REALLOCATIVE IMPACTS OF ENVIRONMENTAL MARKETS

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Abstract

Fears that environmental markets may harm certain groups have fueled political opposition. I study this phenomenon in California's groundwater – a critical input to the state's globally significant agricultural sector – where potential impacts on small farms and employment have hindered market adoption. Novel evidence from detailed farm-level data suggest theoretically ambiguous impacts: (i) high-value crops are more labor intensive and (ii) within-crop variation in water productivity is substantial and positively correlated with labor productivity. Embedding these dimensions of heterogeneity in a microfounded structural model simultaneously generates new sources of welfare gains from trade, and both job creation and destruction. Counterfactual simulations reveal sizable welfare and employment gains accompanied by many small farm exits, corroborating only part of the public discourse.

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1 Introduction

Environmental markets are increasingly promoted as tools to allocate scarce resources such as the rights to fish, use water, and emit pollutants (Costello et al., 2008; Bruno and Jessoe, 2024; Carlson et al., 2000; Salzman et al., 2018).[1] By facilitating transfers of resources to users generating the highest value, market-based approaches promise efficiency gains relative to command-and-control (Samuelson, 1954; Anderson and Libecap, 2014). Yet, concerns that efficiency-based reallocation may generate local harms have fueled vocal oppositions across settings. Fears of unequal socioeconomic impacts across stakeholder groups have derailed market-based management reforms, including transferable quota programs in fisheries (Abbott et al., 2022) and in water rights systems (Hadjigeorgalis, 2008).[2] In California, debates over whether greenhouse gas cap-and-trade might concentrate pollution in disadvantaged communities delayed and nearly halted the state's flagship climate program (Hernandez-Cortes and Meng, 2020).

These concerns have driven calls to quantify the reallocative effects of environmental markets and, where necessary, to mitigate potential harms to affected groups.[3] Failure to do so may threaten the political durability of market-based approaches. Accurately predicting their reallocative impacts is challenging, which may explain the paucity of relevant estimates. First, predicting the market allocation requires recovering each user's shadow value of the resource, given no prior market price. Second, the empirical framework must capture the joint distribution of shadow value and attributes motivating opposition across users – do low-value users tend to cluster in disadvantaged or rural communities? Do they tend to create more jobs? Third, when the outcome of interest is a production input (e.g., labor) jointly used with the traded resource, it is critical to account for systematic heterogeneity in input productivities, scale, and substitution patterns. This paper develops a general framework that addresses these challenges to evaluate the reallocative impacts of environmental markets. I embed non-Hicks neutral production functions within a microfounded model of market liberalization to quantify aggregate gains from trade and reallocative outcomes across groups.

I apply this framework to assess the debated but largely untested reallocative impacts of proposed agricultural groundwater markets in California – the world's fifth-largest agricultural producer and among its most water-stressed. Groundwater, a critical input to agriculture, is subject to regulation for the first time in history under the 2014 Sustainable Groundwater Management Act

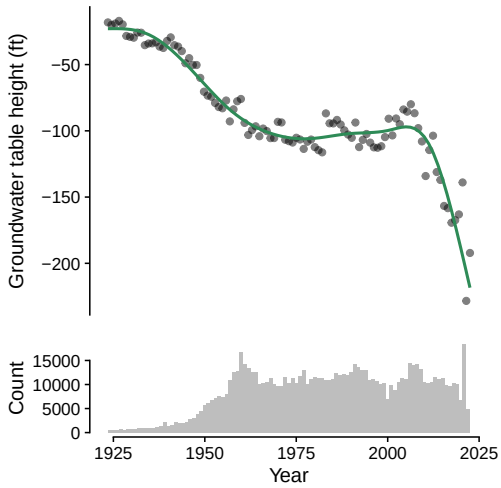
[1] Market-based mechanisms now regulate roughly one-quarter of global greenhouse gas emissions (World Bank Group, 2024), allocate $36 billion worldwide and in conservation Payments for Ecosystem Services (PES) programs, (Salzman et al., 2018), and manage 25% of the global catch in fisheries (EDF, 2025).

[2] The 2006 UN Human Development Report observed that "proposals for transferable water rights have generated an intense debate ... [and] concerns that the market power of large producers and industry will strip small farmers of their access to irrigation water." Opponents of individual transferable quotas (ITQs) are concerned about the livelihoods of small-scale fisheries and the coastal communities they sustain (Young et al., 2018).

[3] In this paper, *reallocative effects* refer to outcomes that arise as a consequence of market-based reallocation of the resource across users. These may include both targeted outcomes, such as producer surplus, and non-targeted outcomes, such as changes in pollution distribution, employment, or farm composition. This paper focuses on non-targeted measurable outcomes frequently cited in oppositions to market-based reforms.

(SGMA). This regulatory measure follows alarming rates of groundwater depletion observed over the past century under laissez faire management.[4] The average groundwater table height fell from –20 to –200 feet over the past century, with nearly half of this decline occurring in just the last two decades (Figure 1). Drawing on lessons from surface water management on the perils of incomplete property rights, SGMA adopted a decentralized, Ostrom-inspired governance structure. Under SGMA, stakeholder-informed local agencies are tasked with determining their own socially optimal groundwater level, defining and enforcing property rights to groundwater use, and designing their own institutional rules for achieving sustainable levels by 2042.[5]

Figure 1: Average height of agricultural groundwater table relative to sea surface in California.



Note: The green line represents a smoothed local polynomial regression based on 841,132 individual well monitoring observations collected from 1925 to 2025 in California's Central Valley. The points indicate the annual mean. The gray histogram shows the number of groundwater samples for each year. **Source:** Author's calculation using data from the California Department of Water Resources Periodic Groundwater Level Measurements dataset.

Because SGMA defines management boundaries along hydrologically connected basins – which avoids costly infrastructural outlays – and formalizes property rights in a data-rich setting informed by experiences from other markets, many view California's groundwater as ripe for trading (see e.g., The Nature Conservency, 2025; Weaver, 2023). A review of sustainability plans by Bruno et al. (2022) shows that over a third of the 107 regulated basins are considering introducing some form of trading mechanism on top of baseline allocations. However, stakeholders interviewed by California Water Commission (2022) expressed fears that groundwater trading programs could drive smaller farms and lower-value crops out of production, reducing farm diversity. The report proposes a number of guardrails, including restricting trading to similar-sized entities and preferential allocations to small farms. These concerns reflect long-held skepticism of water transfer programs in general (Hanek,

[4]Prior to SGMA, landowners with groundwater rights were not subject to any legal requirement to track, report, or regulate the volume of groundwater extracted.

[5]While local groundwater sustainability agencies (GSA) implement these steps, they are still subject to oversight by the state. The resulting average pumping cutbacks required is around 19%, with cuts as high as 40% in some regions (Burlig et al., 2025; Heard et al., 2021).

2003; Hadjigeorgalis, 2008), grounded in fears that the reallocation of water could also diminish local income generation and employment opportunities.

This paper examines the reallocation impacts of proposed local groundwater markets in California in three steps. First, I use a stylized 2-user trade model to illustrate how relative water productivity and the *correlations* between water productivity and relevant user attributes (e.g., farm size and labor productivity) across individual farms, as well as prices, jointly determine the direction and magnitude of the allocation of water and production, size distribution, and employment. A key insight is that if the correlation between water productivity and labor productivity is high *enough*, net labor demand can fall. In such cases, even though trading enables more crops to be harvested ("scale" effect), farms that remain have lower labor share ("compositional" effect). As low-productivity, labor-intensive farms sell allocations and leave production, aggregate productivity rises but employment can fall if the compositional effect dominates. Second, I use restricted-access farm microdata to diagnose the extent and correlational structure of productivity heterogeneity across farms and attributes, introducing a set of new stylized facts. Third, due to the theoretical ambiguity of employment impacts suggested by the results of part two, I conduct a quantitative assessment by estimating production functions, allowing for non-Hicks neutrality, to compare counterfactual outcomes under locally implemented quotas versus markets across nearly 30,000 heterogeneous farms.

I obtain farm-level production and demographic data from the Census of Agriculture (hereafter, the Census) and the Irrigation and Water Management Survey (IWMS), both conducted by the United States Department of Agriculture (USDA) for the years 2007, 2012, and 2017. The Census surveys all farms with gross income above $1,000. I begin by documenting new stylized facts on farm water use in California. First, I find that agricultural groundwater reliance is widespread, with over 80% of farms sourcing more than half of their total irrigation water from groundwater. Second, I show substantial variation in water value across and within crop types. Third, the relationship between water value and labor intensity differs when comparing across crops versus within-crop. Across crops, there is generally a *positive* relationship between water value and labor intensity. For example, the average berry farm generates four times the value and employs five times more labor per dollar of output compared to the average tree nut farm. However, within farms planting the same crop, water value is *negatively* correlated with labor intensity. Part of this correlation is endogenous, as labor-productive farms have less marginal cost. However, I show existence of correlated investments in water- and labor-enhancing technologies beyond the cost-saving channel. Labor-productive farms are also more water-productive, with higher output levels, contributing to the observed correlations.

These facts suggest several implications and provides guidance for empirical analysis. First, groundwater markets would drive significant efficiency gains by reallocating water across and within crop types. Second, the correlation between water value and labor productivity is not a sufficient statistic to judge if the "scale" or "compositional" effects will dominate. The impact on labor demand is ambiguous and depends on the extent to which water is reallocated across crops versus within

crops in the trading region. Motivated by evidence rejecting a Hicks-neutral production function, I model and estimate heterogeneous input productivities across crops and farms to accurately capture farm-specific responses to groundwater regulation. This extends more conventional production function estimation which typically assumes a single total productivity parameter (TFP) for all inputs in the production process.

To be able to quantify farm behavior under an unprecedented change in groundwater policy, I develop a structural model of crop production to (i) quantify farm marginal value of water at any level, (ii) predict farm water trade in a market, and (iii) derive changes to key aggregate outcomes. I derive farm input demand functions under profit maximization to inform their behavior under groundwater trading. Under the no-trading scenarios, farms also maximize profit but are constrained by fixed groundwater quotas and arable land. I estimate the model with farm-level panel data compiled from the Census, IWMS, and complementary hydrological and agricultural datasets. Using my calibrated model, I run three sets of counterfactuals in each county under expected SGMA groundwater reductions.[6] I evaluate outcomes when farms face (i) a uniform quota, (ii) a proportional quota, and (iii) a groundwater market.[7] In all scenarios, the total baseline reduction is 25% of 2017 groundwater use in each county, the estimated median percentage reduction expected by SGMA's deadline in 2042. I also simulate a 35% reduction to model a more aggressive scenario.

My analysis yields three key results. First, I estimate that local groundwater markets could generate significant overall income and employment gains, shifting production toward larger, more efficient farms relative to quotas. Proportional quotas equivalent to a 25% reduction in groundwater use could decrease farm revenue by $6.9 billion, eliminate 94,000 jobs, and lead to the exit of 1,500 farms. These estimates are larger than previous estimates of $5.9 billion and 85,000 jobs (Sunding and Roland-Holst, 2020), as I account for farm heterogeneity. Facilitating groundwater trading will increase farm revenue by $4 billion (8% of sector value), farm employment by 24,000, and lead to the exit of 5,600 more farms. *Put another way, groundwater trading could recover 57% and 26% of revenue and job losses, respectively, from proportional quotas, but increase farm exits 3.7 times.*

The second key finding is that groundwater markets increase farm concentration by reallocating production to larger farms while smaller farms fallow land to sell water. The average farm revenue rises by an estimated 77% from $0.84 million to $1.48 million. Of the 5,600 additional farms that shut down production to sell water, 82% of those are designated as small farms under the USDA's definition.[8] The overall Herfindahl-Hirschman Index (HHI), a commonly used measure of market concentration, increases by 55% under groundwater markets.

[6] I simulate policy counterfactuals at the county level, not at the SGMA basin level, because of data limitations. Cross-basin water trading is unlikely under SGMA because the legal framework prioritizes local management within basins, and inter-basin transfers would require complex coordination and approval from the state agency.

[7] Under a *uniform quota*, all farms are allocated the same volume per acre, determined by the targeted sustainable aggregate volume. A *proportional quota* allocates the equivalent reduction proportionally based on historical groundwater use. A market allows for the frictionless trading of quotas allocated in (i) and (ii).

[8] The USDA defines "small farms" as those with gross cash farm income (GCFI) of less than $350,000 annually.

Third, I show that while profit gains are unambiguous, some counties will see employment and revenue losses. Central Coast counties consistently see revenues and employment gains from trade. These counties are characterized by a sizable share of high-value and labor-intensive berry and vegetable farms. Conversely, I estimate revenue and employment losses from trade in some counties. In these counties, the "compositional" effect dominates the "scale" effect, and efficient farms are characterized by lower non-water input use such as labor, rather than by higher marginal revenues. A defining characteristic across these counties is the high proportion of farms planting the same crop type. Across counties, I show that crop homogeneity dampens revenue and employment gains.

Related literature This paper contributes to a small but growing literature evaluating environmental market when the productivity measure guiding reallocation is systematically correlated with other attributes that impose (previously unmeasured) social costs. Aspelund and Russo (2025) finds that landowner's cost of accepting a conservation contract is positively correlated with their additionality within participants in the USDA Conservation Reserve Program, leading to adverse selection of low value-add bidders. Fowlie et al. (2012), Hernandez-Cortes and Meng (2020), and Shapiro and Walker (2021), in their investigations of whether greenhouse gas cap-and-trade markets move pollution to disadvantaged communities is implicitly testing the hypothesis that firm's abatement cost is spatially correlated with poverty and other "disadvantaged" indicators.

The socioeconomic outcomes investigated in this paper speaks to a broader literature on the local economic impacts of environmental regulations, which are significant concerns for policymakers (Bento et al., 2009; Deschenes, 2011; Curtis, 2018; Sheriff et al., 2019; Deshmukh et al., 2023). Understanding regional impacts is crucial for designing preemptive transition policies that mitigate potential harms and political opposition. If environmental regulations result in reduced economic activity in specific regions, policymakers can focus on implementing repurposing programs for affected workers and producers. Alternatively, if they generate labor demand, policymakers may need to consider workforce development programs to ameliorate potential labor shortages.

In the context of environmental and water markets, economists have largely focused on estimating the aggregate gains from trade; either after they have been implemented (Howitt, 1994; Hearne and Easter, 1997; Carlson et al., 2000; Rafey, 2023; Debaere and Li, 2020; Cicala, 2022) or simulating future gains under different assumptions on market conditions (Vaux and Howitt, 1984; Sunding et al., 2008; Bruno and Jessoe, 2021; Edwards et al., 2018; Arellano-Gonzalez et al., 2021; Escriva-Bou et al., 2023).[9] While these studies have established a foundational understanding of water markets, they have not addressed the reallocative impacts driving opposition from stakeholders and often make simplifying assumptions about the level of heterogeneity.

[9]These simulations often consider transaction or liquidity constraints (Hagerty, 2019; Donna and Espín-Sánchez, 2023; Regnacq et al., 2016) and the impact of market power on efficiency outcomes (Jacoby et al., 2004; Bruno and Sexton, 2020; Tomori et al., 2024). Studies examining regime changes that *enable* water transactions have identified substantial realized economic gains as well (Browne and Ji, 2023; Ayres et al., 2021b).

This paper contributes to the literature by addressing these gaps in two primary ways. First, I examine the impacts of water markets on employment, crop composition, and measures of farm size distribution – primary concerns of local stakeholders. While existing work has highlighted such concerns (Hanek, 2003; Leonard et al., 2019), only one study have addressed them. Escriva-Bou et al. (2023) investigates the economic and employment effects of trading at different regional scales but uses a calibrated optimization model, which assumes homogeneous farms.

Second, I use farm-level data to document substantial variation in input productivities and incorporate this heterogeneity into my model of market liberalization. From a positive standpoint, embedding heterogeneity improves the predictive power of my model for more accurate counterfactual estimates (Melitz, 2003). I further show in a simple conceptual model in Section 2 that modeling farm heterogeneity, specifically along the dual dimensions of water and labor productivity, is crucial for quantifying the sign of labor gains from trade. Prior works assuming representative agents or Hicks neutral production technology may have underestimated the gains from trade and when relevant, their labor impacts (e.g., Costinot et al., 2016; Sotelo, 2020; Bruno and Sexton, 2020). Indeed, my estimates of economic and employment gains are significantly larger than those reported by Escriva-Bou et al. (2023).

Methodologically, my model and estimation strategy use techniques from a rich literature advancing the structural estimation of production functions (Olley and Pakes, 1992; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). Like Zhang (2019) and Doraszelski and Jaumandreu (2018), I estimate non-neutral input productivities across farms, but move beyond descriptive analysis to apply these estimates in a model of input trade liberalization. Unlike in standard settings, farmworkers are typically paid on a piece rate, allowing me to model a direct, proportional relationship between output and labor demand.

Section 2 introduces a simple model that illustrates how water trading can affect labor demand in the presence of correlated productivity parameters, guiding the empirical approach that follows. Section 3 provides background on California's Sustainable Groundwater Management Act, describes key aspects of agricultural production, and introduces the datasets. Section 4 establishes a set of stylized facts that motivate the structural model laid out in Section 5 and provides intuition for interpreting the results of the counterfactual analyses. Section 5.3 describes the estimation strategy. Section 6 presents results from the counterfactual analyses, and Section 7 concludes.

2 Conceptual Framework

I present a simple framework to illustrate how trade liberalization of an input, previously managed under command-and-control, can affect demand for another input – and show how the sign and magnitude of change is governed by their productivity correlation. In what follows, I use water and labor as concrete examples of this more general mechanism. The production function is Hicks

neutral, which relaxes the assumption of a shared productivity term (i.e., total factor productivity) across all inputs. I conceptualize the gains (or losses) from trade under a scenario in which the regulator rations water use under a uniform quota, and frictionless trading occurs between farms in a market setting. This simple model compares gains from trade (GFT) between users in the same crop sector and where wages are zero, in order to highlight the key insight as starkly as possible.

Online Appendix Section C generalizes the model to allow users to plant different crops and have different labor technologies. When wages are non-zero, the effects presented here are magnified. Because the role of crop prices is ultimately an empirical question, I focus here on the case in which users plant the same crop and face a common output price. The general model in Online Appendix Section C generates closed formed solutions for GFT for different aggregate and reallocative outcomes and shows that varying the correlation between farm water and labor productivities (i.e., how much more labor-productive a relatively more water-productive farm is) affects the sign and magnitude of various outcomes of interest to policymakers, including water allocation, production distribution, water price, and total output.

Setup This framework considers an agricultural economy with two farms: a high-productivity type (H) and a low-productivity type (L). Each farm produces output Y using water W and employs labor L for harvesting. The market price of output is normalized to $P = 1$. Let a_i denote the exogenously given water productivity parameter for farm type i, where $i \in \{H, L\}$, and $a_H > a_L$. Let b_i denote the analogous labor productivity parameter for each farm. Both farms are price takers in the output market and face identical input costs for water. The production function for each farm in the growing season is represented as:

$$Y = a_i f(W),$$

where $f(W)$ is a continuously differentiable, strictly increasing, and concave function, i.e., $f'(W) > 0$ and $f''(W) < 0$. After the growing season, farms hire labor given their labor productivity parameter,

$$Y = b_i L,$$

where labor is proportional to output, reflecting the nature of agricultural harvesting.

Water allocation under quota Assume a quota policy where each farm receives an equal allocation of water, denoted by $W^Q = \frac{\overline{W}}{2}$, where $\overline{W}$ is the total restricted water supply. The marginal revenue for each farm type under this allocation is:

$$\text{Marginal Revenue} = a_i f'(W^Q),$$

where W^Q is the fixed water allocation per farm. Given $a_H > a_L$, it follows that the marginal revenue of the high type is larger than that of the low type,

$$a_H f'(W^Q) > a_L f'(W^Q),$$

and there is a misallocation of water under the command-and-control regime. Note that in this simple example, wages are zero, and therefore marginal revenue is the appropriate measure of analysis and drives trade direction in the next section (see Online Appendix Section C for a derivation of marginal *profits* when wages are non-zero). The aggregate labor demand under command-and-control is

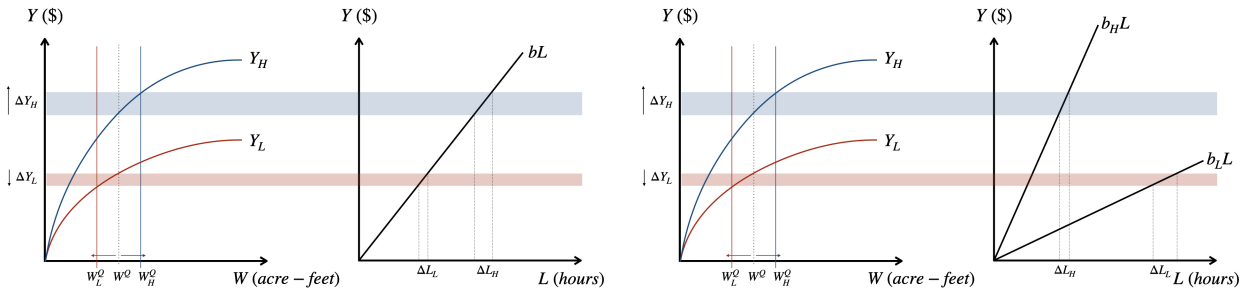
$$L^Q = \frac{a_H f(W^Q)}{b_H} + \frac{a_L f(W^Q)}{b_L}$$

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Figure 2: Graphical framework of the effects of water trading on labor demand.

(a) Water trading leads to *increased* aggregate labor demand, $\Delta L_H + \Delta L_L > 0$

(b) Water trading leads to *decreased* aggregate labor demand, $\Delta L_H + \Delta L_L < 0$



Note: First column of each panel plots the water-revenue curve, with output price normalized to 1, for a high-type (H) farm and a low-type (L) farm. Gray dashed line marks a uniform water allocation under a quota, while red (blue for type H) lines indicate allocations under trading, where marginal revenues (slopes) are equalized. Output gains (blue) and losses (red) are mapped into the second column of each panel, which plots the relationship between labor and revenue. **(a)** shows a scenario where water trading leads to an *increase* in aggregate labor demand as both types have the same labor productivity. **(b)** shows a net *decrease* in labor demand: labor gain from the high-type farm (ΔL_H) is offset by reductions from the low-type farm (ΔL_L) because the high-type farm is sufficiently more labor productive.

Water market Now, consider a setting where water is traded at a market-clearing price v^*, where the water allocation for each type under the market, denoted by W_i^M, satisfies the following two conditions:

$$a_H f'(W_H^M) = a_L f'(W_L^M) = v^*,$$

and total water used equals the total available water in the economy: $W_H^M + W_L^M = \overline{W}$.

Since $a_H > a_L$, $f'(W)$ is decreasing due to concavity, and $f'\left(W_L^M\right) > f'\left(W_H^M\right)$, it must be that

$W_H^M > W_L^M$. Graphically, this is illustrated in the left panel of Figure 2(a) and (b), where the high-type farm ends up with a larger water allocation than the low type. The output gains from trade from the high type (in blue) are larger than the losses from the low type (in red), as constructed by the water market, indicating an increase in allocative efficiency.

Analysis of changes in aggregate labor demand We can express the output GFT as,

$$\begin{aligned}
\text{GFT}(Y) &= \Delta Y_H + \Delta Y_L \\
&= a_H \underbrace{\left[f(W_H^M) - f(W^Q)\right]}_{\text{gains from high type}} + a_L \underbrace{\left[f(W_L^M) - f(W^Q)\right]}_{\text{losses from low type}} \\
&= \underbrace{a_H f(W_H^M) + a_L f(W_L^M)}_{\text{output under market}} - \underbrace{(a_H + a_L)\, f\left(W^Q\right)}_{\text{output under quota}}.
\end{aligned}$$

I first show that GFT(Y) is positive by evaluating the change in total output using a first-order Taylor expansion of $f(W)$ around the initial quota W^Q. If we consider an infinitesimal transfer of water from the low type to the high type denoted by δ (i.e., $W_H^M - W^Q = W^Q - W_L^M = \delta$), we get:

$$\begin{aligned}
f\left(W_H^M\right) &\approx f\left(W^Q\right) + f'\left(W^Q\right)(\delta), \\
f\left(W_L^M\right) &\approx f\left(W^Q\right) + f'\left(W^Q\right)(-\delta).
\end{aligned}$$

Substituting into the GFT expression:

$$\begin{aligned}
\text{GFT}(Y) &= \Delta Y_H + \Delta Y_L \\
&= \underbrace{a_H f(W_H^M) + a_L f(W_L^M)}_{\text{output under market}} - \underbrace{(a_H + a_L)\, f\left(W^Q\right)}_{\text{output under quota}} \\
&= a_H f\left(W^Q\right) + a_H f'\left(W^Q\right)(\delta) + a_L f\left(W^Q\right) \\
&\quad + a_L f'\left(W^Q\right)(-\delta) - (a_H + a_L)\, f\left(W^Q\right) \\
&= f'\left(W^Q\right)\delta\,(a_H - a_L).
\end{aligned}$$

Given that $f'\left(W^Q\right) > 0$, $\delta > 0$, and $a_H > a_L$, it follows that:

$$\text{GFT}(Y) > 0,$$

which is also shown graphically in Figure 2.[10] The gains from trade in terms of labor can be

[10] That output gains from trade is positive in this case is by design of the market. The Taylor expansion expression overstates GFT. As δ increases, $f'(W_H^M)$ actually decreases and $f'(W_L^M)$ increases because of concavity. When δ is large enough such that $a_H f'(W_H^M) = a_L f'(W_L^M)$, all potential gains are realized, and no trade will occur beyond that.

expressed as:

$$\begin{aligned} \text{GFT}(L) &= \Delta L_H + \Delta L_L \\ &= \frac{\Delta Y_H}{b_H} + \frac{\Delta Y_L}{b_L}, \end{aligned} \tag{1}$$

where b_H and b_L are the labor productivity parameters for the high- and low-type farms, respectively. Since $\Delta Y_H > 0$ and $\Delta Y_L < 0$, the larger b_H is relative to b_L, the smaller the labor GFT. Specifically,

$$\text{GFT}(L) < 0 \;\text{ if }\; \left|\frac{\Delta Y_H}{\Delta Y_L}\right| < \left|\frac{b_H}{b_L}\right|,$$

labor demand can decrease under water trading if the relative ratio in output change between the high and low type ("scale" effect) is smaller than the ratio between their respective labor intensity ("compositional" effect). Panel (a) of Figure 2 shows a scenario where $b_H = b_L$, $\left|\frac{b_H}{b_L}\right| = 1$, and there is no compositional effect, and labor GFT follows from more output in the economy. Conversely, panel (b) of Figure 2 shows a scenario where the "scale" effect of increased output from water trading is dominated by the "composition" effect of transferring water to a farm with higher labor productivity, causing aggregate labor income and factor share to be lower.

General model predictions Using an exponential functional form for $f(W)$ in Online Appendix Section C, and a crop-specific parameter to characterize the correlation ($\phi_c = corr(a_i, b_i)$) between water and labor productivities across farms, I derive expressions to analyze how ϕ_c shapes the impacts of market liberalization relative to uniform quotas under non-zero wages.

I show that as ϕ_c increases, (i) more water is allocated to the high type leading to (ii) larger aggregate profit gain and (iii) market-clearing water price, while (iv) labor demand and (v) output *decreases* under market liberalization of water. The intuition for predictions (i)–(iii) is straightforward: as ϕ_c increases, the high type farm is more productive in *both* water and labor use. This induces more water to be transferred to the high type (ii) due to higher profit from reduced labor cost (iii), and a higher water price that reflects the increase in net value generated from each unit of water (i). Simultaneously, higher ϕ_c shifts the source of efficiency gains from growing more (increased production) toward hiring less labor, meaning output rises less as efficiency gains are increasingly driven by increased labor cost savings, explaining both (iv) and (v).

3 Setting and Data

California's groundwater provides a useful, timely, and important setting to study the reallocative impacts of environmental markets. The state's valuable and previously unregulated groundwater is being regulated for the first time in a historic move that would also enable the development of trading mechanisms.

California's Input-Intensive Agricultural Industry As the fifth largest economy and agricultural producer globally, California generated $61.2 billion in crop cash receipts in 2024, contributing two-thirds of the total vegetable, fruit, and nut crops consumed in the U.S. (USDA, 2024). The industry is relatively labor-intensive and high-value compared to those of other states. An acre of corn or soybeans in the Midwest is typically valued at $700-$1,500, while an acre of strawberries in Santa Barbara can generate over $100,000 (Martin, 2023). Farmworkers are needed for planting, pruning, and harvesting many of these delicate crops, which will lose market value if bruised. Online Appendix Figure A.5 shows that labor takes the largest cost share of all required factors of production at around 30% in 2017, supporting almost 900,000 individual workers, a number that continues to grow (Online Appendix Figure B.10B) (Hooker et al., 2024). Online Appendix Section B.3 provides a more thorough discussion on farm labor and water use in California.

The fertile soil and Mediterranean climate in California's Central Valley (CCV) enable the production of a highly diverse set of crops over a long growing season but also makes the region highly reliant on irrigation. Virtually all farmland is irrigated by a combination of surface and groundwater.[11] Over the last few decades, increased agricultural water demand coupled with decreased surface water supplies have caused groundwater levels to deplete at an accelerating rate. Liu et al. (2022) reports a withdrawal rate of 8.6 km^3/year between 2019-2021 compared to the long term average of 1.9 km^3/year since 1962. Supply-side factors are prolonged and intensifying drought conditions and species conservation regulations, while demand drivers can be attributed to the increase in California's acreage of specialty water-intensive crops.[12] For example, almond acreage expanded three-folds from 500,000 to 1,500,000 acres over 2000-2020. These perennial fruit and nut tree crops, are particularly vulnerable to water supply variability, as they require year-round irrigation exceeding 3 acre-feet per year just to remain viable (Haviland et al., 2019). These trends have raised critical concerns regarding the long-term viability of current cropping patterns and groundwater use. Furthermore, groundwater declines have led to wells drying, land subsidence, degrading water quality, and seawater intrusion (CADWR, 2018), prompting the implementation of the Sustainable Groundwater Management Act (SGMA) in 2014.

Sustainable Groundwater Management Act (SGMA) SGMA, implemented during the height of the historic 2012-2017 drought in the Western US, is a landmark legislation that required the formation of Groundwater Sustainability Agencies (GSAs) to independently plan and execute policies for achieving sustainable groundwater water use by 2042 (California Legislature, 2015). These GSAs are tasked with creating and executing Groundwater Sustainability Plans (GSPs) to achieve a stable groundwater level that mitigates six undesirable results.[13] The first decade of

[11]The allocation of surface water is highly engineered and facilitated by an array of canals and aqueducts that redirect water – from snow melt, rivers, lakes, and reservoirs (primarily in Northern California) – to water users all over the state.

[12]According to the California Department of Water Resources, the state's urban water demand has fallen on aggregate and on a per capita basis by almost 10% over the past two decades, driven by conservation efforts.

[13]The undesirable effects include chronic lowering of groundwater levels, reduction in groundwater storage, seawater intrusion, degraded water quality, land subsidence, and negative impacts on beneficial uses of interconnected surface

SGMA implementation focused on delineating hydrologically connected basins, establishing GSAs, engaging stakeholders, and identifying the "sustainable" groundwater level to target in light of the six undesirable impacts defined by the Act. This period also involved the development of comprehensive long-term plans designed to achieve sustainable groundwater management.

Most GSAs, if not all, are beginning with baseline allocations that will gradually be reduced, and over a third are considering implementing some kind of market-based mechanism to achieve groundwater reductions (Bruno et al., 2022). The first groundwater market implemented under SGMA began trading in Ventura County in 2020, followed by a pilot trading program launched in Tulare County in 2024 (Heard et al., 2021).[14] Furthermore, SGMA enables overlying groundwater rights-holders to trade water allocations and participate in subbasin-scale groundwater governance, facilitated by GSAs. While GSAs are now authorized to implement extraction restrictions and create trading systems, they are not authorized to approve cross-basin trade (Cal. Water Code § 10720.5). Therefore, SGMA has significantly minimized conventional transactional and legal barriers to groundwater trading within basins but not across basin boundaries. This renders California a particularly useful setting for exploring the varied consequences of water markets, as each GSA-basin provides a different setting characterized by different crop composition, within-crop farm heterogeneity, and level of initial misallocation.

Political Pushbacks Much like the rest of the nation, California's agricultural sector is primarily composed of "small" farms, where approximately 80% generate less than $350,000 in gross income. Approximately one-quarter of these agricultural enterprises are managed by individuals from diverse backgrounds, including people of color, refugees, and immigrants, who farm a diverse array of truck crops such as heirloom tomatoes, lemongrass, and eggplants (Atume and Voss-Gonzalez, 2022). Small farms hold a prominent place in both federal and state agricultural policy. Organizations such as the California Alliance for Family Farms and the American Farmland Trust, along with numerous state and federal programs, allocate billions of dollars annually to support their viability. Their importance is captured in the words of one irrigation district manager: "We feel like we have failed if we lose even one [small] father–son [family] farm" (personal correspondence). Various reports on groundwater markets have cautioned the impacts of groundwater trading proposed under SGMA on the viability of small and underrepresented farmers (e.g., California Water Commission, 2022). Focus group discussions conducted by the California Water Commission revealed that many perceived risks associated with water trading are related to potential power imbalances that may lead to overpriced groundwater. For instance, small farms that need more groundwater than their initial allocation to turn a profit may be unable to pay for additional water, threatening their viability and local job creation. Tenant farmers may lose access to land if landowners choose to

waters.

[14] M. Fienup, the project lead for the state's first operational groundwater market in Fox Canyon, Ventura, noted that nearly all of California's 34 adjudicated basins are exploring the use of market-based mechanisms, such as auction-based fallowing programs to manage groundwater cutbacks (personal communication, August 29, 2023).

sell water allocations from leased parcels, if water becomes more valuable than rental income.[15] These key community concerns regarding small farm viability, economic diversity, and employment continue to influence public support for groundwater trading but remain largely unquantified. This paper seeks to provide new ex-ante estimates of these reallocative impacts using farm-level data.

3.1 Data

The main data sources are farm-level survey responses from the Census of Agriculture (Census) and Irrigation and Water Management Survey (IWMS) conducted by the U.S. Department of Agriculture's National Agricultural Statistics Service (USDA NASS). I compliment the main datasets with external data on crop prices and farm wages, groundwater levels, and surface water allocations. I provide a short description of them in the rest of this section.

USDA NASS Census of Agriculture I use the Census data provided by USDA NASS for the years 2007, 2012, and 2017 to estimate farm crop production parameters. The COA, conducted every five years, provides individual-level records for each farm that responded, allowing me to create a panel dataset by linking farms across survey waves. The detailed farm-level information and panel nature of the census microdata are critical for recovering and modeling individual farm heterogeneity.

The key variables are production, input use and expenses, acreage harvested, acreage fallowed, and farm characteristics. For production data, I observe total value of crop production and crop output for various crops within each farm. For input use, I observe the number of direct workers hired, number of workers hired through farm labor contractors (FLC), and the acreage of cropped land. The census contains expenses on electricity use, which I use to proxy for groundwater use, supplemented with information from the IWMS (Online Appendix B provides more details), as well as on the following categories defined: planting (fertilizer, chemicals, pesticides, and seeds), harvesting machinery and transportation (fuels, machinery and equipment rental or purchase; and custom work), and land and building (rent, mortgage payments, or tax).[16] Additionally, I observe information on farm ownership type, operator's tenure arrangements, and number of stakeholders – allowing me to evaluate farm productivity across these farm characteristics. I categorize each farm into one of eight crop types following the procedure in Online Appendix B. I highlight key novel facts from these new data in Section 4, while Table A.2 shows a summary of key variables from the Census by crop type.

For the estimation, I require physical quantities of labor, land, water, and intermediate input for

[15] Ruth Dahlquist-Willard, a small farms and specialty crops advisor at the University of California Cooperative Extension, captured this concern: "What is to prevent [a land owner] from deciding to sell the allocation with a piece of rented land instead of continuing to rent it? [Tenant farmers] are the people I'm most worried about" (Atume and Voss-Gonzalez, 2022).

[16] I observe specific expense type as listed in the parentheses, but aggregate them into the four broader categories mentioned.

each farm-year. Physical quantities of direct and FLC-employed workers are reported for the labor variable. I use acreage harvested directly for the land variable. Intermediate inputs in my setting comprise harvesting machinery, storage infrastructure, fuel, and transportation (HST) inputs, which I use as a "proxy variable" to control for and recover farm productivities in the production model (equation (2)) using the estimation strategy described in Section 5.3. I do not observe physical quantities of HST inputs, instead, I assume that within each crop type and year, HST input prices do not differ across farms. Under these conditions, I can back out their physical quantities. Water used is reported directly in the IWMS which only contains a subset of all farms, but not in the Census. Following standard procedure in the literature, I construct the water use variable for farms in the Census using a physical equation relating groundwater depth, pump efficiency, agricultural electricity tariff, and utility expenditure to groundwater volumes (Online Appendix B).

Irrigation and Water Management Survey (IWMS) I also have access to the IWMS dataset, which surveys around 35% of the farms in the COA in the year after the COA schedule (2008, 2013, 2018) as a follow-up. The IWMS contains a rich set of variables including reported quantity of water use by source type, irrigation systems used (e.g., sprinkler, drip, gravity), pump efficiency, energy source used for pumping, and labor for irrigation. It also collects information on the costs associated with irrigation, including equipment, energy, and labor. I use the IWMS to obtain county-level operating pump efficiency and agricultural electricity tariffs. The mean operating pump efficiency in the IWMS responses is 0.60, consistent with the mean of 0.56 reported by Burlig et al. (2025) based on pump tests conducted under Pacific Gas & Electric's (PG&E) energy efficiency program.

Additional data sources The first two datasets in the following section are used to construct the water variable (see Online Appendix Section B), which is a sum of ground and surface water, a key input in the production function to be estimated. The last two datasets are not used in the estimation of production function parameters, but for simulating current and future input demands and level output of produced by each farm under baseline, quotas, and markets counterfactuals.

Groundwater level data from CA Department of Water Resource (DWR) The Periodic Groundwater Levels dataset contains seasonal and long-term groundwater level measurements collected by the Department of Water Resources and cooperating agencies in groundwater basins (DWR, 2022). For each county and year, I calculate the average groundwater depth of all measurements taken, constructing a county-by-year panel of estimated groundwater depths.

Surface irrigation Surface water deliveries and diversions in California can be directly obtained from a dataset constructed and shared by Hagerty (2022). The repository contains data on volumes of reported deliveries, diversions, and allocations of surface water to geographically-identified users in California. Following conventions in the literature validated by surface water sharing rules, I assume that farms within a county who report receiving surface water in the census are sharing

surface water diversions and deliveries equally. This allows me to assign a surface water volume value for each farm-year observed in the Census.

County crop production data I retrieve annual county-level crop acreage, production, value, and unit price data from the California County Ag Commissioners reports compiled by the National Agricultural Statistics Service (USDA CA Ag Comm, 2022).

County crop employment and wages I obtain annual county-level average weekly wages and employment by agricultural NAICS codes, available from the Quarterly Census of Employment & Wages constructed by the California Employment Development Department (QCEW, 2023).

4 Stylized Facts

I establish new facts on farm water and labor use using the universe of crop farm survey responses in the California Census of Agriculture and Irrigation of Water and Management Survey. To my knowledge, this is the first use of microdata from the Census of Agriculture to diagnose and model the prospective impacts of a new regulation. Despite the importance of water in California agriculture, direct information on farm-level water use remains scarce. While interesting in their own right, the empirical facts presented here guide the choice of production functional form in my model, diagnose the implications of introducing heterogeneity, and illustrate the reallocative mechanisms that drive differential counterfactual outcomes across regions.

Fact #1: Groundwater is the primary irrigation source for most producers.

Farm-reported data from IWMS[17] indicates that, on aggregate, between 39-48% of irrigation water came from groundwater pumping over the IWMS years 2003-2022. These figures align with hydrological estimates from the California Department of Water Resources (CDWR), which reported 39% and 49% groundwater reliance for 2013 and 2020, respectively (California Department of Water Resources, 2013, 2020). However, groundwater is the predominant source of irrigation for most farms: *over 80% source more than half of their irrigation from groundwater, and 55% rely on it exclusively.* The fact that surface water accounts for over half of aggregate irrigation volumes suggests a concentration of surface water deliveries among a smaller number of large or well-positioned farms. This variation is reflected in regional heterogeneity in groundwater irrigation share reported by the California Department of Water Resources, which ranges from 1% in the Colorado River region to 94% in the Central Coast (California Department of Water Resources, 2020).

These statistics, derived from the IWMS for the survey years 2008, 2013, and 2018 avoids the

[17]The IWMS asks farmers how much groundwater and surface water they used for crop irrigation each year. This dataset is less comprehensive but provides a direct measure of groundwater use, complementing the electricity-proxied measure calculated from the Census. It may represent a lower bound if farms tend to under-report their usage because they are reluctant to disclose actual figures.

worst period of the historic 2012-2017 California drought. Coupled with farmers' strong aversion to disclosing groundwater extraction volumes, the true extent of agricultural groundwater reliance is likely higher, especially during drought years.[18] These findings underscore the potential widespread impacts of SGMA-driven groundwater reductions on farm operations, particularly in regions with high reliance.

Fact #2: The shadow price of water vary substantially within and across crops.

Figure 3 plots the distribution of farm average value of water (AVW) by crop type, calculated as the revenue less variable input costs per acre-foot of water used.[19] The AVW serves as a valid measure of water productivity across crop types, but it also has the added property of capturing variations in the marginal revenue product of water (MRPW), also the willingness-to-pay for an additional unit of water within each crop type. Under a Cobb-Douglas production function, the MRPW is simply the product of the AVW and a crop-specific parameter.[20] The extended version of the conceptual framework in Section 2 shows that greater within-crop heterogeneity – often assumed away due to data limitations – induces within-crop reallocation of water and production under trading, providing a new source of gains from trade.

I find large within-crop heterogeneity in the value of water applied. The interquartile range spans from \$400/AF for field crops and non-citrus tree farms to \$2,350/AF for berries-type farms. Similar variations in crop water consumption have been identified in a recent study using remote sensing by Boser et al. (2024). Sources of such differences could be due to spatial differences in climate and topography, plant variety, or farming practices; affecting their water productivity. The variations uncovered suggest potentially large gains from trade even within crop types at the current groundwater allocation. Comparing AVW across crops, berries and vegetable/melon farms (mean AVW = \$2,400, \$2,200 respectively) tend to generate more value per AF of water than other crop types such as tree nuts at \$1,110 and citrus at \$1,000. These AVW numbers align with revenue-per-AF estimates compiled from agronomic models of crop water use, hydro-engineering estimates of net water used, and market-level production statistics reported by Medellin-Azuara et al. (2015).

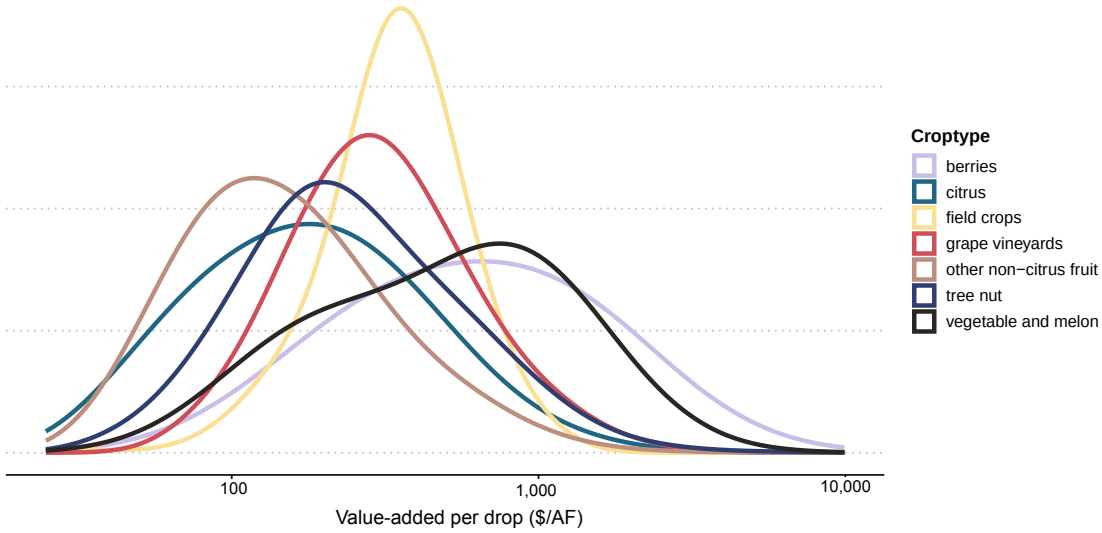
Overall, these results suggest that a water market is likely to reallocate water within *and* across crops, the extent to which depends on the crop composition and distributions of farm water productivity in each trading region. Studies using representative farm models (e.g., Costinot et al., 2016; Sotelo,

[18]The aversion is so strong that the IWMS, a follow-on survey to the Census of Agriculture and the only nationally comprehensive USDA survey on farm-level irrigation water use, is publicly released only at the state level to protect respondent confidentiality. Even in restricted-access settings, NASS confidentiality rules limit cross-survey linkage that would identify individual operations.

[19]The formula for water value is $\frac{Value}{Water} = \frac{P'_{ict}Y_{ict}}{W_{ict}}$, where P'_{ict} represents the output price less proportional variable input costs, including expenditures on labor, planting and soil chemicals, fuels, and machinery rentals for farm i in year t planting crop c. W_{ict} is the total quantity of groundwater and surface water used and Y_{ict} is the farm's output.

[20]Specifically, under $Y_{ict} = A_{ict}K_{ict}^{\beta_{cK}}W_{ict}^{\beta_{cW}}$, where K_{ict} is the amount of land used and β_{cW} and β_{cK} are the land and water output elasticities, respectively; MRPW $= \beta_{cW}P'_{ict}\frac{Y_{ict}}{W_{ict}}$, with β_{cW} varying only by crop.

Figure 3: Empirical distribution of farm average value generated per unit of water by crop type.



Note: The average water value is calculated as the average revenue generated per acre-foot (AF) less variable input costs. Note that the x-axis is shown on $\log_{10}$ scale. The mean water value by crop are \$2,395 (Berries), \$1,006 (Citrus), \$502 (Field crop), \$1,239 (Grape & vineyards), \$792 (Nursery greenhouse), \$1,407 (Non-citrus fruit), \$1,114 (Tree nut), \$2,185 (Vegetable and melon).

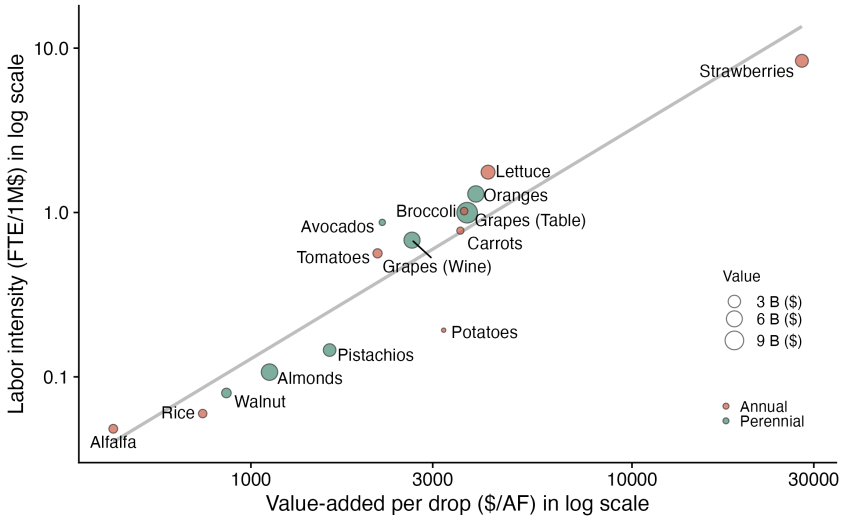
2020; Nath, 2025) to model trade may have underestimated gains given these large ranges in observed productivity across individual farms, with within variances that frequently dominates across-crop variances.

Fact #3: Water value is positively correlated with labor intensity *across* crop but negatively correlated *within* crop.

This section combines two facts to illustrate the competing effects of groundwater trade on labor demand as laid out in Section 2. The framework illustrated that a positive correlation between farm water value and labor productivity (inversely related to labor intensity) will lead to a dampening effect on employment. However, this relationship varies by margin. I first show evidence that high water-value crops are generally more labor-intensive in California.

Figure 4 shows a *positive* relationship between farm value of water and labor intensity across crop type. Of the crop types with significant market share, indicated by larger circles, berry and vegetable crops generate high water values (>\$2000/AF) and have higher labor intensities. These delicate crops are labor-intensive (Online Appendix Figure B.9 shows that these types of farm employ up to 80 employees/month) as they require hand labor for planting, pruning, and especially for harvesting, which is typically done by hand to ensure fruit aesthetic and quality (Calvin et al., 2022). At the same time, berry and vegetable crops enjoy high market value. Conversely, highly-mechanized crops like field crops and tree nuts exhibit relatively lower water values (<\$1500/AF) and lower labor intensity. Tree nuts in particular, require substantial irrigation, especially in California's arid climate.

Figure 4: Average value of water and labor intensity by crop type.



Note: Scatterplot of the average water value (x-axis) and labor intensity (y-axis) of major crop types planted in California. The average water value is calculated as the revenue less proportional variable costs (expenditures on labor, materials, planting, machinery rentals, and fuels) per acre-foot of water. Larger points indicate a larger share of production value and colors indicate crop status (teal: perennial, pink: annual). Axes are in log scale.

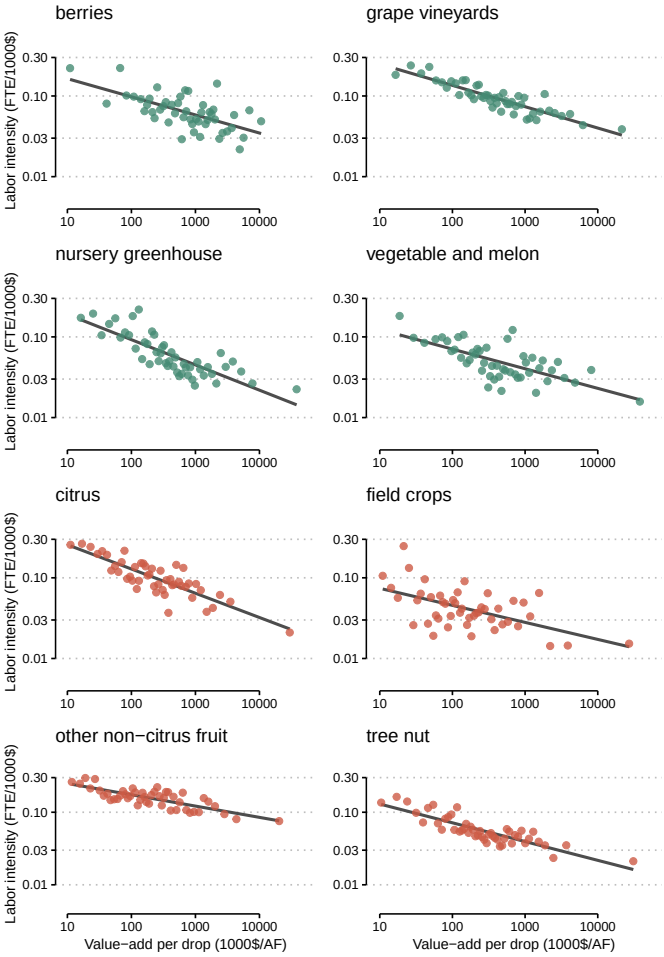
However, with their hardy hulls, they require relatively low labor inputs (10 employees/month; Online Appendix Figure B.9) as their cultivation, harvesting, and packaging are almost fully mechanized (Calvin et al., 2022; Calvin and Martin, 2010).[21] Field crops such as alfalfa generate relatively low returns to water and are highly mechanized throughout their production cycle; as such, they appear in the bottom left corner of the graph.

These findings indicate that a reallocation of water from low water-value crops towards higher water-value crops like vegetables – will increase farm profits *and* employment. However, this narrative is complicated by a second fact, that farm water value and labor intensity are *negatively* correlated within crops – an empirical fact that is only revealed by farm-level data. Figure 5 shows that within crops, farms with higher water value tend to employ *less* labor. This pattern can be explained by two mechanisms. First, farms with higher labor productivity require less labor and incur lower costs, mechanically increasing water value for otherwise similar farms.[22] Second, farms investing in water-saving technologies are likely to also invest in labor-saving technologies, leading to increased productivities for both inputs. *As a result, while groundwater trade across crops is likely to increase labor demand due to increased labor needs, trading within crops may dampen this effect, potentially reducing overall labor demand.*

[21]The description of almond processing is: "Encased in a tough, leathery hull and an inner, protective hard shell, almonds are mechanically shaken from the tree during the fall harvest and sent to handlers to be processed and marketed as a final product." as promoted on the Agricultural Marketing Resource Center website.

[22]Given that labor is used proportionally to output in agriculture, higher labor productivity is mechanically the same as a higher output price.

Figure 5: Average value of water and labor intensity across farms within the same crop type, for eight crop categories.



Note: Figure plots binned scatterplots of the relationship between water value (x-axis, \$/AF) computed as revenue less proportional variable costs (expenditures on labor, materials, planting, machinery rentals, and fuels) per acre-foot of water against labor intensity (y-axis; full-time employment per \$ output). Farms are grouped into bins of 60 based on water value. Each point represents the average water value and labor intensity within a bin. Axes are in log scale. Colors of points denote whether a crop is predominantly handpicked (teal) or mechanized (red). Data have been binned to preserve anonymity in accordance with disclosure requirements of the National Agricultural Statistics Service, U.S. Department of Agriculture.

To investigate the existence of the second mechanism, I computed each farm's labor and water productivities, defined as revenue dollars generated per hour and acre-foot used (b_i and a_i, respectively, in Section 2's conceptual framework).[23] Table A.2 reports substantial within-crop variation in labor productivity: the interquartile range spans \$20–\$60/hour for berries to \$40–\$180/hour for tree nuts. Water productivity also varies widely, with interquartile ranges of \$600–\$4,000/AF for berries to \$200–\$1,000/AF for tree nuts. Panel B of Table 1 reports the coefficient from a linear regression

[23] By computing revenue per acre-foot of water, rather than value-added – which in itself is a function of other inputs including labor used – this measure isolates the contribution of water and removes the role of labor productivity.

of labor productivity on water productivity (ϕ_c), and shows that they are correlated within farms planting the same crop types. For instance, a 1% increase in crop revenue per acre-foot of water is associated with a 0.64% increase in labor productivity for tree nut farmers. The strength of the correlation depends on a key feature – crops with available harvesting technologies (e.g., tree nuts and wine grapes) tend to exhibit higher correlations, while hand-picked crops like berries have correlations statistically indistinguishable from zero (0.05). Within-crop variations in input ratio, given similar input prices, rule out a Hicks-neutral production function.[24]

I embed this empirical regularity in my model, allowing farm labor productivity to depend on their water productivity. I calibrate the parameter using the empirical estimates reported in Panel B of Table 1. It is crucial to model this correlation (ϕ_c) because of the interest in labor outcomes as a result of groundwater trading and to predict gains accurately. As illustrated in Section 2, if relatively more water-productive farms are also *more* labor-productive, then a gain in output from reallocating water optimally may yield zero or even a negative change in labor demand. Models not accounting for correlated productivities also risk underestimating gains from trade by missing profit gains from potentially correlated labor cost savings.

Conversely, in a setting where there is no correlation between water and labor productivities, any groundwater reallocation that *increases output* would naturally increase labor demand. This is the case for a hypothetical region comprising only of berry farms, with a water-labor productivity ratio close to zero ($\phi_c = 0.05$). Ultimately, within a trading region, the magnitude of gains from trade and labor demand changes are governed by the heterogeneity in water productivity across users, crop composition, the water-labor productivity ratios as defined by ϕ_c, input and output prices, and other crop-specific production parameters. Online Appendix Section C derives analytical solutions for a two-farm setting.

5 Empirical Model of Agricultural Production and Water Trade

This section lays out and estimates a structural model of crop production to study how projected cuts to groundwater pumping will impact the reallocation of production with and without groundwater trading. I begin by specifying a model of crop production where groundwater becomes a constrained input under SGMA. Farms are endowed with productivity and produce crop using multiple inputs, including water. Farm productivity, as well as crop specific production parameters, can be recovered from the panel of farm-level input and output data.

Under profit maximizing conditions, I am able to derive closed-form expressions for farm input demands, which allows me to predict how farms will behave under each counterfactual. I consider

[24] I show in Online Appendix Section C that even under the more general constant elasticity of substitution function, a farm-specific Hicks neutral term (TFP=A_i) will *not* yield differentiated input productivities, because more hicks-neutral productive farms will increase production until their marginal profits equate market parameters. Farms will also optimally use input in a fixed ratio, implying that the correlation should be 1.

one counterfactual scenario where groundwater quotas are based on historic pumping or owned acreage, and another where users can freely trade groundwater quotas with other users in cash sales.

5.1 Model

Crop production function I specify a fixed-proportion, Leontief production technology between crop growing and harvesting inputs. The Leontief specification is a plausible description of the crop production process. Conceptually, crop production can be viewed as a two-stage process. In the growing season, farms grow crops using land and water under a Cobb-Douglas technology. In the harvesting season, these crops are picked using labor in farm-specific fixed proportion to output. The prevalence of piece-rate compensation – where workers are paid according to the quantity harvested – justifies modeling labor as a proportional input (Martin et al., 2016).

Each farm i in year t dedicates K_{ict} acres of land to crop type c where $c \in C = \{$*tree nuts; other deciduous fruits; citrus and subtropical; vineyards; field crops; berries; vegetable and melon*$\}$. Farms growing crop c face the same production function defined as follows:

$$Y_{ict} = \min \underbrace{\left\{ e^{\omega_{ict}} W_{ict}^{\beta_{cW}} K_{ict}^{\beta_{cK}}}_{\text{Grow}}, \underbrace{e^{\phi_c \omega_{ict}} \gamma_c L_{ict} \right\}}_{\text{Harvest}} e^{\varepsilon_{ict}}, \quad c \in C, \tag{2}$$

where Y_{ict} is crop output in tons. Crops are sold to the market at price P_{ct} and are produced at productivity level ω_{ict} using water (W, acre-foot), land (K, acres), and labor (L, number of hired workers). Intermediate (M) and other planting inputs are implicitly used in fixed proportions that vary across but not within crop types.[25] Intermediate inputs (M) are used as a control variable for identification of the productivity parameter, ω_{ict}, and consists of harvesting machinery, storage infrastructure, fuel, and transportation (HST). Growing inputs, land and water, are nested in a Cobb-Douglas form while harvesting input labor is used in a fixed proportion with γ_c as the per-ton labor requirement. ϕ_c is a crop-wide parameter that captures the correlation between productivity in the growing and harvesting phases. It captures the fact that some but not all productivity in the growing phase of production translate to productivity in the harvesting phase. Section 2 demonstrates how the productivity correlation is central for accurately predicting the effects of water trading while stylized fact #3 in Section 4 provides empirical evidence that this correlation value differs across crops. ε_{ict} captures measurement error in output and any model misspecification.

The Leontief form assumes a zero elasticity of substitution between growing and harvesting inputs for the following reasons. First, it is a realistic depiction of the farming process. Water and land or soil are physiological inputs for crop tissue growth and cannot be replaced by labor. Conversely, labor, which is a mechanical input primarily involved in physical movement, cannot be substituted

[25] Planting inputs comprise fertilizers, chemicals such as insecticides and lime, and seeds and bulbs.

by water or land.[26] Second, these two groups of inputs are predominantly required for different periods of the cropping season. Water and fertilizer are critical during the growing season, with some labor dedicated to fertilizer application during this period. By contrast, labor and machinery are predominantly utilized during the harvest period. Modern irrigation techniques, such as drip, or sprinkler irrigation have largely automated the process of water application.

5.2 General analytical expressions for output and input demands

From the production function in equation (2), I derive general analytical expressions for water and labor demands as a function of production function parameters ($\boldsymbol{\beta} = [\beta_{cW}, \beta_{cK}, \gamma_c, \phi_c]$), expected productivity ($\mathbb{E}(\omega_{ict})$), realized productivity (ω_{ict}), water price (v), and input prices for labor, composite intermediate and planting materials, and land rental and preparation (s_{ct}, f_{ct}, r_{ict}).

To do this, I assume that farms maximize profits in response to input prices. I use contemporaneous crop and input prices, which vary by crop and year. Land preparation and rental price (r_{ict}) are observed and differs across farms, while labor and composite intermediate and planting costs (s_{ct} and f_{ct}) differs only across crop types. During the growing season, farms choose water (W_{ict}) and, for annual crops, planted acreage (K_{ict}) to maximize expected profits subject to the amount of arable land they own or operate. I assume that farms form expectations according to

$$\mathbb{E}(\omega_{ict}) = \rho_c \omega_{ict-1}$$

where ρ_c is a crop-specific persistence parameter that measures how strongly productivity in crop c is expected to carry over from the previous period. This assumption ensures that farms form expectations consistent with empirically observed persistence in input productivities; information that was available to them at the time, and recoverable by the researcher by virtue of the estimation procedure, described in the next section, and panel structure of the data. In the quota-only counterfactual, farms face constraints on the total amounts of groundwater can use for irrigation. Farm-level surface water allocations are fixed and observed (see Section 3.1). In the market counterfactual, farms optimally choose groundwater volume given a competitive market price, and trade the rest of their allocation for cash. In the harvest season, once crops are grown and productivity shocks realized, each farm demands labor proportionately to output in the fixed ratio $e^{\phi_c \omega_{ict}} \gamma_c$ – to harvest, process, and package the crops. They then optimally select intermediate input M at this stage.

Concretely, each farm i observed to be planting crop c in period t faces the profit maximization problem:

[26] An illuminating anecdote is the news of the asparagus farmer in Oregon who had fields full of asparagus but no harvest labor during the COVID-19 pandemic. He called out to the public via social media to harvest asparagus for free. With no labor, his production was 0.

$$\max_{W,K} \pi_{ict} = \left(P_{ct} - \frac{s_{ct}}{e^{\mathbb{E}(\omega_{ict})\phi_c}\gamma_c} - f_{ct} \right) Y(W,K)_{ict} - vW - r_{ict}K.$$

The first term in parentheses is the per unit income of output crop c net of labor and composite intermediate and planting input costs respectively, since both sets of inputs are used proportionally. The choice variable is water (W) and acreage planted (K). Y is the production function in equation (2). The following input demand and output functions are solutions to the maximization problem.

Perennial crops For perennial crops, farms are not able to adjust acres planted (K) flexibly, since these are orchards, vines, or trees planted with a need for irrigation throughout the year. Water demand is the result of a constrained profit maximization problem with K fixed at $\overline{K_{ic}}$. All other outcomes are derived from water demand as it is the only choice variable for perennial crops. The water demand for each farm is given by

$$\widehat{W^P_{ict}}(v) = \left[\frac{\beta_{cW} \left(P_{ct} - \frac{s_{ct}}{e^{\mathbb{E}(\omega_{ict})\phi_c}\gamma_c} - f_{ct} \right) \overline{K}_{ic}^{\beta_{cK}} e^{\mathbb{E}(\omega_{ict})}}{v} \right]^{\frac{1}{1-\beta_{cW}}}, \tag{3}$$

where v is water price, s_{ct} is farm wage, f_{ct} is per unit cost of intermediate and planting input, and P_{ct} is per unit price of crop c. v has to be iteratively solved numerically given all farms' water demand schedules within each trading region. The optimized output function, using contemporaneous realized productivity, is expressed as

$$\begin{aligned} \widehat{Y^P_{ict}}(v) &= e^{\omega_{ict}} \overline{K}_{ic}^{\beta_{cK}} \widehat{W^P_{ict}}(v)^{\beta_{cW}} \\ &= \overline{K}_{ic}^{\frac{\beta_{cK}}{1-\beta_{cW}}} \left[\frac{\beta_{cW} \left(P_{ct} - \frac{s_t}{e^{\mathbb{E}(\omega_{ict})\phi_c}\gamma_c} - f_t \right) e^{\mathbb{E}(\omega_{ict})}}{v} \right]^{\frac{\beta_{cW}}{1-\beta_{cW}}} e^{\omega_{ict}}. \end{aligned} \tag{4}$$

We can derive the labor demand function, using contemporaneous realized productivity, as follows:

$$\widehat{L^P_{ict}}(v) = \frac{1}{e^{\phi_c \omega_{ict}}\gamma_c} \widehat{Y^P_{ict}}(v). \tag{5}$$

Finally, the profit function is as given:

$$\widehat{\pi^P_{ict}}(v) = \left(P_{ct} - \frac{s_{ct}}{e^{\omega_{ict}\phi_c\gamma_c}} - f_{ct}\right)\widehat{Y^P_{ict}}(v) - \overline{K}_{ic}r_{ict} - v\widehat{W^P_{ict}}(v). \tag{6}$$

If farms are making negative profits, I assume that they sell their water allocations: if $\widehat{\pi^P_{ict}}(v) < 0 \implies \widehat{L^P_{ict}}(v) = \widehat{W^P_{ict}}(v) = \widehat{Y^P_{ict}}(v) = 0$.

Annual crops For annual crops, farms can anticipate the water allocation and groundwater market price and adjust K flexibly. Therefore, $\widehat{K^A_{ict}}(v)$ is also a function of the water price, v, and water demand is expressed as

$$\widehat{W^A_{ict}}(v) = \left[\frac{\left(P_{ct} - \frac{s_{ct}}{e^{\mathbb{E}(\omega_{ict})\phi_c\gamma_c}} - f_{ct}\right)\beta_{cW}\left(\frac{\beta_{cK}}{\beta_{cW}}\frac{v}{r_{ict}}\right)^{\beta_{cK}} e^{\mathbb{E}(\omega_{ict})}}{v}\right]^{\frac{1}{1-\beta_{cW}-\beta_{cK}}}, \tag{7}$$

where the amount of land planted is

$$\widehat{K^A_{ict}}(v) = \left(\frac{\beta_{cK}}{\beta_{cW}}\frac{v}{r_{ict}}\right)\widehat{W^A_{ict}}(v). \tag{8}$$

$\widehat{Y^A_{ict}}(v)$, $\widehat{L^A_{ict}}(v)$, and $\widehat{\pi^A_{ict}}(v)$ are derived analogously to the perennial case as in equations (4), (5), and (6) (from equation (2)), substituting $\overline{K}_{ic}$ with $\widehat{K^A_{ict}}(v)$. The similar shut-down condition for annual crops hold: if $\widehat{\pi^A_{ict}}(v) < 0 \implies \widehat{L^A_{ict}}(v) = \widehat{W^A_{ict}}(v) = \widehat{Y^A_{ict}}(v) = 0$.

Farm behavior under quota The farms present in the dataset are operational farms, it is apparent that it is typical for farms to operate under negative profits. In a given year, anywhere between 5-15% of farms are operating under net losses. Therefore, given no other outside option to earn income under a quota system, I assume that farms keep operating. Given a fixed amount of water under a no-trading scenario, farms optimally choose the amount of land to keep in production, constrained by their individual minimum input threshold, defined as the observed minimum water-to-land ratio for each farm across years.[27] For a perennial crop farmer, I assume they apply the minimum water-to-land ratio to each acre until all allocated water runs out and they fallow the rest. For an annual crop farmer, I assume they choose the optimum amount to plant constrained by

[27] For example, some farms are observed to apply a minimum of 2 AF/acre over the years. Under a flat quota of 1.5 AF, a 10-acre farm receiving 15 AF of water will reduce her cropped acreage to 7.5 acre to meet the minimum 2 AF/year threshold.

water quota ($\overline{W}_{ct}$), given by

$$\widehat{K^A_{ict}}(\overline{W}) = \left[\frac{\beta_{cK} \left(P_{ct} - \frac{s_{ct}}{e^{\mathbb{E}(\omega_{ict})\phi_c}\gamma_c} - f_{ct} \right) \overline{W}_{ct}^{\beta_{cW}} e^{\mathbb{E}(\omega_{ict})}}{r_{ict}} \right]^{\frac{1}{1-\beta_{cK}}}. \tag{9}$$

Farm behavior under markets Under a market, farms have the outside option of selling their allocation of water. Farms first calculate profits from the optimal water and acreage to plant or fallow (if planting an annual crop) given water price following equations (3), (7), and (8). Farms can only increase acreage planted up amount of arable land they own or operate. They shut down if the profits from operating are less than the profits from selling all their quota allocation. Otherwise, they continue to operate and trade the difference between the optimal water demand and their quota allocation at the going water price. Farm water demands are constrained by a crop-specific saturation ratio, defined by the 85th percentile of the observed crop water-to-land ratio in the dataset.[28]

Water markets counterfactual simulation Now suppose that a regulatory agency establishes a water market within each county c after establishing farm water allocations under a quota system. I assume that there are no transaction costs to the groundwater market, farms demand water according to their water demand functions as defined above, and that they are price takers in the water market. The optimal price clears the groundwater market at the aggregate groundwater cap, where q is the proportional reduction in total groundwater used:

$$\sum_{i \in county} \widehat{W_{ict}}(v^*_{county}) = (1-q) \sum_{i \in county} W_{ict}.$$

Using the market-clearing water price and expressions for water demand, labor demand, and the production function, I calculate each farm's input demands and output under a water market, and compare it to outcomes under the two different types of quota.

5.3 Estimation

To identify the production parameters, the empirical strategy needs to address the classic simultaneity problem when variable input demands are correlated with unobserved heterogeneous productivity (Marschak and Andrews, 1944). Taking log of the growing nest of equation (2) and denoting lowercase variables as the log of each variable (i.e., $y_{ict} = \ln Y_{ict}$), I obtain the estimating equation

[28] This is a data-driven way of implementing an asymptotic yield.

$$y_{ict} = \beta_{cW} w_{ict} + \beta_{cK} k_{ict} + \omega_{ict} + \varepsilon_{ict}. \tag{10}$$

In Californian's highly-mechanized agriculture setting, farms who have invested in water use efficiency technologies such as drip irrigation, soil moisture detectors, or techniques such as dry farming will use less water. Their increased output will be correlated with less water use, resulting in an attenuated estimate of β_{cW}.

To obtain unbiased estimates, I rely on an established estimation procedure first proposed by Olley and Pakes (1992), and later refined by Levinsohn and Petrin (2003) and Ackerberg et al. (2015) to estimate production functions (OP-LP-ACF).[29] The approach relies on a set of assumptions on timing, the relationship between an identified proxy variable and productivity, and how productivity evolves over time. The key data requirement is a set of observed intermediate inputs (M_{ict}) that are flexible and adjusted quickly in response to realized productivity shocks. These properties render them useful as a proxy variable for productivity in the growing season, which can then be recovered under repeated observations, bounded by the assumptions described in the next paragraph. I use observed farm harvesting, storage, and transportation (HST) choices as intermediate inputs to proxy for productivity.

5.4 Timing and production assumptions

Rather than using investments, as in Olley and Pakes (1992), as a control to reveal unobserved productivity, I use intermediate input, M_{ict}, as in Levinsohn and Petrin (2003) and Ackerberg et al. (2015). My choice of intermediate input: harvesting, transportation, and storage fulfills the assumptions required for identification.

Assumption 1. At $t-1$, which is the start of the growing season, farms plant K_{ict} acres of land for each crop c. The farm's information set at $t-1$, $\mathcal{I}_{t-1}$, consists of all prior productivities ($\omega_{ic\tau}, \tau < t$), input choices, and prices. Farms pick K_{ict} and W_{ict} to maximize profits given their expected productivity for the current season, which follows the crop-specific persistence process, $\mathbb{E}(\omega_{ict}|\mathcal{I}_{t-1}) = \rho_c \omega_{ict-1}$. During the growing season, farms irrigate using W_{ict} amount of water. Finally, at the end of the growing season, productivity ω_{ict} is realized and $Y_{ict}(\omega_{ict}, W_{ict}, K_{ict})$ of crops are grown, and farms pick M_{ict} (HST) input to process and transport (or store) the crops.

Assumption 2. ω_{ict} follows a first order AR(1) process. Actual productivity can be decomposed into a part expected by the farmer and a "unexpected" productivity part. Farmers that are more productive (with higher ω_{ict-1}) in the last harvest season are expected to be more productive this harvest season as follows:

[29] This method is frequently called the control or proxy method and have been applied in recent work estimating the shadow value of resource use (e.g., Bau and Matray, 2023; Rafey, 2023).

$$\begin{aligned}\omega_{ict} &= \mathbb{E}(\omega_{ict-1}) + \xi_{ict} \\ &= \rho_c \omega_{ict-1} + \xi_{ict}, \qquad \text{where } \xi_{ict} \text{is unanticipated.}\end{aligned} \tag{11}$$

At the end of the growing season, farms hire L_{ict} of labor to harvest $Y_{ict}(\omega_{ict}, W_{ict}, K_{ict})$ and collect revenues, simultaneously picking M_{ict} for transportation and/or storage.

Assumption 3. Intermediate input demand is strictly increasing in ω_{ict} and is a linear function of Y_{ict}, akin to the technological control used in De Loecker and Scott (2025).[30]

Under these assumptions, the estimation procedure allows for serially correlated, unobserved, firm-specific input price shocks for water such as differential groundwater cost, but not intermediate input, which is plausible in my setting as truck rental and fuel cost etc. are services offered in a separate competitive market.

Estimation procedure I estimate equation 10 for each crop type c during the growing season. The estimation follows the structure of OP–LP–ACF production-function methods but adopts a linear proxy following De Loecker and Scott (2025). Rather than inverting a nonlinear control function as in Olley and Pakes (1992), I proxy for unobserved productivity using intermediate inputs in the spirit of Levinsohn and Petrin (2003). I then implement the identification and estimation procedure of Ackerberg et al. (2015), which yields consistent production function parameters under flexible input choices. Online Appendix B.4 provides additional details on the generalized method-of-moments estimator, the moment conditions, and the implementation. My estimation scripts build upon base code sourced from the `prodest` package in `R` (Rovigatti, 2017).

In a second step, I estimate the labor parameter in equation (2). Letting the second nest of the production function bind, that farms are hiring the right amount of workers to harvest the crops grown in the first stage, I obtain the following estimating equation:

$$\ln \frac{Y_{ict}}{L_{ict}} = \ln \gamma_c + \phi_c \omega_{ict} + \epsilon_{ict}. \tag{12}$$

Given that $\frac{Y_{ict}}{L_{ict}}$ is the reduced-form labor productivity, it can be directly calculated from data. I recover $\hat{\omega}_{ict}$ in equation (10) from the estimation procedure described in Online Appendix B.4. $\ln \gamma_c$ and ϕ_c are the intercept and slope parameter from a regression of $\frac{Y_{ict}}{L_{ict}}$ on $\hat{\omega}_{ict}$.

[30] The original approach involves inverting a control or policy function, and requires observing investments, which has its pitfalls as investments tend to be lumpy.

5.5 Estimation Results

Panel A of Table 1 presents the estimated output elasticities for water and land (β_{cW} and β_{cK}, respectively) derived from equation 10 across seven different crop types using the OP-LP-ACF approach described in Section 5.3. I also present estimates using two other common approaches: (1) ordinary least squares with farm and year fixed effects and (2) first-differenced by farm in Online Appendix A.1. Panel B of Table 1 reports the labor intensity parameter γ_c, as well as the water-labor productivity correlation ϕ_c.

Table 1: Production Function Parameter Estimates.

Crop type:	Berries	Citrus	Field crops	Grapes	Other non-citrus trees	Tree nuts	Vegetables
Panel A. Water and land							
β_{cW}	0.356***	0.093**	0.048*	0.244***	0.163***	0.110***	0.412***
	(0.135)	(0.041)	(0.027)	(0.048)	(0.045)	(0.034)	(0.093)
β_{cK}	0.904***	0.987***	0.914***	0.800***	0.944***	0.976***	0.713***
	(0.154)	(0.029)	(0.021)	(0.037)	(0.033)	(0.027)	(0.079)
$IQR(\omega_{ict})$	0.114	0.300	0.677	0.239	0.079	0.125	0.701
Fit statistics							
Observations	426	4,011	1,409	9,992	6,575	10,373	1,573
R^2	0.890	0.855	0.829	0.824	0.809	0.852	0.920
Panel B. Labor							
γ_c	0.009***	0.039***	0.143***	0.017***	0.024***	0.047***	0.052***
	(0.000)	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)
ϕ_c	0.05	0.49***	0.48***	0.74***	0.55***	0.64***	0.46***
	(0.05)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
Fit statistics							
Observations	670	4,256	4,063	10,708	7,128	9,954	2,526
R^2	0.00	0.11	0.07	0.21	0.17	0.14	0.13
Adjusted R^2	0.00	0.11	0.07	0.21	0.17	0.14	0.13

Note: Standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Production function terms estimated with a linear control construction from farm-level observed harvesting, transportation, and storage inputs using the proxy variable approach developed by Levinsohn and Petrin (2003) and modified to account for collinearity in the first stage estimation using Ackerberg et al. (2015)'s procedure. $\hat{\gamma}_c$ was obtained from estimating equation 12 and exponentiating the constant term. Standard errors reported are appropriately derived using the delta method. IQR=interquartile range, difference between the 25th and 75th percentile.

The water-output elasticities in California are high in general and exhibit a larger range compared to Rafey (2023), who estimates elasticities of 0.246 for perennials and 0.206 for annuals using farm-level data in Australia and an estimation strategy based on Ackerberg et al. (2015). Water is much more important for the cultivation of vegetable and berry crops (0.412 and 0.356, respectively) than field crops (0.048) and tree crops (citrus, nuts, and others; 0.093 – 0.163). These results indicate that berry and vegetable production has higher physical output returns to water applied compared to perennial trees and field crops. This is intuitive, as only a relatively small portion of the biomass – such as nuts, fruits, or seeds – of tree and grain crops is harvested and processed into physical output, compared to vegetable and berry crops. The fixed effects and first-differenced estimates (Online Appendix A.1) are biased downward in general and most salient for vegetables and berries,

where simultaneity poses a greater problem. Within-crop water productivity range is largest in vegetable and field crops; and smallest for other non-citrus tree crops and berries.

The land-output elasticity estimates are high and range from 0.713 for vegetables farms to 0.9 for berries and close to 1 for many tree crops such as citrus (0.987) and tree nuts (0.976). These estimates are as expected, as output from tree crops is more directly tied to the total acreage planted. Again, the proxy variable estimator predicts higher estimates of β_{cK}, indicating that productive farms have higher yields per land area, biasing the contribution of land downward in the fixed effects and first-differenced estimates. For the counterfactual analysis, I use unbiased parameter estimates from OP-LP-ACF.

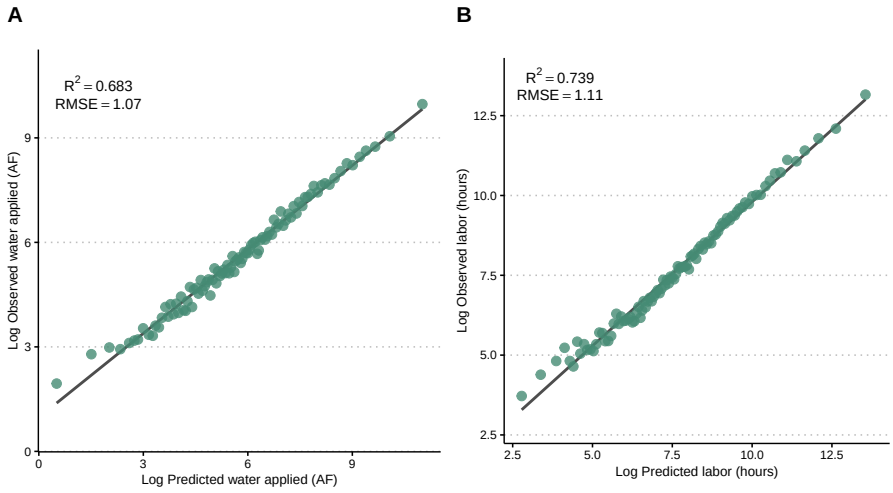
The average labor productivity is lowest for berries at 0.009, almost six times lower than tree nuts and vegetables (0.047 and 0.052, respectively). As explained in Section 4, this is due to the high labor requirements. Berries also exhibit zero correlation between water and labor productivities, compared to all other crops; largely driven by the lack of harvesting aid and machinery.

5.6 Goodness-of-fit

This section uses the estimated parameters from the previous section to assess if the model accurately captures farmers' behavior under observed conditions. Figure 6 plots water use and labor demand against their predicted analog. Because of the Census export requirement, I can only show the binned scatter, where each dot represents 60 farms in the data. These predictions are generated under the model assumption that each farm optimizes its profits given the prevailing conditions for the year, including input and output prices, the farm's expected productivity estimated using the proxy method outlined in Section 5.3, and the specific crop type cultivated.

Figure 6 shows that the model fits the data very well. The binned version of these scatters shown masks a moderate amount of model error. Online Appendix Table A.11 shows that employed labor is 18% underestimated, while groundwater used is around 29% overestimated at the 75% percentile. The (unbinned) R^2 is 0.68 and 0.74, respectively, for water and labor use. The model fit exceeds standards established in recent structural papers (e.g., Costinot et al., 2016; Blaum, 2024; Balboni, 2025). However, the model sometimes mispredicts the extensive margin. Specifically, the model predicts up to 6% of farms who produce and demand zero inputs, when they actually *do* stay in production. I perform a sensitivity analysis of my counterfactuals without the farm shutdown assumption and find that my results do not change meaningfully as these farms on the margin are producing a tiny fraction of overall output and use a similarly minuscule amount of overall water and labor (Online Appendix Figure A.2).

Figure 6: In-sample goodness-of-fit binned scatter plots of water demand, labor demand, and crop output.



Note: The x-axis plots the model-predicted choices for each farm given 2017 prices and each farm's productivity estimate while the y-axis plots the observed 2017 choices in the data. Farms are grouped into bins of 60 based on their x-axis value. Each point represents the average observed and predicted values within a bin. Data have been binned to preserve anonymity in accordance with disclosure requirements of the National Agricultural Statistics Service, U.S. Department of Agriculture. Reported R^2 and RMSE values are calculated from the full (unbinned) sample.

6 Counterfactual Simulations

Using the estimated model of crop production and input demands, I conduct a set of counterfactual simulations to assess the relative impact of county-level groundwater markets on a set of reallocative and economic outcomes across California. In all simulations, the reduction in net groundwater use is set at 25% and 35% for each county, modeling a moderate and aggressive scenario, respectively, under the projected 20-30% reductions expected by 2040 under SGMA policies and future climate change (Burlig et al., 2025; Ayres et al., 2021a). I use the estimated crop production and input demand functions for each farm to simulate what would happen in the following three counterfactuals: (i) *uniform quota* in which groundwater allocation is the same for all farms (e.g., 0.75 AF/acres) and the total groundwater use is reduced by 25% (and 35%), (ii) proportional *quota* in which groundwater allocation is less 25% (and 35%) of historical groundwater use for each farm, and (iii) a groundwater *market* where farms are allowed to trade their groundwater quotas in a free market.

My microfounded approach allows me to summarize outcomes at the state and county levels for each groundwater policy counterfactual. I report farm *revenue* to quantify the economic value of production; and the *number of farms*, the *average farm revenue*, and *overall employment* generated by farms in production to quantify reallocative impacts across farm size and on workers. I report revenues, rather than profits, in order to compare magnitudes to existing estimates from studies who do not have access to input expenditures. County-level maps report profits. I also compute

crop-weighted Herfindahl-Hirschman Index (HHI) as a measure of farm concentration across policy counterfactuals (Online Appendix B contains details on calculating crop-weighted HHI).

SGMA without groundwater trading Column 4 of Table 2 shows that under the most commonly realized groundwater policy counterfactual, a proportional quota (Q) at 25% (Panel A), total crop revenue falls by $6.9 billion (28%), average revenue by $210,000 (20%), and employment by 94,000 (43%). Furthermore, the number of operating farms decreases by 1,519 (7%), and farm concentration, measured by HHI rises by 23% relative to the baseline scenario.[31]

These estimates of SGMA-induced farm impacts are consistent with but present a more dire outlook than prior simulations calibrated using more aggregated data. Escriva-Bou et al. (2023) project reductions of $4.5 billion and 48,000 jobs in crop revenue and employment, respectively, from a 25% reduction in state-wide water supplies. Sunding and Roland-Holst (2020) estimate losses of $5.9 billion in crop revenue and 85,000 agricultural jobs for the San Joaquin Valley only.[32] Both studies do not account for individual farm heterogeneity, treating sub-units as a single farm with different crop compositions (p.22 of Escriva-Bou et al., 2023), thereby only capturing across-crop trades.

A uniform quota (marked U in column 3 of Table 2), which allocates a given supply of groundwater on a uniform per acre basis, will result in smaller economic losses than from a proportional quota but increase farm concentration. Revenue falls by $5.5 billion, employment by 87,000, and average farm revenue by $110,000. The HHI is 85% higher than under a proportional quota. This evidence suggests that current groundwater allocations may be significantly misallocated. While the uniform quota scenario provides an informative benchmark, it is politically unpopular and agronomically infeasible in regions with diverse crop types and water needs. Moving forward, I will assess the impacts of groundwater trading relative to proportional quotas as the baseline.

SGMA with groundwater trading Allowing trading of water allocation will recover approximately 57% and 26% of revenue and employment *losses* from the proportional quota policy counterfactual, respectively. The last column of Table 2 shows the gains (or losses) from trade relative to the proportional quota regime. The revenue and employment gain from water trading amounts to $4 billion in 2017 dollars (8% of reported sectoral revenue) and 24,000 jobs – corresponding to a 22% and 20% increase, respectively. These numbers are approximately twice as large as Escriva-Bou et al. (2023)'s estimates of $1.9 billion and 14,000 jobs gained from local water trading.

Counter to much of the public discourse, I estimate that total agricultural employment will rise under groundwater markets relative to a command-and-control approach using either quota systems under SGMA. However, these gains are accompanied by a 3.7-fold increase in farm exits (+ 5,600)

[31] Groundwater basins in Fox Canyon, Las Posas Valley Basin, and Mojave have adjudicated allocations using proportional (or "pro-rata") bases (Heard et al., 2021). This method is popular as it is deemed more equitable.

[32] San Joaquin Valley comprises eight of the highest crop-producing counties in California including Fresno, Kern, and Tulare.

Table 2: Comparison of outcomes across different groundwater policy counterfactuals for a moderate (25%) and aggressive (35%) groundwater cutback scenario.

Outcome	No cutbacks (B)	Uniform quota (U)	Proportional quota (Q)	Market (M)	% $\Delta^{B\to Q}$	% $\Delta^{Q\to M}$
A. Moderate cutback scenario (25%)						
Revenue (M$)	24656	19147	17731	21713	-28	22
Employment (000' jobs)	216.3	129.3	122.6	146.6	-43.3	19.6
Avg farm revenue (M$)	1.05	0.94	0.84	1.48	-20.30	76.80
Farms in production	21810	20291	20291	14667	-7	-28
Farm concentration (HHI)	14.3	32.6	17.6	27.2	23.1	54.5
B. Aggressive cutback scenario (35%)						
Revenue (M$)		16866	14749	19969	-40	35
Employment (000' jobs)		112.5	101.0	133.7	-53.3	32.4
Avg farm revenue (M$)		0.83	0.73	1.48	-30.80	103.60
Farms in production		20291	20291	13502	-7	-34
Farm concentration (HHI)		36.0	18.0	28.0	25.9	55.6

Note: Table shows the simulated outcomes in each row across different policy counterfactuals (columns 3-5) against the baseline in column 1 for a moderate cutback scenario (25%) in Panel A and for an aggressive scenario (35%) in Panel B. Column 6 shows the percentage change when imposing a proportional quota to achieve the cutback from baseline outcomes in column 1. Column 7 shows the percentage change when allowing for groundwater trading from the proportional quota scenario (% difference between columns 4 and 5). Employment is reported in full-time equivalents (2,080 hours); due to the seasonal and part-time nature of agricultural work, each job typically corresponds to more than two unique workers. HHI=Herfindahl-Hirschman Index, a measure of farm concentration, with higher values indicating greater concentration.

of numerous smaller farms. The average revenue of an operating farm increases by 77% from $0.84 to $1.48 million. The decline in the number of farms and increase in average farm size following the introduction of groundwater trading reflect a shift in farm size distribution, where smaller and less efficient producers exit the market, and remaining operations expand, as captured by the 55% rise in the HHI measure of farm concentration.

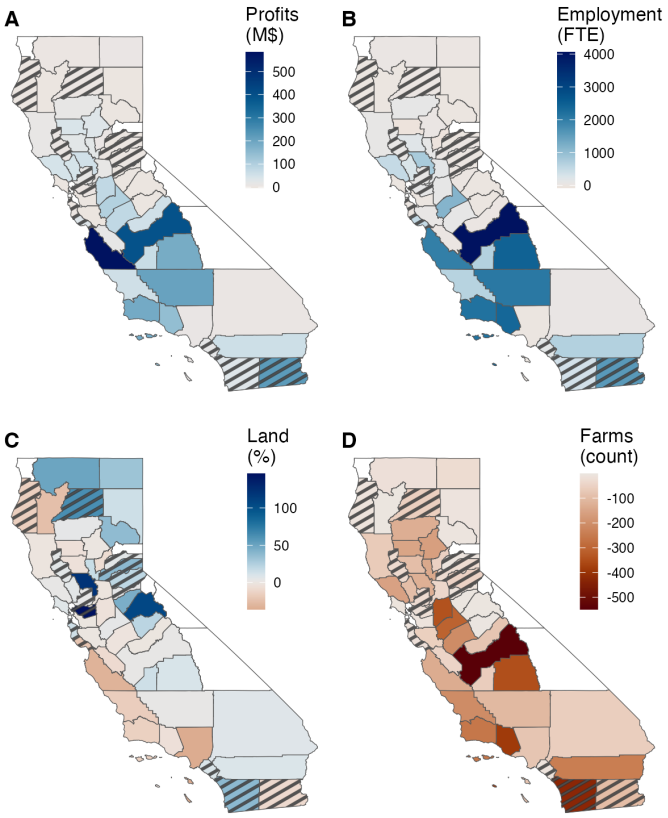
Gains from groundwater trading are more pronounced when groundwater cutbacks are more aggressive. Under the 35% cutback scenario, revenue and employment gains increase to 35% and 32%, respectively. The average farm revenue increases to $1.48 million, similar to the 25% scenario, which suggests that the same farms are buying up water to make up for the 35% shortfall to stay in production, as in the 25% scenario.

Groundwater trading and crop composition Overall, my analysis indicates that groundwater markets will facilitate a shift in water allocation toward higher-value crops such as vegetables, berries, and tree nuts; at the expense of crops like citrus, grapes and vineyards, and other non-citrus fruits (Figure A.3). This reallocation is driven by the relatively higher marginal revenue per unit of water offered by berries ($2,395) and vegetables farms ($2,185, Figure 3). However, because farms' crop specialization are kept fixed, reallocation is constrained by current land use patterns. If farmers are more likely to switch to these higher-value crops under a groundwater market, I may have underestimated revenue and employment gains from trade; if they are more inclined to do so under the quota settings, the estimates will be biased upward.

Recent studies on the effects of increased water prices and scarcity identify land retirement and shifts toward high-value annual crops as the most significant long-run responses (Burlig et al., 2025; Hagerty, 2022). Burlig et al. (2025) finds that a 60% tax on groundwater will cause 9% of farms to fallow; leading to a 50% rise in fallowing. However, as mentioned, it is not clear in which direction the crop-switching adaptation will affect the gains from trade analysis, as farmers are implicitly facing a higher price under more constrained groundwater supplies under the quota regimes as well. While my model captures land retirement and the reallocation of water to *existing* high-value annual crops, it does not consider crop switching. I omit this analysis due to the uncertainties in individual farm-level switching costs, as well as the complexities of soil suitability, local climate adaptability, and other enabling conditions that determine crop switching.

Heterogeneous impacts from trade across county Figure 7 illustrates results from the gains from trade analysis at the county level. The outcomes mapped are farm profit, employment, acres in production, and farm counts. In the following section, I limit my discussion to counties that are groundwater-dependent, relying on groundwater for over 60% of their irrigation.

Figure 7: County-level economic and reallocative gains (or losses) from groundwater trade relative to proportionate quota allocations.



Note: County economic outcome change from allowing trading (market) after a 25% proportional groundwater reduction (quota). **A** farm profits, **B** employment (FTE), **C** land in farms (acres), and **D** farm counts. Counties that are consistently supplied by over 40% surface water are overlaid with a stripe pattern.

Farm profits and employment (Figure 7A, B) increase by varying degrees across California. Profit gains tend to spatially correlate with employment gains. Counties with larger gains from trade tend to be located in the southern half of California. The three counties with the largest profit gains from groundwater trade are Monterey, Fresno, and Kern: between $200-500 million in annual profit gains. The three counties with the largest employment gains from groundwater trade are Fresno, Tulare, and Ventura with 2,000-4,000 FTE gains annually. Notably, these counties are characterized by a high share of labor-intensive and high-value vegetable and berry farms, as shown in Online Appendix Figure A.8. Online Appendix Section C.1 shows that the profit and labor gains from trade are increasing in the deviations of the marginal return to water across farms; which depends on crop price differentials, relative water productivity, water-labor productivity correlations, and input prices. The existence of high-value crops such as lettuce, cauliflower, and strawberries; which dominate these counties, drives large deviations in marginal return to water. Groundwater markets enable such high-value farms to maintain or expand production despite cutbacks in overall groundwater. Online Appendix Table A.12 shows that counties with higher across-crop HHI index, which measures crop diversity, are predicted to have larger profit and labor GFTs.

Figure 7C shows changes in the acres in operation across counties from groundwater trade. The median county sees 5% of land fallowing, but effects vary from around 30% fallowing in Monterey to over 100% *increase* in acreage in northern counties such as Tuolumne and Yolo. These opposing effects are likely driven by the relative type of farms that remain in production in each county. Central coast counties such as Monterey, Santa Barbara, and Ventura tend to specialize in berry and vegetable farms, which tend to be smaller as opposed to the larger field crops farms that dominate the agricultural landscape in the north (Online Appendix Table A.2). I also estimate losses in the *number* of operational farms (Figure 7D) in all counties under a groundwater market. Fresno, Ventura, and Tulare, some of the counties with the largest economic and employment gains, will see the largest losses in farm counts (400–500).

Water price The market price of groundwater will vary widely across counties. Figure A.1 shows that water price ranges from a minimum of $22/AF in Plumas to $723/AF in Monterey. The counties with the highest water prices are concentrated in the Central Coast and South Coast regions due to their larger share of high-value vegetable and berry crops (Online Appendix Figure A.8). This finding aligns with the analytical result in Online Appendix Section C.1, which shows that the market-clearing groundwater price equals a proxy of the average farm marginal return to water within the trading region. The existence of relatively high marginal return farms drives large profit and employment GFTs for these counties. In such areas, the economic loss from an acre-foot of misallocated water is greater, leading to larger gains from groundwater trade. On the other hand, counties with lower groundwater prices are primarily located in the northern third of California, where many farms produce water-intensive crops (e.g., hay and rice), which have lower marginal returns to water.

7 Conclusion

This paper responds to growing calls to quantify the reallocative consequences of environmental markets for small producers and workers. In doing so, I develop a new microfounded framework that accounts for the joint distribution of water value and attributes underlying political opposition (i.e., size and labor intensity) across users. Leveraging rich farm-level data, the framework estimates non–Hicks-neutral production functions to account for heterogeneous input productivities, crop choice, and scale. Although designed to measure reallocative effects, the fine-grained heterogeneity embedded in the data also improves the model's ability to predict welfare gains from trade.

Overall, my findings suggest that implementing groundwater markets in California can yield significant efficiency, output, and employment gains relative to command-and-control management, but the magnitude and sign vary across locations. Groundwater markets will favor larger, more productive farms, leading to increased farm consolidation through the exit of smaller operations. In regions with high crop diversity, water markets also reallocate water toward higher value and more labor-intensive crops, contributing to both higher economic returns and increased employment.

These findings corroborate concerns over small farm viability expressed by stakeholders (California Water Commission, 2022). Should water price be allowed to reflect its true value in a frictionless market, price per acre-foot of water for the median county (Figure A.1) could go up to as much as 15 times the current volumetric rate ($20) charged by the State Water Resources Control Board (CA SWRCB, 2025). Smaller farms, who are observed to be less water-efficient, are more likely to sell their quota allocation, while larger farms are likely to buy quotas. The results reveal an inherent tension between maximizing aggregate production and employment, and preserving farm diversity and the presence of small-scale producers in California.

More broadly, these findings highlight that trading environmental resources implicitly involves reallocating across other dimensions – such as labor, land, or environmental quality – when high-value users differ systematically in these dimensions. In these cases, market-based reallocation may lead to unintended socioeconomic or environmental consequences. For instance, farm-to-urban water trade may decrease supplemental streamflows, transferable quotas in fisheries may increase export of local food supply, and trading pollution credits may concentrate pollution in disadvantaged communities.

I conclude with directions for future research. Future work could examine the hydrogeological implications of market-based groundwater reallocation. Gains from trade may be constrained – or even reversed – if high-value farms impose larger externalities. This can happen if marginal productivity is systematically correlated with environmental damage – either because they have caused it (e.g., land subsidence) or through hydrological connections to aquifers supplying drinking water. In such cases, pumping reallocation caused by groundwater markets could cause further land subsidence, drinking water wells to run dry, or raise contaminant concentrations (Sum, 2024).

Second, future research could incorporate broader margins of farm adjustment. The current framework assumes that farms adjust only on the intensive margin – by scaling production of their existing crop type at the estimated water and labor productivities consistent with observed behavior – or by exiting altogether. In practice, farms may also adapt through crop switching or technology adoption, although both take time and resources. As implementation of SGMA progresses and richer data become available on land-use suitability and capital investments, future work can extend the model to capture these adaptive margins and their implications for long-run efficiency and reallocative outcomes.

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Online Supplementary Appendix for

"Trading the Commons: Reallocative Impacts of Environmental Markets"

Sandy Sum

A Supplemental Figures and Tables

Table A.1: The labor cost share of various crop types and their harvest method and rank (by value) in California.

Crop	Harvest Method	Labor Cost Share	Value (billion) (Rank)
Almonds	**Machines**	**10%**	5.6 (1)
Miscellaneous[33]	Hand	40-60%	5.0 (2)
Grapes (Table)	Hand	30-50%	4.5 (3)
Grapes (Wine)	Both	10-30%	4.5 (3)
Pistachios	**Machines**	**9%**	2.9 (4)
Lettuce	Hand	60%	2.3 (5)
Strawberries	Hand	40-60%	2.0 (6)
Tomatoes	Hand	30-40%	1.2 (7)
Oranges	Hand	20-40%	1.1 (11)
Walnut	**Machines**	**10%**	1 (9)
Broccoli	Hand	50%	0.68 (13)
Carrots	Both	20-40%	0.66 (15)
Asparagus	Hand	70-80%	
Cotton	**Machines**	**3-6%**	
Apples	Both	25-30%	

Note: Red text indicate mechanized crop types.
Sources: Calvin and Martin (2010); Calvin et al. (2022)

Table A.2: Summary statistic of farm variables over 2007, 2012, and 2017 for farms in California, separated by crop type (columns).

Crop type	berries N = 1,179	citrus N = 7,514	field crops N = 5,329	grape vineyards N = 19,820	nursery greenhouse N = 4,898	other non-citrus fruit N = 14,416	tree nut N = 16,755	vegetable and melon N = 4,010
Revenues ($)	431,000	60,000	237,000	100,000	186,000	30,000	120,000	221,000
	[87,000, 3,067,000]	[15,000, 256,000]	[50,000, 560,000]	[33,000, 320,000]	[30,000, 801,000]	[9,000, 101,000]	[36,000, 450,000]	[36,000, 2,392,000]
Production (ton)	122	83	605	71	138	21	47	431
	[25, 821]	[22, 331]	[128, 1,461]	[21, 257]	[23, 637]	[6, 78]	[14, 174]	[65, 4,752]
Labor income share	0.41	0.24	0.13	0.38	0.35	0.35	0.15	0.30
	[0.20, 0.58]	[0.11, 0.48]	[0.06, 0.32]	[0.21, 0.63]	[0.18, 0.58]	[0.18, 0.64]	[0.07, 0.29]	[0.15, 0.55]
Energy income share	0.02	0.09	0.07	0.03	0.05	0.12	0.05	0.04
	[0.01, 0.06]	[0.04, 0.21]	[0.03, 0.15]	[0.02, 0.07]	[0.02, 0.12]	[0.04, 0.41]	[0.03, 0.10]	[0.02, 0.09]
Water prod ($/AF)	1,654.44	383.41	250.28	703.48	695.33	216.22	429.28	748.03
	[554.47, 3,831.22]	[152.00, 838.95]	[109.84, 607.26]	[305.60, 1,559.25]	[265.98, 1,687.01]	[86.12, 657.80]	[193.19, 958.48]	[296.57, 1,800.96]
Labor prod ($/hour)	26.81	54.29	95.90	34.59	35.93	33.12	83.67	41.45
	[17.86, 55.24]	[26.73, 112.45]	[39.36, 226.54]	[20.65, 59.19]	[21.36, 70.49]	[17.80, 67.11]	[43.03, 178.30]	[22.73, 85.55]
Labor/Water exp (ratio)	16	2	2	11	7	3	3	7
	[5, 44]	[1, 6]	[1, 6]	[5, 26]	[3, 17]	[1, 9]	[1, 6]	[3, 17]
Acres harvested	20	18	248	20	5	9	40	31
	[5, 90]	[5, 60]	[75, 550]	[8, 68]	[2, 15]	[3, 30]	[15, 140]	[6, 350]
Price ($/ton)	3,469	746	383	1,284	1,271	1,462	2,498	640
	[3,230, 3,968]	[584, 933]	[341, 435]	[859, 2,183]	[1,195, 1,414]	[1,088, 1,838]	[2,366, 2,914]	[485, 727]
Exp. labor ($)	193,000	15,000	26,000	40,000	57,000	10,000	17,000	85,000
	[22,000, 1,159,000]	[4,000, 58,000]	[6,000, 80,000]	[12,000, 130,000]	[10,000, 291,000]	[3,000, 40,000]	[4,000, 73,000]	[13,000, 600,000]
Exp. land and buildings ($)	2,000	0	1,000	0	0	0	0	4,500
	[0, 67,000]	[0, 0]	[0, 47,000]	[0, 0]	[0, 12,000]	[0, 0]	[0, 0]	[0, 79,000]
Exp. intermediate material ($)	21,956	4,971	33,070	7,500	13,659	3,017	10,000	27,105
	[4,925, 116,119]	[1,342, 18,000]	[8,600, 91,419]	[2,500, 24,325]	[3,500, 57,553]	[1,000, 10,076]	[3,000, 36,252]	[5,162, 215,060]
Exp. soil preparation ($)	33,418	7,000	51,150	7,127	12,675	2,500	16,457	23,750
	[4,538, 295,845]	[1,267, 30,069]	[7,916, 141,884]	[2,000, 25,926]	[1,735, 101,302]	[630, 10,370]	[4,200, 68,000]	[4,642, 390,313]
Received surface water (yes)	65 (7%)	1,728 (26%)	1,612 (36%)	2,060 (12%)	229 (6%)	1,537 (12%)	2,917 (20%)	434 (14%)

Median [IQR]; n (%); prod: short for productivity.

Note: Summaries are over farm-level data from the 2007, 2012, and 2017 Census of Agriculture by National Agricultural Statistics Service, United States Department of Agriculture (NASS USDA).

All summary statistics are weighted to adhere to disclosure protocol.

Any interpretations and conclusions derived from the data represent author viewpoints and are not necessarily those of NASS.

Table A.3: Summary statistics (mean and standard deviation in parentheses) of farm water value (revenue less non-water variable costs), value of production, and acres operated by farm organizational type.

Organization type (N)	**Water value** ($/AF)	**Value of prod.** (million $)	**Acres in prod.**
Others (2,369)	542	0.9085	262
	(2016)	(0.4292)	(1245)
Family (44,941)	620	0.3063	111
	(10600)	(0.1640)	(680)
Partnership (7,757)	834	1.823	440
	(4203)	(6.836)	(1928)
Corporation (8,067)	877	3.563	673
	(5785)	(11.83)	(2041)

A.1 Regression tables for water and land output elasticities

Table A.4: Production Function Estimates: Berries

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.0739^{+}	0.0808^{+}	0.356^{**}
	(0.0376)	(0.0450)	(0.135)
log Land (Acres)	0.7801^{***}	0.767^{***}	0.904^{***}
	(0.0965)	(0.0930)	(0.154)
Fit statistics			
Observations	426	211	426
R^2	0.976	0.285	0.890
Adjusted R^2	0.951	0.278	0.890

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.5: Production Function Estimates: Citrus

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.0679^{***}	0.0585^{***}	0.0934^{*}
	(0.0153)	(0.0149)	(0.0412)
log Land (Acres)	0.869^{***}	0.8751^{***}	0.9870^{***}
	(0.036)	(0.0347)	(0.0288)
Fit statistics			
Observations	4011	2250	4011
R^2	0.948	0.248	0.855
Adjusted R^2	0.907	0.248	0.855

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.6: Production Function Estimates: Field Crops

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.0517***	0.0712***	0.0481+
	(0.0123)	(0.0125)	(0.0274)
log Land (Acres)	0.883***	0.8623***	0.914***
	(0.024)	(0.0296)	(0.021)
Fit Statistics			
Observations	1409	771	1409
R^2	0.962	0.556	0.829
Adjusted R^2	0.929	0.555	0.829

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.7: Production Function Estimates: Grapes

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.07445***	0.11210***	0.2440***
	(0.00954)	(0.00943)	(0.0476)
log Land (Acres)	0.7523***	0.7087***	0.800***
	(0.0279)	(0.0249)	(0.037)
Fit Statistics			
Observations	9992	5630	9992
R^2	0.940	0.167	0.824
Adjusted R^2	0.894	0.167	0.824

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.8: Production Function Estimates: Other Non-Citrus Fruit

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.0985***	0.106***	0.1629***
	(0.0124)	(0.0120)	(0.0447)
log Land (Acres)	0.7508***	0.723***	0.9435***
	(0.0461)	(0.0320)	(0.0328)
Fit Statistics			
Observations	6575	3502	6575
R^2	0.925	0.157	0.809
Adjusted R^2	0.860	0.157	0.809

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.9: Production Function Estimates: Tree Nuts

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.09352***	0.1215***	0.1104**
	(0.00969)	(0.0101)	(0.0341)
log Land (Acres)	0.7665***	0.7147***	0.976***
	(0.0256)	(0.0259)	(0.027)
Fit Statistics			
Observations	10373	5870	10373
R^2	0.942	0.158	0.852
Adjusted R^2	0.897	0.158	0.852

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.10: Production Function Estimates: Vegetables and Melons

Dependent Variable:	log Output		
Model:	FE	FD	ACF
Variables			
log Water (AF)	0.1169***	0.1151***	0.4119***
	(0.0272)	(0.0232)	(0.0928)
log Land (Acres)	0.7457***	0.7497***	0.7129***
	(0.0488)	(0.0429)	(0.0789)
Fit Statistics			
Observations	1537	825	1537
R^2	0.974	0.340	0.920
Adjusted R^2	0.952	0.339	0.919

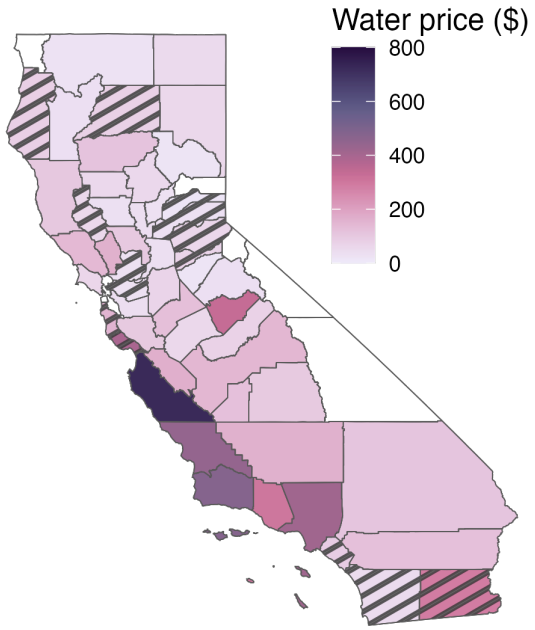
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, +: 0.15*

Notes: FE = fixed effects; FD = first differences; ACF = Ackerberg–Caves–Frazer production function estimator with a linear control construction from farm-level observed harvesting, transportation, and storage inputs. Std. errors clustered by farm id in FE. Estimated coefficient on log Water (AF) correspond to production term β_{cW}, the water output elasticity. Estimated coefficient on log Water (AF) correspond to production term β_{cK}, the land output elasticity.

Table A.11: Quantiles of key observed and model-predicted outcomes.

Metric	**Min (0%)**	**1st Qu. (25%)**	**Median (50%)**	**3rd Qu. (75%)**
Yields (Data)	0.000	11.2	55.0	292
Yields (Predicted)	0.0008	15.8	61.5	304
Labor (Data)	0.000	184	1520	7540
Labor (Predicted)	0.000	330	1420	6140
Water (Data)	0.0155	67.6	231	761
Water (Predicted)	0.000	36.0	223	1080

Figure A.1: Simulated groundwater trading price across counties.



Note: Figure maps the estimated market-clearing groundwater price for each county when groundwater is reduced by 25%. The market-clearing price is obtained via a numerical search starting from $1 and iteratively increasing until net water demand in each county equals net water supply.

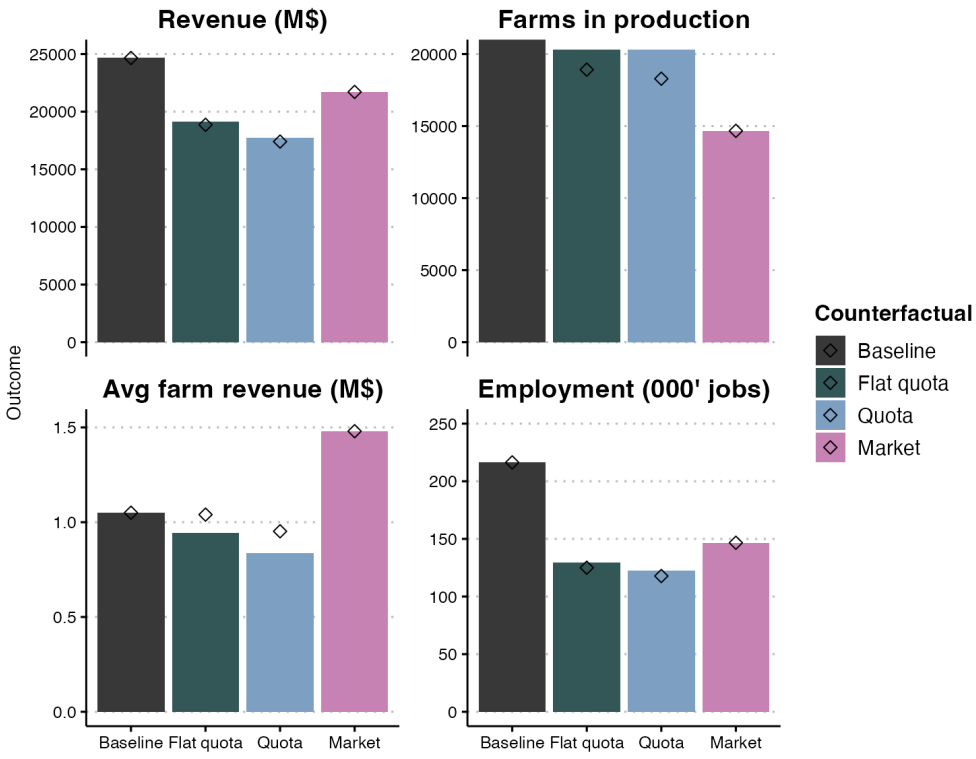
Table A.12: The relationship between the variance of farm water productivity, crop diversity index, and predicted gains from groundwater trade.

Dependent Variable:	$\log \Delta^{Q \to M}$		
Metric	$p \cdot Y$	π	L
Model:	(1)	(2)	(3)
Variables			
$\log \text{var}(MRPW\|_Q)$	0.786***	0.823***	0.715***
	(0.072)	(0.066)	(0.082)
$HHI-$index	-1.26	-1.61**	-1.72*
	(0.856)	(0.755)	(0.943)
Fit statistics			
Observations	48	50	47
R^2	0.72766	0.76961	0.63998
Adjusted R^2	0.71556	0.75981	0.62361

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

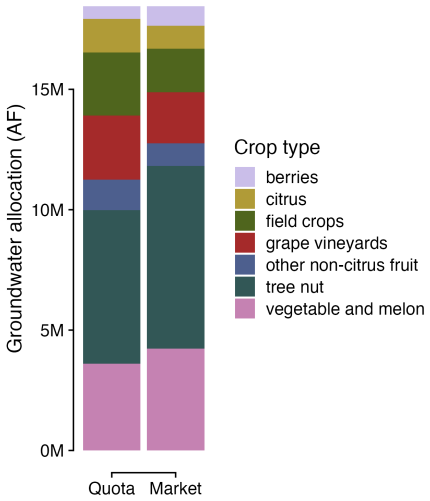
Notes: $MRPW = \frac{\partial \pi}{\partial W_Q}_i$
Columns represent different measures of economic metric: 1. revenue, 2. profit, and 3. labor demand (3).
HHI = the Herfindahl–Hirschman index, a commonly used measure of cross-sector concentration

Figure A.2: Economic and reallocative outcomes over three groundwater policy counterfactuals with the baseline for comparison under different assumption on farm shut-down condition.



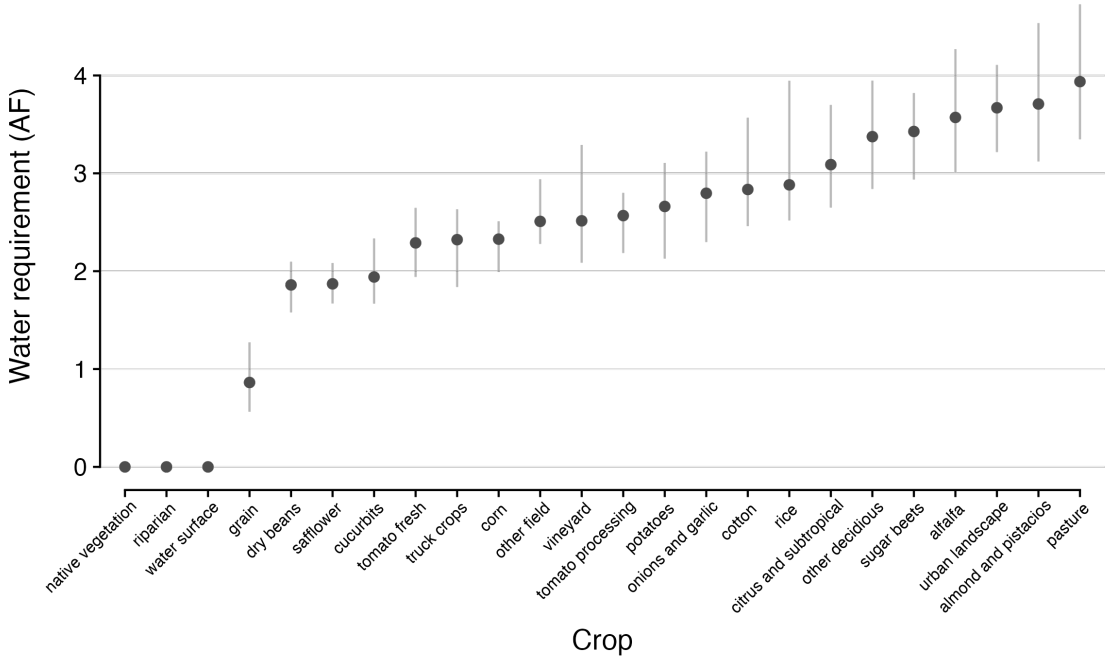
Note: Estimated (and observed for baseline) outcomes over baseline and three groundwater policy counterfactuals: baseline in gray-black; uniform quota (dark green, e.g., each farm gets 0.75 AF/acre), proportional quota (blue), and market (pink). Colored bars depict estimates when assuming that farms do not shut down when faced with negative profits in the flat and proportional quota setting, the dots depict estimates with the shutdown condition. The top row shows net farm revenue and average farm value, while the bottom row shows employment (full-time equivalents), and acres planted (thousand acres).

Figure A.3: Crop composition under different groundwater policy counterfactuals.



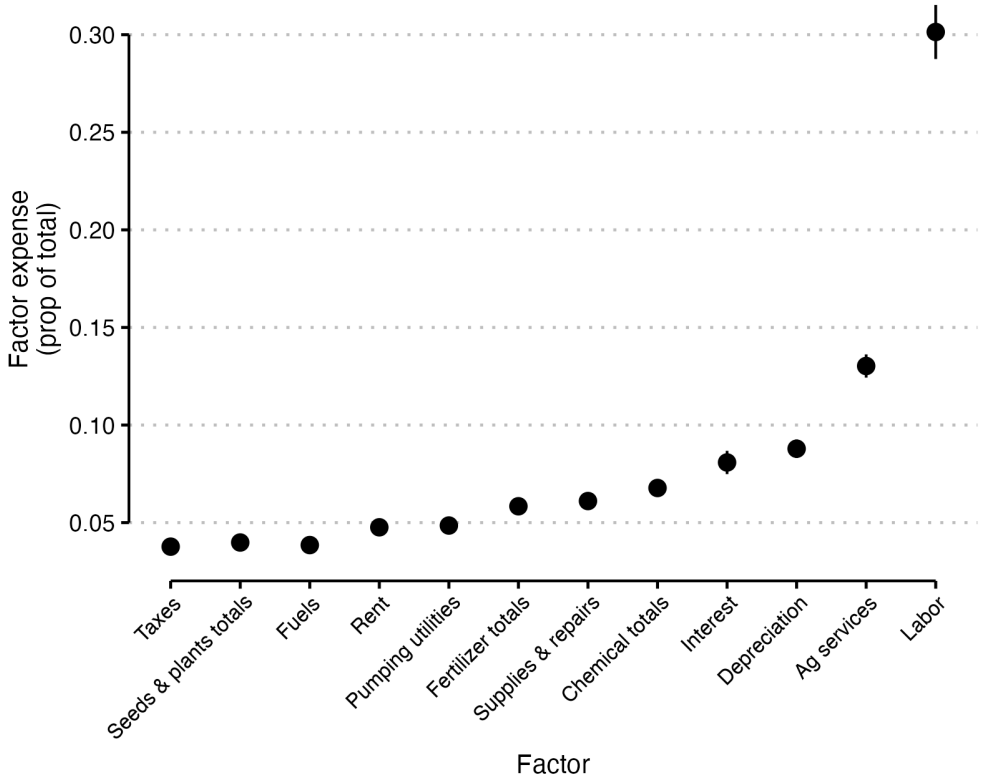
Note: Aggregate water allocation by crop type for a proportional quota on groundwater (left) and a market (right). Overall, we see that water will be allocated to berries and vegetables and melons at the expense of grape vineyards, citrus, field crops, and other non-citrus crops.

Figure A.4: Crop applied-water requirements in California.



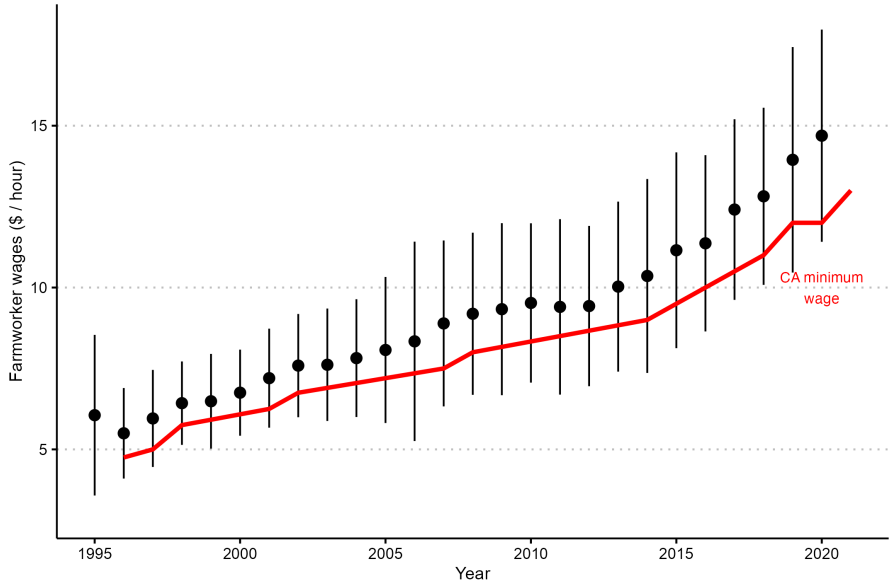
Note: Applied water requirements by crop based on outputs from the Cal-SIMETAW model, which simulates daily soil water balance to estimate crop evapotranspiration (ETc), evapotranspiration of applied water (ETaw), and applied water (AW) under the assumption of 100% irrigation efficiency. The figure displays median applied water (in acre-feet per acre) for each crop, aggregated over counties and years, with vertical lines indicating the interquartile range (25th–75th percentiles) to reflect spatial and temporal variability in water needs.)

Figure A.5: Farm factor cost share in California.



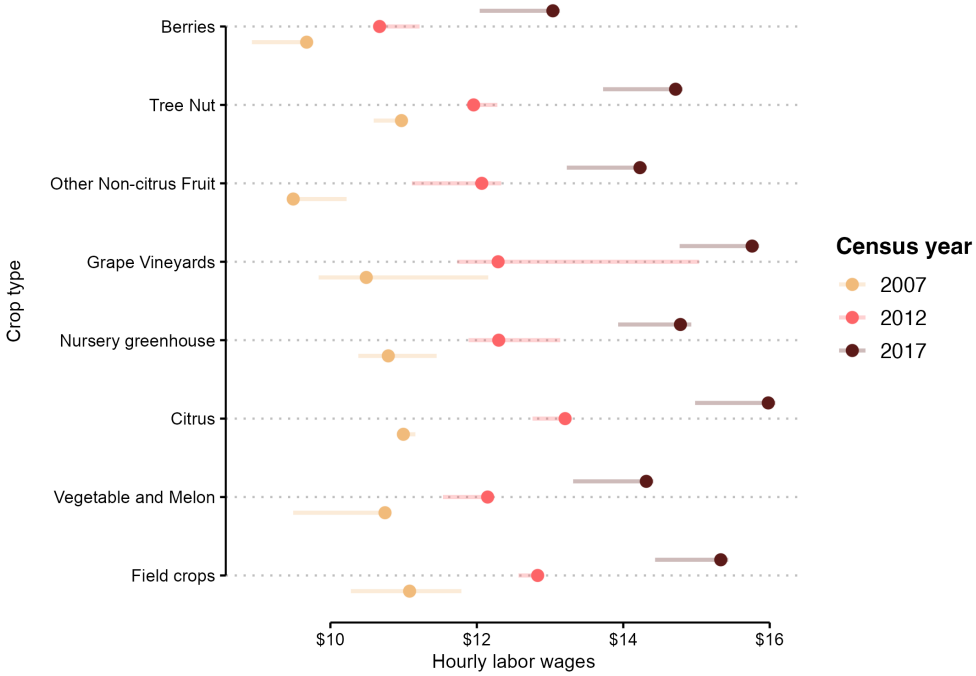
Note: Average (dot) and standard deviation (lines) of factor cost shares of farms in California in 2017. **Source:** Author's calculation based on public data from the National Agricultural Statistics Service, United States Department of Agriculture (NASS USDA).

Figure A.6: Average farm wages across California, 1995-2025.



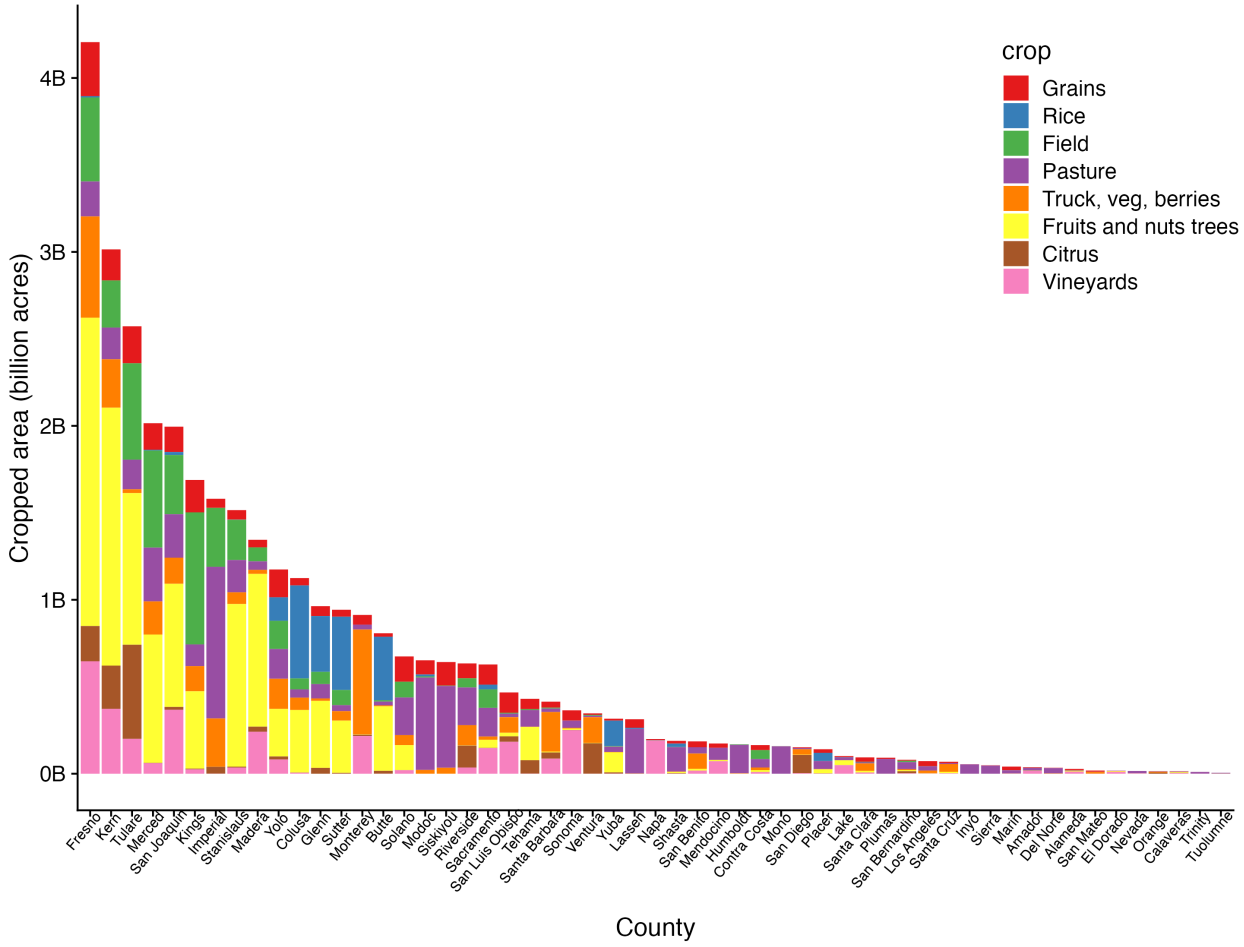
Note: The red line indicates the California minimum wage. **Source:** Author's calculation from the National Agricultural Workers Survey.

Figure A.7: Variation in crop worker wages over census years.



Source: Author's calculation based on public data from the National Agricultural Statistics Service, United States Department of Agriculture (NASS USDA).

Figure A.8: California county crop composition in year 2022.



Source: Author's calculation based on data from the California Department of Food and Agriculture (CDFA).

B Background and Data Appendix

California presents a useful and relevant setting to study the potential reallocative and employment impacts of agricultural water markets. It is the largest and most diverse agricultural state in the US, with almost 900,000 employed in farm jobs annually (Hooker et al., 2024). In 2024, the state's farms produced 16% ($61.2 billion) of crop cash receipts and over two-thirds of the total vegetable, fruit, and nut crops in the U.S. (USDA, 2024). It is the only state in the U.S. to produce and export many water-intensive specialty crops. Over the past decades, farm cash receipts have continued to rise through technological innovations, shifting crop composition, and rising demands for many of California's high-value crop specialties such as almonds, grapes, and strawberries. Agricultural production is geographically concentrated in the Central Valley, a 20,000-square-mile region characterized by fertile soils and a Mediterranean climate. This unique environment enables the production of a highly diverse set of crops but also makes the region reliant on intensive water use. Compared to the rest of the country, farms in the Central Valley are both water- and labor-intensive, and virtually all farmland is irrigated by a combination of surface water and groundwater.[34]

B.1 Agricultural water use

In the past few decades, reductions in surface water deliveries due to prolonged drought conditions and species conservation regulations have led to increased reliance on groundwater, a previously unregulated source. Recent studies using remotely-sensed water storage measurements show persistent and accelerating depletion of groundwater in the Central Valley since the early 1900s (Famiglietti et al., 2011; Liu et al., 2022).

Over the same period, California's acreage of specialty water-intensive crops has increased significantly. For example, almond acreage expanded from 500,000 acres in 2000 to 1,500,000 acres in 2020. Almonds, along with other perennial fruit and nut tree crops, are particularly vulnerable to water supply variability, as they require year-round irrigation exceeding 3 acre-feet per year just to remain viable (Haviland et al., 2019). These trends, along with the aforementioned groundwater depletion over the past two decades, have raised critical concerns regarding the long-term viability of current cropping patterns and groundwater use. Furthermore, groundwater declines have led to wells drying, land subsidence, degrading water quality, and seawater intrusion (CADWR, 2018), prompting the implementation of the Sustainable Groundwater Management Act (SGMA).

B.2 Sustainable Groundwater Management Act

SGMA, implemented during the height of the historic 2012-2017 drought in the Western United States, is a landmark legislation that required the formation of Groundwater Sustainability Agencies (GSAs) to independently plan and execute policies for achieving sustainable groundwater water use by

[34]The allocation of surface water is highly engineered and facilitated by an array of canals and aqueducts that redirect water – from snow melt, rivers, lakes, and reservoirs (primarily in Northern California) – to water users all over the state.

2042 (California Legislature, 2015). These GSAs are tasked with creating and executing Groundwater Sustainability Plans (GSPs) to achieve a stable groundwater level that mitigates six undesirable results.[35] The first decade of SGMA implementation focused on delineating hydrologically connected basins, establishing GSAs, engaging stakeholders, and identifying the "sustainable" groundwater level to target in light of the six undesirable impacts defined by the Act. This period also involved the development of comprehensive long-term plans designed to achieve sustainable groundwater management.

Many GSAs have proposed groundwater quotas, and over half are considering implementing a water market or price-based approaches to achieve groundwater reductions. The first groundwater market implemented under SGMA began trading in Ventura County in 2020, followed by a pilot trading program launched in Tulare County in 2024 (Bruno et al., 2022; Heard et al., 2021).[36] Furthermore, SGMA enables overlying groundwater rights-holders to trade water rights and participate in subbasin-scale groundwater governance, facilitated by GSAs. While GSAs are now authorized to implement extraction restrictions and create trading systems, they are not authorized to approve cross-basin trade (Cal. Water Code § 10720.5). Therefore, SGMA has significantly minimized conventional transactional and legal barriers to water trading within basins but not across basin boundaries. This renders California a particularly policy-relevant setting for exploring the varied consequences of water markets.

B.3 Agricultural employment

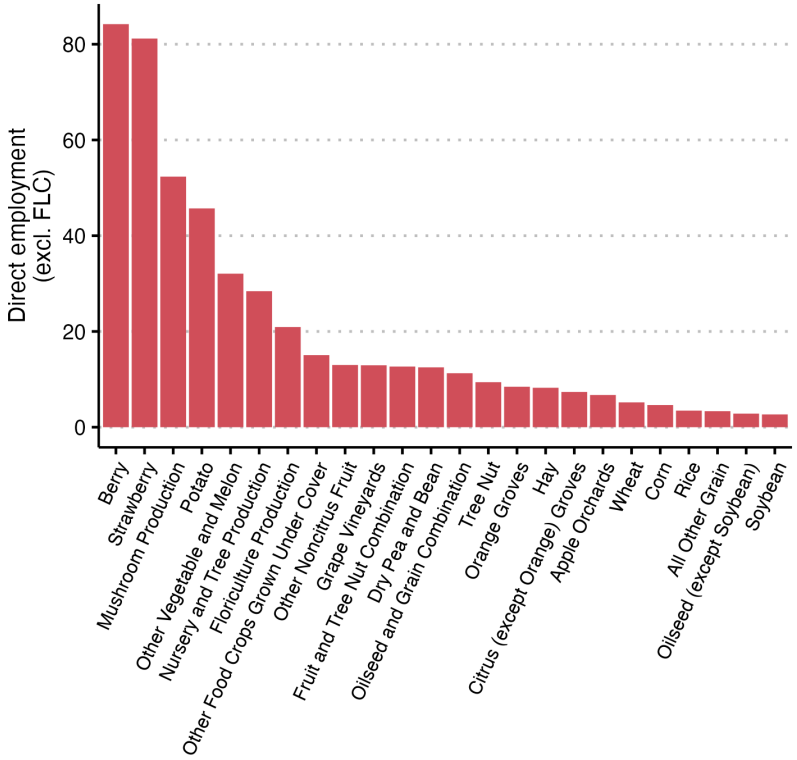
Agriculture in California is relatively labor-intensive and high-value compared to those of other states. An acre of midwestern corn or soybeans is valued at $700-$1,500, while an acre of strawberries in Santa Barbara can easily generate over $100,000 (Martin, 2023). Farm workers are needed in a variety of roles in these high-valued fruits and nuts, vegetables and melons, and horticultural specialty (FVH): crop planters, harvesters, graders and sorters, agricultural inspectors, supervisors, and managers. Appendix Figure A.5 shows that labor takes the largest cost share of all required factors of production at around 30% in 2017.

Agricultural income, employment, and wage depend on crop composition and acreage within the state as labor intensity varies significantly across crop types (Calvin and Martin, 2010). Figure B.9 shows that farms specializing in annual crops such as berries, mushrooms, and vegetables tend to hire more farm workers (50-80 average monthly employment) than farms specializing in perennial tree crops such as tree nuts and orange groves (approximately 10 average monthly employment). This is because annual crops for the fresh market, as opposed to those for the processing market

[35] The undesirable effects include chronic lowering of groundwater levels, reduction in groundwater storage, seawater intrusion, degraded water quality, land subsidence, and negative impacts on beneficial uses of interconnected surface waters.

[36] M. Fienup, the project lead for the state's first operational groundwater market in Fox Canyon, Ventura, noted that nearly all of California's 34 adjudicated basins are exploring the use of market-based mechanisms, such as auction-based fallowing programs to manage groundwater cutbacks (personal communication, August 29, 2023).

Figure B.9: Average monthly direct employment per farm by crop type.



Note: The graph plots average monthly farm direct employment by crop type over 2004-2022. **Source:** Author's calculation using data from the California Employment Development Department.

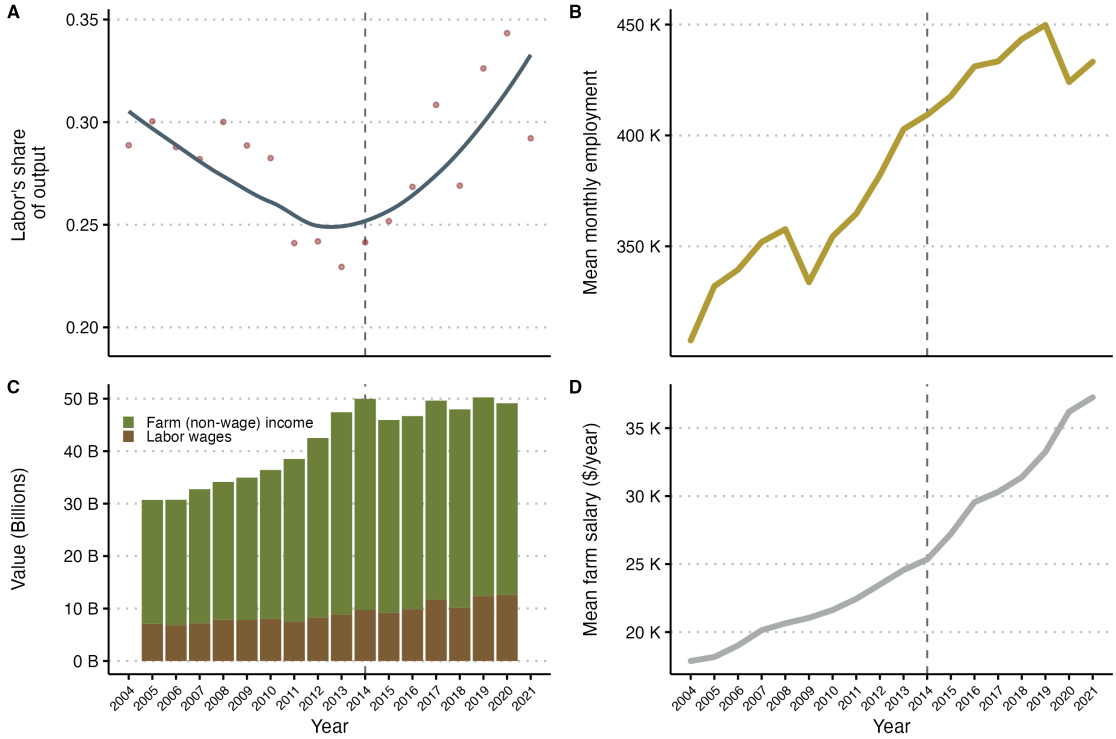
(e.g., for juicing or drying), are still handpicked as they are delicate and lose market value if bruised. Nut tree crops are labor-saving, as their output is hardy enough to be mechanically handled from harvest to shipping.[37] Appendix table A.1 shows that mechanically harvested crops tend to have lower labor cost shares as compared to hand-harvested crops.

In contrast to the falling trends observed in labor share in all other non-farm sectors in the U.S. and elsewhere globally, which have garnered attention from a vast literature seeking to pinpoint the underlying reasons (Bergholt et al., 2022; Grossman and Oberfield, 2021), farm labor share in California has been increasing since 2014. Figure B.10A shows that labor share increased from a low of 25% in 2013 to almost 35% in 2021. Panel B and D of Figure B.10 show increasing monthly employment and salaries since 2004 with sharp but short drops in farm employment during the 2007-2009 recession and the 2019 COVID pandemic outbreak. The increase in farm wages has primarily been driven by the rising California minimum wage, which also applies to agricultural workers (Appendix Figure A.6). These trends suggest that agriculture in California is becoming increasingly labor-intensive, likely driven by the increased demand for labor-intensive high-value

[37] Most nuts are harvested with shaker machines. These nuts are shaken when ripe, fall to the ground, and then are scooped up off the ground with sweeper machines.

crops and fresh produce, along with constraints on mechanization.

Figure B.10: Various statistics of farm labor use in California's agriculture over 2004-2021.



Note: The graph plots **A** farm labor share, **B** mean monthly employment, **C** net income breakdown, and **D** mean farm labor salary from 2004 to 2021. The dotted line marks the year 2014, with two major policy roll-outs: the announcement of the Sustainable Groundwater Management Act (SGMA) and the beginning of annual hikes in California minimum wage after a hiatus of six years since the last minimum wage increase in 2008.

While exact figures do not exist, there are an estimated individual 900,000 farmworkers in California who fill up around 410,000 full-time equivalent jobs (Hooker et al., 2024).[38] Since most farmworkers work part-time or seasonal jobs, there is an average of 2.1 unique workers for each average year-round equivalent job, which is typical (Martin et al., 2016). According to the 2015-2019 National Agricultural Workers Survey (NAWS),[39] the average farmworker is male (69%), in their early 40s (mean age), did not complete high school (93%), and speaks little to no English (36%, 35%). In the past few decades, the nature of farm work has shifted toward a more settled nature, 84% of farmworkers have lived in California for over 10 years and are long-time residents and workers in California (Ornelas et al., 2020).[40] Many farmworkers now reside with their families in agricultural

[38] Farm employers are required to enroll in the state's Unemployment Insurance (UI) system and to report the names and Social Security numbers (SSNs) of all of their employees, including H-2A guest workers. Hooker et al. (2024) counted the number of unique SSNs reported and the hours they log over 2018-2021.

[39] NAWS is designed to provide a representative and comprehensive picture of crop workers within the U.S. and California. It is a random-sample multistage survey that includes undocumented workers.

[40] 13% of farmworkers interviewed in the 2015-2019 NAWS self-identify as "migrant" workers in the sense that they travel for their job (e.g., follow-the-crop or domestic shuttle workers – the practice of moving from farm to farm for work)

communities across the Central Valley. Almost 60% of the farmworkers interviewed in the 2015-2019 NAWS are parents with a median of 2 children living with them in their households. These demographic characteristics suggest that transitioning into other forms of employment may be challenging for farmworkers, especially given language and educational constraints. Potential job losses resulting from SGMA and subsequent groundwater reductions could have far-reaching economic consequences, potentially leading to economic downturns in these rural communities.

B.4 Small and underrepresented farmers

In California, the agricultural sector is primarily composed of "small" farms, where approximately 80% generate less than $350,000 in gross income. Approximately one-quarter of these agricultural enterprises are managed by individuals from diverse backgrounds, including people of color, refugees, and immigrants, who farm a diverse array of truck crops such as beans, lemongrass, and eggplants (Atume and Voss-Gonzalez, 2022). Various reports and white papers on groundwater markets have cautioned about the impacts of groundwater trading and, in general, other management tools being proposed under SGMA on the viability of small and underrepresented farmers (e.g., California Water Commission, 2022; Ayres et al., 2021a). Focus group discussions conducted by the California Water Commission revealed that many perceived risks associated with water trading are related to potential power imbalances that may lead to overpriced groundwater. For instance, small farms that need more groundwater than their initial allocation to turn a profit may be unable to pay for additional water, threatening their viability. Tenant farmers may lose access to land if landowners choose to sell water allocations from leased parcels, if water becomes more valuable than rental income.[41] These key community concerns regarding small farm viability, economic diversity, and employment continue to influence public support for groundwater trading but remain largely unquantified. This paper seeks to provide new evidence on these reallocative impacts.

Categorizing farms into crop types I broadly categorize farms by their NAICS codes, which was provided as part of the census. However, due to farms in California specializing in a diverse array of high-value fruit and nut crops, with substantially differential input requirements and market / production statistics, I opted to use the 4-digit NAICS codes for some categories (as it makes sense to group them together, e.g., field crops) and a combination of several 8-digit NAICS codes for others (e.g., strawberries and other berries are grouped together in one category called "berries"). These defined categories, indicated in bold, and their underlying NAICS codes and labels are presented below. These categories are informed by reading about the dominant Californian agricultural "tribes" in Arax (2019).

1. **field crops.** 1111 Oilseed and Grain Farming

[41] Ruth Dahlquist-Willard, a small farms and specialty crops advisor at the University of California Cooperative Extension, captured this concern: "What is to prevent [a land owner] from deciding to sell the allocation with a piece of rented land instead of continuing to rent it? [Tenant farmers] are the people I'm most worried about" (Atume and Voss-Gonzalez, 2022).

2. **vegetable and melon.** 1112 Vegetable and Melon Farming
3. 1113 Fruit and Tree Nut Farming
   (a) **citrus.** 111320 Citrus (except Orange) Groves + 111310 Orange Groves
   (b) **berries.** 111333 Strawberry Farming + 111334 Berry (except Strawberry) Farming
   (c) **tree nuts.** 111335 Tree Nut Farming
   (d) **other non-citrus tree fruit** 111331 Apple Orchards + 111339 Other Noncitrus Fruit Farming
   (e) **grape vineyards** 111332 Grape Vineyards
4. **nursery greenhouse.** 1114 Greenhouse, Nursery, and Floriculture

I further dropped 13% of farms that had less than 75% of acreage planted in their assigned category, as it may result in errors or noise in the estimation of crop production functions. Specifically, I exclude farms if 25% of their input use are dedicated to another crop type. I am unable to model farms planting different crop types because they report in the census of agriculture *aggregated* input use and expenses without differentiating by crop type. Less than 3% of farms are observed to change crop categories over the three waves of survey I observe.

Constructing the water variable Ground and surface water are used interchangeable and are perfect substitutes:[42]

$$\widehat{W}_{ict} = W^S_{ict} + W^G_{ict}$$

I derive W^S_{ict} from Hagerty (2022), who compiled and publicly released a comprehensive dataset of surface water deliveries and diversions in California. For each farm in the census that reported receiving surface water, I allocated a share of the county-year surface water deliveries based on the dataset provided by Hagerty (2022), which covers agricultural deliveries from 1993 to 2021.

For estimating groundwater pumped (W^G_{ict}) at the farm level, I use utility expenditures in the agriculture census data. Since a large share of electricity in California is used for pumping groundwater, whose only variable input is electricity (See e.g., Burlig et al., 2025; Cooley, 1995; USDA, 2016)), I can back out the volume of groundwater pumped by dividing electricity usage by the estimated energy required to lift an acre-foot of water and the agricultural price of electricity in county c in year t as in the following physical equation, which closely follows the approch used by Burlig et al. (2025):

$$\frac{\mathrm{K_{it}}}{\mathrm{AF}} = \frac{[\text{ L (feet) }_{it}] \times [\text{ Constant }]}{\text{Mean operating pump efficiency (\%)}}$$

[42] I omit precipitation as a source of water in the production function because of its irrelevance in the Central Valley and because it is unlikely to be differentiated across farms within a county. Regions in the California Central Valley receive on average 5-15 inches (0.4-1.2 AF/acre) of precipitation annually, with most of it occurring from December to March (CA OEHHA, 2024). Figure A.4 shows that most crop types planted in California require well over 2 AF/acre of irrigation during the growing season – typically March to November. As such, precipitation contributes an extremely small proportion of water required for agriculture in California.

$$\widehat{W}_{it}^{G} = Expense_{it}^{elec} \div \frac{\widehat{\mathrm{K_{it}}}}{\mathrm{AF}} \div P_{it}^{elec}$$

Where L, lift in feet, is the height that the pump needs to move 1 AF of water through and varies with groundwater levels in county c in year t. I compute space and time-varying lift from densely-measured groundwater levels published by the Department of Water Resources of California (CA DWR). The constant is the amount of energy (kWh) needed to lift 1 AF of water by 1 foot and given by **1.02** = 2,719,226 lbs ÷ 2,655,220 (lb-ft per kWh).

This method of using variation in energy costs to construct water use information has been widely used in recent econometric studies of water demand (Hendricks and Peterson, 2012; Pfeiffer and Lin, 2014; Burlig et al., 2025). Unobserved variations in operating pump efficiency across farms will be recovered as part of the farm productivity term in equation 2, as the estimation framework is designed to capture persistent productivity shocks at the farm level.[43] The identifying assumption requires that farm energy expenses are credible signals of groundwater pumped and used. Energy and groundwater pumping are closely tied in California agriculture, such that one of the largest project response to a major energy shortage in 2000-2001 was to reduce agricultural energy demand by improving groundwater pumping efficiency (See Burt and Howes (2005)). One threat to this assumption is if farm *non-water electricity use* is endogenous and co-vary with agricultural output, which would introduce bias to the estimated water-output elasticity. This threat is minimized given that on-farm non-water electricity use is predominantly for ancillary activities such as internet access, lighting, and telecommunication, which are less likely to be directly linked to production levels.

Estimating procedure In order to estimate β_{cW}, β_{cK}, and ω_{ict} credibly, I will apply the proxy variable approach, which requires characterizing ω_{ict} as a first-order Markov process. I rely on a technological control similar to De Loecker and Scott (2025), rather than inverting a control or policy function as more commonly done. I choose HST (termed "intermediate" in Levinsohn and Petrin (2003)) input (M_{ict}) as my proxy variable, as it fulfills the required assumptions: 1) it is decided at the *end* of the season after productivity shocks (e.g., a bumper crop year from unexpected favorable conditions) have been realized and 2) it is plausibly used in a fixed proportion.

The second implicit condition leads to the following first-order condition:

[43] Burt and Howes (2005), a report on agricultural energy use by sector and region throughout California prepared for the California Energy Commission, shows that operating pump efficiency does not differ unobservable across farm input power or as a function of location within California.

$$Y_{ict} = \beta_{cM} M_{ict} \qquad \text{and}$$
$$y_{ict} = \ln(\beta_{cM}) + m_{ict}$$

Combining with equation (10), we have that

$$\omega_{ict} = \ln(\beta_{cM}) + m_{ict} - \beta_{cW} w_{ict} - \beta_{cK} k_{ict} - \varepsilon_{ict} = f(w_{ict}, k_{ict}, m_{ict}).$$

Productivity is also a simple linear function of the other inputs.

Step 1. Project output y_{ict} on w_{ict}, k_{ict}, and m_{it} to purge the measurement error ε_{ict}. Typically, one would want higher orders polynomials in the inputs to non-parametrically represent the inverted "control" function, but in my setup, the optimal y_{ict} is actually simply a linear function of w_{it}, k_{it}, and m_{it}, so I go ahead and use a first-order polynomial to estimate a composite of the input contribution and productivity effect.

$$y_{it} = \Phi_t(w_{ict}, k_{ict}, m_{ict})$$

Step 2. Obtain $\hat{\Phi}_{ict}$, which is simply the predicted y_{ict} from the regression above.

$$\Phi_{ict} - \beta_{cW} w_{ict} - \beta_{cK} k_{ict} = \omega_{ict} \tag{13}$$

Because ω_{ict} follows an AR(1) process, $\omega_{ict} = \rho\omega_{ict-1} + \xi_{ict}$, where ξ_{ict} is the unexpected/unanticipated part of productivity and $\mathbb{E}(\xi_{ict}|\mathcal{I}_{ict-1} = 0)$. Specifically, since k_{ict} and $m_{ict-1}$was decided before knowing ξ_{ict}, the following moment conditions hold:

$$\mathbb{E}(\xi_{ict}|k_{ict}) = 0$$
$$\mathbb{E}(\xi_{ict}|m_{ict-1}) = 0$$

Step 3. The generalized method of moments is used to recover the estimates of $\boldsymbol{\beta} = [\beta_{cK}, \beta_{cW}]$.

1. Guess candidate values of $\boldsymbol{\beta} = [\beta_{cK}, \beta_{cW}]$.
2. Use equation 13 to compute estimated $\hat{\omega}_{ict}(\boldsymbol{\beta})$ as a function of the candidate parameters.
3. Compute the unexpected part of productivity, termed "innovations" in the literature – I call this unexpected productivity – using the AR(1) process assumption:

$\hat{\xi}_{ict}(\boldsymbol{\beta}) = \hat{\omega}_{ict} - \rho\hat{\omega}_{ict-1}$.

4. This unexpected productivity should be uncorrelated with acreage k_{ict} and last year's intermediate input m_{ict}. Use sample analogue of the moment condition to check.

$$\frac{1}{N}\frac{1}{T}\sum_i\sum_t \widehat{\xi}_{it}\left(\boldsymbol{\beta}\right)k_{ict} = 0$$

$$\frac{1}{N}\frac{1}{T}\sum_i\sum_t \widehat{\xi}_{it}\left(\boldsymbol{\beta}\right)m_{ict-1} = 0$$

5. Iterate over and find $\boldsymbol{\beta}$ that satisfy the moment conditions.

Calculating the Herfindahl-Hirschman Index The Herfindahl-Hirschman Index (HHI) is often used to assess how competitive or concentrated a market is. I use the revenue-weighted HHI to assess farm concentration within each county under a proportional groundwater quota and under trading. The formula to calculate HHI for crop type c is

$$HHI_c = \sum_{i=1}^{N_c}\left(\frac{Y_{ic}}{\sum_{i=1}^{N_c}Y_{ic}}\right)^2,$$

where Y_{ic} is the output (in tons) of farm i growing c in each county, and N_c is the total number of farms planting crop c in the county. The term in the parenthesis is the market share of farm i for crop c.

I report revenue-weighted HHI to give more weight to larger crop markets:

$$HHI_{weighted} = \sum_c w_c HHI_c,$$

where the weights are the revenue share of crop type c within the county.

C Mathematical Appendix

C.1 General model with different crop types and farm productivity heterogeneity

This section develops a simple model to characterize how trade liberalization – of a *previously rationed* (under allocation quotas) environmental input – affects reallocative and aggregate outcomes under observed patterns of heterogeneity among users. In the model, akin to seminal trade papers addressing heterogeneity in firms (Melitz, 2003; Bernard et al., 2007), firms differ in productivity in the use of the environmental input. Crucially, I embed a key feature of heterogeneity observed in my setting: firms that are more productive in the use of the environmental input tend to also be more productive in the use of labor. This *input productivity correlation* differs across sectors depending

on the availability of labor-enhancing technology in that particular sector. I add this empirical regularity to my model to explore how input productivity correlation can alter the reallocative effects of trading environmental inputs and, in turn, affect the aggregate output, profits, productivity, and labor demand. The model also serves as the foundation for my quantitative analysis in Section 5, where I extend the framework in a less tractable but more empirically grounded setting.

For simplicity, I illustrate these relationships in a two-user farm setting where farms produce crop output using two inputs: water (W), the environmental input, and labor (L).[44] Farms are heterogeneous in water and labor productivity. I introduce a new crop-specific parameter ϕ_c, termed the water-labor *productivity correlation* which quantifies how labor productivity varies with water productivity.[45] To highlight the implications of input productivity correlation as starkly as possible, I consider a static model, where farms are operating in perfect competition in the output market, and labor supply is perfectly elastic at the minimum wage.

Setup

I assume there are only two farmers denoted by i pulling from a common aquifer, a low type (L) and a high type (H), and planting on a single acre of land. Type H farm has invested in state-of-the-art water and labor-saving technologies so that $H > L$, where $\omega_i \in \{H, L\}$ denotes productivity. Crops are denoted by c, and valued at P_c per unit output. Farm i begins each cropping season (winter/spring) by planting an acre of land and applying $\overline{W}$ units of water under the rationing (quota-based) management. During the harvesting season (summer/spring), farms hire labor to harvest Y_i tons of crop yield each season.

Henceforth, I drop the farm i subscript and use ω alone to index individual farms, as farms with the same ω for a given crop type will behave symmetrically. Crop production by a farm with water productivity is ω planting crop c is given by:[46]

$$Y = \min \left\{ \underbrace{e^{\omega} W^{\beta_c}}_{\text{Growing}}, \underbrace{e^{\phi_c \omega} \gamma_c L}_{\text{Harvesting}} \right\}, \tag{14}$$

where Y_c is yield of crop c produced from water W and labor L using productivity draw ω.[47] β_c,

[44] This setup can be used to model input cross-elasticity for various different input combination comprising of an environmental input to be liberalized to trade and another input that we care about on aggregate, for example, carbon emissions and related air pollutants (e.g., sulfur dioxide and nitrogen oxide), fishing quotas and local labor, or water quality trading and pesticide use.

[45] In the agricultural setting, crop type is analogous to industry or sector in the firm setting.

[46] The Leontief form presented here is a special case of the CES production function: $Y_i = \left\{ (e^{\omega_i} w)^{\frac{\sigma_c - 1}{\sigma_c}} + \left(e^{\phi \omega_i} L\right)^{\frac{\sigma_c - 1}{\sigma_c}} \right\}^{\frac{\sigma_c}{\sigma_c - 1}}$, when $\sigma_c = 0$. The optimal labor choice under CES is: $L^* = \left(\frac{e^{\phi w_i}}{e^{\omega_i}}\right)^{\sigma_c - 1} \left(\frac{v}{s}\right)^{\sigma_c} W$. As $\sigma_c \longrightarrow 0$, we recover the Leontief solution. Farmworkers, whose main jobs is to harvest crops mostly by hand, are employed in a quantity proportional to output, justifying the Leontief form.

[47] Water productivity ω is a catch-all term that includes all sources of heterogeneity in revenue relative to water

ϕ_c, and γ_c are crop-specific parameters. β_c and γ_c are the standard water-output elasticity and labor intensity parameter for crop c, respectively. $\beta_c \in [0,\ 1]$, representing diminishing marginal returns to water use in cropping on a given plot of land. ϕ_c represents the water-labor productivity correlation – allowing water productivity to influence labor productivity within farms planting the same crop type.

When $\phi_c = 0$, farms differ in water productivity but not labor productivity. All farms hire $\frac{1}{\gamma_c}$ units of labor per unit of output. When $\phi_c = 1$, productivity is neutral, farms that are more water productive are also more labor-productive, by the same proportion. e^{ω} can be interpreted as total factor productivity (TFP). When $0 < \phi_c < 1$ ($\phi_c > 1$), farms that are more water productive are also more labor-productive but less (more) than proportionately so. In my empirical setting, ϕ_c ranges from 0.05 for berries to 0.64 for tree nuts and 0.74 for grapes (Panel B Table 1).

The parameter reflects the fact that there are crop-specific constraints to the development and thus availability of harvest mechanization technologies available to farmers. Different crops have unique physical and biological characteristics that influence how easily they can be harvested by machines. For instance, crops like wheat and rice are well-suited to mechanized harvesting because they grow uniformly and can be effectively collected using combines. Tree nuts, such as almonds and walnuts, are other examples of crops that have successfully integrated mechanized harvesting techniques (Calvin and Martin, 2010). Mechanical tree shakers harvest almonds by shaking the trees to dislodge the nuts, which then fall onto the ground and are collected by sweeper machines. This mechanized process significantly reduces the need for manual labor. The *availability* of harvesting technology for these crops enables farms with sufficient resources to invest in such machinery.

Conversely, crops like berries or many vegetable crops (e.g., asparagus) face challenges in mechanization due to their delicate nature or complex growth patterns. For example, strawberries and raspberries are sensitive to bruising, requiring careful handpicking and packing. Some crops like bell peppers require handpicking but allow for partial mechanization using robot packers or conveyor belts (Calvin et al., 2022; Thompson and Blank, 2000). These constraints mean that such crops often require more manual labor. Farms growing these crops have no options for investing in labor-saving technologies even if they have the means to do so.

Farm behavior

Farms are expected profit maximizers under perfect competition.

Quota Under a quota regime, each farm is constrained to use $\overline{W}$ units of water. From equation (14), the corresponding water allocation, output choice, labor demand, and profit under the quota (denoted by superscript q) are:

input across farms and includes irrigation efficiency, management practice such as timing of application, and soil water holding capacity. For my analysis, I take farm productivity as exogenously determined upon entry.

$$
\begin{aligned}
W^q &= \overline{W} \\
Y_c^q &= e^{\omega}\overline{W}^{\beta_c} \\
L_c^q &= \frac{e^{\omega}}{\gamma_c e^{\phi_c \omega}}\overline{W}^{\beta_c} \\
\pi_c^q &= e^{\omega}\overline{W}^{\beta_c}\left[P_c - \frac{s}{\gamma_c e^{\phi_c \omega}}\right].
\end{aligned} \tag{15}
$$

For simplicity, we assume that there are no pumping costs, so the only input cost incurred is wages for farm labor, s. Under the quota, farms with higher productivity ω will grow more crops and earn higher profit margins. Whether higher water productivity farms hire more labor depends on ϕ_c:

$$
\frac{\partial L_c}{\partial \omega} = \frac{(1-\phi_c)}{\gamma_c} e^{\omega(1-\phi_c)}\overline{W}^{\beta_c}.
$$

If ϕ_c is greater than 1, the derivative is negative. Because high water productivity is accompanied by much higher labor productivity when $\phi_c > 1$, this results the high type farm employing on net less labor even when they are producing more.

These is misallocation of water under the quota setting. The marginal returns to water use generally differs across farms when ω differs, as seen in the expression

$$
\frac{\partial \pi_c}{\partial W}|_{W^q=\overline{W}} = \frac{e^{\omega}\beta_c\left[P_c - \frac{s}{\gamma_c e^{\phi_c \omega}}\right]}{\overline{W}^{1-\beta_c}}.
$$

Specifically, when $\omega_H > \omega_L$, reallocating a unit of water from L to H yields a net welfare gain for the range of $\phi_c \in [0,1]$ observed in our setting because the numerator is increasing in ω. At the given quota $\overline{W}$, farms with larger ω have larger marginal returns to water use.

Proof:

$$
\begin{aligned}
\frac{\partial}{\partial \omega}\ e^{\omega}\beta_c\left[P_c - \frac{s}{\gamma_c e^{\phi_c \omega}}\right] &= e^{\omega}\beta_c\left[\frac{\phi_c s}{\gamma_c e^{\phi_c \omega}}\right] + e^{\omega}\beta_c\left[P_c - \frac{s}{\gamma_c e^{\phi_c \omega}}\right] \\
&= e^{\omega}\beta_c\left[P_c - s\frac{(1-\phi_c)}{\gamma_c e^{\phi_c \omega}}\right] > 0,
\end{aligned}
$$

and by construction, $P_c > \frac{s}{\gamma_c e^{\phi_c \omega}}$, so P_c will definitely be larger than $\frac{s(1-\phi_c)}{\gamma_c e^{\phi_c \omega}}$ given that $\phi_c < 1$. This misallocation arises across crops even in the absence of within-crop heterogeneity (i.e., $w = 1$ for all farms) and provides the rationale for agricultural water trading, particularly in water-scarce settings.

Water trading Under water trading, each farm chooses its optimal water use, W^*, to maximize profits given its productivity draw and crop-specific parameters $(\beta_c, \gamma_c, \phi_c)$. Formally,

$$W_c^* = \arg\max_W P_c Y_c(W) - sL_c(W),$$

where P_c denotes the crop price and s the wage. Since water use W^* is the only choice variable in this setup, all other farm outcomes follow directly from the equations derived under the quota regime, where output, labor, and profits are deterministic functions of water:

$$\begin{aligned}
W_c^* &= \left[\frac{\beta_c(P_c - \frac{s}{\gamma_c e^{\phi_c \omega}})}{v}\right]^{\frac{1}{1-\beta_c}} e^{\frac{\omega}{1-\beta_c}} \\
Y_c^* &= e^{\omega} W^{*\beta_c} \\
L_c^* &= \frac{e^{\omega}}{\gamma_c e^{\phi_c \omega}} W^{*\beta_c} \\
\pi_c^* &= e^{\omega} W^{*\beta_c} \left[P_c - \frac{s}{\gamma_c e^{\phi_c \omega}}\right].
\end{aligned} \tag{16}$$

Market equilibrium condition Analyze the interactions between the two water productivity types H and L. The market for water clears on price v^* such that net demand from H equals to net supply from L:

$$W_c^*(v^*, H, \dots) - \overline{W} = -(W_c^*(v^*, L, \dots) - \overline{W}) \tag{17}$$

Model predictions

Using the market clearing condition from equation (17) and farm input and output choices from (15) and (16), I derive the difference in production outcomes under a quota with and without water trading for low- and high-type users. I present the gains (losses) from trade liberalization (denoted by *) of the allocated quota ($\overline{W}$) for profit (π), output (Y), labor demand (L), as well as the market-clearing water price (v^*) and water allocation (R) in the two-farm setting as ϕ_c increases. Figure 2 visualizes how the different outcomes evolve as a function of ϕ_c.

Under water trade, the water allocation ratio between the high and low type is given as $W_H^* = RW_L^*$ where:

$$R(\phi_c) = \frac{W_H^*}{W_L^*} = \left[\frac{e^H}{e^L}\frac{p_c - \frac{s}{e^{\phi H}\gamma_c}}{p_c - \frac{s}{e^{\phi L}\gamma_c}}\right]^{\frac{1}{1-\beta_c}} = \left\{\frac{P_c - \frac{s}{e^{\phi_c H}\gamma_c}}{P_c - \frac{s}{e^{\phi_c L}\gamma_c}}\right\}^{\frac{1}{1-\beta_c}} \cdot e^{\frac{H-L}{1-\beta_c}}$$

1. $\frac{\partial R(\phi_c)}{\partial \phi_c} > 0$, **water allocation ratio to the high type is increasing in** ϕ_c.

Proof:

$$\ln R(\phi_c) = \frac{1}{1-\beta_c}\left\{\ln\left(P_c - \frac{s}{e^{\phi_c H}\gamma_c}\right) - \ln\left(P_c - \frac{s}{e^{\phi_c L}\gamma_c}\right)\right\} + \frac{H-L}{1-\beta_c}, \text{ and}$$

$$\text{sign}\left[\frac{\partial \ln R(\phi_c)}{\partial \phi_c}\right] = \text{sign}\left[\frac{\partial}{\partial \omega}\left(P_c - \frac{s}{e^{\phi_c \omega}\gamma_c}\right)\right].$$

Let $f(\phi_c, \omega) = P_c - \frac{s}{e^{\phi_c \omega}\gamma_c}$.

If $f\prime(\phi_c, \omega)$ is increasing in ω, then $f\prime(\phi_c, H) - f\prime(\phi_c, L) > 0$, and

$$\text{sign}\left[\frac{\partial \ln R(\phi_c)}{\partial \phi_c}\right] = \text{sign}\left[\phi_c s e^{-\phi_c \omega}\gamma_c\right] > 0.$$

2. $\frac{\partial \Delta^{q\to m}\pi}{\partial \phi_c} > 0$, **profit gains from trade is positive and increasing in** ϕ_c.

Proof: It is sufficient to show that $\frac{\partial^2 \pi}{\partial \phi_c \partial \omega} > 0$ at the quota allocation $\overline{W}$. That is, the initial misallocation of water is greater as ϕ_c increases. As the market reallocates water to address these misallocation, the profit gains must be larger if initial misallocation is larger.

$$\begin{aligned}
\frac{\partial \pi}{\partial \omega} =& e^{\omega}\overline{W}^{\beta_c}\left[P_c - s\frac{1-\phi_c}{\gamma_c e^{\phi_c \omega}}\right] \\
\text{sign}\left[\frac{\partial^2 \pi}{\partial \phi_c \partial \omega}\right] =& \text{sign}\left[\gamma_c e^{\phi_c \omega} s e^{\omega}\overline{W}^{\beta_c} + s e^{\omega}\overline{W}^{\beta_c}(1-\phi_c)\omega\gamma_c e^{\phi_c \omega}\right] \quad \text{(dropping the positive numerator)} \\
=& \text{sign}\left[\gamma_c e^{\phi_c \omega} s e^{\omega}\overline{W}^{\beta_c}[1+\omega(1-\phi_c)]\right] \\
=& \text{sign}\left[(1+\omega(1-\phi_c))\right] > 0 \quad (0 < \phi_c < 1).
\end{aligned}$$

3. $\frac{\partial \Delta^{q\to m} L}{\partial \phi_c} < 0$, **labor demand change is ambiguous in sign and decreasing in** ϕ_c.

$$\Delta^{q\to m} L = \underbrace{\left[\left(\frac{2\overline{W}R(\phi_c)}{1+R(\phi_c)}\right)^{\beta_c} - \overline{W}^{\beta_c}\right]\frac{e^H}{e^{H\phi_c}\gamma_c}}_{\text{Gains from transfer to } H} - \underbrace{\left[\overline{W}^{\beta_c} - \left(\frac{2\overline{W}}{1+R(\phi_c)}\right)^{\beta_c}\right]\frac{e^L}{e^{L\phi_c}\gamma_c}}_{\text{Loss from transfer to } H}$$

$$= \frac{\Delta Y_H(\phi_c)}{e^{H\phi_c}\gamma_c} - (-\frac{\Delta Y_L(\phi_c)}{e^{L\phi_c}\gamma_c}).$$

Proof: The proof that ΔL is decreasing in ϕ_c follows from the proof in the following section. Since $\Delta Y_H(\phi_c) + \Delta Y_L(\phi_c)$ is decreasing in ϕ_c, we need only prove that $e^{H\phi_c}\gamma_c \geq e^{L\phi_c}\gamma_c$, which is fulfilled by construction of $H > L$.

4. $\frac{\partial \Delta^{q\to m}Y}{\partial \phi_c} < 0$, **output gains is positive and decreasing** in ϕ_c.

$$\Delta^{q\to m}Y = \underbrace{\left[\left(\frac{2\overline{W}R(\phi_c)}{1+R(\phi_c)}\right)^{\beta_c} - \overline{W}^{\beta_c}\right]e^H}_{\text{Gains from transfer to } H} - \underbrace{\left[\overline{W}^{\beta_c} - \left(\frac{2\overline{W}}{1+R(\phi_c)}\right)^{\beta_c}\right]e^L}_{\text{Loss from transfer to } H}$$

$$= \Delta Y_H(\phi_c) - (-\Delta Y_L(\phi_c)).$$

Proof:

$$\begin{aligned}\frac{\partial \Delta Y}{\partial \phi_c} &= e^H\beta_c\left(\frac{2\overline{W}R}{1+R}\right)^{\beta_c-1}\cdot\frac{2\overline{W}R'}{(1+R)^2} - e^L\beta_c\left(\frac{2\overline{W}}{1+R}\right)^{\beta_c-1}\cdot\frac{2\overline{W}R'}{(1+R)^2}\\ &= \frac{2\overline{W}R'\beta_c}{(1+R)^2}\left[\frac{2\overline{W}}{1+R}\right]^{\beta_c-1}\left[e^H R^{\beta_c-1} - e^L\right].\end{aligned}$$

Substituting R from 1:

$$\begin{aligned}e^H R^{\beta_c-1} - e^L &= e^H\frac{1}{\frac{e^H}{e^L}\frac{P_c-\frac{s}{e^{\phi_c H}\gamma_c}}{P_c-\frac{s}{e^{\phi_c L}\gamma_c}}} - e^L\\ &= 1 - \frac{P_c - \frac{s}{e^{\phi_c H}\gamma_c}}{P_c - \frac{s}{e^{\phi_c L}\gamma_c}} < 0 \text{ because } H > L.\end{aligned}$$

Then, $\frac{\partial \Delta Y}{\partial \phi_c} < 0$.

5. $\frac{\partial \Delta^{q\to m}v^*}{\partial \phi_c} > 0$, **market-clearing water price is increasing** in ϕ_c.

Proof: Since

$$v = \left[\frac{\left[\beta_c(P_c - \frac{s}{\gamma_c e^{\phi_c H}})e^H\right]^{\frac{1}{1-\beta_c}} + \left[\beta_c(P_c - \frac{s}{\gamma_c e^{\phi_c L}})e^L\right]^{\frac{1}{1-\beta_c}}}{2\overline{W}}\right]^{1-\beta_c},$$

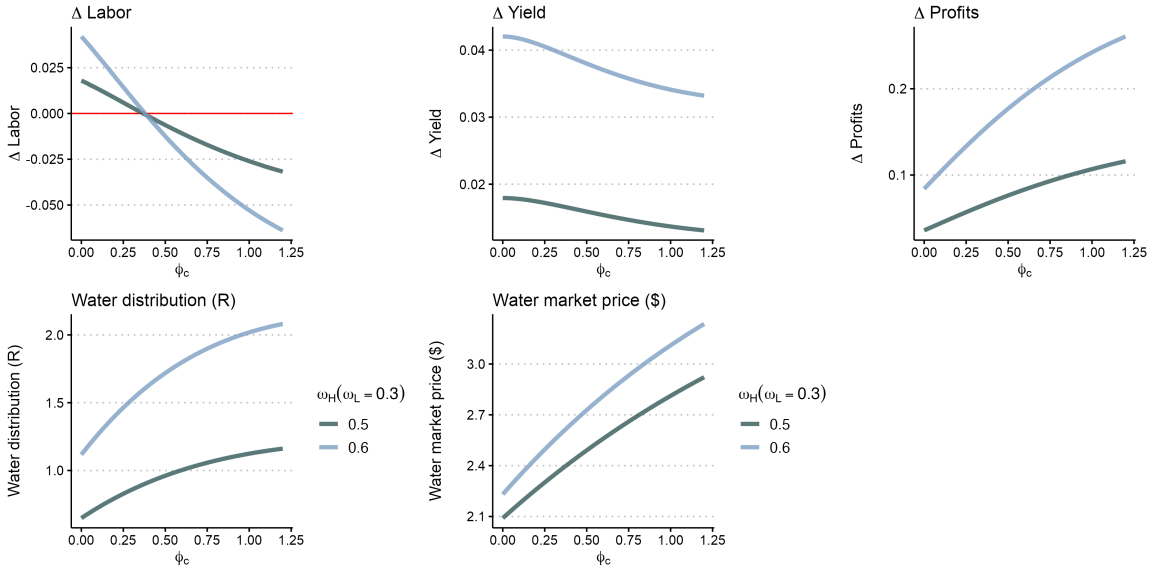
and ϕ_c is in the denominator of the numerator term to be subtracted, v is increasing in ϕ_c.

Figure C.11 shows a visual of the quota to market changes in various outcomes of interest as a function of ϕ_c for two values of high-type farms. The intuition for predictions 1-3 is straightforward, as ϕ_c increases, the high type farm is more productive in *both* water and labor. This induces more water to be transferred to the high type (#1), more net income as labor costs is lowered (#2), and less labor required as the relative labor-productivity of the high type is also greater (#3).

Prediction #4 is less intuitive as it compares the change in total output generated by both farms induced by higher ϕ_c. Prediction #1 indicated that for higher ϕ_c, water allocation to the high type increases. But this is not due to its advantage in growing more crops, but due to its advantage in being able to use less relative labor, leading to greater cost savings. As ϕ_c increases, profit gain increasingly come from larger labor cost saving rather than increased water productivity. This is a result of farms optimizing profit rather than output.

Prediction #5 indicates that the market-clearing price of water equals the average shadow value of water across the two users. The shadow value rises with the water–labor productivity correlation ϕ_c, crop price P_c, farm productivity $\omega = \{H, L\}$, output-water elasticity β_c, but declines with the wage rate s.

Figure C.11: Change in labor demand, output, profits, water distribution ratio ($R(\phi_c)$, and water price when going from a quota to market regime as a function of the water-labor productivity ratio.



Note: This figure plots the simulated gains (or change for water allocation) from trade compared to uniform quota – across a range of water- and labor-productivity correlation values (ϕ_c). Water is initially allocated uniformly across the high (H) and low (L) types under a quota then liberalized to trade. Prices are the same for both users. The blue lines show change from trade in aggregate labor demand, output, profits, high-to-low water ratio, and the market-clearing water price for lower (dark blue) and higher (light blue) differences in water productivity between H and L. The red line marks a change in sign from a positive aggregate effect to negative.

Panel B of Table 1 shows that the empirical ϕ_c ranges from 0.05 to 0.7, which is generally below 1. Studies using production function with Hicks-neutral productivities tend to overestimate net income gains and underestimate labor demand change whiles studies using a Leontief production function assuming no relationship between water and labor productivities will have underestimated income gains and overestimated labor demand change.

C.2 Factor share under a constant elasticity of substitution production function

I present a constant elasticity of substitution (ces) production function to model farm use of water and labor. The purpose is to show that even under typical the most general setting, only factor-augmenting productivities can rationalize the distribution of farm water and labor productivities depicted in Table A.2. Define labor productivity as the crop revenue generated per unit of worker, and water productivity as crop revenue generated per unit of water. For brevity, I drop subscript c and keep the analysis within a single crop type.

$$\text{labor productivity} = \frac{pY}{L}$$
$$\text{water productivity} = \frac{pY}{W}$$

Farms, which are indexed by i, mix water W and labor L to produce output Y, which is priced at p. I omit subscripts c and t for crop type and year for readability. s denotes labor costs s and v denotes water costs v. Let a_i be labor-augmenting productivity and b_i be water-augmenting productivity. If $a_i = b_i = A_i$, then we can factor out A_i as total factor productivity.

$$Y_i = [\underbrace{(a_i L)^{\frac{\sigma-1}{\sigma}} + (b_i W)^{\frac{\sigma-1}{\sigma}}}_{\Phi}]^{\frac{\sigma}{\sigma-1}}$$

$$\begin{aligned} MP_L = \frac{\partial y_i}{\partial L} &= \frac{\sigma}{\sigma-1}\Phi^{\frac{\sigma}{\sigma-1}-1} \cdot \frac{\sigma-1}{\sigma}(a_i L)^{\frac{\sigma-1}{\sigma}-1} \cdot a_i \\ MP_W = \frac{\partial y_i}{\partial W} &= \frac{\sigma}{\sigma-1}\Phi^{\frac{\sigma}{\sigma-1}-1} \cdot \frac{\sigma-1}{\sigma}(b_i W)^{\frac{\sigma-1}{\sigma}-1} \cdot b_i \end{aligned} \tag{18}$$

Under profit maximization, the marginal products must be equal to price-weighted input costs.

$$\begin{aligned} MP_L &= \frac{s}{p} \\ MP_W &= \frac{v}{p} \end{aligned} \tag{19}$$

From these profit-maximization conditions, we can derive the optimal input choice for each farm.

$$
\begin{aligned}
\frac{MP_L}{MP_W} = \left(\frac{a_i L}{b_i W}\right)^{-\frac{1}{\sigma}} \cdot \frac{a_i}{b_i} &= \frac{s}{v} \\
\left(\frac{L}{W}\right)^{-\frac{1}{\sigma}} \left(\frac{a_i}{b_i}\right)^{-\frac{1}{\sigma}} \cdot \frac{a_i}{b_i} &= \frac{s}{v} \\
\left(\frac{L}{W}\right)^{-\frac{1}{\sigma}} \left(\frac{a_i}{b_i}\right)^{1-\frac{1}{\sigma}} &= \frac{s}{v} \\
\left(\frac{L}{W}\right)^{-\frac{1}{\sigma}} &= \frac{s}{v} \cdot \left(\frac{a_i}{b_i}\right)^{1-\frac{1}{\sigma}} \\
\frac{L}{W} &= \left(\frac{v}{s}\right)^{\sigma} \cdot \left(\frac{a_i}{b_i}\right)^{\sigma-1}
\end{aligned} \tag{20}
$$

Under a ces production function, the ratio between farms' optimal labor and water choices are the same if there is no factor-augmenting productivity. When $a_i = b_i$, they cancel out, and all farms use the same ratio of inputs.

$$
\begin{aligned}
MP_L = \Phi^{\frac{\sigma}{\sigma-1}-1} \quad (a_i L)^{\frac{\sigma-1}{\sigma}-1} \cdot a_i \quad &\text{given that } MP_L = \frac{s}{p} \\
&\text{Multiplying both sides by } \frac{L}{Y} \text{ yields} \\
\frac{sL}{pY} = \frac{\Phi^{\frac{\sigma}{\sigma-1}} (a_i L)^{\frac{\sigma-1}{\sigma}} \cdot a_i L}{\Phi \Phi^{\frac{\sigma}{\sigma-1}} \cdot a_i L} \quad &Y = \Phi^{\frac{\sigma}{\sigma-1}} \\
= \frac{(a_i L)^{\frac{\sigma-1}{\sigma}}}{\Phi} \quad &\text{Plug in } Y \\
= \frac{(a_i L)^{\frac{\sigma-1}{\sigma}}}{(a_i L)^{\frac{\sigma-1}{\sigma}} + (b_i W)^{\frac{\sigma-1}{\sigma}}} & \\
\text{labor productivity}^{-1} = \frac{L}{pY} = \frac{s^{-1} (a_i L)^{\frac{\sigma-1}{\sigma}}}{(a_i L)^{\frac{\sigma-1}{\sigma}} + (b_i W)^{\frac{\sigma-1}{\sigma}}} & \\
= \frac{s^{-1} L^{\frac{\sigma-1}{\sigma}}}{L^{\frac{\sigma-1}{\sigma}} + W^{\frac{\sigma-1}{\sigma}}} \quad &\text{if } a_i = b_i \\
= \frac{s^{-1} \left(\frac{L}{W}\right)^{\frac{\sigma-1}{\sigma}}}{\left(\frac{L}{W}\right)^{\frac{\sigma-1}{\sigma}} + 1} &
\end{aligned}
$$

Analogously, water productivity can be similarly derived.

$$\begin{aligned}\text{water productivity}^{-1} = \frac{W}{pY} &= \frac{v^{-1}\left(b_i W\right)^{\frac{\sigma-1}{\sigma}}}{\left(a_i L\right)^{\frac{\sigma-1}{\sigma}} + \left(b_i W\right)^{\frac{\sigma-1}{\sigma}}} \\ &= \frac{v^{-1} W^{\frac{\sigma-1}{\sigma}}}{L^{\frac{\sigma-1}{\sigma}} + W^{\frac{\sigma-1}{\sigma}}} \quad \text{if } a_i = b_i \\ &= \frac{v^{-1}\left(\frac{W}{L}\right)^{\frac{\sigma-1}{\sigma}}}{\left(\frac{W}{L}\right)^{\frac{\sigma-1}{\sigma}} + 1}\end{aligned}$$

Because the ratio $\frac{L}{W}$ is constant for farms when productivity is hicks-neutral ($a_i = b_i$), labor and water productivity are constant for all farms planting the same crop, and only depends on crop-specific parameters. Therefore, the fact that I see huge dispersion in $\frac{pY}{W}$ and $\frac{pY}{L}$ suggests that $a_i \neq b_i$ across farms. While it is true that groundwater pumping cost (v) may differ across farms, since the policy setting is to evaluate groundwater policy within a hydrologically-bounded basin, the assumption of undifferentiated prices is made. Differences in within-crop wages are typically less than \$2 (Figure A.7).