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Inefficient Water Pricing and Incentives for Conservation†

By Ujjayant Chakravorty, Manzoor H. Dar, and Kyle Emerick*

Farmers often buy water using fixed fees—rather than with marginal prices. We use two randomized controlled trials in Bangladesh to study the relationship between marginal prices, adoption of a water-saving technology, and water usage. Our first experiment shows that the technology only saves water when farmers face marginal prices. Our second experiment finds that an encouragement to voluntarily convert to hourly pumping charges does not save water. Taken together, efforts to conserve water work best when farmers face marginal prices, but simply giving an option for marginal pricing is insufficient to trigger water-saving investments and reduce irrigation demands. (*JEL* O13, Q12, Q15, Q16, Q25)

Climate change requires more efficient use of the earth's natural resources. Water is a resource that has received little attention but is expected to become increasingly scarce as populations grow and temperatures rise (Vörösmarty et al. 2000; Schewe et al. 2014). Agriculture is the natural place to look for more efficient ways to use water, accounting for almost 70 percent of all the water consumed (FAO 2016).

A major impediment to water conservation is the absence of marginal prices. Farmers often pay fixed charges that are unrelated to water use. Figure 1 shows that of the 80 countries where we could find information, 54 had regions where water is not priced by volume. Economists have frequently prescribed marginal prices as a way to induce water conservation. Yet there are few empirical studies that have examined the link between marginal pricing and resource use.[1]

We examine the role of marginal prices using two randomized experiments with a technology designed to save water in rice farming. The technology is a perforated plastic pipe, open at both ends, that is planted in a rice field to help the farmer irrigate only when the crop needs water. Using this pipe to schedule irrigations is

* Chakravorty: Tufts University (email: Ujjayant.Chakravorty@tufts.edu); Dar: International Crops Research Institute for the Semi-Arid Tropics (email: m.dar@cgiar.org); Emerick: Tufts University and CEPR (email: kyle.emerick@tufts.edu). Seema Jayachandran was coeditor for this article. We gratefully acknowledge financial support from the International Initiative for Impact Evaluation (3iE) through grant no. DPW1.1081. Emerick is grateful to the Institute of Economic Development at Boston University, where he was a visiting scholar while part of this research was carried out. We acknowledge excellent research assistance by Sean Kim, Xu Dong, Leticia Donoso, Michiyoshi Toya, and Muhammad Ashraful Habib. We are grateful for comments provided by numerous seminar audiences. This study is registered in the AEA RCT registry as AEARCTR-0002168. Pre-analysis plans for both years of the study can be found on this site. The study was approved by the Institutional Review Board for Social and Behavioral Research at Tufts University (study number 1610025).

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[1] Other scholars have studied raising an already existing marginal price in the context of household electricity use and have shown a positive association between electricity prices and development of energy-efficient technologies (Newell, Jaffe, and Stavins 1999; Popp 2002).

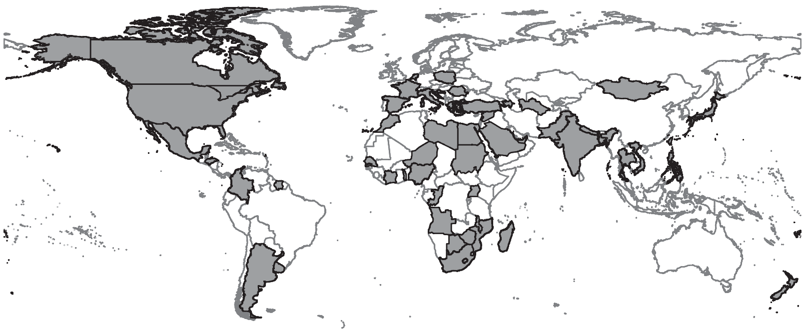

Figure 1. The Distribution of Agricultural Water Pricing across the World

Notes: The map shows shaded countries where at least some irrigation water is not priced volumetrically, usually priced with seasonal contracts by the acre or acre-crop.

Sources: The pricing methods were obtained from FAO (2004). Additional countries were classified using Johansson et al. (2002); Molle (2009); or Wichelns (2010).

referred to as practicing "Alternate Wetting and Drying (AWD)." The technology has been around for almost four decades but is not widely adopted, despite its simplicity and numerous agronomic trials showing that it can reduce water use by about 30 percent.[2]

Do fixed fees for irrigation water inhibit adoption of this technology? Does the technology save water only when farmers face volumetric prices? Does encouraging farmers to voluntarily switch to marginal prices cause them to invest in water-saving technology and use less water?

To answer these questions, our first experiment shows that AWD only saves water when farmers face volumetric prices. This is done by randomly providing 2,000 farmers in Bangladesh with a free pipe and training on how to use it and help with installing it on their plot. The 2,000 control farmers continued to irrigate as before. We placed our sample of 400 villages in different regions. About 35 percent of the sample faced nonzero marginal prices for irrigation water, while the remainder purchased water using a seasonal contract in which the price is based solely on area cultivated, not the volume used.

There are three sources of variation in how farmers pay for water in our sample. First, some villages in our sample have a system where farmers use prepaid cards to buy water by the hour. Second, some farmers in these villages with prepaid pumps have their own cards and pay for water by the hour, while others pay the tube well operator based on area cultivated, not volume used. Third, private tube well owners in certain villages pass through the marginal fuel costs to farmers. We prespecified heterogeneity analysis to estimate whether the effect of the technology depends on volumetric pricing.

[2] Agronomic studies include Cabangon, Castillo, and Tuong (2011) and Bueno et al. (2010) in the Philippines and Belder et al. (2004) and Yao et al. (2012) in China. Other trials have been carried out in Vietnam and Bangladesh (Lampayan et al. 2015).

Using about 7,600 observations of water levels, we find that *on average* AWD leads to a modest and statistically insignificant change in water use. This finding is in sharp contrast to the evidence from agronomic trials. However, in the subsample with volumetric pricing, treatment plots had 19 percent less water and were 21 percent more likely to be dry when observed on random days—estimates that are in line with agronomic evidence. This small plastic pipe generates water savings that are equivalent to about half of the annual residential usage in the United States. In contrast, no such savings exist when farmers face fixed charges.

The profitability of the technology depends on whether farmers face volumetric prices. The technology has no effect on profits under seasonal water charges, consistent with the observation that water management did not change in this setting. Volumetric prices, on the other hand, incentivize use of the pipe: we find a significant increase in farm profits of about 9 percent. Overall, this first experiment suggests that there may be an important market failure that explains why farmers do not use a water-saving technology with proven results in the laboratory: they face a zero marginal price for water.

The complementarity between water-saving technology and marginal prices is estimated from an interaction between our randomized treatment and whether farmers were paying volumetric prices at baseline. This variation is not random. We therefore include several pieces of analysis to examine the robustness of the main finding of the first RCT. First, we show that the heterogeneous effects persist when controlling for interactions between the treatment and many farmer, plot, and agroecological characteristics. Second, our sample is spread across 12 upazilas (administrative units). Much of the variation in volumetric pricing is across these upazilas. We show that the variation across upazilas in volumetric pricing is strongly correlated with the effectiveness of AWD. Using only the more localized variation results in similar point estimates for overall water use, but the estimates are imprecise due to the limited within-upazila variation. Third, we use an additional source of variation to show that AWD only lowers water costs for farmers who are buying water by the hour, as opposed to those who pay fixed fees to the tube well owner. Fourth, we use machine learning methods to investigate the most important dimensions of heterogeneity (Chernozhukov et al. 2018). This analysis picks marginal prices as one of the key sources of heterogeneity.

Our second RCT extends the analysis by testing whether a random encouragement to switch to volumetric pricing can trigger water conservation through the adoption of AWD. Our approach delivers causal estimates of the effects of encouraging hourly irrigation prices on the demand curve for AWD and water usage. We use the term "hourly irrigation" interchangeably with "volumetric" or "marginal prices" for simplicity, even though hourly charges put a price on the electricity used for pumping, not the actual water delivered to the field.[3] Estimating the entire demand curve for AWD allows us to determine whether the encouragement to adopt

[3] In practice these are highly correlated. But farmers farther from the water source will pay a higher price per unit of water used with hourly pricing due to the time it takes for water to flow from the pump to the field. We use the terms interchangeably because the important transition for us is whether farmers face any volumetric price, not necessarily the magnitude of price per unit of water.

marginal prices changes willingness to pay for the water-saving tool. But this is just an intermediate outcome. We look at whether the encouragement can get farmers to accept marginal prices and, as a result, lower their water usage.

In our sample area there are 4,000 community tube wells that are equipped with meters that can take prepaid debit cards and release irrigation water. Farmers can load their own card with funds at a nearby kiosk and obtain irrigation water on demand. However, most farmers do not possess cards and pay a fixed per acre fee instead. We identified 144 such villages that have installed meters, but use of prepaid cards by individual farmers is nonexistent.[4] In order to encourage hourly pricing for water, we randomly selected 96 villages for a campaign to make it costless for farmers to obtain their own debit cards. Many farmers attribute the low rate of individual card ownership to the costs associated with the application process. Our treatment sought to eliminate these costs by organizing a meeting with farmers to explain the purpose of the prepaid cards, help them fill out the paper application, obtain the photograph needed, pay the application fee of $1.9, deliver the forms to the irrigation authority, pick up the cards once complete, and deliver them to farmers. Once in hand, a farmer can load the card with funds—the same way as a mobile phone—and purchase water from the village tube well. We then estimated the demand curve for AWD by sending sales teams to all villages and offering farmers a pipe at a randomly determined village-level price, along with information on its use. The 8 different random prices ranged from 15 to 70 percent of the marginal cost of the pipe. Finally, we observed water management using the same methods as in the first experiment.

The encouragement to adopt hourly pricing *did not* lead to water conservation: observed water levels are similar in treatment and control villages. Statistically, we reject large water savings from the prepaid card treatment, such as the direct effects of AWD from the first experiment. The intervention did not lead to a uniform shift in the demand curve for AWD. There is, however, some evidence that the intervention influenced the shape of the demand curve for AWD. In particular it caused demand to become less price responsive. The demand elasticity for AWD falls by 33 percent from 1.7 to 1.14 when comparing treatment and control villages. At the 4 highest prices, providing farmers with the hourly cards increased purchase of the pipes by 35 percent. But only about one in five farmers installed the pipe in their field. Moreover, only about 40 percent of farmers went on to use the prepaid cards. This low interest to use the cards and pipes together offers the most direct explanation as to why the intervention did not cause farmers to use less water.

Our first experiment found that once farmers face volumetric prices, intensive efforts to promote water-saving technology can succeed in conserving water. Our main takeaway from the second experiment is that *transitioning* to marginal prices

[4] In most cases the tube well operator maintains a few cards, manages the allocation of water to farmers, and provides them with equal per acre bills regardless of their individual consumption. The bills are most often paid in two installments: at the beginning and end of the season. One of the main benefits of this approach—from the perspective of the tube well operator—is the ease of tracking. The operator only needs to observe how much money is being used on his cards and acreage cultivated by each farmer, rather than keep track of the individual hours pumped. The operator levies a markup before calculating the per acre cost to be charged to each farmer. The per acre charge makes it easier to conceal this markup: the per hour cost of pumping is generally known to farmers.

may require more than incentivizing farmers to voluntarily opt in. The incentives we provided failed to trigger a causal chain from switching to hourly prices to adopting water-saving technology to using less water. Our findings suggest that triggering this causal chain requires more intensive intervention, perhaps mandatory conversion to volumetric pricing and/or more extensive involvement to ensure that farmers follow through to install and use the technology.

There may be further reasons why farmers do not want to voluntarily opt in to volumetric pricing. For one, farmers using above-average amounts of water will increase their costs by doing so. As another example, paying by the hour may adversely impact farmers located farther away from the water source relative to those located nearby. Some water can even spill over to other fields during conveyance. A desire for fairness in the community may then cause fixed prices to be favored. This poses challenges to getting farmers to accept marginal prices in developing country settings, where water is often distributed communally (Ostrom and Gardner 1993).

The contribution of our paper is to study the interplay between marginal irrigation prices, adoption of water-saving technology, and water use. Despite the widespread existence of fixed irrigation fees, and calls from economists for institutional reform that introduces marginal prices (see Zilberman and Schoengold 2005), there is little rigorous field evidence investigating the role seasonal water charges play in discouraging farmers from practicing more efficient irrigation methods.[5] Our experiments deliver two insights in this area where the evidence base has been limited. First, our main contribution is to show that marginal prices when they already exist can enable water-saving investments; i.e., the technology we provided led to water conservation only in areas where farmers faced marginal prices. The failure of the technology to conserve water without marginal prices aligns with findings from India, where drip irrigation does not conserve water when electricity for pumping is almost free (Fishman, Giné, and Jacoby 2021). Second, incentives to voluntarily adopt marginal prices do not conserve water, despite making farmers more willing to pay higher prices for water-saving technology. Shifting farmers to marginal prices, so that they can profit from water-saving investments, therefore requires more than just incentives to voluntarily convert.

Even though volumetric pricing is a common policy recommendation, there have been few studies that investigate its role in incentivizing technology adoption and conserving water. Larson, Sekhri, and Sidhu (2016) have studied how financial constraints and informational barriers affect the adoption of water-saving technologies. A broader literature on energy and resources considers both pecuniary and nonpecuniary mechanisms for inducing conservation. Several papers have considered the sensitivity of demand for energy and natural resources to changes in existing *marginal prices* (Nataraj and Hanemann 2011; Ito 2014; Jack, Jayachandran, and Rao 2018). Ito and Zhang (2020) show that replacing fixed electricity charges with

[5] Observational studies from both the US and developing countries have found mixed results on introducing charges for irrigation water. Fishman et al. (2016) use nonexperimental variation to study the water savings from a program in India where farmers voluntarily installed meters and were compensated for electricity savings relative to baseline consumption. They find no effect of the program on groundwater pumping. Smith et al. (2017) show difference-in-difference estimates from an irrigation district in Colorado where farmers self-introduced a groundwater pumping fee. They find large water savings of around a third.

individual meters reduced electricity demand for heating by residential customers in China. Other nonprice mechanisms for natural resource conservation have been considered in the literature. These include paying people directly to avoid cutting down trees (Jayachandran et al. 2017) and using peer comparisons to nudge people to conserve (Ferraro and Price 2013; Allcott and Rogers 2014).

The structure of the paper is as follows. The next section outlines the experimental design of the first RCT. Section II presents the results of that experiment showing how conservation technology only saves water and increases profits when marginal prices exist. Section III describes the second experiment that estimates the effects of encouraging farmers to switch to hourly billing. We show in Section IV how our intervention to encourage hourly billing causes farmers' demand for AWD to become less price responsive but did not lead to conservation of water. Section V provides concluding remarks.

I. Experimental Design to Estimate the Impact of the Conservation Technology

This section describes the experimental design and data collection for the first experiment to characterize the impact of conservation technology on water usage and farm profitability. In particular, we estimate these impacts across a wide geographic region, covering places where water is priced by cropped area and others where it is priced by the hour of pumping.

A. *Sampling*

The experiment took place in three districts: Mymensingh, Rangpur, and Rajshahi. There is variation in the way water is priced in these three regions. The groundwater table is deeper in Rajshahi and Rangpur. Hence, tube wells are costly to dig and therefore almost always government owned. Within these tube wells in Rajshahi, water is priced volumetrically, where farmers can pay for each hour of pumping using a prepaid card. The card is loaded with funds at local shops in the same way that mobile phones are loaded with air time. The farmer can then obtain water by providing his card to a tube well operator—known locally as the "deep driver"—who is employed by the responsible government agency to manage the system. Farmers in our sample villages in Rangpur pay a per acre fee for the right to irrigate their field for the entire season. They simply arrange each irrigation with the tube well operator. Finally, tube wells in Mymensingh are privately owned because a shallower groundwater table reduces the cost of digging a borehole. Tube well owners in this area largely use per acre charges. Contracts occasionally take the form of two-part tariffs where the per acre fee is coupled with a charge for each unit of fuel or electricity used during pumping. We assume that the farmer faces a volumetric price if he resides in a village with a prepaid pump or if he is responsible for the fuel costs of pumping. Farmers not facing volumetric prices pay a fixed seasonal fee per acre cultivated. They do not pay labor costs for applying irrigation. Instead, the tube well operator employs "linemen" who manage irrigation for the entire command area.

We first identified 12 upazilas (administrative units two levels above villages) in these 3 districts. In Rajshahi and Rangpur we obtained a list of villages where water is sold to farmers from government-operated deep tube wells. All villages in Mymensingh were included in the sampling frame since each village usually has at least one tube well owner who sells water to other farmers. Using this sampling frame, we drew a random sample of 400 villages—split evenly across the 3 districts.

Field staff visited each selected village to ensure that farmers were growing rice during the boro (dry) season. If not, then the village was replaced with a randomly drawn village from the same upazila.[6] Once deemed eligible, the teams worked with a village leader to identify ten farmers who were cultivating land near the village tube well.[7] For each of these farmers, the plot located closest to the tube well was mapped out. We refer to this plot as the "study plot" for the remainder of the paper.

B. *Data Collection and Treatment Assignment*

Each of the 4,000 farmers were visited for a baseline survey in November–December of 2016. The survey collected information on household demographics, agricultural production, water management, and water prices for the study plot and one other randomly selected plot of each farmer. Farmers almost entirely plant two rice crops—one in the rainy (*aman*) season and another in the dry (*boro*) season. Precipitation is rare during the boro season, and therefore, rice cultivation requires irrigation.

We randomly assigned each village to one of two groups prior to the start of boro cultivation in 2017—with stratification at the upazila level. Our field staff visited the 200 treatment villages during the period between planting and 10 days after planting. These visits took place from January to March, depending on village-specific planting dates. They trained the 10 farmers on the purpose of AWD and how to use it. Most importantly, they instructed farmers on the precise timing of when to practice AWD during the season. After the training field staff provided each of the farmers with an AWD pipe. Staff then visited the study plots with the group of farmers and assisted with installation.[8] Nothing was done in the remaining 200 villages, which serve as a pure control.

Online Appendix Figure A1 shows an AWD pipe on one of the study plots. The plastic PVC pipe is open at both ends and has holes drilled into the sides, allowing the farmer to observe moisture below the soil surface. Rather than keep the field flooded to ensure continuous absorption by the plant, the farmer can use the pipe to determine when the below-ground water level falls below a 15-centimeter trigger. The field should be irrigated at this time and the process can be repeated until the crop starts to flower, i.e., the reproductive stage begins. The crop needs constant water during this flowering period (60–80 days after planting), and therefore farmers should stop implementation of AWD at this time. The guidelines suggest that the practice of alternatively wetting and drying can be resumed after flowering stops and until the field is drained before harvest.

[6] Replacement occurred in less than 10 percent of villages (36 out of 400).

[7] In the event that a village had more than one tube well, mostly in Mymensingh, survey teams selected the tube well with the largest command area.

[8] Installation is close to costless. It simply requires inserting the pipe deep enough into the mud to allow the farmer to periodically monitor soil moisture up to 15 centimeters below ground.

Table 1 shows summary statistics and demonstrates covariate balance. Note that baseline knowledge of AWD is low. Only about 17 percent of farmers had heard of AWD, and nobody was using the technology at baseline. This suggests that AWD usage in the control group—at least in terms of using a pipe to monitor soil moisture and plan irrigations—should be low.[9] More importantly, just over a third of the farmers face a nonzero marginal price for water.

The map in Figure 2 shows the variation across space in volumetric pricing. Much of the variation is across upazilas. Upazila fixed effects explain 77 percent of the variation in the indicator variable for volumetric pricing. This is due to the prepaid card system being used in most of Rajshahi and not elsewhere. Specifically, 89 percent of farmers in Rajshahi reside in villages where prepaid irrigation cards are used to pump water by the hour. But there is some variation within upazilas, particularly in northern Mymensingh where tube well owners charge farmers for the fuel used in pumping about 15 percent of the time. There are also a few villages within Rajshahi where farmers reported at baseline that prepaid pumps were not being used. The lower-left panel of the map shows that some farmers in Rajshahi use their own hourly cards to buy water, while others still rely on seasonal contracts from the tube well operator. The results below use these different sources of variation in heterogeneity analysis. Online Appendix Table A1 shows that observable covariates remain balanced within this subsample exposed to volumetric pricing.

The experiment required objective measurement of water usage. However, no villages in our sample were equipped to measure individual-level pumping volumes. We therefore designed a unique data collection strategy to observe water usage without individual meters. Survey teams visited each of the study plots on two randomly chosen and *unannounced* days.[10] These visits enable us to observe whether the field was being dried and how much irrigation water stood in it. The random assignment of villages to days allows the treatment-control comparison to be made throughout the growing season. Having this ability is critical because the pipe should not be used during the reproductive (flowering) stage of crop growth. Hence, visiting fields on random days enables us to observe whether the tool is being properly used and measure whether its causal effect varies by the type of water pricing.[11] Online Appendix B uses data on hourly card usage from our second experiment to verify that observed water levels correlate with pumping activity during the previous four days.

Our teams then carried out a follow-up survey in July 2017 after the boro rice crop had been harvested and close to the time of planting for the next rainy season.

[9] A farmer can of course dry his field without using the AWD pipe, as shown in the results that follow. The lack of uptake at baseline should be interpreted as a lack of usage of the pipe to facilitate this process, not evidence that farmers never dry their fields.

[10] The timing of these visits is balanced across treatment and control villages. Regressing the days after planting of the visit on the treatment indicator and strata fixed effects yields a coefficient of -0.65 days and a p-value of 0.54.

[11] The schedule for the measurement of water management included 8,000 observations. We obtained data for 7,596 of them (95 percent). The missing observations resulted from random measurement dates falling after harvesting was completed. Harvesting dates were estimated from information on planting dates and length of the growing cycle from the baseline survey. This is obviously an imperfect proxy for current-year harvesting dates and therefore explains why the data are missing for a small number of cases. Missing data due to this scheduling issue are balanced across treatment and control groups.

Table 1—Summary Statistics and Covariate Balance by Treatment

	Means		
	Control	Treatment	*p*-value
Panel A. Household characteristics			
Age	42.33	42.93	0.251
	(12.05)	(12.23)	
Years education	6.645	6.330	0.125
	(4.863)	(4.525)	
Household size	4.888	4.802	0.467
	(2.202)	(2.159)	
Number livestock owned	2.892	2.701	0.0935
	(2.745)	(2.502)	
Landholdings in acres	2.026	2.003	0.769
	(2.168)	(2.046)	
Owns television	0.636	0.612	0.314
	(0.481)	(0.487)	
Owns refrigerator	0.139	0.129	0.639
	(0.346)	(0.335)	
Owns irrigation shallow tube well	0.0655	0.0595	0.520
	(0.247)	(0.237)	
Heard of AWD?	0.182	0.163	0.328
	(0.386)	(0.369)	
Panel B. Characteristics of study plot			
Plot is rented or sharecropped	0.0875	0.0675	0.136
	(0.283)	(0.251)	
Area in acres	0.427	0.405	0.195
	(0.494)	(0.421)	
Volumetric water price	0.344	0.350	0.754
	(0.475)	(0.477)	
Number crops grown	2.194	2.174	0.611
	(0.480)	(0.481)	
Rice-rice cropping system	0.697	0.698	0.989
	(0.460)	(0.459)	
Number irrigations in boro	20.80	20.55	0.695
	(8.757)	(8.097)	
Revenue per acre in boro	39,866.3	40,133.4	0.700
	(10,534.0)	(14,796.8)	
Cost per acre in boro	22,651.0	22,939.6	0.625
	(10,526.1)	(9,190.8)	
Water cost per acre in boro	6,663.9	6,199.8	0.357
	(8,768.0)	(5,636.1)	
Revenue per acre in aman	27,622.6	27,763.4	0.868
	(11,668.1)	(19,959.8)	

Notes: The table shows mean values of baseline characteristics for control and AWD treatment households in columns 1 and 2, respectively. Column 3 shows the *p*-value from the regression of each characteristic on the treatment indicator and strata (Upazila) fixed effects. Panel A contains household-level variables, and panel B contains variables specific to the study plot nearest the irrigation tube well. "Boro" is the dry season from January to May, and "aman" is the wet season from June to November. All data are based on the baseline survey from November–December 2016.

This survey collected information on self-reported irrigation management, input use, crop yield, revenue, and profit. The data provide the basis for our calculations of profitability and treatment effects of the AWD technique on profit—both with and without volumetric pricing.

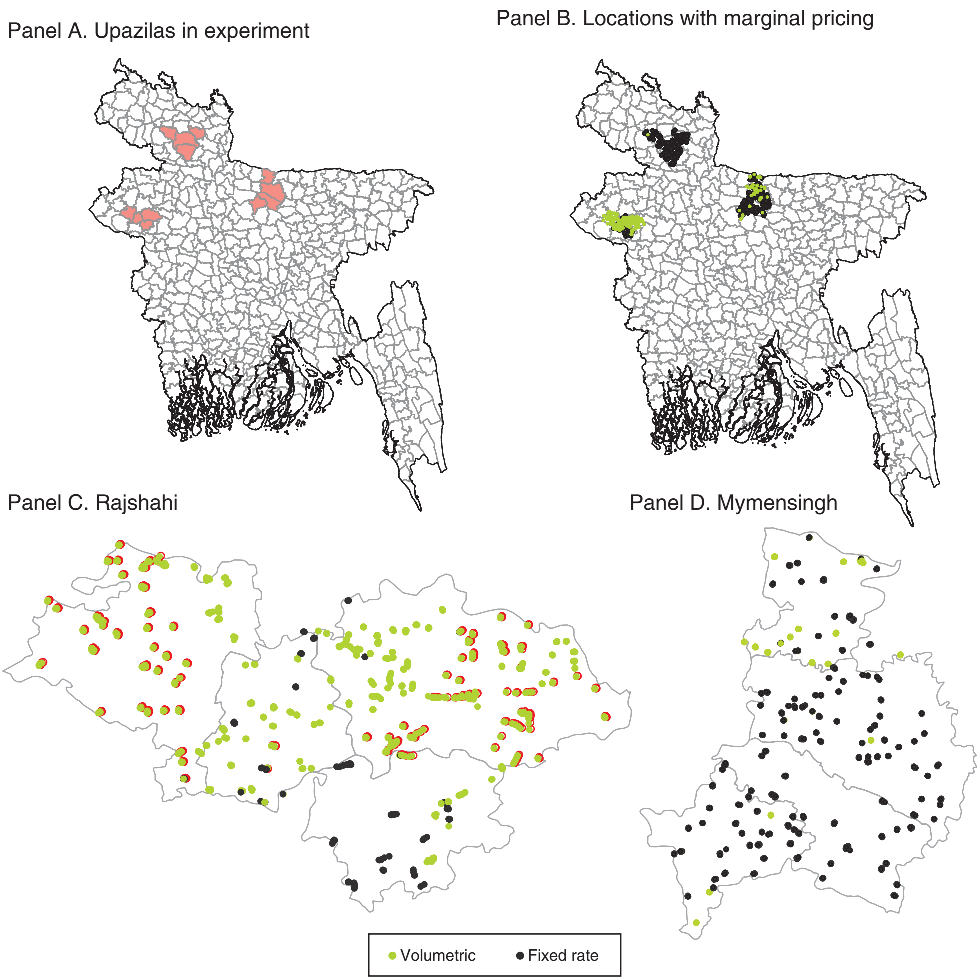

FIGURE 2. MAP OF AREAS WITH VOLUMETRIC PRICING

Notes: The figure shows the location of the study plots in the first RCT. Panel A shows the location of the 12 upazilas. Panel B shows the villages with volumetric pricing from the baseline survey. Panel C zooms in on Rajshahi (the district farthest to the west). It shows the villages with volumetric pricing (in green) and the farmers who use their own hourly cards to buy water (outlined in red). Panel D shows Mymensingh (the district farthest to the east). The farmers shaded in green are those who faced volumetric prices at baseline.

Source: The administrative boundaries of the upazilas are from the GADM database of Global Administrative Areas (Global Administrative Areas 2018).

II. Results: Marginal Prices and the Causal Effect of Conservation Technology

In this section we use the first-year experiment to estimate the causal impact of AWD technology on water management, input costs, and agricultural profits. Our pre-analysis plan specified both the average effect across our entire sample as well as the differential effect for farmers with seasonal water charges versus those with volumetric pricing. The analysis on water use is further broken down by time of the growing season—based on the recommendation that AWD not be practiced during the flowering stage of crop growth.

Our preferred specification is therefore

$$(1) \qquad y_{ivs} = \beta_0 + \beta_1 Treatment_v + \beta_2 Volumetric_{ivs} + \beta_3 Treatment_v \times Volumetric_{ivs} + \alpha_s + \varepsilon_{ivs},$$

where y_{ivs} is the observed outcome for farmer i in village v and upazila s. The treatment indicator, $Treatment_v$, varies only at the village level. The indicator for volumetric pricing varies both across and within upazilas, as was shown above. We estimate equation (1) for the sample of 4,000 study plots, regardless of whether the farmer kept the AWD pipe in that field. When observing water levels, enumerators found that treatment plots did not have the pipe installed only 2 percent of the time. Therefore, the treatment-on-the-treated results would be almost the same as the ITT results. We cluster standard errors at the village level in our main results. Given that much of the variation in volumetric pricing is between upazilas, we also show p-values for the interaction term when standard errors are clustered at the upazila level. Due to the small number of upazilas, we use the wild-cluster bootstrapped standard errors of Cameron, Gelbach, and Miller (2008).

The average effect of the pipe on water management—across the entire sample—is both small and statistically insignificant. Panel A of Table 2 shows in column 1 that the average study plot in treatment villages had only 0.06 cm less water standing in the field. The rest of the top panel shows that the treatment is only effective for farmers who face volumetric water prices, particularly earlier in the growing season. In column 2 introducing the AWD pipe in places with volumetric pricing lowers the amount of observed irrigation water by 0.43 centimeters, or an 18 percent decrease. Column 2 additionally shows that the correlation between volumetric pricing and water use (within strata) is small and statistically insignificant. This result could be driven either by the limited variation within strata or correlation between unobservables and volumetric pricing. We show in online Appendix Table A2 that the volumetric pricing indicator has a negative correlation with water levels and a positive correlation with the probability of dry fields when omitting strata fixed effects.

The proper usage of the tool depends on the time during the growing season. Columns 3–6 of Table 2 show that treatment effects exist only during the first 70 days of the growing season. We prespecified this split in the data to approximately divide the season into the time before and after the start of flowering. Farmers practice AWD during the time up to flowering. Treatment plots had about 13 percent less water during the first 70 days of the season (column 3). This effect exists only with volumetric pricing. Turning to column 4, AWD causes water levels to be lower by 0.83 cm (31 percent) under volumetric pricing. Columns 5–6 show that plots of treatment farmers were managed in the same fashion as those of the control group after the first 70 days of the growing season, regardless of the type of water contract. Therefore, farmers did follow the directions to stop practicing AWD during the time when crop water requirements are high.

Panels B and C look at whether results vary when using only between- or within-upazila variation in volumetric pricing. Panel B confines the identification to the variation between upazilas, which Figure 2 showed was responsible for most

Table 2—Effects of Conservation Technology on Water Levels

	Overall		0–70 days after planting		70+ days after planting	
Panel A. Main results						
Treatment	−0.0614	0.119	−0.350	−0.0485	0.250	0.258
	(0.161)	(0.220)	(0.152)	(0.208)	(0.286)	(0.376)
Treatment × Volumetric Pricing		−0.544		−0.788		0.0138
		(0.287)		(0.287)		(0.474)
		[0.193]		[0.0200]		[0.970]
Volumetric Pricing		−0.107		0.0256		−0.488
		(0.333)		(0.363)		(0.420)
p-value: Treat + Treat × Volumetric		0.021		0.000		0.328
Control mean	2.32	2.32	2.71	2.71	1.86	1.86
Number of observations	7,598	7,596	4,188	4,187	3,410	3,409
Panel B. Between-upazila variation						
Treatment		0.0936		0.0160		0.143
		(0.227)		(0.212)		(0.380)
Treatment × Volumetric Pricing Upazila mean		−0.476		−0.966		0.424
		(0.328)		(0.326)		(0.541)
		[0.256]		[0.00501]		[0.445]
p-Value: Treat + Treat × Volumetric		0.073		0.000		0.096
Panel C. Within-upazila variation						
Treatment		0.240		−0.723		1.667
		(0.757)		(0.766)		(1.155)
Treatment × Volumetric Pricing		−0.762		−0.147		−1.228
		(0.658)		(0.678)		(0.967)
		[0.394]		[0.790]		[0.279]
p-value: Treat + Treat × Volumetric		0.119		0.007		0.511

Notes: The data are from random unannounced visits to the study plots of sample farmers during the 2017 boro (dry) growing season. The dependent variable in all columns is the amount of standing water in the field, measured in centimeters. All regressions include upazila (strata) fixed effects. Panel A shows our main results where the volumetric pricing indicator is measured at the farmer level. Panel B uses only the between-upazila variation in volumetric pricing by interacting the treatment with the *upazila-level average* of the volumetric pricing variable. Panel C uses only the within-upazila variation by including treatment-by-upazila fixed effects. Standard errors that are clustered at the village level are printed in parentheses below each point estimate. The numbers in brackets are p-values when standard errors are clustered at the *upazila level* using the wild-cluster bootstrapping method of Cameron, Gelbach, and Miller (2008).

of the variation. It shows that water usage results are similar when the treatment is interacted with the upazila-level average of volumetric pricing. Panel C includes upazila-by-treatment fixed effects and shows that the within-upazila variation in volumetric pricing is responsible for less of the heterogeneity in the 0–70 days after planting period. The point estimates for overall water usage are similar, but the standard errors are much larger due to there being less variation within upazilas.

Online Appendix Table A3 shows similar results when using a binary dependent variable for observing dry fields with no standing water. The table shows that farmers practice some form of the AWD technique without using PVC pipes: fields in the control group were dry 45 percent of the time. Thus, the correct counterfactual differs from the one used in agronomic experiments where water is maintained in the control field for the entire season.[12]

[12] Agronomic experiments generally compare AWD to “continuous flooding.” This is a system where the farmer never lets the field go dry. The field is re-irrigated when water reaches a low level but before it evaporates entirely.

These results are insensitive to the choice of splitting the sample using a threshold of 70 days: we show in online Appendix Tables A4–A7 that results are similar when we divide the season using a 60- or 80-day cutoff. The online Appendix shows that we detect treatment effects on self-reported water usage. We do not observe heterogeneous impacts when asking farmers how many times they irrigated their fields, but we do when considering the number of times the field was drained (online Appendix Table A8).

Combining these findings, Figure 3 demonstrates how treatment effects varied both across time and by type of water pricing. It shows nonparametric regressions of water levels (top panels) and the indicator for dry fields (middle panels) on days after planting, separately for treatment and control villages. The upper left panel shows that the technology caused a decrease in irrigation withdrawals during the preflowering period of crop growth—but only for farmers paying for water on the margin. The same estimates in the upper right panel establish that AWD had no impact on measured water levels for farmers facing seasonal charges. The middle panel shows a similar pattern with dry fields: we observe that introducing the pipe leads to a noticeable increase in drying in places with volumetric pricing during the early part of the growing season, but no changes are observed for the two-thirds of farmers who pay for water on a seasonal basis. The figure further shows how farmers conserve water when facing volumetric prices, even without AWD: they tend to keep fields dry after flowering. In combination, the evidence suggests that AWD helps farmers with volumetric pricing learn that they can use less water during the early part of the growing season.

The magnitude of our estimates is reasonable. In fact the estimates line up with findings from agronomic trials—but only when prices are set volumetrically. Figure 4 shows 87 impact estimates reported in 26 different agronomic studies. The estimated water savings from these experiments range from 5 to 65 percent, with median savings of 27 percent. Our 18.3 percent effect on water levels when prices are volumetric—from Table 2, column 3—falls near the twenty-fifth percentile of the agronomic estimates. In contrast the null effect with area-based pricing is outside the range of estimates from agronomic trials. This gap between the predicted effects from the laboratory and the field estimates has been shown in the literature on energy efficiency (Fowlie, Greenstone, and Wolfram 2018). In our case the failure of markets to efficiently price water appears to be a critical factor causing the field-based RCT estimates to deviate from those in the laboratory.

Adoption of AWD only increases profit when water is priced at the margin.[13] Column 1 in Table 3 shows that the causal effect of AWD on (log) profits per acre, in the absence of volumetric pricing, is close to zero and statistically insignificant. In contrast the AWD technology increases profits by about 9 percent, when water has a marginal price. Columns 2–4 decompose the heterogeneous profit effect into

[13] We measure revenue per acre by dividing the total output from the plot by plot size to obtain yield, regardless of how much of the output was sold or kept for consumption. We then multiply the yield by the output price for the 98.5 percent of farmers who reported selling output. We use the average sale price for the remaining 1.5 percent of farmers who did not sell any output. We collected input expenditures for fertilizer, pesticide, herbicide, water, planting labor, weeding labor, and harvesting labor. Labor inputs included both family labor and hired labor. We valued family labor by multiplying the number of person days by the daily wage rate from the survey.

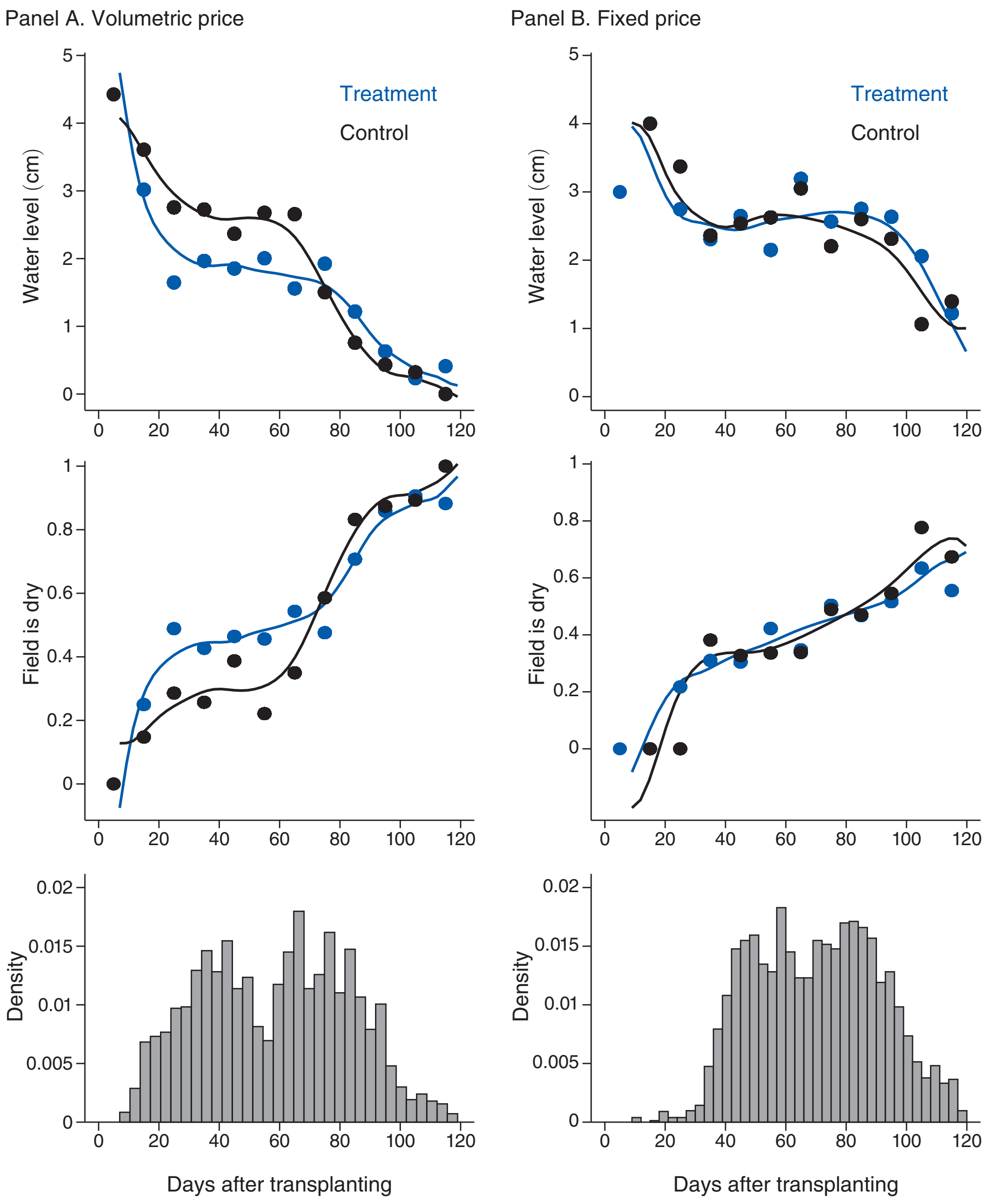

Figure 3. Nonparametric Estimates of Treatment Effect as a Function of Days after Planting

Notes: The figure shows nonparametric fan regressions of water levels in centimeters (top panel) and an indicator for fields with no standing water (middle panel) on the days after transplanting. The dots show average values from ten-day bins, where each dot is centered at the bin midpoint. The bottom panel shows the distributions of observations (histograms of the date of observations, measured in days after planting).

three parts. First, the interaction effect on water costs is negative (column 2). The coefficient is not individually significant ($p = 0.13$), but its magnitude suggests that some of the profit effect comes from a reduction in water costs. Second, we see no effects on crop yield (column 3). This finding is consistent with multiple agronomic

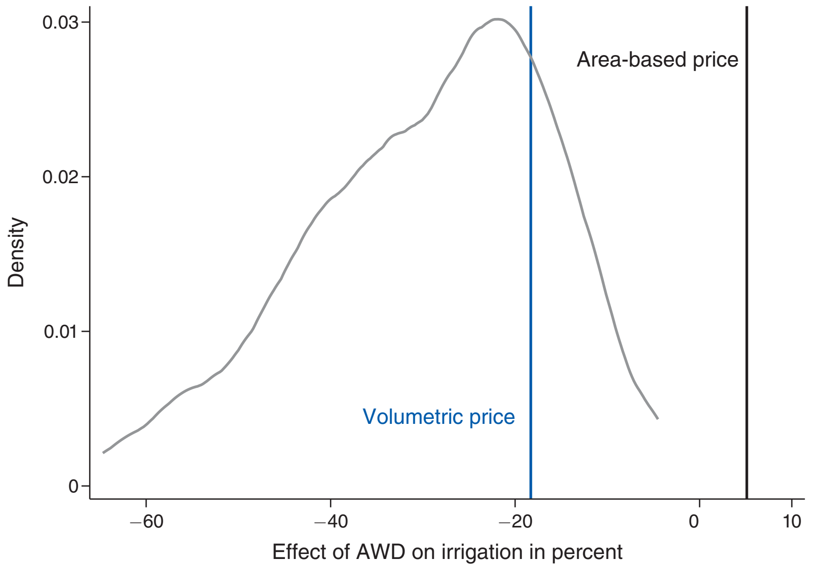

Figure 4. Comparison between Impacts from the RCT and Agronomic Experiments

Notes: The figure shows the kernel density of the impacts of AWD on irrigation volumes (gray line) from 26 studies. These studies report a total of 87 impact estimates, as a single agronomic trial often includes more than one experiment in a single season, is done over multiple seasons, or tests different variants of the AWD technique. The black line shows our estimated treatment effect on water levels with area-based pricing and the blue line for areas with volumetric pricing (from Table 2, column 2).

trials showing that the practice leaves yield unchanged (e.g., Belder et al. 2004 and Yao et al. 2012). Third, we see a positive—but insignificant—interaction effect on revenue.

Avoided water costs account for only a share of the heterogeneous profit effect. The remainder of the effect is driven by lower expenditures on other inputs as well as positive effects on revenue. Neither of these effects are individually significant, but the aggregate of all three is marginally significant.[14] Agronomic studies have found that using AWD can improve some dimensions of grain quality (Norton et al. 2017; Xu et al. 2019). This offers one explanation for any modest effects on revenue that are not driven by crop yield.[15]

In contrast to this variation in volumetric pricing, which is mostly across regions, we do additional heterogeneity analysis that considers whether farmers are using their own hourly cards to buy water. Some farmers within Rajshahi district do not have their own prepaid cards.[16] Instead, these farmers rely on the deep driver (tube well operator) to use his card and then charge them a fixed seasonal price (see the

[14] We provide a breakdown of results on other inputs in online Appendix Tables A9–A13. The heterogeneous effects on nonwater inputs do not show a clear pattern. While the individual coefficients for some inputs are significant, the signs go in opposite directions—leading to the absence of any large aggregate effects.

[15] A regression with log price as the dependent variable yields an interaction effect of 0.018 and a *t*-statistic of 1.16 (regression not shown).

[16] Our baseline survey, and hence the analysis until this point, classified these farmers as paying volumetric prices because their village already had a prepaid pump installed.

Table 3—Effects of Conservation Technology on log Costs, Revenues, and Profits

	Full sample				Rajshahi sample	
	Profit	Water cost	Yield	Revenue	Water cost	Profit
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	−0.036	0.023	−0.001	0.001	0.022	0.026
	(0.046)	(0.024)	(0.014)	(0.017)	(0.062)	(0.044)
Treatment × Volumetric Pricing	0.122	−0.081	0.009	0.029		
	(0.061)	(0.053)	(0.017)	(0.022)		
Volumetric Pricing	−0.123	0.066	0.013	0.003		
	(0.070)	(0.043)	(0.018)	(0.028)		
Treatment × Has Card					−0.209	0.112
					(0.095)	(0.077)
Has Card					0.243	−0.072
					(0.074)	(0.071)
Upazila fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
p-value: Treat + Treat × Volumetric	0.035	0.225	0.417	0.045	0.011	0.030
Number of observations	3,932	3,983	3,982	3,982	1,340	1,332
R^2	0.273	0.347	0.329	0.351	0.455	0.083

Notes: The data are taken from the follow-up survey after harvesting. The dependent variables are log profit per acre (columns 1 and 6), log water cost in taka per acre (columns 2 and 5), log crop yield in kilograms per acre (column 3), and log revenue in taka per acre (column 4). Standard errors are clustered at the village level.

lower left panel of Figure 2 for a map of the variation). The water charge for farmers without their own cards is a function only of acreage cultivated and not the number of hours of pumping. The deep driver essentially averages out the total pumping cost over the entire command area, adds a markup, and bills farmers accordingly. This local institution provides additional heterogeneity. In particular the effect on water costs should be higher for farmers who hold their own cards and thus stand to gain by pumping less groundwater.[17]

Column 5 of Table 3 shows that AWD lowers water costs by about 19 percent for cardholders and has no effect for farmers who pay the deep driver for water. The effect on log profits in column 6 is noisier but goes in the same direction. AWD increases profit by 13 to 14 percent for farmers with cards but has a smaller effect in villages where individual card ownership is absent. These findings help explain the modest effects on avoided water costs in column 2. AWD only lowers the water bill for farmers who use their own prepaid irrigation cards, which is a subset of the farmers in villages with volumetric pricing.

We next try to quantify how much water is conserved by the technology when there is marginal pricing. AWD reduces water costs by Tk931.1 per acre for farmers with hourly irrigation cards.[18] The median plot size is 0.3 acres, and the cost per hour of pumping is Tk120. Combining these three figures delivers an estimated savings of 2.3 hours of pumping per AWD device. The standard government deep tube well has a capacity of 1 cusec, i.e., 1 ft^3/sec or 101.941 m^3/hr.

[17] We did not know about this heterogeneity at the time of designing the study. Therefore, these estimates were not prespecified in our analysis plan.

[18] The analogous regression to Table 3, column 5 with water costs in levels gives a coefficient on the treatment of 108.34 ($p = 0.3$), and the interaction effect is $-1{,}039.37$ ($p = 0.03$). The treatment effect with hourly cards is therefore -931.1.

Thus, a reasonable estimate of averted pumping by using AWD on a single plot is 234.46 m^3 or 0.19 acre feet of water. A conservative agronomic estimate is that 25 percent of the groundwater used in rice would return to the aquifer (Qureshi et al. 2010). Thus, an estimate of the true water savings is 75 percent of the averted pumping, or 0.1425 acre-ft. This volume of water is not trivial. It represents about half of the mean annual household residential consumption in the United States.

As another piece of evidence, we elicited demand for AWD before the following 2018 season in a random set of 152 out of the 400 villages, using the same procedures as the second RCT. Table 4 shows a significant interaction effect on demand between AWD treatment from the prior year and volumetric pricing, using both overall and within-upazila level variation. This finding is in line with our main result that the prior year's AWD treatment only benefited farmers with volumetric pricing.

Robustness.—We next show the robustness of our main finding. We briefly discuss the analysis here and provide more details in online Appendix C. First, a number of characteristics differ between farmers with and without volumetric pricing (online Appendix Table C1). These differences might explain our results if the interaction between treatment and volumetric pricing is picking up some other dimension of heterogeneous returns. Table 5 considers robustness to adding interactions between the treatment and various household- and plot-level characteristics. We obtain a similar result on water levels when interacting the treatment with over 20 observable characteristics of households and plots (column 1). Column 2 shows that controlling for interactions between plot-level soil characteristics and treatment does not change the finding. Lastly, columns 3–6 consider upazila-level averages of soil conditions. The rationale behind this test is that most of the variation in volumetric pricing is across upazilas. It might be that volumetric prices are used in some places because of soil characteristics, such as low soil moisture. If the returns to AWD vary by these more aggregate characteristics, then our estimate would be misleading. None of the four aggregated soil characteristics are confounding our estimate.

We use the machine learning methods in Chernozhukov et al. (2018) to ask which characteristics explain the most heterogeneity. This analysis involves splitting our data into 100 estimation and validation datasets. For each estimation dataset, LASSO regressions are used separately for treatment and control farmers to determine the subset of covariates that best predict water levels. With these sets of covariates, we use OLS regressions to calculate expected water usage under both treatment and control. The difference between these two predictions provides an estimated treatment effect conditional on covariates. We do two things with the predicted treatment effects. First, we verify that they are predictive of actual heterogeneity in each validation dataset. The water savings from AWD are concentrated in the top two quartiles of the distribution of predicted treatment effects—meaning that the covariates predict heterogeneity of the AWD treatment (online Appendix Figure C3). Second, Table 6 shows that farmers predicted to benefit the most from AWD are concentrated among those with volumetric pricing.[19] Farmers in the top

[19] Online Appendix Table C6 shows the corresponding table for individual card ownership in the Rajshahi sample.

Table 4—Follow-Up Demand for AWD in the 2018 Season

	(1)	(2)
Treatment	−0.260	−0.282
	(0.051)	(0.143)
Volumetric Pricing	−0.205	−0.189
	(0.068)	(0.084)
Treatment × Volumetric Pricing	0.213	0.155
	(0.071)	(0.093)
Price	−0.007	−0.007
	(0.001)	(0.001)
Upazila fixed effects	Yes	Yes
Upazila fixed effects × Treatment	No	Yes
Mean in control	0.36	0.36
Number of observations	1,461	1,461
R^2	0.300	0.333

Notes: The table shows estimates of AWD demand from 152 randomly selected villages that were part of the sample of the first RCT. Farmers in each village were visited at the start of the boro season during January 2018. They were offered an AWD pipe at one of the same random prices used in the second demand experiment (Tk20–90 or around \$0.24 to \$1.1). The dependent variable in both regressions is an indicator for whether the farmer purchased the AWD pipe. The treatment variable is an indicator for treatment villages (farmers who received AWD pipes and training) during the previous 2017 season. Standard errors are clustered at the village level.

20 percent of predicted water savings from AWD are overwhelmingly those with volumetric pricing: 93 percent of farmers in the top quintile of predicted water savings have volumetric pricing, while only 5 percent of farmers in the bottom quintile do. Of the covariates analyzed, volumetric pricing explains the most variation in predicted treatment effects. The other covariates that explain the heterogeneity are potentially endogenous to volumetric pricing.

Online Appendix C contains further analysis to investigate the robustness of the heterogeneity finding. Online Appendix Table C2 shows baseline characteristics by prepaid card ownership for the Rajshahi sample, while online Appendix Table C3 shows that the differential effects for card owners are nearly identical when controlling for the interactions between all of these covariates and the AWD treatment. The differential effect of card ownership on water costs does not seem to be driven by plot, household, or geospatial characteristics.[20]

We do not find evidence that the upazila-level heterogeneity (panel B of Table 2) is being driven by an omitted upazila-level correlate of volumetric pricing. This could be the case if the upazilas with more volumetric pricing differ along a key determinant of the benefits of AWD. Online Appendix Figures C1 and C2 show that the heterogeneity results for dry fields and water levels remain similar when controlling one by one for upazila-level averages of 16 covariates. These estimates build on the results in Table 5 by investigating more covariates.[21] The interactions

[20] The plot-level geospatial characteristics are elevation, soil clay content, soil sand content, soil organic carbon content, and soil water content. These variables were calculated by matching plot locations with remote sensing datasets in Google Earth Engine (Gorelick et al. 2017).

[21] We omit the covariates that are likely endogenous to volumetric pricing, such as the cropping system, number of crops grown, and revenues.

Table 5—Robustness of Water-Usage Results to Interactions between the AWD Treatment and Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.165	0.179	0.248	0.228	0.158	0.166
	(0.212)	(0.217)	(0.225)	(0.220)	(0.229)	(0.212)
Treatment × Volumetric Pricing	−0.673	−0.762	−0.926	−0.863	−0.650	−0.675
	(0.301)	(0.344)	(0.368)	(0.349)	(0.393)	(0.305)
Volumetric Pricing	−0.077	−0.084	0.016	−0.018	−0.089	−0.077
	(0.339)	(0.342)	(0.346)	(0.345)	(0.371)	(0.339)
Treatment interacted with						
Soil Clay Content			0.137			
			(0.085)			
Soil Sand Content				−0.063		
				(0.043)		
Soil Carbon Content					0.030	
					(0.275)	
Soil Water Content						−0.003
						(0.080)
Upazila fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Treatment	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	No	No	No
Geo Controls × Treatment	No	Yes	No	No	No	No
Mean in control	2.32	2.32	2.32	2.32	2.32	2.32
p-value: Treat + Treat × Volumetric	0.013	0.012	0.005	0.007	0.062	0.014
Number of observations	7,588	7,468	7,588	7,588	7,588	7,588
R^2	0.051	0.055	0.052	0.052	0.051	0.051

Notes: The data are from random unannounced visits to the study plots of sample farmers during the 2017 boro (dry) growing season. The dependent variable in all columns is the amount of standing water in the field, measured in centimeters. The (baseline) controls in all columns are all of those in Table 1 (age, years of education, household size, number of livestock owned, landholdings, television ownership, refrigerator ownership, tube well ownership, indicator for knowledge of AWD, indicator for a rented or sharecropped plot, plot area, number of crops grown, indicator for growing two rice crops, number of boro irrigations, revenue per acre in boro, boro total cost per acre, and aman revenue per acre). The plot-level geographic control variables (column 2) are elevation, soil clay content, soil sand content, soil organic carbon content, and soil water content. Columns 3–6 add interactions between *upazila-level* average soil characteristics and treatment. Standard errors are clustered at the village level.

between the covariates and the AWD treatment are significant for only 1 of the 16 regressions for water levels and 2 for dry fields. None of the controls lead to substantial changes in the treatment–volumetric pricing interaction.

Our analysis is conducted for the study plot of each farmer. One possibility is that the treatment causes water (or other inputs) to be reallocated away from the study plot and toward other plots of the household. This would cause the treatment effect on household-level outcomes to differ from the plot-level outcomes we have observed thus far. Online Appendix Table A14 shows treatment effects on a randomly selected plot for each farmer, other than the study plot. We find no evidence that the treatment causes water use or other inputs to increase on that plot. If anything, the treatment lowers water costs in areas with volumetric pricing, which is consistent with farmers irrigating more than one plot at a time.

Another concern is that our main finding is a false positive resulting from multiple outcomes being tested. We address this by adjusting the *p*-values for multiple

Table 6—Characteristics of Farmers Most and Least Affected by Conservation Technology

	Mean most affected	Mean least affected	Share variation explained
Volumetric water price	0.934	0.053	0.456
Age	40.941	45.355	0.007
Years education	7.495	4.413	0.037
Household size	4.875	4.586	0.003
Number livestock owned	2.461	2.552	0.000
Landholdings in acres	2.643	1.394	0.049
Owns television	0.760	0.431	0.049
Owns refrigerator	0.144	0.068	0.008
Owns irrigation shallow tube well	0.136	0.011	0.040
Heard of AWD?	0.207	0.030	0.030
Plot is rented or sharecropped	0.081	0.074	0.001
Area in acres	0.377	0.359	0.001
Number crops grown	2.729	1.902	0.308
Rice-rice cropping system	0.271	0.836	0.148
Number irrigations in boro	22.514	18.687	0.011
Revenue per acre in boro	48,567.625	34,707.254	0.205
Cost per acre in boro	26,842.287	23,260.350	0.026
Water cost per acre in boro	10,046.160	5,258.934	0.057
Revenue per acre in aman	40,410.621	19,279.115	0.367

Notes: The table classifies farmers according to their predicted treatment effect from AWD, i.e., the predicted decrease in water usage during the first 70 days after planting. Column 1 shows mean values of characteristics for the 20 percent of farmers who are predicted to conserve the most water if treated. Similarly, column 2 shows mean values for the 20 percent of least affected farmers. Column 3 shows the R^2 of a bivariate regression of the predicted heterogeneity score, s_0, on each characteristic.

inference in online Appendix Table A15. Our main effect—that conservation technology only saves water with marginal prices—remains significant when controlling the false discovery rate using the methods in Anderson (2008). A more conservative test is to control the probability of making at least one false rejection, as in List, Shaikh, and Xu (2019). The effects on self-reported water usage and objective measurements during the preflowering period continue to be significant with this alternative method.

III. Experimental Design to Estimate the Effect of Encouraging Hourly Irrigation

Building on the results from our first experiment, we designed a second RCT. Our goal with the second RCT was to test whether encouraging farmers to convert to hourly prices for pumping can reduce groundwater use—particularly by increasing their willingness to buy and use AWD. The intervention encourages uptake of hourly irrigation by providing incentives; mostly it covers the costs of obtaining a prepaid irrigation card for farmers. Our approach allows us to measure two parameters of interest. First, we trace out the demand curve for AWD both for farmers who were incentivized to use hourly prices and for the control. Second, water usage is the key final outcome. We look at whether the intervention caused farmers to use less water. This section gives more background and outlines the timing of events for this experiment.

In many villages the ratio of prepaid irrigation cards to farmers is less than one. Most commonly, the deep driver or water user's committee maintains a small number of prepaid cards, uses them to provide water to farmers, and then charges each farmer the same fee per acre. In effect this local institution keeps water pricing on a per acre basis, despite technology being in place for each farmer to pay for their pumping by the hour. Multiple factors may explain why individual card usage, and hence volumetric pricing, has not taken effect in these villages: it is costly and time-consuming for farmers to obtain an individual card; coordination difficulties—i.e., problems in creating an efficient queueing system if each person is individually using a card; and concerns about fairness because some plots are far from the tube well and water is lost during transport due to the earthen canals used for conveyance. Combined with highly fragmented landholdings, this will result in differential prices per unit of actual water between farmers. Our treatment tries to incentivize uptake by covering the fixed costs of obtaining a card.

We first identified 144 villages in Rajshahi district—those not included in the sample of our first RCT—where farmers were not using their own prepaid card for pumping. These villages are spread across three upazilas. Field staff worked with a local village leader in November 2017 to identify 25 farmers cultivating rice during the boro season in each of these villages. The villages were then randomly divided into two groups: 96 were assigned to a treatment group where we sought to increase the share of farmers paying for irrigation by the hour by using their own cards; the remaining 48 serve as a control group that retained the status quo of seasonal charges.

Field teams started by organizing a meeting with these 25 farmers. These meetings took place in December 2017 and served four objectives. First, a short baseline questionnaire was administered. Second, farmers were instructed on how the irrigation system can be operated with the individual cards. Third, our field staff explained to farmers that their local NGO was running a program to help with applying for the prepaid card. Specifically, the field staff assisted each farmer in filling out the application form—including obtaining a passport-style photo to be printed on the card. Fourth, there is an application fee of Tk150 (around \$1.8) to be paid at the time of submitting the application. Farmers were instructed that the program would be covering these costs. In addition our partner delivered the application forms to the local upazila office of the agency responsible for producing the cards, collected the printed cards when they were complete, and delivered them to each treatment village prior to planting. Overall, 2,279 of the 2,400 (95 percent) farmers in the treatment group agreed to receive the cards as part of the program.

Our design sought to eliminate the possibility that any future behavior could be a function of the small Tk150 incentive. Therefore, we provided each of the 1,200 farmers in the control group with Tk150 of mobile phone credits right after administration of the baseline survey.

Online Appendix Table A16 shows baseline characteristics for the treatment and control groups in this second RCT. Household and farm characteristics are generally similar across the two groups. The average farmer in this sample pays around Tk1500 (approximately \$18) to irrigate 1 bigha of land (a bigha equals one-third of an acre). Seventy percent pay this money directly to the deep driver as a per bigha fee. The remaining 30 percent pay the fee to a water users committee.

Does this effort to encourage volumetric pricing alter the farmer's demand curve for AWD? To get at this question, we conducted a revealed-preference demand experiment in all 144 villages. A salesperson visited each of the 25 farmers in January or early February 2018, depending on the planting dates in the village. S(he) gave each farmer the opportunity to purchase an AWD pipe at a randomly determined village-level price. We let the price range from Tk20–90. As points of reference, the daily wage for casual agricultural work during the previous boro season was about Tk350. The estimated profit advantage of the pipe was about Tk561 per plot—when farmers faced nonzero marginal prices for water. Farmers who bought the pipe were required to pay cash. The pipe was handed to the farmer, along with instructions on its use, immediately after purchase. Unlike in the first RCT, field staff did not provide any further training or assistance with actually installing the AWD pipe.

In addition to observing these purchasing decisions, we collected data on whether the pipe was installed and measured water levels in the field. Similar to our first RCT, we randomly drew dates to visit each of the 144 villages. These dates were drawn to fall mostly in the 10- to 70-day period after planting, when we observed farmers from the first experiment practicing AWD.[22] During each visit, the enumerator checked all the plots of each farmer to see if an AWD pipe was being used. In addition water levels were measured on the plot closest to the tube well for a random 75 percent of farmers and the farthest plot for the rest of the sample.

IV. Results: Hourly Irrigation, Water Usage, and the Demand for Water-Saving Technology

Our treatment made it easier for farmers to buy water by the hour. But it was not possible to mandate volumetric pricing. Farmers could still choose to pay the tube well operator by the season rather than use the card. This feature allows farmers to reveal their preferred mechanism for paying for water. We investigate this using data from the 1 upazila that provided us complete data on card usage for the 800 treatment farmers. We found that 40.3 percent of them (323) loaded their card at least once during the period from January 12 to August 7, 2018. The median farmer—conditional on loading at least once—spent Tk3,000 ($37.5, or the equivalent of irrigating about two plots with seasonal charges) and loaded the card five times. These distributions have a substantial right tail: a farmer at the ninetieth percentile reloaded the card 22 times and spent Tk21,800.

But these data show that many farmers chose not to use the cards. This provides initial evidence that there are some reasons why farmers prefer fixed charges. One reason for this is that they have to start paying the moment the pump is turned on, which can be well before the water reaches their field. The earthen canals used for conveyance often result in water leaking onto the fields of other farmers. This lowers other farmer's (per acre) costs at the expense of the prepaid card user. Data from the first RCT show a positive association between using an individual card and water costs. Table 3 shows that farmers with their own prepaid cards actually pay about

[22] The visits took place during February 2 to May 23, 2018, with the median visit occurring on April 1.

24 percent more per acre for water. This is only a correlation, but online Appendix Table C3 shows that it is quite robust to controlling for a large set of covariates.

A. *Main Effects on Water Management*

We start with the main effects on observed water management in Table 7. Column 1 shows that the card encouragement increased the probability that an AWD pipe was observed on the field. This 3.4 percentage point effect is large in relative terms because AWD was observed on less than 1 percent of plots in the control group. But the low rate of final usage of AWD (in both types of villages) suggests that the prepaid card treatment did not trigger a causal chain from pricing incentives to technology adoption to water savings. Column 2 adds an interaction term between the AWD offer price and the treatment. There is no interaction effect on AWD usage.

Moving to columns 3–4, we find no differences in water management for prepaid card and control villages. Fields in prepaid card villages had 0.14 cm more water on average, a difference that is both small and statistically insignificant. The confidence interval on the point estimate allows us to reject any decreases in water levels larger than 0.42 cm, or 19 percent of the control mean. Column 4 shows a small and statistically insignificant interaction effect between price and the card treatment.

These results suggest there are other frictions that prevented our prepaid card encouragement from conserving water. For example, use of the prepaid cards may be limited by concerns for equity in the community: the traditional earthen ditches used to move water leak, and this makes paying by the hour costlier for farmers located farther from the tube well. Or the deep drivers (tube well operators) benefiting from the per acre pricing system may have resisted usage of individual cards by farmers. Finally, it may take time for farmers to learn how the prepaid cards work and to adjust behavior. We find some evidence that using the card is correlated with reduced water use later in the season, after farmers have had an opportunity to learn (online Appendix Figure A2). However, this finding is only correlational. Overall, the treatment got 40 percent of farmers to adopt marginal pricing, but this was not enough to change how they manage water.

A mandatory switch to marginal prices could possibly lead to different results. Farmers who use a lot of water, and thus have high potential to conserve, might want to avoid marginal pricing because it can increase their costs. A mandatory switch, however, may induce them to save water. Online Appendix Table A17 investigates characteristics of farmers who were more likely to comply by using the prepaid card. Across villages, compliance was more likely in places with a larger number of baseline irrigations and larger dry season farms. This could be because marginal prices were preferred in villages with more potential to save and where landholdings are less fractured, making it easier to coordinate irrigations with individual card usage. But within villages, farmers using more water at baseline were less likely to use the prepaid cards.[23] Thus, high water users within villages might not comply with a voluntary switch to marginal pricing.

[23] A regression of card usage on village fixed effects and the number of baseline irrigations has a negative estimate that is significant at the 10 percent level.

Table 7—Impacts of Hourly Irrigation Cards on Water Usage and AWD Demand

	AWD installed		Water level		Purchase AWD		Use AWD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Card Treatment	0.0343	0.0424	0.1449	0.3651	0.0430	−0.1428	0.0200	−0.1071
	(0.0104)	(0.0268)	(0.2896)	(0.6997)	(0.0436)	(0.1044)	(0.0278)	(0.1074)
Pipe Price	−0.0004	−0.0002	−0.0026	0.0002	−0.0105	−0.0129	−0.0016	−0.0033
	(0.0002)	(0.0003)	(0.0050)	(0.0121)	(0.0008)	(0.0012)	(0.0006)	(0.0014)
Pipe Price × Card Treatment		−0.0001		−0.0040		0.0034		0.0023
		(0.0004)		(0.0132)		(0.0015)		(0.0015)
Upazila fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean in control	0.008	0.008	2.214	2.214	0.413	0.413	0.068	0.068
Elasticity at price = 55 treat					−1.26	−1.14	−1.01	−0.60
Elasticity at price = 55 control					−1.39	−1.70	−1.31	−2.58
p-value: Equal elasticities						0.009		0.001
Number observations	3,598	3,598	3,600	3,600	3,569	3,569	3,600	3,600
R^2	0.017	0.017	0.012	0.012	0.249	0.254	0.033	0.041

Notes: The data are from the 144 villages that were part of the second-year experiment. The sample consists of 25 farmers per village. Columns 1–4 are for the one plot per farmer where water levels were measured. The specific plot is the closest to the village tube well for 75 percent of random farmers and the furthest plot for the remaining 25 percent of farmers. Columns 5–8 are at the farmer level (either purchasing AWD or using it across all plots). The dependent variables are an indicator for whether an AWD device was installed on the specific plot where water was being measured (columns 1–2), the observed water level on the plot in centimeters (columns 3–4), an indicator for whether the farmer purchased AWD during the demand elicitation (columns 5–6), and an indicator for whether AWD was used at all on any plots (columns 7–8). The card treatment variable is an indicator for villages where the 25 farmers were provided assistance with filling out the application for a prepaid (hourly) irrigation card and a waiver of the Tk150 sign-up fee. Standard errors are clustered at the village level.

B. *Effects of Encouraging Hourly Pricing on the Demand Curve for AWD*

The prepaid card treatment did lead to modest changes in demand for AWD at the farmer level. Column 5 in Table 7 shows that the irrigation card treatment increased the share purchasing AWD by about 4.3 percentage points, or roughly 10 percent. The average effect is indistinguishable from zero due to the significant heterogeneity across price levels. Column 6 shows that the cards made farmers less responsive to AWD prices. Increasing the price by Tk1 leads to a 1.29 percentage point decrease in adoption in the control group. This price responsiveness falls significantly by 0.34 percentage points when we encourage volumetric pricing. The demand elasticity at a price of Tk55—reported at the bottom of column 2—falls by 33 percent from 1.7 to 1.14 with the prepaid card treatment. This difference in elasticities is statistically significant at the 1 percent level.[24] We obtain similar results when prices are measured in logs (online Appendix Table A18).

Figure 5 shows the fitted demand estimates from this regression as lines with the raw adoption rates as dots. Consistent with the regressions, the encouragement intervention reduces price sensitivity for conservation technology. The lower prices result in high take-up rates, and there is no statistical difference between the prepaid card treatment and control. About 65 percent of farmers in the control group purchased pipes at the lowest four prices: this rate remains roughly the same

[24] We rely on delta-method standard errors for this statistical test since the elasticities (and their difference) are a nonlinear function of the parameter estimates.

in treatment villages. In contrast the hourly card intervention caused demand to increase at higher prices. Only 21 percent of farmers in the control group purchased pipes when priced at Tk60 or higher. The intervention increased purchase by about 35 percent at these four higher prices.

Two additional results are apparent in Figure 5. First, demand is elastic. The demand elasticity in the control group is about 1.7 at the midpoint price of Tk55. Delta-method standard errors lead to a rejection of unit elastic demand in the control. This result is consistent with the common finding that demand for improved technology in developing countries is highly price sensitive—even for technologies proven beneficial. As examples, experimental estimates of demand show high sensitivity to prices for health technologies in Kenya (Kremer and Miguel 2007; Dupas 2014b) and crop insurance in Ghana (Karlan et al. 2014). This demand elasticity suggests that even modest subsidies have the potential to induce large increases in the demand for AWD.

Second, willingness to pay for AWD is low when compared to both the profitability of the technology and the estimated marginal production cost. In the first experiment AWD with volumetric pricing increases profits by about Tk1,870 per acre.[25] The median plot in our first-year sample is 0.3 acres, implying that using an AWD pipe on a single plot increases profits by about Tk561—a value well above what farmers are willing to pay.[26] We estimate the marginal cost of AWD production to be Tk133—based on surveys conducted with ten engineering shops.[27] Our findings show no demand at this price, even after promoting hourly pricing for water. However, the optimal subsidy for AWD depends on its external benefits—something we revisit in Section IVD.

This evidence suggests that encouraging farmers to accept volumetric prices leads to some modest changes in their willingness to pay for water-saving technology. But only 18.4 percent of purchasing farmers installed the AWD pipes on one of their rice plots.[28] This low rate of installation, combined with the already modest impacts on purchases, explains why the prepaid card intervention did not affect water management, at least through the channel of AWD adoption.

The regression estimates in columns 7–8 of Table 7 show effects on using the technology on any plot. In column 7 increasing price by Tk1 (about 1.8 percent of the midpoint price of Tk55) causes a decrease in the usage rate by 0.16 percentage points, or 2.3 percent of the mean usage rate among control villages. Column 8 again shows the heterogeneity in price responsiveness. A Tk1 price increase causes a decrease in adoption by 0.33 percentage points in control villages and 0.10 percentage points in treatment villages. While the interaction term is not quite statistically

[25] This estimate is computed from the analogous regression to Table 3, column 1 but with profits measured in levels.

[26] Similar observations have been made in the health and development literature: revealed willingness to pay for water purification in Ghana is orders of magnitude below the estimated benefits to households (Berry, Fischer, and Guiteras 2020).

[27] Field staff visited each shop in June 2018 and asked the owner for a quote to produce two different randomly selected quantities of AWD pipes. Regressing the estimated quotes on quantity delivers a coefficient of Tk133.

[28] A low rate of usage, conditional on purchasing, has been observed for fertilizer trees in Zambia (Oliva et al. 2020) and improved latrines in Cambodia (Ben Yishay et al. 2017). The literature on technology adoption of health products, on the other hand, has generally found larger rates of follow-through (Dupas 2014a).

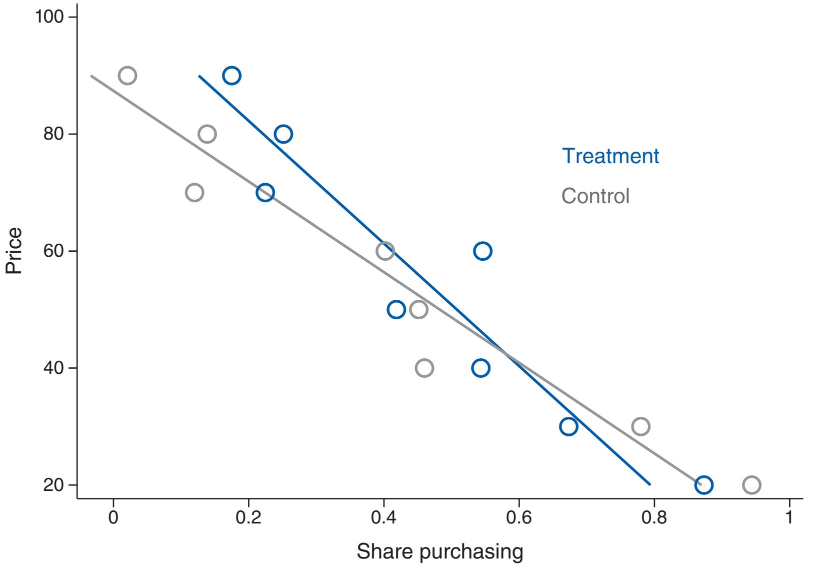

Figure 5. Demand Curve for Conservation Technology by Hourly Card Treatment

Notes: The figure shows linear demand estimates for farmers in the 144 villages that were part of the second-year experiment. The blue dots are raw adoption rates for the 96 treatment villages where prepaid hourly irrigation cards were provided. The blue line is the linear demand estimate for treatment villages. The gray dots are adoption rates in the 48 control villages, and the gray line presents the corresponding linear demand estimate. The estimation sample includes all 25 farmers in each village.

significant ($p = 0.135$), the point estimate shows that around two-thirds of the price responsiveness in control villages is eliminated when introducing hourly pricing. The estimated elasticities at the bottom of the table make this clear. The price-usage elasticity in control villages is 2.58, and this falls by over 75 percent to 0.6 in treatment villages. The difference between the two elasticities is highly significant. Online Appendix Figure A3 visualizes the unconditional price-usage relationship in treatment and control villages.

The difference in elasticities appears to result from how the prepaid cards change the screening ability of prices. Among farmers who purchased a pipe, the correlation between price and usage is significantly larger in prepaid card villages (online Appendix Table A19). In fact this correlation is negative in control villages and weakly positive in prepaid card villages. Screening offers one potential explanation. The prepaid cards put a marginal price on water. Realizing this, farmers carefully evaluate the merits of the AWD pipe. The farmers induced to buy the pipe at higher prices are those who value them most and are the ones most likely to install. In contrast prices do not screen effectively in the absence of volumetric water pricing because farmers stand to gain little from using the pipe for irrigation.[29] This finding

[29] Sunk costs represent another reason why price would be positively correlated with usage. People may use a product more if they paid a higher price to avoid the feeling of "wasting" their investment. Empirical research from health products in Zambia finds no evidence for this behavioral explanation and instead finds evidence for screening (Ashraf, Berry, and Shapiro 2010). Other work on health products finds no relationship between price and usage, conditional on adoption (Cohen and Dupas 2010; Tarozzi et al. 2014).

is similar to Berry, Fischer, and Guiteras (2020), who show that willingness to pay is positively correlated with usage of household water filters in Ghana. In our case willingness to pay higher prices is associated with greater usage of water-saving technology but only in villages where farmers are encouraged to use volumetric pricing for irrigation water.

Anecdotally, there are numerous explanations for not installing AWD. Farmers sometimes report having lost the pipe between the time of purchase and planting. Some farmers reported that they would install the pipe "in a few days."[30] After conferring with others some farmers suggested that it was not feasible to use AWD individually because of coordination externalities. Two examples were common. First, farmers with low-lying land often get water that spills over into their plot when it is being pumped into a nearby higher field. Second, a common per acre water price makes it easy for the tube well operator to irrigate multiple fields at a time. Adoption of AWD by a subset of the farmers becomes less practical when each farmer does not have full control over when their field is irrigated.

The low take-up in our second experiment presents a puzzle when considering the results from our first experiment. Unlike our first experiment, the second RCT took place in villages where farmers were previously not using individual prepaid cards. Some of the coordination difficulties mentioned above may explain both the lack of individual card usage before the experiment and the low uptake of AWD. The intervention in our first experiment included assistance with installing the AWD pipe. The large gap between purchasing and using AWD in the second experiment might highlight the importance of basic training and installation support to ensure that any benefits of AWD are realized.

C. *Other Possible Explanations for the Change in Demand*

Other factors could explain why the treatment in the second experiment had a modest effect on the demand for AWD, beyond the small effect through pricing incentives. For one, farmers who complied now had to pay for water up front rather than throughout the season.[31] Jack and Smith (2020) discuss a number of mechanisms that might explain why South African households use less electricity when converted to a prepaid meter. These include (1) an increase in the effective price of electricity because people can no longer default, (2) a tighter liquidity constraint that forces people to pay before consuming, and (3) the increased salience of pricing making it easier to observe when consumption is about to cause a change in marginal prices with increasing-block tariffs.[32] We argue that some of these alternative mechanisms seem less likely in our setting.

[30] Farmers who purchased pipes were told that AWD should be practiced starting ten days after transplanting. The date of the verification survey was randomized, and survey teams arrived less than 10 days after planting in less than 1 percent of cases. Moreover, the rate of uptake (conditional on purchasing) is only 20 percent for the farmers who were visited more than 50 days after transplanting. Therefore, procrastination, combined with our surveys being early in the season, cannot fully explain the low rate of installation.

[31] The agreements that existed prior to our treatment often involve informal credit, where the water user pays the per acre fee in installments, one at the beginning of the season and another after the harvest.

[32] Residential electricity is often priced in blocks, where the marginal price jumps up at predetermined consumption thresholds.

First, discussions with deep drivers during our fieldwork suggested that default on water bills is rare, mostly because of dynamic incentives. Farmers who do not pay can be cut off from future water access for dry season rice, which is the main income source for most. This explains why default was rare for the seasonal contracts that existed before our treatment.

Second, liquidity constraints could be important in our context. By forcing them to pay for water up front, the prepaid cards exacerbate liquidity problems for farmers who previously could pay for at least part of the water bill after harvesting. If this is important, then the treatment should cause liquidity-constrained farmers to be more willing to pay higher prices for AWD. Online Appendix D tests for interaction effects between the card treatment and various proxies for liquidity constraints. We do not find any evidence that supports the liquidity explanation.

Third, reloading the cards to pay in advance might make prices more salient for farmers, causing them to opt for conservation technology. But in our context farmers chose whether or not to purchase AWD pipes before the season, i.e., before they had started using the cards. Thus, any increase in salience from using the cards could not have taken place at the time AWD pipes were purchased. This differs from Jack and Smith (2020), who find that using prepaid cards for household electricity makes people more aware of their consumption and when they are close to crossing into a higher price bracket.

D. *Implications of Experiments for Subsidy Policy*

We next use our combined results to approximate an optimal subsidy for AWD when water has a marginal price. The technology reduces groundwater pumping, which lowers electricity consumption. There are two policy levers for increasing AWD uptake to reduce externalities from electricity: subsidizing the pipe or taxing electricity directly. Allcott, Mullainathan, and Taubinsky (2014) derive an approximation of the optimal subsidy for an energy-saving durable good when consumers can be inattentive to electricity costs. The approximation requires three derivatives, all of which we can estimate from experimental variation in our data. Online Appendix E provides more details on the calculation.

We calculate an optimal subsidy for AWD of at least Tk113 when electricity is taxed at the social damages from carbon emissions. This amounts to 85 percent of marginal cost. The subsidy would increase to Tk264—almost two times marginal cost—if all farmers who purchased the pipes went on to use them. The rationale for this seemingly large subsidy is that demand and usage of AWD is quite responsive to its own price. In contrast increasing (marginal) electricity prices for irrigation through prepaid cards has only a modest effect on the demand for AWD.

V. Concluding Remarks

Agriculture in developing countries uses a large share of the world's water. Agricultural water conservation is complex because in many settings, irrigation water has no marginal price. Introducing marginal prices is not easy because small farm sizes make individual metering costly. Moreover, pricing agricultural water remains a sensitive issue for elected officials who desire to retain the support of farmers. There have been no experimental studies that test policy mechanisms for putting a marginal price on water.

In this paper we carry out two RCTs to study the link between adoption of conservation technology, water use, and marginal prices for irrigation. We make use of a simple technology called AWD (a perforated pipe) that is known to reduce water use by about 30 percent in rice farming. In the first experiment we randomly provide 2,000 farmers with these AWD pipes and observe that the technology only conserves water in areas where farmers face marginal prices. Relative to the control group, plots of these farmers have 19 percent less water and are 21 percent more likely to be dry when observed on random days. Farm profits increase by 7 percent.

Our second RCT tried to encourage farmers to adopt debit cards that allow them to buy water by the hour. The hypothesis being tested is that shifting farmers to hourly irrigation cards would enable AWD adoption and save water. The intervention eliminated the application costs for these cards. Ninety-five percent of farmers in treatment villages accepted the cards, but only 40 percent went on to use them. We do not find any evidence that the intervention changed how farmers manage water. The point estimates allow us to reject sizable effects—particularly the main effects of AWD alone in the first experiment. The prepaid card intervention did, however, have a modest effect on the farmer's demand for the technology. Farmers in the treatment group were willing to pay higher prices for AWD. Demand elasticity in that group fell by 33 percent. Purchase of the technology went up by 35 percent at the highest prices. But less than one in five of the farmers who purchased went on to use the device.

This finding sheds light on some of the challenges with getting farmers to voluntarily convert to facing marginal prices as a way to enable water-saving investments. There can be other frictions—such as small fragmented landholdings and inefficient conveyance systems—that make it more costly for some farmers to pay for water by the hour. Our first experiment shows that technological solutions to conserve water can be highly effective but only when targeted to places where marginal prices exist and when efforts are made to train farmers and assist them in installing the devices. But the second experiment shows that incentives to voluntarily convert to volumetric pricing may not be enough to trigger these same effects.

In sum how water is priced plays a key role in enabling technology adoption for conservation. As a result, efforts to disseminate water-saving technologies can be more effectively targeted to areas where marginal prices create an incentive for conservation. But there are challenges with getting farmers to move away from fixed charges for irrigation, especially in developing countries where farms are small and water use decisions are often made at the level of the community, and individual farmers may have limited ability to conserve. We see this as an opportunity for future work to find innovate ways to better operationalize marginal prices for irrigation.

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2. Neha Deopa, Daniele Rinaldo. 2024. Quickest Detection of Ecological Regimes for Natural Resource Management. *Environmental and Resource Economics* **87**:5, 1327-1366. [Crossref]
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