Groundwater, energy, and crop choice: Evidence from California agriculture

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Abstract

Groundwater is a key resource for agricultural production globally. Both increasingly rapid draw-downs of aquifers as well the policies intended to increase aquifer sustainability increase costs to agricultural producers, with unknown consequences. In this paper, we empirically estimate how farmers respond to changes in groundwater costs in one of the world's most valuable agricultural areas: California. To do this, we assemble a novel dataset that combines (i) detailed restricted-access microdata on farmers' electricity consumption, (ii) rich data from technical audits of these farmers' pump efficiencies, (iii) measurements of groundwater depths in California aquifers, and (iv) satellite-derived measures of crop types, and use exogenous variation in the price of electricity, itself an important input into groundwater extraction. We find farmers' price elasticities of demand for both electricity (-1.17) and groundwater (-1.12) to be much larger than previous estimates in the literature. We find evidence that crop switching and fallowing is the primary mechanism behind these large elasticity estimates. These results suggest that groundwater management policy may have important impacts on the markets for agricultural products.

Keywords: groundwater, agriculture, electricity
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1 Introduction

Groundwater is an essential input into agricultural production around the globe, responsible for supplying water to 38 percent of irrigated acre worldwide (Siebert et al. (2010)). However, recent scientific evidence documents rapid draw-downs of global aquifers, with key agricultural areas seeing the water table fall by over 4cm per year.[1] Given that global climate change is projected to increase the frequency and severity of droughts (Famiglietti (2014)), governments will face a greater urgency to enact policies to manage common-pool groundwater resources. For agricultural producers who rely on groundwater for irrigation, both groundwater scarcity itself and groundwater management policies increase the costs of growing crops.

In this paper, we generate novel empirical estimates of farmers' response to changes in groundwater pumping costs in California, one of the world's most valuable crop-producing regions. California produces 17 percent of total U.S. crop value, and its farmers rely heavily on groundwater for irrigation. Despite rapidly declining aquifer levels and a series of severe droughts, groundwater extraction remains largely unregulated in California, and most farmers face no meaningful restrictions on pumping. The state is currently implementing its Sustainable Groundwater Management Act, which will introduce sweeping regulations on groundwater use. The effectiveness and economic consequences of any such groundwater regulation depends on both the extent to which farmers will respond to new pumping regulations, and their means of adapting to higher irrigation costs.

We begin by estimating the price elasticity of demand for agricultural groundwater. Despite the importance of groundwater as an agricultural input, estimating this elasticity has historically proven difficult, in large part because groundwater use is typically neither priced nor measured. We overcome these challenges by leveraging the fact that electricity is the main variable input in groundwater extraction. Given data on electricity prices and quantities, along with pump-specific mappings from energy input to groundwater output, we are able to construct accurate measures of groundwater prices and quantities. We assemble a novel dataset that combines (i) confidential electricity consumption data for all agricul-

1. `https://www.nytimes.com/interactive/2019/08/06/climate/world-water-stress.html`

tural customers served by Pacific Gas & Electric (PGE), California's largest electric utility; (ii) technical pump efficiency audits for nearly 12,000 groundwater extraction points; (iii) publicly available groundwater measurements across space and time, for all major California aquifers; and (iv) satellite-derived crop type measurements. Using exogenous variation both in PGE's electricity tariff schedules and in average groundwater levels, we identify demand elasticities for both electricity and groundwater.

We estimate farmers' price elasticity of demand for electricity to be -1.17, which is much more elastic than prior estimates of electricity demand in the residential and commercial/industrial sectors. Next, we estimate farmers' price elasticity of demand for groundwater, where we separately identify the effect of groundwater price changes coming from variation in electricity prices vs. variation in groundwater depths. We recover nearly identical groundwater demand elasticities: -1.39 for electricity-induced price changes vs. -1.37 for depth-induced price changes. These statistically indistinguishable estimates suggest that farmers are equally attentive and responsive to either source of variation in groundwater pumping costs, consistent with the predictions of standard Neoclassical theory. We also estimate a single elasticity of demand for groundwater of -1.12, identified using *only* changes in PGE's agricultural electricity tariffs. These estimates are again much more elastic than previous groundwater demand estimates from the existing literature.

Next, we explore the mechanisms behind the large elasticities we estimate. We consider four possible mechanisms: (i) applying less water to existing crops; (ii) changing irrigation efficiency; (iii) switching water sources; and (iv) switching crops or fallowing. We are able to rule out (i) and (ii), and we develop a stylized model of farm crop choice and irrigation costs to provide theoretical guidance on (iii) and (iv). This model shows that (iii) is only likely at extremely high groundwater pumping costs, at which point farmers may substitute groundwater for water purchased on the open market (Hagerty (2018)). On the other hand, detailed crop budget studies suggest that crop switching and/or fallowing are likely to occur in the range of groundwater prices we calculate from PGE data. This leaves crop switching as the leading candidate mechanism driving farmers' groundwater demand response.

We conduct several empirical tests to provide evidence for crop switching as the primary mechanism. We estimate annual elasticities that are similar to our monthly elasticities, suggesting that farmers are not arbitraging water sources within a growing season. We also find substantial annual elasticities on both the intensive and extensive margins, which is consistent with farmers switching to less-water-intensive crops and fallowing land. We then estimate heterogeneous elasticities and find the largest responsiveness for farms that switch between annual and perennial crops during our sample period, providing additional support for crop switching. Finally, we directly test for crop switching and find suggestive evidence that farmers switch from annual crops to either perennials or fallowing in response to higher prices of electricity or groundwater.

This paper makes three main contributions. First, we provide the first large-scale estimates of electricity demand in a major energy-using sector: agriculture in California, one of the most important agricultural sectors in the world. While many studies estimate the relationship between electricity prices and consumption in the residential sector (Alberini and Filippini (2011); Fell, Li, and Paul (2014); Ito (2014); Deryugina, MacKay, and Reif (2018)), far fewer have focused on commercial/industrial electricity consumption (Paul, Myers, and Palmer (2009); Jessoe and Rapson (2015); Blonz (2016)). To the best of our knowledge, there exists no comparable study estimating the price elasticity of electricity demand in the agricultural sector. By leveraging microdata for thousands of agricultural consumers across PGE's service territory, along with plausibly exogenous changes in farmers' marginal electricity prices, we identify California farmers as relatively elastic electricity consumers.

Second, we estimate the elasticity of groundwater demand for California farmers—a policy-relevant elasticity that has proven elusive due to both data and identification challenges (Mieno and Brozovic (2017)). Our empirical strategy overcomes many of these challenges by combining comprehensive electricity consumption data with technical audits of groundwater pumps, and by leveraging exogenous variation in electricity prices (a major component of pumping costs) to credibly identify changes in farmers' effective price of groundwater. Many previous studies have estimated water demand outside the agricultural sector (Hewitt and Hanemann (1995); Renwick and Green (2000); Olmstead, Hanemann, and Stavins (2007)), while others have focused specifically on groundwater demand in agriculture (Hendricks and Peterson (2012); Pfeiffer and Lin (2014); Badiani and Jessoe (2015)).

We provide well-identified groundwater demand estimates, for thousands of farms from one the most important agricultural regions in the world: California's Central Valley.

Finally, we go beyond simply estimating how farmers respond to groundwater cost increases by providing evidence of *how* they reoptimize in the face of rising input costs. Given that farmers appear to respond Neoclassically to cost increases (either higher electricity prices or greater groundwater depths), our demand estimates imply that they are likely to respond similarly to cost increases associated with groundwater management policies. We show that crop switching (and fallowing) is the primary mechanism underlying our large elasticity estimates. This suggests that price-based groundwater policies could lead to large shifts in crop choice, which would have major welfare implications for land use and agricultural markets.

This paper proceeds as follows. Section 2 provides background on groundwater pumping, California agriculture, and energy use in farming. Sections 3 and 4 describe our data and empirical strategy. Section 5 presents our demand elasticity estimates. We present a simple theoretical model of on-farm water use and test for mechanisms in Section 6. Section 7 concludes.

2 Background

2.1 Agriculture in California

California is a key player in global agricultural production, and represented 17 percent of total U.S. crop value in 2016 (Johnson and Cody (2015)). California's 77,000 farms produce over 400 commodities, including close to half of all fruits, nuts, and vegetables grown in the United States. In fact, California is the sole domestic producer of many high-value crops, including almonds, artichokes, olives, and walnuts (California Department of Food and Agriculture (2011)).

Water is an essential input for California's agricultural production. Nearly 80 percent of the state's annual water consumption occurs in the agricultural sector, where crop irrigation is the primary end use. California has nearly 8.3 million harvested acres of cropland, 7.9

million of which are irrigated (Johnson and Cody (2015)). Farmers may have access to surface water and/or groundwater, and each water source is governed by a complex system of rights.[2]

Surface water Approximately 40 percent of California's surface water is used in agriculture. 61 percent of irrigation water comes from surface sources, with groundwater making up the remaining 39 percent (California Department of Water Resources (2015)). Surface water rights in California follow strict rules. Most farms with access to surface water obtain it via irrigation districts.[3] In addition to obtaining surface water from individual rights or irrigation districts, farmers have a limited ability to purchase water on the open market. However, these trades constitute only a very small share of total water deliveries, and the prices are extremely high (Hagerty (2018)).

Groundwater In normal weather conditions, groundwater supplies 30 to 40 percent of all water end uses in California. However, this rises to close to 60 percent in drought years, when surface water is unusually scarce (California Department of Water Resources (2014)). By contrast to the strictly defined surface water rights, agricultural groundwater rights tend to be far more vague. The typical groundwater right in California is "overlying," meaning that landowners whose property sits above an aquifer have the right to extract the underlying groundwater.[4] The vast majority of groundwater use is unmetered, and users face no variable costs of extraction beyond the energy costs of pumping (Bruno and Jessoe (2018)).[5] Hence, a farmer may extract as much groundwater as he chooses, conditional on owning the overlying property rights.

2. See Sawyers (2007) for more details.

3. Irrigation districts were established between 1860 and 1950, and their boundaries have remained essentially fixed over time. Though some individual farms do have their own water entitlements, the vast majority of these allocations belong to districts. These agricultural cooperatives divert water from large rivers and canals and distribute this water to farmers, with individual farmers receiving water proportional to their acreage within the district (Schlenker, Hanemann, and Fisher (2007)). For a more detailed description of surface water rights in California, see Hagerty (2019).

4. There are also "appropriative" groundwater rights, for users who do not own land above the aquifer, but these rights are lower-priority than the overlying rights. Appropriative rights holders may only exercise these rights in the case of a surplus.

5. There are limited exceptions to this rule: a few irrigation districts impose a per-unit price on groundwater, but this is rare (Bruno and Jessoe (2018)).

Many of California's groundwater basins are "overdrafted," meaning that, annually, withdrawals exceed replenishment. As of 2017, some agricultural regions were facing overdraft of 2 million acre-feet annually. This has led to a substantial decline in groundwater levels in the Central Valley, most notably in the Tulare and San Joaquin groundwater basins, which, combined, lost more than 135 million acre-feet of groundwater since 1925.[6] In 2014, the state faced a severe drought, with groundwater levels reaching historic lows in many portions of the state. 21 of the state's 515 groundwater basins are considered "critically overdrafted."

In response to drought conditions, in September 2014, California lawmakers passed sweeping groundwater legislation. The Sustainable Groundwater Management Act (SGMA), consists of three bills, and represents represents the first statewide regulatory scheme to mitigate over-extraction of groundwater. AB 1739 enables the California Department of Water Resources (DWR) or local groundwater sustainability agencies (GSAs) the ability to charge fees for groundwater extraction, and requires GSAs to prepare groundwater sustainability plans (GSPs). SB 1319 authorizes GSAs to implement these GSPs. SB 1168 requires that uses of groundwater be both reasonable and beneficial, and enables GSAs and the DWR to require groundwater monitoring. In addition, Proposition 1 provided $100 million in funding to support sustainable groundwater management. SGMA represents the future of groundwater management in California. However, the GSPs will not be finalized until 2020 at the earliest, leaving farmers free to extract at will.

2.2 Electricity for pumping

Electricity is an essential input to groundwater pumping. The California Energy Commission reports that water use accounts for 19 percent of California's electricity consumption, and close to 8 percent of the state's energy is used on farms (California Energy Commission (2005)). The state's investor-owned utilities spend nearly $50 million annually to improve energy efficiency in the agricultural sector. This makes water use, and agricultural water use in particular, a key component of California's energy policy goals.

6. See: `https://www.ppic.org/publication/groundwater-in-california/`

To estimate groundwater demand, we exploit the fact that electricity is a major determinant of pumping costs. Several previous papers have used variation in energy costs to estimate the price elasticity of groundwater demand (Hendricks and Peterson (2012), Pfeiffer and Lin (2014), Badiani and Jessoe (2015), and Mieno and Brozovic (2017)). However, Mieno and Brozovic (2017) point out that these estimates may exhibit bias due to (non-classical) measurement error and/or poor identification. Furthermore, data limitations have restricted previous studies to relatively narrow geographies, which may reduce their external validity. By contrast, our sample includes thousands of farms throughout California's Central Valley, one of the most productive agricultural regions in the world. Our data also allow us to overcome the standard measurement issues and identification challenges—via detailed technical audits that precisely characterize the electricity-to-groundwater conversion factor, and via exogenous variation in Pacific Gas & Electric's (PGE) agricultural electricity tariffs.

3 Data

3.1 Electricity data

We begin by estimating how farmers' electricity consumption responds to changes in electricity price. We use confidential customer-level electricity datasets, which PGE's data management team prepared for us under a non-disclosure agreement. These data comprise the universe of agricultural electricity consumers in PGE's service territory, and we observe each customer's monthly bills at the service account level, from 2008–2017. We aggregate service accounts up to 108,172 unique service points (i.e. the physical location of an electricity meter), allowing us to construct "monthified" panel of electricity consumption (in kWh) at the service point (SP) level.[7] We also observe several key covariates for each service point, including its latitude and longitude; an indicator for accounts with solar panels on net-energy metering (NEM), which we drop from our estimation sample; and an identifier to link service point locations to physical electricity meters.

7. PGE's monthly bill cycles are customer-specific, and billing periods typically do not end at the end of a calendar month. 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. Most SPs have a single service account at each point in time, but service accounts often turn over a given SP.

PGE's offers 23 distinct agricultural tariffs, and our billing data report the particular tariff associated with each monthly bill. Prices on each tariff update multiple times per year, and historic prices are publicly available, along with information on tariff-specific rules and eligibility criteria. This allows us to construct a 10-year panel of hourly volumetric (marginal) electricity prices, which we collapse to the monthly level by taking an unweighted average across hours. Then, we assign each service point a monthly average marginal electricity price in \$/kWh.

Table 1 describes each agricultural tariff in detail. Importantly, PGE classifies all agricultural consumers into 5 disjoint categories, based on their physical capital (i.e. pump size; internal combustion engine) and their type of electricity meter (i.e. conventional vs. smart meters).[8] While farmers may switch tariffs *within* categories, they may not switch tariffs *across* categories. This restriction lets us identify price elasticities of demand by instrumenting for farm i's marginal price with the marginal price of its within-category default tariff. Figure 1 plots time series of monthly average marginal prices for 3 of the most common tariffs in our estimation sample. Our identifying variation in electricity prices comes from (i) these time series not moving in parallel, and (ii) across-category tariff switching induced by PGE's large-scale smart meter rollout.

3.2 Pump data

To complement our electricity data, we have rich data on agricultural groundwater pumps collected by PGE's Advanced Pumping Efficiency Program (APEP). These data include the universe of APEP-subsidized pump tests from 2011–2017, and we observe detailed measurements and technical specifications for 21,851 unique tests at 17,107 unique pump locations. Importantly, we also observe identifiers for the electricity meter associated with each pump test. This allows us to match pump tests to electricity service points, thereby isolating a sample of 11,851 service points for which agricultural groundwater pumping is confirmed to

8. Conventional meters record electricity consumption using an analog dial, whereas smart meters can digitally store the full time profile of consumption. During our sample period, PGE gradually phased out conventional meters, replacing them with smart meters capable of supporting time-varying electricity pricing.

be a major end-use.[9] We restrict our empirical analysis to this 11 percent subset of agricultural service points, in order to best isolate groundwater pumpers and avoid incorporating other agricultural electricity end-uses.[10]

Table 2 reports summary statistics for this subset of agricultural service points (in the right column). Compared to the full set of PGE's agricultural customers, APEP-matched service points tend to consume nearly twice as much electricity, and tend to pay lower marginal prices. Only 24 percent of service points shift across tariff categories, and the vast majority of switches are triggered by PGE's smart meter rollout. Figure 2 reveals that APEP-matched service points are heavily concentrated in California's Central Valley, and appear to be a geographically representative subset of PGE's agricultural customers.

Besides helping us identify a subset of agricultural consumers who pump groundwater, APEP data allow us to characterize pump-specific groundwater production functions. Groundwater extracted is Leontief in electricity (for pumps with electric motors), and 1 kWh of electricity in will yield a particular volume of groundwater out (measured in acre-feet (AF)). This kWh per AF relationship is governed by physics:

$$\frac{\text{kWh}}{\text{AF}} = \text{kW} \div \frac{\text{AF}}{\text{hour}} = \frac{[\text{Lift (feet)}] \times [\text{Flow (gallon/minute)}]}{[\text{Operating pump efficiency (\%)}] \times [\text{Constant}]} \div \frac{\text{AF}}{\text{hour}} \tag{1}$$

The power (kW) required to pump 1 acre-foot is directly proportionate to both 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 proportionate to rate at which the pump converts electric energy into the movement of water (i.e. operating pump efficiency). We can simplify (1) by converting from gallons to acre-feet:

$$\Rightarrow \quad \frac{\text{kWh}}{\text{AF}} = \frac{[\text{Lift (feet)}] \times [\text{Constant}]}{\text{Operating pump efficiency (\%)}} \tag{2}$$

9. Pumping is likely the *only* end-use at most matched service points, as PGE typically installs a dedicated meters for each pump.

10. We are currently working on using satellite images to predict whether service points outside the APEP-matched sample are also groundwater pumps. We hope to incorporate these farms into future analysis, as there are likely many groundwater pumps that never received an APEP-subsidized pump test.

For each APEP pump test, we observe measurements of kWh/AF, operating pump efficiency, flow, and lift. We also observe the standing water level, or the baseline groundwater depth in the absence of pumping. Because pumping lowers the water level at a given location, standing water levels help us more accurately calibrate how changes in aquifer depth impact lift for each pump.[11]

3.3 Water data

While a given farm's pumping technology is relatively constant in the short run, its kWh/AF conversion factor is sensitive to short-run changes in groundwater levels. In order to capture these short-run shocks in pumping costs, we use publicly available groundwater data from California's Department of Water Resources collected under the California Statewide Groundwater Elevation Monitoring (CASGEM) Program.[12] These data report depth below the surface at 16,015 unique monitoring stations during our 2008–2017 sample period, with an average of 25 measurements at each location at different points in time. We rasterize all measurements within each month (and quarter), using inverse distance weighting to interpolate a gridded two-dimensional surface of average depth at each point in space. This allows us to construct a monthly (and quarterly) panel of estimated groundwater depths at each electricity service point.

We assign each service point to a groundwater basin, using publicly available shapefiles maintained by the California Department of Water Resources.[13] Groundwater basins are broadly defined by stratigraphic barriers through which water does not travel horizontally. We control for annual changes in water levels that impact all farms within the same water basin. We also obtained shapefiles of irrigation districts in California from the California Department of Water Resources, the California Atlas, and the California Environmental

11. Lift is (approximately) the sum of the standing water level, drawdown (i.e., how much pump i impacts its own depth), and other pump-specific factors (e.g., discharge pressure, gauge corrections, height of the pump above the surface). Drawdown depends on rate of extraction (i.e. flow) and the physical properties of the substrata. Greater flow increases 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.

12. These data are available at: `https://water.ca.gov/Programs/Groundwater-Management/Groundwater-Elevation-Monitoring--CASGEM`

13. Water basin shapefiles are available at `https://water.ca.gov/Programs/Groundwater-Management/Bulletin-118`.

Health Tracking Program, following Hagerty (2019). We spatially match PGE service points to these shapefiles to determine to which irrigation district (if any) each service point belongs.[14] Irrigation districts (a.k.a. water districts) are administrative entities that govern farmers' annual allocations of surface water. Because groundwater and surface water are obvious substitutes, we non-parametrically control for annual shocks to farms' surface water allocations at the water district level. This helps to isolate variation in pumping behavior driven by variation in pumping costs, rather than variation in the availability of groundwater substitutes.

3.4 Groundwater prices and quantities

We merge the above data sources into a panel of groundwater prices and quantities, at the service point by month level. To convert from electricity (kWh or \$/kWh) to groundwater (AF or \$/AF), we simply need to populate a kWh/AF conversion factor for every panel observation. We construct estimates for kWh/AF by parameterizing Equation (2) using (i) monthly (or quarterly) rasters of groundwater depths at each service point; (ii) pump-specific conversions between standing water level and lift, as calculated from APEP pump tests; and (iii) APEP-measured operating pump efficiencies. We take unweighted averages of APEP variables across multiple pumps within a single service point; we also 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.

Table 3 reports summary statistics for this merged panel dataset. We observe 3.45 unique pump tests for the average APEP-matched service point, and APEP data reveal substantial (cross-sectional) variation in operating pump efficiencies and kWh/AF conversion factors. Our constructed kWh/AF estimates tend to moderate extreme values, which compresses the right tail of *measured* kWh/AF (while also slightly shifting this distribution left). Interestingly, implied marginal groundwater prices exhibit far less seasonal variation than marginal electricity prices. This is because groundwater levels tend to be higher in sum-

14. In ongoing work, we are expanding upon this by using data on each irrigation district's water allocations in a heterogeneity analysis.

mer months (compared to winter months), which tends to reduce (constructed) kWh/AF in months when electricity prices are highest.

3.5 Crop data

Common Land Units In order to match electricity meters to cropland, we use the USDA Farm Service Agency's Common Land Unit (CLU) data. We obtained the universe of USDA CLUs in California.[15] A CLU is the smallest contiguous unit of agricultural land under common land cover, land management, and ownership.[16] We link PGE service points to CLUs via a spatial match.[17]

Cropland Data Layer We obtain data on cropped acreage from the U.S. Department of Agriculture's (USDA) Cropland Data Layer (CDL). This satellite-derived product provides information on what crop is being grown at every 30-by-30 meter pixel in the United States from 1997 to 2019. California was added to the CDL starting in 2007. The CDL is generated using satellite imagery in conjunction with a machine learning algorithm, and is ground-truthed against the USDA's Farm Service Agency's farm surveys. In California during our sample period, the CDL reports 83 distinct landcover classifications. We classify these landcover categories into three broad groups: fallow, annual crops, and perennial crops. The fallow category consists of land that is fallowed according to the CDL, as well as grass and pastureland. The major annual crops in our sample are winter wheat, cotton, tomatoes, corn, rice, and strawberries. The major perennial crops are almonds, grapes, walnuts, pistachios, and oranges. We match the CDL to farms using CLUs. In this draft, we assign each CLU to a crop using the modal CDL pixel in the CLU. If this modal crop type does not cover over 50 percent of pixels in the CLU, we label the CLU as having missing data.[18]

15. In the 2008 Farm Bill, the CLU data were made restricted-access. We therefore use the 2008 CLUs for our full sample.

16. The USDA provides more detail on CLUs here: `https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-products/common-land-unit-clu/index`.

17. In ongoing work, we are pursuing a second method of linking service points to land area: using county assessor tax parcels.

18. In ongoing work, we are constructing additional cropping variables, including the share of land in a CLU under different crop types.

4 Empirical strategy

This section outlines our empirical strategy for estimating farmers' demand for groundwater pumping. First, we estimate price elasticities of demand for electricity, for the full sample of agricultural consumers where we can match an electricity meter to a groundwater pump. Next, we estimate price elasticities of demand for groundwater, by translating prices/quantities of electricity into prices/quantitites of water using data on (i) technical pumping production functions and (ii) groundwater depths across space and time.

4.1 Electricity demand

We estimate monthly electricity demand using the following specification:

$$\sinh^{-1}\left(Q_{it}^{\text{elec}}\right) = \beta \log\left(P_{it}^{\text{elec}}\right) + \gamma_i + \delta_t + \varepsilon_{it} \tag{3}$$

The dependent variable is kWh consumed at electricity service point i in month t, transformed using the inverse hyperbolic sine function (which closely approximates the natural log transformation but includes zero in its support).[19] P_{it}^{elec} is unit i's marginal electricity price (in \$/kWh), averaged across all hours in month t. We include unit by month-of-year fixed effects (γ_i), in order to control for within-pump/month average consumption (e.g., service point i in March). We also include month-of-sample fixed effects (δ_t) to control for trends in both electricity prices (which rise over time) and pumping behavior. Alternative specifications include groundwater basin by year fixed effects (to control for time-varying trends in groundwater depth across basins), water district by year fixed effects (to control for annual shocks to surface water allocations), and unit-specific linear time trends. We two-way cluster standard errors by service point and month-of-sample, which accommodates both arbitrary within-unit serial correlations and arbitrary spatial correlations with each monthly cross-section.

19. Since 15 percent of observations in this panel are zeroes, we apply the inverse hyperbolic sine transformation to avoid dropping months where farms consume zero kWh for groundwater pumping.

4.1.1 Identification

To identify the demand elasticity in Equation (3), we must purge any endogenous variation in unit i's marginal electricity price. PGE's agricultural tariff *schedules* are the outcome of statewide regulatory proceedings, and marginal prices are linear in kWh consumed.[20] While an individual farmer cannot plausibly influence how PGE sets prices, most farmers may select between alternative tariff schedules—effectively choosing which marginal electricity price they face. PGE restricts this choice to be within 5 tariff categories defined by farmers' physical capital (e.g. pump size and type) and type of electric meter (i.e. conventional vs. smart meters). We instrument for unit i's marginal price with the marginal price of the default tariff *within* unit i's category (i.e. bolded tariffs in Table 1), which eliminates selection bias from a high-volume pumper choosing a tariff with advantageously low volumetric prices.

Farmers may also shift *across* tariff categories, which could similarly bias our elasticity estimates. If such a shift reflects a change in physical pumping capital—for example, upgrading from a < 35 hp pump to a ≥ 35 hp pump—then a change in marginal price (or within-category marginal default price) would coincide with a mechanical increase in electricity consumption. We control for such endogenous changes in price by interacting unit fixed effects with a categorical variable for the 3 types of physical capital that define PGE tariff categories: small pumps, large pumps, and auxiliary internal combustion engines. On the other hand, if unit i shifted across categories because PGE replaced its conventional meter with a smart meter, we would not expect such a shift to coincide with any other changes to unit i's pumping behavior.[21] Hence, meter-induced shifts in tariff categories are unlikely to lead to *endogenous* changes in unit i marginal electricity price. We also instrument with *lagged* default prices to purge potential endogeneity in the timing of unit i's smart meter installation.

20. By contrast, PGE's residential electricity tariffs use increasing block pricing, where a household's marginal price is endogenous to its own consumption (Ito (2014)). Linear marginal prices simplify our estimation of agricultural electricity demand, because farm i's marginal price is determined *solely* by its tariff schedule.

21. During our 2008–2017 sample period, PGE gradually installed smart meters for the vast majority of its customers. The timing of PGE's smart meter rollout was determined by institutional and geographic factors, which were outside of customers' control. Previous research has established that PGE did not specify the rollout to target customers with particular usage patterns (Blonz (2016)).

In essence, these identifying assumptions amount to an assumption of parallel counterfactual trends across PGE's five tariff categories. One potential concern would be selection into the < 35 hp vs. ≥ 35 hp groups, if (say) sophisticated, price-responsive farmers are more likely to invest in high-capacity pumps. Figure 3 reveals no bunching around this 35 hp benchmark, which suggests that farmers are not choosing their pump sizes to game PGE's rate categories. However, even in the absence of gaming, farmers with small vs. large pumps may differ across key unobservables. To address this concern, we interact month-of-sample fixed effects with horsepower bins, removing any trends in pump size. This yields quite similar results, which supports our parallel trends assumption.

4.2 Groundwater demand

We seek to estimate the causal effect of groundwater price on groundwater consumption, and this demand elasticity is linearly approximated by the coefficient β:

$$\log\left(Q_{it}^{\text{water}}\right) = \beta \log\left(P_{it}^{\text{water}}\right) \tag{4}$$

We construct Q_{it}^{water} and P_{it}^{water} using the *estimated* conversion factor $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$, which has measurement error and is also potentially endogenous. Hence, the same measurement error and endogeneity is present on both the left-hand side and the right-hand side of Equation (4). We can rewrite this expression decomposing $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ on both sides:

$$\log\left(Q_{it}^{\text{elec}}\right) - \log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right) = \beta\left[\log\left(P_{it}^{\text{elec}}\right) + \log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right)\right] \tag{5}$$

Rearranging:

$$\log\left(Q_{it}^{\text{elec}}\right) = \beta \log\left(P_{it}^{\text{elec}}\right) + (\beta + 1)\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right) \tag{6}$$

This expression is algebraically equivalent to Equation (4), but it isolates the endogenous estimated conversion factor in one right-hand-side variable. We estimate an analogous regression specification:

$$\sinh^{-1}\left(Q_{it}^{\text{elec}}\right) = \beta^{\text{e}} \log\left(P_{it}^{\text{elec}}\right) + (\beta^{\text{w}} + 1)\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right) + \gamma_i + \delta_t + \varepsilon_{it} \tag{7}$$

This specification is similar to Equation (3), except that we can now interpret β^{e} and β^{w} as the price elasticity of demand for groundwater. We allow this elasticity to vary depending on the source of variation in pumping costs—groundwater depths may be more salient to farmers than electricity prices, or vice versa.[22] As in the electricity regressions, we purge electricity price endogeneity by instrumenting P^{elec}_{it} with within-category default prices (see description above).

To identify β^{w}, we must overcome three potential sources of bias. First, farmers may choose to alter their pumping technologies in order to change $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$, and such changes are likely correlated with Q^{elec}_{it}. Second, $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ is a function of unit i's groundwater depth, which is mechanically linked to Q^{elec}_{it}—when unit i consumes electricity to extract groundwater, its localized groundwater level falls, thereby increasing $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$. Third, $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ incorporates measurement error both from interpolating rasterized groundwater depths across space and from interpolating/extrapolating unit i's APEP measurements across time.

We instrument for $\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right)$ using logged groundwater depth averaged across unit i's full groundwater basin.[23] This purges potential endogeneity driven by changes in pumping technologies, and eliminates bias induced by measurement error in unit i's pump specifications in month t. It also breaks the mechanical relationship between $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ and Q^{elec}_{it}, as farm i's extraction should have a negligible contemporaneous effect on average groundwater levels across the whole basin. Finally, instrumenting with basin-wide average depth mitigates measurement error from having spatially interpolated groundwater measurements into a (potentially overfit) gridded raster.

While Equation (7) isolates the shared endogenous component of Q^{water} and P^{water} on the right-hand side, a more standard approach would be to estimate:

$$\sinh^{-1}\left(Q^{\text{water}}_{it}\right) = \beta \log\left(P^{\text{water}}_{it}\right) + \gamma_i + \delta_t + \varepsilon_{it} \tag{8}$$

22. A strict Neoclassical interpretation would assume $\beta^{\text{e}} = \beta^{\text{w}}$, as the optimizing farmer should respond to all short-run changes in P^{water}_{it} identically.

23. We instrument with groundwater depth in logs (rather than levels) because logging both sides of Equation (2) implies that $\log(\text{kWh}/\text{AF}_{it})$ is linear in $\log(\text{lift})$, and a percentage change in depth should yield a similar percentage change in lift.

We also estimate Equation (8), instrumenting for $\log(P_{it}^{\text{water}})$ using the logged average marginal electricity price of unit i's within-category default tariff (i.e., the same instrument from Equation (3)). This isolates changes in the effective price of groundwater driven *only* by plausibly exogenous changes in the marginal electricity price. It also removes right-hand-side measurement error in $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$, thereby preventing measurement error in Q_{it}^{water} from biasing our point estimates.[24]

5 Results

5.1 Electricity demand

Table 4 reports results from estimating Equation 3. Column (1) does not instrument for marginal electricity price, yielding an unidentified $\hat{\beta}$ estimate. Column (2) instruments using unit i's within-category default marginal price, which eliminates bias from farmers choosing their own electricity tariffs. The direction of this bias is not obvious *ex ante*, because farmers are choosing between tariffs with both volumetric (\$/kWh) and fixed (\$/kW) price components.[25] Comparing Columns (1) vs. (2), we see that on average, farmers with higher electricity consumption tend to choose tariffs with relatively low fixed charges per kW and relatively high prices per kWh.

Column (3) eliminates the other source of price endogeneity by interacting unit fixed effects with indicators for (i) small pumps ($<$ 35 hp), (ii) large pumps ($\geq$ 35 hp), and (iii) auxiliary internal combustion engines. While only 5 percent of units shift across tariff categories due to changes in their physical capital, the resulting simultaneous changes in

24. In most cases, classical measurement error on the left-hand side does not bias point estimates. However, consider the regression $(Y_i + \eta_i) = \beta(X_i + \omega_i) + \varepsilon$, where η_i and ω_i each denote classical measurement error, and where $\text{Cov}(\eta_i, \omega_i) \neq 0$. After conditioning on $(X_i + \omega_i)$, the remaining measurement error on the left-hand side is no longer *conditionally* classical, and could bias $\hat{\beta}$. In Equation (8), measurement error from $\widehat{\text{kWh/AF}}_{it}$ enters directly on the right-hand side and inversely on the left-hand side. Instrumenting with default electricity prices neutralizes this correlation between left-hand- vs. right-hand-side measurement error.

25. PGE tariffs with relatively high volumetric (i.e. marginal) prices tend to have relatively low fixed prices, and vice versa. Two farmers with the same average electricity consumption may optimally choose different tariffs. Suppose farmer A operates a 300 hp pump for 50 hours per month, while farmer B operates 50 hp pump for 300 hours per month. Farmer A should prefer a low fixed price and a high volumetric price, while farmer B should prefer a high fixed price and a low marginal price.

Q_{it}^{elec} and P_{it}^{elec} induce substantial bias in Column (2) point estimate. Column (3) reports our preferred estimate of -1.17, after having purged both sources of price endogeneity.[26]

The magnitude of this elasticity estimate is surprisingly large, considering that electricity demand tends to be extremely inelastic in other contexts. The literature on electricity demand has focused heavily on the residential sector, and recent estimates have found elasticities of -0.08 to -0.48 in the short run (Reiss and White (2005); Alberini and Filippini (2011); Fell, Li, and Paul (2014)) and -0.09 to -0.73 in the medium-to-long run (Alberini and Filippini (2011); Ito (2014); Deryugina, MacKay, and Reif (2018)).[27] Fewer estimates exist for commercial or industrial electricity demand. Paul, Myers, and Palmer (2009) estimate commercial/industrial elasticities of -0.11 to -0.16 in the short run, and -0.29 to -0.40 in the long run. Jessoe and Rapson (2015) find no demand response to dynamic pricing in these sectors, while Blonz (2016) estimates elasticities of -0.08 to -0.22 using hourly price variation for PGE's small commercial/industrial customers. To our knowledge, we provide the first large-scale estimates of electricity demand elasticities in the agricultural sector.

Columns (4)–(6) report three additional elasticity estimates, each intended to assuage any remaining concerns over price endogeneity. Column (4) includes separate year fixed effects for each water basin and each water district, to control for potential time-varying confounders related to water depth or surface water availability. The resulting point estimate of -1.02 is similar, albeit slightly attenuated. Column (5) instruments with the 6- and 12-month lags of the default price (rather than the contemporaneous default price), to account for potential endogeneity in the timing of PGE's smart meter rollout.[28] This yields a nearly identical point estimate, implying that farmers' electricity consumption did not meaningfully change in anticipation of a smart meter installation. Finally, Column (6) adds 11,175 unit-

26. If we modify Column (3) by interacting month-of-sample fixed effects with bins, we recover a point estimate of -1.15 with a standard error of 0.16. This shows that differential trends in pump size are not biasing our results.

27. These estimates uses monthly or annual variation in electricity prices, which aligns with our empirical strategy. Other studies leverage hourly variation in electricity prices have estimated electricity demand elasticities ranging from -0.03 to -0.25 (Wolak (2011); Jessoe and Rapson (2014); Fowlie et al. (2018); Ito, Ida, and Tanaka (2018)).

28. Recall that farmers may shift across tariff categories (inducing changes to their within-category default price) due to *either* changes in their physical capital *or* the installation of a smart meter.

specific linear time trends, to confirm that we are not identifying $\hat{\beta}$ solely off of monotonic trends in price and quantity. The resulting point estimate of -0.76 is attenuated, as linear trends remove much of the (good) variation in electricity prices over time. Even so, we still find a tightly estimated elasticity that is substantially larger than virtually all previous estimates for the elasticity of electricity demand.

5.2 Groundwater demand

Table 5 presents our results for estimating farmers' groundwater demand. Each column estimates Equation (7) using our preferred strategy for identifying the elasticity with respect to the electricity price: instrumenting for $\log(P_{it}^{\text{elec}})$ with within-category default prices, and interacting unit fixed effects with indicators for each category of physical pumping capital. Note that we report $\hat{\beta}^{\text{e}}$ and $\hat{\beta}^{\text{w}}$, where the latter subtracts 1 from the regression coefficient on $\log(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it})$. We interpret each coefficient as the elasticity of demand for groundwater with respect to one component of the price of groundwater, holding the other component constant.

Column (2) reports our preferred estimates of $\hat{\beta}^{\text{e}}$ and $\hat{\beta}^{\text{w}}$, where we instrument for $\log(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it})$ with logged groundwater depth in month t averaged across unit i's groundwater basin. Comparing $\hat{\beta}^{\text{w}}$ in Columns (2) vs. (1), instrumenting with average depth appears to alleviate bias due to measurement error in $\log(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it})$.[29] The exclusion restriction requires that unit i's pumping behavior have no contemporaneous impact on basin-wide average groundwater depths. Such feedback effects between the dependent variable and the instrument would be extremely unlikely for three reasons: (i) unit i is small relative to the geographic footprint of its groundwater basin; (ii) thousands of other pumpers are also extracting from the same basin; (iii) basin-wide average groundwater levels do not instantaneously reequilibrate after extraction at one point in space. Column (3) restricts the sample to the 3 largest groundwater basins, each of which has over 1,000 units in our estimation

29. We discuss three potential sources of bias in β^{w} in Section 4.2: (i) endogenous changes to pumping technologies, (ii) the mechanical relationship between extraction and depth at a given location, and (iii) measurement error. Bias from (i) and (ii) appear unlikely, as they should bias our β^{w} away from zero, rather than towards zero.

sample.[30] The resulting $\hat{\beta}^{\text{w}}$ estimate is quite similar, which should assuage concerns that the instrument is invalid due to a few large farms located in very small groundwater basins.

The magnitudes of our $\hat{\beta}^{\text{e}}$ estimates are quite similar to results from the electricity-only regressions, especially comparing $\hat{\beta}^{\text{e}} = -1.21$ from Column (1) of Table 5 the analogous estimate of $\hat{\beta} = -1.17$ from Column (3) of Table 4. This is not surprising, since Equation (7) simply adds one regressor to Equation (3). However, $\hat{\beta}^{\text{e}}$ is surprisingly close to our instrumented $\hat{\beta}^{\text{w}}$ estimate (-1.39 vs. -1.37). This implies that a 1 percent change in the effective price of groundwater has the *same* effect on farmers' pumping behavior, whether that change comes via their marginal electricity price or via their pump's kWh/AF conversion factor. It also suggests that farmers are quite attentive to their true costs of pumping, and that they reoptimize their pumping behavior identically in response to either type of price variation—as Neoclassical theory would predict.

Similar to our elasticity estimates for electricity, our groundwater elasticity estimates are also quite large relative to the existing literature. Recent studies have also exploited variation in energy prices, but yielding far smaller magnitudes: Hendricks and Peterson (2012) find an elasticity of -0.10, and Pfeiffer and Lin (2014) find an elasticity of -0.27 (both for agricultural groundwater in Kansas). Bruno and Jessoe (2018) estimate demand elasticities of -0.17 to -0.22 within the Coachella Valley of California, which is a unique setting where groundwater extraction is directly priced. Previous studies have also estimated farmers' elasticity of demand for surface water, most notably Hagerty (2018), who finds an elasticity of -0.23 for surface water in California agriculture. While estimates of surface water demand are often as large as -0.8 in specific locations (Schoengold, Sunding, and Moreno (2014); Hagerty (2018)), we find agricultural groundwater demand to be even more elastic *on average*.[31] Substitution between groundwater and surface water is likely a major factor explaining the large magnitudes of our elasticities estimates.

30. These basins are the San Joaquin Valley, the Sacramento Valley, and the Salinas Valley. The number of agricultural groundwater pumpers in each basin is likely much larger, as our estimation sample comprises only the subset of PGE customers that we can confident match to an APEP-subsidized pump test.

31. Estimates for urban water demand have found similar elasticities, ranging from -0.10 to -0.76 (Nataraj (2011); Ito (2013); Baerenklau, Schwabe, and Dinar (2014); Wichman (2014); Buck et al. (2016); Wichman, Taylor, and Haefen (2016); Hagerty (2018)).

Columns (4)–(6) report three alternate versions of our preferred estimates in Column (2). First, to account for the inherent tradeoff between spatial density vs. temporal frequency of groundwater measurements, Column (4) re-estimates Equation (7) using groundwater data rasterized at the quarterly (rather than monthly) level. Whereas our preferred monthly rasters are able to capture groundwater measurements at greater temporal frequency, quarterly rasters have greater accuracy in the cross-section by incorporating more distinct measurement sites. The resulting $\hat{\beta}^{\mathrm{w}}$ estimate increases in magnitude, however the average depth instrument has less predictive power at the (coarser) quarterly level. Column (5) includes water basin by year and water district by year fixed effects, yielding only slightly attenuated point estimates despite eliminating much of the variation in the average depth instrument. In Column (6), we instrument with 6- and 12-month lags of average depth (rather than contemporaneous depth), as it is possible (albeit unlikely) that farmers pump less in months with lower groundwater levels for some reason other than pumping costs. These lagged instruments substantially increase $\hat{\beta}^{\mathrm{e}}$ and $\hat{\beta}^{\mathrm{w}}$; however, the small first stage F-statistic indicates a weak instrument, and we interpret these results with caution.

Table 6 reports results from estimating Equation (8), with groundwater quantity as the dependent variable, and instrumenting for the composite groundwater price with default electricity prices. While these estimates identify $\hat{\beta}$ using *only* variation in default electricity prices, Table 5 demonstrates that farmers respond almost identically to variation in *either* component of their effective groundwater price. The resulting point estimates are quite similar to, but slightly smaller than, our electricity demand estimates.[32] Interestingly, combining P_{it}^{water} into a single regressor removes much of the variation used to estimate separate coefficients in Table 5. This is because electricity prices and groundwater depths are seasonally correlated—groundwater levels are lowest (making pumping more expensive) in the winter months, when electricity prices are also low. This likely explains why $\hat{\beta}$ estimates in Table 6 are smaller than $\hat{\beta}^{\mathrm{e}}$ and $\hat{\beta}^{\mathrm{w}}$ estimates in Table 5.

32. Again, it is not surprising that Equations (3) and (8) yield similar point estimates, since Q^{water} and P^{water} are multiplicative transformations of Q^{elec} and P^{elec} and both specificaitons are log-log.

6 Economics of groundwater demand response

Having established that California farmers are quite responsive to changes in their groundwater pumping costs, we now turn our attention to the mechanisms underlying this demand elasticity. When we observe a farmer consume less electricity at a pump with a dedicated electricity meter, four possible mechanisms could explain this decrease:

1. The farmer applies less water to existing crops.

2. The pump's kWh-to-AF groundwater production function changes.

3. The farmer switches to an alternate water source.

4. The farmer switches crops or fallows the land.

This first mechanism should manifest in the short run, especially for annuals where the cropping decision may not persist across growing seasons. Two results give us confidence that this is not the main mechanism. First, using hourly electricity data from PGE, we find very limited responses of within-day consumption to within-day price changes. Secondly, we find that farmers are substantially less elastic during the summer growing season than during the winter. Both of these results suggest that farmers are not reducing water use on their crops, conditional on cropping decisions.[33] This implies that small within-crop irrigation adjustments is not the primary mechanism driving our results. By contrast, changes in the kWh-to-AF function should manifest over longer time scales, following pump depreciation, maintenance, and upgrades. As our results do not meaningfully change when we restrict our sample to observations close the timing of pump i's pump test, this mechanism is unlikely to be driving our results.

6.1 A stylized model of farmer decision-making

This leaves two candidate mechanisms: switching water sources and switching crops. Here, we develop a stylized model to characterize the economics underlying both switching margins. Let i index farms, or atomistic pieces of cropland with area A_i. Farm i makes a discrete

33. These results are available on request.

choice to plant crop k from a set of potential crops $\mathcal{K}$, with an outside option of fallowing ($k = 0$). The choice of crop determines *ex ante* expected yields $Y_i(k)$, water required for irrigation $W_i(k)$, and non-irrigation costs $F_i(k)$. Yields, water, and other costs vary cross-sectionally within crops, due to heterogeneous climate, soil quality, irrigation capital, etc.[34] All farms are price-takers in the output market, facing common crop prices p^k. Farm i chooses the crop k that maximizes its profits:

$$\max_{k \in \mathcal{K}} \ \pi_i(k) \ = \ p^k Y_i(k) \ - \ C_i(W_i(k)) \ - \ F_i(k) \tag{9}$$

Irrigation costs $C_i(W)$ are farm-specific and weakly convex in W, since farmers may irrigate using surface water allocated by their water district, pumped groundwater, and/or water purchased on the open market. Water districts typically have the lowest cost per acre-foot, but limited allocations may not be sufficient to meet irrigation needs (especially in drought years). This may force farmers to pump their own groundwater, with costs per acre-foot that are (typically) higher and may increase convexly in the quantity extracted. Open market water prices tend to be much higher than both district-allocated surface water and pumped groundwater, due to high costs of physically moving water. However, district allocations and pumping costs are sufficiently heterogeneous that some California farmers rely on water markets for irrigation (Hagerty (2018)).

The upper left panel of Figure 4 depicts a hypothetical irrigation price schedule for a farm that irrigates with both surface water (allocated by its irrigation district) and pumped groundwater. This representative farm i has chosen crop k^0, and the shaded region under the price function depicts its total cost of irrigating, $C_i(W_i(k^0))$. If the farm experiences a pumping cost shock due to either an electricity price increase or a groundwater depth increase, the groundwater piece of its price schedule will shift up. The upper right panel of Figure 4 illustrates how such a pumping cost shock would increase farm i's cost of irrigating crop k^0 by the shaded area $\Delta C_i(W_i(k^0))$.

34. For simplicity, we abstract away input re-optimization within crops. This focuses our model solely on the planting margin, while also aligning it with standard crop budgeting calculations farmers typically use to make such *ex ante* planting decisions. This stylized static model also ignores the obvious state-dependence inherent in choosing perennial (or annual) crops.

Our econometric results show that such a pumping cost shock (holding the rest of the price schedule constant) causes average groundwater consumption to decrease. The bottom panels of Figure 4 illustrate how this consumption decrease could come through either crop switching or water source substitution. In the lower left panel, farm i switches to a less water-intensive crop k^1, thereby reducing both its groundwater consumption and its total water consumption. In the lower right panel, a larger pumping cost shock causes farm i to switch to the open market backstop; while it continues to consume $W_i(k^0)$ acre-feet of water, new water purchases now crowd out its groundwater consumption. As long as district-allocated surface water is inframarginal for groundwater users (Hagerty (2019)), water source substitution is only likely to occur at extremely high prices. Hagerty (2018) reports the distribution of prices for 671 California water transactions, with a mean price of $221 per acre-foot. Since the PGE data almost never imply pumping costs above $200 per acre-foot, and since California water markets are relatively thin, crop switching (or fallowing) appears far more likely as a mechanism for groundwater demand response.

We use detailed crop budget studies produced by the University of California, Davis to explore the extent to which higher pumping costs may push farmers to either switch crops or fallow. The "Davis Cost Studies" report detailed revenue and cost data for test plots of specific crops across various regions of California.[35] We digitized budget line items for 88 studies covering 65 unique crops, allowing us to compare profitability across crops for a range of hypothetical water prices. Figure 5 plots predicted profits per acre from 5 individual crop studies that are all specific to the Southern San Joaquín Valley. Several stylized patterns emerge from this figure. First, as the water price increases, profits fall faster for more water-intensive crops. Second, within both tree and field crops, there are switching points at which a small increase in the *average* price per acre-foot may cause a farmer to switch to a less water-intensive crop.[36] Third, for field crops, increasing water prices may lead to negative profits before or after a given switching point, which may cause a farmer to fallow. Fourth, the hypothetical groundwater prices where switching or fallowing might occur are far below

35. Current cost studies are available at `https://coststudies.ucdavis.edu/en/current/`.

36. Since crop choice is discrete, the relevant water price both in the Davis Cost Studies and in our stylized model is the average price per acre-foot, *not* the marginal price per acre-foot. This implies that inframarginal surface water allocations will dampen the impact of groundwater cost shocks on crop switching.

$221 per acre-foot, the average price on the open water market. While these comparisons are only illustrative and numerous data caveats apply,[37] they do provide additional support for crop switching (or fallowing) as the mechanism underlying our groundwater demand estimates.

6.2 Empirical tests

We take the model in Section 6.1 to data using several simple empirical tests. First, we replace our monthly elasticity estimates with annual elasticities. While using monthly data enables us to include granular fixed effects to non-parametrically control for unobserved factors which may impact electricity and groundwater usage, the monthly timescale is somewhat mismatched with the timing of farm decision-making, much of which occurs on an annual timescale. We estimate annual elasticities using modified versions of Equations (3) and (8), on data that we aggregate to the yearly level:

$$\sinh^{-1}\left(Q_{iy}^{\text{elec}}\right) = \beta \log\left(P_{iy}^{\text{elec}}\right) + \gamma_i + \delta_y + \varepsilon_{iy} \tag{10}$$

and

$$\sinh^{-1}\left(Q_{iy}^{\text{water}}\right) = \beta \log\left(P_{iy}^{\text{water}}\right) + \gamma_i + \delta_y + \varepsilon_{iy} \tag{11}$$

where the unit of observation is now the service point-(i)-by-year-(y). As in Sections 4.1–4.2, we instrument for the price of electricity (groundwater) with the default price of electricity. Though there is less identifying variation in this annual model, our first-stage F-statistics remain high: 2286 for electricity and 2065 for water. Columns (1) and (4) of Table 7 present the main annual results. We find an annual price elasticity of -1.10 for electricity and -0.96 for groundwater. These annual elasticities being similar to our monthly estimates suggests that farmers are not simply arbitraging between low and high groundwater prices by switching to surface water.

We then test the extent to which our estimated elasticities are driven by intensive-versus-extensive margin changes in electricity and groundwater use behavior. To test for

37. For example, Figure 5 compares cost studies from different years, without adjusting commodity prices. It also ignores dynamics, which are crucial for almond, plum, and alfalfa planting decisions.

intensive-margin results, we restrict the sample to only service points that never have a year of electricity bills with zero consumption. To test for extensive-margin results, we replace our dependent variable with an indicator for positive consumption in year y. Columns (2) and (5) of Table 7 present the intensive margin results, and Columns (3) and (6) present the extensive margin results. We find an intensive margin elasticity of demand of -0.43 for electricity and -0.40 for water. We also find that a 1 percent increase in electricity or groundwater prices increases the likelihood that farmers do not pump by 4 percent. All estimates are statistically significant at the 5 percent level. These results are consistent with a combination of crop switching and fallowing. If water source substitution were the primary mechanism, and small changes in pumping costs induced incremental substitution, we would expect to find an intensive margin elasticity closer to the magnitude of our combined estimates.

Next, we test whether farmers growing different types of crops respond heterogeneously to changes in groundwater costs. For this analysis, we continue to use data aggregated to the annual level. We assign service point i to a Common Land Unit (CLU) based on its latitude and longitude. As described in Section 3, we use the Cropland Data Layer to classify each pixel in a CLU as annual, perennial, or fallowed. We then assign crop types to CLUs based on the crop type of the modal pixel, for CLUs where the modal crop type covers more than 50 percent of the CLU. We then classify service points into three categories, which are held fixed throughout our sample. "Annuals" are service points in CLUs that are always farming annual crops or are fallowed; "perennials" are service points in CLUs that are always farming perennial crops or are fallowed; and "switchers" are service points in CLUs that switch between annual and perennial crops during our sample.

We now estimate Equations (10) and (11) separately for service points in each of these three categories. Table 8 reports the results of this test. We find that, for both electricity and groundwater, annual-only farmers are much less elastic than perennial-only farmers, who are much less elastic than switchers. For electricity (groundwater), we estimate that annual-only farmers have a demand elasticity of -0.23 (-0.16), which is not statistically distinguishable from zero. Perennial-only farmers have elasticities of -1.15 and -0.97, close to our central annual estimates of -1.10 and -0.96. Switchers are more than twice as elastic as perennial-only farmers, with elasticities of -2.65 and -2.63. These striking results suggest that farmers that switch between annual and perennial crops (and to a lesser extent, perennial-only farmers) are driving our elasticity estimates. This lends support to the notion that crop switching is an important mechanism underlying our elastic demand estimates.

Finally, we estimate the causal impact of electricity and groundwater pricing on cropping decisions. To do this, we estimate:

$$1[\text{Crop type} = c]_{iy} = \beta \log\left(P^{\text{elec}}_{iy}\right) + \gamma_i + \delta_y + \varepsilon_{iy} \tag{12}$$

and the equivalent for groundwater. The dependent variable, $1[\text{Crop type} = c]_{iy}$ is an indicator, equal to one if service point i has a certain type of landcover, $c \in \{\text{annual, perennial, fallow}\}$ in year y, and zero otherwise. We estimate Equation (12) separately for each of the three crop types. Table 9 presents these results. We find some evidence that, as the prices of electricity and groundwater rise, the likelihood that farmers grow annuals declines. These effects are noisy—statistically significant at the 10 percent level—but economically meaningful: for a 1 percent increase in electricity or groundwater price, cropping of annuals falls by 4 percent. We find positive point estimates for perennials (0.02) and fallowing (0.03) for both electricity and groundwater, but these estimates are not significant at the 10 percent level. While these regressions are somewhat underpowered, the point estimates suggest that farmers respond to increased groundwater costs by switching crops.

7 Conclusion

This paper estimates how a key sector—agriculture—responds to changes in the cost of inputs—electricity and groundwater. We study the California agricultural sector, which produces 17 percent of total U.S. crop value. Because California farmers depend on irrigation, water scarcity has the potential to threaten farm production and profitability. This threat is only exacerbated by climate change, which is projected to increase the frequency and severity of droughts.

To understand how California farms respond to rising water costs, we overcome previous measurement challenges with a novel dataset of restricted-access data on farmers' electricity consumption and groundwater pump efficiencies. We combined these data with government measurements of groundwater depths and satellite-derived land use designations for the universe of farmers in the Pacific Gas and Electric utility service territory, which covers the majority of the farmland in the state. We leverage exogenous variation in electricity tariffs over time to estimate farmers' price elasticity of demand for electricity, and find a surprising large elasticity estimate of -1.17. Then, we use physics to compute groundwater costs and groundwater quantities for each pump in our sample, and estimate the price elasticity of groundwater demand to be -1.12. These elasticities are much larger than previous estimates in the electricity and groundwater literatures.

We then explore the mechanisms underlying farmers' groundwater demand response. We develop a stylized model of farmer decisions under changing water prices, which highlights the potential relevance of crop switching or fallowing. We then empirically evaluate the role of crop switching in a series of simple empirical tests. We find evidence consistent with crop switching being the primary mechanism driving our estimated demand elasticities. First, our monthly and annual elasticity estimates are similar, suggesting that within-year surface water substitution is not driving our results. Second, farmers respond strongly on the extensive margin of groundwater pumping, which is challenging from an agronomic perspective without switching crops. Third, we find the largest elasticities, -2.65 for electricity and -2.63 for groundwater, amongst farmers who switch between annual and perennial crops during our sample. Finally, we estimate that a 1 percent increase in groundwater or electricity prices leads to a 4 percent decrease in the likelihood of planting annual crops (as opposed to perennial crops or fallowing), though this estimate is noisy.

Our results have important implications for groundwater management policies, such as California's Sustainable Groundwater Management Act (SGMA). As global aquifers continue to fall to new historic lows (Famiglietti (2014)), governments seek policies to manage common-pool groundwater resources and disincentivize farmers from "racing to the bottom." While the type of policy may vary across settings (e.g. Ryan and Sudarshan (2020)), it is important to understand both the extent to which farmers are likely to respond by reducing groundwater extraction and any (unintended) consequences of their demand response. Our large elasticity estimates imply that incremental groundwater management efforts have the potential to yield meaningful improvements in groundwater sustainability. The crop switching mechanism also signals a potential second-best benefit of groundwater management: if unpriced groundwater has led to suboptimal allocation of land to crops, where farmers fail to internalize the externalities of their own groundwater extraction, then pricing groundwater may reduce crop misallocation by inducing farmers to plant fewer acres of low-value, water-intensive crops.

In ongoing work, we are extending these results along three dimensions. First, we are incorporating data from Southern California Edison, thereby covering nearly all of California's farmland. Second, we are studying how changes in surface water availability influence both groundwater extraction and cropping decisions, by incorporating data from Hagerty (2019). Third, we aim to quantify the effects of droughts on electricity demand, groundwater extraction, and agricultural land use.

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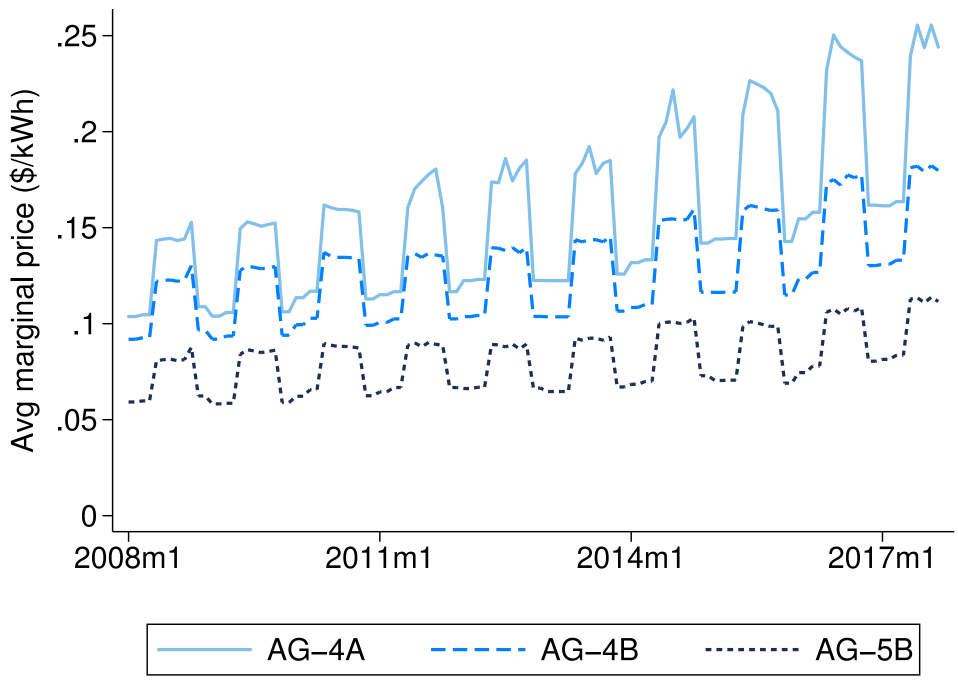
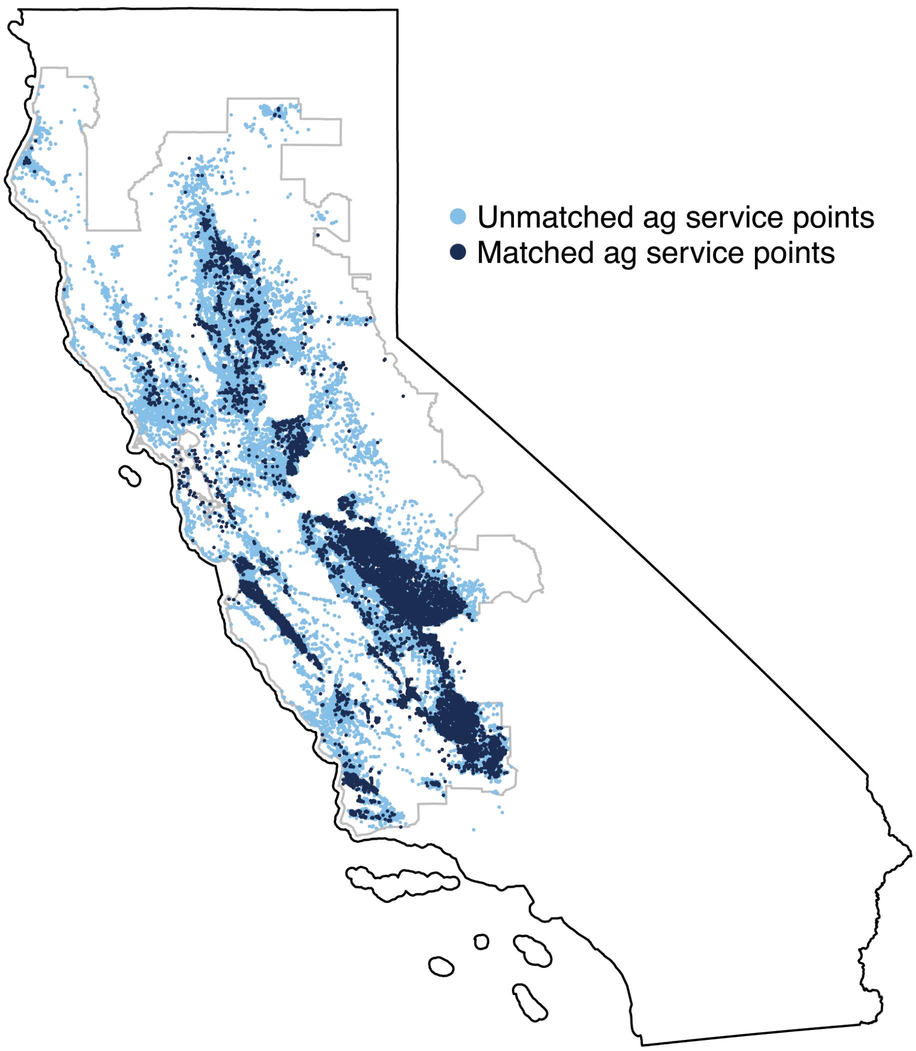
Figures and Tables

Figure 1: Average Marginal Electricity Prices



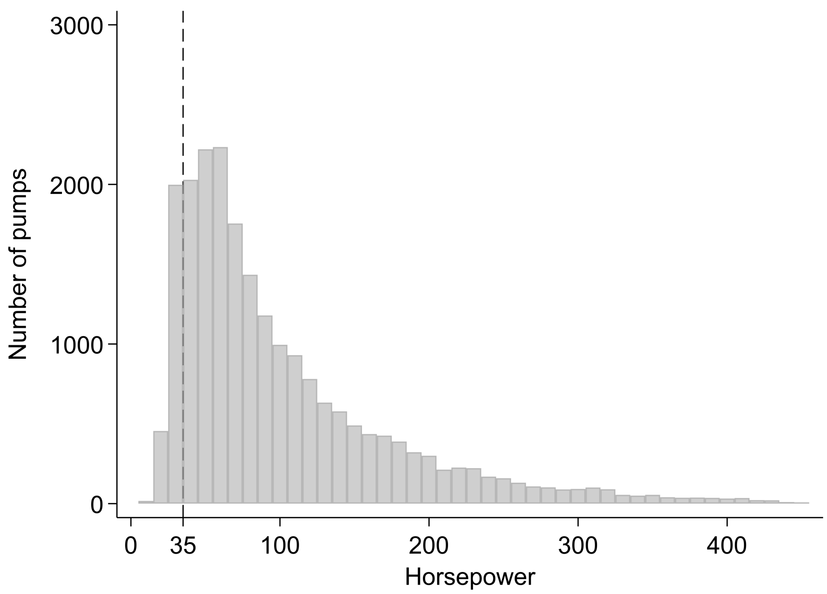
Notes: This figure reports the times series of monthly average marginal electricity prices ($/kWh) for three of the most common agricultural tariffs. Prices are systematically higher during summer months (May–October). Much of our identifying variation in monthly electricity prices comes from these monthly price times series not rising perfectly in parallel.

Figure 2: PGE Agricultural Customers



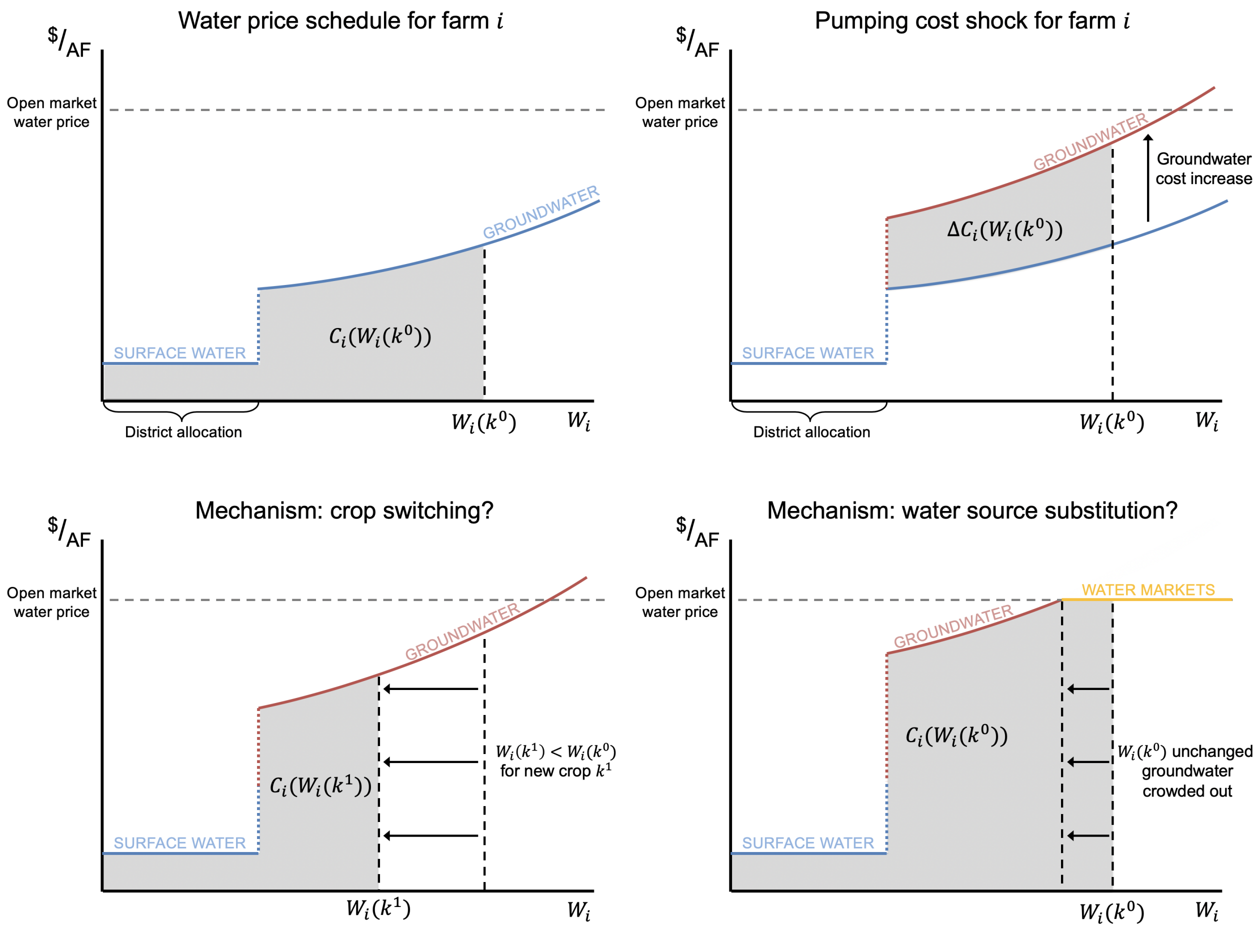
Notes: This figure maps the locations of all agricultural service points served by PGE. Dark blue dots indicate the 11,851 service point that we can match directly to an APEP pump test. Light blue dots indicate unmatched agricultural service points. The light grey outline is the geographic boundary of PGE's service territory.

Figure 3: Histogram of pump horsepower



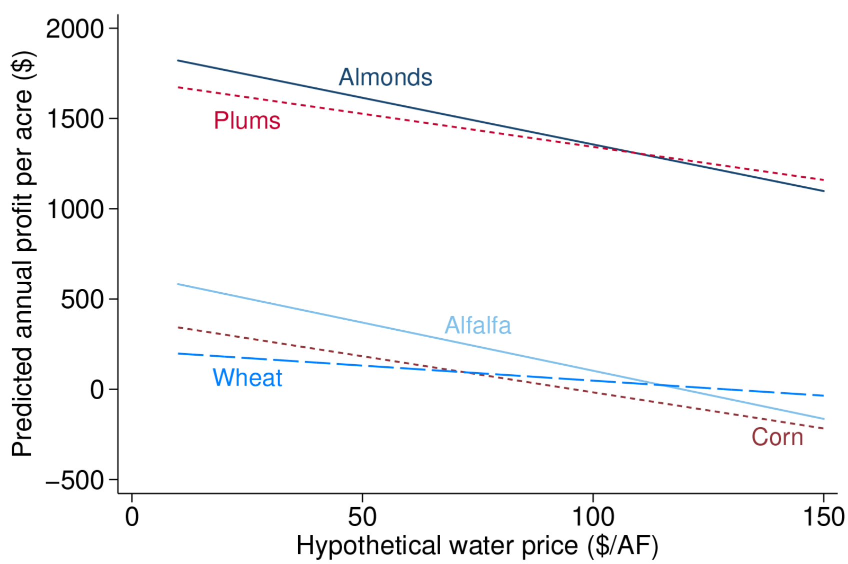
Notes: This is a histogram of measured horsepower for all 21,851 tests in our APEP pump test dataset. We observe no bunching on either side of the 35 hp cutoff that determines whether PGE classifies pumps as small or large. Bunching would be a sign that farmers optimize against PGE's tariff schedules when making pump investment decisions.

Figure 4: Modeling farm i's water costs and groundwater demand response



Notes: This figure presents a stylized water price schedule for a representative farm i. The price schedule is nonlinear and comprises water from up to three sources: (i) a low-cost allocation of surface water from farm i's irrigation district; (ii) medium-cost groundwater pumping, with costs that rise gradually in own extraction; and (iii) a high-cost backstop of open market water transactions, for which we assume farm i is a price taker. For crop k^0 requiring $W_i(k^0)$ acre/feet of water, farm i's irrigation costs $C_i(W_i(k^0))$ are represented by the shaded region in the top-left panel. If farm i experiences a pumping cost shock (due to either an electricity price increase or a groundwater depth increase), its groundwater costs shift up and its total irrigation costs increase by the shaded region $\Delta C_i(W_i(k^0))$ in the top-right panel. The bottom panels illustrate two ways that this pumping cost shock increase translate to a reduction in farm i's groundwater consumption. First, the farmer may respond to this pumping cost shock by switching from crop k^0 to a less water intensive crop k^1, as in the bottom-left panel. Second, for a large enough cost shock, the farmer may continue to grow crop k^0, but substitute away from groundwater using open market water purchases.

Figure 5: Profits in the Southern San Joaquín Valley Under Varying Water Prices



Notes: This figure plots annual profits per acre by crop, as reported by the UC Davis Cost Studies. We focus on five crop-specific studies in the Southern San Joaquín Valley, and vary the average cost of water for irrigation while holding all other assumptions constant.

Table 1: PGE Agricultural Tariffs

Category	Tariff	Description	Percent
Small pumps, conventional meters single motor < 35 hp, or multiple motors summing to < 15 hp	**1A**	High price per kWh (not time-varying), fixed charge per hp connected	3.0
Large pumps, conventional meters single motor ≥ 35 hp, or multiple motors summing to ≥ 15 hp, or single overloaded motor ≥ 15 hp	**1B**	High price per kWh (not time-varying), fixed charge per max kW consumed	8.1
Small pumps, smart meters single motor < 35 hp, or multiple motors summing to < 15 hp	**4A** (4D)	High prices per kWh (higher in peak hours), fixed charges per hp connected, very high peak prices on 14 summer Event Days	7.2
	5A (5D)	Lower prices per kWh (peak & offpeak), no Event Day price increases, higher fixed charges per hp	2.7
	RA (RD)	Lower peak prices per kWh, higher off-peak prices per kWh, no Event Day price increases, choice between MTW or WTF peak days	1.2
	VA (VD)	Lower peak prices per kWh, higher off-peak prices per kWh, no Event Day price increases, choice of 3 shorter 4-hour peak periods	0.9
Large pumps, smart meters single motor ≥ 35 hp, or multiple motors summing to ≥ 15 hp, or single overloaded motor ≥ 15 hp	**4B** (4E)	High prices per kWh (higher in peak hours), fixed charges per max kW consumed	20.1
	5B (5E)	Much lower prices per kWh (peak & offpeak), higher fixed charge per max kW	37.8
	4C (4F)	Slightly lower prices per kWh (peak & offpeak), higher fixed charges per kW shifted to peak, very high peak prices on 14 summer Event Days	2.4
	5C (5F)	Much lower prices per kWh (peak & offpeak), higher fixed charges per kW shifted to peak, very high peak prices on 14 summer Event Days	7.8
	RB (RE)	Higher prices per kWh (peak & off-peak), choice between MTW or WTF peak days, lower fixed charges per max kW (in summer)	1.5
	VB (VF)	Higher prices per kWh (peak & off-peak), choice of 3 shorter 4-hour peak periods, lower fixed charges per max kW (in summer)	0.6
Customers transitioning off internal combustion engines	**ICE**	Very low price per kWh (high in peak hours), fixed charge per max kW consumed	6.8

Notes: This table provides a rough summary of PGE's 23 electricity tariffs for agricultural customers. The first column lists the 5 disjoint categories of customers, defined (primarily) by physical pumping capital and electricity meters. Effective default tarrifs within each group are in bold, and farmers may switch tariffs *within* a category (but not *across* categories). All tariffs have fixed ($/kW) and volumetric ($/kWh) prices that vary by summer vs. winter. All time-of-use tariffs (i.e. all but 1A and 1B) also vary between peak (12:00pm–6:00pm on summer weekdays), partial peak (8:30am–9:30pm on weekends), and off-peak periods. DEF tariffs are functionally equivalent to their ABC analogs, and are holdovers for the earliest customers to adopt time-of-use pricing. Actual tariffs are far more complex, and tariff documents are available at `https://www.pge.com/tariffs/index.page`. The right-most column reports the percent of observations in our main estimation sample on each tariff.

Table 2: Summary Statistics – Electricity Data

	All Ag Customers	Matched to Pumps
Service point-month observations	9,991,458	1,168,553
Unique service points (SPs)	108,172	11,851
SPs that switch tariff categories	44,414	2,844
SPs that switch categories (pumping capital)	3,454	561
SPs that switch categories (smart meters)	43,045	2,553
Share of SP-months on time-varying tariffs	0.702	0.886
Share of SP-months on peak-day tariffs	0.295	0.152
Monthly electricity consumption (kWh)	6080.9	12055.7
	(39783.1)	(25075.1)
Monthly electricity consumption (kWh), summer	8249.6	17589.1
	(45660.8)	(29818.5)
Monthly electricity consumption (kWh), winter	3849.7	6362.8
	(32498.8)	(17232.5)
Average marginal electricity price ($/kWh)	0.148	0.113
	(0.050)	(0.042)
Average marginal electricity price ($/kWh), summer	0.171	0.130
	(0.051)	(0.044)
Average marginal electricity price ($/kWh), winter	0.126	0.096
	(0.037)	(0.032)
Average monthly bill ($, non-zero bills)	936.66	1814.15
	(4662.71)	(3285.26)
Average monthly bill ($, non-zero bills), summer	1398.90	2821.16
	(5847.34)	(4020.99)
Average monthly bill ($, non-zero bills), winter	456.17	764.99
	(2888.86)	(1742.21)

Notes: The left column reports summary statistics for the universe of agricultural electricity customers in PGE service territory, from 2008–2017. The right column includes the subset of agricultural customers that we successfully match to a groundwater pump in the APEP pump test dataset—i.e., our main estimation sample. "Pumping capital" denotes tariff category switches driven by shifts between small pumps ($<$ 35 hp) and large pumps ($\geq$ 35 hp), or adding/removing an auxiliary internal combustion engine. Most tariff category switches were driven by PGE's smart meter rollout. Time-varying tariffs (i.e. all except 1A and 1B) have higher marginal prices during peak demand hours. Peak-day tariffs (i.e. 4A, 4D, 4C, 4F, 5C, 5F) have very high marginal prices during peak hours on the 14 highest-demand summer days. Monthly bills include both volumetric ($/kWh) and fixed charges ($/kW, $/hp, and $/day). Summer months are May–October. Standard deviations of sample means in parentheses.

Table 3: Summary Statistics – Pump Tests and Groundwater Consumption

	Matched to Pumps
Service point-month observations	1,168,553
Unique service points (SPs)	11,851
Matched APEP points per SP	3.45
	(8.80)
Operating pump efficiency (%)	54.46
	(11.52)
kWh per AF conversion factor (APEP measured)	430.30
	(254.21)
kWh per AF conversion factor (constructed)	346.94
	(206.03)
Monthly groundwater consumption (AF)	49.0
	(151.7)
Monthly groundwater consumption (AF), summer	74.0
	(191.9)
Monthly groundwater consumption (AF), winter	23.4
	(86.6)
Average marginal groundwater price ($/AF)	39.91
	(29.63)
Average marginal groundwater price ($/AF), summer	41.76
	(31.34)
Average marginal groundwater price ($/AF), winter	38.01
	(27.63)

Notes: These summary stats are from the merged panel of groundwater prices and quantities, which combines electricity data, pump test data, and groundwater data. We observe 3.45 unique APEP pump tests for the average matched service point, although 37 percent of service points match to only a single APEP test. Our constructed kWh per AF conversion factor (i.e. $\widehat{\text{kWh/AF}}_{it}$) uses monthly groundwater rasters to capture changes in (measured) kWh per AF over time, and estimation error compresses the right tail of distribution of measured kWh per AF. Monthly groundwater consumption divides electricity consumption (kWh) by $\widehat{\text{kWh/AF}}_{it}$. Grounwater prices multiply marignal electricity prices ($/kWh) by $\widehat{\text{kWh/AF}}_{it}$. Summer months are May–October. Standard deviations of sample means in parentheses.

Table 4: Estimated Demand Elasticities – Electricity

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$\log\left(P_{it}^{\text{elec}}\right)$	-1.31^{***}	-1.58^{***}	-1.17^{***}	-1.02^{***}	-1.18^{***}	-0.76^{***}
	(0.11)	(0.17)	(0.16)	(0.14)	(0.21)	(0.17)
Instrument(s):						
Default $\log\left(P_{it}^{\text{elec}}\right)$		Yes	Yes	Yes		Yes
Default $\log\left(P_{it}^{\text{elec}}\right)$, lagged					Yes	
Fixed effects:						
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes	Yes
Unit × physical capital			Yes	Yes	Yes	Yes
Water basin × year				Yes		
Water district × year				Yes		
Unit-specific linear time trends						Yes
Service point units	11,175	11,175	11,175	11,121	10,924	11,175
Months	117	117	117	117	105	117
Observations	1.05M	1.05M	1.05M	1.04M	0.91M	1.05M
First stage F-statistic		4136	7382	7508	757	4776

Notes: Each regression estimates Equation (3) at the service point by month level, where the dependent variable is the inverse hyperbolic sine transformation of electricity consumed by service point i in month t. We estimate IV specifications via two-stage least squares, instrumenting with either unit i's within-category default logged electricity price in month t *or* the 6- and 12-month lags of this variable. "Physical capital" is a categorical variable for (i) small pumps, (ii) large pumps, and (iii) internal combustion engines, and unit × physical capital fixed effects control for shifts in tariff category triggered by the installation of new pumping equipment. Water basin × year fixed effects control for broad geographic trends in groundwater depth. Water district × year fixed effects control for annual variation in surface water allocations. All regressions drop solar NEM customers, customers with bad geocodes, and months with irregular electricity bills (e.g. first/last bills, bills longer/shorter than 1 month, overlapping bills for a single account). Standard errors (in parentheses) are clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5: Estimated Demand Elasticities – Groundwater

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$\log\left(P_{it}^{\text{elec}}\right)$: $\hat{\beta}^{\text{e}}$	-1.21^{***}	-1.39^{***}	-1.38^{***}	-1.26^{***}	-1.23^{***}	-1.68^{***}
	(0.17)	(0.18)	(0.19)	(0.17)	(0.16)	(0.21)
$\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right)$: $\hat{\beta}^{\text{w}}$	-0.92^{***}	-1.37^{***}	-1.32^{***}	-1.72^{***}	-1.24^{***}	-2.04^{***}
	(0.11)	(0.25)	(0.28)	(0.30)	(0.24)	(0.45)
Instrument(s):						
Default $\log\left(P_{it}^{\text{elec}}\right)$	Yes	Yes	Yes	Yes	Yes	Yes
log (Avg depth in basin)		Yes	Yes	Yes	Yes	
log (Avg depth in basin), lagged						Yes
Fixed effects:						
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes	Yes
Water basin × year					Yes	
Water district × year					Yes	
Groundwater time step	Month	Month	Month	Quarter	Month	Month
Only basins with > 1000 SPs			Yes			
Service point units	10,159	10,121	9,324	10,134	10,086	9,890
Months	117	116	116	117	116	105
Observations	0.93M	0.83M	0.80M	0.89M	0.83M	0.70M
First stage F-statistic	6932	129	144	61	69	20

Notes: Each regression estimates Equation (7) at the service point by month level, where the dependent variable is the inverse hyperbolic sine transformation of electricity consumed by service point i in month t. We report estimates for $\hat{\beta}^{\text{e}}$ and $\hat{\beta}^{\text{w}}$, where the latter subtracts 1 from the estimated coefficient on $\log\left(\widehat{\text{kWh}/\text{AF}}_{it}\right)$. We estimate IV specifications via two-stage least squares, and all regressions instrument for P_{it}^{elec} with unit i's within-category default logged electricity price in month t (consistent with our preferred specification from Table 4). We instrument for $\log\left(\widehat{\text{kWh}/\text{AF}}_{it}\right)$ with either logged average groundwater depth across unit i's basin, or the 6- and 12-month lags of this variable. "Physical capital" is a categorical variable for (i) small pumps, (ii) large pumps, and (iii) internal combustion engines, and unit × physical capital fixed effects control for shifts in tariff category triggered by the installation of new pumping equipment. Water basin × year fixed effects control for broad geographic trends in groundwater depth. Water district × year fixed effects control for annual variation in surface water allocations. Column (3) restricts the sample to only the three most common water basins (San Joaquin Valley, Sacramento Valley, and Salinas Valley), each of which contains over 1000 unique SPs in our estimation sample. Column (4) uses a quarterly panel of groundwater depths to construct $\log\left(\widehat{\text{kWh}/\text{AF}}_{it}\right)$ and the instrument, rather than a monthly panel. All regressions drop solar NEM customers, customers with bad geocodes, months with irregular electricity bills (e.g. first/last bills, bills longer/shorter than 1 month, overlapping bills for a single account), and pumps with implausible test measurements. Standard errors (in parentheses) are clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Estimated Demand Elasticities – Groundwater

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$\log(P_{it}^{\text{water}})$	-0.81^{***}	-1.12^{***}	-1.16^{***}	-1.12^{***}	-0.97^{***}	-1.14^{***}
	(0.09)	(0.15)	(0.17)	(0.15)	(0.14)	(0.21)
Instrument(s):						
Default $\log(P_{it}^{\text{elec}})$		Yes	Yes	Yes	Yes	
Default $\log(P_{it}^{\text{elec}})$, lagged						Yes
Fixed effects:						
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes	Yes
Water basin × year					Yes	
Water district × year					Yes	
Groundwater time step	Month	Month	Month	Quarter	Month	Month
Only basins with > 1000 SPs			Yes			
Service point units	10,159	10,159	9,342	10,159	10,118	9,926
Months	117	117	117	117	117	105
Observations	0.93M	0.93M	0.85M	0.93M	0.93M	0.82M
First stage F-statistic		2835	2735	2846	4633	486

Notes: Each regression estimates Equation (8) at the service point by month level, where the dependent variable is the inverse hyperbolic sine transformation of groudnwater consumed by service point i in month t. We estimate IV specifications via two-stage least squares, and Columns (2)–(5) instrument for P_{it}^{water} with unit i's within-category default logged electricity price. Column (6) instruments with the 6- and 12- month lags of this variable. "Physical capital" is a categorical variable for (i) small pumps, (ii) large pumps, and (iii) internal combustion engines, and unit × physical capital fixed effects control for shifts in tariff category triggered by the installation of new pumping equipment. Water basin × year fixed effects control for broad geographic trends in groundwater depth. Water district × year fixed effects control for annual variation in surface water allocations. Column (3) restricts the sample to only the three most common water basins (San Joaquin Valley, Sacramento Valley, and Salinas Valley), each of which contains over 1000 unique SPs in our estimation sample. Column (4) uses a quarterly panel of groundwater depths to construct both Q_{it}^{water} and P_{it}^{water}, rather than a monthly panel. All regressions drop solar NEM customers, customers with bad geocodes, months with irregular electricity bills (e.g. first/last bills, bills longer/shorter than 1 month, overlapping bills for a single account), and pumps with implausible test measurements. Standard errors (in parentheses) are clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: Annual Demand Elasticities – Electricity and Groundwater

	Electricity			Groundwater		
	Overall elasticity (1)	Intensive margin (2)	Extensive margin (3)	Overall elasticity (4)	Intensive margin (5)	Extensive margin (6)
$\log(P_{iy}^{\text{elec}})$	-1.10^{***}	-0.43^{***}	-0.04^{**}			
	(0.26)	(0.12)	(0.01)			
$\log(P_{iy}^{\text{water}})$				-0.96^{***}	-0.40^{**}	-0.04^{**}
				(0.24)	(0.12)	(0.01)
Outcome:						
$\sinh^{-1}(Q_{iy})$	Yes	Yes		Yes	Yes	
$1[Q_{iy} > 0]$			Yes			Yes
Instrument:						
Default $\log(P_{iy}^{\text{elec}})$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
Unit × physical capital	Yes	Yes	Yes	Yes	Yes	Yes
Water basin × year	Yes	Yes	Yes	Yes	Yes	Yes
Water district × year	Yes	Yes	Yes	Yes	Yes	Yes
Restricted sample		Yes			Yes	
Service point units	10,005	8,328	10,005	8,960	7,385	8,960
Years	9	9	9	9	9	9
Observations	57,415	48,642	57,415	51,110	42,881	51,110
First stage F-statistic	2286	1925	2286	2065	1653	2065

Notes: Each regression estimates Equation (10) or Equation (11) at the service point by year level. Columns (1)–(3) report results for electricity consumption, and Columns (4)–(6) report results for groundwater consumption. Columns (1) and (4) report demand elasticities for electricity and water, respectively. Columns (2) and (5) report analogous demand elasticities for the subset of service points that consume electricity or water, respectively, in every year of our sample. Columns (3) and (6) report semi-elasticities for the extensive margins by replacing the outcome variable with a binary indicator of electricity or water consumption, respectively. We estimate these regressions using two-stage least squares, instrumenting with unit i's within-category default logged electricity price in year y. "Physical capital" is a categorical variable for (i) small pumps, (ii) large pumps, and (iii) internal combustion engines, and unit × physical capital fixed effects control for shifts in tariff category triggered by the installation of new pumping equipment. Water basin × year fixed effects control for broad geographic trends in groundwater depth. Water district × year fixed effects control for annual variation in surface water allocations. All regressions drop solar NEM customers, customers with bad geocodes, years with irregular electricity bills (e.g. first/last bills, bills longer/shorter than 1 month, overlapping bills for a single account), and incomplete years. Standard errors (in parentheses) are clustered by service point and by year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: Annual Demand Elasticity Heterogeneity – Electricity and Groundwater

	Electricity			Groundwater		
	Annuals	Perennials	Switchers	Annuals	Perennials	Switchers
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P_{iy}^{\text{elec}})$	-0.23	-1.15^{***}	-2.65^{***}			
	(0.20)	(0.29)	(0.71)			
$\log(P_{iy}^{\text{water}})$				-0.16	-0.97^{***}	-2.63^{***}
				(0.19)	(0.28)	(0.69)
Instrument:						
Default $\log(P_{iy}^{\text{elec}})$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
Unit × physical capital	Yes	Yes	Yes	Yes	Yes	Yes
Water basin × year	Yes	Yes	Yes	Yes	Yes	Yes
Water district × year	Yes	Yes	Yes	Yes	Yes	Yes
Service point units	3,675	6,839	708	3,382	6,017	649
Years	9	9	9	9	9	9
Observations	21,016	39,239	3,932	19,241	34,274	3,577
First stage F-statistic	862	1707	566	1003	1656	276

Notes: Each regression estimates Equation (10) or Equation (11) at the service point by year level for a subset of service points. Columns (1)–(3) report results for electricity consumption, and Columns (4)–(6) report results for groundwater consumption. Columns (1) and (4) report demand elasticities for service points that have an annual crop or are fallowed in every year of our sample. Columns (2) and (5) report demand elasticities for service points that have a perennial crop or are fallowed in every year of our sample. Columns (3) and (6) report demand elasticities for service points that switch between annual and perennial crops during our sample. We estimate these regressions using two-stage least squares, instrumenting with unit i's within-category default logged electricity price in year y. "Physical capital" is a categorical variable for (i) small pumps, (ii) large pumps, and (iii) internal combustion engines, and unit × physical capital fixed effects control for shifts in tariff category triggered by the installation of new pumping equipment. Water basin × year fixed effects control for broad geographic trends in groundwater depth. Water district × year fixed effects control for annual variation in surface water allocations. All regressions drop solar NEM customers, customers with bad geocodes, years with irregular electricity bills (e.g. first/last bills, bills longer/shorter than 1 month, overlapping bills for a single account), and incomplete years. Standard errors (in parentheses) are clustered by service point and by year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Annual Cropping Response to Input Costs

	Electricity			Groundwater		
	Annuals	Perennials	Fallow	Annuals	Perennials	Fallow
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P_{iy}^{\text{elec}})$	-0.04^{*}	0.02	0.03			
	(0.02)	(0.02)	(0.02)			
$\log(P_{iy}^{\text{water}})$				-0.04^{*}	0.02	0.03
				(0.02)	(0.02)	(0.02)
Instrument:						
Default $\log(P_{iy}^{\text{elec}})$	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects:						
Unit × physical capital	Yes	Yes	Yes	Yes	Yes	Yes
Water basin × year	Yes	Yes	Yes	Yes	Yes	Yes
Water district × year	Yes	Yes	Yes	Yes	Yes	Yes
Service point units	8,823	8,823	8,823	7,868	7,868	7,868
Years	9	9	9	9	9	9
Observations	43,207	43,207	43,207	38,178	38,178	38,178
First stage F-statistic	2093	2093	2093	1581	1581	1581

Notes: Each regression estimates Equation (12) at the service point by year level for different categories of crops. Columns (1)–(3) report results for the cropping response to electricity price, and Columns (4)–(6) report results for the cropping response to groundwater price. Columns (1) and (4) report the semi-elasticity of having an annual crop with respect to the price of electricity or water, respectively. Columns (2) and (5) report the semi-elasticity of having a perennial crop with respect to the price of electricity or water, respectively. Columns (3) and (6) report the semi-elasticity of fallowing with respect to the price of electricity or water, respectively. We estimate these regressions using two-stage least squares, instrumenting with unit i's within-category default logged electricity price in year y. "Physical capital" is a categorical variable for (i) small pumps, (ii) large pumps, and (iii) internal combustion engines, and unit × physical capital fixed effects control for shifts in tariff category triggered by the installation of new pumping equipment. Water basin × year fixed effects control for broad geographic trends in groundwater depth. Water district × year fixed effects control for annual variation in surface water allocations. All regressions drop solar NEM customers, customers with bad geocodes, years with irregular electricity bills (e.g. first/last bills, bills longer/shorter than 1 month, overlapping bills for a single account), and incomplete years. Standard errors (in parentheses) are clustered by service point and by year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.