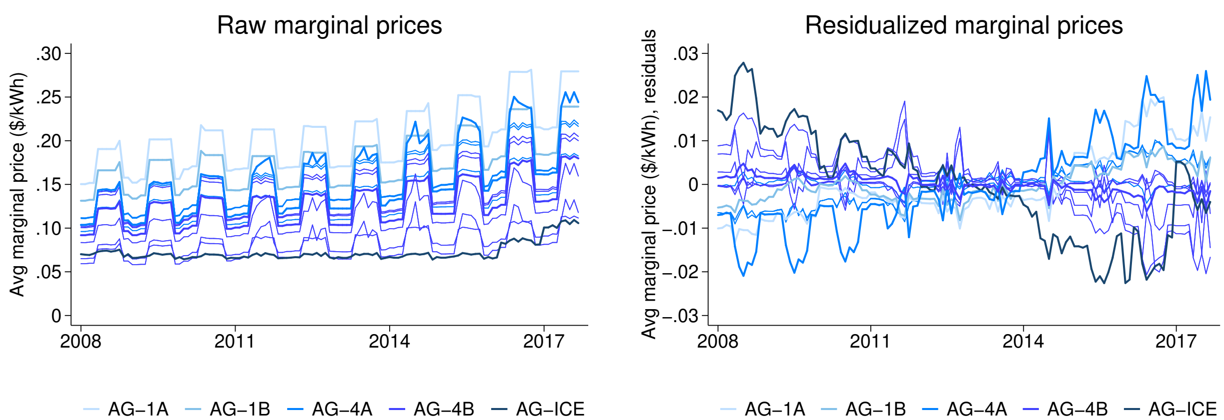
Appendix A PGE electricity prices

As described in Section 3 of the main text, PGE offers 23 distinct agricultural tariffs, which fall into 5 categories, depending on a farmer's meter type (conventional vs. smart) and pumping capital (small, large, or previously powered by an internal combustion engine). Here, we present additional details on these rates. Table A1 describes each rate in detail, including a description of the eligibility category, the broad pricing schedule on each rate, and the share of customers on each rate within our sample. Figure A1 shows a time series of each rate over our sample. This is analogous to Figure 3 in the main text, but shows all rates in addition to the "default" within-category rate. All rates that are the same color in Figure A1 belong to the same category; the default rate for each category is bolded. The left panel shows the raw rate time series. The right panel shows residualized rates, after partialling out tariff × month-of-year fixed effects and month-of-sample fixed effects.

Figure A1: Average marginal electricity prices (all rates)



Notes: This figure plots times series of monthly average marginal electricity prices ($/kWh) for all of PGE agricultural tariffs. These 23 tariffs are divided into 5 mutually-exclusive categories, based on the type of electricity meter on a farm (smart vs. conventional) and a farm's pumping capital (small, large, or previously internal combustion engine). All rates belonging to the same category are the same color. The five "default" rates, which we also show in main text Figure 3 are bolded. The left panel plots raw average marginal prices for each month in our estimation sample, taking unweighted averages across all hours. The right panel plots residuals of these same five time series, after partialling out tariff × month-of-year fixed effects and month-of-sample fixed effects (aligning with the fixed effects we use in estimation). AG-1A and AG-1B are non-time-varying rates (i.e. constant marginal price for all hours within a month), whereas AG-4A and AG-4B are time-varying rates (i.e. higher marginal prices during peak hours and weekdays). AG-1A and AG-4A are for small pumps ($<$ 35 hp), whereas AG-1B and AG-4B are for large pumps ($\geq$ 35 hp). AG-ICE is a time-varying rate for customers with auxiliary internal combustion engines. Marginal prices are systematically higher during summer months (May–October). Our identifying variation comes (a) strict restrictions that segment customers into categories; (b) the fact that the residualized default prices do not move in parallel; and (c) PGE's smart meter rollout, which exogenously shifted many customers from the AG-1A/1B default tariffs to the AG-4A/4B default tariffs with lower marginal prices.

Table A1: 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 (VE)	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.

Appendix B Groundwater demand estimation

In Section 4.2 of the main text, we present an approach for estimating the price elasticity of demand for groundwater. Here, we use a decomposition approach and estimate the elasticity with respect to electricity prices and water pumping costs separately.

As in Section 4.2, we aim to estimate causal effect of groundwater price on groundwater consumption, and this demand elasticity is linearly approximated by the coefficient β:

$$\log\left(Q_{it}^{\text{water}}\right) = \beta \log\left(P_{it}^{\text{water}}\right) \tag{3}$$

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 (3). We can rewrite this expression decomposing $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ on both sides:

$$\log\left(Q_{it}^{\text{elec}}\right) - \log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right) = \beta\left[\log\left(P_{it}^{\text{elec}}\right) + \log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right)\right] \tag{4}$$

Rearranging:

$$\log\left(Q_{it}^{\text{elec}}\right) = \beta \log\left(P_{it}^{\text{elec}}\right) + (\beta + 1)\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right) \tag{5}$$

This expression is algebraically equivalent to Equation (3), but it isolates the endogenous estimated conversion factor in one right-hand-side variable. We estimate an analogous regression specification:

$$\sinh^{-1}\left(Q_{it}^{\text{elec}}\right) = \beta^{\text{e}} \log\left(P_{it}^{\text{elec}}\right) + (\beta^{\text{w}} + 1)\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right) + \gamma_i + \delta_t + \varepsilon_{it} \tag{6}$$

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.[1] As in the electricity regressions, as well as those in the main text, we purge electricity price endogeneity by instrumenting P_{it}^{elec} with within-category default prices.

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_{it}^{elec}. Second, $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ is a function of unit i's groundwater depth, which is mechanically linked to Q_{it}^{elec}—when unit i consumes electricity to extract groundwater,

1. 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_{it}^{water} identically.

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 $\log(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it})$ using logged groundwater depth averaged across unit i's full groundwater basin.[2] 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.

Table B2 presents our results for estimating farmers' groundwater demand. Each column estimates Equation (6) using our preferred strategy for identifying the elasticity with respect to the electricity price: instrumenting for $\log(P^{\text{elec}}_{it})$ 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.

In Column (1), we present a quasi-OLS specification: while we instrument for $\log(P^{\text{elec}}_{it})$ with the within-category default electricity price, we do not instrument for $\log(\text{kWh}/\text{AF}_{it})$. In this specification, we recover a somewhat lower elasticity of demand with respect to pumping costs (-0.99) than with respect to electricity prices (-1.21).

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 $\log(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it})$, and our estimate rises to (-1.51).[3] 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

2. 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.

3. 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.

(3) restricts the sample to the 3 largest groundwater basins, each of which has over 1,000 units in our estimation sample.[4]

The magnitudes of our $\hat{\beta}^{\mathrm{e}}$ estimates are relatively similar (if slightly larger) than the results in our electricity-only regressions, especially comparing $\hat{\beta}^{\mathrm{e}} = -1.21$ from Column (1) of Table B2 with the analogous estimate ($\hat{\beta} = -1.17$) from Column (3) of Table 3. This is not surprising, since Equation (6) simply adds one regressor to Equation (3). $\hat{\beta}^{\mathrm{e}}$ is quite close to our instrumented $\hat{\beta}^{\mathrm{w}}$ estimate (-1.27 vs. -1.51). This implies that a 1 percent change in the effective price of groundwater has close to 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 relatively similarly in response to either type of price variation—as Neoclassical theory would predict.

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 (6) 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 decreases in magnitude slightly, and comes closer to the $\hat{\beta}^{\mathrm{e}}$ estimate. 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 marginally increase $\hat{\beta}^{\mathrm{e}}$ and substantially increase $\hat{\beta}^{\mathrm{w}}$; however, the small first stage F-statistic indicates a weak instrument, and we interpret these results with caution.

4. 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.

Table B2: Estimated demand elasticities decomposed – Groundwater

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$\log\left(P^{\text{elec}}_{it}\right)$: $\hat{\beta}^{\text{e}}$	-1.21^{***}	-1.27^{***}	-1.27^{***}	-1.23^{***}	-1.05^{***}	-1.47^{***}
	(0.17)	(0.17)	(0.18)	(0.17)	(0.16)	(0.19)
$\log\left(\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}\right)$: $\hat{\beta}^{\text{w}}$	-0.99^{***}	-1.51^{***}	-1.47^{***}	-1.25^{***}	-1.14^{***}	-2.09^{***}
	(0.10)	(0.32)	(0.38)	(0.33)	(0.28)	(0.56)
Instrument(s):						
Default $\log\left(P^{\text{elec}}_{it}\right)$	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	10,155	10,141	9,337	10,141	10,140	10,108
Months	117	117	117	117	117	105
Observations	0.93M	0.87M	0.83M	0.91M	0.87M	0.77M
First stage F-statistic	6935	87	71	49	55	18

Notes: Each regression estimates Equation (6) 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 $\log(\widehat{\text{kWh}/\text{AF}}_{it})$. We estimate IV specifications via two-stage least squares, and all regressions instrument for P^{elec}_{it} with unit i's within-category default logged electricity price in month t (consistent with our preferred specification from Table 3). We instrument for $\log(\widehat{\text{kWh}/\text{AF}}_{it})$ 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 $\log(\widehat{\text{kWh}/\text{AF}}_{it})$ 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 two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix C Discrete choice modeling framework

To arrive at the discrete choice model we present in Section 6.2.2 of the main text, we begin with a general model of farm profits:

$$\pi_{iy}(k) = r_{iyk} - c_{iyk} + \varepsilon_{iyk}$$

where $\pi_{iy}(k)$ is the profit for farmer i in year y growing crop type k, r_{iyk} is farm revenues, c_{iyk} are farm costs, and ε_{iyk} is an error term. Rewriting revenues as a function of crop prices p_{ky} (common across farmers) and quantity grown q_{iyk}, and decomposing costs into non-water costs and water costs, we can re-write this as:

$$\begin{aligned}\pi_{iy}(k) &= p_{yk}q_{iyk} - c_{iyk}^{\text{non-water}} - c_{iyk}^{\text{water}} + \varepsilon_{iyk} \\ &= p_{yt}q_{iyk} - c_{iyk}^{\text{non-water}} - p_{iy}^{\text{water}}q_{iyk}^{water} + \varepsilon_{iyk}\end{aligned}$$

Assuming yield and per-unit costs are constant within county c, and denoting acreage as A_{iy}:

$$\begin{aligned}\pi_{iy}(k) &= \alpha_{cyk} + \gamma_{cyk}A_{iy} - p_{iy}^{\text{water}}q_{iyk}^{water} + \varepsilon_{iyk} \\ &= \alpha_{cyk} + \gamma_{cyk}A_{iy} + \beta_{cyk}A_{iy}p_{iy}^{\text{water}} + \varepsilon_{iyk}\end{aligned}$$

Assuming all costs scale with acres (i.e. $\alpha_{cky} = 0$):

$$\pi_{iy}(k) = \gamma_{cyk} + \beta_{cyk}p_{iy}^{\text{water}} + \varepsilon_{iyk}$$

And, finally, assume that the impact of water prices on profits is time-invariant and location-invariant (i.e. $\beta_{cyk} = \beta_k \ \forall \ y, c$):

$$\pi_{iy}(k) = \gamma_{cyy} + \beta_k p_{iy}^{\text{water}} + \varepsilon_{iyk}$$

Farmer i maximizes profits by choosing crop k (identical to Equation (9 in the main text):

$$\max_{k \in \mathcal{K}} \pi_{iy}(k) = \gamma_{cky} + \beta_k p_{iy}^{\text{water}} + \varepsilon_{iyk}$$

We further assume that the error terms are i.i.d. Normal: $\varepsilon_{iyk} \sim \mathcal{N}(0, \sigma)$, and estimate this model using the instrumental variables probit model described in the main text.

Appendix D Additional tables and figures

In this Appendix, we present a variety of sensitivity analyses and robustness checks which build upon the results we present in the main text.

D.1 Instrumenting with modal tariffs

In our main estimates, we instrument for $\log(P_{it}^{\text{elec}})$ and $\log(P_{it}^{\text{water}})$ using the "default" within-category electricity tariff for each of PGE's 5 rate categories. For the AG-1A, AG-1B, and AG-ICE tariffs, this designation is trivial – each of these rates is a singleton within its category. However, for the small pumps and smart meters category and the large pumps and small meters category, there are 8 and 12 separate tariffs, respectively. We define the default tariff as the rate within each category that has the least complex marginal pricing structure: AG-4A and AG-4B. In Appendix Table D3, we instead present results where we instrument for $\log(P_{it}^{\text{elec}})$ with the *modal* tariff in each category: AG-1A, AG-1B, AG-ICE, AG-4A, and AG-5B. Our preferred specification, shown in Column (2), produces an identical elasticity (-1.17) to our preferred estimate in Table 3 in the main text.

Table D3: Instrumenting with within-category modal tariffs – Electricity

	(1) IV	(2) IV	(3) IV	(4) IV
$\log\left(P_{it}^{\text{elec}}\right)$	-1.53^{***}	-1.17^{***}	-1.00^{***}	-1.19^{***}
	(0.15)	(0.16)	(0.15)	(0.20)
Instrument(s):				
Modal $\log\left(P_{it}^{\text{elec}}\right)$	Yes	Yes	Yes	
Modal $\log\left(P_{it}^{\text{elec}}\right)$, lagged				Yes
Fixed effects:				
Unit × month-of-year	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes
Unit × physical capital		Yes	Yes	Yes
Water basin × year			Yes	
Water district × year			Yes	
Service point units	11,173	11,173	11,142	10,922
Months	117	117	117	105
Observations	1.05M	1.05M	1.04M	0.91M
First stage F-statistic	5796	5006	5202	1043

Notes: This table reestimates Columns (2)–(5) from Table 3, instrumenting with the average marginal price of the modal tariff within each category. These instruments produce very similar results, demonstrating that our main results are not sensitive to our choice of default tariff. See notes under Table 3 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.2 Sensitivity to trends in pump characteristics

A potential endogeneity concern in our setting is farmers choosing their pumping capital in order to attain a more favorable electricity tariff. We find no evidence of farmers "bunching" pump characteristics around the 35 hp cutoff in Figure 4, and we include a unit × physical capital fixed effect in our preferred specifications to help control for this. Ultimately, our identification strategy relies on a parallel-trends type argument, which requires that electricity consumption for farmers in different tariff categories would be trending similarly in the absence of differential rate increases or decreases over time. To provide evidence in support of this assumption, in Appendix Table D4, we interact our month-of-sample fixed effects with bins of three different pump characteristics: horsepower, kW, and operating pump efficiency (OPE). We use 11 bins in horsepower: 1 below PGE's 35 hp cutoff, and 10 bins for deciles of the horsepower distribution above 35 hp. We similarly use 11 bins in kW: 1 for measured kW for pumps below PGE's 35 hp cutoff (equivalent to 26.1 kW), and 10 for each decile of kW for pumps above this 35 hp cutoff. Finally, we use 10 bins for OPE. In Columns (1)–(3) of Table D4, we exclude our unit × physical capital fixed effect, and find larger elasticities

Table D4: Sensitivity to trends in HP, kW, and OPE – Electricity

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$\log\left(P_{it}^{\text{elec}}\right)$	-1.56^{***}	-1.54^{***}	-1.60^{***}	-1.15^{***}	-1.13^{***}	-1.17^{***}
	(0.16)	(0.16)	(0.17)	(0.16)	(0.16)	(0.16)
Month-of-sample FEs interaction	HP bins	kW bins	OPE bins	HP bins	kW bins	OPE bins
IV: Default $\log\left(P_{it}^{\text{elec}}\right)$	Yes	Yes	Yes	Yes	Yes	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
Service point units	11,173	11,173	11,173	11,173	11,173	11,173
Months	117	117	117	117	117	117
Observations	1.05M	1.05M	1.05M	1.05M	1.05M	1.05M
First stage F-statistic	3983	4056	4164	6989	7123	7406

Notes: This table conducts sensitivity analysis on our monthly electricity regressions by interacting month-of-sample fixed effects with bins of pump horsepower, kW, and operating efficiency. Columns (1)–(3) replicate Column (2) from Table 3, while Columns (4)–(6) replicate Column (3) from Table 3. Columns (1) and (4) interact month-of-sample fixed effects with 11 bins of nameplate horsepower: 1 bin below PGE's 35 hp cutoff, and 10 bins for deciles of the distribution of hp above this cutoff. Columns (2) and (5) interact month-of-sample fixed effects with 11 bins of kW usage, as measured in APEP pump tests: 1 bin below PGE's 35 hp cutoff (equivalent to 26.1 kW), and 10 bins for deciles of the distribution of measured kW above this cutoff. Columns (3) and (6) interact month-of-sample fixed effects with 10 bins for deciles of operating pump efficiency recorded in APEP pump tests. See notes under Table 3 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

than in our preferred model. In Columns (4)–(6), we include this fixed effect, and recover estimates that are quantitatively similar to our preferred estimate (-1.17 from Table 3), providing reassurance that our results are not being driven by differential sorting into tariff categories over time.

D.3 Sensitivity to $\widehat{\text{kWh/AF}}$ construction

Because we do not observe groundwater extraction or costs directly, we must construct Q_{it}^{water} and P_{it}^{water} by scaling our electricity data by a conversion factor:

$$\widehat{\frac{\text{kWh}}{\text{AF}}}_{it} = \frac{[\text{Lift (feet)}] \times [\text{Constant}]}{\text{Operating pump efficiency } (\%)_{it}}$$

While operating pump efficiency is a variable in our data, lift is a function of the pump's drawdown and the static water level. We use rasterized versions of CASGEM well measurements to construct lift. Appendix Table D5 presents sensitivity analyses for our groundwater elasticity estimates using a variety of approaches to construct $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$. In Column (1), we instrument *only* with the (log of) the average groundwater depth in each unit's basin. The resulting point estimate, (-1.36), lies between our preferred electricity-instrument-only estimate of (-1.12) presented in Table 4 and our preferred dual-instrument $\hat{\beta}^{\text{w}}$ estimate of -1.51 presented in Appendix Table B2. In Column (2), we use only the average depth instrument, and assign units $\widehat{\frac{\text{kWh}}{\text{AF}}}_{it}$ directly from an APEP test, rather than attempting to estimate it. In Columns (3)–(6), we use the electricity instrument only. In Column (3), we remove units that do not have reliable measures of drawdown in their APEP test data. In Column (4), we predict drawdown as a function of groundwater depth, rather than retaining a static drawdown measurement from an APEP test. In Column (5), we again predict drawdown, this time using the average basin-wide groundwater level. In Column (6), we restrict our sample to units that have a groundwater depth measurement within 8 miles prior to rasterization. Across all specifications, we find estimates that are quantitatively similar to our central estimate of -1.12.

Table D5: Sensitivity to $\widehat{\text{kWh/AF}}$ construction – Groundwater

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$\log(P^{\text{water}}_{it})$	-1.36^{***}	-1.09^{***}	-1.26^{***}	-1.12^{***}	-1.13^{***}	-1.28^{***}
	(0.32)	(0.15)	(0.37)	(0.16)	(0.15)	(0.18)
$\widehat{\text{kWh/AF}}_{it}$ criteria:						
Measured, not estimated		Yes				
Drop tests with bad drawdown			Yes			
Time-varying predicted drawdown				Yes	Yes	
Mean groundwater depth					Yes	
Depth measured w/in 8 miles						Yes
Instrument:						
log (Avg depth in basin)	Yes	Yes				
Default $\log(P^{\text{elec}}_{it})$			Yes	Yes	Yes	Yes
Fixed effects:						
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes	
Month-of-sample	Yes	Yes	Yes	Yes	Yes	
Unit × physical capital	Yes	Yes	Yes	Yes	Yes	
Groundwater time step	Month	Month	Month	Month	Month	Month
Service point units	10,141	10,155	1,562	10,155	10,155	9,930
Months	117	117	117	117	117	117
Observations	0.87M	0.93M	0.12M	0.93M	0.93M	0.45M
First stage F-statistic	161	5398	645	2824	2420	2382

Notes: Each regression replicates our preferred specification from Column (2) of Table 4, while altering our preferred method of specifying units' kWh/AF conversion factor. Columns (1)–(2) maintain our preferred $\widehat{\text{kWh/AF}}$ definition, but instrument for groundwater price using basin-wide average groundwater depths. This leverages only variation in P^{water} driven by changes in depth. Column (2) directly assigns kWh/AF as measured in an APEP pump test, which yields a P^{water} variable that is independent of changes in groundwater depth. Column (3) removes units without a reliable drawdown measurement from an APEP pump test. Columns (4)–(5) construct $\widehat{\text{kWh/AF}}$ using predicted drawdown as a function of groundwater depth, rather than fixed drawdown within pumps over time. Column (5) also applies basin-wide average depth to construct $\widehat{\text{kWh/AF}}$, rather than using localized measurements from groundwater rasters. Column (6) uses rasterized groundwater measurements, but drop the (roughly half of) observations without a contemporaneous groundwater measurement within 8 miles. See notes under Table 4 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.4 Sensitivity to geographic controls

In our preferred specifications in Tables 3 and 4, we include unit-by-month-of-year fixed effects and month-of-sample fixed effects. However, it is possible that confounders that vary both by location and time remain. In Appendix Tables D6 and D7, we add additional geographic controls by interacting our month-of-sample fixed effects with fixed effects for a

Table D6: Sensitivity to geographic controls – Electricity

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
$\log\left(P^{\text{elec}}_{it}\right)$	-1.12^{***}	-1.09^{***}	-1.08^{***}	-1.10^{***}	-1.02^{***}
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Month-of-sample FEs interaction	Climate zone	County	Basin	Sub-Basin	Water district
IV: Default $\log\left(P^{\text{elec}}_{it}\right)$	Yes	Yes	Yes	Yes	Yes
Fixed effects:					
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes
Service point units	11,167	11,170	11,159	11,151	11,156
Months	117	117	117	117	117
Observations	1.04M	1.05M	1.04M	1.04M	1.04M
First stage F-statistic	7548	7527	7375	7579	7648

Notes: This table conducts sensitivity analysis on our preferred electricity specification from Column (3) of Table 3, by interacting month-of-sample fixed effects with different geographic variables. California comprises 16 climate zones, and PGE agriculture customers are distributed across 11 distinct climate zones. Sub-basins are administrative sub-divisions of groundwater basins; this estimation sample includes agricultural consumers from 46 unique groundwater basins and 95 unique sub-basins. The sample also includes units assigned to 125 unique water districts; Column (5) includes a separate set of month-of-sample fixed effects for units not assigned to a water district. See notes under Table 3 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

variety of different geographic scales that may be relevant for agricultural production: climate zone, county, groundwater basin, groundwater sub-basin, and water district to allay these concerns. In Appendix Table D6, we present results for electricity. When we interact our month-of-sample fixed effects with these geographic fixed effects, we find very similar estimates to those in Table 3. Including month-of-sample-by-water-district fixed effects attenuates the estimates the most, to -1.02, though we cannot reject that this is the same as the -1.12 in our preferred specification. Appendix Table D7, presents results for groundwater. When we interact our month-of-sample fixed effects with these geographic fixed effects, we again find very similar estimates to those in Table 4. Once again, including month-of-sample-by-water-district fixed effects attenuates the estimates the most, to -0.95, though this elasticity is still large and highly statistically significant.

Table D7: Sensitivity to geographic controls – Water

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
$\log(P_{it}^{\text{water}})$	-1.08^{***}	-1.05^{***}	-1.05^{***}	-1.05^{***}	-0.95^{***}
	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)
Month-of-sample FEs interaction	Climate zone	County	Basin	Sub-Basin	Water district
IV: Default $\log(P_{it}^{\text{elec}})$	Yes	Yes	Yes	Yes	Yes
Fixed effects:					
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes
Service point units	10,150	10,152	10,142	10,135	10,136
Months	117	117	117	117	117
Observations	0.93M	0.93M	0.93M	0.93M	0.93M
First stage F-statistic	3827	4379	3573	4511	4239

Notes: This table conducts sensitivity analysis on our preferred water specification from Column (2) of Table 4, by interacting month-of-sample fixed effects with different geographic variables. California comprises 16 climate zones, and PGE agriculture customers are distributed across 11 distinct climate zones. Sub-basins are administrative sub-divisions of groundwater basins; this estimation sample includes agricultural consumers from 46 unique groundwater basins and 95 unique sub-basins. The sample also includes units assigned to 125 unique water districts; Column (5) includes a separate set of month-of-sample fixed effects for units not assigned to a water district. See notes under Table 3 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.5 Sensitivity to weather controls

Weather is a key input in the agricultural production process. While we do not include weather controls in our main estimates, because we expect weather to be orthogonal to our within-category electricity tariff instrument, conditional on unit-by-month-of-year and month-of-sample fixed effects. Nevertheless, we present sensitivities to the inclusion of weather controls here. We obtained gridded daily temperature and precipitation data from PRISM, and geographically matched this weather data to our units using CLU centroids. We average daily maximum and minimum temperatures and sum daily precipitation over all days in each month to construct monthly weather controls. Appendix Table D8 presents the results of adding weather controls to our main estimates. In Columns (1) and (4), we add a monthly precipitation control to our electricity and water regressions, respectively. In Columns (2) and (5), we also add average daily minimum and maximum temperature. In Columns (3) and (6), we also add 1-month-lagged temperature and precipitation. Across all specifications, our electricity and groundwater elasticity estimates remain quantitatively similar to our preferred estimates in Table 3 and 4: -1.17 and -1.12, respectively.

Table D8: Sensitivity to weather controls

	Electricity			Groundwater		
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
$\log(P^{\text{elec}}_{it})$	-1.18^{***}	-1.17^{***}	-1.19^{***}	-1.12^{***}	-1.12^{***}	-1.14^{***}
	(0.16)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)
Weather controls:						
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Temperature		Yes	Yes		Yes	Yes
Lagged precipitation			Yes			Yes
Lagged temperature			Yes			Yes
IV: Default $\log(P^{\text{elec}}_{it})$	Yes	Yes	Yes	Yes	Yes	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
Service point units	11,173	11,173	11,172	10,155	10,155	10,154
Months	117	117	116	117	117	116
Observations	1.05M	1.05M	1.04M	0.93M	0.93M	0.93M
First stage F-statistic	7387	7390	7348	3033	3054	2977

Notes: This table adds weather controls to our preferred specifications for electricity (Column (3) of Table 3) and groundwater (Column (2) of Table 4). We assign daily precipitation, maximum temperature, and minimum temperatures to each unit's latitude and longitude, using daily rasters from PRISM. We sum daily precipitation over all days in each month, and average daily maximum and minimum temperatures over all days in each month. Columns (3) and (6) control for 1-month lags in all three variables. See notes under Tables 3 and Table 4 for further details. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.6 Sensitivity to field assignments

Our PGE data are geographically resolved to the service point (SP) level. In order to estimate impacts of electricity and groundwater costs on land use, we must match these SPs to geographic features with agricultural meaning. We use the USDA's Common Land Unit (CLU) as our main agricultural unit of analysis. A CLU is defined as "is the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer in agricultural land associated with USDA farm programs. CLU boundaries are delineated from relatively permanent features such as fence lines, roads, and/or waterways."[5] We use a 2008 CLU shapefile: in the 2008

5. https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-products/common-land-unit-clu/index

Table D9: Sensitivity to CLU assignments and groupings – Groundwater

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
$\log\left(P_{it}^{\text{water}}\right)$	-1.11^{***}	-1.09^{***}	-1.35^{***}	-0.96^{***}	-1.09^{***}
	(0.19)	(0.16)	(0.26)	(0.19)	(0.17)
Sample criteria:					
Inside CLU polygon	Yes				
Drop CLU inconsistencies		Yes			
Pumps per CLU group			1	2+	
Cluster by CLU group					Yes
IV: Default $\log\left(P_{it}^{\text{elec}}\right)$	Yes	Yes	Yes	Yes	Yes
Fixed effects:					
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes
Groundwater time step	Month	Month	Month	Month	Month
Service point units	5,913	9,702	2,677	7,072	4,708
Months	117	117	117	117	117
Observations	0.55M	0.89M	0.25M	0.65M	0.90M
First stage F-statistic	2059	2896	1334	2009	2548

Notes: Each regression replicates our preferred specification in Column (2) from Table 4, while conducting sensitivity on unit-specific assignments to CLU polygons (i.e. fields). Column (1) includes only units with coordinates that are fully inside their assigned CLU polygon. Column (2) drops units with inconsistent, problematic, or internally conflicting CLU assignments. Columns (3)–(5) group CLUs that lie within the same tax parcels. Columns (3) includes only units that are the singleton (confirmed) groundwater pump in their CLU group. Columns (4) includes units in CLU groups with multiple (confirmed) groundwater pumps. Columns (5) two-way clusters by CLU group and by month-of-sample, with 4708 unique CLU groups. See notes under Table 4 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample, except in Column (5). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Farm Bill, CLUs were deemed to be confidential, and future shapefiles were not made publicly available. In part because PGE's SPs often lie at the edge of property boundaries (i.e., on roads, and therefore easily accessible), there is the potential for measurement error in the SP–CLU match. In Appendix Table D9, we present sensitivities on this assignment process. In Column (1), we keep only units that lie within a CLU polygon. In Column (2), we drop units with inconsistent CLU assignments. In Column (3), we restrict the sample to SPs whose CLUs do not contain any other APEP pumps. In Column (4), we restrict the sample to SPs whose CLUs contain multiple pumps. In Column (5), we two-way cluster our standard errors by CLU and month-of-sample. We find similar elasticities across all specifications.

D.7 Sensitivity to functional form

In our main specifications in Tables 3 and 4, we use the inverse hyperbolic sine (IHS) transformation for our dependent variables, $\sinh^{-1}(Q_{it}^{\text{elec}})$ and $\sinh^{-1}(Q_{it}^{\text{water}})$, since 14 percent of our monthly observations are zeroes. The IHS behaves much like the log, but admits zeroes (Bellemare and Wichman (2020)). Here, we present sensitivities using different dependent variables: the IHS transformation, excluding zero-valued observations, $\log(Q)$, $\log(1+Q)$, and $\log(1+100Q)$. Appendix Table D10 presents electricity results, and Appendix Table D11 presents groundwater results. Both tables are laid out identically. In Column (1), we replicate our preferred specification from the main text, where we use the IHS transformation with no sample restrictions. In Column (2), we retain the IHS transformation, but only use strictly positive-valued observations, to match the sample used by the standard log. We find that our estimates attenuate strongly, moving from an elasticity of -1.17 to -0.31 (electricity) and -1.12 to -0.30 (water). Reassuringly, we find identical point estimates when we use $\log(Q)$ as the dependent variable in Column (3). In Column (4), we use $\log(1+Q)$, in order to use the log while retaining the zero-valued observations, and our point estimates rise (a much larger -0.78 for electricity; a smaller -0.36 for water). Finally, Column (5) uses $\log(1+100Q)$, and we again recover less attenuated estimates: -1.12 for electricity and -0.71 for water. This suggests that our choice of functional form is not driving our results. However, zeroes are important in this context, because they are likely associated with farmers fallowing their land or switching crops. Finding that our elasticity estimates are driven in part by these mechanisms is consistent with our discussion in Section 6 in the main text, and echoed by our intensive-vs.-extensive margin results in Table 6.

Table D10: Sensitivity to IHS vs. log transformation – Electricity

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
$\log(P_{it}^{\text{elec}})$	-1.17^{***}	-0.31^{***}	-0.31^{***}	-0.78^{***}	-1.12^{***}
	(0.16)	(0.08)	(0.08)	(0.11)	(0.15)
LHS transformation:	$\sinh^{-1}(Q)$	$\sinh^{-1}(Q)$	$\log(Q)$	$\log(1+Q)$	$\log(1+100Q)$
Sample restriction:					
$Q_{it} > 0$		Yes	Yes		
IV: Default $\log(P_{it}^{\text{elec}})$	Yes	Yes	Yes	Yes	Yes
Fixed effects:					
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes
Service point units	11,173	11,109	11,109	11,173	11,173
Months	117	117	117	117	117
Observations	1.05M	0.89M	0.89M	1.05M	1.05M
First stage F-statistic	7382	6841	6841	7382	7382

Notes: This table conducts sensitivity analysis on the transformation of the dependent variable Q^{elec}. Column (1) reproduces our preferred specification from Column (3) of Table 3 using the inverse hyperbolic sine transformation. where the dependent variable is the inverse hyperbolic sine transformation of electricity consumed by service point i in month t. Column (2) uses the same transformation but removed zeros to align with the natural log transformation in Column (3). Columns (4)–(5) apply the natural log + 1 transformation. Column (5) also scales the dependent variable by 100, which nearly matches our results using the inverse hyperbolic sine transformation. See notes under Table 3 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D11: Sensitivity to IHS vs. log transformation – Water

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV
$\log(P_{it}^{\text{water}})$	-1.12^{***}	-0.30^{***}	-0.30^{***}	-0.36^{***}	-0.71^{***}
	(0.15)	(0.08)	(0.08)	(0.05)	(0.10)
LHS transformation:	$\sinh^{-1}(Q)$	$\sinh^{-1}(Q)$	$\log(Q)$	$\log(1+Q)$	$\log(1+100Q)$
Sample restriction:					
$Q_{it} > 0$		Yes	Yes		
IV: Default $\log(P_{it}^{\text{elec}})$	Yes	Yes	Yes	Yes	Yes
Fixed effects:					
Unit × month-of-year	Yes	Yes	Yes	Yes	Yes
Month-of-sample	Yes	Yes	Yes	Yes	Yes
Unit × physical capital	Yes	Yes	Yes	Yes	Yes
Service point units	10,155	10,091	10,091	10,155	10,155
Months	117	117	117	117	117
Observations	0.93M	0.79M	0.79M	0.93M	0.93M
First stage F-statistic	3021	2629	2629	3021	3021

Notes: This table conducts sensitivity analysis on the transformation of the dependent variable Q^{water}. Column (1) reproduces our preferred specification from Column (2) of Table 4 using the inverse hyperbolic sine transformation. where the dependent variable is the inverse hyperbolic sine transformation of electricity consumed by service point i in month t. Column (2) uses the same transformation but removed zeros to align with the natural log transformation in Column (3). Columns (4)–(5) apply the natural log + 1 transformation. Column (5) also scales the dependent variable by 100, which nearly matches our results using the inverse hyperbolic sine transformation. See notes under Table 4 for further detail. Standard errors (in parentheses) are two-way clustered by service point and by month-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.