Targeted Subsidies for Water Conservation in Smallholder Agriculture*

Humnath Bhandari†
International Rice Research Institute

Ujjayant Chakravorty‡
Tufts University

Muhammad Ashraful Habib§
International Rice Research Institute

Kyle Emerick¶
Tufts University and CEPR

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Abstract

Groundwater depletion threatens long-term food security in developing countries. Moreover, groundwater pumping contributes to climate change. We evaluate the effect of targeted subsidies for technology to use groundwater more efficiently in agriculture. Using a randomized controlled trial across 360 villages in Bangladesh, we show that subsidies reduce electricity used for pumping by 38 percent, but only when targeted to water sellers. Subsidizing technology to individual farmers has smaller effects. Features of the groundwater market can explain this result. Natural monopolist water sellers charge fixed fees to farmers, but maintain a role in irrigation planning, incentivizing them to adopt conservation practices.

Keywords: Agriculture, Groundwater, Subsidies

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†IRRI Bangladesh Office, 103, Block-F, Rd No 1, Dhaka, 1213, Bangladesh. Email: h.bhandari@irri.org

‡Department of Economics. 8 Upper Campus Rd., Medford, MA 02155. Email: ujjayant.chakravorty@tufts.edu

§IRRI Bangladesh Office, 103, Block-F, Rd No 1, Dhaka, 1213, Bangladesh. Email: m.habib@irri.org

¶Department of Economics. 8 Upper Campus Rd., Medford, MA 02155. Email: kyle.emerick@tufts.edu

1 Introduction

Groundwater access makes agriculture more productive and can reduce poverty in rural areas (Sekhri, 2014; Hornbeck and Keskin, 2015; Jain et al., 2021). But increasing groundwater depletion poses a problem for agriculture (Vörösmarty et al., 2000; Konikow and Kendy, 2005; Rodell, Velicogna, and Famiglietti, 2009; Schewe et al., 2014; Famiglietti, 2014). At the same time, groundwater pumping emits carbon dioxide and contributes to climate change. These issues raise the question of how to use groundwater more efficiently in agriculture?

One key issue is that like other resources, water suffers from common pool problems. As a result, various local institutions emerge to allocate water. For instance, irrigation districts govern allocation to farmers in the American west (Coman, 1911). In less developed countries, collective action by farmer groups can help mitigate the common pool problem inherent in irrigation (Ostrom, 1990). Moreover, market imperfections in developing countries prevent farmers from operating at large scales (Foster and Rosenzweig, 2022). A typical village consists of hundreds of tiny plots cultivated by different people. Water markets emerge in this setting because large fixed costs of drilling create economies of scale, making it efficient for a single pump owner to sell water to nearby farmers.

In this paper, we ask who benefits from resource conservation when markets allocate natural resources? We study a water-saving technology in an environment where water itself has no price, costly will drilling creates a barrier to entry, and a natural monopolist pump owner sells water to farmers. This type of market institution exists in many settings (Jacoby, Murgai, and Ur Rehman, 2004; Wang et al., 2007; Banerji, Meenakshi, and Khanna, 2012; Fishman, Giné, and Jacoby, 2021), but it complicates the benefits (if any) from using water more efficiently. Several possibilities exist. On the one hand, natural monopolist water sellers may be providing *too little* water to farmers. Corrective action in this case can lower welfare (Buchanan, 1969). On the other hand, farmers may enjoy greater profits if technology lowers their water costs. Or, monopolist water sellers may use technology to their benefit if extraction costs are not priced into contracts.

We implement a randomized field experiment to study the distribution of benefits from subsidizing a water-saving technology. The technology is a perforated plastic pipe that is planted into the rice field to plan irrigation based on crop-water needs. Using this pipe is called Alternate Wetting and Drying (AWD). The technology is ideal for our experiment for two reasons. First, subsidies can be efficient because AWD reduces the consumption of electricity, which is priced below its social marginal cost.[1] Second, our setting in Bangladesh exemplifies the case where neighboring farmers obtain water from a monopoly supplier. This allows us to test whether benefits vary when subsidies are available to water sellers, rather than buyers.

To do this, we introduced subsidies in one of three ways. In 105 villages, we went individually to farmers and offered AWD pipes at either an 85 or 55 percent subsidy, which was cross randomized at the village level. In another 105 villages, these same subsidies were offered at a village meeting, giving farmers an opportunity to deliberate on the decision. In the third set of villages, we provided the subsidy offers directly to the owner of the tube well — and not to individual farmers who buy water from the owner. Lastly, 45 villages serve as a control group where no subsidies were offered.

We have two primary results. First, targeted subsidies to tube well owners reduce electricity used for irrigation after two years by 38 percent. Rice yields do not change — indicating an increase in water-use efficiency. The quantity of electricity saved amounts to about 1,200 kilowatt-hours per year, or 11 percent of the annual consumption for an average household in the United States. The program costs amount to 1.7 cents per kilowatt-hour saved, a figure that is in line with the most cost effective interventions to use energy more efficiently in the United States (Allcott and Mullainathan, 2010).

We only find these effects when the subsidies are targeted to water sellers. At first glance, it is counter-intuitive that a water seller would be willing to pay for a technology that decreases the demand for water. But the finding can be explained by how farmers and tubewell owners manage water in a setting with tiny fragmented plots. Specifically, farmers pay a fixed fee per acre of cultivated area to access water. The electricity charges, i.e. the marginal costs of extracting the water, are borne by the tubewell owner. To deal with the principal-agent problem, farmers do not decide on their own when to irrigate. Instead, the owner operates the pump and decides jointly with farmers when the land needs water, often irrigating multiple plots at a time. This way of making decisions creates incentives for the tube well owner — rather than farmers — to use water more efficiently. Our experiment shows evidence that owners respond to these incentives: owners are more than twice as likely to be involved in using the AWD pipes when subsidies are targeted to them, as compared to targeting to individual farmers.

Our second finding is that water sellers do not pass through the cost savings in the

[1] Subsidies are used for energy efficiency in developed countries where taxing electricity is rare (Allcott and Greenstone, 2017). In our experimental setting, the marginal price of electricity for pumping groundwater is about 5 cents per kilowatt-hour. This is around half of the social marginal cost of electricity generation in the United States (Borenstein and Bushnell, 2019). The external costs of electricity consumption in Bangladesh are likely higher because the grid relies more on coal.

form of lower per-acre water prices. The effect of the owner treatment on water prices during the second year is close to zero. The confidence interval on this effect allows us to rule out price decreases of 6 percent or more. We do not find any evidence that tube well owners pass through benefits in other ways, such as through more flexible payment schedules. But the treatments have no effect on rice yields. Taken together, these findings suggest that water sellers have enough control to use the technology to their benefit, without compromising productivity of farmers. Providing water sellers with ownership over technology adoption decisions is therefore more effective than targeting individual farmers who do not face the same incentives.

We show consistency between these findings and a model where monopolist water sellers use first degree price discrimination to extract all surplus from the *effective water* that is absorbed by the crop. Using AWD involves no change in effective water — it just reduces the amount pumped. Therefore, using the technology does not change the profit maximizing water fee.

We contribute to the literature in two ways. First, we show how technological change in agriculture can require targeting agents other than the end user. Standard models of technology adoption assume that farmers make individual profit maximizing decisions for each of their plots. The key barriers to adoption in this case become access to credit, information, and risk-reducing instruments (Magruder, 2018). However, in reality, fragmented landholdings make joint management of resources common. In our case, water sellers play an important role in optimizing the use of water-saving technology. Failing to recognize this role makes policies to promote the technology to individual farmers (the status quo in our sample) ineffective. The issue we study is not unique to water. Smallholder dairy farmers in Ethiopia organize into cooperatives that play an important role in technology adoption (Chagwiza, Muradian, and Ruben, 2016). As another example, mechanizing agriculture can improve welfare (Caunedo and Kala, 2021). But small fragmented plots limit the profitability of some types of mechanization (Wang et al., 2020). Designing interventions that recognize this and coordinate adoption across farmers may allow greater mechanization.

Second, our experiment provides new insights on reducing externalities under a market-based allocation of natural resources. Farmers buy water from other villagers in most of Bangladesh. Such markets exist elsewhere. We show that water sellers — rather than buyers — face short-run incentives to increase efficiency. Subsidies for sellers make technology effective at reducing externalities.

Other policies to reduce groundwater depletion have been limited. For instance, community monitoring of groundwater resources has had mixed success (Cooperman, McLarty, and Seim, 2021; Del Carpio, Alpizar, and Ferraro, 2021). Another approach is to ration electricity. Ryan and Sudarshan (2022) show that rationing can result in the socially optimal amount of pumping. But rationing is still inefficient because it leads to misallocation across farmers. Pigouvian taxes for pumping may then be efficient. Relatedly, Chakravorty, Dar, and Emerick (2021) show that providing AWD to farmers conserves water, but only in places where farmers face marginal prices for pumping. The same incentives exist when farmers have their own wells (Lybbert et al., 2018). Overall, the literature focuses on the individual farmer and her incentive (or disincentive) to conserve. Our work shows that policies directed at sellers can benefit them as well as reduce the external costs of pumping.

2 Conceptual Framework

In this section we provide a simple conceptual framework that helps to further understand the context and motivate the experiment. Specifically, we show how under some circumstances, the AWD technology may lower water use, benefit the tubewell owner through lower electricity costs, yet result in no change in water prices or rice yields.

Since plot sizes are small, it is not economically feasible for each plot to have its own well. That is, water supply in the village is characterized by increasing returns to scale: if a farmer invests in a pump, average costs decline as more water is delivered. Local geography and the fixed costs of installing a pump determine the number of pumps in the village. Water flows by gravity. There may be multiple high points, which necessitate more than one pump per village — as we show below in the data. The tubewell owner is still a monopolist in this segmented market — his buyers cannot obtain water from another well owner without costly investment to transport it.

We make two assumptions about farmer demands for water that match our setting. First, each farmer has the same demand curve. This makes sense in our context because farmers grow the same crop on similar quality plots. Productivity dispersion — and thus heterogeneous water demands — would create an opportunity for the owner to increase profits through price discrimination.[2] Our data show limited productivity dispersion. Within command areas, the difference in (log) rice yields at baseline between the 10th and 90th percentiles of the distribution is only 0.196. This contrasts with work in other agricultural settings where the gap in TFP between the 10th and 90th percentiles of the

[2]Besides identical demands, other reasons exist for uniform prices. For example, villagers find price discrimination to be inequitable, even if the costs of delivering water to certain parts of the command area are higher.

distribution ranges from 0.8 to 1.5 (Gollin and Udry, 2021).[3] The key distinction in our setting is that each command area is small, averaging only 13 acres in size. Farmer productivities are far less heterogeneous within this small area as opposed to across broader geographies.

Second, rice productivity suffers under water stress, but output plateaus at some water level. Over-irrigating rice to the point that output declines requires vast amounts of water. Consistent with this, field trials show that such a production function fits the data well for cereal crops (Grimm, Paris, and Williams, 1987). As a result, demand becomes perfectly inelastic at the quantity of water where output plateaus. Consider such a plot-level demand curve $D^{-1}(q)$ as shown in the left panel of Figure 1, where q represents the "effective" units of water absorbed by the crop aggregated over the entire season (Caswell and Zilberman, 1986). The word "effective" implies that this is the volume of water that reaches the roots of the plant. It is a proportion of the water extracted from the ground, which is a function of distance to the tube well and geography. From the farmer's perspective, demand depends only on the effective water absorbed by the crop, not the amount that gets pumped. Farmers have no willingness to pay for water beyond $\bar{q}$ because that is the region where output has plateaued.

However, in order to deliver $\bar{q}$ units of water, the well owner must supply a larger volume $\bar{q}_s$ that accounts for the losses incurred during irrigation. The difference $\bar{q}_s - \bar{q}$ is the volume of water extracted that ends up not being absorbed by the crop. It depends on a number of factors, including distance of the plot from the well, the height of the plot relative to neighboring plots, and evapotranspiration. Water is moved along unpaved ditches, which can make these losses large for plots furthest from the well (Tolley and Hastings, 1960). In practice, the owner delivers water with a number of irrigations during the season. During each irrigation, the plot is flooded up to the level of a few centimeters.

There are N farmers in the village. The owner offers the following take it or leave it offer to the farmer of the form (q_i, T_i) where q_i is the water delivered on the farm and T_i is the payment per acre the farmer makes per season. Let the farmer's utility function from irrigation be given by $u_i(q_i)$. The farmer accepts this contract if and only if $u_i(q_i) - T_i \geq 0$. The monopolist can extract the total surplus from the farmer by engaging in perfect price discrimination, but can not charge the farmer for the conveyance losses since they are difficult to apportion, especially when he tries to minimize these losses by scheduling water to groups of plots in close proximity. The monopolist must satisfy the added constraint

[3] This comparison is conservative for two reasons. First, we look at variance in crop yields rather than TFP. Second, Gollin and Udry (2021) correct their dispersion estimates for measurement error in survey data. Variance in yield in our sample includes both productivity dispersion and measurement error.

that the aggregate losses from conveyance are no larger than the profits from supplying water. He solves

$$\max_{q_1,..,q_N} \sum_{i=1}^{N} u_i(q_i) - c_i(q_i), \tag{1}$$

subject to the constraint that $\sum_{i=1}^{N} T_i \geq \sum_{i=1}^{N} c(q_{si})$ where q_{si} has an additional subscript i because water sent may differ by consumer. The monopoly must make non-negative profits, that include the cost of conveyance. The textbook solution to this problem is that the monopolist supplies the socially optimal quantity of water and extracts all of the consumer's surplus through the fixed charge. In the figure, if the monopolist extracts $\bar{q}_s$ to deliver effective water $\bar{q}$, then he extracts the entire surplus which is the shaded area A as shown in the figure. Since all farmers are identical, this transfer payment is charged in the form of a seasonal per-acre fee, which we observe in the data to be the same for all farmers in the village.[4]

The right panel in Figure 1 shows the aggregate demand for the whole command area, and the average and marginal variable costs of water supply. The owner faces a constant cost of electricity, which is the only variable input to supplying water. Thus, marginal costs are constant. We denote the aggregate quantities for effective water and water supplied, as $\bar{Q}$ and $\bar{Q}_s$, respectively. Note that area B — the shaded area below the demand curve and above the MC curve — denotes the producer surplus on effective water obtained by the monopolist.

The monopolist maximizes profits by providing $\bar{Q}$ units of effective water, as long as marginal costs intersect the demand curve below the point at which it becomes perfectly inelastic. But the owner has imperfect information on how much water needs to be supplied for the crop to receive this amount. The foregone profit from providing less than $\bar{Q}$ can be high because this would require the owner to reduce per-acre fees. As long as the marginal cost of pumping is low, which is likely the case due to electricity subsidies, it is better for the owner to "play it safe" and ensure that each field receives at least the optimal amount.[5] We show the amount of water extracted as $\bar{Q}_s$. The owner earns a producer surplus equal to area B, but pays for electricity to pump water that is not effective, which lowers aggregate surplus by areas C+D.

Now we consider the role of the AWD technology. Being able to see the below-

[4]If farmers' demand curves were not identical, e.g., due to their differential productivities, the monopolist may still levy a uniform per acre fee, but some farmers may be unable to pay this seasonal rate if their surplus was lower. This may explain why some plots are left fallow during the cropping season as observed in the satellite data.

[5]The per-unit cost of electricity for agricultural users in our sample is \$0.05 per kwh. The average generation cost, not including other sources of variable costs, is \$0.074 per kwh (USAID, 2021).

ground water level allows the owner to reduce the total number of irrigations. Irrigating less frequently saves on distribution losses. The aggregate volume of water declines from $\bar{Q}_s$ to $\hat{Q}_s$, the extent of the reduction may differ among individual plots. The aggregate losses to the owner now fall to area C. However, the volume of effective water delivered to each farmer remains the same, meaning that yield is unaffected. Consumer surplus remains the same and thus the monopolist can maintain the per-acre water fee of T_i, as before the treatment.

The figure illustrates a case where the AWD tool reduces the consumption of electricity by helping the owner to determine the amount of applied water to achieve effective water $\bar{Q}$. However, a different scenario would yield the opposite prediction. The owner chooses the value of $\bar{Q}_s$. If they are providing too little water, then the amount of effective water before the treatment will be less than $\bar{Q}$. In that case, using AWD will inform the owner that more applied water is needed. This increases the fixed payment T_i, crop yield, and the amount of electricity used.

In sum, the conceptual framework clarifies two possible scenarios: one where the AWD tool conserves electricity and one where it could increase electricity but allow the owner to extract more consumer surplus from farmers. Motivated by this framework, our experiment investigates how technology changes the equilibrium in water markets. In particular, we can compare the size (and sign) of area D across the different approaches to subsidizing AWD.

3 Experimental Design and Data

Sample, Baseline Data Collection, and Interventions

Our experiment takes place in 360 villages in the Mymensingh and Kishoreganj districts of Bangladesh. Our partner NGO helped identify 40 villages in each of 9 upazilas. To be included, the villages needed to be using electricity to pump groundwater for production of boro (dry-season) rice. Once in the village, a surveyor first identified all of the electric pumps currently in use. The average number of active pumps was 2.6 per village. When there were multiple pumps, we randomly selected a single one to be included in the experiment. The resulting sample has 360 unique villages / pumps / command areas.[6]

A surveyor first did a village-level baseline with the pump owner. These surveys took place in December 2018. We collected the names of all farmers buying water from

[6]The command area is the land that draws water from the pump. We use the terms village, pump, and command area interchangeably throughout the text.

the pump, the GIS boundaries of the command area, the GIS coordinates of the pump, and water prices during the most recent season. We then randomly selected eight people for a farmer-level baseline. This amounts to roughly half the farmers from the command area. The survey included questions about agricultural production during the previous year, the relationship between the farmer and tube well owner, and information on who decides when a field should be irrigated.

Traditionally, farmers and tube well owners decide when fields should be irrigated. The standard practice is to irrigate, wait for several days until there is no more standing water, and then re-flood the field. The AWD device provides more information on when water should be re-applied. Specifically, it allows one to see how much water is below the surface of the soil. Rather than re-flood the field right away, the pipe allows the farmer to wait until the water level is 15 centimeters below ground level. By extending the periods of drying, using the tool reduces the total amount of water applied throughout the season. Agronomic trials find that using AWD reduces water use by at least 30 percent without changing crop yield (Yao et al., 2012; Howell, Shrestha, and Dodd, 2015).

We delivered the interventions at the time of planting for the boro rice crop, which the median village in our sample plants on January 20th.[7] Right before this time, we offered subsidized AWD pipes in the treated villages. Using the nine upazilas as strata, we randomized our sample of 360 villages into four groups. First, 45 villages (5 per upazila) make up the control group.

Second, we offered AWD subsidies directly to farmers with door-to-door visits in 105 villages, i.e. 11-12 villages per upazila. This arm of the experiment mirrors the status quo where government extension workers target new technologies to farmers. In our case, someone went to each farmer's house, told them how the AWD device works, and offered it to them at the subsidized price.

The third arm provided the same subsidies and information, but the enumerator gave the offer only to the tube well owner. We allowed the owner to choose their desired quantity, with the upper limit being the total number of farmers in the command area. This arm of the experiment provides a test of whether the technology is used more effectively by water sellers, as opposed to farmers. It contrasts a standard model where the farmer makes technology decisions based on individual returns with one where another villager is involved in those decisions.

Fourth, we organized village meetings in the last group of 105 villages. As we show

[7] Planting dates do not vary much within villages. At baseline, village fixed effects explain 78.4% of the variation in planting dates. Boro rice requires irrigation. Planning irrigation requires crops to be at a similar stage of growth, making it necessary for farmers to plant at the same time.

below, irrigation management involves collective decision making. We had enumerators invite all farmers in the command area to the meeting. The tube well owner has land in the command area in most cases. As such, the owner was often part of the meeting. We offered subsidies at the meeting as a way to facilitate joint decisions on adoption and use. We hypothesized that meetings would allow farmers to plan and jointly decide whether to purchase and how to use the AWD pipes. This could make the subsidies more effective because irrigation water is frequently delivered to multiple farmers at a time.

We offered the AWD pipes at a random price of either 30 or 60 Bangladeshi Taka (approx. 85 BDT = 1 USD). These correspond to subsidies of 77 and 55 percent, respectively.[8] For logistical reasons, the price was randomized at the union level, of which we have 57 in the experiment.[9] Of the 105 door-to-door villages, 55 received the high subsidy and 50 received the low subsidy. There are 54 high subsidy and 51 low subsidy meeting villages. The sample sizes are 58 and 47 for owner villages.

Our teams returned one year later around December 2019 to again offer subsidized AWD pipes in the 315 treatment villages. We did this for two reasons. First, farmers do not always save the pipes for use next season, even though they can be re-used. Second, the additional visit allows farmers or water sellers to purchase pipes to use on more land — especially if the first year was a trial period. The subsidy amounts remained the same in each village. Villages stayed in the same treatment group for how the subsidies were offered.

Baseline Summary Statistics

Table 1 shows baseline characteristics across treatment arms.[10] The table shows three notable features of our sample. First, each pump covers a small amount of land where many farmers manage contiguous plots. The average pump in the control group irrigates about 13 acres and serves 16 farmers. Farmers cultivate an average of 0.71 acres in the command area during the dry season. These 0.71 acres usually consist of more than one plot.[11] As a comparison, 40 acres is a standard plot size in the U.S. midwest. In our setting, that amount of land would be cultivated by almost 50 farmers (see Figure S1 for a visual of this comparison).

[8] In Chakravorty, Dar, and Emerick (2021), we asked 10 shop owners for quotes to produce AWD pipes. Each shop owner provided quotes for two different randomly determined quantities. The estimated marginal cost from these data is 133 BDT per AWD pipe.

[9] Unions are administrative units one level above villages, but one level below upazilas.

[10] The variation across subsidy levels turns out to be less important for our results. We compare characteristics across the three main treatment arms.

[11] The average number of plots in the command area is 2.45 per farmer.

Second, multiple plots can be irrigated at a time. We asked each farmer about how irrigation is managed for one of their randomly selected plots in the command area. Almost 36 percent in the control group respond that the plot is irrigated at the same time as other plots, *which are cultivated by other farmers*.

Third, the tube well owner helps decide when to irrigate for 74 percent of plots. The owner decides on their own in 42 percent of cases, while it is a joint decision the remaining 32 percent of the time. Owner involvement correlates strongly with the practice of irrigating multiple plots at a time. Approximately 24 percent of plots where the owner is not involved are irrigated jointly with others. This figure increases by almost 75 percent to 41.8 percent when the owner helps decide when to irrigate. Overall, these descriptive statistics show that coordination and planning around irrigation for a single plot includes multiple people including, sometimes exclusively, the water seller.

Electricity Data Collection

We use the amount of electricity used by the pump as our main outcome variable. Electricity fuels groundwater pumping. Electricity generation emits greenhouse gases and electricity in our sample is priced below its social marginal cost. Subsidizing technology to pump less groundwater aims to reduce this externality.

Our survey teams measured electricity usage directly over the next two seasons. Starting in the first year, we obtained an initial reading of the electricity meter. Most of these readings were done in December 2018 and January 2019. A surveyor recorded the value on the meter and took a picture for verifying consistency with future readings. We repeated this process two more times, once in March and another time in late April right before the harvesting time. Based on this timing, we use the reading from late April as the end-of-season electricity observation.

While electricity provides an objective measure of groundwater pumping, we did not obtain two usable electricity readings for some villages. There are a few common reasons. The meter can stop working and need to be replaced in the middle of the season. In some cases, the incorrect meter was read at either the beginning or end of the season. Whenever possible, we extracted the missing data from a copy of the electricity bill, which we viewed during a later survey with the tube well owner. Overall, we obtain first-year electricity usage for 307, or 85 percent of villages.

Enumerators repeated a similar process during the second year. The initial readings were taken towards the end of January or in early February. The final readings were taken in June of 2020, a few weeks after harvesting. We again relied on electricity bills in cases where they could provide information to correct malfunctions or incorrect meter readings. We have second-year electricity usage for 305 of the 360 villages. Table S1 shows that the missing outcome data is uncorrelated with treatment.

Followup Surveys

We collected follow up surveys after both the 2019 and 2020 seasons. For both seasons, we surveyed the same 8 farmers that participated in the baseline. A total of 2,820 farmers were surveyed in July of 2019, after the first year of the study. We attempted phone surveys with the same farmers again after the 2020 season in September, but surveyors were only able to reach 2,242 (79.5 percent) of the sample.[12]

We used surveys with the tube well owners to collect other village-level outcomes. Our first survey in July 2019 collected information on water prices, how many people negotiated prices, who negotiated prices, and salaries paid to linemen who manage irrigation. We did a similar phone survey with owners after the second season in June 2020.

4 Results

4.1 Regression Specification

Our main analysis regresses each outcome on treatment indicators, upazila fixed effects, and individual- or village-level controls. We use the following specification:

$$y_{vs} = \beta_0 + \beta_1 owner_{vs} + \beta_2 doortodoor_{vs} + \beta_3 meeting_{vs} + x_{vs}\delta + \alpha_s + \varepsilon_{vs}, \tag{2}$$

where y_{vs} is the outcome in village v and upazila s, and $owner_{vs}$, $doortodoor_{vs}$, and $meeting_{vs}$ are indicators for the three treatment arms. We include all the baseline variables from Table 1 as control variables to improve precision.[13] Our randomization was stratified by upazila. We therefore include upazila fixed effects in all specifications. We report heteroskedasticity robust standard errors. Some of our analysis uses farmer-level data. For this analysis, we use the same specification, but cluster standard errors at the village level.

[12]Table S1 shows that attrition from this phone survey is uncorrelated with the treatments.
[13]We use village averages of the farmer level characteristics.

4.2 Take up of Energy Efficient Technology

Farmers purchased the most pipes in the meeting villages. Column 1 in Table 2 shows that sales increased by 2.21 pipes per village in meeting villages. This represents a 20.8 percent increase relative to the average of 10.7 farmers that bought in door-to-door villages. Owners purchased about 0.55 pipes more than farmers in door-to-door villages, but we cannot reject equal demand in the owner and door-to-door villages. This table shows aggregate results across the two subsidy levels. Table S2 shows results by subsidy level.

Only a subset of the purchased pipes went on to be used. Actual uptake is similar for the three treatments. Column 2 in Table 2 shows that an average of 4 pipes were used in the door-to-door treatment. The point estimates for meeting and owner villages are small and statistically indistinguishable from zero.

We gave the option to buy AWD pipes again before the second year. But few were sold. We sold an average of 1.6 in the door-to-door villages. Again, the effect of meetings on sales is large and significant in column 3, but actual installations of the device during year 2 are not significantly different between the three treatment arms (column 4).

We have two key takeaways from the analysis on uptake. First, the number of pipes used is similar across treatments — something we also show with the farmer followup surveys (Figure S2). Second, farmers and owners use the technology on select plots of 3 or 4 farmers, despite buying more. The technology provides information on soil moisture and hence when to irrigate. That information can help with planning for multiple plots, particularly when the plots are so close together and have similar soil. Thus, the AWD pipes do not need to be used on every plot to provide information that is relevant for the whole command area. Building on this, we we find that across all three treatments, pipe installations were more likely on the plots of owners and their families (Figure S3).

4.3 Electricity Savings from Technological Subsidies

We use meter readings from two points in time to approximate electricity usage. The baseline reading occurred early in the season. The final reading occurred towards the end of the season. We compute the total electricity usage for village v in year t as follows:

$$elec_{vt} = \frac{meter_{vt}^{final} - meter_{vt}^{base}}{date_{vt}^{final} - date_{vt}^{base}} \times (date_{vt}^{harvest} - date_{vt}^{plant}). \tag{3}$$

The terms $meter_{vt}^{base}$ and $meter_{vt}^{final}$ represent the baseline and final readings, respectively. The fraction on the left gives the estimated daily usage because the numerator is electricity consumed and the denominator is the number of days in between the two readings. Our baseline reading often happened before planting. We use the planting date as the baseline date in these cases. Similarly, we use the harvesting date as the final date when our final reading happened after harvesting. The meters do not tick up between planting and harvesting because the pumps are used solely for irrigating boro rice.

Table 3 shows our main results where the outcome is the log of seasonal electricity usage. In column 1, the point estimates for year one are negative, but imprecisely estimated and statistically insignificant. This may be explained by hesitancy to use the technology. We find a strong correlation between the adoption rate in year 1 and electricity usage (Table S4). Turning to column 2, treatment villages consumed less electricity for irrigation in year 2. Targeted subsidies to the tube well owner save the most electricity. Specifically, the point estimate of -0.478 log points translates to a 38 percent decrease in the amount of electricity used for irrigation. The average tube well in the control group uses about 4,670 kwh in a season. Therefore, the amount of electricity saved converts to almost 1,775 kwh. To interpret the magnitude of the estimate, the average residential customer in the United States uses about 10,715 kwh in a year. The electricity saved from the AWD subsidies to water sellers represents 16.5 percent of average annual residential consumption in the United States.

We can reject the hypothesis that targeting subsidies individually to farmers produces the same effects in year 2 as targeting them to tube well owners. Providing subsidies through village meetings, on the other hand, lowered electricity use by around 30 percent in year 2. We cannot reject equality of this effect and the effect of targeting owners. However, the subsidies are more costly to provide in this way because the meetings led to greater uptake without saving more electricity. Column 3 shows the estimates from pooling the two years together. The strongest effects continue to be in the owner arm because of the greater effectiveness of that treatment in year 2. The treatment effects on year 2 electricity consumption are robust to measuring electricity in levels instead of logs. Leaving the control variables out of the regression does not meaningfully change the results (Table S3).

Differences in take up across the treatments cannot explain the effectiveness of subsidizing conservation technology for water sellers. Table 2 showed that sellers buy and install the same number of AWD devices as when farmers make individual decisions. Instead, we find evidence that when tube well owners buy the AWD devices, they are more likely to participate in using the devices to plan irrigation. We asked each adopter during the year 2 followup about who is monitoring the AWD pipe. Table 4 compares the responses across treatments. Column 1 shows that farmers with AWD pipes on their field in owner villages are about 21 percentage points less likely to report that they themselves monitor the pipe. Turning to the rest of the table, we find that owners are 13.7 percentage points more likely to monitor the pipes in villages where they were targeted with subsidies. This effect amounts to a more than doubling in the likelihood of owner involvement — relative to the door-to-door or meeting villages.

These findings offer one mechanism that can explain our main result: the owner more actively participates in managing the AWD technology to save water when they receive subsidy benefits. In contrast, farmers are more likely to oversee the technology when they themselves make the adoption decision. But individual farmers face no incentive to conserve water because of fixed prices. Well owners, on the other hand, have incentives to use the technology in a way that reduces pumping.

4.4 Farm-Level Outcomes

By reducing water costs, the AWD treatment benefits water sellers who pay for the electricity used in pumping. We next ask whether any benefits are passed through to farmers during the second year. For this, we use the follow up survey with farmers after year 2 harvesting.

The results in Figure 2 show that the treatments do not affect individual farmers. Starting with rice yields, farmers in all three groups obtain similar yields as those in the control group. The 95 percent confidence interval allows us to reject yield decreases of 7.1% or more, or yield increases of 6.2% or more. Agronomic studies show that practicing AWD reduces water use without affecting yield. The null effects on rice productivity align with the agronomic trials.

We investigate two other ways in which benefits could trickle down to farmers. First, we collected data from farmers on the per-acre water prices charged by tube well owners. We find no evidence that prices paid by farmers adjust to the water savings of the owner. In the middle panel of Figure 2, we can reject price decreases of 5.7% or more during year 2 in the owner treatment — the arm or the experiment where electricity costs fell by about 38 percent. Water prices and crop yield for farmers stayed the same, but electricity costs for tube well owners decreased.

Water sellers may pass through benefits in other forms, however. One possibility is through their flexibility in when they require payments from farmers. Sellers sometimes allow farmers to pay for water in multiple installments, or they allow payments to be made later in the season rather than upfront near planting. Unlike water prices, the timing of payments varies within villages.[14] We calculate a simple measure of payment flexibility. To do this, we collected dates and amounts for each installment paid to the owner. We use planting and harvesting dates to compute the share of the total water bill that is paid after the first half of the season, including post harvesting. On average during year 2, farmers pay 72 percent of the water bill after the midway point in the season. The top panel in Figure 2 shows that the owner treatment had no effect on this measure of payment flexibility. If anything, the door-to-door treatment had a modest positive effect, even though the electricity savings were the smallest in that arm.

In combination, these findings indicate that owners retain the rents from using technology to conserve water. This happens even though farmers in the owner villages estimate that less electricity is being used, speak to more other farmers about irrigation, and are more likely to negotiate water prices after the first year (Table S5). Monopoly water sellers rationing quantities can explain the lack of price effects. They set per-acre prices to capture consumer surplus from water buyers. Each farmer's demand curve is based on the amount of effective water that the crop absorbs, not the amount of pumped water or electricity usage. The AWD technology helps the water seller use water more efficiently without affecting crop output of farmers. By not affecting the amount of consumer surplus obtained by farmers, the monopoly seller does not need to lower water prices.

4.5 Costs per unit of Energy Saved

We estimate that subsidizing technology for tube well owners costs about 1.7 cents per kwh saved. To arrive at this figure, we calculate annual electricity savings as $4785.97 * (e^{-.289} - 1) = 1,200\ kwh$ because the average control village used 4785.97 kwh annually, and the owner treatment reduced log electricity usage by .289 (Table 3 column 3). The total estimated savings from the intervention are therefore 2,400 kwh. We focus on the owner villages because the experimental results suggest that would be the most effective way to scale the subsidies.

We estimate two components of costs. First, we sold 12.93 pipes per village in the owner villages across the two years. Based on surveys with 10 local engineering shops, we estimate average costs of producing a single pipe of 135 taka = $1.62.[15] The corresponding total costs of producing the AWD pipes is then $20.95 per village. Second, we assume $10

[14] Village fixed effects explain over 90% of the variation in water prices. They explain 54 and 63 percent of the variation in the number of installments during years 1 and 2, respectively.

[15] These surveys were done in 2018 during the data collection for Chakravorty, Dar, and Emerick (2021). Each shop owner was asked to provide a quote for producing two different quantities. The estimated marginal cost from these data points is 133 taka and the average cost is 135 taka.

delivery costs each year to make a total cost of $40.95. This implies a cost per conserved kwh of $1.7.

The Bangladesh Department of Environment estimates that their electricity grid produces 1.47 lbs of CO2 per kwh of generation. Applying this figure, the treatment effect from the owner intervention amounts to 1.6 MT of CO2. A $25.6 cost per ton of avoided CO2 implies that the intervention is one of the more cost effective ways of reducing emissions (Gillingham and Stock, 2018). Factoring in the benefits of lower water bills for owners would cause the cost per unit of avoided CO2 emissions to become negative. To see this, agricultural electricity is priced at 4 taka per kwh, meaning that electricity savings of 2,400 kwh translate to about $115 of avoided costs for water sellers.

Lastly, we show that subsidizing technology for Bangladeshi tube well owners costs less per unit of energy saved than many interventions for reducing energy usage of homes and businesses. Figure 3 compares the costs per unit of energy saved with estimates that we compiled from 10 studies on energy efficiency.[16] Our estimate falls in line with the more cost effective of these interventions.

Our estimate might be conservative since we have assumed that any energy benefits disappear after two years. Additionally, most agronomic trials find that using AWD reduces methane emissions from rice paddies, an environmental benefit that we do not factor in. On the other hand, there may be components of costs that we fail to include, such as if there are costs of looking into the AWD pipes. Due to this, we acknowledge that our cost effectiveness estimate gives an approximation.

5 Conclusion

Management decisions in developing country agriculture can extend beyond the smallholder farmer. In the case of irrigation water, a valuable resource that is dwindling in many places, water sellers in Bangladesh charge fixed usage fees and effectively ration water to farmers. Water is pumped using electricity, which emits greenhouse gases. Technology exists to use water more efficiently and limit these externalities. But the standard model of technology adoption assumes farmers make individual decisions. It fails to account for how water management involves multiple agents who face different incentives.

This paper finds that subsidizing irrigation technology can reduce externalities from groundwater pumping. The effectiveness of the subsidies depends on who receives them: subsidies to water sellers are most effective, likely because the structure of contracts creates incentives for them to conserve. Our results show that farmers, on the other hand, do

[16] We discuss the details of how we estimated cost effectiveness from each study in Appendix A3.

not benefit from receiving subsidies for water-saving technology. From a policy perspective, the Bangladesh government lists the technology we study as one of their intended contributions to reduce greenhouse gas emissions under the Paris Agreement. Yet, current efforts to promote it involve training individual farmers. Our main finding sheds light on how achieving this policy goal may become easier when accounting for how the institutional environment incentivizes water sellers to conserve.

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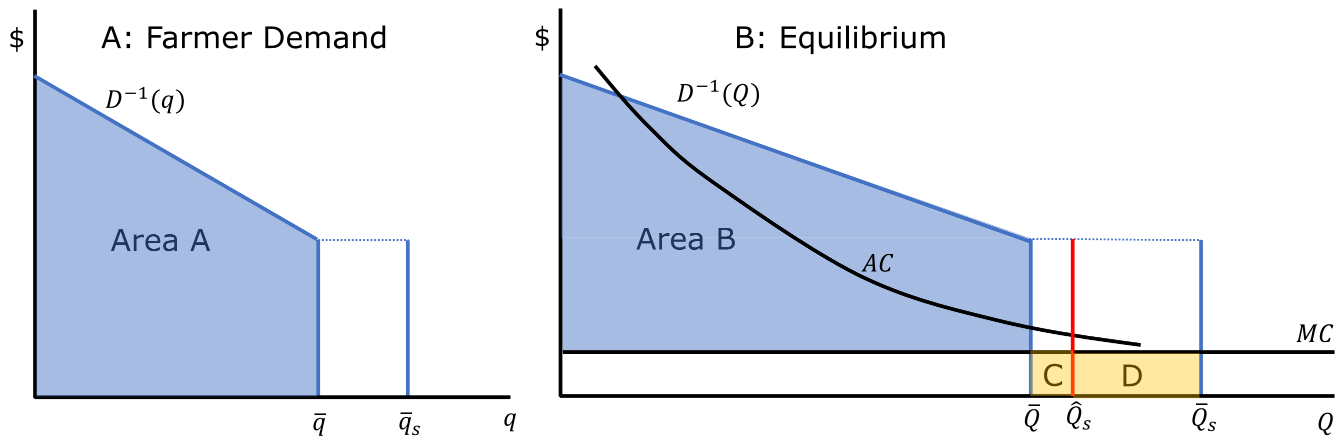
Tables and Figures

Figure 1: Graphical representation of technology's effect on water use, prices, and seller profits



Notes: The figure gives a graphical representation of the water market in our experiment. There are N homogenous consumers of water (farmers) who buy from a monopolist water seller (tube well owner). Panel A on the left shows the water demand curve of the representative farmer. The demand depends only on the amount of effective water which is the amount absorbed by the roots of the crop. The demand curve becomes perfectly inelastic at $\bar{q}$ because water beyond $\bar{q}$ does not increase yield. Tube well owners charge fixed prices per acre of cultivation. The owner sets that price equal to area under the demand curve (Area A), i.e. practices perfect price discrimination. To deliver $\bar{q}$ units of effective water, the owner needs to extract $\bar{q}_s$ units, due to conveyance losses. Panel B on the right shows the market equilibrium. The perfect price discriminating monopolist captures all the area under the demand curve as revenue, earning a producer surplus of B. The marginal cost of extracting water consists entirely of electricity costs, which are constant. Delivering $\bar{Q}$ total units of effective water requires extracting $\bar{Q}_s$ units. This reduces producer surplus by area C+D. The AWD technology helps the owner to optimize irrigation. That is, it allows him to reduce the amount of extracted water without reducing the amount effectively absorbed by the crop. The amount of applied water moves from $\bar{Q}_s$ to $\hat{Q}_s$, which causes the loss from pumping more than is absorbed to fall to area C. The lower electricity costs equal to area D benefit the owner. But the amount of effective water to the crop is unchanged. Crop yields stay the same and the monopolist is still able to charge the area under the demand curve since the same amount of effective water is delivered.

Table 1: Summary Statistics and Covariate Balance by Treatment

	(1) Control	(2) Door-to-Door	(3) Meeting	(4) Owner	(5) p-value
Command areas (N=360)					
Number farmers	16.2	17.5	19.5**	17.5	.106
	(7.3)	(8.2)	(9.1)	(7.8)	
Total acres: GIS	12.7	14.4	16	13.5	.53
	(10)	(12)	(18)	(13)	
Water price per acre	5,677	5,600	5,535	5,751	.369
	(971)	(1,152)	(1,048)	(1,238)	
Baseline farmers (N=2958)					
Age	43.9	43.9	43.7	43.8	.997
	(13)	(12)	(13)	(12)	
Years education	5.62	6.11	5.98	6.02	.759
	(4.6)	(4.3)	(5)	(4.5)	
Boro rice acres	1.02	1.22	1.08	1.05	.525
	(.78)	(3.1)	(.92)	(2.7)	
Boro rice acres in command area	.711	.79	.822*	.73	.258
	(.45)	(.69)	(1.2)	(.51)	
Heard of AWD	.164	.115	.131	.111	.529
	(.37)	(.32)	(.34)	(.31)	
Livestock owned	2.23	2.51	2.62*	2.42	.287
	(1.8)	(2.7)	(5.1)	(2)	
Number crops	2	2.01	2	2	.956
	(.14)	(.23)	(.18)	(.22)	
Joint irrigation with others	.358	.395	.355	.369	.934
	(.48)	(.49)	(.48)	(.48)	
Owner helps decide irrigation	.742	.765	.737	.715	.854
	(.44)	(.42)	(.44)	(.45)	
Immediate family of tubewell owner	.263	.215	.22	.256	.383
	(.44)	(.41)	(.41)	(.44)	

The table shows mean values of baseline characteristics for control, door-to-door, meeting, and owner villages. Columns 1-4 show means with standard deviations below in parentheses. We assess balance by regressing each characteristic on the three treatment variables and upazila (strata) fixed effects. The asterisks in columns 2-4 denote a statistically significant difference with the control group at the 1% ***, 5% **, or 10% * levels. Column 5 displays the p-value of the joint test of the indicators for the three treatments.

Table 2: Technology Uptake Across Treatments

	Year 1		Year 2	
	(1) Buy	(2) Install	(3) Buy	(4) Install
Meeting	2.21***	0.79	0.87***	0.63
	(0.77)	(0.70)	(0.28)	(0.45)
Owner	0.55	-0.17	0.38	0.29
	(0.76)	(0.65)	(0.27)	(0.39)
Upazila FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean Outcome in Door-to-Door	10.65	3.97	1.60	2.82
P-value: Meeting = Owner	0.037	0.146	0.121	0.518
R^2	0.540	0.209	0.106	0.166
Observations	313	313	313	311

The table shows village-level regressions from the AWD pipe sales (columns 1 and 3) and the follow up surveys with tube well owners (columns 2 and 4). The sample consists of the 315 villages in the door-to-door, owner, and meeting villages. The omitted group in each regression is the 105 villages where subsidies were offered door-to-door to farmers. The dependent variable in columns 1 and 3 is the total number of pipes that were sold in the village, either during the door-to-door sales, meeting, or direct visit to the well owner. The dependent variable in columns 2 and 4 is the number of pipes that were installed in the command area, which during year 2 can include ones that were bought in addition to those saved from the previous year. Many purchased pipes go unused, explaining the difference in mean outcomes between columns 1 and 2. The controls include all of the covariates in Table 1. Heteroskedasticity robust standard errors are displayed in parentheses below the point estimates. Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

Table 3: Effects of Technology Subsidies on Electricity Usage for Groundwater Pumping

	(1) Year 1	(2) Year 2	(3) Both Years
Door-to-Door	-0.116	-0.191	-0.152
	(0.207)	(0.161)	(0.154)
Meeting	-0.143	-0.304*	-0.217
	(0.192)	(0.171)	(0.153)
Owner	-0.129	-0.478***	-0.289**
	(0.180)	(0.165)	(0.144)
Upazila FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean Elec in Control (kwh)	4902.23	4669.70	4785.97
P-value: Door = Meeting	0.862	0.374	0.571
P-value: Door = Owner	0.930	0.025	0.214
P-value: Meeting = Owner	0.916	0.184	0.505
R^2	0.359	0.347	0.329
Observations	307	305	612

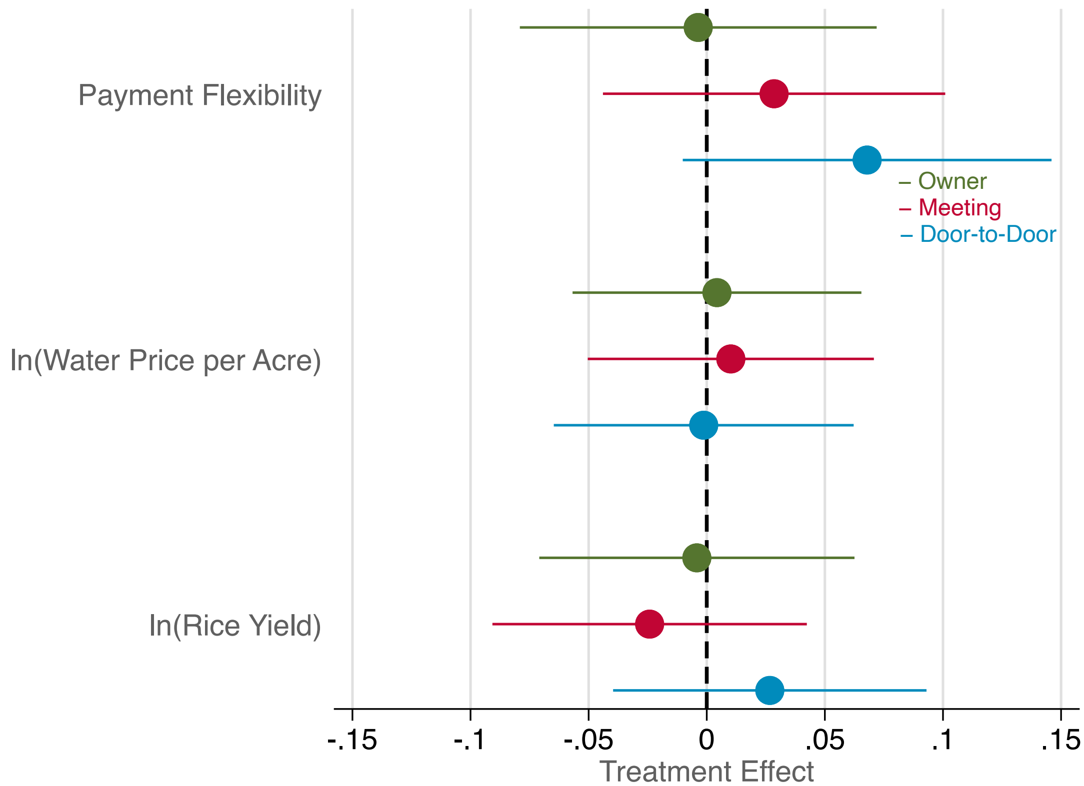
The table shows village-level regressions of log electricity consumption on the treatment indicators, upazila fixed effects, and village- and household-level controls. The dependent variable in all three regressions is the log of electricity usage, as described in Equation (3). Columns 1 and 2 show the results separately for the first and second years. Column 3 shows pooled results where both years are pooled together. The controls include all of the covariates in Table 1. Additionally, the pooled regression in column 3 includes a dummy variable for year 2. Heteroskedasticity robust standard errors are displayed in parentheses below the point estimates in columns 1 and 2. Standard errors are clustered at the village level in column 3. Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

Table 4: Involvement of farmers and owners in managing AWD pipes in year 2

	AWD pipe overseen by:			
	(1) Farmer	(2) Family	(3) Owner	(4) Lineman
Meeting	-0.185**	0.009	-0.026	-0.010
	(0.077)	(0.055)	(0.058)	(0.065)
Owner	-0.212***	0.060	0.137*	-0.102
	(0.076)	(0.060)	(0.069)	(0.083)
Strata FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean in Door-to-Door	0.618	0.235	0.110	0.463
P-value: Meeting = Owner	0.742	0.305	0.025	0.227
R^2	0.248	0.406	0.224	0.388
Observations	423	423	423	423

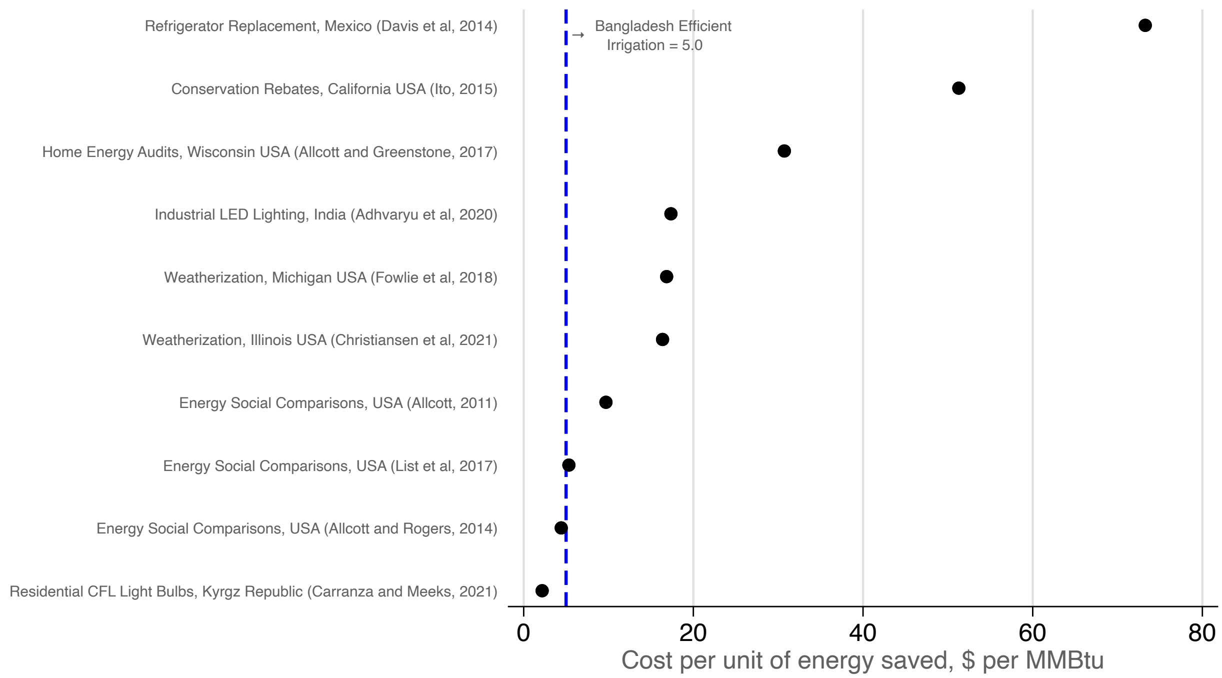
The table shows regression results from the year 2 follow up survey with farmers. The data are limited to the farmers that adopted AWD on the randomly selected plot asked about during the survey. Respondents were asked who oversees the AWD pipe for water management. They could give multiple responses. Each column in the table shows a regression of whether the respondent listed themselves (column 1), family members (column 2), the tube well owner (column 3), or the lineman (column 4) as a person who helps oversee the AWD pipe. We limit the data to the meeting, owner, and door-to-door villages. The door-to-door villages are the omitted group in each regression. We cluster all standard errors at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

Figure 2: Treatment effects on outcomes for farmers



Notes: The figure shows regression results from the year 2 follow up survey with farmers. We show results for three outcome variables: a payment flexibility measure, the log of water prices per acre, and the log of rice yield. The payment flexibility measure is defined as the share of the total water bill that was paid during the second half of the season, which we calculated using village-level planting and harvesting dates along with the dates for each of the installments that were paid to the tube well owner. We regressed each outcome on the treatment indicators, strata fixed effects, and the control variables listed in Table 1. The dots in the figure show the point estimates (treatment effects) from the regressions, while the bands show 95% confidence intervals. All standard errors are clustered at the village level.

Figure 3: Comparison of costs per unit of energy saved with studies on energy efficiency



Notes: The figure compares our approximation of cost effectiveness to estimates from 10 papers on residential or industrial energy efficiency throughout the world. The vertical blue line shows the estimate from the owner treatment in our study. For each paper in the literature, the dot provides the estimated cost in USD per mmBTU of energy saved by the intervention. See Appendix A3 for details on how we used information from each paper to arrive at the cost effectiveness figure.

Supplemental Appendix

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A1 Supplementary Tables

Table S1: Missing outcome data across treatment groups

	Village Electricity		Year 2 Farmer Followup
	(1)	(2)	(3)
	Year 2	Year 1	Year 2
Door-to-Door	-0.013	0.016	0.048
	(0.063)	(0.061)	(0.045)
Meeting	0.028	-0.029	-0.003
	(0.063)	(0.059)	(0.043)
Owner	-0.024	-0.025	0.044
	(0.061)	(0.060)	(0.042)
Upazila FE	Yes	Yes	Yes
Mean Level in Control	0.156	0.156	0.194
P-value: Door = Meeting	0.395	0.334	0.202
P-value: Door = Owner	0.823	0.389	0.912
P-value: Meeting = Owner	0.268	0.930	0.208
R^2	0.129	0.095	0.234
Observations	360	360	2876

The table shows the relationship between missing data and treatment. Columns 1 and 2 are for electricity usage, our main outcome variable. Column 3 is for non-response in the year 2 follow up phone survey with farmers. The dependent variable in columns 1-2 is an indicator for villages where we have missing electricity data. The dependent variable in column 3 is an indicator for not being reached during the survey. The asterisks denote statistical significance at the 1% ***, 5% **, or 10% * levels.

Table S2: Differential Price Sensitivity Across Treatments

	Year 1		Year 2	
	(1) Buy	(2) Install	(3) Buy	(4) Install
High Price	-4.28***	-0.91	-0.35	-0.02
	(1.19)	(0.91)	(0.34)	(0.43)
Meeting	2.78***	2.04**	1.25***	1.05
	(0.96)	(1.01)	(0.41)	(0.78)
Owner	0.14	0.22	0.28	0.31
	(0.95)	(0.78)	(0.37)	(0.48)
High Price * Meeting	-1.02	-2.58**	-0.75	-0.86
	(1.48)	(1.19)	(0.62)	(0.98)
High Price * Owner	0.67	-0.98	0.18	-0.05
	(1.42)	(1.04)	(0.49)	(0.65)
Upazila FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean Outcome in Door-to-Door	10.65	3.97	1.60	2.82
P-value: Meeting = Owner	0.007	0.067	0.042	0.381
P-value: Meeting*High = Owner*High	0.304	0.169	0.153	0.442
R^2	0.610	0.254	0.128	0.171
Observations	313	313	313	311

The table shows village-level regressions from the AWD pipe sales (columns 1 and 3) and the follow up surveys with tube well owners (columns 2 and 4). The sample consists of the 315 villages in the door-to-door, owner, and meeting villages. The omitted group in each regression is the 105 villages where subsidies were offered door-to-door to farmers. The dependent variable in columns 1 and 3 is the total number of pipes that were sold in the village, either during the door-to-door sales, meeting, or direct visit to the well owner. The dependent variable in columns 2 and 4 is the number of pipes that were installed in the command area, which during year 2 can include ones that were bought in addition to those saved from the previous year. Many purchased pipes go unused, explaining the difference in mean outcomes between columns 1 and 2. The variable High Price is a binary variable for unions where prices were randomly set at 60 BDT per device. The price in the remaining villages was 30 BDT. The controls include all of the covariates in Table 1. Standard errors are clustered at the union level (the unit of price randomization). Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

Table S3: Robustness of Main Effects on Electricity

	Year 1			Year 2		
	(1) Level	(2) Level	(3) Log	(4) Level	(5) Level	(6) Log
Door-to-Door	-251.743	167.109	-0.016	-452.232	-136.780	-0.115
	(822.836)	(974.801)	(0.227)	(745.126)	(849.568)	(0.179)
Meeting	-550.491	748.600	0.123	-1453.458**	-639.693	-0.140
	(874.570)	(1003.635)	(0.213)	(727.330)	(793.361)	(0.181)
Owner	-766.082	-370.140	-0.026	-1719.919**	-1569.096*	-0.437**
	(797.133)	(951.348)	(0.209)	(701.193)	(813.921)	(0.183)
Upazila FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	No	No	Yes	No	No
Mean in Control	4902.2	4902.2		4669.7	4669.7	
P-value: Door = Meeting	0.641	0.421	0.408	0.087	0.417	0.850
P-value: Door = Owner	0.342	0.411	0.955	0.033	0.027	0.019
P-value: Meeting = Owner	0.731	0.116	0.315	0.641	0.104	0.031
R^2	0.409	0.136	0.146	0.338	0.136	0.188
Observations	307	307	307	305	305	305

The table shows robustness of the electricity results to not including the control variables and measuring electricity in levels rather than logs. Columns 1-3 are for year 1, and columns 4-6 are for year 2. The dependent variable in columns 1-2 and 4-5 is electricity usage in kwh, following Equation (3) in the main text. The dependent variable in columns 3 and 6 is the log of electricity usage. The controls include all of the covariates in Table 1. Heteroskedasticity robust standard errors are displayed in parentheses below the point estimates. Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

Table S4: Correlation between village AWD adoption and electricity use

	Year 1		Year 2	
	(1)	(2)	(3)	(4)
At least 1 AWD Device	-0.186		-0.248*	
	(0.119)		(0.128)	
AWD adoption rate		-0.444**		-0.344
		(0.211)		(0.246)
Upazila FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
R^2	0.355	0.363	0.371	0.381
Observations	303	303	268	267

The table shows the correlation between usage of AWD and electricity usage in year 1 (columns 1-2) and year 2 (columns 3-4). We use the follow up survey with 8 farmers per village to estimate the share of farmers in the command area using AWD. Columns 1 and 3 regress the log of electricity consumption on a binary variable for at least one farmer reporting AWD use on their plot, upazila fixed effects, and the control variables from Table 1. Columns 2 and 4 show results from a similar regression, but where we use the share of farmers adopting AWD instead of an indicator for at least one adopter. Heteroskedasticity robust standard errors are displayed in parentheses below the point estimates. Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

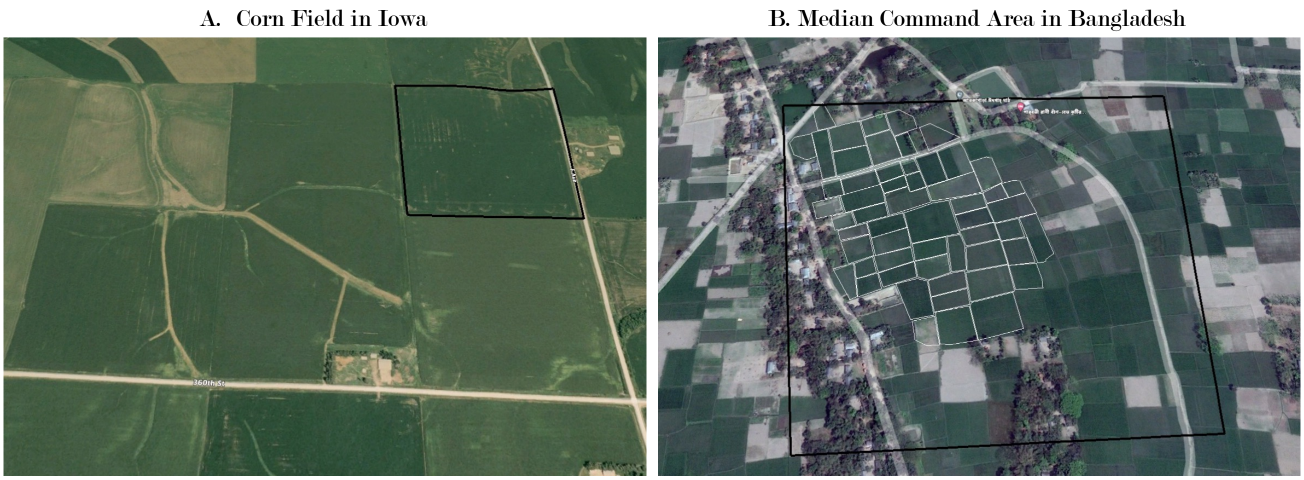
Table S5: Treatment effects on farmer estimates of village electricity usage, communication about irrigation, and negotiating water prices

	Electricity	N Farmers Spoken to		N Farmers Negotiate	
	(1)	(2)	(3)	(4)	(5)
	Year 1	Year 1	Year 2	Year 1	Year 2
Door-to-Door	-0.167**	0.487	0.626***	0.743	0.004
	(0.080)	(0.299)	(0.229)	(0.763)	(0.722)
Meeting	-0.157*	0.699**	0.207	1.066	0.361
	(0.081)	(0.319)	(0.210)	(0.781)	(0.761)
Owner	-0.163**	0.681**	0.507**	1.880**	0.522
	(0.082)	(0.332)	(0.203)	(0.779)	(0.737)
Strata FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean Level in Control		2.032	1.900	4.279	4.136
P-value: Door = Meeting	0.861	0.393	0.061	0.664	0.610
P-value: Door = Owner	0.943	0.473	0.580	0.120	0.422
P-value: Meeting = Owner	0.920	0.952	0.128	0.282	0.824
R^2	0.593	0.245	0.289	0.238	0.235
Observations	1979	2784	2228	348	345

The table shows treatment effects from both the farmer follow up surveys (columns 1-3) and the surveys with tube well owners. Column 1 shows results from the follow up survey in year 2 where farmers were asked to estimate the overall electricity usage in the current season. The dependent variable is the log of the farmer's estimated electricity usage. Columns 2 and 3 show results on the number of farmers that the respondent spoke to about dry-season irrigation. This question was asked during both year 1 and year 2 follow ups. The outcome variable in columns 4 and 5 is the number of farmers that negotiated water prices. We asked this to tube well owners during the follow up surveys with them after each season. Standard errors in columns 1-3 are clustered at the village level. We report heteroskedasticity robust standard errors in columns 4 and 5. Asterisks indicate statistical significance at the 1% ***, 5% **, or 10% * levels.

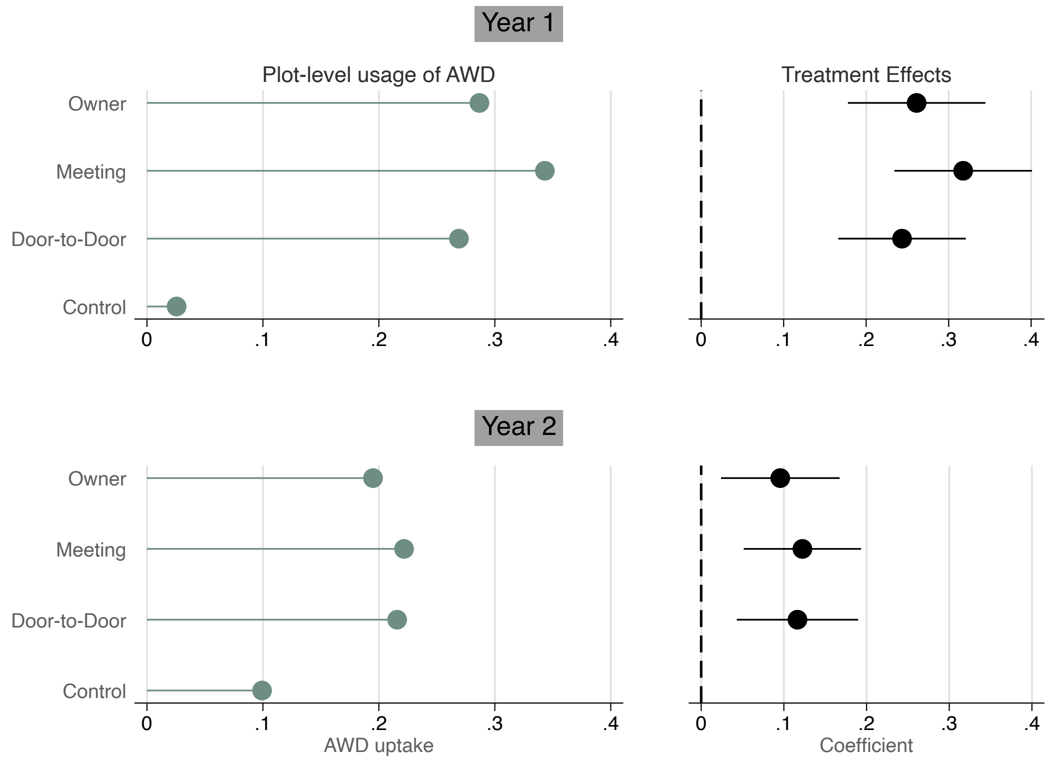
A2 Supplementary Figures

Figure S1: Fractured landholdings in Bangladesh compared to a corn field in the United States



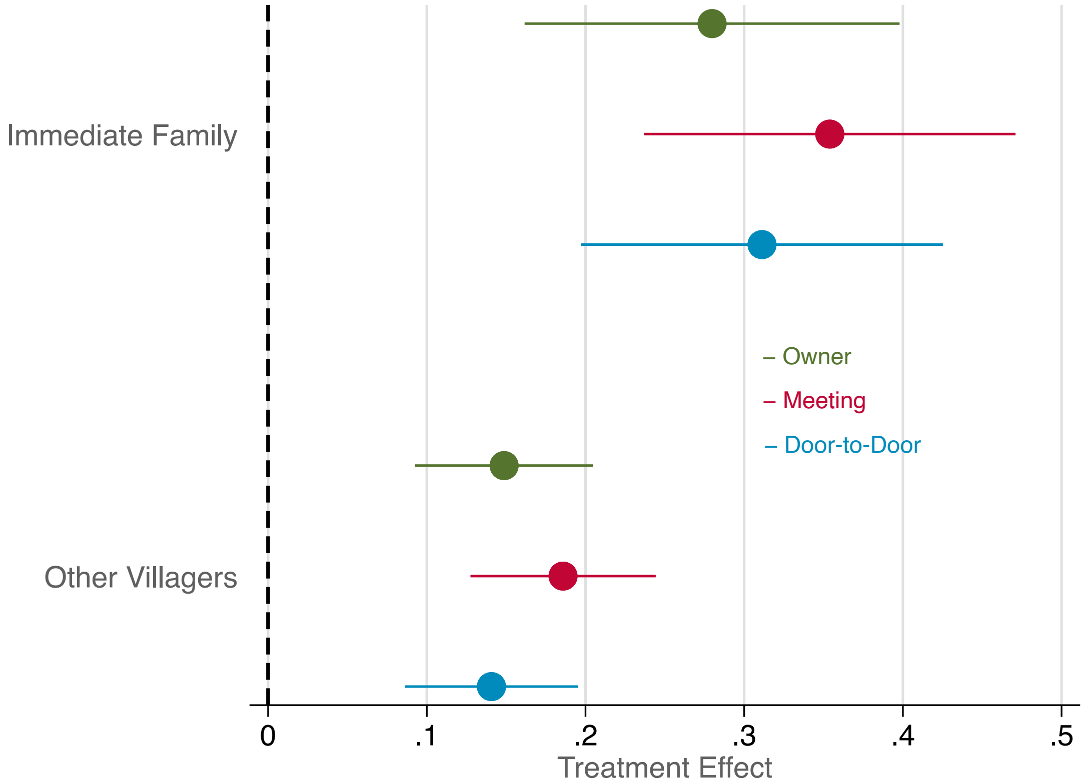
Notes: Panel A shows a satellite image from Iowa. The black boundary is a quarter-quarter section, amounting to an approximately 40 acre corn field. Panel B shows the median command area — in terms of average plot size — in our sample in Bangladesh. The plots in the command area are outlined in white. The command area is 13 acres and has 56 plots that are cultivated by 18 different farmers. The black square is 40 acres, the same size as the Iowa corn field in Panel A.

Figure S2: Effects on plot-level AWD usage



Notes: The figure shows differences in plot-level uptake of AWD across treatments in year 1 (top panel) and year 2 (bottom panel). Each farmer was asked about one random plot in the command area of the tube well. The figure is constructed using results from a regression of a binary variable for uptake on the treatments, upazila fixed effects, and the control variables, with standard errors clustered at the village level. The graphs on the left show the average rate of usage in the control group (bottom bar) and the mean in the control group plus the treatment effect from the regression in the other three rows. The right panel shows the treatment effects from the regression (dots) along with the 95% confidence intervals (bands).

Figure S3: Treatment effects on AWD usage separate by family ties with tube well owner



Notes: The figure shows results from plot-level data pooled across the two years of the study. We regressed a binary variable for using AWD on the treatment indicators, upazila fixed effects, a year dummy, and the control variables. This regression was done separately for two subsamples of the data. The top panel limits the data to the tube well owner and their immediate family (siblings, children, parents). The top panel includes 1,207 observations. The bottom panel is for the other villagers that are not the owner or their immediate family (N=3,818). All standard errors are clustered at the village level.

A3 Benchmarking Cost Effectiveness with the Literature

Figure 3 in the main text compares cost effectiveness with estimates from various residential and industrial energy efficiency programs. Here we describe how information from each paper was taken to produce the figure.

Fowlie, Greenstone, and Wolfram (2018): The note to Table 7 provides an average retrofit cost of $4,585. The text on page 1624 gives the annual energy savings of 17 MMBtu per year. The lifespan of the investments is 16 years, meaning that the intervention is expected to save a total of 272 mmBTU. This implies a cost of $16.86 per MMBtu.

Allcott and Rogers (2014): Table 7 shows cost-benefit calculations across 3 sites of their study. The 3 cost effectiveness measures are 1.4, 1.79, and 1.35 cents per kwh. The average of these 3 numbers is 1.51 cents / kwh. Standardizing units gives $4.43 per mmBTU.

Allcott (2011): Cost effectiveness in this paper is measured as annualized cost of the Home Energy Reports divided by kwh of electricity savings. The bottom of page 1088 gives 3.31 cents per kwh, which amounts to $9.7 per mmBTU.

List et al. (2017): Table 4 provides a cost effectiveness figure of 1.82 cents / kwh. This equates to $5.33 per mmBTU.

Davis, Fuchs, and Gertler (2014): Table 6 gives a mean annual decrease in electricity consumption from refrigerator replacement of 135 kwh per year = 0.46 mmBTU per year. The bottom of Table 6 gives program costs of $0.25 per kwh. This works out to $73.27 per mmBTU.

Ito (2015): The end of the introduction provides cost effectiveness figures. The study took place in two sites: coastal areas and inland areas. Overall (across both areas) the cost per kwh saved was 17.5 cents. This works out to $51.29 per mmBTU.

Christensen et al. (2021): Table 1 provides cost per home upgrade of $5312.62. The energy savings from the intervention is 14.83% (Table 2). The average household consumes 9.12 mmBTU per month in Table 1. This makes 16.23 mmBTU per year. The text on page 27 indicates that the investments have a 20 year lifespan, meaning that the program saves 324.4 mmBTU at a cost of $5312.62 (16.37 $/mmBTU).

Allcott and Greenstone (2017): Table 5 shows daily gas reductions of 0.128 therms = 4.67 mmBTU per year. For electricity, the daily savings are 1.013 kwh = 1.26 mmBTU per year. The total savings are therefore 5.93 mmBTU per year. The text on page 14 notes that 95% of investments have a 20 year lifespan. Thus, cumulative energy savings amount to 118.6 mmBTU. Table 7 gives program costs of $5.08 million. There were 1,394 audited households, making average costs of $3644.19 per household. The cost effectiveness figure is $30.73 per mmBTU.

Adhvaryu, Kala, and Nyshadham (2020): Table 7 gives cost-benefit calculations. The cost per bulb is $8.53 and energy savings per bulb amount to 18 kwh per year. We assume an 8-year measure lifespan for LEDs. This gives 144 kwh over the life of the bulb. This works out to 5.92 cents per kwh = $17.36 per mmBTU.

Carranza and Meeks (2021): Table 6 shows overall energy savings of 444 kwh per year, accounting for spillovers. The lifespan of a CFL bulb about one third that of LEDs. We therefore assume a lifespan of 2.67 years, meaning total energy savings of 1184 kwh. Table A13 shows program costs of $8.81 per household. Dividing the two figures and converting units, we arrive at $2.18 per mmBTU.