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GROUNDWATER AND CROP CHOICE IN THE SHORT AND LONG RUN

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ABSTRACT

How do agents respond to policy when investments have high upfront costs and lasting payoffs? We estimate farmers' short- and long-run responses to changes in groundwater pumping costs in California, one of the world's most valuable agricultural regions, where perennial crops with these investment dynamics are prevalent. We leverage quasi-experimental variation in groundwater costs driven by regulated electricity tariffs to estimate a dynamic discrete choice model of land use with state dependence and forward-looking farmers. Farmers' short-run elasticity of groundwater demand is 0.72, but temporary cost shocks do not induce crop switching. In contrast, their long-run elasticity is 0.48, driven by a shift away from unsustainable short-run coping strategies and towards meaningful reductions in water-intensive perennial cropping and increased fallowing. California's flagship groundwater sustainability targets will require a 47% tax in regulated areas on average, which would lower perennial acreage by 10% and increase fallowing by 18%.

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1 Introduction

Water is a precious natural resource, which economists have studied for over a century (Coman (1911)). Agriculture contributes 90% of global freshwater consumption (Carleton, Crews, and Nath (2024)); irrigation enables both high-value crop production and farmer adaptation to climate shocks (Schlenker, Hanemann, and Fisher (2005); Hultgren et al. (2022)). Groundwater is a major source of irrigation, supplying over 35% of irrigated acres worldwide (Carleton, Crews, and Nath (2023)). As a textbook common-pool resource (Ostrom (1990); Provencher and Burt (1993)), groundwater is being extracted more quickly than it is naturally recharged in key farming regions—leading to rapid aquifer depletion (Jasechko et al. (2024)), which will necessitate long-run groundwater management.

The efficacy of policies to curb aquifer depletion depends on how farmers respond in both the short and long run. These responses could differ substantially for different time horizons if farmer choices include dynamic considerations. Perennial crops are inherently dynamic, requiring large upfront investment costs and yielding multiple years of production. As a result, a farmer may respond to a short-run groundwater cost shock (e.g., a drought that raises pumping costs) by applying less water to her perennial crop for a single growing season. However, faced with a long-run cost shock (e.g., a permanent groundwater tax), she may instead choose to switch to a less-water-intensive annual crop. Such long-run adjustments will be difficult to detect in a short-run analysis alone. These features are not unique to agriculture: a wide variety of settings are characterized by agents making dynamic investment decisions. Understanding the effectiveness and broader consequences of policy therefore requires long-run estimates.

This paper generates novel empirical estimates of farmers' short- *and* long-run responses to changes in groundwater pumping costs in California, one of the world's most valuable agricultural regions. California farmers produce 18% of total U.S. crop value, and rely heavily on groundwater for irrigation (Bruno (2017); Liu et al. (2022)). Yet despite rapidly declining aquifer levels and a series of severe droughts, most California farmers currently face no meaningful restrictions on groundwater extraction. The state is in the process of implementing the Sustainable Groundwater Management Act (SGMA)—its first comprehensive groundwater regulations, which are designed to achieve groundwater sustainability by 2042.[1] The effectiveness and economic consequences of any such permanent groundwater regulation hinge on both the extent of farmers' response and their means of adapting to higher irrigation costs over the long run.

We ask two main research questions. First, what is the elasticity of demand for agricultural groundwater over the short and long run? Second, to what extent do farmers switch crops in response to higher groundwater costs? Despite the importance of these questions, answers have proven elusive because (i) groundwater extraction is rarely priced or measured, (ii) there is a dearth of plausibly exogenous variation in groundwater costs, and (iii) modeling how forward-looking farmers respond to cost shocks is a complex dynamic problem.

We overcome these challenges using a new measurement strategy, quasi-experimental variation in groundwater costs, and a dynamic discrete choice model. First, we leverage the fact that electricity is the main variable input in groundwater pumping. We assemble data on electricity prices and quantities for all agricultural consumers served by Pacific Gas & Electric (PG&E). Combining these data with newly constructed pump-specific production functions enables us to recover groundwater costs and quantities for farmers across the majority of California's Central Valley. Second, we use exogenous variation in PG&E's regulated electricity tariffs, which change farmers' groundwater costs differentially across space and over time. Third, to understand farmers' long-run responses to changing groundwater costs, we use this exogenous variation in electricity prices to identify a dynamic discrete choice model of farmers' cropping decisions. We use the conditional choice probability (CCP) approach (Scott (2013); Kalouptsidi, Scott, and Souza-Rodrigues (2021)) in order to estimate model parameters without making parametric assumptions about farmer expectations.

A static model of short-run farm profits would mischaracterize the decisions of farmers in California, where 62% of total crop revenues come from perennials such as almonds, grapes, and alfalfa. Since these crops have high upfront planting costs and produce multiple years of harvests, accurately characterizing crop choices in this setting requires modeling state dependence and forward-looking farmers. We embed these features into a dynamic discrete

1. While SGMA grants local agencies flexibility over the instruments they use to achieve these reductions, more than half are proposing price-based approaches (Bruno, Hagerty, and Wardle (2022)).

choice model of crop choice, in which farmers are able to reduce water use *both* by switching crops *and* by using less water conditional on crop choice (behavior documented in Boser et al. (2024)). We identify model parameters using exogenous variation in groundwater costs driven by changes in regulated electricity prices.

We first provide reduced-form evidence that farmers respond to pumping costs. Leveraging exogenous year-over-year variation in electricity tariffs in an instrumental variables approach, we find that farmers reduce groundwater consumption in response to pumping cost shocks.[2] This effect is driven by changing water use conditional on crop choice, rather than by crop switching—as evidenced by (i) null reduced-form estimates of land use change and (ii) a quantitatively similar estimate of groundwater response after conditioning on crop choice. We use this conditional reduced-form estimate to calibrate the intensive-margin response in our dynamic model.[3]

Next, we use our dynamic model to measure the effects of short-run price changes on land use change. To do so, we solve for farmers' value functions via a fixed-point algorithm, simulating the model forward until it reaches a steady state, and then inject an (unanticipated) one-year cost shock into the model.[4] We estimate that such a short-run price change would lead to essentially no change in crop choice, with semi-elasticities of 0.0002 for annuals, −0.003 for fruit/nut perennials, −0.002 for hay perennials, and 0.005 for non-crop (fallowing). This yields an overall short-run groundwater elasticity of −0.72.

We also use our model to compute long-run semi-elasticities of land use change. In contrast to a short-run price shock, we find that farmers *do* switch crops in response to permanent groundwater cost changes, with semi-elasticities of 0.064 for annuals, −0.117 for fruit/nut perennials, −0.009 for hay perennials, and 0.062 for non-crop. These results reveal that forward-looking farmers operating state-dependent fields will react very differently to

2. Mieno and Brozovic (2017) point out that prior studies using energy data to estimate groundwater demand often recover biased estimates, due to significant measurement error or a lack of identifying variation. Our detailed microdata and quasi-experimental identification help us overcome these challenges.

3. To translate this estimate into an intensive-margin response for the dynamic model, we use long differences to calibrate the share of the within-crop elasticity that can be sustained over multiple years. We find that farmers have approximately 50% of this intensive-margin response available to them in the long run.

4. In order to capture the true short-run impact in our dynamic framework, we assume that farmers know that the shock will only last for one year when it arrives, though its arrival is a surprise.

a short-run cost shock vs. a permanent one. In particular, permanent price changes induce farmers to switch into less-water-intensive crops, while short-run shocks do not.

Combining these land-use changes with farmers' intensive-margin adjustments, we estimate long-run demand elasticities of -0.48 for both groundwater and electricity. These long-run elasticity estimates are meaningfully smaller than our short-run estimates—suggesting that over a longer time horizon, the mechanism of farmer responses shifts away from unsustainable short-run strategies and towards incurring the fixed costs of crop switching. These results align with prior evidence that in dynamic settings, long-run elasticities need not be larger than short-run elasticities.[5] Our results further demonstrate how short- and long-run responses to environmental policy may diverge substantially, as different mechanisms—yielding different elasticities—are privately optimal over different time horizons.

Finally, we simulate farmers' long-run responses to counterfactual groundwater taxes, which internalize open-access externalities and may be used to achieve sustainable levels of groundwater extraction.[6] According to the state's Groundwater Sustainability Plans (GSPs), achieving "sustainable yield" under SGMA in overdrafted regions of our sample will require groundwater pumping reductions of 16.7% on average, with substantial variation across locations. Our simulations suggest that, on average, a 46.5% tax on groundwater pumping would be required to achieve this sustainability target. The taxes required to achieve these goals—which vary meaningfully over space—would reduce fruit/nut perennial acres by 9.5%, not change hay perennials, increase annual acres by 5.5%, and increase fallowing by 18.0% compared to our no-tax scenario. These results imply that non-trivial groundwater taxes can achieve SGMA's sustainability goals, and that doing so will induce meaningful changes to California's 20 million acres of cropland.

5. See Hall (1991); Gowisankaran and Rysman (2012); Castillo (2021); and Lemoine (2024). Hall (1991) provides a useful analogy: whereas workers may flexibly respond to temporary wage shocks by reducing their work hours, permanent wage reductions may cause them incur the fixed costs of changing careers. As in our setting, the short-run mechanism is unsustainable, while the long-run mechanism involves fixed costs.

6. Groundwater extraction creates two main externalities (Provencher and Burt (1993)). The "stock externality" arises when agents fail to fully account for the future value of resource, leading to depletion that is faster than the social planner's optimal extraction path. The "pumping cost" externality arises when one agent's extraction lowers water levels and increases pumping costs for other (nearby) users in the short run. Other externalities might include land subsidence and air pollution from soil drying.

This paper makes four contributions. First, and most importantly, we use dynamic discrete choice methods to generate short- and long-run demand elasticity estimates for agricultural groundwater. We find that these elasticities differ markedly in both their magnitudes and their underlying mechanisms. Our preferred approach captures key dynamics in agricultural land use, in contrast to previous static estimates of groundwater demand (e.g., Hendricks and Peterson (2012); Bruno and Jessoe (2021a); Pfeiffer and Lin (2014); Smith et al. (2017)).[7] Bruno, Jessoe, and Hanemann (2024) use a reduced-form approach to study land use and groundwater dynamics over five years, in response to voluntary water pricing in a single water district in California's Pajaro Valley. Our results build on this work: we capture both short- and long-run land use and groundwater responses to groundwater cost shocks across the majority of California's farming areas.

Our findings highlight the value of long-run environmental policy analysis. While our results come from one key context—California groundwater—the lesson that agents may respond differently to short- vs. long-run policies is applicable wherever resource management requires a long time horizon, including forests (Araujo, Costa, and Sant'Anna (Forthcoming); Hsiao (2024); Balboni et al. (2023)), fish (Costello et al. (2010)), the global climate (Nordhaus (2019)), and other renewable (Gordon (1954)) and nonrenewable (Hotelling (1931)) resources. More broadly, the dynamics of perennial cropping, which are driven by high upfront costs followed by a multi-year payoff, mirror a wide range of investments, including vehicles (Dahl (2014)), household appliances (Dubin and McFadden (1984)), and pollution control technologies (Blundell, Gowrisankaran, and Langer (2020)).

Second, we estimate long-run agricultural *electricity* demand, accounting for crop investment dynamics. Long-term investments are major determinants of electricity use across sectors, including durable appliances (McRae (2015)), energy efficiency upgrades (Fowlie, Greenstone, and Wolfram (2018)), and solar panels (Borenstein (2017)).[8] Despite the influ-

7. Scheierling, Loomis, and Young (2006) conduct a meta-analysis of 24 earlier papers estimating agricultural water demand. Most of these studies rely on agronomic models or field crops experiments with restrictive assumptions on farmers' response to changing water costs. In contrast, more recent estimates of agricultural water demand rely on observed farmer responses (e.g., Bruno and Jessoe (2021b)).

8. Suppose an electricity price shock causes a household to invest in insulation. Properly modeling this investment decision requires forward-looking expectations (i.e., the household will be less likely to invest in insulation if it believes the price increase to be short-lived) and state-dependence (i.e., after investing in insulation, the household is unlikely to make similar investments in future periods).

ence of investment dynamics on electricity use, existing work in this area is limited.[9] We extend a small recent literature, which uses quasi-experimental variation to estimate long-run electricity demand in the residential sector (Deryugina, MacKay, and Reif (2020); Feehan (2018); Buchsbaum (2023)), by combining quasi-random price changes with a structural model of a major commercial electricity end-use: groundwater pumping. We provide one of the first long-run estimates of electricity demand derived from a model of forward-looking agents that make state-dependent investments (following Rapson (2014)). Our results are among the first rigorous estimates of long-run electricity demand in the agricultural sector, which consumes nearly 8% of California's electricity.

Third, we estimate the short- and long-run impacts of water costs on land use. While agricultural economists have long studied the effect of output prices on cropping patterns (e.g., Nerlove (1956); Roberts and Schlenker (2013); Scott (2013)), fewer studies have documented how groundwater costs impact crop choice, which has important implications for agricultural output markets.[10] We build on Hornbeck and Keskin (2014) by demonstrating that farmers change crops in response to groundwater costs in the long run, but not in the short run.[11] Our work complements recent studies of surface water irrigation (Rafey (2023); Hagerty (2022); Hagerty (2023)), where regulatory and market institutions are far more mature. We extend recent studies of localized groundwater regulations (Ayres, Meng, and Plantinga (2021); Bruno, Jessoe, and Hanemann (2024)) by providing estimates of land use change under groundwater policy—for the majority of California's farmland—in both the short and long run.

Fourth, we extend the literature on groundwater management by simulating farmer responses to (counterfactual) groundwater policy, in the context of California's landmark SGMA regulation. Natural scientists have uncovered substantial groundwater depletion in key agricultural regions across the globe (Fan, Li, and Miguez-Macho (2013); Rodell et

9. Numerous studies have using quasi-experimental variation to estimate short-run electricity demand, mainly in the residential sector (e.g., Fell, Li, and Paul (2014); Ito (2014)). There are few short-run estimates of commercial/industrial electricity demand (exceptions include Jessoe and Rapson (2015); Blonz (2022)).

10. Blakeslee, Fishman, and Srinivasan (2020) and Ryan and Sudarshan (2022) show that groundwater depletion hurts long-run farm profits in India, but there is far less evidence from high-income countries.

11. Dinar (1994) uses a dynamic theory model to show that rising energy costs are likely to impact crop choice. Caswell and Zilberman (1986) analyze the theoretical relationship between energy demand and irrigation technology choice, a separate determinant of irrigation costs.

al. (2018)). However, large-scale groundwater regulation remains rare (Carleton, Crews, and Nath (2023)), as the few existing policies are mostly local in scope.[12] In this context, SGMA stands to be one of the world's most consequential groundwater regulations. Early work on SGMA has focused on the political economy of (Bruno, Hagerty, and Wardle (2022)) and anticipatory responses to (Bruno and Hagerty (2024)) the regulation. We contribute novel estimates of the impact of groundwater pricing, demonstrating that stringent policies will be required to achieve SGMA's sustainability goals—which will alter the landscape of some of the most valuable cropland on earth.

This paper proceeds as follows. Section 2 provides background on groundwater pumping and energy use in California agriculture. Section 3 describes our data. Section 4 presents our identifying variation and reduced-form estimates. Section 5 outlines our structural model and presents our dynamic estimates and counterfactual simulations. Section 6 concludes.

2 Background

2.1 Agriculture and irrigation in California

California is a major player in global agricultural production. The state produced $32 billion in crop value in 2019, representing 18% of the U.S. total—including 75% of the total value of U.S. fruits and nuts, and 57% of the total value of U.S. vegetables (USDA (2021)). California's 77,000 farms produce over 400 commodities, and they are the exclusive domestic producers of almonds, artichokes, olives, walnuts, and numerous other high-value crops (California Department of Food and Agriculture (2011)).

Irrigation is essential for farming in California due to scant summer precipitation. 95% of the state's 8.3 million harvested acres are irrigated (Johnson and Cody (2015)), and the agricultural sector is responsible for 80% of the state's total water consumption. Many of California's crops use large amounts of water. For example, hay, almonds, grapes, and rice—four of California's top crops by acreage—all require at least 3 acre-feet per acre per

12. For example, groundwater regulations exist in parts of Kansas (Drysdale and Hendricks (2018)), parts of Colorado (Smith et al. (2017)), and small regions of California (Bruno, Jessoe, and Hanemann (2024); Ayres, Meng, and Plantinga (2021)).

year, with rice using 5 acre-feet per acre per year (Bruno (2019)).[13] To water these thirsty crops, farmers rely on two water sources with vastly different governance structures (Sawyers (2007)): in an average year, 61% of irrigation comes from surface water, while 39% comes from groundwater (California Department of Water Resources (2015)).

Surface water Surface water in California is strictly regulated. Almost all farms with access to surface water obtain it via water districts. Most water districts function as co-operatives that divert water from rivers and canals for distribution to farmers in their geographic territory.[14] Individual farmers typically receive water allocations proportional to their acreage within the district (Schlenker, Hanemann, and Fisher (2007)); these allocations fluctuate from year to year depending on scarcity (e.g., the amount of snowpack). Importantly, farmers pay a lower marginal cost for district water allocations than for self-pumped groundwater (Hagerty (2022)). We therefore treat district water consumption as inframarginal to any observed groundwater use—since a farmer is unlikely to incur groundwater pumping costs without exhausting her annual allocation of (cheaper) district water.

Farmers also have a limited ability to purchase surface water on the open market. However, such transactions constitute only a very small share of total water deliveries, at prices much higher than marginal groundwater pumping costs (Hagerty (2023)).[15] We therefore assume that purchased water is not a viable substitute for agricultural groundwater.

Groundwater Groundwater supplies 30–40% of all water end uses in California in a normal year, and close to 60% in drought years when surface water is scarce (California Department of Water Resources (2014)). Unlike surface water, agricultural groundwater rights in California tend to be far more vague. The typical groundwater right is "overlying," meaning that a landowner whose property sits above an aquifer has the right to extract the underlying groundwater.[16] Historically, the vast majority of groundwater use has been unmetered,

13. For comparison, the average California household uses 0.52 acre-feet per year (Hanak et al. (2011)).

14. Districts were established between 1860 and 1950, and their boundaries have remained essentially fixed. Though some farms have individual water entitlements, the vast majority of surface water allocations come from districts. Hagerty (2022) provides a detailed description of surface water rights in California.

15. In our sample, the 99th percentile of marginal groundwater pumping costs is $137 per acre-foot. By contrast, Hagerty (2023) reports an *average* transaction price of $221 per acre-foot on the open market.

16. Pre- and post-SGMA, overlying rightsholders face few restrictions to drilling new groundwater wells, which cost $75,000 on average and typically reach 300–500 feet (Hadachek et al. (2024)). New wells must be

with users facing no variable prices beyond the costs of pump operation (Bruno and Jessoe (2021a)).[17] This has enabled farmers to extract vast amounts of groundwater to irrigate their overlying cropland.

Nearly all groundwater pumps in California run on electricity, the sole variable input to groundwater production.[18] This makes groundwater pumping the dominant electricity end use in the agricultural sector, which accounts for nearly 8% of the state's electricity consumption (California Energy Commission (2005)). Our empirical strategy leverages exogenous variation in electricity prices to instrument for groundwater pumping costs.[19]

2.2 Groundwater depletion and management policy

Due to California's longstanding open-access groundwater regime, many of the state's groundwater basins are "overdrafted"—meaning that withdrawals exceed the pace of replenishment, often by millions of acre-feet each year. The Central Valley has seen substantial groundwater losses, where the "critically overdrafted" Tulare and San Joaquin basins lost a combined 120 million acre-feet of groundwater from 1925–2008 (Konikow (2013)). California's groundwater depletion has been accelerating: while the average depletion rate from 1961–2021 was approximately 1.5 million acre-feet per year, a series of severe droughts increased this rate to 7 million acre-feet per year from 2019–2021 (Liu et al. (2022)). Panel A of Figure 1 shows that much of the Central Valley faced 10% average annual increases in groundwater depths (i.e., reductions in aquifer levels) during our 2008–19 study period, with greater losses in the southern half of the Valley. Panel B illustrates that these same areas are home to concentrated production of (high-value, water-intensive) fruit and nut perennial crops.

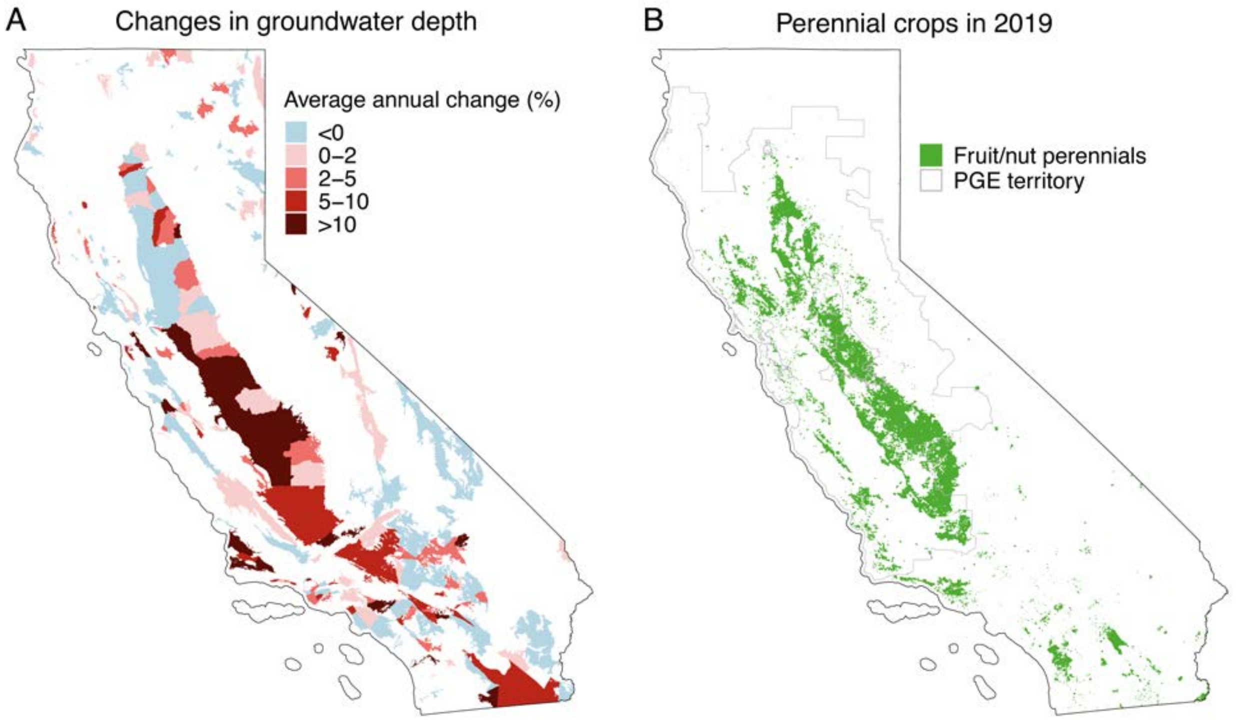
reported to the Department of Water Resources, and construction usually lasts less than one week (Central Valley Flood Protection Board (2020)). There are also "appropriative" groundwater rights, for users who do not own land above the aquifer. Users may only exercise appropriative rights in the case of a surplus.

17. There are limited exceptions to this rule, where a few irrigation districts impose a per-unit price on groundwater (e.g., the Pajaro Valley described in Bruno and Jessoe (2021a)).

18. Per the 2018 Census of Agriculture's Irrigation and Water Management Survey, California farms operate 94,698 pumps, of which 84,856 are powered by electricity, with only 8,043 powered by diesel (United States Department of Agriculture (2018)).

19. While previous studies have used variation in energy costs to estimate the price elasticity of groundwater demand (e.g., Hendricks and Peterson (2012); Pfeiffer and Lin (2014); Badiani and Jessoe (2019); among others) Mieno and Brozovic (2017) argue that prior estimates tend to be limited by a combination of (non-classical) measurement error, a lack of micro-level identifying variation, and relatively narrow geographies—challenges we overcome with our instrumental variables approach and data spanning PG&E.

Figure 1: Groundwater depletion and perennial crops



Notes: Panel A plots California's groundwater sub-basins, shading based on the average annualized change in depth during our 2008–2019 sample period. A 10% change in depth corresponds to a 10% increase in groundwater pumping costs, holding all else constant. This map averages depth measurements across each sub-basin from April–June of each year, to remove seasonality. Panel B plots the extent of fruit and nut perennial cropping from 2019, shading parcels for which "fruit/nut perennial" was the modal crop category. We also plot PGE's service territory in gray, which encompasses most of this perennial acreage.

A severe drought beginning in 2011 raised serious concerns about the future sustainability of California's groundwater resources. In September 2014, state lawmakers responded by passing the Sustainable Groundwater Management Act (SGMA). This sweeping legislation represented the first statewide effort to regulate groundwater extraction across all agricultural areas in the state, which are responsible for 90% of groundwater pumping (Bruno, Hagerty, and Wardle (2022)). SGMA comprises three separate bills. AB 1739 empowers California's Department of Water Resources (DWR) or local groundwater sustainability agencies (GSAs) to charge fees for groundwater extraction, and it requires GSAs to prepare groundwater sustainability plans (GSPs). SB 1319 authorizes GSAs to implement these GSPs. SB 1168 mandates that groundwater end uses be both reasonable and beneficial, and it enables GSAs and the DWR to require groundwater monitoring.

SGMA represents the future of groundwater management in California, with the goal of long-run sustainability—with each basin operating within its sustainable yield and avoiding "undesirable results."[20] Critically over-drafted (other medium- and high-priority) basins were required to submit GSPs by 2020 (2022) and are required to achieve sustainability by 2040 (2042).[21] Using data from the universe of GSPs, we calculate an average required reduction in pumping of 16.7% among regions in our sample currently experiencing overdraft.[22]

GSAs have a variety of tools at their disposal for reducing groundwater pumping, including price instruments (such as taxes or fees), quantity instruments (including both tradable and non-tradable allocations), ad-hoc pumping restrictions, and other conservation incentives (Bruno, Hagerty, and Wardle (2022)). Researchers predict these policy instruments will induce a variety of behavioral changes, including reducing irrigation intensity, shifting towards less water-intensive crops, and/or land fallowing (Bruno (2019)).

3 Data

3.1 PG&E data

We use confidential customer-level microdata from all of PG&E's agricultural service points (i.e., electricity meter locations).[23] For each service point, we observe monthly billing data from 2008–2019. These data report the service point's latitude and longitude, monthly electricity consumption (in kilowatt-hours, or kWh), monthly bill amount (in dollars), and electricity tariff. We use PG&E's published agricultural tariff schedules to calculate average marginal electricity prices (in $/kWh) for each service point-month.[24]

In addition, we leverage a unique PG&E dataset of agricultural groundwater pump audits, conducted as part of an ongoing energy efficiency program.[25] We observe detailed

20. Undesirable results include "chronic lowering of groundwater levels," "significant and unreasonable reduction of groundwater storage," "significant and unreasonable seawater intrusion," significant and unreasonable degraded water quality," "significant and unreasonable land subsidence," or "depletions of interconnected surface water" (California Department of Water Resources (2017)).

21. All SGMA implementation has occurred after our 2008–2019 analysis period. Bruno and Hagerty (2024) argue that there has not been anticipatory action to reduce groundwater use in response to SGMA's passage.

22. See Appendix C.6 for more details on our GSP data.

23. Appendix C provides further details on the data described in this section.

24. We drop the 9% of PG&E agricultural customers that ever have solar panels from our analysis, since their billed electricity use is net of (unobserved) solar production (i.e., we do not observe their actual electricity consumption).

25. PG&E heavily subsidizes these pump audits, such that farmers bear (close to) zero cost, while contractors are incentivized to recruit and test as many pumps as possible.

measurements and technical specifications from over 30,000 pump tests from 2011–2019. We match pump tests to service points in our billing data using electricity meter identifiers, isolating a subset of service points with confirmed agricultural groundwater pumps.[26]

3.2 Constructing groundwater prices and quantities

Physics governs the relationship between kWh of electricity input and acre-feet (AF) of groundwater output for each pump:

$$\text{AF} \;=\; \frac{\text{Operating pump efficiency (\%)}}{[\text{Lift (feet)}] \times 1.0241} \times \text{kWh} \tag{1}$$

PG&E's pump audit data report the operating efficiency of each pump. To parameterize lift—the vertical distance from the groundwater source to the surface—we combine PG&E's measurements with publicly available data on groundwater depths from California's Department of Water Resources. Since these depth measurements vary across space and time, we condition Equation (1) on contemporaneous groundwater levels at each service point.[27] Using these pump-specific production functions and data on electricity quantities and prices, we compute groundwater use (in AF) and marginal groundwater costs (in \$/AF) for each confirmed pump in our sample over time.

Deriving groundwater use from electricity, pump test, and groundwater depth data introduces multiple sources of measurement error, including: infrequent pump tests, spatial and temporal interpolation of depth measurements, and challenges in modeling how pumps impact their own depth. We address measurement error by instrumenting for marginal pumping costs using PG&E's electricity tariffs, which are uncorrelated with the parameterization of Equation (1) (see Section 4.1 for details on our instrumental variables approach).

26. PG&E typically installs a dedicated meter for each groundwater pump. Nearly all pump tests match to an agricultural service point. Focusing our analysis on this matched subset of confirmed pumps ensures that we are measuring energy used for pumping, avoiding other agricultural electricity end uses (e.g., refrigeration, barn lighting, or heating greenhouses). We drop service points for which a matched pump test reports a non-well water source (e.g., canal), ensuring that our sample comprises confirmed *groundwater* pumps.

27. We rasterize thousands of depth measurements for each sample month. Calculating lift also requires pump-specific measures of drawdown (i.e., how much a pump's extraction impacts its own depth), which depends on rate of flow and subsurface characteristics. We parameterize drawdown using the value reported in each pump test. Appendix C.3 provides further details on how we apply and parameterize Equation (1).

We restrict our analysis to confirmed pumps (i.e., those with matched groundwater pump tests) for two reasons. First, to estimate how groundwater use responds to changes in costs, we require pump audit data to convert from electricity to groundwater. Second, and perhaps more importantly, we are interested in the impact of groundwater cost shocks on *groundwater* extraction. Limiting our sample to confirmed pumps prevents us from mistakenly incorporating other agricultural electricity uses not directly related to groundwater.[28]

3.3 Land use data

We use California county assessor tax parcels as farm boundaries, as in Bruno, Jessoe, and Hanemann (2024). We spatially merge PG&E service points to parcel polygons, linking each groundwater pump to the fields that it most likely irrigates. Then, we match parcel polygons to the USDA's Cropland Data Layer (CDL), which reports annual satellite-derived crop coverage for each 30m^2 pixel in California. We classify CDL-reported land types into five mutually-exclusive and exhaustive categories: annuals, fruit/nut perennials, hay perennials, non-crop (i.e., fallow cropland), and not croppable.[29] We also link parcels to groundwater sub-basins (to enable controls for common shocks to groundwater depth) and to water districts (to enable controls for surface water allocations).

3.4 Summary statistics

Panel A of Table 1 compares our preferred sample, including *only* confirmed pumps, to all other PG&E agricultural service points. While these two groups face similar marginal electricity prices ($0.13/kWh vs. $0.16/kWh), confirmed pumps have much greater energy consumption (10,133 vs. 4,519 kWh/month). This is unsurprising, as groundwater pumping is far more energy-intensive than other farm end-uses. To the extent that our matching process filters out (unconfirmed) groundwater pumps that never received PG&E pump tests, our

28. This sample restriction is conservative, since it removes any groundwater pumps that did not receive PG&E pump audits. However, we recover similar reduced-form estimates if we expand the sample to include all PG&E agricultural customers (see Table 2, Columns (2)–(3)). We can also rule out cone-of-depression spillover effects from unobserved pumps that we omit from our sample (see Appendix Table B7).

29. Our analysis removes all not-croppable acreage (e.g., development, forests), adjusting the denominator of each parcel to include only cropland. Due to measurement error in the CDL (as discussed in Hagerty (2022)) and to ease computational burden, we use crop categories rather than individual crop classifications.

Table 1: Summary statistics

	Confirmed pumps	Other agricultural users
A. Service point-level statistics		
Unique service points (SPs)	10,146	83,721
Months observed (2008–2019)	102.7	101.9
	(42.0)	(43.2)
Average electricity use (kWh/month)	10,133	4,519
	(13,789)	(27,204)
Average marginal electricity price (\$/kWh)	0.13	0.16
	(0.03)	(0.04)
Average electricity bill (\$/month)	1,825.78	781.12
	(2,006.48)	(3,181.37)
Average groundwater use (AF/month)	33.26	
	(42.52)	
Average marginal groundwater cost (\$/AF)	47.69	
	(25.91)	
B. Parcel-level statistics (acreage-weighted)		
Unique parcels	7,127	41,732
Count of SPs per parcel	1.92	2.00
	(1.71)	(1.56)
"Croppable" area of parcel (acres)	331.43	284.65
	(395.63)	(425.10)
Average share of annual crops	0.218	0.235
	(0.272)	(0.313)
Average share of fruit/nut perennial crops	0.449	0.304
	(0.397)	(0.375)
Average share of hay perennial crops	0.245	0.366
	(0.275)	(0.376)
Average share of noncrop (fallow)	0.089	0.095
	(0.139)	(0.163)
Average groundwater use (AF/acre per year)	4.201	
	(5.127)	
Parcel within surface water district (1/0)	0.600	0.609
	(0.490)	(0.488)

Notes: We report means and standard deviations (in parentheses) across unit-specific averages. Panel A uses monthly billing data for all PG&E agricultural electricity service points (i.e. the physical locations of electricity meters). The vast majority of our analysis focuses on the SPs in the left column, for which we observe PG&E pump audits, thereby (i) confirming that the SP operates a vertical groundwater pump, and (ii) letting us populate Equation (1) to convert from kWh to AF. The right column includes all remaining agricultural SPs, for which we cannot calculate AF/month or \$/AF: we cannot distinguish groundwater pumps from other agricultural electricity end uses (e.g. refrigeration), let alone parameterize pump-specific production functions. Panel B aggregates up to the parcel level, our main unit of analysis. The left column includes our core sample for reduced-form and structural estimation: agricultural parcels that contain SPs in the left column of Panel A. The right column includes the additional parcels that contain SPs in the right column of Panel A (but not in the left column). For consistency with our reduced-form and structural analyses, Panel B: weights parcels by (time-invariant) croppable acreage; uses croppable (rather than total) acreage to denominate crop shares; omits parcels with less than 1 or greater than 5,000 croppable acres; and omits parcels with annual electricity bills exceeding \$3,000 per croppable acre.

preferred sample is skewed towards larger pumps that are most important for groundwater management policy. The average confirmed pump produces 33.26 AF of groundwater per month at a marginal cost of \$47.69/AF.[30]

Panel B aggregates from the service point-month to the parcel-year, our unit of analysis. This yields a preferred sample (left column) of 7,127 parcels containing confirmed pumps. The average in-sample parcel has 331 croppable acres, with 22%, 45%, 25%, and 9% of acres in annuals, fruit/nut perennials, hay perennials, and non-crop, respectively. Compared to parcels in the right column containing other agricultural users (i.e., parcels where electricity is not necessarily used for irrigation), our sample is selected towards larger parcels with more fruit/nut perennials and less hay perennials. Across all four categories, in-sample parcels use an average of 4.2 AF of groundwater per acre per year.[31]

4 Reduced form estimation and results

In this section, we use a panel fixed effects approach to measure farmer responses to groundwater pumping costs on an annual time scale. We present two sets of reduced-form results: the effects of year-over-year cost shocks on electricity and groundwater consumption, and the impacts of these same cost shocks on crop choice.

This section serves four purposes. First, we introduce our variation in groundwater pumping costs, which also underpins our dynamic discrete choice model, and argue that it is plausibly exogenous. Second, we show a proof-of-concept that farmers indeed respond to changes in groundwater costs by altering their pumping behavior. Third, we generate a key input into our structural model: the short-run "intensive-margin" elasticity of groundwater demand with respect to groundwater cost, conditional on crop choice. Fourth, we demonstrate that farmers do not respond to year-over-year changes in groundwater costs

30. Farmers face far more variation in groundwater costs than in electricity prices, due to both dispersion in pumping efficiencies and changing groundwater depths.

31. This average (which comes from applying Equation (1) to PG&E data) aligns with irrigation budgets in agronomic studies. For example, almond orchards in California's San Joaquin Valley are estimated to require 3–5 AF per acre per year (https://coststudies.ucdavis.edu/current/commodities/almonds). We cannot calculate a comparable statistic for parcels containing (unconfirmed) pump(s) that PG&E did not test.

by switching crops—suggesting that there may be differences between short- and long-run responses to groundwater costs, which we will estimate using our dynamic model.

4.1 Groundwater responses to cost shocks

We estimate the effect of cost shocks on groundwater usage via the following two-stage least squares specification:

$$\log\left(Q_{it}^{\text{water}}\right) = \gamma \widehat{\log\left(P_{it}^{\text{water}}\right)} + \psi_i + \delta_t + \epsilon_{it} \tag{2}$$

$$\log\left(P_{it}^{\text{water}}\right) = \theta \log\left(P_{it}^{\text{elecDefault}}\right) + \psi_i + \delta_t + \nu_{it} \tag{3}$$

The outcome variable is the natural logarithm of groundwater extracted at parcel i in year t. The explanatory variable is the natural logarithm of the marginal cost of groundwater. ψ_i and δ_t are a set of cross-sectional and time fixed effects, which we describe below. ϵ_{it} and ν_{it} are idiosyncratic errors, which we two-way cluster by parcel and county-by-year. We weight these regressions by each parcel's croppable acreage (excluding forests, development, etc.), making our estimates representative per acre of cropland.[32]

To econometrically identify the cost response γ in Equation (2), we leverage both cross-sectional and time-series variation in PG&E's electricity tariff schedules—a key component of P_{it}^{water}. We argue that these tariffs schedules are plausibly exogenous with respect to groundwater pumping decisions. Electricity tariff schedules are the outcome of statewide regulatory proceedings, which individual farmers cannot plausibly influence. Moreover, tariff decisions are made 1–3 years in advance and do not reflect current conditions (e.g., droughts). To assuage any remaining concerns about using these tariffs for identification, Appendix B demonstrates that our results are robust to controlling for: contemporaneous and lagged weather, drought indices, groundwater depths, and differential geographic trends.[33]

While PG&E's tariff *schedules* are plausibly exogenous, however, the marginal electricity price that a farmer faces is potentially endogenous—since an individual farmer may select

32. Appendix Table B9 shows that our estimates attenuate slightly (though retain statistical significance) when we omit these weights, suggesting that larger parcels tend to be more groundwater-cost-responsive.

33. Since PG&E's agricultural tariff schedules apply uniformly across their service territory (unlike geographically differentiated residential tariffs (Buchsbaum (2023))), selection over space is of limited concern.

their actual electricity rate from a menu of tariffs.[34] However, PG&E restricts these choices by sorting farmers into four mutually exclusive tariff categories based on their pump's capacity (smaller vs. larger than 35 horsepower) and their electricity meter type (conventional analog vs. digital smart meters). We leverage these category restrictions for identification by instrumenting for the marginal cost of water (P_{it}^{water}) using the "default" marginal electricity price for farmer i's category ($P_{it}^{\text{elecDefault}}$).[35]

This instrument relies only on plausibly exogenous variation in PG&Es tariff schedules, thereby eliminating several potential sources of bias. First, the instrument eliminates selection bias driven by farmers' tariff choices (e.g., a high-volume pumper choosing a tariff with a low volumetric price). Second, it addresses simultaneity bias that arises when a pump's own extraction increases local groundwater depths, thereby increasing its own pumping costs. Third, it purges other potentially endogenous variation in the marginal cost of groundwater (e.g., drought, which both increases groundwater pumping costs and changes farmers' water needs). Finally, it addresses potential measurement error in P_{it}^{water} that may arise when parameterizing Equation (1).[36]

This instrumental variables approach identifies γ off of differential changes in electricity prices *across* tariff categories over time. Panel A of Figure 2 plots raw time series of $P_{it}^{\text{elecDefault}}$ during our sample period. Panel B plots these same time series partialling out tariff and year fixed effects (a tariff-level analog of the fixed effects in Equations (2)–(3)), illustrating the identifying variation we use in both our reduced-form and structural estimation.

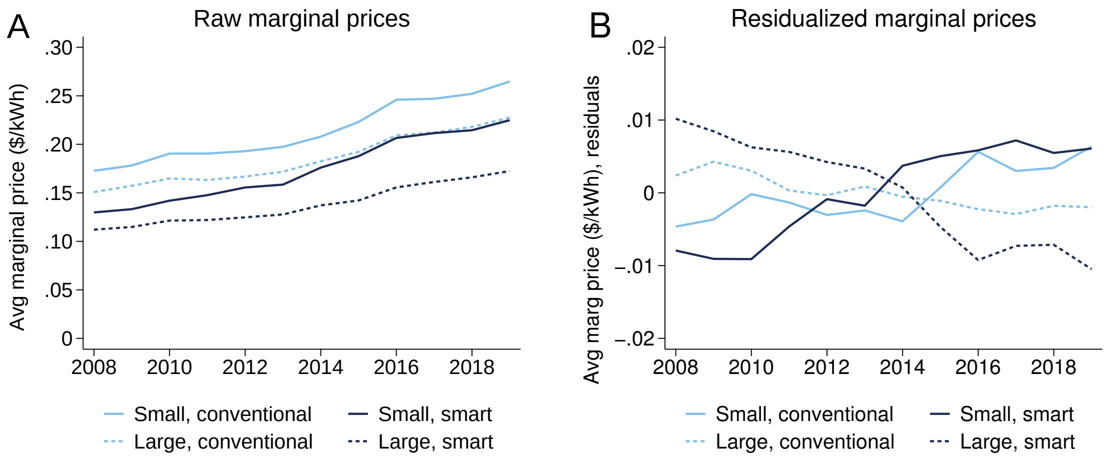
We include a series of fixed effects to address remaining potential confounders in our regressions. Parcel fixed effects address time-invariant differences across parcels, including

34. Unlike PG&E's residential tariffs, which have increasing block prices, making a household's marginal price endogenous to its own consumption (Ito (2014)), PG&E's agricultural tariffs have linear volumetric prices. This means that unit i's marginal electricity price in a given hour depends solely on its tariff.

35. Small-conventional and large-conventional categories each comprise a single (default) tariff. Small-smart and large-smart categories comprise 8 and 12 tariffs respectively. We assign the simplest (i.e., least time-varying) tariff in each category as the default tariff; instrumenting with each category's modal tariff yields similar results (see Appendix Table B8). We omit a fifth category reserved for the 1.7% of farmers transitioning from internal combustion to electric power, since they are likely not comparable to the rest of our sample, and we do not observe them before they consumed electricity.

36. In Equation (2), measurement error from converting kWh to AF enters in P_{it}^{water} (i.e., \$/kWh $\div$ AF/kWh) and in Q_{it}^{water} (i.e., kWh $\times$ AF/kWh). Instrumenting with default electricity prices negates the correlation between left-hand-side and right-hand-side measurement error. An un-instrumented OLS regression returns a larger elasticity (in absolute value), which we report in Appendix Table B8.

Figure 2: Marginal electricity prices for four default tariffs



Notes: This figure plots times series of annual average marginal electricity prices ($/kWh) for PGE's four default agricultural tariffs. Panel A plots raw average marginal prices for each year in our estimation sample, taking unweighted averages across all hours (marginal prices are higher in summer months and on weekdays). Panel B plots residuals of these four time series after partialing out tariff and year fixed effects (aligning with the fixed effects we use when estimating Equations (2)–(3)). The four tariff categories are defined by customers' physical capital: small ($<$ 35 hp) vs. large ($\geq$ 35 hp) pumps, and conventional vs. smart meters. Our identifying variation comes from differential price changes across default tariffs, as well as PGE's smart meter rollout—which exogenously shifted many customers from conventional to smart categories, lowering their marginal price.

selection into tariff categories (e.g., parcel A has a larger pump than parcel B, and thus uses more electricity at a lower marginal price)—though we observe no bunching at the 35 horsepower cutoff between small vs. large pumps.[37] We also include parcel $\times$ $\mathbf{1}$[large pump] fixed effects, which address any simultaneity due to farmers moving across tariff categories (i.e., a small-to-large-pump switch mechanically increases Q_{it}^{water} and decreases $P_{it}^{\text{elecDefault}}$), though only 4% of service points make such a switch during our sample. Year fixed effects absorb time-varying conditions that are common across all parcels (e.g., crop prices). We also include groundwater-basin-by-year and water-district-by-year fixed effects, which absorb shocks common to relatively small geographic areas, including surface water availability and basin-wide groundwater depths.

Table 2 presents our results from estimating Equations (2)–(3). A 1% increase in groundwater costs leads farmers to reduce groundwater use by 0.938% (Column (1); $p <$ 0.01), demonstrating that farmers do change pumping behavior in response to groundwater cost shocks. We also estimate the analogous model for electricity (replacing Q_{it}^{water} and P_{it}^{water} with Q_{it}^{elec} and P_{it}^{elec}), which yields a nearly identical 0.899% reduction in electricity usage

37. See Appendix Figure C2. Appendix Table B4 reveals that our results are similar if we interact month-of-sample fixed effects with deciles of horsepower.

Table 2: Groundwater use responds to annual variation in pumping costs

	(1) $\log(Q^{\text{water}})$	(2) $\log(Q^{\text{elec}})$	(3) $\log(Q^{\text{elec}})$
$\log(P^{\text{water}}$ (\$/AF))	-0.938^{***}		
	(0.220)		
$\log(P^{\text{elec}}$ (\$/kWh))		-0.899^{***}	-0.734^{***}
		(0.224)	(0.092)
Include all parcels with agricultural SPs			Yes
Parcel units	7,104	7,104	46,563
County-years	367	367	506
Parcel-year observations	60,490	60,490	391,707
First-stage estimates			
$\log(P^{\text{elecDefault}}$ (\$/kWh))	1.418^{***}	1.284^{***}	1.078^{***}
	(0.043)	(0.024)	(0.008)
Kleibergen-Paap F-statistic	1094	1494	8575

Notes: Column (1) estimates Equations (2)–(3) at the parcel-year level using two-stage least squares. The outcome variable is the natural logarithm of groundwater consumption; we instrument for pumping costs with default electricity prices. This recovers an estimate of the cost elasticity of groundwater demand. Column (2) uses the quantity and price of electricity (which we observe directly), rather than the quantity and price of groundwater (which we construct). Columns (1)–(2) use the sample of parcels containing confirmed pumps (i.e., Table 1, Panel B, left column). Column (3) is analogous to Column (2), expanding the sample to include all parcels containing PG&E agricultural customers (i.e., Table 1, Panel B, both columns). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump] (to capture tariff category switches), year, groundwater basin $\times$ year (to capture trends in depth), and water district $\times$ year (to capture changes in surface water availability). Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

due to a 1% electricity cost shock (Column (2); $p < 0.01$). When we include *all* parcels with agricultural users (i.e., both columns of Panel B of Table 1, rather than just the left column), we find a similar 0.734% reduction due to a 1% electricity cost shock (Column (3); $p < 0.01$). Even though our sample of confirmed pumps differs from other agricultural users, comparing Columns (2) vs. (3) reveals that this selection does not create a meaningful difference in how farmers respond to cost shocks.[38]

While our instrument and fixed effects eliminate major threats to identification, we also address a series of remaining possible concerns.

Smart meter rollout During our sample period, PG&E gradually replaced remaining conventional (analog) meters with smart (digital) meters. As part of this broad smart meter

38. We cannot make the analogous comparison to Column (1), as we lack the necessary inputs to the electricity-to-groundwater conversion for parcels without confirmed pumps.

rollout, we observe 21% of the service points in our sample switching from conventional- to smart-meter categories. Since the rollout's timing reflected institutional factors outside of farmers' control, meter-induced category switches provide plausibly exogenous variation in $P_{it}^{\text{elecDefault}}$.[39] To assuage any concerns about endogenous meter upgrades, Appendix Tables B4 and B5 show that our estimates are robust to controlling for differential time trends in covariates that could have predicted the smart meter rollout.[40]

Weather realizations PG&E's tariff schedule should be uncorrelated with climatic conditions, especially after controlling for parcel, year, basin-by-year, and water-district-by-year fixed effects. Appendix Table B6 confirms that our estimates are robust to controlling for local weather realizations and drought severity, assuaging any concerns that correlations between weather and electricity prices could be generating omitted variables bias.[41]

Cone of depression spillovers Between-well spillovers could potentially violate our exclusion restriction: if parcel i experiences the same shock to default electricity prices as its neighboring parcel j, and if j responds by altering their pumping behavior, the resulting change in parcel j's cone of depression could impact parcel i's groundwater depth—in turn impacting parcel i's pumping behavior.[42] Appendix Table B7 explicitly models such spillovers, by controlling for average default electricity prices of parcel i's neighbors.[43] This does not meaningfully alter our results, assuaging concerns of bias due to localized spillovers.

39. The rollout affected both agricultural and non-agricultural customers. Previous research has established that PG&E did not design their smart meter rollout to target customers with particular usage patterns (Blonz (2022)). Since farmers could not influence the timing of their meter upgrades, it is highly unlikely that these upgrades are systematically correlated with unobserved changes in pumping behavior.

40. These covariates include: pump size, pump efficiency, county, climate zone, maximum electricity usage (reflecting customer-specific switching benefits to PG&E), and age of service point.

41. We control for parcel-specific temperature and precipitation, separately for all 12 months of the current and preceding year. Our county-year drought controls include five levels of increasing severity.

42. Cones of depression form when extraction from a well temporarily removes groundwater from the surrounding areas of the aquifer, typically within a radius of a few miles (Alley, Reilly, and Franke (1999)).

43. We control for the average $P_{(-i)t}^{\text{elecDefault}}$ for neighbors within radii of 1, 2, and 10 miles. We specify this control separately for neighbors in our main estimation sample (i.e., confirmed pumpers), and for all other neighbors on PG&E agricultural tariffs (to capture the effects of other potential pumpers). We also control for the count of neighbors of each type, to address the possibility of greater spillover intensities in areas with a higher density of pumps. Groundwater-basin-by-year fixed effects control for broader geographic spillovers due to common shocks to default electricity prices.

Unobserved pump upgrades Higher groundwater costs could induce farmers to invest in pump efficiency improvements. Since we do not observe groundwater use directly (instead inferring it from electricity consumption), we could mistake these efficiency upgrades for groundwater pumping reductions (rather than reductions in the amount of electricity need to pump an acre-foot of water). Appendix Table B1 addresses this concern by restricting the sample to parcel-years proximate to an observed pump test, thereby minimizing the possibility of bias from unobserved efficiency improvements. If anything, this slightly increases the magnitudes of our estimates, suggesting that the pump efficiency channel is not driving our results by biasing our construction of Q_{it}^{water}.

kWh-to-AF conversions As we discuss in Section 3.2, converting from electricity to groundwater introduces multiple sources of measurement error. Our instrument, $P_{it}^{\text{elecDefault}}$, eliminates these sources of measurement error, since electricity tariffs are not correlated with the timing and specifics of pump audits or groundwater depth readings. Still, Appendix Tables B2 and B3 show that our estimates are robust to: alternative parameterizations of lift in Equation (1), dropping pumps with questionable audit data, and dropping pumps far from contemporaneous groundwater readings.

4.2 Groundwater responses and crop choice

Having shown that farmers respond to groundwater cost shocks, we next estimate the extent to which they respond on the *intensive margin*—that is, holding constant their existing crop category (i.e., annuals, fruit/nut perennials, hay perennials, or non-crop). This intensive-margin elasticity is a key input to our dynamic structural model of crop choice, since counterfactual groundwater costs will alter *both* farmers' crop choices *and* their irrigation behavior conditional on crop choices.

To estimate the intensive-margin elasticity, we restrict our sample to parcels that chose the same crop category as the preceding year, while also adding parcel-by-crop-category fixed effects to control for parcel-crop-specific irrigation needs. We report these results in Columns (1) and (2) of Table 3. Our conditional point estimates of -0.843 for groundwater and -0.804 for electricity (both $p < 0.01$) are only slightly smaller than estimates of the unconditional responses shown in Table 2. This indicates that farmers' responses to year-on-year cost shocks are driven by the intensive margin, rather than the crop switching margin.[44]

Table 3: Short-run responses do not reflect crop switching

	(1) log(Q^{water})	(2) log(Q^{elec})	(3) Share annuals	(4) Share perennials	(5) Share hay	(6) Share non-crop
$\log\left(P^{\text{water}}\ (\$/\text{AF})\right)$	-0.843^{***}		0.002	-0.003	-0.004	0.005
	(0.238)		(0.017)	(0.020)	(0.019)	(0.017)
$\log\left(P^{\text{elec}}\ (\$/\text{AF})\right)$		-0.804^{***}				
		(0.238)				
Intensive margin	Yes	Yes				
Parcel units	6,997	6,997	7,131	7,131	7,131	7,131
County-years	334	334	367	367	367	367
Parcel-year observations	46,202	46,202	61,910	61,910	61,910	61,910
First-stage estimates						
$\log\left(P^{\text{elecDefault}}\ (\$/\text{kWh})\right)$	1.316^{***}	1.234^{***}	1.425^{***}	1.425^{***}	1.425^{***}	1.425^{***}
	(0.050)	(0.029)	(0.043)	(0.043)	(0.043)	(0.043)
Kleibergen-Paap F-statistic	690	1079	1092	1092	1092	1092

Notes: Columns (1)–(2) are identical to Columns (1)–(2) of Table 2, except that we restrict the sample to parcel-years with the same modal crop category (i.e., annuals, fruit/nut perennials, hay perennials, non-crop) as the preceding year and interact parcel fixed effects with the four categories. This isolates the within-crop intensive margin of groundwater use, shutting down the crop-switching channel that we structurally estimate below. Columns (3)–(6) are identical to Column (1) of Table 2, except that the outcome variables are the share of acres in a crop category for each parcel-year. All regressions include the following fixed effects: parcel, parcel × $\mathbf{1}$[large pump] (to capture tariff category switches), year, groundwater basin × year (to capture trends in depth), and water district × year (to capture varying surface water availability). Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Columns (3)–(6) of Table 3 provide direct reduced-form tests of this crop switching margin, by replacing the dependent variable in Equation (2) with the share of parcel i's (croppable) acres allocated to a specific crop category in year t. These regressions corroborate our intensive-margin results: for all four crop types, we recover precise null estimates of the effect of year-on-year groundwater costs shocks on crop switching. Together, these regressions provide suggestive evidence that farmers are unlikely to switch crops in response to short-run price changes. To fully quantify the impact of both short- and long-run price changes on crop choice, groundwater use, and electricity use, we next turn to our dynamic model.

44. As we describe in Section 5.3 and Appendix A.3, our counterfactual simulations use a version of this reduced-form groundwater response, adjusted for the fact that some short-run intensive-margin responses are unlikely to persist over multiple years. We calibrate this adjustment using long differences.

5 Structural estimation and results

We specify a dynamic discrete choice model of farmers' cropping decisions that captures two key features of our setting. First, since many California farmers make long-run investments in perennial crops, we incorporate state dependence in annual cropping decisions. Second, because SGMA introduces permanent changes to groundwater policy, we let farmers' annual decisions reflect rational forward-looking expectations.

We use a conditional choice probability approach (Scott (2013); Kalouptsidi, Scott, and Souza-Rodrigues (2021)) to estimate parameters without needing to specify the evolution of individual market-level states. We then use our estimated dynamic model to simulate responses to both short- and long-run counterfactual groundwater taxes. These simulations generate short- and long-run (semi-)elasticities of crop choice, groundwater use, and electricity use with respect to the marginal cost of groundwater. Our model closely follows Scott (2013), who estimates how changes in crop revenues impact land use. We extend this prior work by (i) estimating land use responses to input costs rather than output prices; (ii) expanding from two to four land-use categories; (iii) allowing for both intensive- and extensive-margin responses to water costs in counterfactual simulations; (iv) incorporating expectations over drought, a key market state variable, in simulations; (v) going beyond land use to generate elasticities for electricity and groundwater; and (vi) estimating both short- and long-run elasticities.

5.1 Model of crop choice

We model annual profits on a given field as a function of crop choice, with crop-specific groundwater pumping costs. Each year, a farmer chooses a crop $c \in \mathcal{C} = \{$annuals, fruit/nut perennials, hay perennials, non-crop$\}$ to maximize expected discounted profits over an infinite time horizon.[45] Profits from crop choice c depend on two state variables: the field state and the market state. The field state $k \in \mathcal{K}$ represents field-level characteristics at the start

45. We aggregate crops into these four broad categories both for model tractability and to avoid concerns about measurement error in the CDL. Fruit/nut crops and hay crops are both perennials, but have different cost structures: whereas hay requires low upfront costs and can be harvested soon after planting, orchards and vineyards require high upfront costs and take longer to reach maturity. We use "fruit/nut" to refer to perennial fruit and nut crops, and "hay" to refer to perennial hay crops (e.g., alfalfa).

of a growing season, which depend on past cropping decisions. The market state $\omega \in \Omega$ is the set of market-level variables that affect the expected profitability of each crop, such as input prices, output demand, government policies, and widespread weather events (e.g. drought). The market state is known to all farmers but is not fully observed by the econometrician.

Assumption 1: Profit function Annual profits on a given field in year t depend on crop choice c_t, field state k_t, market state ω_t, and a vector of idiosyncratic shocks ε_t. We define the profit function as:

$$\pi(c_t, k_t, \omega_t, \varepsilon_t) = \alpha_G G(c_t, \omega_t) + \alpha(c_t, k_t) + \xi(c_t, k_t, \omega_t) + \varepsilon_{ct} \tag{4}$$

$G(c_t, \omega_t)$ is the total variable cost of groundwater pumping, which depends on the water requirements of crop c_t and the market state ω_t; we estimate the parameter α_G.[46] $\alpha(c_t, k_t)$ represents the time-invariant component of average net returns to crop c_t, excluding groundwater costs and net of the costs of transitioning from field state k_t to crop c_t; we estimate these parameters. $\xi(c_t, k_t, \omega_t)$ represents the time-varying component of average net returns to crop c_t in field state k_t, which depends on the market state ω_t. Finally, ε_{ct} is an idiosyncratic shock to profits for crop c_t in year t, which we assume is independent and identically distributed Type-I extreme value; we denote the joint distribution of the vector ε_t as $F^{\varepsilon}(\varepsilon_t)$.

Assumption 2: State dependence and renewal actions Crop choice dynamics enter through the transition cost component of $\alpha(c_t, k_t)$.[47] Accounting for state dependence is essential given California's abundance of perennial crops, which are harvested across multiple years from a single planting. Growing a perennial crop in consecutive years incurs much lower costs than switching *into* the same perennial crop because the latter comes with an upfront investment cost.

46. We use total variable costs, rather than total costs, because fixed fees on electricity bills are crop-choice invariant. Assuming Q^{water} responds only on the extensive (crop choice) margin, a percent change in marginal cost (measured in \$/AF) is equivalent to the same percent change in total variable cost (measured in \$), meaning (semi-)elasticities with respect to both cost measures are identical. If Q^{water} also responds on the intensive margin, a percent change in marginal cost yields a smaller percent change in total variable cost. Our simulations below consider both margins, necessitating this marginal vs. variable cost distinction.

47. As Scott (2013) discusses, it is common for dynamic incentives to enter only through an intercept term.

Formally, we assume the field state in year t is Markovian and depends on only the preceding year's crop choice, not on choices in prior years: $k_t = c_{t-1}$. Thus, profit in year t is unaffected by choices made prior to year $t-1$. This assumption captures the salient feature of perennial cropping in our setting—high upfront costs followed by a stream of annual harvests with lower recurring costs.[48] As a result, any crop choice $c \in \mathcal{C}$ is a "renewal action," meaning that choice c_t will yield a particular field state in the following year k_{t+1} regardless of states in prior years (Kalouptsidi, Scott, and Souza-Rodrigues (2021)).[49]

Assumption 3: Small fields We assume that the market state ω_t evolves following a Markov process that is independent of the crop choice on any single field. That is, the distribution of the market state, $F^{\omega}(\omega_t)$, satisfies $F^{\omega}(\omega_{t+1} \mid c_t, \omega_t) = F^{\omega}(\omega_{t+1} \mid \omega_t)$ for all c_t on each field. This assumption implies that fields are small relative to the size of their market, causing farmers to treat ω_t as exogenous. Following from this assumption, we also treat each field as independent.[50]

Value function and conditional choice probabilities Under Equation (4), the expected discounted stream of future profits from a given field is given by the value function:

$$V(k_t, \omega_t, \varepsilon_t) = \max_{c_t \in \mathcal{C}} \left\{ \pi(c_t, k_t, \omega_t, \varepsilon_t) + \beta E\left[V(k_{t+1}, \omega_{t+1}, \varepsilon_{t+1}) \mid c_t, \omega_t \right] \right\} \tag{5}$$

We assume the common discount factor $\beta = 0.9$ following the literature (e.g., Scott (2013); Hsiao (2024)). The resulting conditional choice probabilities (CCPs), or the probability that

48. This assumption is sufficient to generate distinct responses to short-run transient cost shocks vs. long-run permanent cost shocks. Without field state dependence, farmers might unrealistically tear out their almond orchards in response to a single-year shock and then replant almonds the following year. By assuming even a single year of field state dependence, we impose crop switching costs that would likely make this kind of response unprofitable. In doing so, we abstract from second-order dynamic considerations that are less likely to impact the long-run cropping response, such as the time it takes for young perennials to reach maturity and bear fruit, because (i) modeling multiple perennial vintages would be less tractable and (ii) growth profiles vary substantially across crops within our "fruit/nut perennials" category.

49. For estimation, we rely on fallowing being a renewal action: choosing $c_t =$ non-crop effectively resets the transition costs in the following year, regardless of the cropping history.

50. If one landowner operates multiple fields, this assumption implies that maximizing profits jointly across fields would be equivalent to maximizing profits for each field independently.

the farmer chooses crop c_t conditional on being in field state k_t, are:

$$p(c_t, k_t, \omega_t) = \frac{\exp\left[v(c_t, k_t, \omega_t)\right]}{\sum_{c'_t \in \mathcal{C}} \exp\left[v(c'_t, k_t, \omega_t)\right]} \tag{6}$$

where $v(c_t, k_t, \omega_t)$ gives the conditional value of selecting crop choice c_t in field state k_t, which follows from the value function in Equation (5).[51] This expression emphasizes that CCPs contain information about the relative value of making different crop choices.

$$\begin{aligned}
\ln\left[\frac{p(c_t, k_t, \omega_t)}{p(c'_t, k_t, \omega_t)}\right] + \beta \ln\left[\frac{p(r_{t+1}, c_t, \omega_{t+1})}{p(r_{t+1}, c'_t, \omega_{t+1})}\right] &= \alpha_G\left[G(c_t, \omega_t) - G(c'_t, \omega_t)\right] \\
&+ \alpha(c_t, k_t) - \alpha(c'_t, k_t) + \beta\left[\alpha(r_{t+1}, c_t) - \alpha(r_{t+1}, c'_t)\right] \\
&+ \xi(c_t, k_t, \omega_t) - \xi(c'_t, k_t, \omega_t) + \beta\left[\xi(r_{t+1}, c_t, \omega_{t+1}) - \xi(r_{t+1}, c'_t, \omega_{t+1})\right] \\
&+ \beta\left[e^V(c_t, \omega_t, \omega_{t+1}) - e^V(c'_t, \omega_t, \omega_{t+1})\right]
\end{aligned} \tag{7}$$

Each side of Equation (7) is equivalent to the difference in values between choosing c_t or c'_t in year t, followed by renewal action r_{t+1}, and then choosing optimally in all following years.

5.2 Estimation

To empirically estimate Equation (7), we require CCPs and total variable groundwater costs for each crop in the choice set, as well as an instrument for (potential) groundwater cost endogeneity.[52] We construct these variables using data from all fields in a "market" in which farmers face a similar choice environment—including similar transition costs, crop-specific groundwater costs, and market states. We define markets using three criteria: electricity tariff, surface water availability, and geography.[53] We construct CCPs by aggregating crop choices within each market, and we use observed groundwater costs in the market to construct crop-specific pumping costs.

51. See Appendix A.1 for mathematical definitions of the *ex ante* and conditional value functions.

52. For each field, we observe groundwater costs for the *chosen* crop, but not CCPs or groundwater costs for all other possible crop choices.

53. We first split by PG&E's small- and large-pump tariff categories. For surface water availability and geography, we then group fields by water district or (if not in a water district) by county. For water districts where we observe fewer than 30 parcels, we instead group by counties to ensure sufficient observations within a market. Appendix A.2 provides more details on market construction.

5.2.1 Variable construction

Conditional choice probabilities We observe land use at a 30-meter resolution in the CDL. We calculate CCPs from the observed pixel-level sequence of crop choices in parcels in our sample. We aggregate pixel-level conditional choices within each market:

$$p_m(c_t, k_t, \omega_{mt}) = \frac{n_{mckt}}{\sum_{c' \in \mathcal{C}} n_{mc'kt}}$$

where n_{mckt} is the count of pixels in market m with crop c after starting in field state k in year t. The denominator is the count of all pixels in market m in field state k in year t. As in Scott (2013), we smooth CCPs over space to ensure no CCP has a value of zero or one.[54]

Groundwater cost, groundwater use, and electricity use For each parcel, we observe realized groundwater pumping costs, groundwater quantity, and electricity quantity. We project these outcomes at the parcel level using the following OLS specification:

$$O_{ft} = \sum_{c \neq 0} \left(\zeta_m^c F_{ft}^c + \kappa_m^c F_{ft}^c \cdot t \right) + \eta_f + \phi_{mt} + \iota_{ft} \tag{8}$$

where O_{ft} is the per-acre outcome (pumping cost, groundwater quantity, or electricity quantity) for parcel f in year t. F_{ft}^c is the fraction of parcel f planted with crop c in year t, omitting non-crop ($c = 0$) to avoid collinearity. η_f are parcel fixed effects, ϕ_{mt} are market-year fixed effects, and ι_{ft} is an idiosyncratic error term. $\zeta_m^c + \kappa_m^c t$ recovers the average per-acre outcome for crop c in market m and year t (relative to choosing non-crop), which is identified from within-parcel crop switches. These market-specific coefficients accommodate geographic variation in both groundwater needs (e.g., due to surface water allocations) and irrigation needs within each crop category c (e.g., grape- vs. almond-growing regions).

54. We smooth a market's CCPs using other markets with similar surface water availability (i.e., in vs. out of a water district) and electricity tariff (i.e., small- vs. large-pump tariffs). Smoothing weights are inversely proportional to the square of the distance between the market centroids. Formally, the smoothed CCPs are:

$$\hat{p}_m(c_t, k_t, \omega_{mt}) = \frac{\sum_{m' \in \mathcal{M}} w_{mm'} p_{m'}(c_t, k_t, \omega_{m't})}{\sum_{m' \in \mathcal{M}} w_{mm'}}$$

where weight $w_{mm'} = (1 + d_{mm'})^{-2}$ if markets m and m' have similar electricity tariffs and surface water availability, and 0 otherwise. $d_{mm'}$ is the distance between centroids of m and m' in kilometers.

Using these fitted regression models, we project per-acre outcomes for each parcel-year under each crop category. Then, we aggregate projections up to the market-crop-year by taking an acreage-weighted median of all parcels within that market-year.[55] This aggregation yields total variable groundwater costs $G_{mct} = G_m(c_t, \omega_{mt})$, groundwater quantities $\hat{Q}^{\text{water}}_{mct}$, and electricity quantities $\hat{Q}^{\text{elec}}_{mct}$, each at the market-crop-year level and measured per-acre.[56]

5.2.2 Identification

Equation (7) holds for any choice of crops c_t and c'_t in year t followed by any renewal action r_{t+1} in year $t+1$. To generate an estimable regression equation, we set both the comparison crop c'_t and the renewal action r_{t+1} to be the non-crop category (i.e., $c'_t = r_{t+1} = 0$), leaving c_t to denote any of the three other crop choices. We estimate the resulting regression equation at the market level, using the data described above and weighting markets by acreage:

$$\ln\left[\frac{p_m(c_t, k_t, \omega_{mt})}{p_m(0, k_t, \omega_{mt})}\right] + \beta \ln\left[\frac{p_m(0, c_t, \omega_{mt+1})}{p_m(0, 0, \omega_{mt+1})}\right] = \alpha_G \Delta G_{mct} + \tilde{\Delta}\alpha_{mck} + \tilde{\Delta}\xi_{mckt} + \Delta e^V_{mct} \quad (9)$$

The outcome variable is the difference in values between a cropping sequence in which crop c is chosen in year t vs. one in which non-crop is chosen in year t, which we construct from our calculated CCPs. Each right-hand-side term represents a component of this difference.[57] ΔG_{mct} is the difference in pumping costs between crop choice c and non-crop in year t. $\tilde{\Delta}\alpha_{mck}$ is a set of intercept terms capturing the difference in the present value of average net returns between the two cropping sequences. $\tilde{\Delta}\xi_{mckt}$ is an unobserved term that reflects the difference in time-varying net returns, and Δe^V_{mct} is the unobserved difference in expectational errors; their sum is the regression's composite error term. Our main objects of interest are the groundwater cost parameter α_G and the intercepts $\tilde{\Delta}\alpha_{mck}$, which we use to recover the

55. This procedure yields crop-specific estimates for total variable pumping costs, groundwater quantities, and electricity quantities for a typical acre in each market and year. Taking acreage-weighted means yields similar results (see Appendix Figure A2). We further calculate a time-invariant market-level measure of each crop-specific outcome by taking the weighted median over all parcel-years in a market, which we use as steady-state costs and quantities in our counterfactual simulations. We also aggregate separately by drought vs. non-drought years to incorporate drought expectation in our counterfactual simulations.

56. We use $\hat{Q}$ to differentiate these per-acre quantity projections from the *observed* quantities Q^{water} and Q^{elec} used in our reduced-form analysis.

57. We use Δ to denote a contemporaneous difference between c_t and c'_t, and $\tilde{\Delta}$ to denote this contemporaneous difference plus a discounted difference in year $t+1$. Equation (A3) in Appendix A.1 provides definitions for each of these terms.

profit intercept parameters $\alpha_m(c_t, k_t)$. We cluster our standard errors at the market-by-year level, to allow for correlation across contemporaneous crop choices and field states within each market.

Instrumenting for groundwater cost In order to recover consistent estimates of α_G, we require $\mathbb{E}[\tilde{\Delta}\xi_{mckt} + \Delta e^V_{mct} \mid \Delta G_{mct}] = 0$. While the expectational error Δe^V_{mct} is uncorrelated with ΔG_{mct} by construction, unobserved net returns $\tilde{\Delta}\xi_{mckt}$ may be correlated with ΔG_{mct}.[58] As a result, we must instrument for ΔG_{mct}, the groundwater pumping costs for crop c (relative to non-crop) in market m in year t.

We construct an instrument for ΔG_{mct} which uses plausibly exogenous variation in PG&E's electricity tariff schedules, akin to our reduced-form approach in Section 4. Here, we require an instrument for *total* variable pumping cost, which we generate by combining two exogenous factors: time-varying electricity prices and cross-sectionally-varying electricity quantity needs. The price component is the average default electricity price in market m in year t, $P^{\text{elecDefault}}_{mt}$, which is plausibly excludable because exogenous electricity tariffs are only correlated with groundwater demand through pumping costs (as shown in Section 4.1).[59] The quantity component is the average amount of electricity needed for groundwater pumping for crop c (relative to non-crop) in market m, $\Delta\hat{Q}^{\text{elec}}_{mc}$, which is plausibly excludable because it is uncorrelated with annual variation in the market state. In an approach similar to a shift-share, we instrument with the product of these two components: $P^{\text{elecDefault}}_{mt} \times \Delta\hat{Q}^{\text{elec}}_{mc}$. This instrument is strongly correlated with ΔG_{mct}, since changes to default electricity prices impact the variable costs of groundwater pumping. It also satisfies the exclusion restriction, since each component is plausibly excludable.

Recovering profit intercept parameters We require estimates of 16 profit intercepts for each market—one $\alpha_m(c_t, k_t)$ for each crop choice-field state pair. However, Equation (9) only includes 12 $\tilde{\Delta}\alpha_{mck}$ intercept terms for each market, since we use the non-crop category as the

58. For example, weather could affect groundwater pumping costs for crop c (relative to non-crop) by altering water requirements, and weather could also affect (relative) net returns by influencing output prices.

59. Our markets partition small vs. large pump categories. $P^{\text{elecDefault}}_{mt}$ collapses from four to two tariff categories, averaging over the composition of conventional and smart meters within each market-year. We assign each parcel's modal pump size before defining markets, such that $P^{\text{elecDefault}}_{mt}$ eliminates variation from any potentially endogenous switches between small- and large-pump tariff categories.

comparison. Recovering all 16 intercepts therefore requires additional assumptions.[60] First, we normalize $\alpha_m(0,0) = 0$, where both field state and crop choice are non-crop. Second, we assume that switching from crop c to non-crop costs half as much as switching from non-crop to crop c. Third, we assume there is no transition cost to remain in the same crop.[61]

5.3 Counterfactual simulations

We use the estimated model to simulate counterfactuals under short- and long-run groundwater tax scenarios. For short-run scenarios, we simulate a long-run steady state using baseline groundwater costs and then add a one-year marginal cost shock (i.e., a short-run tax). For long-run scenarios, we simulate the long-run steady state under a permanent marginal cost change (i.e., a long-run tax) that affects every year. In each scenario, we proceed as follows. First, we use Equation (4) to calculate expected annual profit—a function of that scenario's groundwater tax—for each crop choice in each state in every market. Second, we combine these profits with a fixed point algorithm to solve for the continuation values, which follow from Equation (5), for each crop choice at each state in each market. Third, we use these continuation values to calculate CCPs in each market, per Equation (6). Finally, starting from an initial distribution of field states in each market, we iteratively apply these CCPs to solve for crop choices and, therefore, groundwater and electricity use over a 20-year period.[62] To simulate these counterfactuals, we require two additional assumptions.

Assumption CF1: Drought state Drought, which is included in the market state ω_{mt}, is a key determinant of annual groundwater pumping costs.[63] To incorporate drought conditions in our simulations, we project groundwater costs separately for drought vs. non-drought years and calculate profits under each market state. The resulting continuation values and

60. As described by Scott (2013) and Kalouptsidi, Scott, and Souza-Rodrigues (2021), dynamic discrete choice models are typically not fully identified (Magnac and Thesmar (2002)). See Appendix A.2 for a mathematical statement of these assumptions.

61. $\alpha_m(c_t, k_t)$ incorporates both net returns to crop c_t and any additional transition costs due to field state k_t. For $c_t = k_t$, we assume that all costs are recurring (e.g., the yearly cost of replanting an annual crop) and are therefore captured by the net returns component.

62. We initialize the field states using each market's average distribution of field states for 2008–2019.

63. Drought can increase groundwater needs due to low precipitation levels and curtailed surface water allocations. It can also increase groundwater scarcity, which raises marginal pumping costs. Both effects increase farmers' groundwater expenditures.

CCPs become functions of both current drought and future expectations of drought. We assume farmers' expectation of drought in any future year is i.i.d. with probability equal to the frequency of drought in our sample.[64]

Assumption CF2: Intensive-margin elasticity Our reduced-form analysis shows that farmers respond to groundwater cost shocks on the intensive margin (i.e., adjust their water use conditional on crop choice). We therefore also allow farmers to adjust each crop's groundwater use in response to counterfactual groundwater taxes.[65] In our short-run tax scenarios, we set this intensive-margin elasticity equal to the intensive-margin response we estimate in our reduced-form analysis: -0.843 (Column (1) of Table 3).

To calibrate a long-run intensive-margin elasticity for the long-run tax scenarios, we estimate a series of long-differences regressions (analogous to our reduced-form Equations (2)–(3)) using increasingly longer differences. These estimates imply that roughly 50% of our short-run intensive-margin response is likely to persist in the long run, translating into a long-run intensive-margin elasticity of -0.422.[66] This intensive-margin elasticity reduces groundwater and electricity consumption for a particular crop, thereby increasing the crop's total variable groundwater cost by less than the tax rate.[67] This additional margin of response alters expected profits for each crop under counterfactual groundwater taxes, which subsequently alters continuation values, CCPs, and therefore counterfactual crop choices.

64. California declared severe droughts in 7 of our 12 sample years (2008–2009 and 2012–2016). We also simulate alternate simulations with higher/lower probabilities of drought (see Appendix Figure A2).

65. The profit function (Equation (4)) includes total variable pumping costs, or the product of groundwater quantity and marginal cost: $G = Q^{\text{water}} \times P^{\text{water}}$. A marginal groundwater tax will cause farmers to reoptimize Q^{water} within each crop c (i.e., $\partial Q^{\text{water}}/\partial P^{\text{water}}$). This intensive-margin response is already accounted for when projecting *factual* pumping costs and quantities, which we then use to estimate Equation (9), because observed Q^{water} has been optimized to *factual* P^{water}. However, simulating counterfactual P^{water} necessitates assumptions on this optimal $\partial Q^{\text{water}}/\partial P^{\text{water}}$ response.

66. Our short-run intensive-margin response is identified using short-run cost shocks. However, our long-run tax counterfactuals simulate a permanent cost shock, and many intensive-margin responses may not persist over the long run. For example, while a farmer may respond to a one-year groundwater cost shock by allowing her crop to fail, she is unlikely let the same crop fail year after year. Alternative simulations vary this assumption of 50% persistence (see Appendix Table A2). Appendix A.3 describes these long-difference regressions, and Appendix Figure A1 presents their results.

67. Suppose the marginal cost of pumping increases by 20% due to a tax. With an intensive-margin elasticity of -0.422, farmers reduce crop-specific groundwater use by 7.4%. As a result, the total variable cost of pumping increases by only 11.1%, not the full 20%.

Counterfactual groundwater tax scenarios Our baseline scenario sets total variable groundwater costs equal to the time-invariant projection for that market and crop. For our short-run tax counterfactuals, we increase the marginal cost of pumping only in a single year of the 20-year simulation; we assume farmers do not anticipate this shock, but know that it will persist for only one year. For our long-run tax counterfactuals, we increase pumping costs in all years and assume farmers know this tax will persist permanently. Since we use crop-specific groundwater costs, a given tax increases total variable costs relatively more for more water-intensive crops, which can induce crop switching. Further, because our dynamic model captures forward-looking behavior, short- and long-run taxes can induce different magnitudes and patterns of crop switching.

(Semi-)elasticities Following Scott (2013), we calculate long-run (semi-)elasticities by comparing the final year of each tax scenario to the final year of the baseline scenario. For short-run (semi-)elasticities, we instead compare the tax and baseline scenarios in the year when the short-run tax occurs. The semi-elasticity of crop c with respect to the marginal cost of pumping groundwater is:

$$\frac{\sum_{m\in\mathcal{M}}\left(A'_{mc}-A_{mc}\right)}{\sum_{m\in\mathcal{M}}\sum_{c\in\mathcal{C}}A_{mc}}\bigg/\tau$$

where A_{mc} is the acreage in market m planted to crop c in the baseline scenario, A'_{mc} is the comparable acreage in the tax scenario, and τ is the percentage tax on marginal groundwater costs. The corresponding pumping cost elasticities of groundwater and electricity are:[68]

$$\frac{\sum_{m\in\mathcal{M}}\sum_{c\in\mathcal{C}}\left(A'_{mc}\hat{Q}'_{mc}-A_{mc}\hat{Q}_{mc}\right)}{\sum_{m\in\mathcal{M}}\sum_{c\in\mathcal{C}}A_{mc}\hat{Q}_{mc}}\Bigg/\tau$$

where $\hat{Q}_{mc}$ is the time-invariant projection $\hat{Q}^{\text{water}}_{mc}$ or $\hat{Q}^{\text{elec}}_{mc}$, and $\hat{Q}'_{mc}$ is the analogous quantity after any tax-induced intensive-margin adjustments. We conduct inference on these (semi-)elasticities by taking 500 draws from the sampling distribution of our estimated groundwater

68. Because a τ% change in electricity price translates to the same τ% change in marginal groundwater pumping costs (see Equation (1)), this expression recovers the elasticity of groundwater use with respect to marginal groundwater cost, and the elasticity of electricity use with respect to marginal electricity price.

cost parameter α_G. For each draw, we first recover the corresponding $\alpha_m(c_t, k_t)$ parameters, and we then proceed to simulate both the baseline and tax scenarios using the same parameter draw. This sampling yields 500 sets of (semi-)elasticities for each tax scenario. Our reported (semi-)elasticities are the means of these distributions, and our reported 95% confidence intervals span the 2.5th and 97.5th percentiles of the distributions.

5.4 Model results

Figure 3 presents our main discrete choice results. Panel A plots semi-elasticities of land use, while Panel B presents demand elasticities for groundwater and electricity, in response to both a short- and a long-run 20% tax on the marginal cost of groundwater pumping.[69] Panels C and D plot the corresponding time profiles of these land-use, groundwater, and electricity responses.

Short-run (semi-)elasticities For the short-run tax scenario, we recover short-run semi-elasticities with respect to marginal groundwater costs of 0.0002 (s.e. 0.0002) for annuals, -0.003 (s.e. 0.001) for fruit/nut perennials, -0.002 (s.e. 0.001) for hay perennials, and 0.005 (s.e. 0.002) for non-crop (fallowing).[70] Farmers instead respond to the one-year tax by reducing water use on existing crops, yielding short-run elasticities of -0.718 (s.e. 0.002) for groundwater and -0.689 (s.e. 0.002) for electricity.[71]

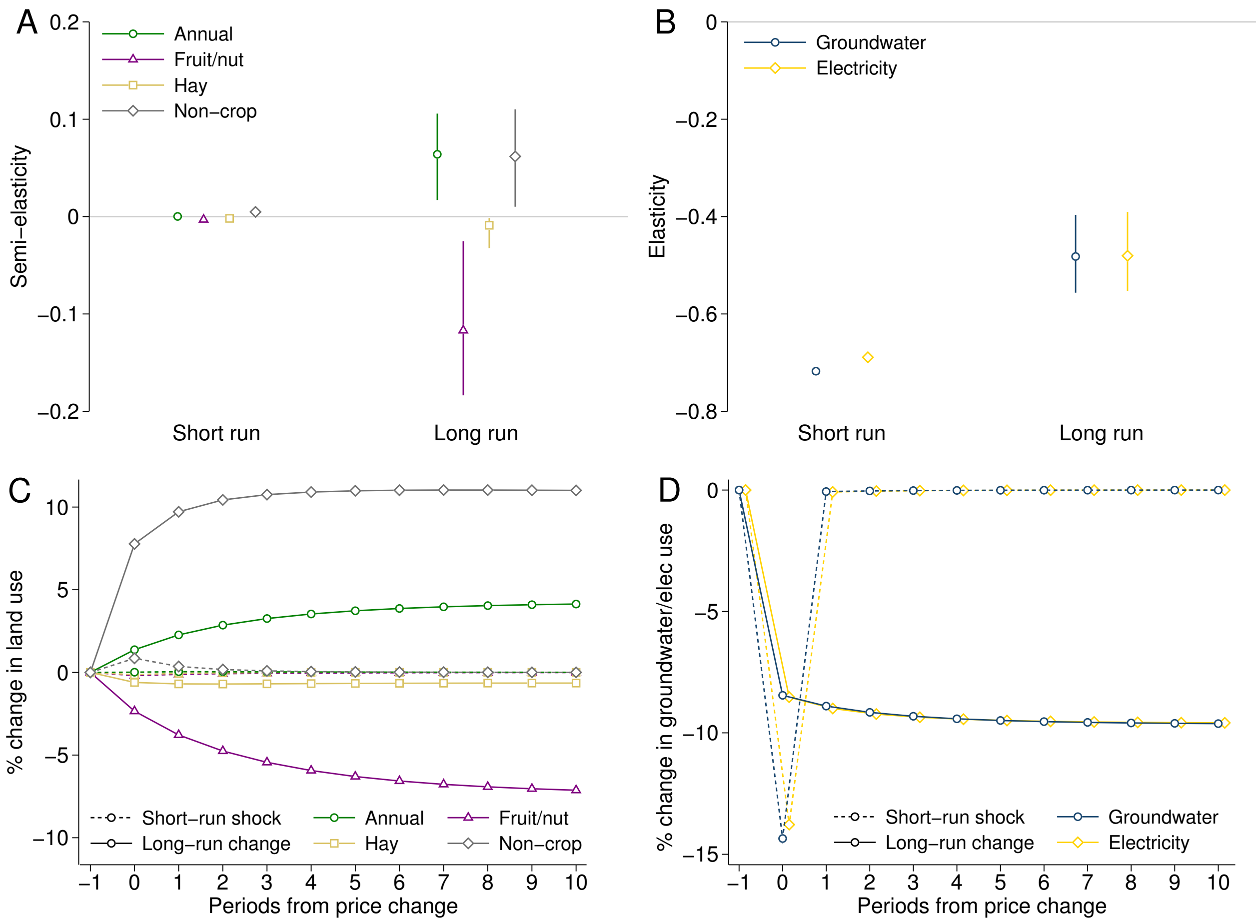
These results imply that a short-run pumping cost shock induces only minimal crop switching, which occurs only in the year of the shock (Panel C). Instead, farmers achieve groundwater reductions by applying less water to the crops they are already growing—and these sharp reductions occur only in the year of the shock, which farmers know to be temporary (Panel D).

69. Appendix Table A2 presents these results in tabular form. Appendix Table A1 presents the parameter estimates resulting from estimating Equation (9). Appendix Figure A2 presents robustness to parcel sample selection and aggregation to the market level.

70. These magnitudes broadly align with our reduced-form estimates in Table 3, where we find precise null cropping responses to year-on-year changes in marginal groundwater costs.

71. These short-run elasticities are nearly identical to the elasticity calculated by applying a 20% non-marginal cost increase to Equation (2) with a marginal elasticity of $\gamma = -0.843$ or -0.804.

Figure 3: Short- and long-run elasticities with respect to groundwater pumping cost



Notes: This figure plots short- and long-run (semi-)elasticities of land use (panel A) and groundwater and electricity use (panel B) with respect to marginal groundwater cost, as well as the time path of these responses (panels C and D). To recover short-run (semi-)elasticities, we simulate the model with baseline costs until it reaches a steady state, and then increase groundwater costs by 20% for one year. Farmers do not anticipate the shock, but they know it will only last for one year. To recover long-run (semi-)elasticities, we increase groundwater pumping costs by 20% and simulate the model forward. Farmers know that this price change is permanent. In both the short- and long-run, farmers can respond to groundwater cost changes on both the crop-switching margin and by reducing water use conditional on crop choice (the "intensive margin"). In the short-run, farmers' intensive-margin elasticity is −0.843 (Table 3, Column (1)). In the long-run, farmers have 50% of this intensive-margin response available to them, per our long-difference model discussed in Section 5.3 and Appendix A.3. Panel A shows semi-elasticities for annual crops (circles), hay perennials (squares), fruit/nut perennials (triangles), and non-crop (diamonds). Panel B shows elasticities of demand for electricity (diamonds) and groundwater (circles). In Panels A and B, we report the means over 500 draws for each model; 95% confidence intervals (vertical lines) plot the 2.5th and 97.5th percentiles over draws. In Panels C and D, dashed lines plot the time profile of responses for the same short-run scenario, for a one-year 20% cost shock in period 0. Solid lines plot the time profile of response for the same long-run scenario, for a permanent 20% cost shock starting in period 0. In each scenario, we compare outcomes to a baseline with no price change.

Long-run (semi-)elasticities When the groundwater cost change is permanent, and farmers have a smaller intensive-margin response, we find greater crop switching. On net, these effects yield smaller groundwater and electricity elasticities in the long run than in the short run. In our central case (which includes an intensive-margin elasticity of −0.422), we recover cropping semi-elasticities that are orders of magnitude larger than their short-run counterparts: 0.064 (s.e. 0.024) for annuals, −0.117 (s.e. 0.043) for fruit/nut perennials, −0.009 (s.e. 0.009) for hay perennials, and 0.062 (s.e. 0.027) for non-crop. We find overall elasticities of −0.482 (s.e. 0.044) for groundwater and −0.480 (s.e. 0.043) for electricity—showing that substitution between the intensive and extensive margins is incomplete.[72]

Unlike for a temporary cost shock, farmers' responses to a permanent cost shock persist over the long run. Panel C of Figure 3 shows large switches away from fruit/nut perennials and into annuals and fallowing in the first year of the simulation. These switching patterns continue over subsequent years, and eventually the simulation converges to a new long-run steady state with a substantially different crop mix than without the price change. Panel D of Figure 3 reveals that while the initial groundwater/electricity response is more muted than for a temporary cost shock (due to a smaller intensive-margin elasticity), this initial response persists (and even increases over time), giving the new long-run steady state.

Discussion We find that farmers switch crops only minimally in response to temporary groundwater cost shocks. Instead, their primary response to a short-run cost shock is to apply less water to existing crops, which occurs only in the year of the shock. In stark contrast, we find substantial and persistent crop switching in response to permanent cost changes, which translates into meaningful long-run reductions in groundwater and electricity use. However, due to a smaller intensive-margin elasticity over the long run, our overall long-run elasticities of groundwater and electricity demand are smaller than their short-run counterparts.

Our results build on prior work measuring agricultural groundwater demand (e.g., Pfeiffer and Lin (2014); Bruno, Jessoe, and Hanemann (2024)) by (i) estimating *both* short- and long-run elasticities in the same policy-relevant setting, (ii) showing that they are meaningfully different, and (iii) illustrating how this difference reflects mechanisms that vary by time horizon. Our results also connect to Hagerty (2022), who estimates that California farm-

72. Appendix Table A2 presents additional long-run (semi-)elasticities. Our "0% IM" scenario assumes zero intensive-margin elasticity, meaning that farmers only respond to changes in marginal groundwater costs on the crop-switching margin; our "25% IM" and "75% IM" scenarios assume long-run intensive-margin elasticities of −0.211 and −0.623, respectively (i.e., 25% and 75% of our short-run estimate). In the 0% IM scenario, we recover larger crop semi-elasticities, as farmers can only respond to the groundwater price increase by switching crops, but smaller groundwater and electricity elasticities, as farmers lose a margin of response. In the 25% IM (75% IM) scenario, the crop semi-elasticities are somewhat larger (smaller) than in our central 50% IM scenario, while the groundwater and electricity elasticities are somewhat smaller (larger).

ers have a smaller response to *surface* water scarcity in the long run than in the short run (albeit a narrower long-/short-run gap than we find for groundwater). While we find crop switching only in the long run—driven by the large fixed costs of changing crops—Hagerty (2022) finds that short-run surface water shocks increase fallowing. These results are consistent with surface-water-dependent farmers being less flexible in the short run (i.e., forced to fallow) than farmers with groundwater access, but having greater flexibility to respond to long-run surface water shortages by drilling new groundwater wells (Hadachek et al. (2024)). Thus, the mechanisms underlying farmer responses to both groundwater cost increases and surface water shortages appear to differ across time horizons.

Moreover, our results illustrate how incorporating dynamics can undo the classic economic intuition that longer time horizons lead to larger elasticities (e.g., Castillo (2021); Lemoine (2024)). As with previous models showing the potential for smaller long-run elasticities than short-run elasticities (e.g., Gowisankaran and Rysman (2012) for durable goods; Hall (1991) for labor supply), this pattern stems from differing mechanisms underlying farmers' groundwater demand response.[73] Whereas intensive-margin reductions in irrigation are not sustainable over longer time horizons, the crop-switching mechanism requires longer time horizons to justify incurring the fixed costs of uprooting or planting crops.

5.5 Impacts of counterfactual groundwater policy

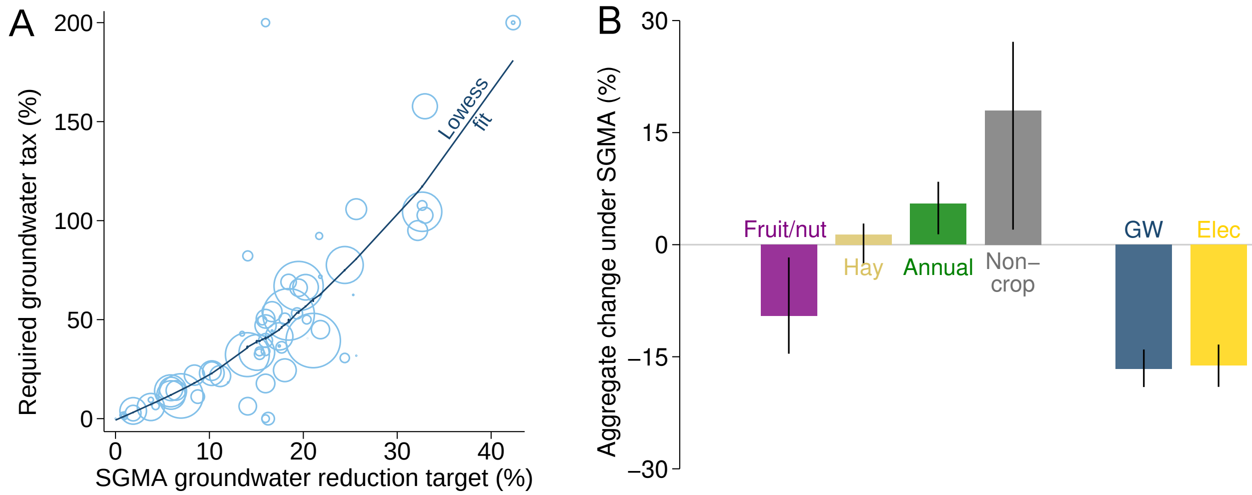
Finally, we use our dynamic model to quantify the potential effectiveness of California's landmark groundwater policy, SGMA.[74] While SGMA's stringency varies substantially across Groundwater Sustainability Agencies, the overdrafted areas of our sample will require a 16.7% reduction in groundwater use on average.[75] We use our model to recover the groundwater tax that would be required to achieve SGMA's spatially heterogeneous targets, and

73. For durable goods in Gowisankaran and Rysman (2012), the short-run mechanism is waiting for an advantageous price shock, whereas in the long run, households must decide whether or not to make a purchase at all. For labor supply in Hall (1991), short-run mechanisms involve intertemporal substitution to work more in high-wage periods, whereas long-run mechanisms relate to secular trends in labor supply.

74. In order to stem rapid aquifer drawdown, the majority of SGMA groundwater sustainability plans are proposing price-based instruments (Bruno, Hagerty, and Wardle (2022)). Our results speak directly to these plans, while providing a heuristic for tringencies of and possible responses to non-price instruments.

75. Note that PG&E's boundary excludes the southern part of the Central Valley which are severely overdrafted. SGMA required *all* GSAs in medium- and high-priority basins to submit GSPs. However, 57 of the 120 GSPs in our data report *no* required groundwater pumping reductions. We only report statistics

Figure 4: SGMA: Required groundwater taxes and farmer responses



Notes: Panel A plots market-specific SGMA groundwater reduction targets (on the horizontal axis), and our estimates of the long-run groundwater tax stringency that would be required to meet these targets (on the vertical axis). The size of each dot indicates each market's total groundwater extraction in our no-tax baseline, scaled by the share of the market belonging to a SGMA-regulated area; the solid navy line is a Lowess fit, similarly weighted. Panel B plots the aggregate effect of these market-specific taxes on land use, groundwater use, and electricity use. Each bar shows the percent change in land or resource use under a SGMA counterfactual compared to baseline with no taxes. Bars report means over 500 draws that are common to all markets; 95% confidence intervals (vertical lines) plot the 2.5th and 97.5th percentiles over these draws.

to simulate the resulting impacts on crop choice and groundwater use. To do so, for each of our 82 markets, we calculate the area of the market within overdrafted GSAs and the average reduction in groundwater pumping required by tholse GSAs. Then, we take our estimated dynamic model (with its market-specific crop switching costs) and, for each market, loop over groundwater tax stringencies until converging on a tax that achieves the reduction target of the market's overdrafted areas.[76]

Panel A of Figure 4 plots these market-specific taxes against the reduction requirements in each market, for markets with groundwater pumping reduction requirements. Achieving long-run sustainability in these markets (i.e., 16.7% for the average market) will require a 46.5% groundwater tax on average. However, there is meaningful variation across markets: the 25th and 75th percentile reductions are 10.3% and 21.1%, and the 25th and

for locations with binding SGMA requirements (i.e., those that require reductions to achieve sustainability). Appendix C.6 describes our Groundwater Sustainability Plan (GSP) data.

76. We compute each market's required reduction weighting by its fraction of croppable acreage in each overdrafted GSA. This effectively drops cropland that falls either outside of any GSA or inside a non-overdrafted GSA, since neither faces any SGMA compliance obligation. 11 of our 82 markets contain no overdrafted SGMA-regulated areas. Thus, our policy counterfactual applies only to SGMA-regulated areas of the remaining 71 markets. These adjustments are necessary since our market footprints (which importantly align with water district borders to eliminate any confounding effects of changing surface water allocations) do not cleanly map to GSA boundaries.

75th percentile required taxes are 21.5% and 67.0%.[77] Our simulated taxes rise more-than-proportionally with reduction requirements, consistent with increasing marginal costs of groundwater conservation.

Panel B shows how these taxes would impact aggregate crop choice, groundwater use, and electricity use. Our model predicts that achieving SGMA targets would lead to a 9.5% decline in fruit/nut perennials, a 1.4% increase in hay perennials (not statistically different from zero), a 5.5% increase in annuals, and an 18.0% increase in fallowing, all compared to our no-tax scenario. These correspond to 16.6% and 16.1% reductions in groundwater and electricity, respectively. These results illustrate that SGMA's sustainability targets are likely attainable through groundwater taxes, which in turn will lead to changes in land use.

6 Conclusion

This paper estimates how agents—California farmers—respond to environmental policy—groundwater pricing—in both the short and long run. We leverage quasi-random variation in groundwater costs to estimate the elasticity of demand for groundwater over different time horizons. We provide reduced-form evidence that farmers respond to year-on-year groundwater pumping cost shocks by reducing water consumption. Since long-lived perennial tree crops are common in this setting, we build and estimate a dynamic discrete choice model where farmers are forward-looking and fields are state-dependent. Using this model, we first recover a short-run elasticity of groundwater demand of -0.72, finding that farmers do not switch crops in response to temporary cost shocks but instead reduce irrigation holding crop fixed. We then recover a long-run elasticity of groundwater demand of -0.48, finding that permanent cost increases cause farmers to switch out of thirsty fruit/nut perennials and into annual crops and fallowing.

We use our dynamic model to simulate California's flagship groundwater management policy. For the average area where the policy will bind, we find that the equivalent of a 46.5% tax on groundwater pumping costs will be required to achieve the state's sustainability

77. For all statistics in our SGMA policy counterfactual, we weight markets by their quantity of groundwater pumping in our no-tax baseline scenario.

goals—with meaningful heterogeneity in the necessary tax stringency across locations. These results imply that California's Sustainable Groundwater Management Act will alter the landscape of crop production across California by incentivizing large shifts away from fruit and nut perennials and towards exit from agriculture. An important topic for future research will be to quantify the regulation's general equilibrium impacts: to what extent will these land use changes impact crop prices earned by farmers and food prices faced by consumers? Given that California dominates the U.S. market for fruits, nuts, and vegetables, any such price effects could have major welfare consequences.

Our work broadly underscores the importance of using dynamic models to analyze environmental and resource management policies. Our results further highlight that agents' long-run responses need not be larger than their short-run counterparts. These lessons likely apply across a broad range of settings. For example, distinguishing between short- and long-run response margins is crucial in the context of climate policy, where short-run adaptation options may not be feasible (or optimal) in the long run, and vice versa.

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Groundwater and Crop Choice in the Short and Long Run

Supplementary Appendix: For Online Publication

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Appendix contents

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A Details on dynamic discrete choice estimation

A.1 Model of crop choice

Our model of crop choice and derivation of an estimating equation follow closely from and build upon Scott (2013) and Kalouptsidi, Scott, and Souza-Rodrigues (2021). First, from Assumptions 1–3 in the main text, the value function for a given field is:

$$V(k_t, \omega_t, \varepsilon_t) = \max_{c_t \in \mathcal{C}} \{\pi(c_t, k_t, \omega_t, \varepsilon_t) + \beta E\left[V(k_{t+1}, \omega_{t+1}, \varepsilon_{t+1}) \mid c_t, \omega_t\right]\}$$

as shown in Equation (5) in the main text. This value function gives rise to the *ex ante* value function:

$$\bar{V}(k_t, \omega_t) \equiv \int V(k_t, \omega_t, \varepsilon_t) dF^{\varepsilon}(\varepsilon_t)$$

and the conditional value function:

$$v(c_t, k_t, \omega_t) \equiv \bar{\pi}(c_t, k_t, \omega_t) + \beta E\left[\bar{V}(k_{t+1}, \omega_{t+1}) \mid c_t, \omega_t\right] \tag{A1}$$

where $\bar{\pi}(c_t, k_t, \omega_t) \equiv \pi(c_t, k_t, \omega_t, 0)$ represents an expected profit function with the idiosyncratic shock equal to zero. As shown in Equation (6) in the main text, conditional choice probabilities depend on these conditional value functions:

$$p(c_t, k_t, \omega_t) = \frac{\exp\left[v(c_t, k_t, \omega_t)\right]}{\sum_{c_t' \in \mathcal{C}} \exp\left[v(c_t', k_t, \omega_t)\right]}$$

We next invoke the Arcidiacono-Miller Lemma (Arcidiacono and Miller (2011)), which follows from the Hotz-Miller inversion (Hotz and Miller (1993)) and yields a new expression for the *ex ante* value function written as a function of the conditional value and conditional choice probability:

$$\bar{V}(k_t, \omega_t) = v(c_t, k_t, \omega_t) - \ln p(c_t, k_t, \omega_t) + \gamma \tag{A2}$$

where γ is the Euler constant. In words, the *ex ante* value equals the conditional value after making any crop choice c_t plus a correction term to account for the relative value of crop c_t compared to the rest of the choice set. This expression further shows that CCPs contain information about the values of making different crop choices.

We continue to follow Scott (2013) and Kalouptsidi, Scott, and Souza-Rodrigues (2021) to derive an Euler equation that will yield an estimating equation for this dynamic discrete choice model. We consider two sequences of crop choices in years t and $t+1$. In the first sequence, the farmer chooses crop c_t in year t followed by a choice that we denote r_{t+1} in year $t+1$. In the second sequence, the farmer instead chooses crop c_t' in year t followed by the same r_{t+1} in year $t+1$. In each case, the farmer then chooses optimally in years $t+2$ and beyond. To generate an Euler equation, we compare the value of these two cropping sequences.

We first combine Equations (A1) and (A2) to generate an expression for expected profit of any crop choice in year t:

$$\bar{\pi}(c_t, k_t, \omega_t) = \bar{V}(k_t, \omega_t) - \beta E\left[\bar{V}(k_{t+1}, \omega_{t+1}) \mid c_t, \omega_t\right] + \ln p(c_t, k_t, \omega_t) - \gamma$$

We then decompose the continuation value into its realization and its expectational error, with expectational error defined as the difference between expectation and realization:

$$e^V(c_t, \omega_t, \omega_{t+1}) \equiv E\left[\bar{V}(k_{t+1}, \omega'_{t+1}) \mid c_t, \omega_t\right] - \bar{V}(c_t, \omega_{t+1})$$

This decomposition yields:

$$\bar{\pi}(c_t, k_t, \omega_t) + \beta e^V(c_t, \omega_t, \omega_{t+1}) = \bar{V}(k_t, \omega_t) - \beta \bar{V}(c_t, \omega_{t+1}) + \ln p(c_t, k_t, \omega_t) - \gamma$$

with only realized values (rather than expected values) on the right-hand side.

Next, we eliminate the realized continuation values from this expression, first by differencing the equation across the two different crop choices in year t, c_t and c'_t:

$$\begin{aligned}\ln\left[\frac{p(c_t, k_t, \omega_t)}{p(c'_t, k_t, \omega_t)}\right] &= \bar{\pi}(c_t, k_t, \omega_t) - \bar{\pi}(c'_t, k_t, \omega_t) + \beta\left[e^V(c_t, \omega_t, \omega_{t+1}) - e^V(c'_t, \omega_t, \omega_{t+1})\right] \\ &\quad + \beta\left[\bar{V}(c_t, \omega_{t+1}) - \bar{V}(c'_t, \omega_{t+1})\right]\end{aligned}$$

In words, the CCP term on the left-hand side equals the difference in values from choosing crop c versus crop c' in year t and then choosing crops optimally in all future years.

We then use Equation (A2) to substitute for the continuation values in year $t+1$. That equality holds for all crop choices, including choice r_{t+1} from the cropping sequences described above:

$$\begin{aligned}\ln\left[\frac{p(c_t, k_t, \omega_t)}{p(c'_t, k_t, \omega_t)}\right] &= \bar{\pi}(c_t, k_t, \omega_t) - \bar{\pi}(c'_t, k_t, \omega_t) + \beta\left[e^V(c_t, \omega_t, \omega_{t+1}) - e^V(c'_t, \omega_t, \omega_{t+1})\right] \\ &\quad + \beta\left[v(r_{t+1}, c_t, \omega_{t+1}) - v(r_{t+1}, c'_t, \omega_{t+1})\right] - \beta \ln\left[\frac{p(r_{t+1}, c_t, \omega_{t+1})}{p(r_{t+1}, c'_t, \omega_{t+1})}\right]\end{aligned}$$

Because any crop choice is a renewal action in this setting[2]—including the choice of crop r_{t+1} in year $t+1$—the field state in year $t+2$ will depend only on the choice of r_{t+1} in year $t+1$ and not on the crop choice in year t. In that case, the continuation values in year $t+2$ will be the same regardless of whether crop c_t or crop c'_t is chosen in year t, so the difference in conditional values reduces to:

$$v(r_{t+1}, c_t, \omega_{t+1}) - v(r_{t+1}, c'_t, \omega_{t+1}) = \bar{\pi}(r_{t+1}, c_t, \omega_{t+1}) - \bar{\pi}(r_{t+1}, c'_t, \omega_{t+1})$$

2. Kalouptsidi, Scott, and Souza-Rodrigues (2021) use the term "renewal action" to denote any choice c_t that yields a particular field state k_{t+1} in the following year regardless of states in years prior to year t. Since we model state-dependence as having only one-year memory, all crop choices $c_t \in \mathcal{C}$ are renewal actions.

Then the above expression simplifies to:

$$\ln\left[\frac{p(c_t,k_t,\omega_t)}{p(c_t',k_t,\omega_t)}\right] = \bar{\pi}(c_t,k_t,\omega_t) - \bar{\pi}(c_t',k_t,\omega_t) + \beta\left[e^V(c_t,\omega_t,\omega_{t+1}) - e^V(c_t',\omega_t,\omega_{t+1})\right]$$
$$+ \beta\left[\bar{\pi}(r_{t+1},c_t,\omega_{t+1}) - \bar{\pi}(r_{t+1},c_t',\omega_{t+1})\right] - \beta\ln\left[\frac{p(r_{t+1},c_t,\omega_{t+1})}{p(r_{t+1},c_t',\omega_{t+1})}\right]$$

We next expand the profit terms, as in Equation (4) in the main text, which yields an Euler equation. We rearrange the expression to get Equation (7) in the main text:

$$\begin{aligned}\ln\left[\frac{p(c_t,k_t,\omega_t)}{p(c_t',k_t,\omega_t)}\right] + \beta\ln\left[\frac{p(r_{t+1},c_t,\omega_{t+1})}{p(r_{t+1},c_t',\omega_{t+1})}\right] &= \alpha_G\left[G(c_t,\omega_t) - G(c_t',\omega_t)\right]\\ &+ \alpha(c_t,k_t) - \alpha(c_t',k_t) + \beta\left[\alpha(r_{t+1},c_t) - \alpha(r_{t+1},c_t')\right]\\ &+ \xi(c_t,k_t,\omega_t) - \xi(c_t',k_t,\omega_t) + \beta\left[\xi(r_{t+1},c_t,\omega_{t+1}) - \xi(r_{t+1},c_t',\omega_{t+1})\right]\\ &+ \beta\left[e^V(c_t,\omega_t,\omega_{t+1}) - e^V(c_t',\omega_t,\omega_{t+1})\right]\end{aligned}$$

Each side of this expression is equivalent to the difference in values between the two sequences of crop choices that we describe above: choosing c_t or c_t' in year t, followed by renewal action r_{t+1}, and then choosing optimally in all following years.

This equality holds for any choices of c_t, c_t', and r_{t+1}. To generate our estimating equation, we set both c_t' and r_{t+1} equal to the non-crop category—which we denote with 0—while c_t represents one of the other three crop choices. Then our estimating equation is a simple linear regression:

$$Y_{ckt} = \alpha_G\Delta G_{ct} + \tilde{\Delta}\alpha_{ck} + \tilde{\Delta}\xi_{ckt} + \Delta e^V_{ct} \tag{A3}$$

where

$$\begin{aligned}Y_{ckt} &= \ln\left[\frac{p(c_t,k_t,\omega_t)}{p(0,k_t,\omega_t)}\right] + \beta\ln\left[\frac{p(0,c_t,\omega_{t+1})}{p(0,0,\omega_{t+1})}\right]\\ \Delta G_{ct} &= G(c_t,\omega_t) - G(0,\omega_t)\\ \tilde{\Delta}\alpha_{ck} &= \alpha(c_t,k_t) - \alpha(0,k_t) + \beta\left[\alpha(0,c_t) - \alpha(0,0)\right]\\ \tilde{\Delta}\xi_{ckt} &= \xi(c_t,k_t,\omega_t) - \xi(0,k_t,\omega_t) + \beta\left[\xi(0,c_t,\omega_{t+1}) - \xi(0,0,\omega_{t+1})\right]\\ \Delta e^V_{ct} &= \beta\left[e^V(c_t,\omega_t,\omega_{t+1}) - e^V(0,\omega_t,\omega_{t+1})\right]\end{aligned}$$

A.2 Estimation

Market construction We estimate the above regression at the market level, grouping farmers who face a similar choice environment. We define a market according to three criteria: electricity price, surface water availability, and geographic proximity. Because small pumps and large pumps face different marginal electricity prices, we first partition parcels based on whether their groundwater pump is on a small- or large-pump tariff.[3] To account for the final two criteria, we further split parcels by water districts—thereby grouping farms with comparable surface water allocations within contained geographic areas.[4] For parcels located outside of any water district (a.k.a., in "white areas"), we define county-level pseudo-water districts; these units retain the small vs. large tariff split, while also grouping farms with comparable surface water access (i.e., allocations of zero) in contained geographic areas.

Recovering profit intercept parameters Estimating Equation (A3) returns 12 $\tilde{\Delta}\alpha_{mck}$ regression intercept terms for each market, which we use to recover the 16 profit intercepts for each market, $\alpha_m(c_t, k_t)$. To do this, we must make additional assumptions. First, we normalize $\alpha_m(0, 0) = 0$, where both field state and crop choice are non-crop. Second, we decompose $\alpha_m(c_t, k_t) = R_m(c_t) - T_m(c_t, k_t)$, where $R_m(c_t)$ is time-invariant net returns to crop c_t (excluding groundwater costs), and $T_m(c_t, k_t)$ is the time-invariant cost of transitioning from field state k_t to crop c_t. We assume $T_m(0, c_{t-1}) = 0.5 \times T_m(c_t, 0)$, such that switching from crop c to fallow costs half as much as switching from fallow to crop c.[5] Third, we assume there is no transition cost to remain in the same crop: $T_m(c_t, c_{t-1}) = 0$.[6]

A.3 Calibrating the intensive-margin elasticity

In our main counterfactual simulations, we assume farmers adjust each crop's groundwater use in response to a counterfactual groundwater tax. Our reduced-form analysis shows that, conditional on the crop they are growing, farmers respond to a 1% increase in groundwater cost by reducing groundwater use by 0.843% (Column (1) of Table 3). Since this estimate comes from annual variation in pumping costs, we assume the same value for our short-run intensive-margin elasticity in the structural model. However, the long-run intensive-margin elasticity will likely differ from this short-run estimate, as farmers may have less (or more) of an ability to adjust water use conditional on crop choice in the long run.

We calibrate the long-run intensive-margin elasticity using a series of first-difference regressions with increasingly long gaps between observations. We estimate first-difference analogs of Equations (2)–(3) at the parcel-year level:

3. For parcels containing both small and large pumps (multiple pumps and/or pumps that change capacity), we assign the modal category based on observed groundwater use.

4. Appendix C.5 provides more information on our use of water districts. For some smaller water districts, we observe too few fields to be confident in the construction of our market-level variables (especially after having already split by small vs. large tariff categories). We consider a water district-tariff group to be too small if it contains fewer than 30 (in-sample) parcels. In this case, we create a composite water district-tariff group comprising all water districts in the county (still retaining the small vs. large tariff split).

5. Different coefficients relating $T_m(0, c_{t-1})$ to $T_m(c_t, 0)$ yield nearly identical $\alpha_m(c_t, k_t)$ parameters.

6. Any recurring costs, such as the cost of replanting an annual crop every year, are captured by $R_m(c_t)$. Then, $T_m(c_t, c'_{t-1})$ for $c_t \neq c'_{t-1}$ reflects the additional costs incurred when switching crops.

$$\Delta \log \left(Q_{it}^{\text{water}}\right) = \gamma \Delta \widehat{\log \left(P_{it}^{\text{water}}\right)} + \delta_{it} + \epsilon_{it} \quad \text{(A4)}$$

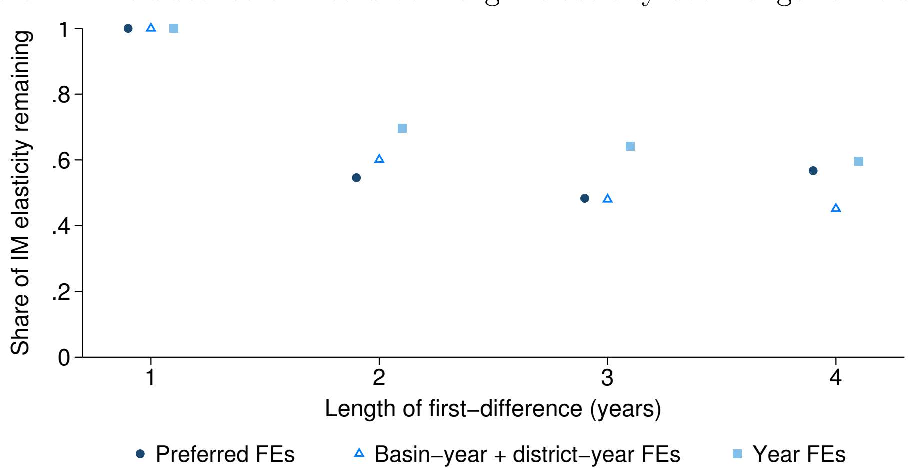
$$\Delta \log \left(P_{it}^{\text{water}}\right) = \theta \Delta \log \left(P_{it}^{\text{elecDefault}}\right) + \psi_{it} + \nu_{it} \quad \text{(A5)}$$

where the Δ operator denotes a within-parcel first difference over $\{1, 2, 3, 4\}$ years. Increasing the length of the first difference allows us to understand the extent to which the intensive-margin response persists over longer time frames.

To ensure that we capture only within-crop adjustments—rather than the effect of crop switching—we apply sample restrictions comparable to the "intensive-margin" restriction in Column (1) of Table 3. That is, we restrict the sample of observations to parcels that do not change crop type over the period of long-differencing. For example, for a four-year difference, we only include parcel-years for which the modal crop choice satisfies $c_t = c_{t-1} = c_{t-2} = c_{t-3} = c_{t-4}$.[7] As a result, this restriction becomes increasingly strict for longer differences.

Our preferred fixed effects are analogous to the regressions in Table 3: parcel-by-$\mathbf{1}$[small/large pump switch] (to capture tariff category switches), groundwater-basin-by-year (to capture trends in depth), and water-district-by-year (to capture varying surface water availability). In alternate specifications, we remove the parcel-switch fixed effect or use only a year fixed effect.

Figure A1: Persistence of intensive-margin elasticity over longer time scales



Notes: We estimate the first-difference analog of the annual versions of Equations (2)–(3), as shown in Equations (A4)–(A5) using 1-, 2-, 3-, and 4-year differences. Each regression applies the "intensive-margin" restriction as in Column (1) of Table 3, which becomes increasingly restrictive for longer differences (e.g., for a 4-year difference, $c_t = c_{t-1} = c_{t-2} = c_{t-3} = c_{t-4}$). This figure plots the ratio of each first-difference point estimate and its corresponding 1-year first-difference point estimate, to show how intensive-margin demand response attenuates over multiple years of groundwater cost shocks. Our preferred fixed effects are exactly analogous to the fixed effects used in Table 3; averaging these three ratios motivates our use of 50% IM as a central scenario. More parsimonious fixed effects imply a similar intensive-margin response. We do not report confidence intervals, as they are not identified for ratios of coefficients.

7. As discussed in Appendix C.4, we use the modal crop choice because our intensive-margin restrictions necessitate imposing discreteness in crop choices.

Figure A1 reports results of these regressions. To focus on how the intensive-margin elasticity evolves over longer time horizons, we report our $\hat{\gamma}$ estimates normalized by the 1-year difference effect. Using our preferred fixed effects, the average of the 2-, 3-, and 4-year differences is roughly 50% of the 1-year difference; this share is relatively stable over time after the 1-year difference. Therefore, we assume the long-run intensive-margin elasticity equals 50% of the short-run intensive-margin response: -0.422.

A.4 Model results

Parameter estimates Table A1 reports the results of our dynamic model estimation. The groundwater cost parameter α_G is common to all markets. As expected, the estimated value is negative, indicating that greater groundwater costs reduce profits. The profit intercept parameters $\alpha(c, k)$ are market-specific, and we report the average values over all markets. We find that remaining in the same crop type ($c = k$) yields weakly positive annual returns net of groundwater cost, while switching to a different crop type yields a negative annual return. These results are expected in this setting, in which switching crop type requires a

Table A1: Dynamic discrete choice parameter estimates

A. Groundwater cost parameter: α_G				
		-0.017^{**}		
		(0.007)		
B. Profit intercept parameters: $\alpha(c, k)$				
	Field state (k)			
	Annual	Fruit/nut	Hay	Non-crop
Crop choice (c)				
Annual	1.70	−1.09	−0.05	−0.10
	[1.11, 2.28]	[−1.68, −0.52]	[−0.64, 0.52]	[−0.69, 0.47]
Fruit/nut	−1.11	2.27	−0.14	−0.43
	[−2.04, −0.22]	[1.34, 3.16]	[−1.06, 0.75]	[−1.35, 0.46]
Hay	−0.10	−0.37	2.08	−0.46
	[−1.10, 0.87]	[−1.37, 0.60]	[1.08, 3.04]	[−1.46, 0.51]
Non-crop†	−0.90	−1.35	−1.27	0.00

Notes: Panel A displays our estimated groundwater cost parameter, α_G, which we obtain from estimating Equation (9). The standard error (in parentheses) is clustered at the market-year level. Panel B displays our average profit intercept parameters. The parameters are recovered at the market level, and we average over all markets to generate this table. 95% confidence intervals (in brackets) are constructed from the 2.5th and 97.5th percentile of the α_G sampling distribution across 500 draws. Because of our normalizations, comparing the profit intercept parameters to a null hypothesis of zero is not appropriate, so we do not report significance on these estimates. Significance of α_G: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
† Because of our normalizations to recover all 16 $\alpha(c, k)$ terms, the intercept terms for the non-crop choice have no variation across draws from the sampling distribution.

Table A2: Short- and long-run elasticities with respect to groundwater pumping cost

	Short run	**Long run**			
		0% IM	25% IM	**50% IM**	75% IM
	(1)	(2)	(3)	(4)	(5)
Crop semi-elasticities					
Annual	0.000	0.119**	0.092**	0.064**	0.039**
	[−0.000, 0.001]	[0.040, 0.185]	[0.020, 0.148]	[0.017, 0.106]	[0.007, 0.068]
Fruit/nut	−0.003***	−0.222**	−0.169**	−0.117**	−0.071**
	[−0.006, −0.001]	[−0.324, −0.062]	[−0.258, −0.029]	[−0.184, −0.025]	[−0.115, −0.011]
Hay	−0.002***	−0.019**	−0.014**	−0.009**	−0.005**
	[−0.004, −0.000]	[−0.064, −0.002]	[−0.050, −0.002]	[−0.032, −0.001]	[−0.020, −0.001]
Non-crop	0.005***	0.122**	0.092**	0.062**	0.037**
	[0.001, 0.009]	[0.026, 0.204]	[0.011, 0.160]	[0.010, 0.110]	[0.004, 0.067]
Elasticities					
Groundwater	−0.718***	−0.236**	−0.359***	−0.482***	−0.609***
	[−0.723, −0.714]	[−0.367, −0.072]	[−0.465, −0.220]	[−0.556, −0.396]	[−0.656, −0.555]
Electricity	−0.689***	−0.258**	−0.369***	−0.480***	−0.596***
	[−0.693, −0.684]	[−0.388, −0.094]	[−0.475, −0.224]	[−0.553, −0.390]	[−0.640, −0.536]

Notes: This table reports the short- and long-run (semi-)elasticities of land use and groundwater and electricity use with respect to groundwater cost, estimated using our discrete choice model. To recover short-run (semi-)elasticities (Column (1)), we simulate the model with baseline costs until it reaches a stead state, and then increase groundwater costs by 20% for one year. While the shock is unanticipated by farmers, once it arrives, they are aware that it only lasts for one year. To recover long-run (semi-)elasticities (Columns (2)–(5)), we increase groundwater pumping costs by 20% and simulate the model forward. Farmers are aware that this price change is permanent. In , farmers can only respond to groundwater cost changes by changing crops. In farmers can also respond on the intensive-margin, by reducing water use conditional on crop choice by 25%, 50%, or 75% of our within-crop reduced-form elasticity respectively. Our preferred model is 50% IM, based on our calibration using long-differences. The 95% confidence intervals (in brackets) are constructed from the 2.5th and 97.5th percentile over draws. We report Columns (1) and (4) graphically in Figure 3. Significance: *** 99% of simulation draws have the same sign; ** 95% of draws, * 90% of draws.

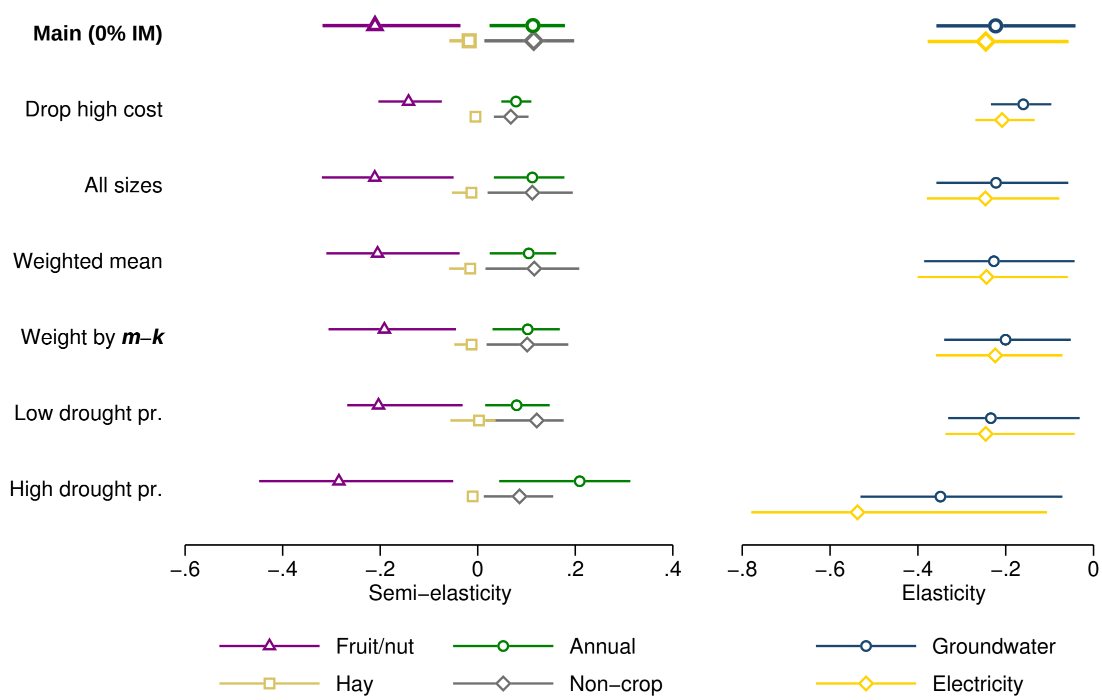
large upfront investment—such as planting or removing an entire orchard of trees—that pays out over a longer time horizon.

(Semi-)elasticities Table A2 reports the land-use semi-elasticities and the groundwater and electricity elasticities that result from our counterfactual simulations. Figure 3 in the main text depicts the short-run results (Column (1)) and the long-run, 50% IM results (Column (4)). This table reports three additional long-run scenarios: 0% IM (in which farmers cannot respond on the intensive margin and can only change crops), 25% IM (in which farmers respond with 25% of the short-run intensive-margin elasticity), and 75% IM (in which farmers respond with 75% of the short-run intensive-margin elasticity). As expected, allowing for a greater intensive-margin effect mutes the crop-switching response while intensifying the groundwater/electricity response.

A.5 Robustness

Figure A2 plots robustness test for our long-run (semi-)elasticities, reporting results for six alternate model specifications. Each of these counterfactual simulations omits the intensive-margin response (0% IM) to focus on the crop-switching margin. Thus, the comparable "main" results in the top row reproduce our 0% IM results depicted in Column (2) of Table A2. (Semi-)elasticities of land use and groundwater and electricity use are robust to parcel sample selection ("Drop high cost" and "All size"), market-level variable construction ("Weighted mean"), estimation weighting ("Weight by m-k"), and drought assumptions ("Low drought pr." and "High drought pr."). Our structural estimates are broadly robust to each of these alternate specifications. The only notable departure from our main results is the sensitivity "High drought pr.", where we increase farmers' subjective probability of experiencing a drought from 58% to 75%. This increased risk of drought intensifies the crop switching effect from fruit/nut perennials into annuals, which increases the magnitudes of the long-run elasticities for groundwater and electricity.

Figure A2: Robustness of long-run (semi-)elasticities



Notes: This figure plots robustness checks on our long-run (semi-)elasticities of land use (left plot) and groundwater and electricity use (right plot) with respect to groundwater cost. The top row reproduces the 0% IM results from Column (2) of Table A2, which is the point of comparison for each robustness check. In "Drop high cost," we drop parcels with groundwater costs $> \$5,000$ per acre (rather than our preferred threshold of $> \$3,000$ per acre). In "All sizes," we include parcels of all sizes (rather than our preferred exclusion of parcels smaller than 1 acre and greater than 5,000 acres). In "Weighted mean," we aggregate data to the market level using the weighted means (rather than our preferred weighted medians) of parcel data. In "Weight by m-k," we weight observations by croppable acres of the market-field state (rather than by our preferred weights by croppable acres of the market). In "Low drought pr." and "High drought pr.," we assume the probability of a drought is 0.4 and 0.75, respectively (rather than our preferred probability of 0.58). The left plot shows semi-elasticities for annual crops (circles), hay perennials (squares), fruit/nut perennials (triangles), and non-crop (diamonds). The right plot shows the electricity of demand for groundwater (circles) and electricity (diamonds), for the same six sensitivities. The reported semi-elasticities and elasticities are the means over 500 draws for each model. The plotted 95% confidence intervals (horizontal lines) show the 2.5th and 97.5th percentile over draws.

B Reduced-form sensitivity analysis

Tables B1–B9 present a series of robustness checks for our reduced-form estimate of groundwater cost response in Column (1) of Table 2 (odd columns), and for our intensive-margin groundwater demand estimate in Column (1) of Table 3 (even columns).

B.1 Addressing measurement error

Unobserved pump upgrades If higher electricity costs incentivized farmers to invest in (unobserved) pump efficiency improvements, we could mistakenly interpret these energy efficiency improvements as reductions in groundwater use (rather than reductions in the electricity needed to produce the same quantity of groundwater). Such unobserved "drift" in our kWh-to-AF conversion factors would bias our groundwater estimates away from zero. In Table B1, we minimize the potential for unobserved drift in AF/kWh ratios by restricting our sample to parcel-years for which every constituent SP has an observed pump test within m months of each month in that calendar year (i.e., observations with more contemporaneous parameterizations of operating pump efficiency and lift in Equation (1)). If anything, this increases the magnitudes of our point estimates, suggesting that unobserved pump efficiency improvements are not biasing our estimates away from zero.

Table B1: Reduced-form sensitivity – months to nearest pump test

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^{\text{water}}$ (\$/AF))	-0.793^{***}	-0.636^{**}	-1.021^{***}	-1.029^{***}	-1.240^{***}	-1.397^{***}
	(0.242)	(0.265)	(0.208)	(0.272)	(0.240)	(0.318)
Pump tests within	48 months		24 months		12 months	
Intensive margin		Yes		Yes		Yes
Parcel units	7,008	6,893	6,921	6,725	6,823	6,478
County-years	356	329	316	313	283	279
Parcel-year observations	47,495	37,861	33,895	27,816	24,562	20,118
First-stage estimates						
$\log(P^{\text{elecDefault}}$ (\$/kWh))	1.446^{***}	1.408^{***}	1.408^{***}	1.464^{***}	1.596^{***}	1.596^{***}
	(0.055)	(0.058)	(0.075)	(0.079)	(0.101)	(0.111)
Kleibergen-Paap F-stat	692	421	398	261	248	153

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, restricting the sample to parcel-years for which all constituent SP-months occur within m months of an observed pump test. Progressively restricting the sample in this way does not systematically attenuate our point estimates. This assuages concerns that unobserved pump efficiency upgrades (incentivized by higher costs) are biasing our electricity-to-groundwater conversions away from zero. Odd (even) regressions are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

kWh-to-AF conversions Table B2 reports sensitivity analyses on our parameterization of lift in Equation (1). Columns (1)–(2) use pump-specific drawdown predictions for months without an observed pump test, rather than our preferred approach of fixing drawdown at measured levels that don't vary with depth. Columns (3)–(4) remove pumps with missing or questionable drawdown measurements, rather than our preferred approach of populating drawdown for these pumps using between-pump predictions. Columns (5)–(6) parameterize groundwater depth using the average of measurements across the full groundwater basin for each sample month, rather than our preferred approach of using month-specific rasters to estimate localized depths (which could be prone to between-pump spillovers from "cones of depression"). All three sensitivities yield similar point estimates, which is unsurprising given that our electricity price instrument is unlikely to be correlated with drawdown or depth.

Table B3 tests three sample restrictions related to our kWh-to-AF conversions. We find similar point estimates for parcels containing SPs with either exactly one vs. multiple observed pump tests (Columns (1)–(2) vs. (3)–(4)). We also find similar estimates for parcel-years with below-median distance to their nearest groundwater measurement in both summer and winter months (Columns (5)–(6)). As with Table B2, these results are unsurprising given that our instrument should be uncorrelated with the number of pump tests, between-test extrapolation/interpolation, or the accuracy of our groundwater depth rasters.

Table B2: Reduced-form sensitivity – parameterization of kWh-to-AF conversion

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(P^{\text{water}}\ (\$/\text{AF})\right)$	-0.936^{***}	-0.843^{***}	-0.868^{***}	-0.660^{**}	-0.941^{***}	-0.850^{***}
	(0.221)	(0.237)	(0.256)	(0.266)	(0.221)	(0.242)
Sensitivity	Predicted drawdown (instead of fixed)		Drop suspect drawdown measurements		Basin-month avg depth (instead of rasterized)	
Intensive margin		Yes		Yes		Yes
Parcel units	7,104	6,997	6,302	6,187	7,104	6,997
County-years	367	334	367	334	367	334
Parcel-year observations	60,490	46,202	51,391	39,828	60,490	46,202
First-stage estimates						
$\log\left(P^{\text{elecDefault}}\ (\$/\text{kWh})\right)$	1.417^{***}	1.388^{***}	1.388^{***}	1.371^{***}	1.410^{***}	1.373^{***}
	(0.043)	(0.044)	(0.042)	(0.042)	(0.042)	(0.042)
Kleibergen-Paap F-stat	1068	696	1115	795	1148	724

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, focusing on components of the kWh-to-AF conversion. Columns (1)–(2) use time-varying predictions of pump-specific drawdown (i.e., the translation from depth to lift), rather than our preferred parameterization that fixes drawdown at the level reported in each pump test. Columns (3)–(4) remove pump tests where the reported drawdown measurement is questionable (e.g., extreme values, internal inconsistencies). Columns (5)–(6) use monthly average groundwater depths across each basin, rather than our preferred parameterization that rasterizes depth at each SP location. Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel × $\mathbf{1}$[large pump], year, groundwater basin × year, and water district × year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B3: Reduced-form sensitivity – kWh-to-AF-related sample restrictions

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^{\text{water}}$ (\$/AF))	-0.861^{***}	-0.662^{**}	-1.038^{***}	-1.212^{***}	-0.837^{**}	-0.924^{***}
	(0.304)	(0.278)	(0.241)	(0.374)	(0.371)	(0.331)
Sample restriction	SPs with exactly one pump test		SPs with multiple pump tests		GW measurements w/in 10 miles (in season)	
Intensive margin		Yes		Yes		Yes
Parcel units	4,403	4,306	2,862	2,829	4,160	3,946
County-years	355	325	342	310	265	241
Parcel-year observations	35,837	27,949	24,653	18,253	23,882	19,045
First-stage estimates						
$\log(P^{\text{elecDefault}}$ (\$/kWh))	1.359^{***}	1.329^{***}	1.329^{***}	1.419^{***}	1.532^{***}	1.510^{***}
	(0.046)	(0.047)	(0.076)	(0.075)	(0.066)	(0.070)
Kleibergen-Paap F-stat	874	586	376	222	537	354

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, for sample restrictions related to our kWh-to-AF conversions. Columns (1)–(2) include only parcels containing SPs with exactly one observed pump test. Columns (3)–(4) include only parcels containing SPs with multiple observed pump tests. Columns (5)–(6) include parcel-years for which the nearest groundwater measurement averaged less than 10 miles (the median) in both summer and winter of year t. Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.2 Identification checks

Time-varying confounders Table B4 interacts year fixed effects with baseline pump characteristics (horsepower and operating pump efficiency) and county, showing that our estimates are robust to time-varying confounders correlated with these cross-sectional factors.

Table B5 tests for time-varying confounders related to the timing of PG&E's smart meter rollout. It seems plausible that PG&E might have prioritized replacing smart meters based on: the age of customers' accounts (proxied by the earliest SP start date in Columns (1)–(2)), customers' expected load on the grid (proxied by 2008 maximum monthly kWh of a constituent SP in Columns (3)–(4)), or air conditioning demand among nearby households (proxied by climate zone in Columns (5)–(6)). Our reduced-form estimates are largely unchanged when we interact these proxies with year fixed effects, which assuages concerns about selection in the timing of smart meter switches.

Table B6 shows that our results are robust to controlling for weather realizations (contemporaneous and lagged, separately for each month of the year), drought severity (by county-year, for five separate severities: "abnormal", "moderate", "severe", "extreme", and "exceptional"), and the distance from to the nearest contemporaneous groundwater measurement (averaged across constituent SPs and over all months of the year).

Table B4: Reduced-form sensitivity – time-varying confounders

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^{\text{water}}$ (\$/AF))	-0.880^{***}	-0.763^{***}	-0.935^{***}	-0.833^{***}	-0.914^{***}	-0.822^{***}
	(0.200)	(0.227)	(0.221)	(0.239)	(0.220)	(0.242)
Interact year FEs with	Initial HP		Initial OPE		County	
Intensive margin		Yes		Yes		Yes
Parcel units	7,104	6,997	7,104	6,997	7,104	6,997
County-years	367	334	367	334	367	334
Parcel-year observations	60,490	46,202	60,490	46,202	60,490	46,202
First-stage estimates						
$\log(P^{\text{elecDefault}}$ (\$/kWh))	1.434^{***}	1.401^{***}	1.401^{***}	1.372^{***}	1.408^{***}	1.367^{***}
	(0.043)	(0.044)	(0.042)	(0.042)	(0.043)	(0.044)
Kleibergen-Paap F-stat	1127	709	1131	731	1081	676

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, interacting year fixed effects with the following cross-sectional fixed effects: earliest observed nameplate horsepower of pump (Columns (1)–(2)); earliest observed operating pump efficiency (Columns (3)–(4)); and county (Columns (5)–(6)). Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions also include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B5: Reduced-form sensitivity – smart meter rollout

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^{\text{water}}$ (\$/AF))	-0.928^{***}	-0.835^{***}	-0.757^{***}	-0.767^{***}	-0.985^{***}	-0.828^{***}
	(0.220)	(0.240)	(0.205)	(0.213)	(0.198)	(0.234)
Interact year FEs with	Earliest SP start date in PG&E data		Max monthly kWh for SP in 2008		Climate zone	
Intensive margin		Yes		Yes		Yes
Parcel units	7,078	6,974	5,511	5,457	7,104	6,997
County-years	367	334	360	328	367	334
Parcel-year observations	60,458	46,175	52,164	39,393	60,490	46,202
First-stage estimates						
$\log(P^{\text{elecDefault}}$ (\$/kWh))	1.426^{***}	1.388^{***}	1.388^{***}	1.396^{***}	1.421^{***}	1.386^{***}
	(0.043)	(0.044)	(0.045)	(0.045)	(0.043)	(0.044)
Kleibergen-Paap F-stat	1085	689	998	657	1102	715

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, focusing on factors that might have been correlated with PG&E's smart meter rollout. We interact year fixed effects with following cross-sectional continuous variables: the earliest account open date at an SP within the parcel (Columns (1)–(2)); the log of maximum monthly kWh consumed in 2008, the first year of our sample period (Columns (3)–(4)); and climate zone (Columns (5)–(6)). Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B6: Reduced-form sensitivity – adding time-varying controls

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(P^{\text{water}}\ (\$/\text{AF})\right)$	-1.053^{***}	-0.815^{***}	-0.921^{***}	-0.824^{***}	-0.938^{***}	-0.852^{***}
	(0.213)	(0.234)	(0.219)	(0.237)	(0.220)	(0.238)
Control variables	Monthly precipitation and temperature		Drought severity by county-year		Distance to depth measurement	
Intensive margin		Yes		Yes		Yes
Parcel units	6,996	6,896	7,104	6,997	7,104	6,997
County-years	336	334	367	334	367	334
Parcel-year observations	53,868	44,557	60,490	46,202	60,490	46,202
First-stage estimates						
$\log\left(P^{\text{elecDefault}}\ (\$/\text{kWh})\right)$	1.398^{***}	1.364^{***}	1.364^{***}	1.383^{***}	1.418^{***}	1.384^{***}
	(0.046)	(0.047)	(0.043)	(0.044)	(0.043)	(0.044)
Kleibergen-Paap F-stat	917	689	1102	698	1100	699

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, adding time-varying controls. Columns (1)–(2) control for month-specific precipitation and temperature (e.g. 12 variables for precipitation in each month of year t, and for each month of year $t-1$). Columns (3)–(4) control for the share of each county year classified as a drought, separately for five severities ("abnormal", "moderate", "severe", "extreme", and "exceptional"). Columns (5)–(6) control for the average distance to the nearest groundwater depth measurement for the summer and winter months of year t. Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Neighbor spillovers Table B7 addresses a potential violation of our IV exclusion restriction: if a decrease in $P_{it}^{\text{elecDefault}}$ is simultaneously experienced by parcel i's neighbors, these neighbors may increase their groundwater consumption, which can generate contemporaneous between-pump interference (i.e., cones of depression) because multiple farmers share the same aquifer, which in turn lowers the groundwater level at parcel i, increasing i's marginal pumping costs. To address this possible spillover channel, we control for the average default electricity price of parcel i's neighbors within a certain geographic radius—including separate controls for the average price of neighboring in-sample parcels (i.e., confirmed pumpers most likely to impact parcel i's costs) and for the average price of neighboring agricultural service points (i.e., all other agricultural users—including any unconfirmed pumpers—that are not included in our estimation sample). We also interact these two average-price-of-neighbors controls with the count of neighbors (of each type) to model the intensity of potential spillovers, as more neighbors should lead to more between-well interference. Appendix Table B7 demonstrates that including these controls does not meaningfully alter our reduced-form estimates, defining neighbors using radii of 1, 2, or 10 miles.[8] This provides strong evidence that between-well interference is driving an exclusion violation in this setting, and is therefore unlikely to bias our IV estimates.

8. These radii are informed by the cone of depression analysis in Alley, Reilly, and Franke (1999).

Table B7: Reduced-form sensitivity – controlling for spillovers via neighbors' electricity prices

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(P^{\text{water}}\ (\$/\text{AF})\right)$	-1.013^{***}	-0.939^{***}	-1.060^{***}	-0.908^{***}	-0.934^{***}	-0.818^{***}
	(0.199)	(0.235)	(0.202)	(0.233)	(0.217)	(0.235)
Control for neighbors' prices	within 1-mile radius		within 2-mile radius		within 10-mile radius	
Intensive margin		Yes		Yes		Yes
Parcel units	6,331	6,233	6,921	6,814	7,097	6,990
County-years	360	325	360	326	360	327
Parcel-year observations	52,070	39,784	58,366	44,560	60,407	46,133
First-stage estimates						
$\log\left(P^{\text{elecDefault}}\ (\$/\text{kWh})\right)$	1.391^{***}	1.362^{***}	1.362^{***}	1.372^{***}	1.421^{***}	1.389^{***}
	(0.044)	(0.045)	(0.044)	(0.045)	(0.043)	(0.044)
Kleibergen-Paap F-stat	982	632	1036	662	1097	705

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, controlling for potential spillovers through neighbors' electricity prices (which could influence neighbors' pumping behavior, thereby indirectly impacting farmer i's groundwater depth). Each regression includes four time-varying controls: the average $P_{it}^{\text{elecDefault}}$ of neighboring in-sample parcels (i.e., confirmed pumpers), the average $P_{it}^{\text{elecDefault}}$ of neighboring agricultural service points (i.e., including all latent pumpers), and the interaction of each of these averages with the number of neighbors of the respective type (to control for the intensity of this potential spillover channel). We define neighbors using three distance radii: 1 mile, 2 miles, and 10 miles. Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.3 Additional robustness checks

Table B8 conducts sensitivity analysis on our IV specification. Columns (1)–(2) show that our results are similar if we instrument using the modal tariff in each category (rather than the default tariff). Columns (3)–(4) present the uninstrumented OLS, which is biased slightly towards zero likely due to measurement error in our kWh-to-AF conversions. Columns (5)–(6) present the reduced-form OLS, for comparison.

Finally, Table B9 conducts sensitivity analysis on our parcel-year sample. Columns (1)–(2) include the following outliers omitted from both our reduced-form and structural analyses: parcels with (i) less than 1 croppable acre (reported acreage is prone to measurement error); (ii) greater than 5,000 croppable acres (unlikely to be irrigated by our observed pumps); and (iii) monthly electricity bills exceeding \$3,000 per croppable acre (either highly abnormal groundwater use or measurement error in the denominator). Including these outlier parcels produces similar results. Columns (3)–(4) remove our (preferred) croppable-acreage weights, yielding attenuated elasticity estimates; this suggests that larger parcels tend to be relatively more groundwater-cost-responsive than smaller parcels. Finally, Column (5) uses a service-point-by-year panel, which produces an estimate similar to Column (3).[9] This suggests that aggregating up from SPs to parcels does not meaningfully alter our econometric estimates.

9. The appropriate comparison here is between Column (5) and Column (3)— since SPs do not have croppable acreage *per se*, and do not easily map to a definition of the intensive margin.

Table B8: Reduced-form sensitivity – IV specification

	$\log(Q^{\text{water}})$					
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	OLS	OLS	OLS	OLS
$\log\left(P^{\text{water}}\ (\$/\text{AF})\right)$	-0.865^{***}	-0.761^{***}	-0.819^{***}	-0.759^{***}		
	(0.233)	(0.245)	(0.094)	(0.117)		
$\log\left(P^{\text{elecDefault}}\ (\$/\text{kWh})\right)$					-1.330^{***}	-1.110^{***}
					(0.320)	(0.318)
Intensive margin		Yes		Yes		Yes
Parcel units	7,104	6,997	7,104	6,997	7,104	6,997
County-years	367	334	367	334	367	334
Parcel-year observations	60,490	46,202	60,490	46,202	60,490	46,202
First-stage estimates						
$\log\left(\text{Modal } P^{\text{elec}}\ (\$/\text{kWh})\right)$	0.626^{***}	0.616^{***}				
	(0.017)	(0.017)				
Kleibergen-Paap F-stat	1386	892				

Notes: This table conducts sensitivity analysis on Column (1) of Table 2 and on Column (1) of Table 3, focusing on our instrumental variables specification. Columns (1)–(2) use an alternate instrument: the modal tariff in each category, rather than the default tariff. Columns (3)–(4) present the uninstrumented OLS estimate. Columns (5)–(6) present the reduced form of our preferred specification. Odd (even) columns are otherwise identical to Column (1) of Table 2 (Column (1) of Table 3). Regressions include the following fixed effects: parcel, parcel $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Regressions are weighted by each parcel's "croppable" acreage (excluding forests, development, etc.). Standard errors (in parentheses) are two-way clustered by parcel and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B9: Reduced-form sensitivity – parcels and acreage weights

	$\log(Q^{\text{water}})$				
	(1)	(2)	(3)	(4)	(5)
$\log\left(P^{\text{water}}\ (\$/\text{AF})\right)$	-0.942^{***}	-0.846^{***}	-0.667^{***}	-0.532^{**}	-0.531^{***}
	(0.220)	(0.238)	(0.159)	(0.215)	(0.133)
Sensitivity	Include outlier parcels		Remove acreage weights		SP-year panel
Intensive margin		Yes		Yes	
Parcel units (or SP in Col (5))	7,742	7,619	6,786	6,565	9,575
County-years	367	334	367	332	367
Observations	66,031	49,826	59,736	45,330	83,675
First-stage estimates					
$\log\left(P^{\text{elecDefault}}\ (\$/\text{kWh})\right)$	1.418^{***}	1.316^{***}	1.316^{***}	1.226^{***}	1.332^{***}
	(0.043)	(0.050)	(0.030)	(0.038)	(0.029)
Kleibergen-Paap F-stat	1104	694	1856	1032	2044

Notes: Columns (1)–(2) include parcels with bills over \$3,000 per croppable acre and with croppable areas $\notin [1, 5000]$ acres, all of which we drop from our preferred parcel-year specifications. Columns (3)–(4) remove the regression weights by each parcel's "croppable" acreage. Columns (1) and (3) are otherwise identical to Column (1) of Table 2. Columns (2) and (4) are otherwise identical to Column (1) of Table 3. Column (5) is analogous to Column (3) but estimates the groundwater elasticity at the SP-level, rather than the (more aggregated) parcel level. All regressions include the following fixed effects: unit, unit $\times$ $\mathbf{1}$[large pump], year, groundwater basin $\times$ year, and water district $\times$ year. Standard errors (in parentheses) are two-way clustered by unit and county-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

C Data

C.1 PG&E data

PG&E monthly billing data We use confidential customer-level electricity data, which PG&E's data management team prepared for us under a non-disclosure agreement. These data comprise the universe of agricultural electricity consumers in PG&E's service territory, and we observe each customer's monthly bills at the service account level for 2008–2019. We aggregate service accounts up to 112,032 unique service points (i.e. the physical location of an electricity meter) and construct a "monthified" panel of electricity consumption (in kWh) at the service point (SP) level.[10] We observe several key covariates for each service point: its latitude and longitude, its climate zone, its electricity tariff, and indicators for accounts with solar panels on net-energy metering (which we drop from our estimation sample). Our data also include meter identifiers to link service point locations to physical electricity meters. Figure C1 maps all agricultural service points in our dataset.

PG&E's Advanced Pumping Efficiency Program PG&E also provided rich audit data on agricultural groundwater pumps, collected as part of the utility's Advanced Pumping Efficiency Program (APEP), which subsidized pump tests for agricultural consumers across PG&E service territory. We observe the universe of APEP-subsidized pump tests from 2011–2019: 33,747 unique tests at 24,642 unique pump locations. For each test, the data report detailed measurements including: operating pump efficiency, horsepower, standing water level, drawdown, lift (a.k.a. total dynamic head), flow (in gallons per minute), and kWh/AF.[11] We also observe pump make/model, water source (e.g., well, canal, reservoir, etc.), water use (i.e., irrigation vs. commercial or residential), and the electricity meter identifier. The latter lets us match pump tests to electricity service points, thereby isolating a sample of 12,419 service points for which agricultural groundwater pumping is the confirmed end-use.[12] We restrict our empirical analysis to this 11% subset of agricultural service points (plotted in dark blue in Figure C1), in order to avoid incorporating other agricultural electricity end uses.[13] We further drop any APEP-matched service points where the pump

10. PG&E's monthly bill cycles are customer-specific, and most billing periods do not line up with calendar months. We "monthify" billed kWh for each SP by splitting/weight-averaging multiple bills in a single calendar month, in order to create a SP by month panel. This is standard practice in the economics literature on electricity demand (e.g. Ito (2014)). Most service points have a single service account at each point in time, but service accounts frequently turn over within a given service point.

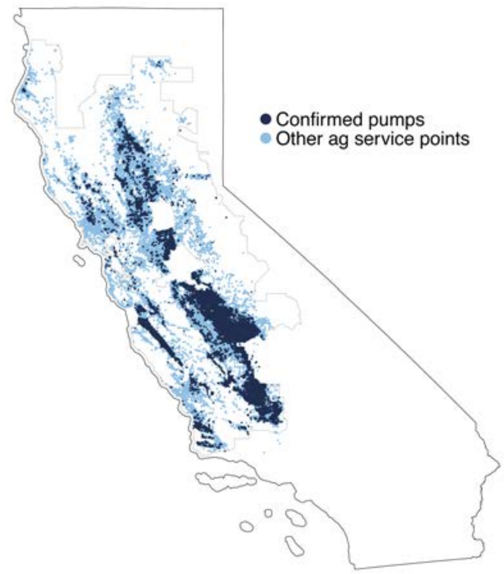
11. Measured kWh/AF serves as an important cross-check for computing groundwater quantities. Whereas the pump test data report kWh/AF at the time of each test, our electricity-to-water conversions account for variation in groundwater depth over time.

12. Pumping is almost certainly the only end use at APEP-matched service points, as PG&E typically installs a dedicated meter for each groundwater pump.

13. This limits our sample by dropping agricultural groundwater pumps that did not receive APEP pump tests (Table 1, Panel A, right column). Absent a pump test, we cannot precisely identify which of these service points are in fact groundwater pumps. However, Column (3) of Table 2 show that expanding our sample to include both columns of Table 1 yields a similar short-run elasticity estimate.

test data indicate a non-well pump (e.g., horizontal booster pumps reporting water source = "canal") or list a non-agricultural end use (e.g., "municipal") from our estimation sample.[14]

Figure C1: PGE agricultural customers



Notes: This figure maps the locations of all agricultural service points served by PGE, from 2008–2019. Dark blue dots indicate the 12,419 service points that are confirmed pumps (i.e. matched to an APEP test for a groundwater pump). Light blue dots indicate all other agricultural service points. The light grey outline indicates PGE's service territory.

PG&E agricultural tariffs PG&E offered 23 distinct agricultural tariffs during our sample period. Our billing data report the specific tariff associated with each monthly bill. Prices on each tariff are updated multiple times per year, and historic prices are publicly available, along with information on tariff-specific eligibility criteria.[15] We use these data to construct a 2008–2019 panel of hourly volumetric (i.e., marginal) electricity prices, which we collapse to the monthly level by taking an unweighted average across hours.[16]

22 of PG&E's 23 agricultural tariffs are divided into four mutually exclusive categories, based on pump size ("small" pumps $<$ 35 horsepower, and "large" pumps $\geq$ 35 horsepower) and electricity meter type (conventional analog meters, and digital smart meters).[17] The small-conventional and large-conventional categories comprise a single tariff. The small-smart and large-smart categories comprise 8 and 12 tariffs respectively; we define the least time-varying tariff as the default in each of these categories, which serves as our instrument.

The remaining (23rd) tariff comprises a fifth category: farmers who have recently transitioned from internal combustion engines to electricity. We omit this 1.7% subset of confirmed

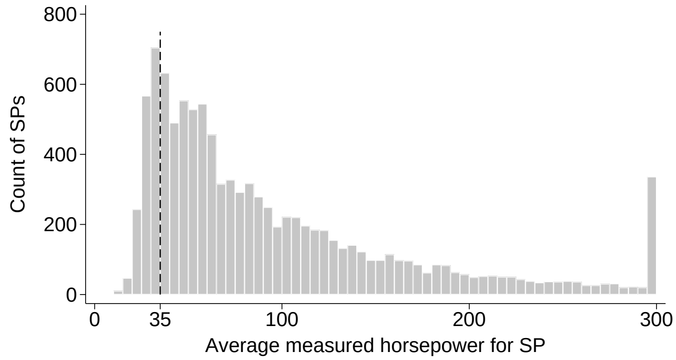
14. We relax the latter restriction when aggregating from SPs to parcels, since our parcel-level analyses weight parcels by croppable acreage. These weights effectively remove non-agricultural water uses with far fewer false positives than the (often miscoded) "water end-use" variable provided by the APEP database.

15. See here: https://www.pge.com/tariffs/en/rate-information.html

16. Importantly, unlike PG&E's residential electricity prices, its agricultural tariffs are not tiered: a farm's marginal price does not depend on its consumption.

17. The 35 horsepower cutoff applies to pumps with a single motor. The few pumps with multiple motors are defined as "large" if all motors sum to at least 15 horsepower of load. Conventional meters record electricity consumption using an analog dial, while smart meters digitally store the full time profile of consumption.

Figure C2: Histogram of pump horsepower



Notes: This is a histogram of measured horsepower from APEP pump tests, averaged for each PGE service point in our estimation sample. This reveals no evidence of bunching at the 35 hp cutoff that defines PGE's small- vs. large-pump tariff categories. Bunching would be consistent with farmers' optimizing against tariff categories when making pump investments.

pumps from our analysis entirely, for two reasons: (i) they likely represent an idiosyncratic group of pumps that is less likely to be comparable to pumps in the other four categories, and (ii) we do not observe groundwater consumption prior to switching to electricity, and we worry about selection in the timing of these switches. Our results are not sensitive to this decision to exclude this fifth category.

For our reduced-form analysis, we take unweighted averages over all sample months to construct the annual average marginal electricity price ($/kWh) for each tariff. For our structural analysis, we construct average total variable costs for each tariff by subtracting off fixed charges from each tariff (i.e., non-trivial charges assessed per day, per billing period, or per kW, all of which are independent of farmers' level of consumption).

C.2 Groundwater data

We use publicly available groundwater data from California's Department of Water Resources (DWR) collected under the California Statewide Groundwater Elevation Monitoring Program.[18] These data report depth below the surface at 16,852 unique monitoring stations during our 2008–2019 sample period, with an average of 33 measurements at each location at different points in time. We rasterize all measurements from each sample month, using inverse distance weighting to interpolate a gridded two-dimensional surface of average depth at each point in space.[19] Using these monthly rasters and service point geocoordinates, we construct a service point-month panel of groundwater depths. We also store the distance from each service point to its nearest measurement site in each month; this facilitates a robustness check where we remove observations with a high degree of spatial interpolation in groundwater depths (see Columns (5)–(6) of Appendix Table B3).

We assign each service point to a groundwater basin and sub-basin, using publicly available shapefiles from the DWR.[20] (Sub-)basins are defined by stratigraphic barriers that

18. https://water.ca.gov/Programs/Groundwater-Management/Groundwater-Elevation-Monitoring--CASGEM
19. Before rasterizing, we drop depth measurements that are flagged as having questionable accuracy.
20. See here: https://water.ca.gov/Programs/Groundwater-Management/Bulletin-118

limit the horizontal movement of groundwater. California has 425 basins and 517 sub-basins (only 6% of basins contain more than one sub-basin); our main sample includes farms located within 54 basins and 104 sub-basins. Our reduced-form analysis controls for changes in depth that impact all farms within the same basin (via basin-by-year fixed effects).

C.3 Constructing groundwater quantities and prices

Energy is the sole variable input to groundwater production, and the vast majority of agricultural groundwater pumps in California are powered by electricity (United States Department of Agriculture (2018)). Holding pump characteristics and groundwater depths fixed, the relationship between the quantity of groundwater extracted (measured in acre-feet, or AF) and the quantity of electricity (in kWh) consumed is governed by physics:

$$\frac{\text{kWh}}{\text{AF}} = \text{kW} \div \frac{\text{AF}}{\text{hour}} = \frac{[\text{Lift (feet)}] \times [\text{Flow (gallon/minute)}]}{[\text{Operating pump efficiency (\%)}] \times 5310} \div \frac{\text{AF}}{\text{hour}} \tag{C1}$$

The power (kW) needed to pump 1 acre-foot is directly proportional to the vertical distance the water must travel to the surface (i.e., lift) and the speed at which the water travels (i.e., flow). It is inversely proportional to the rate at which the pump converts electric energy into the movement of water (i.e., operating pump efficiency, or OPE). We can simplify Equation (C1) by converting from gallons to acre-feet, arriving at Equation (1) in the main text.

We parameterize Equation (1) for confirmed pumps at the service point-month level, such that we capture the within-year time profile of kWh-per-AF conversion rates *before* aggregating up to the parcel-year.[21] We use OPE as reported in the PG&E pump test data. We extrapolate each service point's first pump test backwards, extrapolate its last pump test forwards, and interpolate between multiple pump tests using a triangular kernel in time.

We parameterize lift by combining DWR groundwater depths and PG&E pump test measurements. Lift is the sum of three components: (i) standing water level (i.e., baseline groundwater depth in the absence of pumping), (ii) drawdown (i.e., how much pump i impacts its own depth), and (iii) minor pump-specific correction factors (i.e., discharge pressure, gauge corrections, pump height above the surface).[22] We populate the standing water level (the largest component of lift) using the monthly groundwater rasters described above. We parameterize drawdown using the values reported in the pump test data.[23] Finally, we apply discharge pressure, gauge corrections, and other pump-specific adjustments as reported in the APEP database.[24]

21. Parameterizing Equation (1) annually would lead to systematically inaccurate Q^{water} conversions, since months with shallower groundwater depths (i.e., more AF per kWh) tend to have greater groundwater use.

22. Drawdown depends on rate of extraction (i.e. flow) and the physical properties of the substrata. Greater flow means greater drawdown, as water levels fall with faster extraction. More transmissive (or porous) rock formations have lower drawdown, because water levels are able to horizontally reequilibrate more quickly.

23. Where reported drawdown is missing or internally inconsistent, we populate drawdown by modeling it as a function of the standing water level and location fixed effects (to account for properties of the substrata).

24. We extrapolate beyond the first/last pump tests and interpolate between tests for these characteristics.

Appendix Table B2 presents sensitivity analysis on how we construct lift. Columns (1)–(2) replace reported drawdown with our drawdown predictions. Columns (3)–(4) drop pumps where reported drawdown is missing/suspect and thus populated using our predictions (as described above). Columns (5)–(6) parameterize lift using basin-wide average monthly groundwater depths, rather than depths extracted from monthly rasters—thereby removing any potential for localized feedback effects of pumping on depth (e.g., "cones of depression"). Our results are similar in all cases, which is unsurprising given that our electricity price instrument is not correlated with the components of Equation (1).

C.4 Constructing crop choice at the parcel level

Our data on cropped acreage come from the U.S. Department of Agriculture's (USDA) Cropland Data Layer (CDL).[25] This product provides annual crop coverage at every 30-by-30 meter pixel in the United States from 1997 to 2019. California was added to the CDL in 2007. The CDL is generated using satellite imagery in conjunction with a machine learning algorithm, and its land classifications are ground-truthed against the USDA's Farm Service Agency's farm surveys. The CDL reports 97 distinct crops that were grown in California during our sample period. We classify these 97 crops into three broad categories: annual crops, fruit and nut perennial crops, and hay perennial crops. The major annual crops in our sample are winter wheat, cotton, tomatoes, corn, and rice. The major fruit and nut perennial crops are almonds, grapes, walnuts, pistachios, and oranges. The hay perennials category is dominated by alfalfa. Two additional categories are non-crop (which the CDL reports as "fallow/idle cropland"), and not croppable (i.e., forest, shrubland, and development).

Using parcel shapefiles obtained from California county tax assessors' offices, we cookie-cutter each annual CDL image to construct parcel polygons. This yields a parcel-year panel of the shares of land cover by category (e.g., the fraction of acres in parcel f that were crop category c in year t). For parcels that are spatially merged to our sample of confirmed-pump service points, these fractions serve as outcome variables in our reduced-form analysis (i.e., Columns (3)–(6) of Table 3). They also enter our structural analysis as F^c_{ft} in Equation (8). However, for our intensive-margin regressions (Columns (1)–(2) of Table 3), we restrict the sample such that the parcel's *modal* crop choice is the same in adjacent years. Finally, we use year-on-year transitions at the pixel level to calculate conditional choice probabilities.[26] In all cases, we remove "not croppable" acreage from the denominator of each parcel-year.

C.5 Defining markets using surface water districts

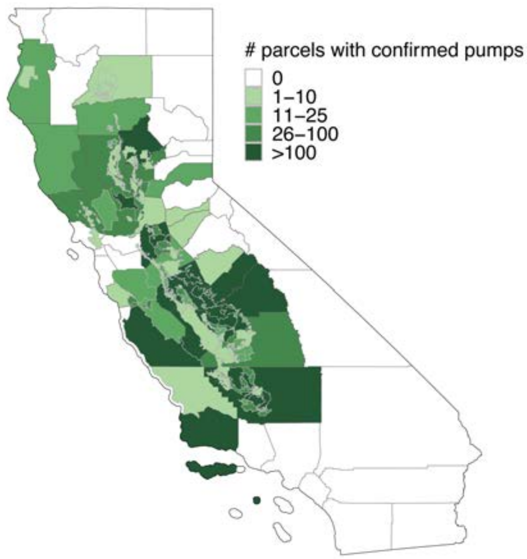
Following Hagerty (2022), we spatially merge parcels to water districts. Shapefiles for California's water districts come from the California DWR, the California Atlas, and the California

25. See here: https://www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php

26. We use all pixels contained within parcels in market m that merge to confirmed-pump service points, dropping not croppable pixels. Calculating CCPs at the pixel level (as opposed to using parcel-specific modes) helps to increase coverage across all possible switches within a market.

Environmental Health Tracking Program.[27] Water districts are administrative entities that govern farmers' annual allocations of surface water.[28] Individual water districts typically offer their constituent farmers a common per-acre allocation at substantially lower marginal price than farmers' marginal cost of groundwater pumping.

Figure C3: Water districts and counties used to construct markets



Notes: This figure maps the number of parcels with confirmed-pump service points by water district and (for parcels not in a water district) by county. We use water districts (plotted with thick grey borders) and counties-less-water-districts to construct markets in our dynamic discrete choice analysis. Note that our market definitions further subdivide these polygons by small- vs. large-pump tariffs, and then aggregate water districts with fewer than 30 parcels up to the county level (preserving the small- vs. large-pump split). We drop markets with fewer than 15 parcels after this within-county, within-pump-size aggregation.

Since groundwater and surface water are obvious substitutes, this cost advantage for surface water is key: we can assume that farmers exhaust their (inframarginal) surface water allocations before pumping groundwater, rendering any positive observed groundwater pumping the marginal source of irrigation.[29] In our reduced-form analysis, we non-parametrically control for annual shocks to surface water allocations at the water district level. This helps to isolate changes in pumping behavior driven by variation in pumping cost shocks, rather than by variation in the availability of groundwater substitutes.

For our structural analysis, we use water districts to define "markets." This grouping combines farmers who are geographically proximate and likely to have similar conditional value functions for a given field state and crop choice. It also absorbs heterogeneous surface water allocations and annual shocks to these allocations, which occur at the water district level. For the 40% of confirmed-pump parcels that are not in a water district (i.e., not

27. We thank Nick Hagerty for providing these shapefiles, and for his help in understanding and processing these surface water data.

28. As Hagerty (2022) describes, the term "water district" refers to multiple types of organizations that provide/sell water to irrigators within a defined area, including: irrigation districts, county water agencies, water conservation and flood control districts, reclamation districts, and mutual water companies.

29. A third source of water for irrigation is the open market. However, Hagerty (2023) suggests that purchased water is almost always more expensive than the groundwater costs for farmers in our dataset.

receiving surface water allocations), we use counties to define "markets." Figure C3 maps water districts (with thick grey borders) and counties, where shading indicates the number of parcels with confirmed-pump service points in each polygon. These polygons do not directly correspond to the markets used in our structural analysis, since (i) we further subdivide parcels by small vs. large pump categories, and (ii) we then aggregate water-district-by-pump-size units with fewer than 30 in-sample parcels up to the county level. We drop markets with fewer than 15 in-sample parcels after this within-county, within-pump-size aggregation—since small samples in these markets generate extremely unstable projections of groundwater use, electricity use, and cost.[30]

C.6 SGMA data

To quantify the reductions in groundwater pumping that will be required under SGMA, we collect data from the Groundwater Sustainability Plans (GSPs) that Groundwater Sustainability Agencies (GSAs) submitted to the California Department of Water Resources. All GSAs in the 90 high- and medium-priority basins were required to submit GSPs by January 31, 2022 (California Department of Water Resources (2024)). As of the time of writing, there were 120 available GSPs.[31] We downloaded all available GSPs and extracted two pieces of information from each: (i) annual average groundwater pumping; and (ii) "sustainable yield," or "the maximum amount of water calculated over a base period representative of long-term conditions in the basin and including any temporary surplus that can be withdrawn annually from a groundwater supply without causing an undesirable result" (California Department of Water Resources (2017)).[32] We were able to populate these two numbers for 111 out of the 120 available GSPs.[33]

Our measure of interest is the percent reduction in groundwater pumping that will be needed to meet each GSP's SGMA target, which we define as:

$$\frac{\text{current pumping} - \text{sustainable yield}}{\text{current pumping}} \times 100$$

Figure C4 plots this statistic for all (available) GSAs. 63 GSPs report overdraft conditions, or sustainable yield that is below current pumping levels; 57 GSPs report current pumping

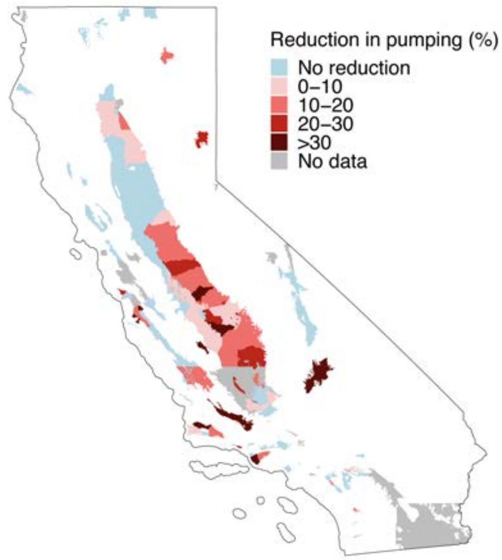
30. Appendix A.2 provides further details on how we construct markets.

31. GSPs are available from the Department of Water Resources: https://sgma.water.ca.gov/portal/gsp/all

32. GSPs are detailed documents, frequently over 1,000 pages long. Where possible, we draw these numbers from the executive summary. Otherwise, we extract these numbers from the GSP's water budget section.

33. Of the 90 basins where GSPs were required, 71 basins' GSPs were fully approved as of January 2024. 13 basins' GSPs were deemed incomplete, and 6 basins' GSPs were deemed inadequate. We include all available GSPs—whether approved or not—in our GSP data, as these are the best available representation of groundwater pumping reductions required under SGMA. We expect that, if anything, the final approved GSPs will be more stringent than the proposals, making our summary statistics underestimates of the ultimate regulatory stringency.

Figure C4: GSP sustainability targets under SGMA



Notes: This figure maps the Groundwater Sustainability Agencies (GSAs) within California's medium- and high-priority basins, which were required to submit Groundwater Sustainability Plans (GSPs) to the Department of Water Resources. The shading reflects the percentage reduction in groundwater pumping that will be required to reach sustainability according to each GSP. See surrounding text for details.

levels at or below sustainable yield, thereby already achieving sustainability.[34] Bringing the average overdrafted GSP into sustainability under this definition will require reductions in pumping of 17.4% (weighting GSPs by historical groundwater pumping levels). Looking at only the overdrafted GSPs within PG&E's territory, this weighted average falls to 16.9%. We convert to the market level using the average required reductions in overdrafted GSPs that overlap with our market boundaries, weighting by the fraction of the market's croppable acreage in each GSP. This yields a weighted average reduction target of 16.7% in our sample.

C.7 Weather data

We obtained daily temperature and precipitation rasters from the PRISM climate group, a standard source in the agriculture economics literature (see, e.g., Schlenker and Roberts (2009)).[35] Using gridded data with a 4km-by-4km resolution, we extract daily maximum temperature, minimum temperature, and precipitation at each SP location.

C.8 Drought data

We use historic drought data from the National Oceanic and Atmospheric Administration (NOAA), which publishes weekly maps of drought intensity across the U.S. NOAA uses

34. It is possible that the GSPs *understate* the true magnitude of overdraft. Bruno, Jessoe, and Hanemann (2024) compares reported overdraft to the results from running the C2VSim hydrology model, and finds they are broadly similar (average reported overdraft: 0.085 AF/acre; average modeled overdraft: 0.094 AF/acre). To the extent that the GSPs are underestimates, our policy estimates will be conservative.

35. These data are available at https://prism.oregonstate.edu/.

six drought categories of increasing severity: "No Drought", "Abnormally Dry", "Moderate", "Severe", "Extreme", and "Exceptional".[36] We aggregate these data to the county-year, quantifying the average share of each county's area that falls into each category in each year.

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36. These maps are available here: https://www.drought.gov/data-maps-tools/us-drought-monitor