Price Incentives for Conservation: Experimental Evidence from Groundwater Irrigation

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Invited Session prepared for presentation at the 2025 AAEA & WAEA Joint Annual Meeting in Denver, CO; July 27-29, 2025

Preliminary Draft: Please Do Not Quote or Cite

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May 30, 2024

Abstract

Groundwater is a vital input to agricultural production worldwide, but a widespread lack of effective regulation leads to overconsumption and depletion. We evaluate a program of price incentives for voluntary groundwater conservation among smallholder farmers in Gujarat, India, where water (and the electricity used to pump it) is scarce and unregulated. To do so, we install meters and offer payments for reduced groundwater pumping in a randomized controlled trial. Price incentives work: The program reduced hours of irrigation by 24 percent. Most of the conservation is achieved by a price within a realistic policy range; doubling the price has little additional effect. Payment expenditures per unit energy conserved are near the cost of expanding electricity supply, suggesting that payments for groundwater conservation may be a cost-effective policy tool where pricing is politically infeasible.

*Hagerty: Montana State University. Zucker: UC Santa Cruz. We are grateful to Jasmin Korat, Mustufa Patel, Gokul Sampath, Neha Doshi, and Getsie Immanuel for outstanding project management and research assistance; Piyush Gandhi and Brooke Banning for excellent research assistance; Gaddala Ganesh, Aditya Madhusudan, Isha Fuletra, and Suresh Bharda for excellent project assistance and field support; and many survey enumerators with J-PAL South Asia for data collection. We thank Naveen Patidar and the staff of the Aga Khan Rural Support Programme (India) and the Aga Khan Foundation for implementation support. Funding for this research was generously provided by the King Climate Action Initiative, the International Growth Centre, the Weiss Fund for Research in Development Economics, and the Abdul Latif Jameel World Water and Food Security Lab (J-WAFS) at MIT. This research has IRB approval from the Institute for Financial Management and Research and is registered on the AEA RCT registry (ID number AEARCTR-0009337).

1 Introduction

Groundwater is a major source of irrigation and drinking water worldwide, especially for farmers in low- and middle-income countries (Ministry of Agriculture of the Government of India, 2014). But in many parts of the world, a lack of regulation is leading to overconsumption and depletion, which can increase poverty and conflict and reduce farm income, wealth, and employment (Sekhri, 2014; Blakeslee et al., 2020). In addition, electricity used to pump groundwater is often typically not priced volumetrically, exacerbating depletion while draining revenue from electric utilities and disincentivizing grid expansion (Burgess et al., 2020). Many regulatory tools are available to address this textbook common-pool resource problem, ranging from quantity restrictions and tradeable quotas to simple price instruments. Despite this, groundwater pumping is currently unregulated in much of the world, suggesting that a new approach could be helpful.

This paper experimentally evaluates a program of payments for voluntary groundwater conservation among smallholder farmers in Gujarat, India, where both water and electricity are scarce and largely unregulated. Between Fall 2022 and Spring 2023, we installed meters and offered payments for reduced groundwater pumping in a randomized controlled trial. The basic design is to (1) meter the groundwater pumps of all study participants, (2) offer randomly selected participants payments for reduced pumping relative to a "benchmark" quantity, and (3) compare groundwater consumption by these farmers to that of the rest of the sample. The program was implemented in collaboration with the Aga Khan Rural Support Programme (India), a trusted organization with a long history in the study area.

We first ask how this program affected groundwater and electricity consumption, studying conservation payments as a potential policy tool in itself. For other natural resources worldwide, it is common for governments to offer payments for conservation instead of penalties for using them. For groundwater in developing countries, conservation payments may be able to overcome typical political constraints to pricing water or electricity. High energy subsidies are often seen as valuable means of redistribution; in India, reform efforts are commonly met with forceful protests (Sovacool, 2017). Conservation payments instead invert the distributional consequences of Pigouvian fees.

We then use the experimental variation introduced by this program to estimate the price elasticity of demand for groundwater irrigation in smallholder agriculture. Treatment-group farmers were randomized into high- and low-price groups, providing additional variation to trace out the demand curve. While the overall treatment effects depend on specific design parameters of our program, a demand model yields potentially more generalizable information. The demand for groundwater is an important input to the design of any type of groundwater or rural electricity regulation, but evidence has been scarce. Our project provides two crucial missing ingredients: price variation, and direct measurement of pump operation.

First, we find that payments for groundwater conservation work. Farmers offered conservation payments irrigated for 24 percent fewer hours than farmers assigned to the control group, with a 95 percent confidence interval of $(13, 34)$ percent. The effects are similar when we convert irrigation time to energy use—we estimate that treatment farmers reduced electricity consumption by 151 kilowatt-hours (kWh) per month relative to the control-group mean of 611 kWh. Treatment effects increased over the three months of the intervention, suggesting a durable response. Higher prices do not have much additional effect conditional on overall program eligibility.

Second, we estimate demand for groundwater irrigation using the full range of price variation in our experiment. To do so, we use assignment to the treatment group and sub-treatment groups as instruments for the actual price faced by each participant at the margin. In a conservation payments program, not all participants are truly marginal—some participants find their benchmark too low to affect their decisions, while others exceed the maximum payment. We find that irrigation hours fall by 1 hour per farmer-month for every 5 INR increase in the hourly price, implying a price elasticity of 0.2.

Last, we assess the cost-effectiveness of payments for groundwater conservation from the perspective of an electric utility. At the margin, is it cheaper for a utility to increase supply or to reduce demand through conservation payments? We find that our program is cost-competitive with typical costs of electricity procurement in northwestern India. Our program spent 6.1 INR in total conservation payments for every kWh of energy saved, a cost that is slightly greater than the average costs of electricity provision for the utility in our study area (and may be lower than marginal costs) and slightly lower than costs in a nearby state. Considering the additional social costs of groundwater depletion and of emissions from electricity generation, it appears likely that paying farmers to reduce their groundwater irrigation would bring greater social benefits than purchasing more electricity and distributing it for free.

The central contribution of this paper is to provide experimental evidence on the response to marginal prices for groundwater irrigation. Because price variation is scarce for an open-access resource, many early studies used proxies for the cost of pumping (Gonzalez-Alvarez et al., 2006; Hendricks and Peterson, 2012). Several observational studies find evidence that marginal prices reduce groundwater use, in both the U.S. (Smith et al., 2017; Bruno and Jessoe, 2021) and in South Asia (Meenakshi et al., 2013;

Chakravorty et al., 2023). However, studies in developing countries often rely on self-reported pumping data or proxies for water use, which may be unreliable or noisy; installing meters allows us to directly measure irrigation behavior. Chakravorty et al. (2023) use an encouragement design to experimentally induce a volumetric price; they do not find effects on water use, but this may be because relatively few farmers adopted the price. We build most directly upon two papers that found mixed results in non-randomized pilots of similar programs by electric utilities in Gujarat and Punjab (Fishman et al., 2016; Mitra et al., 2023). By working instead with a local non-governmental organization, we are able to randomize participants, directly measure pumping at the individual level, and trace the demand curve to prices well beyond what utilities have been willing to test.

Our project also contributes to the broader literature on payments for environmental services (PES). Our intervention has the same basic structure as hundreds of programs designed to incentivize the provision of environmental services, ranging from increased forest or wetland cover, to reduced input intensity in agriculture.[1] Despite their prevalence, rigorous evaluation of these types of programs has been limited (see Pattanayak et al. (2010) and Börner et al. (2017) for reviews). Most existing evaluations use covariate matching and are unable to address selection bias, a particular concern for a voluntary program. The exceptions are three randomized controlled trials of programs to reduce deforestation in Uganda (Jayachandran et al., 2017), encourage tree planting in Malawi (Jack and Cardona Santos, 2017), and reduce crop burning in India (Jack et al., 2023). Our study shows that PES models are feasible and can be effective in a novel context: reducing energy and water use in agriculture.

Finally, we contribute to literature connecting the price response of electricity consumption in developing countries to policy decisions about energy-sector investment and reform. Experimental and quasi-experimental studies are still limited, but a few have been conducted recently on rural households in Columbia (McRae, 2015), urban households in South Africa (Jack and Smith, 2016), and new grid connections in Kenya (Lee et al., 2018).

[1]For example, in the United States alone, payments are available to farmers for actions to mitigate flood and wildfire risks, provide habitat for endangered species, salinity mitigation, and water and energy conservation.

2 Study Setting and Experimental Design

2.1 Enrollment and Sample

We implemented a randomized controlled trial among groundwater-irrigating farmers in Saurashtra, a water-scarce region of Gujarat state, India. The study villages are located in the inland districts of Rajkot, Surendranagar, and Morbi (shown in Figure 1). Groundwater depletion is a concern within the study area, and nearby areas are marked by some of the most rapid groundwater depletion rates both within India and globally (Jasechko et al., 2024). While the primary source of employment in the study area is in agriculture (Registrar General and Census Commissioner of India (2001)), there are also a number of industrial occupation opportunities.

We recruited our sample using lists of villagers currently or formerly participating in agricultural outreach programs with our implementing partner, the Aga Khan Rural Support Program (AKRSP), and its sister agency the Aga Khan Foundation (AKF). The outreach programs included Better Cotton Initiative, which aims to improve the sustainability of the global cotton supply; Farmer Producer Groups, which aim to empower farmers in marketing produce and procuring high-quality inputs; and various micro-irrigation subsidy and support programs. Surveyors approached farmers on these lists, as well as any farmers who shared water with those on the lists, to determine eligibility.

In order to be eligible for the study, the household's primary agricultural decision-maker (PAD) was required to meet the following criteria: Planted crops and irrigated primarily using groundwater in the previous Rabi season; planned to irrigate during the coming Rabi season; had no more than two active wells on their primary farm; had electric-powered pumps on all active wells; did not have multiple pump starters in use on any active well; and did not belong to a network of sharing irrigation sources among groups of farmers larger than four.

We enrolled a total of 1,347 farmers who met the eligibility criteria, completed a baseline survey, and consented to the full study (including installation of an hours of use meter on the pumpsets used to irrigate their primary farm). Of these, 236 attrited prior to randomization, and another 122 prior to the final data collection visit, leaving an analysis sample of 989 farmers.

2.2 Interventions

The experiment had two overarching treatment arms: *conservation credit* farmers were eligible to receive payments for conserving groundwater below a benchmark, whereas *control* farmers received no such incentives.

Conservation credits Our study utilizes random variation in whether participants were assigned to four versions of the Conservation Credits intervention arms, as shown in Figure 2. Participants in the Conservation Credits arms had an hours-of-use meter installed on the electric pump starter of their primary irrigation source or sources.[2] The meter measures the total hours of irrigation done by the farmer.

Meters were installed in Fall of 2022, and were read monthly by survey staff from December 2022 through March 2023 (Figure 3). We took three actions to discourage tampering and removal. First, stickers were placed at the easiest disconnection points such that disconnection would tear the sticker, enabling easy detection. Second, in the case that meter removal or tampering was detected, participants were disqualified from receiving conservation incentives. Finally, participants were rewarded 100 INR per meter for keeping their meters installed without tampering through the final meter reading.

Farmers in the Conservation Credits arms were informed of their treatment assignment at the first meter reading in December 2022. Farmers were incentivized for conserving water for the following four months of the winter growing season, known as the Rabi season, from January-March. This is the period of peak irrigation; as there is typically no rainfall during Rabi, agriculture is entirely dependent on irrigation. At each meter reading, farmers were informed of their benchmark for the following month, and the payment for the previous month was calculated. Payments were awarded at a fixed rate for consuming fewer hours of irrigation than the monthly benchmark, according the formula:

$$\text{Payment}_{it} = \min\left(\max\left(0, \text{price}_i \times ((\text{hours benchmark})_{it} - (\text{hours consumed})_{it})\right), (\text{max payment})_i\right) \quad (1)$$

where price_i is the per-hour incentive rate, $(\text{hours benchmark})_{it}$ is an individual-month-specific benchmark, $(\text{hours consumed})_{it}$ is the monthly meter reading, and $(\text{max payment})_i$ is the maximum monthly payment.[3] Payments were pro-rated in the case that meter readings were not exactly 31 days apart. The payments were later disbursed via electronic bank transfer.

[2]Farmers in our sample had up to two wells on their primary farm, and therefore up to two metered pump starters.

[3]The maximum monthly payment was 4,000 INR for farmers with one well and 6,000 INR for farmers with two wells. These maximums were not pro-rated.

Conservation Credit Sub-treatments The four Conservation Credits sub-treatments differ along two dimensions: the per-hour incentive rate, and the benchmark. Individuals assigned a *high price* received 100 INR (1.20 USD) per hour conserved, and those assigned a *low price* received 50 INR (0.60 USD) per hour conserved. The prices were chosen to encompass realistic ranges of groundwater prices that a policymaker might wish to set. The low price represents the approximate cost of electricity provision for the median farmer and is similar to the price offered in a program in Punjab (Mitra et al., 2023).[4] The high price allows us to study the response to prices well beyond those piloted by electric utilities in India to date, which might be justified by the additional social costs of groundwater depletion and electricity generation.

Individualized benchmarks were set using a formula that optimized the expected number of marginal farmers as a function of first-month pumping data (i.e., after meter installation but before treatment assignment was revealed to surveyors or farmers). Individuals assigned the *high* and *low benchmark* received 115% and 85%, respectively, of their formula-based benchmark, rounded to the nearest 10-hour increment.

Control Participants in the Control arm also had hours-of-use meters installed and read monthly for four months, and were rewarded 100 INR per meter for keeping the meters installed for the duration of the intervention. However, these farmers were not incentivized for conservation.

2.3 Randomization

Randomization was conducted at the level of farmer-sharing group: that is, the set of farmers who mentioned at the baseline survey that they used any common irrigation sources. By randomizing at the sharing group level, we minimize the possibility that conservation credits will spillover to control farmers.

Randomization was stratified by forecasted hours of irrigation and size of water-sharing group. Specifically, the final sample of water-sharing groups was ordered first by number of farmers, and second by forecasted hours of irrigation.[5] Groups were randomly

[4] A price of 50 INR per hour is approximately equal to the unsubsidized average cost of electricity supply in Gujarat for the median pumpset in our sample. That is: (5.4 INR/kWh average cost of electricity provision in Gujarat) * (5 hp pump brake power) / (40% typical motor efficiency) * (0.75 kW/HP conversion factor) = 50 INR/hr. The Punjab program offered an incentive of 4.0 INR/kWh, which translates to different per-hour prices for different farmers depending on pump power, but would be approximately 37 INR per hour for the median pumpset in our sample. For more details on this calculation see Section 3.2 and Table 5.

[5] Forecasted hours of irrigation were created using a random forest using baseline survey data and geological mapping data. Forecasts were fit using a sample of farmers in Saurashtra from a previous project.

allocated in equal proportion between the Control and Conservation Credit arms using a pseudo-random number generator (Stata software) within each ordered pair. Pairs were then combined into ordered cells of eight farmer-sharing groups, within which the four groups allocated the Conservation Credit arm were randomly allocated in equal proportion between the four Conservation Credits sub-treatments.

3 Data and Summary Statistics

3.1 Data Sources

Our analysis rests on data from two sources: a baseline survey and meter reading data. First, we conducted a baseline survey with both self-reported and field measurement components prior to randomizing participants into treatments. Self-reported data include demographic and socioeconomic characteristics, such as landholding size and household size; cropping, crop management, and irrigation decisions in the previous year; the power of the primary pumpsets; and water conservation strategies and attitudes. Field measurements include the precise geolocation and depth-to-water of each well on the participant's largest farm where measurement is safe and feasible. We also collect the names and contact details of any farmers who use water from the primary farm or whose water is used on the primary farm in order to sort our sample into water-sharing groups consisting of all farmers who are connected through water sharing relationships. Baseline data was collected electronically through tablet surveys.

Second, we directly measure groundwater pumping for all study participants using hours-of-use meters installed on the pump starter of each participant's primary irrigation source.[6] Surveyors recorded meter readings each month using a digital tablet survey. Meter data quality was assured through random audits, in which a research associate compared the digitally recorded meter readings with dated, geo-located photographs of the meter dial included on the tablet survey.

3.2 Outcome Variables

Our primary outcome variable is monthly hours of groundwater irrigation. Meters show cumulative duration of pump operation, so we calculate monthly irrigation hours as the difference between values shown on the meter at the current visit and previous month's visit. Because not all meter-reading visits occurred at exact monthly intervals, we rescale

[6] Analog hours-of-use meters manufactured by Nishant Engineers (model: NE53/6S).

observed hours to a 31-day rate so that observations are comparable across farmers and months.

Our secondary outcome variable is energy consumption in irrigation. Energy use is not observed directly but rather converted from hours of irrigation using known functional relationships from physics. The formula is:

$$E = \frac{P_b}{\eta_m} \times t \tag{2}$$

where E is energy consumed, t is duration of pump operation, P_b is the power rating of the pump's motor ("brake horsepower"), and η_m is the motor efficiency, a unitless constant between zero and one.[7]

We collect t and P_b in meter-reading and baseline surveys. Motor efficiency η_m is difficult to measure accurately and would have required use of electricity meters, with which many study participants were uncomfortable. Instead, we draw an estimate of motor efficiency from the literature in the most similar setting we can find: 40 percent (Mitra et al., 2023).

Note that our energy use variable is not simply a monotone transformation of irrigation hours, since it also depends on pump power, which varies across farmers. That said, pump power does not endogenously respond to the program,[8] so energy use can be seen as a rescaling of units combined with a reweighting of farmers within the sample. Either way, average treatment effects may be substantively different if individual treatment effects are heterogeneous and correlated with pump power. Similarly, individual-level price elasticities of demand for energy and hours are equal, but aggregate price elasticities may differ due to this reweighting.

3.3 Descriptive Statistics and Balance Checks

Descriptive statistics. Table 1 reports baseline characteristics of the experimental sample. In both this table and all subsequent analysis, the sample is restricted to farmers who completed all rounds of data collection: the baseline survey, meter installation, the baseline meter reading, and all three meter-reading visits during the intervention.

[7] To obtain E in kilowatt-hours (kWh) when P_b is measured in horsepower (hp), the formula also requires the unit conversion of 0.7457 kW per hp.

[8] In a longer-term incentive program, farmers could make investments in new pumps. Our program lasted for only one irrigation season, and participants were unable to replace a pump without removing the meter and becoming disqualified from the program.

Our sample consists predominantly of smallholder farmers; the mean plot area of their primary farm is 1.95 hectares.[9] Most participants are literate, have completed primary and secondary education, and identify with a "scheduled caste/scheduled tribe/other backward caste" designation. Only half own a plow or tractor. Cotton is the primary crop in our sample, with sorghum/millet, groundnut, and pulses as the next most common crops. Farmers are at least somewhat diversified in their crops, with a mean count of distinct crops around 2.

Most participants have only one active well; some have two. Some wells are dugwells and others are borewells (tubewells); the most common type of well is a dug-*cum*-borewell, in which a borehole is drilled into the bottom or side of a dugwell in order to access additional pockets of water. The average well is 59 meters deep, but many are considerably deeper. The most common electric pump installed in each well is rated at 5 horsepower, but some are more powerful.

Many farmers in our sample are already using cultivation practices that conserve water. 41 percent use a drip irrigation system, 69 percent use raised beds, and 19 percent use rotational, strip, or zero tillage. Local water markets are rare in our context: Only 1 percent report having purchased water for irrigation. Farmers sometimes share irrigation sources with neighbors, usually relatives, but water sharing is not a large share of irrigation in our sample: About 10 percent of pump operation during the previous (2021-22) irrigation season was directed to irrigation off the primary farm, which includes both neighbors and secondary farms also held by the respondent.

Balance. Columns 3 and 4 of Table 1 report means of baseline characteristics separately for the overall treatment and control groups. The two groups appear similar across all characteristics. We formally check for balance test between the main treatment and control groups using a Wald F-test for joint orthogonality of all characteristics reported in this table. The F-statistic is small and the p-value is large, so we fail to reject the null hypothesis that treatment-control differences are zero for all characteristics.

Our sample includes more farmers in the treatment group than in the control group, implying that attrition rates were different across the two groups. Differential attrition would bias the results if attrition is correlated with characteristics that predict the outcome variable. But we do not see evidence that the treatment and control groups are differentially selected across a range of baseline characteristics.

[9] The Indian government typically defines farmers holding less than 2 hectares as "small and marginal farmers".

4 Program evaluation

We first evaluate our conservation payments program as implemented, by estimating intent-to-treat (ITT) effects of eligibility for the overall intervention. We estimate OLS regressions of the following form:

$$Y_{it} = \alpha_t + \tau \cdot \text{ConservationCredits}_i + \gamma' \mathbf{X}_{it} + \varepsilon_{it}, \tag{3}$$

where Y_{it} is a outcome variable for farmer i at monthly visit t, and $\text{ConservationCredits}_i$ is an indicator for being in the overall treatment group and therefore eligible for payments. X_{it} is a vector of individual-specific covariates chosen by post-double-selection LASSO (Belloni et al., 2013),[10] with each chosen covariate centered and interacted with the treatment variable (following Lin (2013) and Athey and Imbens (2017)). Standard errors are clustered by randomization pair (following de Chaisemartin and Ramirez-Cuellar (2024)), which nests months within farmer and farmers within groups of neighbors that reported sharing water prior to the intervention.[11]

Since our primary outcome variables are right-skewed, we also estimate the same specifications as Poisson regressions, following Chen and Roth (2024):

$$Y_{it} = \exp\{\alpha_t + \tau \cdot \text{ConservationCredits}_i + \gamma' \mathbf{X}_{it}\} \cdot u_{it}, \tag{4}$$

Estimated via pseudo-maximum likelihood, Poisson regressions have the potential to more precisely estimate regression-adjusted treatment effects when covariates have multiplicative effects on the outcome. They directly recover a transformation of the average treatment effect as a proportion of the control mean (Silva and Tenreyro, 2006).[12]

4.1 Conservation payments reduce irrigation time and energy use

Table 2 presents estimated effects of overall program eligibility on hours of irrigation, the variable directly measured by our meters. Our preferred estimate is the covariate-adjusted specification in column (3): Farmers assigned to the program operated their

[10] We implement post double-selection LASSO in Stata with the user-written commands pdslasso and ivlasso (Ahrens et al., 2018).

[11] We omit randomization pair fixed effects following Bai et al. (2023), who show that they complicate the interpretation of the estimand and do not necessarily reduce bias from differential attrition.

[12] Our primary outcome variables sometimes take a value of zero, so we cannot run log-linear OLS regressions. We avoid other "log-like" transformations, such as the inverse hyperbolic sine, because they are sensitive to the choice of units (Mullahy and Norton, 2023) and because any notion of an individual-level percentage change is undefined for a variable that admits zero (Chen and Roth, 2024).

pump for an average of 11 fewer hours per month during the intervention period than control-group farmers. This effect represents a 24 percent reduction relative to the control-group mean of 47 hours per month, and the 99% confidence interval excludes zero.[13]

Results are broadly robust to alternative specifications. Column (7) shows the same specification as column (3) but estimated using Poisson regression, indicating that the program led to a 17 percent reduction ($e^{-0.19} - 1$) in irrigation hours. Estimates are less precise without covariate adjustment (columns (1) and (5)) but the 90% confidence intervals still exclude zero. Columns (2) and (5) include village fixed effects and no other covariates, a parsimonious example of a fully saturated regression model. We include this specification to confirm that the main result is similar in a specification guaranteed to be unbiased for the average treatment effect even in finite samples (Athey and Imbens, 2017).

Effects on energy use are shown in Table 3. Again our preferred estimate is in column (3): Program eligibility reduced energy use by 151 kWh per month, a 25 percent reduction compared with a control-group mean of 611 kWh per month. Alternative specifications are broadly consistent though less precise than the irrigation hours regressions. Point estimates without covariate adjustment are much smaller but so imprecise that we cannot reject equality with our preferred specification.

4.2 Treatment effects increased over time

To investigate seasonal patterns in treatment effects, we augment our primary regressions to estimate separate treatment effects in each month of the program. Results are plotted in Figure 4 for both OLS and Poisson estimates of our preferred specification, which includes controls selected by double LASSO.

Average effects of the program increased in magnitude over the course of the experiment, from 7 hours in the first month to 12 and 14 hours in the last two months of the program. (We can reject that the first and second, or the first and third months, are equal, at a 5 percent significance level.) These differences are even more dramatic when expressed as a percentage of the control mean, which declined over time. Treatment effects estimated using Poisson regression increased from 5 percent in the first month to 21 and 28 percent in the second and third months.

We see two likely explanations for the growing response over time. One possible reason is increasing trust in the program. Because the conservation credits program was

[13]Covariates included in this regression are selected by double LASSO: Baseline hours of irrigation (i.e., between meter installation and the intervention visit), depth of deepest well, indicators for whether the farmer's deepest well is a borewell or a dug-cum-borewell, and indicators for four specific villages.

a completely new concept, it seems likely that participants would have changed their behavior only tentatively in the first month. After they saw real cash appear in their bank accounts, they responded less cautiously. Another possible reason is that demand for irrigation becomes more elastic later in the growing season. For many crops, water application is most critical during an early phase of growth. After this early phase, yields may be less sensitive to irrigation amounts, and so farmers would become more sensitive to the price of irrigation. We do not currently have data to distinguish between these explanations, but we expect both are at play.

4.3 Higher prices have little additional effect

Next, we go beyond the effects of the program overall to investigate whether the level of price incentive affects irrigation behavior, conditional on program participation. We compare the high- and low-price sub-treatment groups by interacting the overall treatment variable with an indicator for being in the high-price subgroup.[14] The results are in columns (4) and (8) of Tables 2 and 3.

Across specifications and outcomes, the main effects of the program remain large and statistically significant, while the interaction effects are smaller and not statistically significant. This says that being offered a price incentive of 50 INR per hour, relative to not being offered a price incentive at all, has a greater effect on conservation than increasing the price from 50 to 100 INR per hour. This result is consistent with a convex demand curve: There may be many low-cost opportunities to conserve water and energy resources that are left on the table when marginal resource prices are zero but adopted when prices are positive, but once that low-hanging fruit is picked, resource conservation faces more rapidly rising opportunity costs.

While none of the interaction effects are statistically significant, the magnitude of the point estimates vary considerably across specifications and outcomes. The Poisson estimate for hours of irrigation suggests that higher prices have no independent effect, while the OLS estimate for energy use is about two-thirds as large as the main effect of the program. We expect future versions of this paper will be able to improve precision and resolve these discrepancies by incorporating additional covariates and applying double debiased machine learning to relax functional forms of the regression adjustment.

[14] We also interact all centered covariates with this sub-treatment indicator.

5 Demand estimation

We now use the experimental variation introduced by our program to estimate the slope of demand for groundwater irrigation. The idea is that in a program of payments for voluntary conservation, not all farmers are actually marginal to the incentive, unlike as they would be under a universal volumetric electricity price or groundwater pumping fee. Even for farmers offered payments, the marginal price is zero for those who pump for more hours than the benchmark, as well as for those who reach the maximum payment. Figure 5 illustrates these cases relative to the budget set created by a conservation payments program.

As a result, the treatment effect depends on specific design parameters of our program: price, benchmarks, and maximum payments. In contrast, a demand model gives us potentially more generalizable information as to how the farmers in our sample would adjust their irrigation behavior under other types of programs.

To estimate demand, we estimate instrumental variables regressions of irrigation on price, instrumenting for price with the experimental treatment groups:

$$Y_{it} = \alpha_t + \beta p_{it} + \gamma' \mathbf{X}_{it} + \varepsilon_{it}, \tag{5}$$

where $p_{it} \in \{0, 50, 100\}$ represents the effective marginal price of an hour of irrigation faced by farmer i in month t. Effective marginal price in each month is zero for control-group farmers, for treatment-group farmers who did not receive a payment, and for treatment-group farmers who reached the maximum payment. For farmers who received a payment that was less than the maximum, their effective marginal price is the price offered to them, depending on their sub-treatment group (50 or 100 INR per hour).

To boost precision while avoiding overfitting and weak instruments concerns, we use the instrumental variables LASSO method of Belloni et al. (2012). Our set of candidate instruments consists of indicators for each of the four conservation credit sub-treatments, and their interactions with baseline characteristics. We again include month-specific intercepts, choose covariates using double-LASSO, and cluster standard errors by randomization pair.

Intuitively, IV estimates take our ITT estimates and scale them by the fraction of the sample who was in position to respond to the price incentive. Benchmarks were set too low for many farmers to reach, and too high for other farmers, such that they would have reached the maximum payment even without behavior change. The IV estimates instead attribute the full program response to the farmers for whom benchmarks were set appropriately enough to affect their behavior. This method is in the spirit of quasi-experimental estimates of the elasticity of taxable income from non-linear budget sets (as summarized by Saez et al., 2012) and of electricity demand (Ito, 2014).

5.1 Results

Table 4 reports results. Column (1) reports the first-stage relationship for an IV specification with only one instrument: overall eligibility for the conservation credits program. The estimate says that the average effective marginal price in the treatment group was 42 INR per hour.[15] This first-stage relationship is strong, with a very large F-statistic.

Column (2) shows the IV estimate with this one instrument and no covariates, while specifications in columns (3) and (4) add instruments and covariates. Moving across the table, first-stage F-statistics remain strong, while the IV estimates gain precision. Our preferred estimate is in column (4), in which both instruments and covariates are selected by double LASSO. The coefficient of -0.19 implies that average monthly irrigation hours fall by 1 hour for every 5 INR increase in the hourly price. At the middle price of 50, and the control mean of irrigation hours, this implies a price elasticity of 0.20.

We also use this IV approach to plot a demand curve in Figure 6. To construct this graph, we estimate an IV regression with two endogenous variables – indicators for facing marginal prices of 50 and 100 INR/hour – and instruments and controls again chosen by double LASSO. We then plot fitted values from this model at prices of 0, 50, and 100.

One limitation of these IV estimates is that they may overstate the true price elasticity. The exclusion restriction is that the program affected irrigation only through the effective marginal price at the end of the meter reading period. This assumption will be violated if the program affected irrigation for farmers who do not end up facing positive marginal prices in a given month – for example, if they attempted to conserve below the benchmark but failed to reach their target. This is a fundamental limitation of this method for estimating demand.

However, we can still bound the price elasticity using the IV and reduced-form estimates. The IV estimate loads the entire reduced-form effect of the program onto the fraction of farmers with a positive effective marginal price. If some farmers change their behavior but are not observed in this group, then the true proportion of farmers affected by the program is greater than indicated by the first stage. On the other hand, it is unlikely that all farmers in the treatment group were affected by the program, so the true proportion is less than 1. The true price elasticity is then bounded above by the IV estimate, and

[15] This value represents a weighted average of the proportion of each group that was marginal, multiplied by the price offered. We separately calculate that 58 percent of farmer-months in the sample faced a positive marginal price.

bounded below by the reduced-form estimate: $(0.16, 0.20)$.[16]

6 Cost-effectiveness

Finally, we consider the cost-effectiveness of the conservation credits intervention as implemented in the study, from the perspective of an electricity utility. For now we set aside the social costs of groundwater depletion and focus solely on energy. Suppose political constraints rule out straightforward volumetric prices for electricity. Might a utility company find it less costly to reduce demand via a conservation payments program than to increase supply by procuring additional electricity?

We calculate the cost of reducing electricity demand through this program as the ratio of total expenditures on conservation payments to total energy conserved. Note this ratio is not just a rescaling of our demand estimates, because it includes payments made to inframarginal farmers. For total energy conserved as a result of the program, we use the preferred OLS estimate from Table 2 because it is more precise than the Poisson estimate. Table 5 shows further details of this calculation, parameters used, and results.

We estimate that the conservation credits intervention reduced electricity use at a cost of 6.1 INR per kWh conserved. This value appears to be similar to published estimates of the costs of electricity procurement. It is slightly greater than the average cost of electricity procurement per unit sold by the electric utility in our study area, 5.4 INR per kWh, but the marginal costs of electricity procurement are likely greater than than average costs. It is also lower than the cost of electricity procurement in the nearby state of Punjab.

In this calculation, we only consider expenditures on conservation payments and omit other program costs such as meter hardware and personnel and travel expenses for reading meters. We do so for two reasons. First, electric utilities obtain other benefits from metering their customers, so we prefer to consider the perspective of a utility that is already collecting this data. Second, metering costs in a permanent program would likely be lower than in our short-term intervention. It would likely be more cost-effective to install smart meters that can be read remotely, saving the labor and travel expenses, the fixed cost of which would then be amortized over a longer period.

It is also worth considering the social costs of groundwater depletion and of air pollution from electricity generation. A utility company may not include these costs in a cost-effectiveness calculation, but a government may want to consider them as motiva-

[16] Scaling the ITT effect of -11 hours by the average price offered in the treatment group (75 INR per hour) gives a reduced-form effect of -0.15 hr/INR. At the middle price of 50, and the control mean of irrigation hours, this implies a price elasticity of 0.16.

tion for subsidizing a conservation payments program. Estimating the negative externalities from groundwater extraction is beyond the scope of this study. But even relatively small estimates of these social costs would likely make it socially optimal for a utility to offer conservation payments before expanding electricity supply.

7 Conclusion

This study finds that moderately sized incentives for groundwater conservation lead farmers to reduce groundwater irrigation by approximately 20 percent. Impacts increase over time, indicating that the response to incentives can be sustained. And this is a short-term response: Our program lasted for only one irrigation season and was introduced after crops were already planted. In a longer-term program, the response would likely be even greater, since farmers would be able to substitute crops and adjust other inputs.

These findings suggest that conservation credits, a policy solution similar to existing "payments for environmental services" programs, are an effective tool for managing groundwater and energy resources in India. In many settings — and perhaps especially in the setting of agricultural groundwater extraction in India — Pigouvian taxes may be politically infeasible. By exchanging corrective taxes for subsidies, conservation credits overcome the political barriers to taxing the agricultural sector, while still introducing marginal incentives for conservation. Thus, conservation credits may be a particularly promising policy approach for reducing inefficient groundwater extraction.

We also find that the program effect is large relative to total cost of incentives: as designed, the overall expenditure per unit of energy conserved is similar to the per-unit cost a utility company would face in procuring electricity. This suggests that a utility capable of rolling out conservation credits at low fixed cost could potentially save money if the program were carefully designed. Our program uses a combination of individual-specific benchmarks (set using verifiable baseline irrigation information) and maximum payments to avoid extreme payments for infra-marginal behavior. Yet our program design leaves room for further improvements in benchmark targeting and careful setting of maximum payments. Understanding how to optimally set benchmarks and maximum payments, including understanding the best information to use for setting these parameters, is a key question for future work.

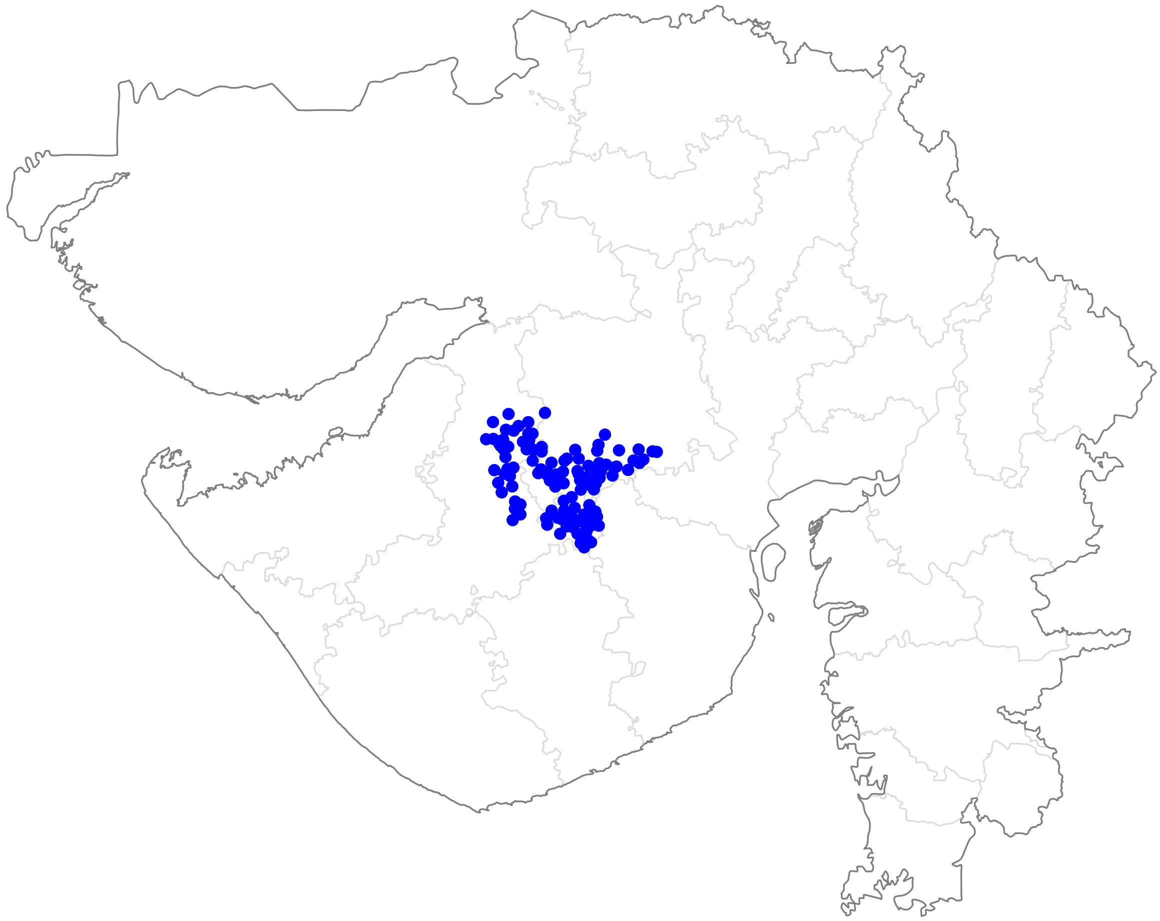


Figure 1: Villages in Study Area

Notes: This figure shows the villages in Gujarat, India where participants were enrolled as blue dots.

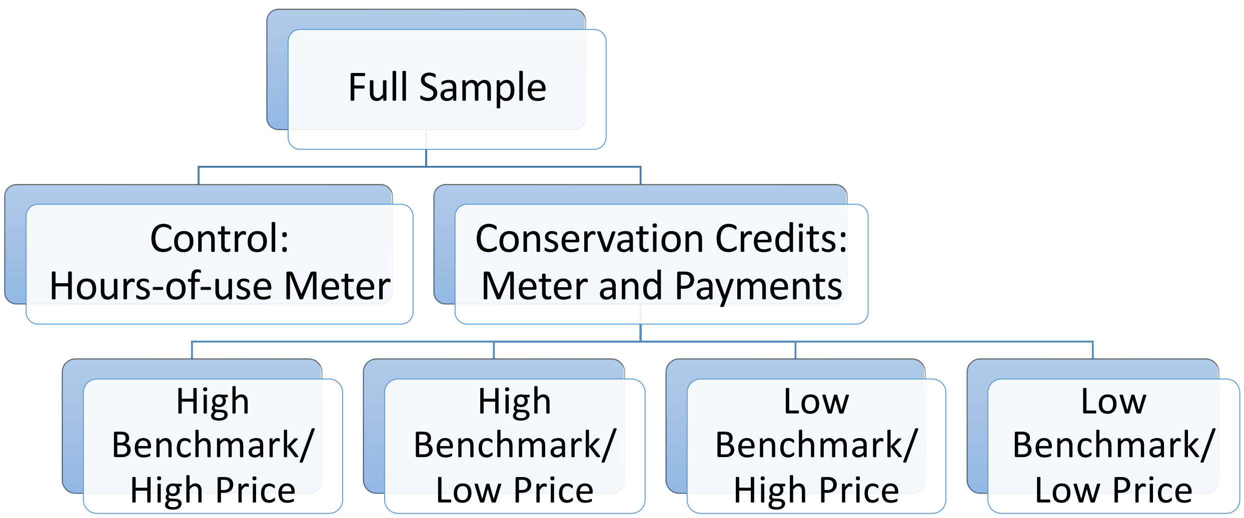


Figure 2: Intervention Design

Notes: This figure illustrates the four interventions used in the randomized experiment. Farmer sharing pools were assigned in equal proportion to the Control and Conservation Credits groups. Within the Conservation Credits group, the four sub-treatments were assigned in equal proportion.

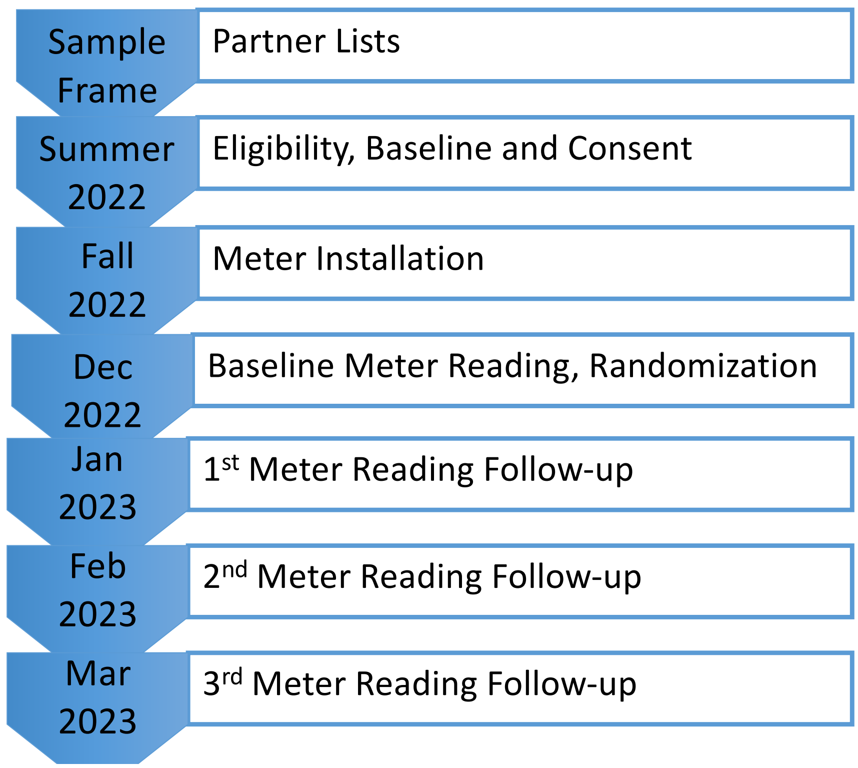
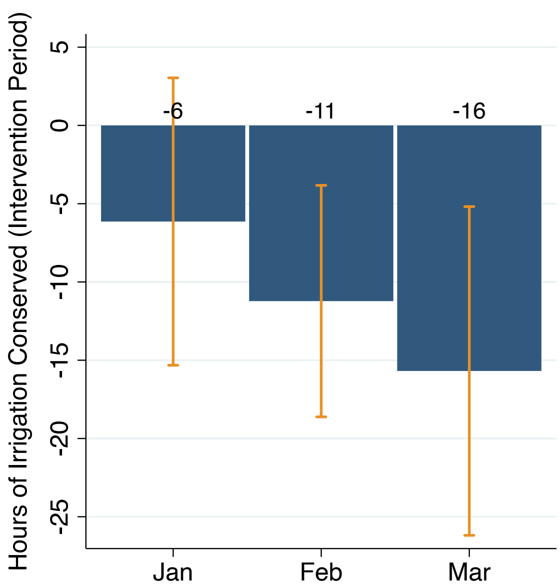
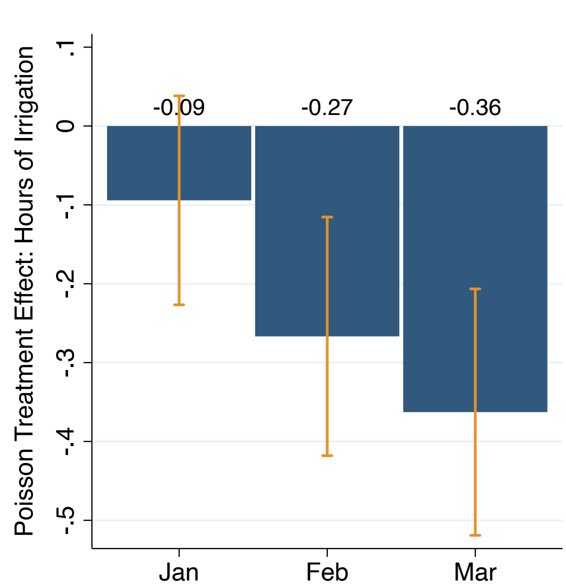


Figure 3: Experiment Timeline

Notes: This figure displays the timeline of our experimental intervention and data collection processes.



(a) OLS



(b) Poisson

Figure 4: Treatment effects of conservation credits grew over time

Notes: This figure plots the treatment effect of offering Conservation Credits on hours of irrigation across the three months of the intervention period. Treatment effects are estimated using double-LASSO selected controls. Error bars represent 95% confidence intervals.

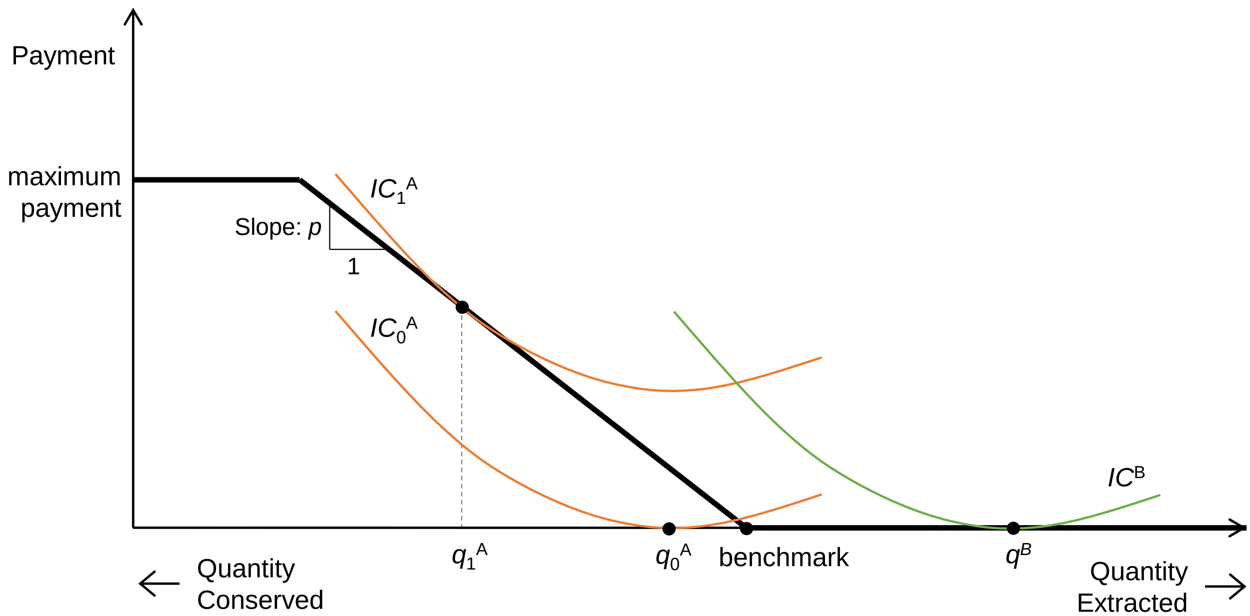


Figure 5: Budget set of conservation credits.

This figure shows the general form of the budget set created by a conservation credit program, along with indifference curves of two representative participants. The payment equals the price p times the quantity units conserved below the benchmark, up to a maximum payment. Irrigator A is marginal and will respond to the program by reducing quantity extracted. Irrigator B is extra-marginal, and does not change quantity extraction in response to the program.

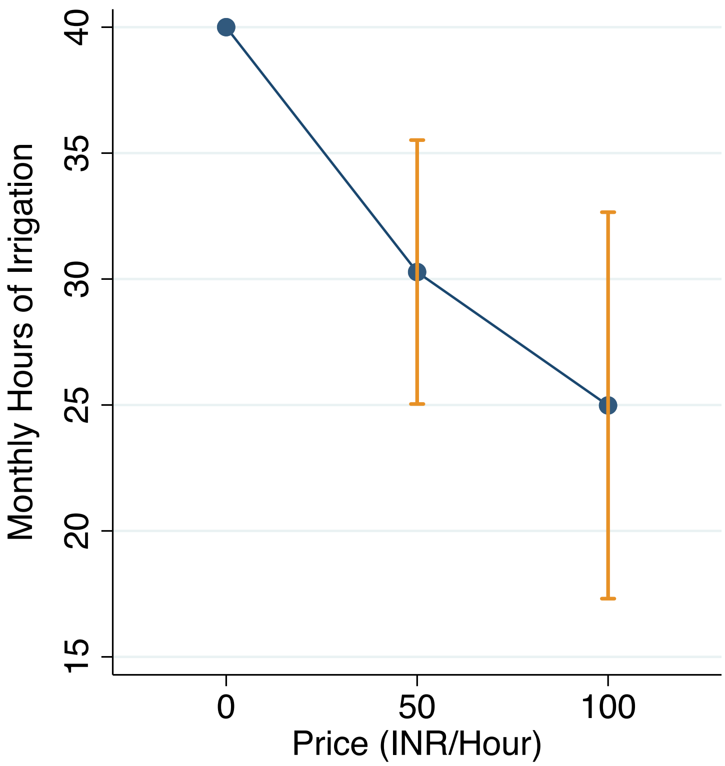


Figure 6: Demand for Hours of Irrigation

Notes: This figure plots the estimated demand curve for groundwater irrigation identified using experimental variation in the marginal price of an hour of groundwater irrigation. Price effects are estimated using instrumental variables regression with double-LASSO selected controls and instruments (selected from our four Conservation Credits sub-treatments and their interactions with selected control variables). Error bars represent 95% confidence intervals.

Table 1: *Baseline Summary Statistics in Full Sample and by Treatment Group*

	Full Sample		Control	Treatment
	(1)	(2)	(3)	(4)
	Mean	SD	Mean	Mean
A. Demographics				
Household size	6.34	2.85	6.46	6.22
Scheduled caste/tribe or other backwards caste	0.86	0.34	0.86	0.87
Muslim	0.09	0.28	0.09	0.09
Years of education (household head)	10.94	3.39	10.88	11.00
Literacy (household head)	0.82	0.38	0.83	0.81
B. Farm statistics				
Plot hectares	1.95	1.35	1.97	1.92
Number of crops cultivated	1.96	1.08	2.01	1.91
Fraction of farmed area planted with cotton	0.53	0.41	0.54	0.53
Fraction of farmed area planted with sorghum/millet	0.15	0.25	0.15	0.16
Fraction of farmed area planted with groundnut	0.15	0.25	0.14	0.15
Fraction of farmed area planted with pulses	0.11	0.21	0.11	0.10
Has cow, ox, or buffalo	0.92	0.27	0.93	0.91
Has plow or tractor	0.50	0.50	0.50	0.50
C. Well Statistics				
Total number of active wells	1.19	0.39	1.19	1.19
Deepest well is dugwell	0.24	0.43	0.23	0.26
Deepest well is borewell	0.25	0.43	0.23	0.27
Deepest well is dug-cum-borewell	0.51	0.50	0.55	0.47
Deepest well: ever deepened	0.17	0.37	0.17	0.17
Deepest well: depth (meters)	58.62	85.17	53.66	63.12
Deepest well: max water level (meters)	16.07	36.60	14.68	17.33
Deepest well: pump power	5.61	3.27	5.46	5.75
D. Irrigation Statistics				
Pre-intervention monthly irrigation hours	71.71	71.09	69.81	73.43
Total self-reported hours of irrigation on farm	340.97	2205.91	327.45	353.25
Total self-reported hours of irrigation off farm	32.46	153.97	32.17	32.73
Purchased water for irrigation	0.01	0.11	0.01	0.01
Used drip irrigation	0.41	0.49	0.42	0.41
Used sprinkler irrigation	0.01	0.10	0.01	0.02
Used raised beds	0.69	0.46	0.69	0.68
Used rotational, strip, or zero-tillage	0.19	0.39	0.17	0.20
Used farm bunds	0.09	0.29	0.10	0.08
Test for joint orthogonality of covariates				
F-statistic			0.64	
P-value			0.93	
Sample size				
Number of individuals	989		471	518
Percent of sample	100.0		47.6	52.4

Notes: This table summarizes baseline characteristics of the sample of farmers who completed all three meter reading survey rounds during the intervention. The F-statistic and associated P-value test the joint orthogonality of all characteristics listed in the table to treatment assignment relative to the control group.

Table 2: Intent to Treat Impacts of Conservation Credits on Hours of Irrigation

	OLS				Poisson			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conservation Credits	-5.97*	-9.92***	-11.1***	-9.10***	-0.14*	-0.23***	-0.19***	-0.21***
	[3.46]	[3.21]	[2.51]	[3.24]	[0.079]	[0.073]	[0.062]	[0.075]
Conservation Credits × High Price				-3.26				-0.016
				[3.50]				[0.086]
Control Mean	46.59	46.59	46.59	46.59	46.59	46.59	46.59	46.59
Month FEs		X				X		X
Village FEs		X				X		
Lasso Controls			X	X			X	X
N Clusters	479	479	479	479	479	479	479	479
N Farmers	989	989	989	989	989	989	989	989
N Observations	2,967	2,967	2,967	2,967	2,967	2,967	2,967	2,967

Notes: The sample includes all farmers who completed all three meter reading survey rounds during the intervention. The outcome is monthly hours of irrigation by the farmer during the three intervention months (scaled to 31 days). Controls, selected by double-LASSO, are baseline irrigation hours, depth of deepest well, indicators for deepest well type, a selection of village dummy variables, and a dummy variable for the final month. Following selection, controls are centered and interacted with the treatment indicator or indicators. Standard errors clustered at the randomization pair level are in brackets.

Table 3: Intent to Treat Impacts of Conservation Credits on Energy Use (kWh)

	OLS				Poisson			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conservation Credits	-23.8	-98.7	-153.0***	-126.8**	-0.040	-0.17	-0.15**	-0.18*
	[70.3]	[64.5]	[42.3]	[53.3]	[0.12]	[0.11]	[0.072]	[0.093]
Conservation Credits × High Price				-81.5				-0.081
				[57.0]				[0.11]
Control Mean	610.81	610.81	610.81	610.81	610.81	610.81	611.25	610.81
Month FEs		X		X		X		X
Village FEs		X				X		
Lasso Controls			X	X			X	X
N Clusters	479	479	479	479	479	479	479	479
N Farmers	989	989	989	989	989	989	988	989
N Observations	2,967	2,967	2,967	2,967	2,967	2,967	2,965	2,967

Notes: The sample includes all farmers who completed all three meter reading survey rounds during the intervention. The outcome is monthly kWh of energy used for irrigation by the farmer during the three intervention period months (scaled to 31 days). Energy use is calculated from hours of irrigation as described in Section 2. Controls, selected by double-LASSO, are baseline irrigation kWh, baseline irrigation hours, depth of deepest well, a selection of village dummy variables, and a dummy variable for the final month. Following selection, controls are centered and interacted with the treatment indicator or indicators. Standard errors clustered at the randomization pair level are in brackets.

Table 4: Demand for Groundwater Irrigation: Instrumental Variables Estimation

	First Stage	IV		
	(1)	(2)	(3)	(4)
Marginal Price (INR/Hour)		-0.14*	-0.13*	-0.19***
		[0.080]	[0.078]	[0.046]
Conservation Credits	42.2***			
	[1.44]			
Outcome Control Mean	0.00	46.59	46.59	46.48
CD Wald F-stat		1,562.17	450.7	35.4
Fixed Effects		Month	Month	LASSO
Controls				LASSO
Instruments		Treatment	Sub-Treatments	LASSO
N Instruments		1	4	29
N Clusters		494	494	492
N Farmers		989	989	981
N Observations		2,967	2,967	2,943

Notes: The sample includes farmer-months among farmers who remained in the experiment until the final meter reading. The outcome is the monthly hours of irrigation in each of the three intervention period survey rounds. The marginal price of an hour of irrigation is instrumented using the the overall Conservation Credit treatment in Columns 2, using all four Conservation Credit sub-treatments in Column 3, and using additional high-dimensional instruments selected by double-LASSO in Column 4. Standard errors clustered at the randomization pair level are in brackets.

Table 5: Cost-Effectiveness of Conservation Payments

Parameter	Value	Unit	Source
Panel A: Parameters used			
Pump motor efficiency, from a similar context	40%	-	Mitra, Balasubramanya, & Brouwer (2023)
Unit conversion constant	0.7457	kW per hp	Known constant
Mean duration of intervention	3.7	Months	Meter reading data
Panel B: Calculation of cost-effectiveness			
Average effect of program on electricity use, monthly	-150.8	kWh/month per farmer	Table 2, column (3)
Average effect of program, scaled to rabi season	-552.6	kWh per farmer	Calculated
Average conservation payments, rabi season	3369	INR per farmer	Program implementation data
Average expenditure per unit electricity conserved	6.1	INR/kWh	Calculated
Panel C: Comparisons of cost-effectiveness			
Cost of reducing electricity use through this program	6.1	INR/kWh	From above
Average cost of electricity procurement per unit sold, Gujarat	5.4	INR/kWh	Paschim Gujarat Vij Company Ltd. (2021)
Cost of electricity procurement, Punjab	7.9	INR/kWh	Mitra, Balasubramanya, & Brouwer (2023)

References

Ahrens, A., Hansen, C., and Schaffer, M. E. (2018). pdslasso and ivlasso: Progams for post-selection and post-regularization ols or iv estimation and inference. *Statistical Software Components, Boston College Department of Economics*.

Athey, S. and Imbens, G. W. (2017). The state of applied econometrics: Causality and policy evaluation. volume 31, pages 3–32. American Economic Association.

Bai, Y., Hsieh, M. H., Liu, J., and Tabord-Meehan, M. (2023). Revisiting the analysis of matched-pair and stratified experiments in the presence of attrition. *Journal of Applied Econometrics*.

Belloni, A., Chen, D., Chernozhukov, V., and Hansen, C. (2012). Sparse Models and Methods for Optimal Instruments with an Application to Eminent Domain. *Econometrica*, 80(6):2369–2429.

Belloni, A., Chernozhukov, V., and Hansen, C. (2013). Inference on treatment effects after selection among high-dimensional controls. *Review of Economic Studies*, 81(2):608–650.

Blakeslee, D., Fishman, R., and Srinivasan, V. (2020). Way down in the hole: Adaptation to long-term water loss in rural india. *American Economic Review*, 110(1):200–224.

Börner, J., Baylis, K., Corbera, E., Ezzine-de Blas, D., Honey-Rosés, J., Persson, U. M., and Wunder, S. (2017). The Effectiveness of Payments for Environmental Services. *World Development*, 96:359–374.

Bruno, E. M. and Jessoe, K. (2021). Missing markets: Evidence on agricultural groundwater demand from volumetric pricing. *Journal of Public Economics*, 196.

Burgess, R., Greenstone, M., Ryan, N., and Sudarshan, A. (2020). The consequences of treating electricity as a right. *Journal of Economic Perspectives*, 34(1):145–69.

Chakravorty, U., Dar, M. H., and Emerick, K. (2023). Inefficient water pricing and incentives for conservation. *American Economic Journal: Applied Economics*, 15(1):319–50.

Chen, J. and Roth, J. (2024). Logs with zeros? some problems and solutions. *Working Paper*.

de Chaisemartin, C. and Ramirez-Cuellar, J. (2024). At what level should one cluster standard errors in paired and small-strata experiments? *American Economic Journal: Applied Economics*, 16:193–212.

Fishman, R., Lall, U., Modi, V., and Parekh, N. (2016). Can Electricity Pricing Save India's Groundwater? Field Evidence from a Novel Policy Mechanism in Gujarat. *Journal of the Association of Environmental and Resource Economists*, 3(4):819–855.

Gonzalez-Alvarez, Y., Keeler, A. G., and Mullen, J. D. (2006). Farm-level irrigation and the marginal cost of water use: Evidence from Georgia. *Journal of Environmental Management*, 80(4):311–317.

Hendricks, N. P. and Peterson, J. M. (2012). Fixed Effects Estimation of the Intensive and Extensive Margins of Irrigation Water Demand.

Ito, K. (2014). Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing. *American Economic Review*, 104(2):537–563.

Jack, B. K. and Cardona Santos, E. (2017). The leakage and livelihood impacts of PES contracts: A targeting experiment in Malawi. *Land Use Policy*, 63:645–658.

Jack, B. K., Jayachandran, S., Kala, N., and Pande, R. (2023). Money (not) to burn: Payments for ecosystem services to reduce crop residue burning. *Working Paper*.

Jack, B. K. and Smith, G. (2016). Charging Ahead: Prepaid Electricity Metering in South Africa. *NBER Working Paper Series*.

Jasechko, S., Seybold, H., Perrone, D., Fan, Y., Shamsudduha, M., Taylor, R. G., Fallatah, O., and Kirchner, J. W. (2024). Rapid groundwater decline and some cases of recovery in aquifers globally. *Nature*, 625:715–721.

Jayachandran, S., De Laat, J., Lambin, E. F., Stanton, C. Y., Audy, R., and Thomas, N. E. (2017). Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science*, 357(6348):267–273.

Lee, K., Miguel, E., and Wolfram, C. (2018). Experimental Evidence on the Economics of Rural Electrification. *Working Paper*.

Lin, W. (2013). Agnostic notes on regression adjustments to experimental data: Reexamining freedman's critique. *Annals of Applied Statistics*, 7:295–318.

McRae, S. (2015). Infrastructure Quality and the Subsidy Trap. *American Economic Review*, 105(1):35–66.

Meenakshi, J., Banerji, A., Mukherji, A., and Gupta, A. (2013). Does marginal cost pricing of electricity affect groundwater pumping behaviour of farmers? Evidence from India. *3ie Impact Evaluation Report*, 4.

Ministry of Agriculture of the Government of India (2014). Agriculture Census 2010-11.

Mitra, A., Balasubramanya, S., and Brouwer, R. (2023). Can cash incentives modify groundwater pumping behaviors? evidence from an experiment in punjab. *American Journal of Agricultural Economics*, 105:861–887.

Mullahy, J. and Norton, E. C. (2023). Why transform y? the pitfalls of transformed regressions with a mass at zero*. *Oxford Bulletin of Economics and Statistics*.

Pattanayak, S. K., Wunder, S., and Ferraro, P. J. (2010). Show me the money: Do payments supply environmental services in developing countries? *Review of Environmental Economics and Policy*, 4(2):254–274.

Registrar General and Census Commissioner of India (2001). Census of India 2001.

Saez, E., Slemrod, J., and Giertz, S. H. (2012). The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review. *Journal of Economic Literature*, 50(1):3–50.

Sekhri, S. (2014). Wells, water, and welfare: The impact of access to groundwater on rural poverty and conflict. *American Economic Journal: Applied Economics*, 6(3):76–102.

Silva, J. M. C. S. and Tenreyro, S. (2006). The log of gravity.

Smith, S. M., Andersson, K., Cody, K. C., Cox, M., and Ficklin, D. (2017). Responding to a groundwater crisis: The effects of self-imposed economic incentives. *Journal of the Association of Environmental and Resource Economists*, 4(4):985–1023.

Sovacool, B. K. (2017). Reviewing, Reforming, and Rethinking Global Energy Subsidies: Towards a Political Economy Research Agenda. *Ecological Economics*, 135:150–163.

A Covariates included in LASSO-Selection

The following variables are fed into each double-selection LASSO:

- 121 Village indicators
- 2 Survey visit (i.e., month) indicators
- Average daily hours of pumping in the first month
- Average daily energy use in the first month (calculated)
- Total wells on the primary farm
- Whether deepest well has ever been deepened
- Water level on deepest well
- Whether deepest well went dry the previous Kharif season
- Depth of deepest well
- Indicators for deepest well being borewell or dug-cum-borewell (dugwell is omitted well type)
- Pump power for pump on deepest well
- Number of crops cultivated
- Indicator for above-median number of crops cultivated
- Fraction of farmed area planted with cotton
- Fraction of farmed area planted with sorghum or millet
- Fraction of farmed area planted with groundnut
- Fraction of farmed area planted with pulses
- Total self-reported hours of irrigation on primary farm, previous Kharif season
- Total self-reported hours of irrigation off primary farm, previous Kharif season
- Indicator for whether purchased water for irrigation during previous Kharif season
- Indicator for used drip irrigation previous Kharif

- Indicators for use of raised beds, farm bunds, and low/zero-tillage practices (common water conservation practices)
- Years of education (household head)
- Above-median years of education (household head)
- Indicators for Hindu and Muslim (omitted religion is other)
- Indicator for Scheduled Caste/Scheduled Tribe/Other Backwards Caste