining the redefinition (or "adjudication") of historical water rights in the western United States includes event studies of the Snake River Basin (Browne 2017), the Rio Grande Valley (Debaere and Li 2017), and the Mojave Desert (Ayres, Meng, and Plantinga 2019). These studies infer a value of water rights from the differential evolution of land values for parcels with and without adjudication.

this paper's framework analyzes gains from trade within an existing water market; its counterfactuals make within-farm comparisons, rather than comparisons across farms that face different—and potentially endogenous—water property regimes; and the resulting distribution of gains from trade across farms can be used to analyze channels of water market value, such as the dispersion and intensity of local environmental shocks.

More generally, this paper contributes to a growing literature studying the relationship between misallocation and factor market structure. To assess misallocation, these studies often estimate models of firm production.[8] A core tension in applying these methods lies in maintaining assumptions to identify production functions and productivity without ruling out potential sources of misallocation due to incomplete or imperfect factor markets. Specifically, this paper contributes to the literature on using control functions to estimate production functions (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015), where unobserved input price variation typically poses a threat to identification. My approach overcomes this challenge by using a regulatory source of variation to identify the model, which differs from some recent work that relies on instruments constructed from endogenous variables, such as lagged input decisions or prices (De Loecker et al. 2016; Doraszelski and Jaumandreu 2018).

The remainder of this paper is organized as follows. Section I describes irrigated agricultural production, the institutional background, and the data used. Section II then introduces an econometric model of water-based agricultural production in a regulated river system. Sections III and IV describe the main empirical strategy, its key restrictions, and parameter estimates and robustness. Section V analyzes the realized gains from trade. Section VI concludes.

I. 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 govern river diversions. These production possibilities determine the value of reallocating water across farms, within the constraints imposed by the natural and regulatory environments. Section IA introduces the data sources used, then Section IB and IC describe the agricultural production process and differences across operation types. Section ID outlines the institutions that regulate water rights, river diversions, and trade. Sections IE and IF discuss patterns of water trading in the data indicating potential sources of gains from trade.

A. *Data Sources*

The main analysis uses 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 in the southern Murray-Darling Basin (sMDB) from the 2006–2007

[8]For example, evaluations of environmental and energy markets, such as Carlson et al. (2000); Borenstein, Bushnell, and Wolak (2002); and Fowlie, Reguant, and Ryan (2016); as well as studies of misallocation across electricity generators (Cicala 2022); tobacco supply chains (Rubens 2020); and oil cartels (Asker, Collard-Wexler, and De Loecker 2019).

to 2014–2015 annual waves of a rotating panel survey conducted by the Australian Department of Agriculture.[9] The survey collects characteristics, input choices, and production levels from irrigated 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 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.[10] Fourth, I draw on administrative water trading data on transaction prices and trade flows from the Murray-Darling Basin Authority (MDBA), which regulates the water market, as well as from state governments and private brokers.[11] Online Appendix B contains more details.

B. *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).

Land and Scale of Operation.—The average irrigated farm surveyed produces annual output valued at approximately AU$700,000, irrigates 296 hectares (ha), and operates a total area of 563 ha. Size varies by operation type, as discussed below, and the size distribution is skewed, with the median farm irrigating 104 ha of crops or pasture with a total area operated of 189 ha (online Appendix Table A2). 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 seventy-fifth percentile farm size in the US 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 uses 680 ML for irrigation (Table 1), roughly the average annual consumption of 4,000 Australian households (ABS 2016). River water is the primary source of irrigation for these farms, with groundwater accounting for only between 10–15 percent of irrigation in the sMDB, due to limited volume and salinity (Turral et al. 2005). Valued at average market prices—AU$235 per megaliter over all years—this implies total irrigation costs equal to 13.8 percent of revenue from 2007–2015.

[9] Accessed through a nondisclosure agreement signed by the author. Hughes (2011) uses an earlier version of these data to estimate short-run marginal products of water for Department of Agriculture research purposes. 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 (ABARES, 2007-2015). Each data point entails an on-site visit by an analyst lasting four to six hours. See Ashton and Oliver (2014, pp. 35–36) for more details on the survey construction.

[10] 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, Gupta, and Rathakumar (2016, pp. 45–46).

[11] Market-level records of the price, volume, date, and origin- and destination-region for every water trade between 2008–2015, are obtained from the MDBA 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.

Table 1—Water Rights, Trading, and Prices

	$N \times T$	Mean	St. dev.	q10	q25	q50	q75	q90
Panel								
Total irrigation, ML	2,059	679.0	1,377.1	18	70	210	641.9	1,564.6
Permanent rights, nominal ML	2,059	876.4	1,246.6	74.8	160	406	1,084	2,257.1
Permanent rights, realized ML	2,059	519.1	815.9	31.5	84	231.8	600.5	1,268.9
Buy annual water, $\{0, 1\}$	2,059	0.321	0.467	0	0	0	1	1
Volume bought, ML	661	288.7	462.2	20	40	100	320	736
Sell annual water, $\{0, 1\}$	2,059	0.199	0.399	0	0	0	0	1
Volume sold, ML	409	135.3	155.7	20	42	90	160	300
Buy entitlements, $\{0, 1\}$	976	0.092	0.289	0	0	0	0	0
Entitlements bought, nominal ML	90	251.7	528.4	1.9	8.5	50	250.2	522.5
Sell entitlements, $\{0, 1\}$	976	0.154	0.361	0	0	0	0	1
Entitlements sold, nominal ML	150	298.2	499.9	2.9	20	130.5	356.8	702.5
Within								
Ever trade annual water rights, $\{0, 1\}$	1,094	0.600	0.490	0	0	1	1	1
Ever buy annual water rights, $\{0, 1\}$	1,094	0.407	0.491	0	0	0	1	1
Ever sell annual water rights, $\{0, 1\}$	1,094	0.271	0.444	0	0	0	1	1
Ever buy and ever sell, $\{0, 1\}$	1,094	0.078	0.268	0	0	0	0	0
Annual trade frequency	656	0.829	0.248	0.500	0.600	1	1	1
Annual buy frequency	656	0.535	0.432	0	0	0.500	1	1
Annual sell frequency	656	0.349	0.434	0	0	0	1	1
Annual buy and sell frequency	656	0.055	0.204	0	0	0	0	0
Market								
Annual regional water price, AU\$/ML	2,059	234.5	198.9	24.6	55.0	160.3	338.7	621.9
Transaction-level water price, AU\$/ML	80,599	227.3	252.8	40	62	123	309	500
Transaction-level volume, ML	80,599	100.8	275.3	7	15	40	100	200

Notes: Farm-level irrigation, water rights, and trading from 2007 to 2015. Volumes denominated in megaliters (ML). Nominal permanent rights calculated as the farm's share of the total entitlement volume on issue. Realized permanent rights reported as the farm's share of the actual entitlement volume in that year. Number of observations falls for permanent rights (entitlements) because they are only defined for farms observed at least twice and each farm observation after the first. Annual regional water prices are defined for each farm in each year as the volume-weighted average price over all transactions occurring in that farm's region in that year.

Sources: ABARES Survey of Irrigated Farms; MDBA administrative water transaction data.

Farms adjust irrigation between years in response to changing economic and environmental conditions. These adjustment possibilities differ across farm types, as discussed below. Over all farms, the average within-farm standard deviation in irrigation from 2007 to 2015 is 245.8 ML or 32.7 percent 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 ($R^2 = 0.68$).

Rainfall and Evapotranspiration.—The total water available for a given crop over the growing cycle also depends on precipitation. I obtain these data from the Australian Bureau of Meteorology (BoM)(BoM 2005–2020a). Seasonal rainfall data are matched to each farm with georeferenced data by ABARES analysts. The value of rainwater for crop growth depends on when the rainfall occurs relative to the planting and growing seasons, as well as other environmental factors, such as temperature, wind, humidity, and sunlight, which affect the rate of crop evapotranspiration (the plant's natural water demand). I account for these seasonal aspects of productionby adapting the modern approach to calculating crop-specific evapotranspiration, the Penman-Monteith equation (Allen et al. 1998), which is widely used by farmers for irrigation planning and scheduling, as well as government agencies to summarize the effect of evolving environmental conditions on crop water requirements.

This approach to account for evapotranspiration requires three auxiliary data sources in addition to local rainfall over time: first, reference evapotranspiration, which the BoM calculates using daily data on rainfall, temperature, humidity, wind, and sunlight, as well as soil characteristics (BoM 2005–2020b); second, evapotranspiration coefficients for the growing cycles of each crop, which I take from standard reference manuals (FAO 1998a); third, growing season lengths and approximate planting dates for each crop, which I obtain from various Australian agricultural industry sources (USDA IPAD 2022). These three sources allow me to calculate Penman-Monteith monthly crop evapotranspiration on each farm. To incorporate this measure into the model of annual production, I take "effective rainfall" for each farm-crop-year, defined as the integral of rainfall over that crop's growing season, limited by the water requirements over time implied by evapotranspiration.

Natural water availability varies substantially across both space and time. Annual rainfall, reported in online Appendix Table A1, averages 403 millimeters (mm) but ranges over more than an order of magnitude from 112.2 to 1,950.8 mm across farms and years. Average annual rainfall rises to three to four times its drought levels once the drought abates (2010–2012), then diminishes again after 2013. The standard deviation of annual rainfall across years (169 mm) is comparable to its spatial variation across farms within each year (136 mm). Average effective rainfall for crops, 221 mm, is well below annual rainfall, since some seasons matter more for crop production than others (and some not at all), and evapotranspiration constraints occasionally bind.

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 AU$684.20 per 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 online Appendix Table A2, comprise 20.4 percent and 22.3 percent of all revenue, respectively, or 24.2 percent and 19.4 percent for the median farm-year. In estimation, I require that farms have nonzero materials inputs, which holds for 99.6 percent of farms in the original sample.

C. *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": (i) *perennial farms*, primarily growing perennial irrigated crops on orchards or vineyards; (ii) *annual farms*, specializing in yearly crops, such as wheat and rice; and (iii) *dairy farms*, which grow annual pasture and also some annual crops. In the medium run, farms specialize: 86.8 percent 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 crop types: (i) perennial irrigated, (ii) annual irrigated, (iii) annual nonirrigated, and (iv) annual pasture. This classification reflects several aspects of agricultural production (Hughes 2011). First, adjustment margins differ by crop type. Perennial irrigators grow perennial crops, such as fruits and wine grapes, on orchards and vineyards. Trees and vines take five to ten years to mature and require continuous watering (Ashton and van Dijk 2017). In contrast, annual crops and pasture are replanted and sown at the beginning of each year.

Second, water-intensity varies substantially across crop types, as shown in online Appendix Table A1. Most obviously, nonirrigated annual crops require zero irrigation. This creates an important margin of adjustment for annual operators, who may plant both irrigated and nonirrigated annual crop types. Irrigation rates are similar across perennial and annual irrigated crops, averaging 5.72 and 5.75 megaliters per hectare, respectively, but are much lower for pasture (2.78 ML per hectare).

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 percent 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 below.

Consistent with these differences in production, online Appendix Table A1 shows that revenue per hectare differs substantially across the four crop types, with perennial crops generating higher average revenues (about AU$11,000 per hectare) compared with annual irrigated crops and pasture (AU$5,000 and AU$6,300 per hectare) and nonirrigated annual crops (AU$400 per hectare).

D. *River Regulation and Trade*

River water in the sMDB is regulated at federal, state, and regional levels. Federal regulation under the Australian Government 2007 Water Act restricts total diversions 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.

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. Online Appendix Figure A1 draws realized allocation paths for each region. Realized allocations averaged 67.2 percent 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 percent 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 nineteenth century, but individual users could not hold water entitlements until the 1980s. Initially, these entitlements were generally defined based on historical usage (NWC 2011), with few transfers prior to the Water Act. Annual allocation trade, in contrast, dates to the early 1990s. Water trades occur bilaterally between farms, typically through water exchange intermediaries. The Australian Competition and Consumer Commission, which regulates these intermediaries, reported ad valorem commission rates for nine intermediaries of 1–4 percent (ACCC 2010, Appendix 1).

The river network's hydrological connectivity then determines the physical constraints on water trading at a given moment in time. Flow constraints are a function of infrastructure as well as evolving environmental conditions (MDBA 2013). River water originates in the Snowy Mountains Scheme, a collection of reservoirs and dams with 22,000 gigaliters of storage capacity, then flows westward throughout the southern connected zone (online Appendix Figure A2), subject to the river network's minimum and maximum flow constraints. Schedule D of the Water Act specifies baseline rules for allowable trades, complemented by additional transfer rules from river operators at MDBA and state governments. Water cannot typically move upstream, whereas downstream transfers are limited by upstream dam capacity, channel flow capacity, and transmission losses. Flow constraints on interregional trade are automatically triggered as temporary bans when net trade balances reach certain thresholds (Hughes, Gupta, and Rathakumar 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 minimize evaporation) and state government priorities.

E. *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 (online Appendix Figures A1 and A3). Water allocation prices fluctuate across years by more than an order of magnitude, peaking at the height of the Millennium drought at AU$624 per megaliter in 2008 and bottoming at AU$23 per megaliter in 2012. Rainfall, superimposed in Figure 1, and regional water allocations (online Appendix Figure A1) exhibit the inverse pattern, peaking at the drought's end in 2011–2012.

In addition to annual water price fluctuations, water prices vary substantially within years. The whiskers in Figure 1, panel A illustrate wide interdecile intervals of yearly water price distributions, calculated over all water market transactions in that year. The standard deviation of transaction prices exceeds 70 percent of the mean in an average year. Online Appendix Figure A4 plots daily water spot prices

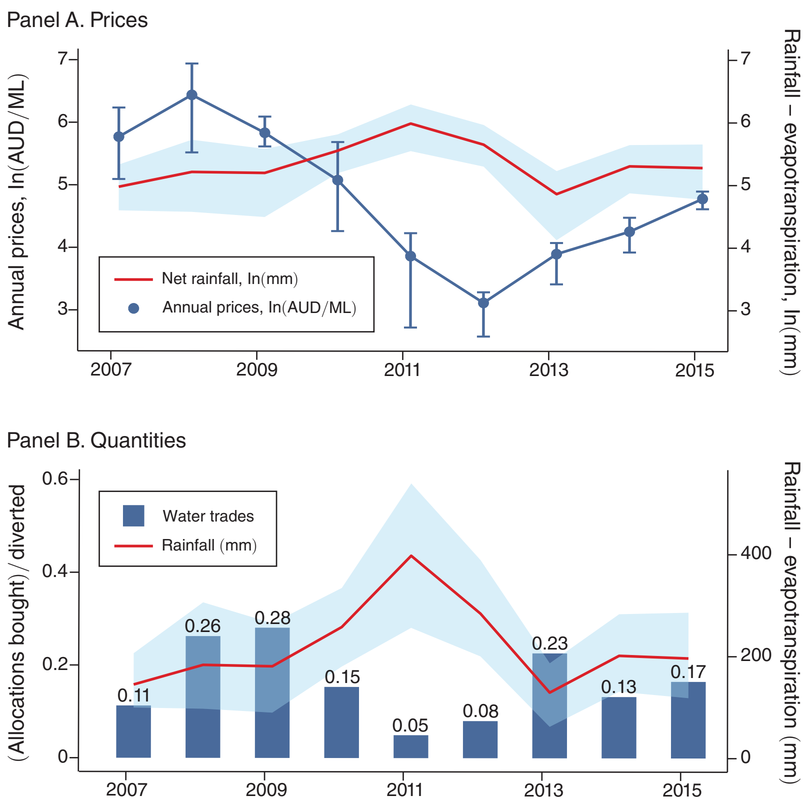

FIGURE 1. WATER MARKET OUTCOMES AND RAINFALL, 2007–2015

Notes: 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 adjusted for evapotranspiration. Panel B: fraction of total irrigation volumes bought on the annual water market in each year (blue bars) and the same rainfall series (in levels).

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

for two illustrative years. The high-frequency nature of this daily market implies that even farms with the flexibility to adjust planting at the start of each year face substantial water price uncertainty.

Although water prices are less dispersed across the river network than across time, moderate interregional daily price dispersion exists, with a coefficient of variation of 12 percent 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 percent of the mean (online Appendix Table A4).

F. *Farm-Level Water-Trading Patterns*

Water trading is an endogenous decision, but it is useful to understand in a statistical sense how the decision to trade correlates with observables. Together with evolving water scarcity, water trade participation and volumes vary substantially across years. Most striking is the evident comovement between annual scarcity and reallocation. Figure 1, panel B 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 percent of irrigation in 2008–2009, compared with 12.6 percent in 2010–2015.

Trade volumes also closely track water market participation. While more than half (60 percent) of farms trade annual water allocations in at least one year, participation in each year ranges from 18 to 66 percent of farms, falling to its lowest level when the drought abates in 2011. Participation decisions are strongly correlated over time, in the sense that farms who trade in at least one year will trade, buy, and sell in 82 percent, 53 percent, and 35 percent, respectively, of all years in which they appear in the data (Table 1).

Geography and farm type also predict trade, with farms in the Murrumbidgee region more likely to sell and less likely to buy annual water allocations than their counterparts in other regions (online Appendix Table A6). In contrast, farms in South Australia or growing annual crops are much more likely to buy. These patterns corroborate interregional trade flow data that show South Australia and Victoria are net importers and the Murrumbidgee is a net exporter during the period considered (Hughes, Gupta, and Rathakumar 2016, p. 15).

Evolving rainfall conditions are also a significant predictor of farm water trading. Table 2 shows results from a linear probability model of the indicator for trade regressed against rainfall and water endowments. Farms with relatively less rainfall in 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 farm water-trading decisions over time even after controlling for differences across years, regions, and operation types.

Taken together, these correlations indicate that annual water trading responds to changing environmental conditions and endowments. These correlations motivate the model below, which (i) controls for rainfall directly in the production function, (ii) distinguishes between crop types, and (iii) allows crop productivity to evolve 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.

II. 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 IIA 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 IIB describes planting, growing, and harvest seasons and defines the timing of input choices within the year. Section IIC discusses the model's remaining economic restrictions.

Table 2—Annual Water Trading Decisions and Rainfall

	Dependent variable: Buy, $\mathbf{1}\{\Delta_{it} > 0\}$			
	(1)	(2)	(3)	(4)
Panel A. Annual purchases				
$\ln(net\_rainfall_{it})$	−0.162	−0.059	0.00002	−0.143
	(0.032)	(0.034)	(0.035)	(0.050)
$\ln(water\_endowment_{it})$	0.006	0.019	0.022	−0.080
	(0.010)	(0.010)	(0.010)	(0.026)
Year fixed effects	✓	✓	✓	✓
Region fixed effects		✓	✓	
Region × year fixed effects			✓	
Farm fixed effects				✓
Observations	2,059	2,059	2,059	2,059
Adjusted R^2	0.111	0.139	0.184	0.397
	Sell, $\mathbf{1}\{\Delta_{it} < 0\}$			
Panel B. Annual sales				
$\ln(net\_rainfall_{it})$	0.141	0.029	−0.00003	0.063
	(0.030)	(0.031)	(0.032)	(0.037)
$\ln(water\_endowment_{it})$	0.040	0.026	0.023	0.044
	(0.009)	(0.009)	(0.009)	(0.023)
Year fixed effects	✓	✓	✓	✓
Region fixed effects		✓	✓	
Region × year fixed effects			✓	
Farm fixed effects				✓
Observations	2,059	2,059	2,059	2,059
Adjusted R^2	0.084	0.126	0.165	0.459

Notes: The unit of observation is the farm-year. Regressions of the indicator for trading annual water rights on effective rainfall (annual rainfall adjusted for evapotranspiration), realized permanent water endowments, and fixed effects denoted by check marks. Every regression includes crop type fixed effects. Standard errors block-bootstrapped at the farm level (1,000 iterations) in parentheses.

A. *Production*

Production cycles occur in each year, indexed by $t \in \{0, 1, 2, \ldots\}$, reflecting the annual nature of agricultural production. Farms, indexed by i, inhabit the river basin. I abstract from issues of entry or exit.[12] Each farm i specializes in annual, perennial, or dairy operations, and produces crop types $c \in \mathcal{C}_i$, where

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

as discussed in Section IC.

[12] 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 nonfarmland.

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_{ict}^L, and total materials, X_{ict}^M, for all farms, as well as feed, X_{ict}^F, and cows, X_{ict}^D, for dairy farms. Rainfall and evapotranspiration, $E_{ict} = \left(E_{ict}^R, E_{ict}^V\right)$, enter production in terms of effective rainwater, defined in megaliters as

$$R_{ict} = \left(E_{ict}^R - E_{ict}^V\right) K_{ict}, \tag{1}$$

which is the volume of rainwater, limited by evapotranspiration, incident to 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 $P_{c_k 0}$ (Australian dollars per tonne) measured for crops c_k in each type c as described in online Appendix B. Output for crop type c on farm i in year t is given by

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

where ω_{ict} is unobserved productivity and ε_{ict} is measurement error. The specific form of F_c in the second line of (2) is not important for identification.[13] The nested constant elasticity of substitution (CES) form is chosen to allow irrigation-output elasticities to vary across farms through irrigation, rainfall, and land inputs. 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, $\mathcal{W}_{ict} \equiv \alpha_c\left(W_{ict} + \vartheta_c R_{ict}\right)^{\frac{\sigma_c - 1}{\sigma_c}} + \left(1 - \alpha_c\right) K_{ict}^{\frac{\sigma_c - 1}{\sigma_c}}$, is taken as unity.

The annual production function defined in (2) assumes that output depends only on the total volume of irrigation and rainwater applied throughout the year. In practice, the timing of irrigation and rainfall throughout the season affects crop yields. While one major concern is rainfall occurring outside of the growing season or in excess of a crop's watering requirements, the measure of effective rainfall that incorporates crop evapotranspiration, as well as the sophisticated irrigation scheduling schemes used by most farms (Ashton and Oliver 2014), alleviates much of this concern.[14] In addition, the annual production function will not capture the effects of irrigation on harvests in future years, a concern of particular relevance for trees and vines. For example, if a farm irrigates in some years to sustain trees for future years, without affecting the current year's harvest, then the value of this water will not be captured by (2).

[13] That is, given any functional form, the assumptions in Section III will identify F_c.

[14] A related concern is that seasonal shocks to rainfall or irrigation opportunities will affect irrigation scheduling and lead two farms with the same annual irrigation and effective rainfall to produce different levels of output. Equation (2) approximates these shocks through productivity, but this will rule out intraseasonal gains from trading that arise from improved irrigation scheduling (Beare, Bell, and Fisher 1998).

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 relative efficiency ϑ_c of rainwater, 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 or feed required to maintain them, I impose a zero elasticity of substitution between these two factors, extending (2) to

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

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

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

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." Through this unobserved term, total factor productivity differs arbitrarily across farms and crop types, allowing the marginal product of water to differ across otherwise identical farms in each year. However, Hicks neutrality rules out unobserved differences in irrigation efficiency at the farm-crop level, which may be a crucial aspect of the response to water scarcity. 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 ϑ_c to depend on t or other observed farm characteristics such as the value of the farm's irrigation equipment.

A final restriction on productivity is that, while farms anticipate their future productivity and make long-run decisions given these beliefs, farms cannot directly influence their unobserved productivity through investment. They can affect their future production possibilities through land use, for example, by reallocating land from one crop type to another. However, a farm's past irrigation, materials, and labor inputs cannot affect its current or future productivity within each crop type. This assumption also rules out unobserved actions that raise future performance.

B. *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 online Appendix Figure A6, 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_{ict}^D. The farm's information at $t-1$ includes its productivity, its land and dairy cow inputs, and all past decisions, prices, and endowments. I denote this information set as

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

At $t-b$, the growing season (approximately June to October), farms observe

$$\mathcal{F}_{i,t-b} = \left(\mathcal{F}_{i,t-1}, E_{it}, P_{it}^W, \bar{W}_{rt}, \left\{\omega_{ic,t-b}\right\}_c\right),$$

decide water inputs W_{ict}, and, if $c =$ dairy, purchase feed, X_{ict}^F. Finally, farms learn their final productivity ω_{ict} and crop prices P_{ict} for each c, as well as wages $P_{X,it}^L$, then finalize labor X_{ict}^L and annual materials X_{ict}^M decisions and harvest crops Q_{ict} (November to 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 at the same time as hiring labor and/or buying materials. The empirical strategy primarily requires that (i) land decisions are determined at the start of the season, (ii) irrigation responds to water-sharing rules and is not chosen after the final materials decision with new information, and (iii) the farm knows its productivity and prices when it finalizes its labor and materials decisions.

C. *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.

Output Markets.—Agricultural producers are small and agricultural commodities exhibit minimal differentiation relative to many other consumer goods. Australia also 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 neither materials nor 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). This rules out all dynamic aspects of these factors, such as labor adjustment costs that depend on past levels, or current materials that affect future output. The assumption on labor can be relaxed (Ackerberg, Caves, and Frazer 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 assign 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 the empirical strategy. It means that materials demand under the timing of Section IIB admits a nonparametric representation,

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

which can be used, under the additional statistical assumptions below, to control for productivity's persistence over time. Note that, in contrast to the market for materials, where (6) rules out any other friction that creates variation across farms, water market access may differ unobservably across farms and over time. This flexibility is important given that actual water prices and trading constraints evolve over the growing season and differ across the river network (Section IE).

III. Empirical Strategy

The empirical strategy to identify and estimate the multifactor production function in Section II must account for the dynamic dependence of irrigation, labor, materials, and land decisions on productivity. First, Section IIIA introduces statistical assumptions that allow me to control for the expected component of productivity by inverting static materials demand. Second, Section IIIB introduces an instrument for irrigation based on water-sharing rules. Section IIIC discusses how the water rights instrument weakens some of the restrictions on water market structure and irrigation decisions that would be implied by standard methods of identifying production functions. Section IIID describes the first-order conditions used for the remaining two flexible factors and Section IIIE specifies the estimating equations.

A. *Assumptions*

The following allows observed materials to proxy for unobserved productivity:

ASSUMPTION 1: *Materials demand χ_{ct}, given in (6), is strictly increasing in ω_{ict} for all c and t.*

Assumption 1 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_{ict}^M (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

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

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

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

which allows (7) to be recovered from the path of $\big(\omega_{ict}\big)_{t\geq 0}$ with ψ_{ct}, I assume the following.

ASSUMPTION 2 (Markov): *Productivity $\big(\omega_{ict}\big)_{t\geq 0}$ evolves as an exogenous, first-order Markov process for each* i, c, *and* t.

Assumption 2 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, as discussed in Section IIA, farms cannot influence the evolution of productivity over time. Second, Assumption 2 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 Assumption 1: 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.

B. *Water Rights Instrument*

Even when the anticipated component of productivity is known (or controlled for as in Section IIIE), the flexible factors still depend on the productivity innovation, which will bias a production function estimated without instruments. The timing of agricultural input decisions given in Section IIB suggests several potential sources of variation in water inputs, though some of these (e.g., water prices) are likely endogenous. I use

$$Z_{ict}^W = \begin{cases} \rho_{i0}\bar{W}_{rt}, & \text{if } c = \text{ annual irrigated crops, pasture, or perennial crops;} \\ E_{it}^R, & \text{if } c = \text{ annual nonirrigated crops.} \end{cases} \tag{9}$$

For irrigated crops, the instrument for water is the interaction of annual regional allocations, $\bar{W}_{rt}$, and a farm's initial water endowment at baseline, ρ_{i0}. Interacting allocations and historical endowments acts to increase the variation from the region-year to the farm-year, improving precision with a predetermined measure of the irrigation operation's size. These permanent rights were inherited well before the time of planting, and the identification strategy controls for the anticipated component of productivity at the time of planting, making such characteristics a natural source of identifying variation within the model.[15] For nonirrigated crops, the instrument for water is farm-specific rainfall, which provides exogenous variation in (rain)water applied to the crops given the predetermined land decision.

The instruments in (9), where relevant, will identify the relationship between irrigation and agricultural production if water allocation rules $\bar{W}_{rt}$ satisfy

$$E\left[\rho_{i0}\bar{W}_{rt}\xi_{ict}\,|\,\mathcal{F}_{i,t-b}\right] \;=\; 0 \tag{10}$$

for each i, c, and t. This assumption is satisfied if a farm's productivity shock is conditionally independent from river diversion caps and baseline water rights, given the farm's expected productivity and planting decisions at the start of the year. The primary justification for this assumption is the mechanical nature of diversion formulas.[16]

The primary threat is that the current and historical environmental conditions that determine allocation caps directly affect crop productivity innovations. To some extent, controlling for rainfall and crop evapotranspiration over the growing cycle mitigates this concern. In addition, the control for expected productivity allows allocations to be correlated with past levels of productivity. Exclusion is likely satisfied in cases where productivity shocks arise from a farmer's specific skills in growing certain crops and the farm's exposure to wind, sun, or other local conditions that year. In contrast, exclusion rules out innovations in productivity that arise primarily from unexpected regional shocks correlated with diversion cap announcements—for example, if greater inflows from the high mountain ranges lead to more generous diversion caps and also correlate with a warmer spring and lower likelihood of frost.

Another concern, independent of the economic interpretation of productivity, is that river extraction caps may be determined by political processes that react to farms' annual productivity shocks. For example, a regulator may seek to maximize output and take advantage of high productivity shocks by releasing more water from the reservoirs. Alternatively, a regulator may have distributional motives and aim to compensate farms with greater regional water allocations when they have low productivity shocks (and higher marginal utilities of consumption). Although water market institutions clearly reflect agricultural interests, both the rules in Schedule E and my conversations with river operators at MDBA suggest that regulatory agencies

[15] This will not be the case if inherited water entitlements affect future crop productivity innovations through unobserved states that cannot be inferred directly from the productivity process. Although this will violate Assumption 2, in practice it may be a real concern. For example, one can imagine unobserved capital investments that are correlated with inherited entitlements, informative about the farm's distribution of productivity shocks, and not directly predictable from the productivity process.

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

follow rigid water-sharing formulas, rather than responding directly to agricultural industry interest groups.

C. *Discussion of Identifying Variation*

The control function approach requires exogenous variation in each flexible input, but rules out any variation in demand for materials across all farms growing c at t. A perfect control for ω_{ict} solves the endogeneity problem in (2) for static inputs (Olley and Pakes 1996), but raises functional dependence issues. Ackerberg, Caves, and Frazer's (2015) solution to this functional dependence is to construct moments based on the productivity innovation ξ_{ict} that control only for the expected component of productivity $\psi_{ct}(\omega_{ic,t-1})$, but these moments, in turn, require stronger identifying assumptions—or better instruments.

First, note that functional dependence is not a concern despite the use of a common materials demand function. This is because, like Ackerberg, Caves, and Frazer (2015), materials demand in (6) is conditioned on other flexible inputs, so those other flexible inputs may differ arbitrarily across firms. Here, irrigation may vary across otherwise identical farms due to water allocations, water prices, and any unobserved constraints on trade realized between planting and irrigation decisions. These sources of identifying variation do not affect output except through irrigation volumes, so they do not influence the optimal X_{ict}^{M} conditional on W_{ict} and are therefore consistent with the control function.

Second, the water rights instrument given by (9) provides observed variation in irrigation outside of the model, thereby replacing some of the assumptions commonly used to identify production functions. For example, lagged inputs are commonly used as instruments, because observed input choices are highly correlated over time (Ackerberg et al. 2007, p. 4223) and excluded if $E[\xi_{ict} | \mathcal{F}_{i,t-1}] = 0$. However, many natural sources of input variation across firms used to break functional dependence, such as adjustment costs or autocorrelated factor prices, can violate $E[W_{ic,t-1}\xi_{ict}] = 0$.[17] The water rights instrument, in contrast, allows irrigation decisions to depend on the farm's beliefs about their future productivity innovations, serially correlated trading constraints to constrain irrigation decisions over time, and the distribution of crop productivities to affect water prices and trading, just not allocation rules or predetermined initial rights. This is still a strong assumption, but relies primarily on variation generated by the underlying institutions, rather than restrictions on equilibrium decisions.

[17] For example, if irrigation involves adjustment costs, then a farm's past irrigation should depend on its beliefs about the current distribution of productivity. Alternatively, if irrigation is autocorrelated through autocorrelated input prices, then using lagged irrigation as an instrument requires that the distribution of current productivity innovations does not correlate with past water prices, so that either past water prices do not depend on beliefs over future productivity, or water prices are independent of productivity. Either restriction is problematic in a setting where prices depend on forward-looking water storage and the distribution of productivity innovations are a source of the gains from trade.

D. *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 multicrop 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 $E[\varepsilon_{ict}] = 0$ and $E[\xi_{ict} | \mathcal{F}_{i,t-1}] = 0$. To identify materials' contribution to F_c separately from χ_{ct}, I use (2) and the assumption of static optimality, which imply that β_{cM} is identified from the first-order conditions,

$$(11) \qquad E[\varepsilon_{ict} | \mathcal{F}_{it}] = E\Big[\ln\beta_{cj} - \ln\big(P^j_{X,it} X^j_{ict}\big) + \ln\big(P_{ict} Q_{ict}\big) | \mathcal{F}_{it}\Big] = 0$$

for $j = M$. This contrasts with Ackerberg, Caves, and Frazer (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 (11) for $j = L$, because (11) is more efficient and does not require assuming that $E\big[P^L_{X,it} \xi_{ict}\big] = 0$.

Multicrop Farms.—Irrigation volumes, land allocations, and physical output are observed at the crop level, but labor and materials only at the farm level. Apportioning labor and materials to crop type is not a problem for the 65.5 percent of farms growing only a single crop type. To address this for the remaining farms, I apportion farm-level labor and materials inputs to crop types using elasticity-weighted realized revenue shares.[18] 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.

E. *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 $\ln F_c(\cdot) + \omega_{ict} = \Phi_{ict}$,

[18] I estimate these elasticity weights in a zeroth stage from the revenue shares of farms producing a single crop type. If elasticities do not differ across c, unweighted revenue shares can be used directly (e.g., Collard-Wexler and De Loecker 2015). Using only single-crop farms for this zeroth stage raises selection concerns if β_{cM}/β_{cL} differs significantly for multicrop farms. Here, the estimated distributions of irrigated crop productivities across single- and multicrop farms appear nearly identical (online Appendix Table A8). Where selection issues appear severe, it may be appropriate to correct the sample used in the zeroth stage for selection, e.g., by matching on observables such as farm size.

$$(12) \qquad \Phi_{ict} = \Phi_{ct}\big(X_{ict}^M; W_{ict}, R_{ict}, K_{ict}, X_{ict}^L, P_{ict}\big),$$

to eliminate the measurement error ε_{ict}. I estimate (12) by regressing $\ln Q_{ict}$ on transformations of

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

to obtain $\hat{\Phi}_{ict}$ 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.

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

$$(13) \qquad E\Big[\Big(q_{ict} - f_{ict} - \psi_c\big(\hat{\Phi}_{ic,t-1} - f_{ic,t-1}\big)\Big) \otimes \mathbf{Z}_{ict}'\Big] = 0,$$

where lowercase letters denote natural logs, and f_{ict} denotes f_c evaluated at i's observed inputs in year t. I then estimate (13) using two-step generalized method of moments with an algorithm inspired by Ackerberg, Caves, and Frazer (2015, Appendix A4) to concentrate out ψ_{ct} as described in online Appendix A.1.

IV. 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 helps predict 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.

A. *Production Technologies*

Benchmark estimates of the main production function parameters are reported in Table 3. Water plays a significant role in the production of crops for Australian farms, with average implied irrigation-output elasticities of 0.246, 0.206, and 0.164 for irrigated perennial crops, annual crops, and pasture, respectively. The significant differences across crop types suggest that the technical differences in these operations discussed in Section IC translate into meaningful differences for production. Within crop types, irrigation elasticities also differ across farm-years—for example, the interdecile range of these elasticities for perennial operations is $[0.141, 0.326]$—reflecting differences in inputs and rainfall as well as the flexibility of the nested CES function in (2).

Labor and materials also play significant roles in production, with $\hat{\beta}_{cL} + \hat{\beta}_{cM}$ ranging from 0.25 (for $c =$ dairy) to 0.6 (for annual crops). The relative importance of these two factors differs by operation, with output in perennial operations being about one-and-a-half times more elastic to labor than annual operations, consistent with the greater labor inputs required to maintain more sophisticated irrigation operation schemes. The estimates of the role of labor in production are

Table 3—Production Function Estimates

	Perennial (1)	Annual irrigated (2)	Annual nonirrigated (3)	Dairy (4)
Irrigation				
Average irrigation-output elasticity $E\left[\frac{\partial f_c}{\partial w}\right]$	0.246	0.206	0.230	0.164
	(0.037)	(0.029)	(0.061)	(0.051)
Interquartile range of $\frac{\partial f_c}{\partial w}$ *across i, t*	[0.207, 0.301]	[0.151, 0.265]	[0.222, 0.240]	[0.104, 0.209]
Tenth to ninetieth percentile range	[0.141, 0.326]	[0.087, 0.297]	[0.215, 0.245]	[0.075, 0.263]
Water-land aggregator				
Scale coefficient, β_{cW}	0.631	0.526	0.311	0.782
	(0.047)	(0.070)	(0.097)	(0.043)
Irrigation share, α_c	0.599	0.513	—	0.385
	(0.046)	(0.016)		(0.125)
Land share, $1-\alpha_c$	0.401	0.487	0.409	
	(0.046)	(0.016)	(0.007)	
Rainwater coefficient, ϑ_c	1.081	1.048	0.591	0.148
	(0.151)	(0.163)	(0.007)	(0.245)
Elasticity of substitution, σ_c	1.575	1.451	3.211	
	(0.199)	(0.218)	(1.137)	
Other factors				
Labor elasticity, β_{cL}	0.352	0.201	0.335	0.147
	(0.016)	(0.015)	(0.027)	(0.007)
Materials elasticity, β_{cM}	0.186	0.404	0.558	0.110
	(0.008)	(0.021)	(0.030)	(0.003)
Feed share, α_F				0.615
				(0.125)
Pasture-feed elasticity of substitution, σ_F				3.331
				(2.161)
Returns to scale, $\sum_j \beta_{cj}$	1.169	1.131	1.204	1.039
	(0.050)	(0.081)	(0.088)	(0.043)
J-statistic	0.969	1.103	1.456	1.004
Adjusted R^2	0.807	0.797	0.802	0.876
Observations	510	170	208	254

Notes: Results from the generalized method of moments procedure described in Section III 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 IIIB. Mean, interquartile, and interdecile ranges of $\left\{\frac{\partial f_c}{\partial w}\right\}$ calculated at observed inputs over all i, t. Adjusted R^2 reports the fit of the first-stage polynomial $\hat{\Phi}_{ict} = \omega_{ict} + f_{ict}$ on q_{ict}. Standard errors block-bootstrapped at the farm level (5,000 iterations) in parentheses.

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.

While the estimated returns to scale for dairy are close to 1, they exceed 1 for both perennial and annual operations, where $\sum_j \hat{\beta}_{cj} = 1.17$ and 1.13. This could reflect unobserved constraints on large-scale expansion (e.g., total landholdings) that prevent farms from growing their operations to profit from increasing returns from scale.

The distributions of productivity estimates for each crop type, $\hat{\omega}_{ict} = \hat{\Phi}_{ict} - \hat{f}_{ict}$, are reported in online Appendix Table A7. Within types, irrigated crop productivities lie within a narrow range, with standard deviations between 0.56 and 1.16. In contrast, farm productivities are much more dispersed; $\hat{\omega}_{it} \equiv \ln \sum_c e^{\hat{\omega}_{ict}} \frac{P_{ict} Q_{ict}}{\sum_c P_{ict} Q_{ict}}$ has a standard deviation of 2.71. Productivity also persists across farms over time, with estimated persistence significantly above zero but also below one. Persistence is greatest for perennials ($\hat{\varrho}_c = 0.630$), compared with annual (0.432) and dairy (0.324), consistent with the discussion in Section IC that perennial operations have relatively fewer options for annual adjustment.

B. *Productivity Predicts Trade*

A natural preliminary question is whether productivity predicts water trade. Table 4 tests this hypothesis by regressing an indicator for buying (selling) water allocations on the estimated productivities and the same controls from Table 2. More productive farms buy annual water allocations and less productive farms sell water, consistent with economic intuition. The positive relationship between trade and productivity survives controls for year, region, region-by-year, and farm fixed effects, indicating that the estimates of unobserved technology matter for interpreting water-trading behavior. Increasing productivity by one standard deviation raises (lowers) the probability of buying (selling) annual water by about 32–44 percent (33–52 percent) of the mean.

In addition, while past productivity predicts trade, much of the relationship between annual productivity and trading decisions appears driven by productivity innovations. The even columns of Table 4 decompose the effect of $\hat{\omega}_{it}$ into $\hat{\omega}_{i,t-1} + \hat{\xi}_{it}$. Water trading 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 percent and decreasing the sale probability by 0–9 percent.

C. *Water Shadow Values*

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

$$\hat{\lambda}_{ict}(W, X_{ict}, K_{ict}, R_{ict}) = P_{ict} e^{\hat{\omega}_{ict}} E\left[e^{\varepsilon_{ict}}\right] \frac{\partial F_c(W, X_{ict}, K_{ict}, R_{ict})}{\partial W}, \tag{14}$$

which is purged of measurement error ε_{ict}. The rest of this paper omits the constant $E\left[e^{\varepsilon_{ict}}\right]$ in notation where relevant. Equation (14) captures the marginal effect of an additional megaliter of irrigation on expected time-t revenue. Note that (14) uses (ex ante) productivity, $\hat{\omega}_{ict}$, rather than the traditional Solow residual, $\hat{\omega}_{ict} + \varepsilon_{ict} =$

Table 4—Water Trading Decisions and Estimated Productivity

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Buy annual allocations								
Productivity, $\hat{\omega}_{it}$	0.059		0.071		0.069		0.078	
	(0.019)		(0.020)		(0.018)		(0.030)	
Productivity innovation, $\hat{\xi}_{it}$		0.086		0.102		0.078		0.147
		(0.028)		(0.030)		(0.028)		(0.039)
Lagged productivity, $\hat{\omega}_{i,t-1}$		0.031		0.045		0.044		0.065
		(0.027)		(0.028)		(0.025)		(0.042)
Panel B. Sell annual allocations								
Productivity, $\hat{\omega}_{it}$	−0.032		−0.033		−0.036		−0.012	
	(0.018)		(0.018)		(0.018)		(0.026)	
Productivity innovation, $\hat{\xi}_{it}$		−0.039		−0.029		−0.016		−0.038
		(0.029)		(0.030)		(0.031)		(0.040)
Lagged productivity, $\hat{\omega}_{i,t-1}$		−0.053		−0.032		−0.037		−0.051
		(0.023)		(0.024)		(0.022)		(0.044)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects			✓	✓	✓	✓		
Region × year fixed effects					✓	✓		
Farm fixed effects							✓	✓
Observations	2,059	976	2,059	976	2,059	976	2,059	976
Adjusted R^2	0.116	0.148	0.146	0.181	0.190	0.236	0.401	0.443

Notes: 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 2 (natural logarithms of effective 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: $\hat{\omega}_{it} \equiv \ln \sum_c \exp(\hat{\omega}_{ict}) \frac{P_{ict}Q_{ict}}{\sum_c P_{ict}Q_{ict}}$. Standard errors block-bootstrapped at the farm level (2,500 iterations) in parentheses.

$q_{ict} - \hat{f}_{ict}$. In this paper, $\hat{\omega}_{ict}$ is more appropriate to assess dispersion in shadow values, because farms learn ε_{ict} only after making input decisions.[19]

Two other aspects of the shadow value functions are of note. First, the production functions exhibit rapidly diminishing marginal returns to irrigation, as shown by the plots of shadow value functions in online Appendix Figure A7. This convexity of production in water scarcity will affect the value of trade. Second, at observed inputs, the distribution of shadow values across firms exhibits substantial variation, both across and between crop types (online Appendix Table A9 and Figure A8). Perennial operations, such as vineyards or orchards, have the highest estimated values, with median marginal values close to the ninetieth-percentile water price. Irrigated annual crops and pasture have much higher values than nonirrigated crops, but values 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

[19] More generally, in cases where the assumptions used here to identify production functions are likely to hold, using ex ante rather than realized productivity is important to avoid conflating measurement or expectational error with factor misallocation. In cases where ex ante productivity cannot be reliably recovered (e.g., due to concerns of misspecification), realized productivity may be more appropriate.

(Scheierling, Loomis, and Young 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, Fulginiti, and Perrin (2019), who find marginal values of irrigation in the midwestern United States averaging US$196 per acre or about AU$205 per megaliter.

At observed input levels, the last column of online Appendix Table A9 shows that shadow values for irrigated farms are similar to average observed water transaction prices discussed in Section IE but not used in estimation (see also online Appendix Figure A9). Furthermore, the average estimated shadow value of (rain)water for non-irrigated annual crops is considerably less than the average water transaction price. Given that the water price data are not used in estimation and that the shadow values of water are not calibrated to equalize the marginal products of water across farms, these comparisons suggest the estimated production technologies are not unreasonable.

D. *Robustness*

The benchmark production function allows for arbitrary productivity, but constrains the parameters (θ_c, ψ_c) to be constant across t. Given the substantial changes in environmental conditions and water market prices over 2007–2015, online Appendix Tables A10, A11, and A12 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 $\exp(\zeta_{ict}) W_{ict}$ as described in online Appendix A.2. I study common water-augmenting technical change across farms, which takes the form $\zeta_{ict} = \zeta_t$. I also consider efficiency that differs with observed irrigation equipment, $\zeta_{ict} = \zeta_{\text{irrig}} \mathbf{1}\{i \text{ has irrigation equipment at } t\}$. 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. Online Appendix Tables A13 and A14 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 on irrigation specifically (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, Fulginiti, and Perrin 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. Online Appendix Table A13 also contains results from two important special cases of (2), Cobb-Douglas ($\sigma_c = 1$) and Leontief ($\sigma_c \to 0$).

Finally, given the particular importance of rainfall for the value of water, online Appendix Tables A16, A17, and A18 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. Restricting rainfall's presence in the production function to total factor productivity (i.e., $\vartheta_c = 0$) inflates the estimated $\frac{\partial \hat{f}_c}{\partial w}$ by a factor of more than $\frac{3}{2}$.

V. Valuing the Water Market

I now apply the estimates of Section IV—which used irrigation volumes and crop yields at the farm level to recover production technologies—to the water trading data not used in estimation. I focus on three main results from the market-based water reallocation from the initial pretrade endowments described in Section VA. First, water trading reduces dispersion in estimated shadow water values across farms, although considerable dispersion remains (Section VB). Second, and most importantly, integrating over the observed trade flows, the efficiency gains from this reallocation are substantial (Section VC). Third, this value is concentrated in water-scarce years and water-scarce regions (Section VD). I then discuss some important limitations (Section VE) and policy implications (Section VF) of these findings.

A. *Pretrade Water Allocations*

The central exercise of this paper is to contrast observed irrigation under the water market with alternative initial water endowments. I obtain the pretrade allocation using input levels without annual allocation trades, $W^a_{ict} = W_{ict} - \Delta_{ict}$. Allocation trades are observed as net purchases Δ_{it} for each farm. I allocate trade volumes for farms growing more than one irrigated crop in proportion to water application rates, so that $\Delta_{ict} = \frac{W_{ict}}{\sum_{c'} W_{ic't}} \Delta_{it}$, though results are insensitive to allocating trade volumes optimally across c. This reallocation involves 13.3 percent of total irrigation volume.

The results in the next three sections analyze the value of the market mechanism as it operates in the world relative to this distribution of pretrade endowments.

B. *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 pretrade shadow values for water than the sellers with whom they trade. Although the data do not match buyers with sellers, Figure 2 reports the distributions of farm-level pretrade shadow values conditional on the direction of trade. The upper panel of Figure 2 shows that water-buying farms have pretrade shadow values that are more dispersed and on average greater than water-selling farms; the lower panel 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 between these two distributions may indicate the presence of residual constraints on trade.

In an efficient water market without trading frictions, shadow values should converge across traders with nonzero posttrade inputs. Online Appendix Figure A10 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

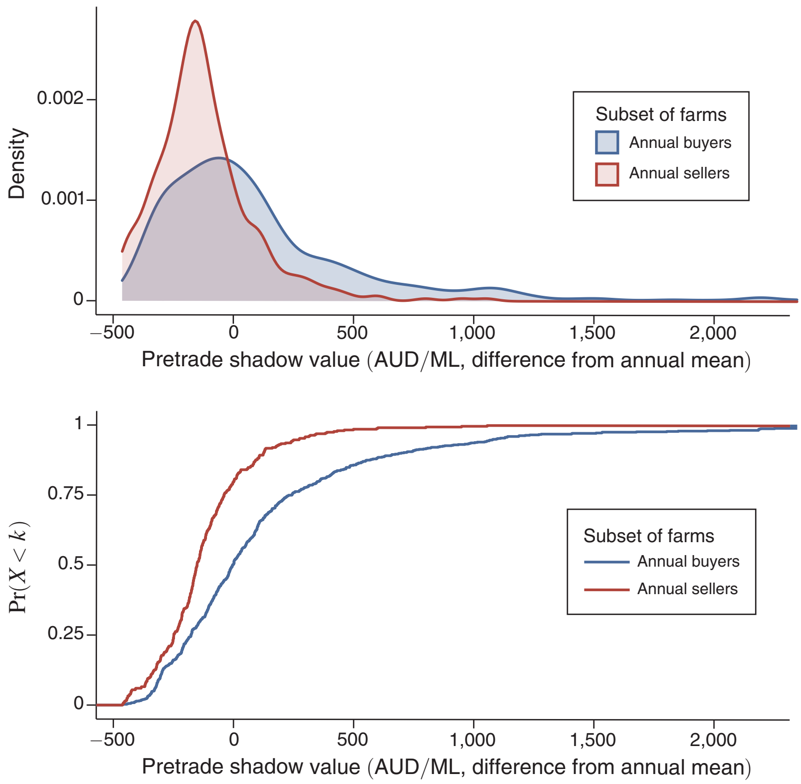

FIGURE 2. PRETRADE SHADOW VALUES

Notes: Conditional probability densities (top) and cumulative distribution function (bottom) of farm-crop-level shadow water values, centered at the annual average, 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.

(2007–2009), but substantial dispersion remains. Online Appendix Table A19 quantifies these effects for water-trading farms using ordinal dispersion measures as in Syverson (2004). The estimates show that water trading does reduce the interquartile range of shadow values for water traders in each year. However, none of these declines are statistically significant at a 10 percent level.

C. *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 pretrade misallocation requires an inframarginal 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

$$(15)\quad \Pi_{it}(W_{it}) = \max_{X_{it}} \sum_c P_{ict} e^{\omega_{ict}} F_c(W_{ict}, X_{ict}, K_{ict}, R_{ict}) - P_{X,it} \cdot X_{ict} - \Gamma_{it}^W(W_{it}),$$

TABLE 5—REALIZED GAINS FROM WATER TRADING

	Gains from trade			Reallocation	
	Percent	Percent, traders	AUD/ML	Realloc (percent)	Traders (percent)
Annual	0.051	0.091	338.52	0.133	0.51
	[0.016, 0.071]	[0.037, 0.127]	[−21.23, 467.53]	[0.117, 0.148]	[0.48, 0.53]

Notes: Estimated gains from observed water trading, 2007–2015, from pretrade endowments described in Section VA. Gains from trade defined as discounted sum of (16) 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. Reverse percentile bootstrap confidence intervals reported at the 90 percent level and constructed from 5,000 draws block-bootstrapped at the farm level.

which is revenue minus the costs of labor and materials, $P_{X,it} \cdot X_{ict}$, and irrigation, $\Gamma_{it}^{W}(W) = P_{it}^{W}\sum_c W_c$, where P_{it}^{W} denotes the average volume-weighted water price in i's region in year t.[20] The value of producing in year t using equilibrium water inputs rather than pretrade water endowments—the "realized gains from trade"—is then

$$\text{GFT}_t = \sum_i \Pi_{it}(W_{it}) - \sum_i \Pi_{it}(W_{it}^{a}) \tag{16}$$

for W^a as defined in Section VA. Note that using (15) to evaluate the gains from trade also strengthens the assumption of Section II 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 5 reports the total gains from trade, $\text{GFT} = \sum_t \delta^t \text{GFT}_t$, over 2007–2015, taking $\delta = 1 - \bar{r} = 0.956$ from the real market interest rate $\bar{r}$ faced by Australian farms during this period ABARES (2017). The total gains from trade equal 5.1 percent of total irrigated output from 2007–2015. Confidence intervals for the total gains, $[1.6\%, 7.1\%]$ at the 90 percent level, clearly bound these gains from zero.[21] 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 (online Appendix Table A20). In years in which water is abundant, 2011–2013, zero gains from trade cannot be rejected and the lower bounds of the 90 percent confidence intervals lie strictly below zero.

Importantly, the gains from trade estimates do not seem to be driven by the specification of production or profit functions. Results for three alternative specifications of the production function—translog and the two specifications with water-augmenting

[20] The irrigation cost function assumes that reallocation does not change total conveyance costs and that variable irrigation costs differ across farms only through water prices. Because the ABARES survey is not an administrative dataset and does not contain all traders, this form of the irrigation cost function also implies that (16) accounts for trade surpluses and deficits at market prices.

[21] These intervals are block-bootstrapped at the farm level and account for both parametric and trading uncertainty, with (θ, ψ) re-estimated for each draw prior to the calculation of the welfare outcome. Standard confidence intervals are constructed with the basic (reverse percentile) bootstrap.

technical change defined in Section IVD—reveal gains from trade that range from 4.0 to 5.5 percent of output (Table 7, panel E). Results without discounting, as well as results that constrain labor and materials adjustment or hold both inputs fixed, also resemble the baseline estimates, though constraining the adjustment of flexible factors somewhat dampens the gains from trade to between 3.7 and 4.5 percent of output (Table 7, panel D).

How do the realized gains from trade compare with similar natural shocks to water resources? Consider a uniform reduction in water resource availability across all farms that would lower output to its pretrade level. This number, −10.5 percent, 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 sMDB predict median declines of surface water availability of 11 percent by 2030 due to 1°C of global warming (MDBA 2019). This is not to suggest that the annual gains from a water market can offset the adverse effects of climate change, but does indicate that the gains are large even relative to other major shocks to water resources.

D. *Water Scarcity and the Value of Water Market Access*

Another vital question that arises from water's natural variability is whether regions receiving particularly low water allocations in a given year (relative to other years) realize greater gains from water market access.

Table 6 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 as a proxy for water scarcity, panel A stratifies (16) 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. Water scarcity amplifies both the extent and cost of misallocation, with greater reallocation in below-median years (16 percent relative to 12 percent) as well as higher average surplus per trade (AU$570 per megaliter compared with AU$221 per megaliter).

Similarly, it is possible to assess whether farms with relatively less rainfall have larger estimated gains from annual water trading. The gains from trade for below-median-rainfall farms (7.0 percent) is nearly twice that of above-median-rainfall farms (4.0 percent). Stratifying by quartile gives gains from trade for farms in the bottom rainfall quartile of 11.4 percent, compared with 4.9, 5.9, and 1.7 percent for the second, third, and fourth quartiles. Across space, a similar pattern emerges. Panel C stratifies farms within each year by quartile of that year's rainfall. Gains from trade are 6.3 percent for farms with rainfall below that year's median, compared with only 4.1 percent for farms receiving above-median rainfall. The within-farm differences in rainfall over time (panel D) are similar, with gains of 8.5 percent for years with below-median rainfall versus 3.1 percent in above-median years.

E. *Discussion and Interpretation of Results*

The analysis above is limited to recovering the realized value of annual water trade. In general, this value will differ in several respects from the overall value of

Table 6—Water Scarcity and the Gains from Annual Trade

	Gains from trade			Reallocation	
	Percent	Percent, traders	AUD/ML	Realloc (percent)	Traders (percent)
All	0.051	0.091	338.52	0.133	0.51
	[0.016, 0.071]	[0.037, 0.127]	[−21.23, 467.53]	[0.117, 0.148]	[0.48, 0.53]
Panel A. Regional water allocations					
Below median	0.079	0.122	573.03	0.163	0.58
	[0.018, 0.123]	[0.039, 0.189]	[−251.01, 863.48]	[0.140, 0.184]	[0.54, 0.61]
Above median	0.035	0.069	221.10	0.122	0.43
	[0.011, 0.052]	[0.027, 0.101]	[39.03, 328.92]	[0.102, 0.140]	[0.40, 0.46]
Q1	0.114	0.166	713.20	0.185	0.64
	[0.067, 0.228]	[0.099, 0.333]	[101.40, 1,426.22]	[0.151, 0.215]	[0.60, 0.67]
Q2	0.048	0.079	406.45	0.142	0.50
	[−0.060, 0.069]	[−0.054, 0.115]	[−1,025.55, 600.72]	[0.115, 0.168]	[0.46, 0.54]
Q3	0.041	0.065	189.98	0.134	0.56
	[0.012, 0.070]	[0.024, 0.112]	[28.93, 325.55]	[0.104, 0.164]	[0.51, 0.61]
Q4	0.032	0.071	244.66	0.114	0.37
	[0.003, 0.050]	[0.014, 0.108]	[0.14, 373.42]	[0.088, 0.137]	[0.33, 0.41]
Panel B. Rainfall					
Below median	0.070	0.111	358.90	0.149	0.59
	[0.014, 0.111]	[0.031, 0.176]	[−117.46, 547.44]	[0.122, 0.174]	[0.56, 0.62]
Above median	0.040	0.076	318.46	0.120	0.41
	[0.009, 0.058]	[0.029, 0.112]	[−11.85, 482.77]	[0.102, 0.138]	[0.38, 0.44]
Q1	0.114	0.170	587.99	0.177	0.60
	[0.058, 0.271]	[0.108, 0.400]	[200.61, 1,403.26]	[0.137, 0.215]	[0.56, 0.63]
Q2	0.049	0.080	251.64	0.139	0.58
	[−0.024, 0.068]	[−0.031, 0.108]	[−392.69, 325.67]	[0.110, 0.165]	[0.54, 0.61]
Q3	0.059	0.083	354.98	0.171	0.58
	[0.017, 0.093]	[0.028, 0.131]	[−61.21, 572.28]	[0.144, 0.198]	[0.54, 0.62]
Q4	0.017	0.057	224.32	0.068	0.24
	[−0.005, 0.027]	[0.001, 0.089]	[−73.63, 355.07]	[0.046, 0.087]	[0.20, 0.28]

(*Continued*)

Notes: Estimated gains from observed annual water trading, for all farms 2007–2015 and then subsets specified by row. See Table 5 for additional details. Panel A stratifies the data by $\bar{W}_{rt}$ quartile, calculated across years within each region; panel B stratifies the data by rainfall quartile calculated over all farm-years. Reverse percentile bootstrap confidence intervals reported at the 90 percent level and constructed from 5,000 draws block-bootstrapped at the farm level. Online Appendix Figure A11 plots the first column.

a permanent transition from fixed water property rights to an annual water market. Here, I discuss three features likely to be particularly important: first, the extent of initial misallocation; second, trading costs; third, longer-run economic responses.

Sensitivity to Initial Allocation.—A crucial caveat to any measure of the value of annual water reallocation is its sensitivity to the initial allocation. With a different allocation of initial water rights, the gains from trade could be larger or smaller. For example, if the initial allocation is close to ex ante optimal, then (16) might be interpreted as the value of flexibility from trading over the course of the season; alternatively, if the initial allocation is random, then (16) might capture a mixture of this value of flexibility as well as some "historical" misallocation.

While the empirical framework does not model the initial allocation of permanent water rights, the data provide some ways to assess how the specific choice of the

Table 6—Water Scarcity and the Gains from Annual Trade (*Continued*)

	Gains from trade			Reallocation	
	Percent	Percent, traders	AUD/ML	Realloc (percent)	Traders (percent)
All	0.051	0.091	338.52	0.133	0.51
	[0.016, 0.071]	[0.037, 0.127]	[−21.23, 467.53]	[0.117, 0.148]	[0.48, 0.53]
Panel C. Within-year rainfall					
Below median	0.063	0.103	331.36	0.130	0.56
	[0.027, 0.102]	[0.058, 0.167]	[73.09, 537.35]	[0.107, 0.151]	[0.54, 0.59]
Above median	0.041	0.079	348.80	0.138	0.44
	[−0.007, 0.056]	[−0.005, 0.107]	[−259.76, 472.08]	[0.116, 0.159]	[0.41, 0.47]
Q1	0.061	0.119	353.54	0.121	0.55
	[0.019, 0.122]	[0.068, 0.241]	[107.73, 713.51]	[0.081, 0.155]	[0.51, 0.59]
Q2	0.065	0.093	316.96	0.137	0.58
	[0.019, 0.101]	[0.036, 0.143]	[−34.64, 503.07]	[0.110, 0.159]	[0.54, 0.62]
Q3	0.039	0.073	312.53	0.133	0.46
	[−0.002, 0.064]	[0.003, 0.119]	[−122.15, 503.02]	[0.105, 0.159]	[0.42, 0.50]
Q4	0.042	0.087	395.92	0.145	0.42
	[−0.033, 0.063]	[−0.046, 0.122]	[−738.82, 588.08]	[0.109, 0.180]	[0.38, 0.47]
Panel D. Within-farm rainfall					
Below median	0.085	0.116	462.39	0.167	0.61
	[0.034, 0.136]	[0.049, 0.186]	[26.30, 733.96]	[0.138, 0.195]	[0.58, 0.65]
Above median	0.031	0.074	319.78	0.104	0.40
	[0.006, 0.058]	[0.034, 0.136]	[11.22, 591.35]	[0.082, 0.124]	[0.36, 0.43]
Q1	0.091	0.120	472.06	0.163	0.62
	[0.035, 0.142]	[0.048, 0.186]	[−3.01, 732.64]	[0.133, 0.190]	[0.58, 0.66]
Q2	0.064	0.102	422.18	0.189	0.60
	[0.006, 0.121]	[0.027, 0.191]	[−170.17, 785.48]	[0.138, 0.242]	[0.54, 0.67]
Q3	0.021	0.039	211.52	0.105	0.51
	[0.004, 0.074]	[0.012, 0.135]	[−11.12, 825.73]	[0.073, 0.137]	[0.45, 0.56]
Q4	0.035	0.094	365.91	0.103	0.34
	[−0.004, 0.059]	[0.032, 0.154]	[−108.47, 625.94]	[0.076, 0.127]	[0.30, 0.38]

Notes: 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). Reverse percentile bootstrap confidence intervals reported at the 90 percent level and constructed from 5,000 draws block-bootstrapped at the farm level. Online Appendix Figure A11 plots the first column.

initial allocation affects the results. It is straightforward to recalculate the annual gains for alternative initial allocations, but for these comparisons to be meaningful, they should involve local, within-sample changes in the distribution of permanent rights. Using data on entitlement transfers, Table 7, panel A reports gains from trade for two alternative distributions of initial endowments: one, surface and groundwater entitlements at baseline (rather than at t); two, surface entitlements at baseline and groundwater rights at t. The small differences between excluding or including permanent trades suggests that the definition of initial endowments is not a major driver of the results.

A related but distinct question is how much of the value of annual water trading could be attained by changing the initial allocation. Given that trading histories are observed for each farm, one way to explore this possibility is to calculate the share of (16) that arises from "permanent" traders, defined as farms who buy in every year or sell in every year, relative to "idiosyncratic" traders, who buy or sell in some years but not others. Idiosyncratic traders account for 73.6 percent of the

Table 7—Sensitivity of Gains from Trade

	Gains from trade		
	Percent	Percent, traders	AUD/ML
Panel A. Sensitivity to initial endowments			
Benchmark	0.051	0.091	338.52
	[0.016, 0.071]	[0.037, 0.127]	[−21.23, 467.53]
Initial endowments at t_0, surface + ground	0.057	0.084	348.70
	[0.009, 0.083]	[0.016, 0.121]	[−71.90, 506.91]
Initial endowments at t_0, surface only	0.047	0.070	286.32
	[0.011, 0.066]	[0.019, 0.100]	[−42.24, 409.68]
Panel B. Transaction costs (AU$)			
Variable trade costs ($10/ML)	0.049	0.087	323.97
	[0.013, 0.068]	[0.032, 0.123]	[−34.42, 452.99]
Variable and fixed trade costs ($500/trade + $10/ML)	0.049	0.086	320.47
	[0.013, 0.068]	[0.031, 0.122]	[−37.96, 449.52]
Ad valorem trade costs (10 percent of trade)	0.049	0.087	324.23
	[0.013, 0.068]	[0.032, 0.123]	[−34.13, 453.04]
Panel C. Land reallocation			
Sellers use 10 percent more land under autarky	0.043	0.076	282.61
	[0.008, 0.066]	[0.021, 0.119]	[−49.92, 438.46]
Sellers use *X* percent more land under autarky	0.038	0.068	251.36
	[0.003, 0.065]	[0.012, 0.116]	[−76.91, 426.40]
Buyers use 10 percent less land under autarky	0.077	0.137	510.46
	[0.036, 0.091]	[0.076, 0.162]	[52.53, 614.06]
Buyers use *X* percent less land under autarky	0.095	0.169	625.97
	[0.048, 0.109]	[0.100, 0.193]	[83.45, 735.83]
Sellers, buyers use 10 percent more, less land under autarky	0.082	0.145	538.81
	[0.036, 0.099]	[0.077, 0.176]	[48.42, 662.92]
Panel D. Profit function			
No discounting	0.050	0.088	284.92
	[0.015, 0.069]	[0.036, 0.123]	[−17.87, 393.51]
Labor, materials held fixed at observed levels	0.039	0.072	150.93
	[0.015, 0.066]	[0.030, 0.122]	[49.28, 254.53]
Optimal labor, materials constrained to $X_{ict} \leq 2X_{ict}$	0.037	0.068	189.47
	[0.016, 0.059]	[0.032, 0.108]	[67.32, 299.57]
Optimal labor, materials constrained to $X_{ict} \leq 5X_{ict}$	0.045	0.080	258.89
	[0.020, 0.065]	[0.040, 0.118]	[88.74, 377.30]
Panel E. Production function			
Translog	0.055	0.102	242.37
	[0.015, 0.165]	[0.031, 0.301]	[52.06, 726.18]
Water-augmenting technology I	0.040	0.071	264.38
	[−0.002, 0.056]	[0.002, 0.101]	[−127.87, 372.91]
Water-augmenting technology II	0.048	0.085	316.46
	[0.010, 0.071]	[0.025, 0.127]	[−50.39, 469.44]

Notes: Sensitivity of estimated gains from observed annual water trading from 2007 to 2015 (in Table 5) to alternative specifications described in Section VE (A–C) and Section VC (D–E). Panels A–B: alternative endowments and transaction costs defined in Section VE. Panel C: land reallocation counterfactual. For 10 percent, sellers' $K^a_{ict} = 1.1K_{ict}$ and buyers' $K^a_{ict} = 0.9K_{ict}$. For *X* percent, sellers' $K^a_{ict} = \min\{W^a_{ict}/W_{ict}, 1.2\} \cdot K_{ict}$ and buyers' $K^a_{ict} = \max\{W^a_{ict}/W_{ict}, 0.8\} \cdot K_{ict}$. Panel E: production functions. "Water-augmenting technology I" includes observed irrigation equipment as in (online Appendix equation A5) and "II" includes common irrigation efficiency over time as in (online Appendix equation A4). See online Appendix Tables A10–A12 (columns 2, 3, and 5) for the production parameters used for these calculations. Reverse percentile bootstrap confidence intervals reported at the 90 percent level and constructed from 5,000 draws block-bootstrapped at the farm level.

total gains from 2007 to 2015, though their influence differs by crop type, with 92.7 percent of perennial farms' gains occurring through idiosyncratic trades compared with less than half (49.7 percent) for dairy farms. Across regions, idiosyncratic trading appears more important in South Australia and Victoria Murray (77.5 percent and 79.6 percent of gains) than in the Murrumbidgee (65.3 percent). These shares indicate some inefficiency in initial endowments—i.e., water entitlement transfers could improve allocative efficiency. However, the lion's share of the estimated value of water reallocation occurs through idiosyncratic annual trading, indicating that the annual water spot market serves an important role that cannot be replaced by permanent transfers of water rights.

Trading Costs.—A second caveat is that the estimates above take the river network's existing conveyance infrastructure as given and rule out the possibility that some of the annual water reallocation involves unavoidable, additional transport costs. This assumption reflects the fact that most of the economic costs of allocating water across users—such as the conveyance network, irrigation canals, river gauges and meters—are also incurred in river systems with fixed water property rights. However, some costs of water allocation may be trade specific. Such trade-specific costs could include, for example, time and effort spent searching for trading opportunities, environmental analyses to determine third-party flow externalities, or various conveyance and water delivery costs that differ across buyers and sellers.

If there were no water trading constraints, then to the extent that such trade costs are incurred by farms, one might take the annual value of a farm's observed trade as an upper bound on its transaction costs using revealed preference. Similarly, farm-year-specific trading costs could be bounded below using the valuations of nontraders. With trading constraints, however, such bounds cannot be obtained because trading costs are not separately identified from constraints. Moreover, many costs of water markets are born by other entities, such as local regulators or affected third parties, who may be unable to recover costs directly from farms. Such costs are not identified from the farm's problem. Finally, the trading frictions within a river network are likely to evolve with investments by stakeholders and with participants' and regulators' experience with trade, further complicating the interpretation of such cost estimates.

Despite these identification issues, unavoidable transaction costs specific to water trading may play an important role in the adoption and design of water markets and it is important to consider the robustness of the results to these concerns. A simple way of evaluating the sensitivity of the main empirical results is to augment (16) with plausible costs of water trading. Table 7, panel B considers three forms of transaction costs: variable costs per megaliter, fixed costs per trade, and ad valorem costs proportional to the market value of trade, set to AU$20 per megaliter, AU$1000 per trade, and 10 percent, respectively, to exceed most reported transaction costs (ACCC 2021, Table C5). None of the scenarios appreciably alter the gains from trade, which fall from 5.1 to 4.9 percent in every case. This is not surprising in the linear case, given that the external estimates for trade costs fall well below the average surplus estimates, but is not immediately obvious in the second and third cases, particularly for ad valorem costs, given that higher water prices in the data coincide with the years with the largest gains from trade.

Longer-Run Changes.—Finally, while the assumptions of the annual production model in Section II seem appropriate to study annual trade, they rule out several aspects of production relevant to evaluating more permanent changes in the economic environment. In particular, the empirical framework relies on annual variation in water to identify the relationship between water and agricultural output in (2), which will capture how farms adapt to annual water variability, but not to permanent changes. Separately, the gains from trade in (16) hold fixed farms' total land allocation decisions at the start of the growing season. This seems reasonable to assess annual water trade motivated by annual fluctuations. However, farmers' longer-run incentives to invest in certain crop types will more generally depend on future opportunities to trade. For example, the prospect of water trade during drought years may enable some farmers to allocate more land to higher-value perennials that need water on a regular basis. These forms of land reallocation and related investments are not captured by the estimated annual gains from trade, but may be crucial to water markets' total value.

To understand the qualitative implications of relaxing these assumptions, consider the case in which irrigation and investment (say, in land) are complements. For farms that use less water under the market than under autarky (i.e., those with "excessively generous" pretrade water rights), investment and therefore marginal values should fall, as these farms had overinvested due to their surfeit of water. In contrast, for farms that increase irrigation, investment will become more attractive. How the water market transition affects average productivity will depend on these two countervailing forces. Whether accounting for investment will raise or lower the value of trade relative to (16) depends on the above considerations as well as investment costs.

Table 7, panel C evaluates some implications of one potential investment channel, land reallocation, on the estimated gains from trade. Though an exact calculation of equilibrium land reallocation requires both beliefs as well as land adjustment and planting costs, the existing estimates contain the cross-partial derivatives of profits with respect to land and water across water-trading farms, which reveal some incentives for land reallocation and their implications for the value of annual water trading.

First, I evaluate how the annual gains from trade can overestimate the long-run value of trade by ruling out adaptation by water sellers under autarky. Specifically, farms without the opportunity to sell water might expand their landholdings. To assess the sensitivity of the main results to this possibility, I recalculate (16) assuming that water-selling farms use 10 percent more land under autarky than under the market. I also conduct the same exercise assuming that land expands by the same percentage as the farm's irrigation under autarky, up to a 20 percent increase. Table 7, panel C shows that the gains from trade fall to 4.3 percent and 3.8 percent respectively, but remain sizable.

Second, I conduct a similar exercise to assess the extent to which an annual estimator may underestimate the long-run value of water market access by ruling out greater investment by water-buying farms. Specifically, I recalculate gains from trade assuming that water-buying farms use 10 percent less land under autarky than the market, and then in proportion to the decrease in their water volumes, up to no more than 20 percent. The estimates, 7.7 percent and 9.5 percent, indicate that moderate contractions in the planting area of farms under autarky can substantially increase the estimated gains from trade.

Finally, to compare the two, I assume that all trading farms adjust their autarky land allocations in proportion to trade as above. In this case, the estimated annual gains from trade equal 8.2 percent of output, considerably higher than the benchmark estimate of 5.1 percent without land adaptation. This indicates that the value of land expansion for water-buying farms under the market (relative to autarky) exceeds the value of expansion of water-selling farms under autarky (relative to the market), which is consistent with the earlier finding that water, on average, flows from lower- to higher-value irrigators and a production function where water increases the productivity of land.

F. *Policy Implications*

The empirical results have at least three main policy implications for water allocation.

First, the findings inform the extent of government support for water markets in Australia, which is subject to ongoing policy debate (ACCC 2021). In particular, the estimated total gains from trade highlight two relevant aspects of these markets. One, while market power and other frictions may exist, the annual market's net effect is to improve allocative efficiency. That is, on average, water flows from irrigators with lower marginal products to irrigators with higher marginal products. This would not be the case if these markets solely functioned to enrich unproductive water barons at the expense of more productive local farms, as some have suggested. Two, water markets require public investment to monitor and coordinate decentralized trade and investigate anticompetitive practices. The market's estimated flow benefits, of about five percent of aggregate irrigated agricultural output (Walsh et al 2021), or AU$2.3 billion over 2007–2015, provide a lower bound on the value of maintaining this infrastructure.

Second, the results provide similar qualitative takeaways for policymakers outside of Australia interested in allocating water through markets. While they do not show that water markets elsewhere will deliver similar efficiency gains, they demonstrate that such gains are possible using modern monitoring technology in an arid region. This paper also identifies an important source of water markets' prospective value, the extent of a river system's underlying hydrological variability. Usefully, many features of this variability can be measured directly from historical river inflows and rainfall, without needing to collect economic data.

Third, the paper's empirical findings have implications for water markets in a changing climate. While the exact effects on water remain uncertain, there is a consensus that climate change will increase natural water variability. In theory, water markets can help to address this variability in at least two ways. Efficient annual trade should reallocate water from places of relative abundance to places of relative scarcity, lowering the costs of idiosyncratic variability across the river trading network. Furthermore, by increasing the productive efficiency of a basin's aggregate water endowment, a water market makes drier years less costly, helping irrigators adapt to aggregate shocks.

This paper's results provide empirical support for both of these channels of water market value. Water trading appears to make drier years less costly, making water reallocation through markets a natural candidate to improve river basins' resilience to greater cyclicality in aggregate water supply. Furthermore, water trading is most valuable for places experiencing relative scarcity, making water markets an instrument for adapting to greater variability across the river network. Importantly, the hydrological shocks predicted under climate change (MDBA 2010) lie within the range of observed water variability (online Appendix Table A21), which supports the within-sample estimates as evidence that water markets will become more valuable under future climate change.

VI. Conclusion

Severe droughts and looming climate change have renewed calls for water markets to allocate resources more efficiently and to forestall increasing scarcity. From the viewpoint of economic theory, water markets can improve allocative efficiency under ideal conditions, but several hydrological realities make these markets inherently incomplete and imperfectly competitive, and there has been limited evidence to date that these markets have delivered benefits in practice.

This paper considers water trading in Australia's sMDB. To value water and evaluate water trading, relative to a world of fixed property rights, this paper estimates the production functions for crops that rely on water (i.e., irrigation) using input and output data from irrigated farms subject to varying regional water diversion limits. Together with price and allocation data, the value of water and trading can be recovered, and compared to environments without trade. Usefully, the approach does not rely on a specific form of water market access, transaction costs, or trading constraints. This allows the paper to test whether the market improves allocative efficiency, in contrast to prior approaches, which commonly rely on specific forms of water market conduct to infer the value of water or to predict water reallocation.

The main empirical findings show that substantial gains from water trade are possible using modern monitoring technology in an arid region. Water trading increased producer surplus by 4–6 percent of irrigated agricultural output for surveyed farms. In terms of factor misallocation, more efficient water allocation across farms increased the industry's total factor productivity by approximately one-half percent per year during this period, for an industry with annual productivity growth of 1–2 percent from 1970 to present. In terms of aggregate water resources, reverting to pretrade endowments lowers output to the same level as an 10.5 percent uniform decline in water resources, in a region where climate forecasts project median reductions in surface water of 11 percent from 1°C of warming. The gains from trade increase substantially during drought, implying that water markets can help adapt to natural forms of variability arising from cyclical shocks such as droughts and other hydrological changes in a warmer climate.

These findings raise a range of questions for future work, especially related to water market design. In particular, the focus on agricultural users while holding diversion caps fixed avoids the question of environmental protection, the other primary value of river water in the sMDB (Grafton et al. 2011). In addition, many of the evolving constraints on trade discussed here arise from decisions by irrigators and river operators, indicating potential benefits to a coordinated market design relative to decentralized bilateral trading, for similar reasons as in electricity markets (Wilson 2002). Finally, dams and other water storage technologies allow the conservation of river water between years, creating water stocks that affect annual trade and help to manage future drought risk (Hughes et al. 2013). Understanding the value of the intertemporal water trade enabled by such infrastructure will be particularly crucial in a world where water resources are less evenly or predictably distributed across time.

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