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Impact of alternate wetting and drying on farm incomes and water savings in Bangladesh

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3ie accepted the final version of the report, *Impact of alternate wetting and drying on farm incomes and water savings in Bangladesh*, as partial fulfilment of requirements under grant DPW1.1081 awarded through Development Priorities Window 1. The report is technically sound and 3ie is making it available to the public in this final report version as it was received. No further work has been done.

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Impact of alternate wetting and drying on farm incomes and water savings in Bangladesh

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Summary

In recent years, rice in Bangladesh is increasingly being grown in the dry (boro) season which lasts from January to May. Unlike the rice grown in the monsoon season when there is rain, boro rice is mainly produced with ground water irrigation.

The treatment being studied is a water-management technique for irrigated rice called Alternate Wetting and Drying (AWD). AWD involves inserting a perforated PVC pipe into the soil to allow the farmer to observe soil moisture below the surface. The AWD guidelines suggest that the farmer let the field dry until the water level reaches 15 cm below the surface — which has a visible marking within the pipe. Once this water level is reached, the farmer should re-irrigate the field up to a level that depends on the current status of the crop. The process of alternatively wetting and drying the field should be practiced until the time that the crop starts to flower or reproduce. The farmer should keep sufficient water in the field during flowering because the crop water requirements are much higher during flowering relative to the previous vegetative stage of growth. The farmer also drains the field approximately one to two weeks before harvest, regardless of their chosen method of irrigation. AWD is meant to reduced total irrigation withdraw relative to a system where the field is never allowed to dry, i.e. “continuous flooding”.

Previous studies suggest that this simple technology saves about 25-30% of irrigation water. AWD has been developed and tested since 2004 but no systematic evaluation was undertaken until now. A precious 3ie funded non-experimental study Meenakshi et al. (2012) in West Bengal found that metering may reduce water use in the dry season and also reduce water sales.

The goal of the project is to evaluate the effect of AWD relative to conventional flood irrigation in rice. Our main question is: what is the impact of AWD adoption on farm incomes and water savings? How do these impacts vary across different physical and institutional environments such as shallow and deep water tables, pricing regimes for irrigation water and communal vs private tube well ownership? What is the farmer’s willingness to pay for AWD technology? Because of the positive effect of AWD in reducing the depletion of groundwater stocks and lowering methane emissions from rice fields, there may be a gap between private and social benefits of the technology, necessitating the use of subsidies for widespread adoption by farmers.

In Phase 1 we start with 400 villages in Rajshahi, Rangpur and Mymensingh division of Bangladesh, divided into two experimental groups. Ten farmers in the 200 treatment villages were provided with the AWD pipe and instructions on its benefits and training on using it to measure soil moisture. The farmers in the remaining 200 villages act as a pure control. This first phase allows us to estimate the average treatment effect of AWD across the whole population of farmers.

We find that the profitability of the AWD technology depends crucially on whether farmers face volumetric prices. AWD has no effect on profits with 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 technology: we find a significant increase in farm profits of about 7%. Overall, this first experiment suggests that there may be a fundamental market failure that explains why farmers do not value a

water- saving technology with proven results in the laboratory: they face a zero marginal price of water.

In Phase 2, we conducted a RCT to estimate the causal effect of encouraging hourly irrigation prices on the valuation of water-saving technology by farmers. In Northwestern Bangladesh, 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 cards with funds at a nearby kiosk and obtain irrigation water on demand. This solution is low-cost, implementable and aligns incentives for efficient water use. Our treatment seeks to increase the penetration of prepaid card usage in order to examine the causal link between pricing policy and technology adoption and to test a scalable solution for implementing volumetric pricing.[1]

We identified 144 villages which have installed meters, but use of prepaid cards by individual farmers is almost non-existent.[2] In order to encourage hourly pricing for water, we randomly selected 96 villages for a campaign to assist farmers in obtaining 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 reduce 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.

Encouraging hourly billing in the second RCT causes the demand for AWD to become less price responsive. Demand elasticity falls by 33% from 1.7 to 1.14 when comparing treatment and control villages. At the four highest prices, the hourly cards increase purchase of AWD by 35%. We find no effect on uptake at the four lowest prices. This demand experiment also lets us estimate the value farmers place on this conservation technology. Consumer surplus — when measured at our median price of $0.7 — increases by 64% in prepaid card treatment villages.

Yet, demand for AWD is low, both among treatment and control farmers. Using a survey with local shop owners, we estimate the marginal cost of production of the pipe to be $1.66 — a price well above the level at which demand falls to zero. Only about 20% of the purchasing farmers were found to be using the technology when field staff returned to check on usage. Nonetheless, we estimate that a 1% increase in price decreases

[1] It is scalable because the policymaker only needs to provide farmers with payment cards and install a single meter at each pump, rather than individual meters for each plot.

[2] 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 at the 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.

usage by 2.6% in control villages but only by 0.6% for farmers with hourly irrigation cards. That is, the price-usage elasticity shows the same pattern as the price-purchase elasticity.

From a policy point of view, we show that if the incentives are aligned correctly, there is a demand for the AWD technology. We see higher purchase and usage rates, and water savings and a small but significant increase in farm profits. Policy makers should consider two options: first, promote the AWD technology in areas where farmers pay volumetric pricing. Second, consider mechanisms that can allow a transition from seasonal water prices to paying by volume. This could be done by retrofitting existing tubewells to accept debit cards wherever possible, streamlining the system for debit card application, reducing application costs and creating infrastructure such that these cards can be easily recharged, and retrofiting tubewells that work with debit cards.

Contents

List of figures and tables

Abbreviations and Acronyms

AEA	American Economic Association
AWD	Alternate Wetting and Drying
Aman	Rice grown in the monsoon (wet) season
ATE	Average Treatment Effect
BADC	Bangladesh Agricultural Development Corporation
BAU	Bangladesh Agricultural University
BDT	Bangladeshi Taka
BMDA	Barind Multi-purpose Development Authority
Boro	Rice grown in the dry season
CH4	Formula for Methane Gas
DD	Deep Driver
DTW	Deep Tube Well
GPS	Global Positioning System
ICC	Intra-Cluster Correlation Coefficient
IRRI	International Rice Research Institute
ITT	Intention to Treat
MDE	Minimum Detectable Effect
NGO	Non-Governmental Organization
ODK	Open Data Kit
RCT	Randomized Control Trial
STW	Shallow Tube Well
T	Treatment
TOC	Theory of Change

1. Introduction

We use two randomized controlled trials in Bangladesh to study a simple water conservation technology for rice production called “Alternate Wetting and Drying (AWD).” Despite proven results in agronomic trials, our first experiment shows that AWD only saves water and increases profits in villages where farmers pay a marginal price for water, but not when they pay fixed seasonal charges. The second RCT randomly distributed debit cards that can be used to pay volumetric prices for irrigation water. This low-cost, scalable intervention causes farmers to place more value on the water-saving technology. Demand for the technology becomes less price-sensitive.

This study is the first rigorous field experiment that examines the role of pricing mechanisms in agricultural water use, although numerous agronomic studies have been done in experiment stations, see, e.g., Zhang et al. (2012). It shows that a lack of incentives — created by water pricing — inhibits technology adoption and use. Facilitating access to debit cards for hourly irrigation alters demand and increases the value farmers place on water-saving technology. While many economists have highlighted the need for water pricing reform as a means to increased conservation, there is little evidence that policy intervention can alter pricing regimes at the local level, especially in developing countries. Our study shows that modest efforts to lower application costs and increase farmer access to marginal pricing have significant positive effects on the demand for water-conservation technology. These findings have implications for numerous countries across the world where fixed prices for agricultural water persist while at the same time water is becoming increasingly scarce.

In Sections 2 and 3 we discuss the intervention and evaluation questions and methods. In Section 4, we discuss implementation fidelity. In Sections 5 and 6, we discuss in detail the procedure and results for the two phases of the study conducted. In Section 7 we estimate the social benefits of the technology. In Sections 8 and 9 we provide discussion and conclusions and recommendations.

2. Intervention

2.1 Description

We are using a combination of a cluster randomized control trial with partial equilibrium welfare analysis to rigorously measure the impact of AWD. In Phase 1 we start with 400 villages in Rajshahi, Rangpur and Mymensingh districts of Bangladesh. These areas were chosen to encompass the different water sources and ways in which farmers pay for irrigation water in the country. We elaborate more on this in Section 3.2. The villages were first divided into two experimental groups. Ten farmers in the 200 treatment villages were randomly selected who cultivated plots close to the tubewell. They were provided with the AWD pipe free of cost. We also provided that same group of farmers with a training on the benefits of the AWD pipe and how to use it to measure soil moisture. The training was conducted as a classroom session simultaneously with all 10 farmers. After the training the field staff went to the study plot of each farmer and assisted them 1-by-1 with the installation of the pipe. Both the training and installation was administered by employees of a local NGO who themselves were trained by IRRI, Bangladesh Agricultural University, and the Department of Agricultural Extension.

The farmers in the remaining 200 villages act as a pure control. This delivers our counterfactual for estimating the average treatment effect of AWD across the whole population of farmers.

For phase 2 of the study, farmers are drawn from a new set of villages distinct from phase 1 villages. We chose 144 villages – 96 of them received the treatment in the form of access to debit card applications while the rest of the 48 villages served a control. 25 farmers were selected in each village. All of them received the random AWD price offer (i.e. subsidy).

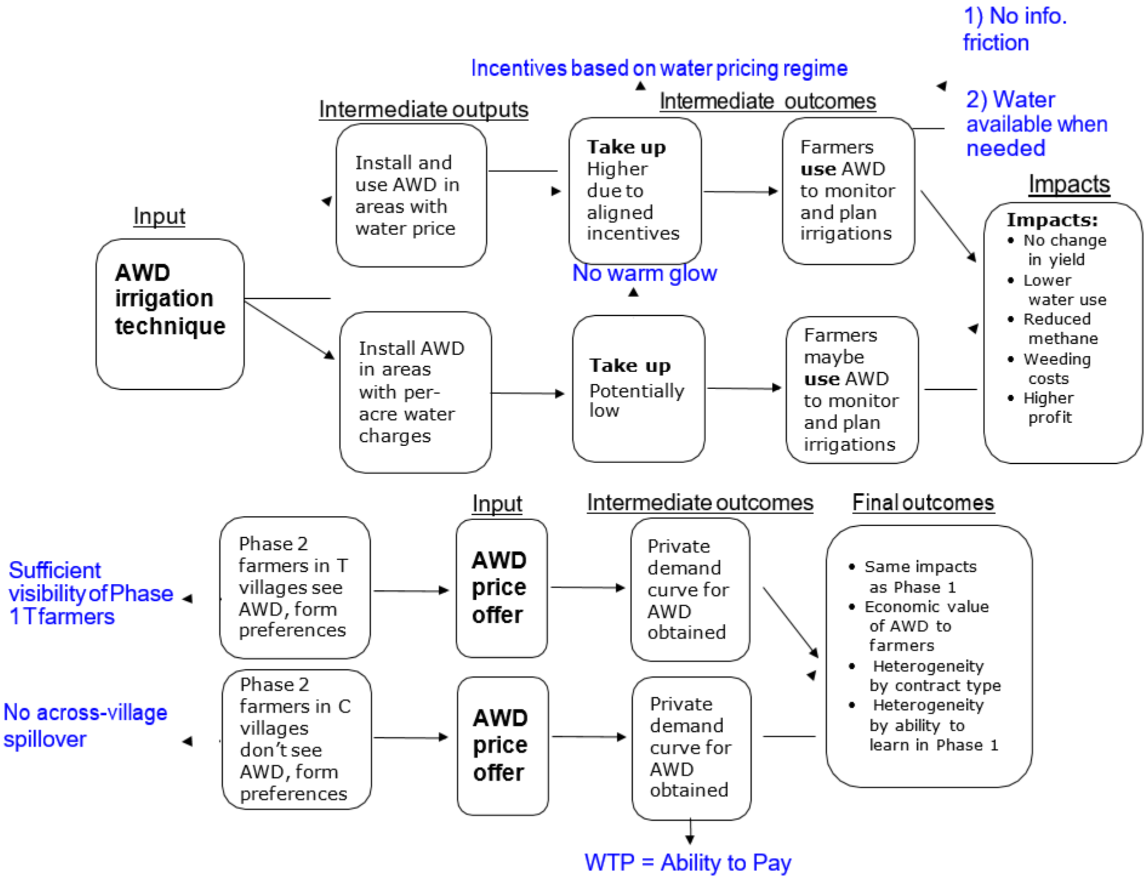
2.2 Theory of change

The causal pathway in the theory of change is shown in Figure 1. Focusing on phase I of the study, the key input will be the actual AWD pipe. The first intermediate outcome will be for the pipe to be installed and used. The TOC divides this outcome into two possibilities. First, we expect installation and take up (where take up refers to actually using the pipe) to be higher in areas where incentives are aligned, i.e. in areas where farmers pay a marginal price for their irrigation water (the top pathway). Second, we expect take up to be lower in areas where water is not priced volumetrically (the bottom pathway). This hypothesis is based on two assumptions that are highlighted in blue: the existence of a marginal price for water is a key incentive for adoption and that there is no warm glow effect where farmers are willing to use AWD and save water just for the purposes of helping the environment and saving water for future generations. Notably, the existence of such an effect only works in favor of finding impacts of AWD on intermediate and final outcomes.

After the AWD pipe is installed and farmers begin to use it, the next step in the causal chain is for continued use throughout the season. Farmers will need to use the AWD pipe as a soil moisture monitor — meaning they will need to look in it periodically and decide when to irrigate. There are again two key assumptions underlying this pathway (in blue in the TOC). First, farmers know how to use the AWD pipe. We will address this by providing all farmers with simple and easy-to-follow guidelines at the time of installation. Second, farmers can only use AWD if they can obtain water when they need it.

All of these things translate into final impacts on crop yield (where we expect no change), water use (decrease), methane production from rice (decrease), weeding costs (possibly increase) and agricultural profit (unclear). Various studies have reported a de- crease in methane production and potentially higher weeding costs because weeds tend to grow in under less flooded conditions, see e.g., Alam et al. (2009).

Figure 1: Theory of change



2.3 Monitoring plan

A baseline survey was conducted for each of the 10 farmers in all the 400 villages from the treatment and control groups. This was done mostly in December 2016. This survey was designed to elicit demographic information, and important information about cropping systems and water payment mechanisms. AWD pipes were installed in early 2017 in plots for the 10 farmers in the 200 treatment villages. Farmers receiving the pipe were assisted with the installation and received training on the use of the technology.

Throughout the rice growing season, we measured the water levels on each study plot twice. These measurements were carried out around dates that were randomly selected. These measurements were in the form of the height of the standing water in the plot. Pictures were also taken of the plot to corroborate the measurement.

Methane emissions were measured using a closed chamber technique in consultation with scientific experts on methane gas chromatography. 104 villages were selected at random for this measurement. One plot was randomly drawn from each village. 10 methane readings were taken for 24 of these plots, and three readings were taken for each of the remaining 80 plots. All were taken on randomly selected days. The total number of observations was 480, where each observation is composed of 3 vials of gas. However, a failure of the gas chromatograph equipment resulted in noisy results for the effect of treatment on methane emissions. We do not report those results in this document.

Finally, a follow-up survey was done after the boro season for all 4,000 farmers in the sample. The goal is to measure profitability of the AWD technology and collect information on water use.

For the phase 2 experiment, in addition to observing AWD purchasing decisions, and tracing out the demand curve with and without the introduction of individual volumetric water pricing, we collected data on whether the pipe was installed and 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 in the 10-70 day period after planting, when we observed farmers from the first experiment practicing AWD. The visits took place during February 2nd - May 23rd 2018, with the median visit occurring on April 1st.

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% of farmers and the farthest plot for the rest of the sample. These additional data allow us to decompose any treatment effects into effects on initial valuation at the time of purchase and actual usage during the season.

Ensuring high quality for the intervention has been of prime importance. First, the NGO which executed much of the intervention and the PIs of this study have a long relationship through other similar interventions. Moreover, field staff were selected, trained and supervised by a member of our team Muhammad Ashraful Habib, who is employed by IRRI. Each survey was preceded by a full day of training and a full day of field data

collection with the trainer. For the gas sample experiment, additional levels of training at both the classroom and field levels were imparted by scientists of the Bangladesh Agricultural University and the International Fertilizer Development Center.

3. Evaluation

3.1 Primary and secondary questions

The main evaluation questions are as follows:

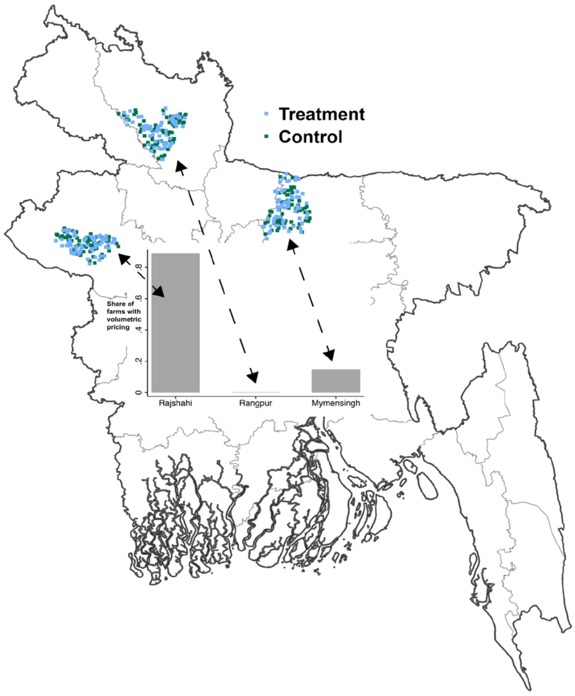
1. What is the average impact of AWD on water savings from irrigated rice?
2. What is AWD's impact on other input usage, such as herbicide expenditures and weeding labor?
3. What is AWD's impact on overall profitability from the plot?
4. Does AWD have external benefits by saving water or reducing methane emissions from rice paddies?
5. How do the farmer's revealed private benefits (demand curve) compare to both the costs of AWD and the estimated external benefits (if any)?

3.2 Design and Methods

The experiment is a randomized control trial in 400 villages of Bangladesh. It is a cluster randomized design with a village-level treatment. In Phase 1, the villages are split equally into treatment and control groups. The number of farmers included per village is 10, making a total sample size of 4000. The average treatment effect (ATE) of AWD was identified from a regression of the main outcomes on the village-level treatment indicator and strata fixed effects.

The sample for our first RCT consists of 400 villages in Rajshahi, Rangpur, and Mymensingh districts of Bangladesh (134 in Rajshahi, 133 in Mymensingh, and 133 in Rangpur). The villages have been randomly divided into two experimental groups, with stratification at the upazila (subdistrict) level. Figure 2 shows a map of the sample villages and their treatment assignment. The farmers in the 200 treatment villages have been provided with the AWD pipe, training on its use, and assistance with its installation. The farmers in the remaining 200 villages serve as a pure control.

Figure 2: Map of treatment and control villages



Source: https://gadm.org/maps.html

The map shows the treatment villages (in blue) and the control villages (in green). The bar chart embedded in the map shows the share of households (by division) where the study plot has volumetric water pricing.

The map also demonstrates what the baseline tells us about an important component of our design: the frequency of volumetric water pricing across districts. Farmers in Rajshahi largely report paying hourly prices for pumping water and this is far less prevalent in the other districts of Rangpur and Mymensingh. We repeatedly return to this feature of our data in the discussion that follows.

Figure 3 provides a diagrammatic representation of the experiment, while Figure 4 shows a timeline of the interventions and surveys. This first phase of the study allows us to estimate the ATE's of AWD across the whole population of farmers. Most importantly, we can estimate its impact on crop yield and the environmental benefits that come through reduced water use. Since continuously flooded rice increases CH_4 emissions, we will quantify the effects of AWD on CH_4 emissions — by measuring CH_4 emissions in selected treatment and control plots. All of these effects will be identified from a regression of the main outcomes on the village-level treatment indicator and strata fixed effects. The estimates will be Intention to Treat (ITT) since we cannot guarantee that any farmer will maintain the AWD pipe or practice its proper use.

The ratio of prepaid irrigation cards to farmers in many villages is less than one. In some areas this phenomenon is extreme: the deep driver or water user's committee in the village 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 the fact that technology is 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 and plots as well. Our treatment targets the fixed costs of obtaining a card as a barrier to individual ownership.

We first identified 144 villages in Rajshahi district — not included in the sample of our first RCT — where most farmers were not using their own prepaid card for pumping. These villages are spread across three upazilas, two of which were included in our first experiment. 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 150 Bangladeshi Taka (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%) farmers in the treatment group agreed to receive the cards as part of the program.

Does this effort to introduce volumetric pricing cause farmers to place greater value on the AWD technology? To get at this question, we conducted a revealed-preference demand experiment in all 144 villages. A sales person 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 20-90 taka. As points of reference, the daily wage for casual agricultural work during the previous boro season was about 350 taka. The estimated profit advantage of AWD was about 561 taka 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, and tracing out the demand curve with and without the introduction of individual volumetric water pricing, we collected data on whether the pipe was installed and 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 in the 10-70 day period after planting, when we observed farmers from the first experiment practicing AWD. 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% of farmers and the farthest plot for the rest of the sample. These additional data allow us to decompose any treatment effects into effects on initial valuation at the time of purchase and actual usage during the season.

In Phase 2, the 144 villages selected were all from Rajshahi but not part of the Phase 1 experiment. In these villages most farmers were not using their own prepaid card for pumping. They are spread across three upazilas, two of which were included in our first experiment. 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. We worked with a village leader to identify farmers — rather than select them randomly — because our sample required farmers that were not using their own prepaid irrigation cards. The villages were then randomly divided into two groups using a random number generator in Stata. 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 150 Bangladeshi Taka (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%) 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 150 Taka gift to cover the application cost. Therefore, we provided each of the 25 farmers in the control group with 150 Taka of mobile phone credits right after administration of the baseline survey.

3.3 Ethics

We did not encounter any ethical issues during the two phases. Farmers voluntarily accepted the offer to install an AWD device in their field. No problems were reported by the enumerators. Farmers were not required to keep the AWD pipe on their field and could dispose of it as they wish. In the second phase, farmers again voluntarily chose to buy the device at the offered price, and install or dispose of the pipe. The study has been approved by the Institutional Review Board for Social, Behavioral, and Educational Research at Tufts University.

Figure 3: Diagram of experimental design

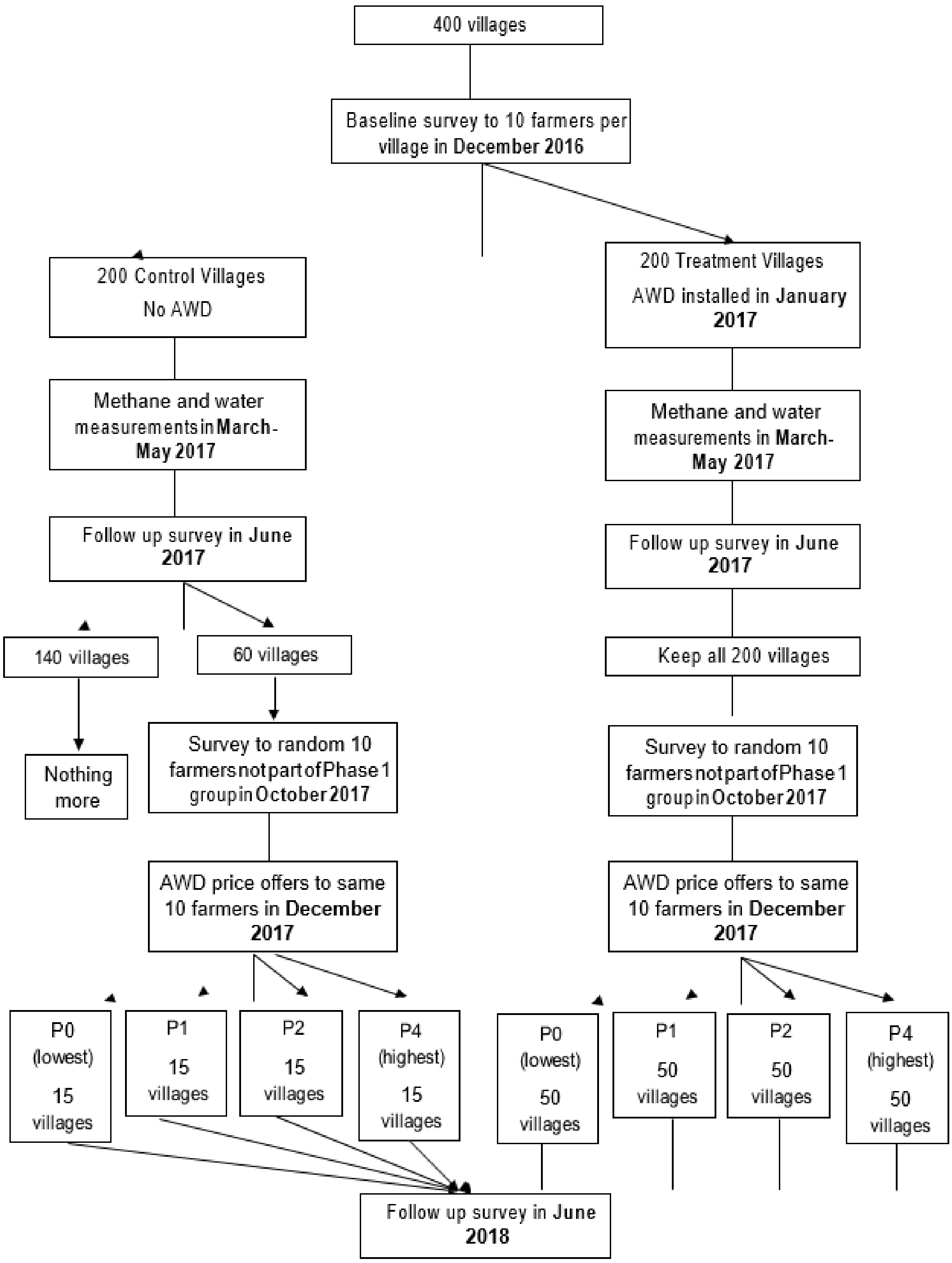


Figure 4: Timeline of activities

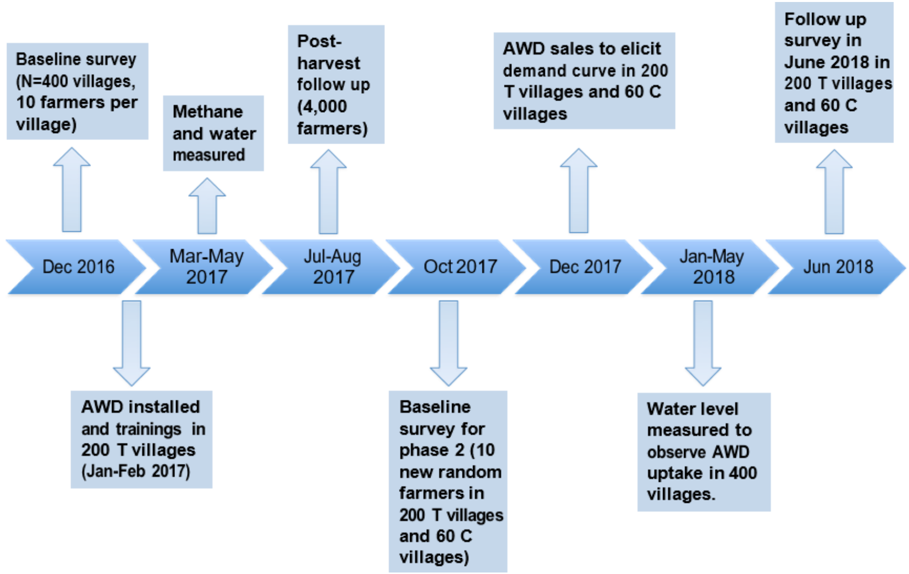


Figure 5: A sample photo taken during AWD installation

3.4 Sampling and data collection

In this section we discuss the sampling and data collection. The survey instruments are included in online Appendix B. The 12 upazilas were selected based on local knowledge of IRRI Bangladesh researchers. The selection was based on two primary criteria. First, the upazilas had to be in areas where rice is the dominant crop in the boro season. This was validated using satellite imagery of boro rice areas from IRRI. Second, the upazilas in Rajshahi and Rangpur districts needed to have some area covered by government deep tube wells.

Within these upazilas, eligible villages were next identified. Villages in Rajshahi and Rangpur were only considered to be eligible if they have deep tube well (DTW) irrigation for boro rice. This effectively means that every village in the sample in these two districts has a government tube well run by either the Barind Multipurpose Development Authority (BMDA) or the Bangladesh Agricultural Development Corporation (BADC). We selected all villages in Mymensingh based on the census. The 400 villages in the sample were drawn randomly from the set of eligible villages.

Within each village, enumerators went to a village leader and identified the 10 farmers that were cultivating plots close to the tube well used for irrigation. In the event that there was more than one tube well, enumerators were instructed to focus on the tube well with the largest command area. In most cases that tube well services more than 10 farmers. Enumerators asked the village leader for the names of the 10 *closest* farmers. These farmers were then asked for consent to participate and in rare cases farmers that did not consent were replaced with the next closest farmer. These 10 farmers constitute the main sample for measuring the effectiveness of AWD. One limitation is that we selected the farmers closest to the tube well rather than a random sample from the command area. It would have otherwise been prohibitively costly to collect further data on water management. Nonetheless, our hypothesis on pricing incentives and conservation is meant to test a particular behavior that seems generalizable. That is, there is no reason to think that farmers further from the tube well would respond to incentives any differently than those closer. In addition to identifying the farmers, the enumerators took the GPS coordinates of the plots identified by the village leader, which we refer to as the study plots. Figure 6 gives an example of the study plots and the location of the tube well for one of the villages. The farmer that manages the study plot is the respondent to our surveys when available. If not available, surveys are carried out with an available household member that has knowledge of management for that plot.

For the second experiment, a similar process was followed to identify the 25 farmers in each village. In the 96 treatment villages, 95% of the farmers agreed to obtain the debit card.

Figure 6: Example of study plots in one village

The map shows an example of the 10 study plots for one of the experimental villages. The green shaded areas are the plots while the red dot is the tube well that is used to irrigate those plots.

The experiment required objective measurement of water usage. However, no villages in our sample were equipped to measure individual-level pumping volumes. We there- fore 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. 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 AWD tool should not be used during the reproductive stage of crop growth. Hence, visiting fields on random days gives us the ability to verify if the tool is being properly used and whether the causal effect of AWD varies by the type of water pricing. The schedule for the measurement of water management included 8,000 observations. We obtained data for 7,596 of them (95%). The missing observations resulted from random measurement dates falling after harvesting was completed.[3]

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. 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.

We conducted a second RCT to estimate the causal effect of encouraging hourly irrigation prices on the valuation of water-saving technology by farmers. In Northwestern Bangladesh, 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 cards with funds at a nearby kiosk and obtain irrigation water on demand. This solution is low-cost, implementable and aligns incentives for efficient water use. Our treatment seeks to increase the penetration of prepaid card usage in order to examine the causal link between pricing policy and technology adoption and to test a scalable solution for implementing volumetric pricing.[4]

We identified 144 villages which have installed meters, but use of prepaid cards by individual farmers is almost non-existent.[5] In order to encourage hourly pricing for water, we randomly selected 96 villages for a campaign to assist farmers in obtaining their own debit cards. Many farmers attribute the low rate of individual card ownership to the costs

[3] 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 there- fore explains why the data are missing for a small number of cases. Missing data due to this scheduling issue is balanced across treatment and control groups.

[4] It is scalable because the policymaker only needs to provide farmers with payment cards and install a single meter at each pump, rather than individual meters for each plot.

[5] 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.

associated with the application process. Our treatment sought to reduce 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.

This nudge towards hourly water pricing changes how farmers value water-saving technology. We estimate the demand curve for AWD by sending sales teams to all villages and offering farmers an AWD pipe at a randomly determined village-level price, along with information on its use. The eight different random prices ranged from 15 to 70% of the marginal cost of the pipe.

4. Findings

4.1 Intervention implementation fidelity

The original plan was to estimate the demand for the AWD device in Phase 2. In the final phase 3 of the proposal, we had planned to focus on understanding whether subsidies for AWD can be precisely targeted. The plan was to return to the 120 control villages from Phase 1 and offer AWD at subsidized prices to farmers that were not part of Phase 1. In 60 randomly chosen villages we would set a uniform subsidy at a level determined by our Phase 2 analysis. These villages would be compared with the other 60 villages where we customize the subsidy offer based on the farmer's elicited discount rate (elicited after Phase 1 with an incentivized choice experiment). Comparing uptake across these villages would be informative of whether subsidies for conserving water are more effective when we use simple economic theory to optimally set their levels for different farmers.

Since the Phase 1 results suggested that the existence of the marginal price for water was a critical factor that affected the benefits from AWD, in Phase 2, we now conduct the debit card encouragement first, followed by the demand elicitation experiment in the same treament and control villages. This revised experiment in Phase 2 allowed us to estimate the causal effect of debit card possession on the demand for AWD. We believe that this correction was a marked improvement from the original plan.

During our implementation of the first phase, and interaction with farmers during several visits and organized village meetings, it became clear to us that discount rates may have little to do with the uptake of the AWD. Other factors had a larger and more immediate role in affecting the performance of the AWD technology, such as the marginal price of water and spillover effects relating to water distribution within the village. Clusters of farmers located in close proximity within the command area of the tubewell may receive irrigation water at the same time, and adoption decisions may be related to specific farmer characteristics such as location of farmers in relation to the distribution system and gradient of the field. For example, if a cluster of farms receive water during the same irrigation cycle because they are close to each other, a single farmer may not adopt the AWD device because his irrigation schedule may now diverge from his neighbors.

The phase 2 experiment was carried out in new villages and only in Rajshahi district where tubewells are equipped with meters that can accept debit cards. The details of the experiment are described elsewhere and not repeated here.

We made sure that the interventions were consistent across the two experiments. The training given by enumerators was effective – this is clearly observed from the water use shown in Fig 7. Farmers were asked to not use the pipe during flowering, and that is exactly what we observe around the 70 day mark. Evidence that the pipes were installed was obtained through photographs of the pipe in the farmer's plot taken when the enumerator visited for water measurements. In RCT 2, cards were distributed to farmers and we recorded the names of the farmers with their card numbers. That ensured that these farmers received the cards.

5. Impact Analysis

5.1 Descriptive statistics and balance tables

In Table 1, we show the summary statistics for baseline variables. Baseline covariates are well balanced across treatment arms. Table 2 shows mean values of baseline characteristics in addition to p-values from regressions of each characteristic on treatment and strata fixed effects. We report balance for the covariates which were previously used to describe the sample. Only one of the 19 characteristics tested is significantly different between treatment and control arms at the 10% level.

Our pre-analysis plan contains several tests of heterogeneous treatment effects as a function of whether the water price is linked to usage. Most of the variation is across upazilas. This combined with our treatment assignment being stratified by upazila helps balance the randomization within pricing regimes. Table 3 verifies this. Focusing on the sample with volumetric prices, two of the 18 characteristics are significantly different between treatment and control households.

In combination, the randomization succeeded at generating comparable treatment and control groups both for the whole sample and within the sample where incentives align for AWD adoption. Our simple regressions of the main outcomes on treatment and strata fixed effects will therefore generate estimate treatment effects that are internally valid for our sample. Our pre-analysis plan also includes regressions that control for these baseline characteristics. However, these findings suggest that the estimated effects are likely to change little when including these controls.

Table 3 shows baseline characteristics for the treatment and control groups in the second RCT and Table 4 shows covariate balance. Household and farm characteristics are generally similar across the two groups. Household size is the only characteristic not balanced across treatment and con- trol villages. The average farmer in this sample pays around 1500 taka (approximately $18) to irrigate one bigah of land (a bigah equals one-third of an acre). 70% pay this money directly to the deep driver as a per-bigah fee. The remaining 30% pay the fee to a water users committee.

5.2 Effect on water use

Our pre-analysis plan (online Appendix C) guides the impact analysis. We use the first-year experiment to estimate the causal impact of AWD technology on water management, input costs, and agricultural profits.

Table 1: Summary statistics of household demographic variables

		By District:		
	(1)	(2) Rajshahi	(3) Rangpur	(4) Mymensingh
Age	42.63	41.88	42.66	43.36
	(12.15)	(11.92)	(11.81)	(12.66)
Years Education	6.488	7	7.326	5.134
	(4.699)	(4.738)	(4.485)	(4.573)
Household Size	4.945	4.692	4.792	5.353
	(6.693)	(2.037)	(1.795)	(11.27)
Number Livestock Owned	2.796	2.358	3.362	2.672
	(2.628)	(2.549)	(2.641)	(2.593)
Landholdings in Acres	2.014	2.354	1.958	1.729
	(2.108)	(2.261)	(2.183)	(1.804)
Owns Television	0.624	0.792	0.543	0.537
	(0.484)	(0.406)	(0.498)	(0.499)
Owns Refrigerator	0.134	0.108	0.106	0.188
	(0.340)	(0.310)	(0.308)	(0.391)
Owns Irrigation Shallow Tubewell	0.0625	0.0672	0.0677	0.0526
	(0.242)	(0.250)	(0.251)	(0.223)
Heard of AWD?	0.172	0.117	0.132	0.268
	(0.378)	(0.322)	(0.339)	(0.443)

The table shows mean values and standard deviations of baseline demographic variables for all 4,000 households in the sample. Column 1 shows statistics for the entire sample, while Columns 2-4 show separate summary statistics for the three districts. Age and years of education are for the survey respondent, which is the decision maker on the study plot if that person was available. The baseline was administered to decision maker for the study plot for 78% of respondents.

Table 2: Covariate balance across treatment arms

	Control (Means)	Treatment (Means)	p-value
Panel A: Household Characteristics			
Age	42.33 (12.05)	42.93 (12.23)	0.251
Years Education	6.645 (4.863)	6.330 (4.525)	0.125
Household Size	4.888 (2.202)	4.802 (2.159)	0.467
Number Livestock Owned	2.892 (2.745)	2.701 (2.502)	0.0935
Landholdings in Acres	2.026 (2.168)	2.003 (2.046)	0.769
Owns Television	0.636 (0.481)	0.612 (0.487)	0.314
Owns Refrigerator	0.139 (0.346)	0.129 (0.335)	0.639
Owns Irrigation Shallow Tubewell	0.0655 (0.247)	0.0595 (0.237)	0.520
Heard of AWD?	0.182 (0.386)	0.163 (0.369)	0.328
Panel B: Characteristics of Study Plot			
Plot is Rented or Sharecropped	0.0875 (0.283)	0.0675 (0.251)	0.136
Area in Acres	0.427 (0.494)	0.405 (0.421)	0.195
Volumetric Water Price	0.344 (0.475)	0.350 (0.477)	0.754
Number Crops Grown	2.194 (0.480)	2.174 (0.481)	0.611
Rice-Rice Cropping System	0.697 (0.460)	0.698 (0.459)	0.989
Number Irrigations in Boro	20.80 (8.757)	20.55 (8.097)	0.695
Revenue per Acre in Boro	39866.3 (10534.0)	40133.4 (14796.8)	0.700
Cost per Acre in Boro	22651.0 (10526.1)	22939.6 (9190.8)	0.625
Water Cost per Acre in Boro	6663.9 (8768.0)	6199.8 (5636.1)	0.357
Revenue per Acre in Aman	27622.6 (11668.1)	27763.4 (19959.8)	0.868

The table shows mean values of each baseline characteristic and standard deviations for control (Column 1) and treatment (Column 2) farmers. Column 3 gives the p-value from a regression of the characteristic on treatment and strata (upazila) fixed effects, where standard errors are clustered at the village level.

Table 3: Balance of baseline characteristics for volumetric pricing experiment

	Means		
	Control	Hourly Card	p-value
Age	39.24	39.74	0.445
	(10.28)	(11.18)	
Years Education	7.253	7.008	0.451
	(4.131)	(4.267)	
Household Size	4.489	4.232	0.0184
	(1.649)	(1.840)	
Number Livestock Owned	2.686	2.812	0.507
	(2.052)	(2.357)	
Landholdings in Acres	1.598	1.609	0.967
	(1.640)	(1.418)	
Owns Television	0.887	0.870	0.366
	(0.317)	(0.336)	
Owns Refrigerator	0.195	0.192	0.824
	(0.396)	(0.394)	
Owns Irrigation Shallow Tubewell	0.0569	0.0421	0.439
	(0.232)	(0.201)	
Seasonal Water Price (taka per bigah)	1522.3	1481.9	0.626
	(427.6)	(372.3)	
Usual Number Irrigations	18.98	18.74	0.985
	(8.178)	(8.506)	
Pays Deep Driver for Irrigation	0.708	0.707	0.919
	(0.455)	(0.455)	

The table shows mean values of baseline characteristics for farmers in the 48 control (column 1) and 96 prepaid-card treatment villages (column 2). Standard deviations are displayed below each mean value in parentheses. Column 3 shows the p-value from the regression of each characteristic on the treatment indicator and strata (Upazila) fixed effects. The data are based on the baseline survey carried out with 25 farmers per village during December 2017.

Table 4: Covariate balance across treatment arms for sample of households with volumetric pricing

	Means		
	Control	Treatment	p-value
Panel A: Household Characteristics			
Age	42.76 (11.99)	42.88 (12.25)	0.784
Years Education	6.565 (4.879)	6.629 (4.365)	0.723
Household Size	4.754 (2.136)	4.791 (2.126)	0.860
Number Livestock Owned	2.651 (2.818)	2.316 (2.379)	0.0834
Landholdings in Acres	2.411 (2.315)	2.339 (2.291)	0.997
Owns Television	0.696 (0.460)	0.719 (0.450)	0.499
Owns Refrigerator	0.0959 (0.295)	0.114 (0.318)	0.392
Owns Irrigation Shallow Tubewell	0.0785 (0.269)	0.0529 (0.224)	0.213
Heard of AWD?	0.119 (0.324)	0.136 (0.343)	0.449
Panel B: Characteristics of Study Plot			
Plot is Rented or Sharecropped	0.102 (0.303)	0.0571 (0.232)	0.0454
Area in Acres	0.380 (0.532)	0.374 (0.390)	0.850
Number Crops Grown	2.425 (0.627)	2.320 (0.624)	0.333
Rice-Rice Cropping System	0.382 (0.486)	0.409 (0.492)	0.474
Number Irrigations in Boro	19.99 (9.643)	20.75 (8.375)	0.334
Revenue per Acre in Boro	45455.4 (9352.6)	46416.6 (20243.7)	0.316
Cost per Acre in Boro	25731.0 (15180.6)	26070.9 (12215.2)	0.762
Water Cost per Acre in Boro	9637.6 (14293.5)	8200.9 (8846.5)	0.107
Revenue per Acre in Aman	31138.6 (13754.1)	29215.6 (23735.9)	0.639

Data are only for the 1,388 households that report volumetric water pricing at baseline. The table shows mean values of each baseline characteristic and standard deviations for control (Column 1) and treatment (Column 2) farmers. Column 3 gives the p-value from a regression of the characteristic on treatment and strata (upazila) fixed effects, where standard errors are clustered at the village level.

Our preferred specification is therefore,

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

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 mostly across upazilas, but can occasionally vary within these strata.[6] We estimate equation (1) for the sample of 4,000 study plots, regardless of whether the farmer kept the AWD pipe in that field, chose to move it elsewhere, or removed it entirely — all of which happened rarely. We report both these heterogeneous effects and the average treatment effect.

The average effect of AWD on water management — across the entire sample — is both small and statistically insignificant. Table 4 shows in column 1 that the average study plot in treatment villages had only 0.06 cm less water standing in the field. Increased uptake of the AWD practice should increase the likelihood that study plots of treatment farmers are being dried, i.e. have no standing water in the field. Column 2 shows that the treatment increases the effect on drying by about 1.9 percentage points — or about 4% — but this average effect is noisy. It is also clear that farmers practice some form of the AWD technique without using PVC pipes: fields in the control group were dry 45% of the time. Thus, the correct counterfactual for AWD differs from the one used in agronomic experiments where water is maintained in the control field for the entire season.[7]

5.3 Heterogeneity of impacts

We found significant heterogeneity of impacts between farmers who pay a fixed charge for water and those who pay be the volume of water used. As discussed earlier, the water savings were significant for those who paid volumetric prices.

Table 4 shows that AWD is only effective for farmers who face volumetric water prices. In column 3, AWD generates an effect on water levels only for farmers facing nonzero marginal prices. Introducing AWD in places with volumetric pricing lowers the amount of observed irrigation water by 0.43 centimeters, or an 18% decrease. The probability of a plot being dry also increases by 8.4 percentage points (19%). Finally, the third row of the table shows that the correlation between volumetric pricing and water use (within strata) is small and statistically insignificant. This result could be driven by either the limited variation within strata, or correlation between unobservables and volumetric pricing.[8]

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[6] Upazila fixed effects explain 77% of the variation in the indicator variable for volumetric pricing. The remaining variation within upazilas is largely due to three factors: 1) some villages in Mymensingh have a system where the tube well owner collects payment for the fuel used in pumping, while other nearby villages do not, 2) a few villages in Rajshahi did not have the prepaid card system for irrigation and 3) the tube well owner (who always faces a nonzero marginal price) may be part of the sample in Mymensingh villages.

[7] 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 evaporating entirely.

[8] The volumetric pricing indicator has a negative correlation with water levels and a positive correlation with the probability of fields being dried when dropping strata fixed effects and therefore using variation across upazilas.

Table 5: Effects of AWD treatment on water usage

	(1) Level	(2) Dry	(3) Level	(4) Dry
Treatment	-0.061	0.019	0.119	-0.012
	(0.161)	(0.023)	(0.220)	(0.027)
Treatment * Volumetric Pricing			-0.544*	0.096*
			(0.287)	(0.050)
Volumetric Pricing			-0.107	-0.058
			(0.333)	(0.060)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.32	0.45	2.32	0.45
p-Value: Treat+Treat*Volumetric			0.021	0.047
Number of Observations	7598	7598	7596	7596
R squared	0.033	0.035	0.036	0.037

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 columns 1 and 3 is the amount of standing water in the field, measured in centimeters. The dependent variable in columns 2 and 4 is an indicator variable for a dry field with no standing water. Volumetric pricing is an indicator for farmers for whom the water price is tied to usage, either through hourly charges or fuel payments. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Combining these findings, Figure 7 demonstrates how the effectiveness of AWD varied both across time and by type of water pricing. It shows nonparametric regressions of water levels (top panel) and the indicator for dry fields (middle panel) on days after planting, separately for treatment and control villages. The upper left panel shows that AWD caused a decrease in irrigation withdrawals during the pre-flowering 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 AWD 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 that pay for water on a seasonal basis. The figure also helps visualize how farmers conserve water when facing volumetric prices, even without AWD.

Namely, farmers tend to keep fields dry after flowering, regardless of whether they are using AWD pipes.

Table 5 shows the exact magnitude of these impacts. Under volumetric pricing, AWD causes water levels to be lower by 0.83 cm (31%) and leads to a 17.3 percentage point increase in the occurrence of dry fields (54%) during the first 70 days of the growing season. In contrast, the effect of AWD during this time is close to zero and statistically insignificant for farmers facing seasonal contracts. Columns 3 and 4 verify the visual results 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. These results are insensitive to the choice of splitting the sample using a threshold of 70 days: we show in Tables 6 and 7 that results are similar when we divide the season using a 60 or 80 day cutoff.

Table 6: Heterogeneous effects by first 70 days of the growing season

	0-70 Days After Planting		70+ Days After Planting	
	(1)	(2)	(3)	(4)
	Level	Dry	Level	Dry
Treatment	-0.048	-0.012	0.258	-0.003
	(0.208)	(0.032)	(0.376)	(0.039)
Treatment * Volumetric Pricing	-	0.185**	0.014	-0.071
	(0.287)	(0.054)	(0.474)	(0.075)
Volumetric Pricing	0.026	-0.082	-0.488	0.023
	(0.363)	(0.065)	(0.420)	(0.066)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.71	0.32	1.86	0.59
p-Value: Treat+Treat*Volumetric	0.000	0.000	0.328	0.244
Number of Observations	4187	4187	3409	3409
R squared	0.027	0.043	0.086	0.114

The data are from random unannounced visits to the study plots of sample farmers during the 2017 boro (dry) growing season. Columns 1 and 2 are for measurements taken up to 70 days after transplanting.

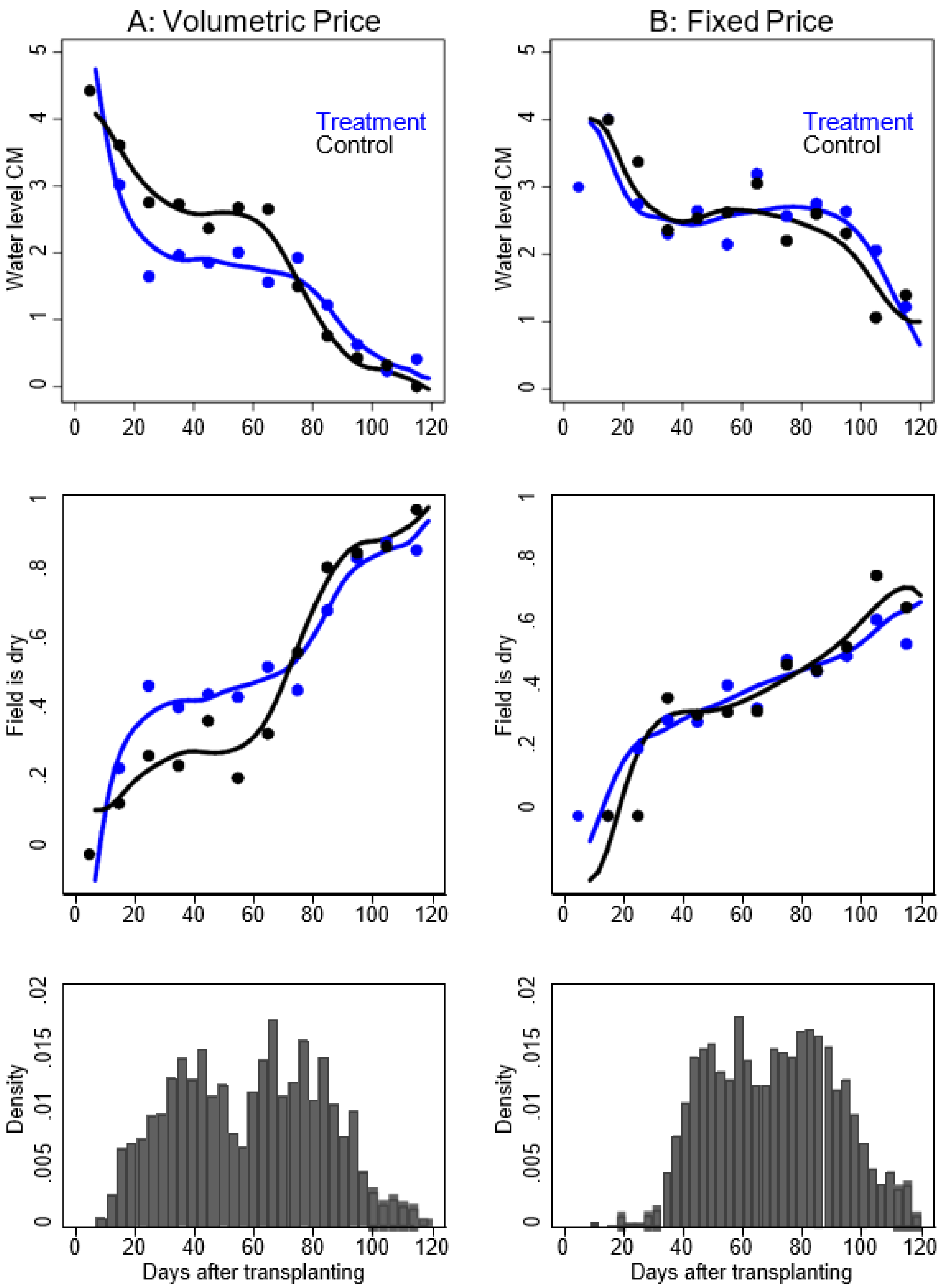
Columns 3 and 4 are for measurements taken more than 70 days after transplanting. The dependent variable in columns 1 and 3 is the amount of standing water in the field, measured in centimeters. The dependent variable in columns 2 and 4 is an indicator variable for a dry field with no standing water.

Volumetric pricing is an indicator for farmers for whom the water price is tied to usage, either through hourly charges or payments for diesel fuel. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Our estimates line up with findings from agronomic trials only when prices are set volumetrically. Figure 8 shows 87 impact estimates reported in 26 different agronomic studies. The estimated water savings from these experiments range from 5 to 65%, with median savings of 27%. Our 19.2% effect on water levels when prices are volumetric — from Table 4 column 3 — falls right at the 25th percentile of the agronomic estimates. In contrast, the null effect with area-based pricing is outside the range of estimates from agronomic trials. 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.

Our post-harvest follow up survey included a module on irrigation management. Using these data, column 1 in Table 8 shows that farmers given AWD report 3.6 fewer irrigations, which amounts to a 19% impact since the average plot in the control group was irrigated about 19 times, or once every 5-6 days. Yet, all treatment farmers report irrigating their fields less, regardless of whether their village has volumetric pricing (column 2). Experimenter demand effects offer a reasonable explanation for this finding: treatment farmers knew that practicing AWD reduces the number of irrigations and responded accordingly — even if they did not practice AWD as recommended. Turning to columns 3 and 4, treatment farmers report 2.2 additional drainages, which corresponds to a 91% increase relative to the control group. This effect is significantly larger for farmers in villages with volumetric pricing, as shown in column 4.

Figure 7: Nonparametric estimates of AWD treatment effect as a function of days after planting



Notes: Figure shows non-parametric 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 10-day bins, where each dot is centered at the bin midpoint. The bottom panel shows the density of days after transplanting.

Table 7: Separate effects by time of growing season, 0-60 and 60+ days after planting

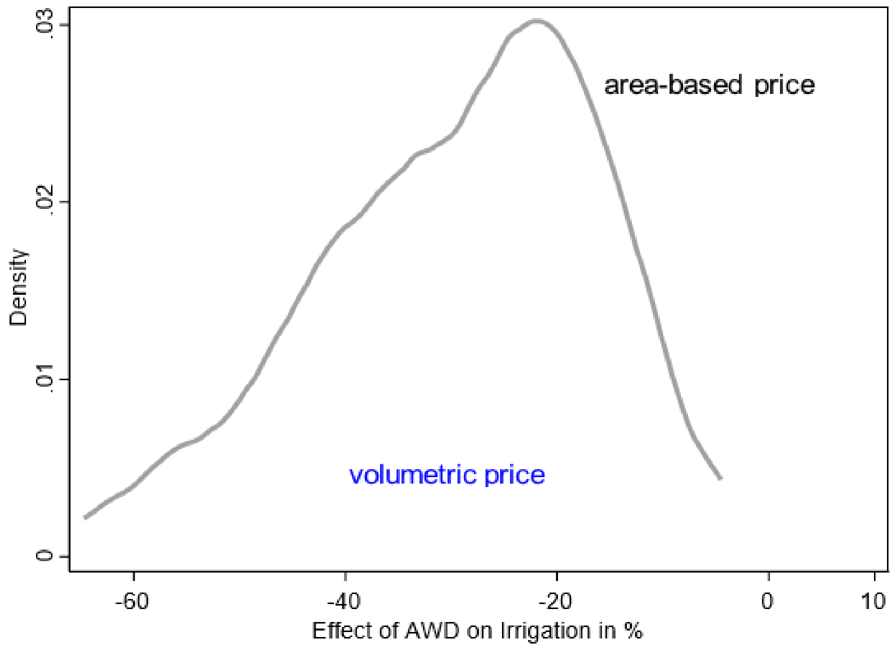
	0-60 Days After Planting		60+ Days After Planting	
	(1) Level	(2) Dry	(3) Level	(4) Dry
Treatment	-	0.071*	0.094	0.001
	(0.149)	(0.030)	(0.248)	(0.030)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.65	0.31	2.11	0.54
Number of Observations	3148	3148	4450	4450
R squared	0.037	0.036	0.057	0.068

The data are from random unannounced visits to the study plots of sample farmers during the 2017 boro (dry) growing season. Columns 1 and 2 are for measurements taken up to 60 days after transplanting.

Columns 3 and 4 are for measurements taken more than 60 days after transplanting. The dependent variable in columns 1 and 3 is the amount of standing water in the field, measured in centimeters. The dependent variable in columns 2 and 4 is an indicator variable for a dry field with no standing water.

Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Figure 8: Comparison between impacts from the RCT and agronomic experiments



Notes: Figure shows the kernel density of the impacts of AWD on irrigation volumes (grey 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 4 column 3).

Table 8: Separate effects by time of growing season, 0-80 and 80+ days after planting

	0-80 Days After Planting		80+ Days After Planting	
	(1) Level	(2) Dry	(3) Level	(4) Dry
Treatment	-0.213	0.045*	0.251	-0.029
	(0.152)	(0.025)	(0.334)	(0.039)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.55	0.36	1.80	0.63
Number of Observations	5316	5316	2282	2282
R squared	0.033	0.052	0.100	0.130

The data are from random unannounced visits to the study plots of sample farmers during the 2017 boro (dry) growing season. Columns 1 and 2 are for measurements taken up to 80 days after transplanting.

Columns 3 and 4 are for measurements taken more than 80 days after transplanting. The dependent variable in columns 1 and 3 is the amount of standing water in the field, measured in centimeters. The dependent variable in columns 2 and 4 is an indicator variable for a dry field with no standing water.

Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

5.4 Effect on costs and profits

Adoption of AWD only increases profit when water is priced at the margin.[9] Column 1 in Table 9 shows that the causal effect of AWD on profits per acre, in the absence of volumetric pricing, is close to zero and statistically insignificant. In contrast, the AWD technology increases profits by approximately 1,870 taka (about $23) per acre, or about 7%, when water has a marginal price. Columns 2-4 decompose the effect, showing that the overall effect on profitability comes from lower water costs and higher revenues, not increases in yield.[10] Columns 5-8 report similar results when all outcomes are measured in logs rather than levels. In Tables 10 and 11 we provide a breakdown of the effect of the treatment on material and labor expenditures.

Overall, AWD leads to positive returns only when water is priced at the margin. This conclusion is robust to trimming outliers in the profit distribution, controlling for a broad

[9] 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% of farmers that reported selling output. We use the average sale price for the remaining 1.5% of farmers that 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.

[10] The fact that AWD leaves yield unchanged is consistent with agronomic experiments (Belder et al., 2004; Yao et al., 2012). The positive — although insignificant — effect on revenue is therefore driven by higher prices. AWD leading to higher output prices is consistent with a claim sometimes made that periodic drying of fields improves grain quality.

set of baseline covariates, and interacting those covariates with treatment. Consistent with the survey estimates, we also find no difference in satellite-measured greenness between treatment and control plots. Despite using less water, the plots of treatment farmers appear no less green. We also find evidence that treatment effects on adoption and water usage persist for another year after the experiment.[11]

Finally, we find that within Rajshahi district — where prepaid pumps allow water to be priced by the hour — some farmers do not have their own prepaid cards.[12] Instead, farmers rely on the deep driver (tubewell operator) to use his card and then charge them a fixed seasonal price. This charge 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 and bills farmers accordingly. This local institution provides additional heterogeneity. In particular, the profits from AWD should be higher for farmers that hold their own cards and thus stand to gain by pumping less groundwater. We test this idea in the study villages in Rajshahi.[13]

Column 1 of Table 12 shows that AWD lowers water costs by about 931 taka — or 17% — for cardholders and has no effect for farmers that pay the deep driver for water. The effect on profits and log profits in columns 2 and 3 is noisier, but goes in the same direction. AWD increases profit by 11 to 12% for farmers with cards, but it has a smaller effect in villages where individual card ownership is absent. The system where farmers hold their own prepaid cards and pay for water by the hour is however not randomly assigned.[14] The observed heterogeneity could therefore result from factors correlated with card ownership, rather than card ownership itself. Columns 4 through 6 test whether the interaction effects are sensitive to interacting the AWD treatment indicator with a large set of baseline characteristics. The interaction effects between the AWD treatment and having an individual prepaid card remain similar — and actually increase — when allowing for the impact of AWD to also depend on observable characteristics. The evidence further points to inefficient water pricing as a barrier to AWD uptake.

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[11] We consider the persistence of treatment effects over time by using a subsample of villages where we elicit demand in the same way as in the second RCT, described later in the paper. In particular, farmers in 112 randomly selected treatment villages and 56 randomly selected control villages were offered an AWD pipe for the 2018 season at one of eight random prices. These offers took place in both treatment and control villages, but Table **??** shows that initial treatment farmers were still 70% more likely to be using AWD — on any plot — during the 2018 season. Using water measurements from one of those plots, treatment plots had 17% less water and were 39% more likely to be dry. Measurements were taken on the plot closest to the village tube well for a random 75% of farmers and the farthest plot for the remaining 25%. We see that the treatment effect on second-year adoption is larger amongst farmers with volumetric prices, but the interaction term is imprecisely estimated. We do not find heterogeneity in this "first-stage" relationship for the specific plot where enumerators measured water levels.

[12] 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.

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

[14] Farmers who have their own cards are older, have larger households, own more livestock, are less likely to own their own private tube well, and report irrigating their field more often during the boro season at baseline.

Table 9: Effects on self-reported water use

	Number Irrigations		Times Drained	
	(1)	(2)	(3)	(4)
Treatment	-3.589***	-3.590***	2.207***	1.888***
	(0.486)	(0.607)	(0.225)	(0.258)
Treatment * Volumetric Pricing		-0.015		0.918*
		(0.994)		(0.497)
Volumetric Pricing		1.082		0.032
		(1.263)		(0.433)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	19.10	19.10	2.42	2.42
p-Value: Treat+Treat*Volumetric		0.000		0.000
Number of Observations	3985	3984	3983	3982
R squared	0.539	0.540	0.359	0.366

The data are taken from the followup survey after harvesting. The dependent variables are the number of times the field was irrigated (columns 1-2) and the number of times the field was drained or dried (columns 3-4). Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Table 10: Effects of AWD on costs, revenues, and profits

					Log:			
	(1) Profit	(2) Water Cost	(3) Yield	(4) Revenue	(5) Profit	(6) Water Cost	(7) Yield	(8) Revenue
Treatment	-338.316	133.089	4.051	178.885	-0.036	0.023	-0.001	0.001
	(901.831)	(124.857)	(30.189)	(820.028)	(0.046)	(0.024)	(0.014)	(0.017)
Treatment * Volumetric Pricing	2205.179*	-435.469	10.295	1222.695	0.122**	-0.081	0.009	0.029
	(1293.913)	(279.224)	(37.221)	(1153.819)	(0.061)	(0.053)	(0.017)	(0.022)
Volumetric Pricing	-711.475	372.471	27.800	350.272	-0.123*	0.066	0.013	0.003
	(1332.595)	(226.509)	(37.246)	(1321.963)	(0.070)	(0.043)	(0.018)	(0.028)
Strata Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	27133.39	4897.18	2269.16	52696.04	10.12	8.45	7.71	10.85
p-Value: Treat+Treat*Volumetric	0.049	0.226	0.515	0.091	0.035	0.225	0.417	0.045
Number of Observations	3982	3983	3982	3982	3932	3983	3982	3982
R squared	0.298	0.365	0.352	0.390	0.273	0.347	0.329	0.351

The data are taken from the followup survey after harvesting. The dependent variables are profit per acre (column 1), water cost in taka per acre (column 2), crop yield in kilograms per acre (column 3), and revenue in taka per acre (column 4). Columns 5 through 8 show the same regressions with the log of profit, water cost, yield, and revenue, respectively. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Table 11: Effects on material input expenditure

	Fertilizer					Chemicals	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	N apps	Urea	TSP	Potash	Other	Pesticide	Herbicide
Treatment	-0.004	-5.653	3.685	5.868	-24.266*	-106.318*	34.564**
	(0.044)	(31.897)	(36.014)	(18.581)	(13.634)	(56.998)	(12.265)
Strata Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	2.67	1513.80	1073.34	586.13	115.56	1542.37	301.71
Number of Observations	3986	3983	3983	3983	3983	3983	3983
R squared	0.187	0.270	0.215	0.187	0.150	0.391	0.131

The data are taken from the followup survey after harvesting. The dependent variables are number of times fertilizer was applied (column 1), fertilizer expenditure per acre (columns 2-5), and chemical expenditure per acre (columns 6-7). All expenditures are recorded in Bangladeshi taka per acre. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Table 12: Effects on labor expenditure

	Hired			Family		
	(1)	(2)	(3)	(4)	(5)	(6)
	Plant	Weed	Harvest	Plant	Weed	Harvest
Treatment	107.067	172.178*	120.103	25.970	-94.987	-49.090
	(82.276)	(83.377)	(174.900)	(59.703)	(72.594)	(75.184)
Strata Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	3706.13	1907.60	6605.49	862.73	1298.77	1160.69
Number of Observations	3983	3981	3983	3978	3983	3982
R squared	0.234	0.138	0.216	0.259	0.204	0.271

The data are taken from the followup survey after harvesting. The dependent variables are expenditure per acre on hired labor (columns 1-3), and imputed expenditure on family labor (columns 4-6). All expenditures are recorded in Bangladeshi taka per acre. Family labor expenditure is imputed by multiplying observed person days by the daily wage rate. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Table 13: Effects separately by card ownership in villages with prepaid irrigation pumps

	(1)	(2)	(3)	(4)	(5)	(6)
	Water Cost	Profit	Log Profit	Water Cost	Profit	Log Profit
Treatment	108.3	1210.6	0.0260	-76.76	350.8	-0.00565
	(358.0)	(1202.1)	(0.0438)	(408.3)	(1571.8)	(0.0527)
Treatment * Has Card	-1039.4**	2524.1	0.112	-1164.6**	3793.0**	0.147**
	(485.1)	(2074.7)	(0.0773)	(472.1)	(1827.4)	(0.0646)
Has Card	1184.3***	-1253.7	-0.0722	1321.4***	-2246.7	-0.0868
	(409.1)	(1872.9)	(0.0708)	(411.2)	(1576.9)	(0.0560)
Strata Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	Yes	Yes	Yes
Treatment*Covariates	No	No	No	Yes	Yes	Yes
Mean in Control	5611.93	29999.22	10.27	5608.07	30025.35	10.27
p-Value: Treat+Treat*Has	0.006	0.028	0.030	0.000	0.009	0.007
Number of observations	1340	1340	1332	1337	1337	1329

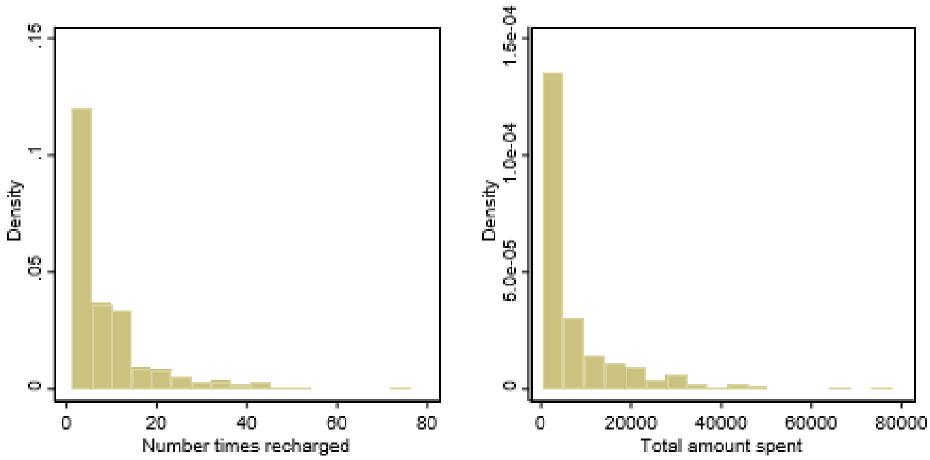
The data are from the follow up survey and are limited to the Rajshahi district where some farmers have their own prepaid irrigation card to pay for water by the hour. The variable “Has Card” is an indicator variable for farmers that report having their own prepaid card. The dependent variables are the cost of water per acre (columns 1 and 4), profit per acre (columns 2 and 5), and log profit per acre (columns 3 and 6). Columns 4-6 include demeaned farmer covariates from baseline and interactions between these demeaned covariates and the AWD treatment indicator. The covariates included are all of those in Table**??** (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). Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

5.5 Effect on demand for AWD

Our findings until this point suggest that lack of a marginal price for water creates a disincentive for the adoption of water-conserving technology. But the findings from the first RCT do not allow us to firmly rule out that unobservables correlated with the existence of nonzero marginal prices drive the heterogeneous impact of AWD. With this limitation in mind, we designed the phase 2 experiment to randomly facilitate volumetric pricing and measure its effect on demand for AWD. This section discusses the timing of events and results for the debit card experiment.

We now show some descriptive “first stage” evidence that some farmers did use the prepaid cards. The experiment was carried out in three upazilas, one of which provided us complete data on card usage for the 800 treatment farmers. We found that 40.3% of them (323) loaded their card at least once during the period from January 12th to August 7th, 2018. The median farmer — conditional on loading at least once — spent 3,000 taka ($37.5 or the equivalent of irrigating about 2 plots with seasonal charges) and loaded the card five times. These distributions have a substantial right tail: a farmer at the 90th percentile reloaded the card 22 times and spent 21,800 taka (Figure 9).

Figure 9: Densities of number recharges and amount spent for farmers using prepaid cards



Notes: The figure is for farmers in the one upazila (Paba) that provided us with usage data on the prepaid cards. Both graphs are for the 323 farmers that used the card. The left panel shows the density of the number of times the card was recharged, while the right figure shows the density of the total amount spent (in taka).

Does the demand curve for AWD change when farmers are encouraged to pay for water by the hour of pumping? To answer this question, we combine the random variation in village-level AWD prices with the random encouragement of prepaid card usage. The main specification is,

$$Adoption_{ivs} = \beta_0 + \beta_1 Card_{vs} + \beta_2 Price_{vs} + \beta_3 Card_{vs} * Price_{vs} + \alpha_s + \varepsilon_{ivs}, \quad (2)$$

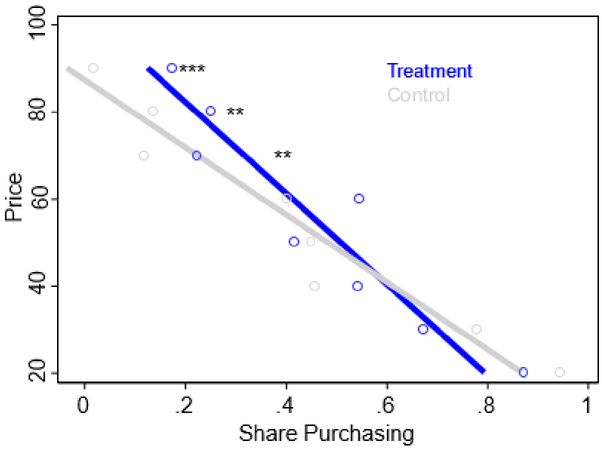
where $Adoption_{ivs}$ is an indicator for whether farmer *i* purchased the AWD pipe, $Card_{vs}$ equals one if village *v* in upazila *s* is one of the 96 prepaid card villages, and $Price_{vs}$ is the random AWD price offered in the village. As in our previous analysis, standard errors continue to be clustered at the village level.

Figure 10 shows the fitted demand estimates from (2) as lines with the raw adoption rates as dots. Shifting farmers to hourly charges reduces price sensitivity for AWD. Our lower prices result in high take up rates and no statistical difference between the prepaid card treatment and control. About 65% of farmers in the control group purchased pipes at the lowest four prices: this rate remains roughly the same in treatment villages. In contrast, introducing hourly irrigation cards caused AWD demand to increase at higher prices. Only 21% of farmers in the control group purchased pipes when priced at 60 taka or higher. Hourly pricing increased purchases by approximately 35% at these four higher prices.

The take-up rate of the device depends on the randomized price offered in the village and whether farmers were treatment or control. As shown in Figure 10 , the share of farmers purchasing the device was ranged from 60-80% at lower prices and about 20% at the highest prices offered. The take-up was significantly higher at higher prices for treatment farmers.

Two additional results are apparent in Figure 10. First, demand is elastic. The demand elasticity in the control group is about 1.7 at the midpoint price of 55 taka. 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.

Figure 10: Demand curve by volumetric pricing treatment



Notes: 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 grey dots are adoption rates in the 48 control villages and the grey line presents the corresponding linear demand estimate. Asterisks denote that the marginal impact of the treatment (from the linear demand estimates) is statistically significant (1% $***$, 5% $**$, and 10% $*$). The estimation sample includes all 25 farmers in each village.

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 1,870 taka per acre. 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 561 taka — a value well above what farmers are willing to pay. We estimate the marginal cost of AWD production to be 133 taka — based on surveys conducted with 10 engineering shops.[15] Our findings show no demand at this price, even after promoting hourly pricing for water. However, the socially optimal price of AWD depends on its external benefits. These may include reduced greenhouse gas emissions from electricity, reduced methane emissions from rice fields, and the social benefit of the groundwater not extracted and available to others, discussed later in this report.

Table 14 shows the corresponding regression results. Column 1 gives the average treatment effect across all price levels. The irrigation card treatment led to an increase in the AWD purchasing rate by about 4.3 percentage points, or roughly 10%. The aver- age effect is indistinguishable from zero due to the significant heterogeneity across price

[15] Field staff visited each shop in June 2018 and asked the owner for a quote to produce two different ran- domly selected quantities of AWD pipes. Regressing the estimated quotes on quantity delivers a coefficient of 133 taka.

levels. Column 2 provides the main estimates corresponding to the specification in (2). Demand for water-saving technology is less responsive to price in villages where we introduce hourly irrigation cards. Increasing the price by 1 taka leads to a 1.29 percentage point decrease in adoption without volumetric pricing. This price responsiveness falls significantly by 0.34 percentage points when we facilitate volumetric pricing. The demand elasticity at a price of 55 taka — reported at the bottom of column 2 — falls by 33% from 1.7 to 1.14 with the prepaid card treatment. This difference in elasticities is statistically significant at the 1% level.[16] We also pre-specified a functional form where prices are measured in logs. Columns 3 and 4 show that this additional specification gives similar results. Overall, introducing a pricing mechanism that puts a marginal price on water increases farmers willingness to pay for water-conserving technology.

The estimated demand curves can be used to calculate the gain in consumer surplus that results from encouraging volumetric prices. Figure 11 shows the percentage in- crease in consumer surplus between farmers with and without hourly irrigation cards. For instance, when priced at 55 taka — the median price in our demand experiment — nudging farmers to adopt volumetric pricing causes consumer surplus from AWD to increase by almost 64%. These gains in consumer surplus are largest at higher prices, as seen in Figure 10.

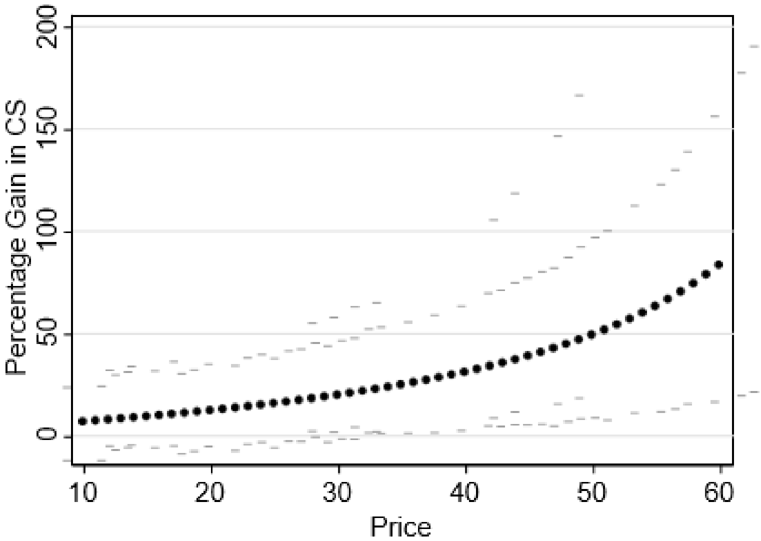
Table 14: Impacts of volumetric pricing treatment on demand for water-saving technology

	(1)	(2)	(3)	(4)
Card Treatment	0.0430	-0.1428	0.0353	-0.5510**
	(0.0436)	(0.1044)	(0.0428)	(0.2622)
Pipe Price	-0.0105***	-0.0129***		
	(0.0008)	(0.0012)		
Pipe Price * Card Treatment		0.0034**		
		(0.0015)		
Log Pipe Price			-0.5084***	-0.6123***
			(0.0351)	(0.0489)
Log Pipe Price * Card Treatment				0.1497**
				(0.0654)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	0.413	0.413	0.413	0.413
Elasticity at Price=55 Treat	-1.26	-1.14	-1.25	-1.13
Elasticity at Price=55 Control	-1.39	-1.70	-1.37	-1.70
P-value: Equal Elasticities		0.009		0.025
Number Obs	3569	3569	3569	3569
R squared	0.249	0.254	0.256	0.260

The data are from the 144 villages that were part of the second-year experiment. The sample consists of 25 farmers per village. The dependent variable in all regressions is an indicator if the farmer purchased the AWD pipe at the randomly set price. Prices were set randomly at the village level and range from 20 to 90 taka (around \$0.24 to \$1.1). The volumetric 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 150 taka sign-up fee. The p-value for equal elasticities is based on standard errors from the delta method. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

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

Figure 11: Effect of volumetric pricing treatment on consumer surplus from AWD



Notes: The figure shows the gain in consumer surplus (of AWD) from the prepaid card treatment (measured in %) as black dots. The black dots are the percentage difference between the two surpluses at various prices *p*. The 90% confidence intervals (whiskers) are estimated from 1,000 bootstrapped samples where the range of each whisker shows the 5th to 95th percentiles of the distribution of percentage changes in consumer surplus.

The intervention in our first experiment included assistance with installing the AWD pipe. Providing farmers with the AWD tool, some basic training, and installation sup- port led to reduced water use and increased profitability for farmers paying for water by the hour. The large gap between purchasing and using AWD in the second experiment highlights the importance of basic training and installation support to ensure that the full benefits of AWD are realized.[17]

Figure 12 shows that despite the low rate of installation, the unconditional price-usage relationship remains steeper in prepaid-card villages. The dashed lines in the figure show usage (installation), while the solid lines show the demand curves (purchasing). The number of treatment farmers buying AWD pipes ranges from about 260 at a price of 20 taka to around 70 at a price of 90 taka. The average number of users across all the 9 price points is around 25. At prices above 60 taka, only 1.4% of farmers installed AWD in control villages. Approximately 7.4% did so in treatment villages. The regression estimates in Table 16 provide exact magnitudes. In column 1, increasing price by one taka (about 1.8% of the midpoint price of 55 taka) causes a decrease in the usage rate by 0.16 percentage points, or 2.3% of the mean usage rate amongst control villages. Column 2 again shows the heterogeneity in price responsiveness. A one taka 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 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.

[17] We also measured water levels on a single plot per farmer. Table 15 shows that the interaction between price and the volumetric treatment does not have a positive coefficient for these specific plots. This lack of a “first-stage” relationship may explain why we do not observe any effect on water management on these plots.

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% to 0.6 in treatment villages. The difference between the two elasticities is highly significant. Columns 3-4 demonstrate that similar results are obtained with log prices.

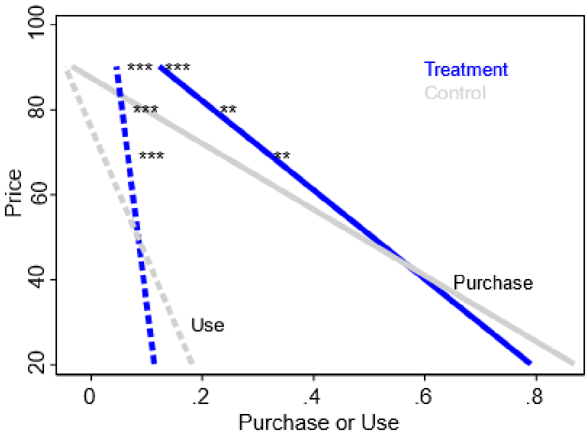
The difference in elasticities appears to result from how the prepaid cards change the screening ability of prices. Among farmers who purchased an AWD pipe, the correlation between price and usage is significantly larger in prepaid card villages. In fact, the price-usage correlation is negative in control villages and weakly positive in pre- paid 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 AWD pipe at higher prices are those that value them most and are the ones most likely to install. In contrast, prices for conservation technology do not screen effectively in the absence of volumetric water pricing because farmers stand to gain little from using the pipe for irrigation.

Table 15: Relationship between the prepaid card treatment and observed water management on one field per farmer

	(1) AWD installed	(2) Water Level	(3) Dry Field
Card Treatment	0.0424	0.3651	-0.0988
	(0.0268)	(0.6997)	(0.1334)
Pipe Price	-0.0002	0.0002	0.0010
	(0.0003)	(0.0121)	(0.0021)
Pipe Price * Card Treatment	-0.0001	-0.0040	0.0008
	(0.0004)	(0.0132)	(0.0024)
Strata Fixed Effects	Yes	Yes	Yes
Mean in Control	0.008	2.214	0.393
P-value: Price+Price*Volumetric	0.165	0.469	0.136
Number Obs	3598	3600	3600
R squared	0.017	0.012	0.014

The data are from the 144 villages that were part of the second-year experiment. The sample consists of 25 farmers per village. The data are for one plot per farmer. The chosen plot is the closest to the village tube well for 75% of random farmers and the furthest plot for the remaining 25% of farmers. Prices were set randomly at the village level and range from 20 to 90 taka (around \$0.24 to \$1.1). The volumetric 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 150 taka sign-up fee. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

Figure 12: AWD usage as a function of price and prepaid card treatment



Notes: The figure shows the demand curves for AWD as solid lines, where uptake is measured as purchasing the pipe from the door-to-door salesperson. The solid lines merely replicate the demand curves from Figure 10. The dashed lines instead consider usage, where usage is defined as an enumerator being able to verify that an AWD pipe was installed in one of the farmer's fields. The blue lines are for farmers in the 96 treatment villages where prepaid hourly irrigation cards were provided. The grey lines are for the 48 control villages. Asterisks denote a statistically significant treatment effect of the hourly irrigation cards (1% $***$, 5% $**$, and 10% $*$). The sample in each village is the 25 farmers that were identified at the start of the experiment.

Table 16: Impacts of hourly irrigation cards on installation of conservation technology

	(1)	(2)	(3)	(4)
Card Treatment	0.0200	-0.1071	0.0187	-0.4848
	(0.0278)	(0.1074)	(0.0279)	(0.3321)
Pipe Price	-0.0016***	-0.0033**		
	(0.0006)	(0.0014)		
Pipe Price * Card Treatment		0.0023		
		(0.0015)		
Log Pipe Price			-0.0763**	-0.1665**
			(0.0307)	(0.0739)
Log Pipe Price * Card Treatment				0.1287
				(0.0795)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	0.068	0.068	0.068	0.068
Elasticity at Price=55 Treat	-1.01	-0.60	-0.95	-0.45
Elasticity at Price=55 Control	-1.31	-2.58	-1.23	-3.08
P-value: Equal Elasticities		0.001		0.005
Number Obs	3600	3600	3600	3600
R squared	0.033	0.041	0.033	0.043

The data are from the 144 villages that were part of the second-year experiment. The sample consists of 25 farmers per village. The dependent variable in all regressions is an indicator equal to one if it was verified that the farmer installed AWD on one of their plots. Prices were set randomly at the village level and range from 20 to 90 taka (around \$0.24 to \$1.1). The volumetric 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 150 taka sign-up fee. Standard errors are clustered at the village level. The p-value for equal elasticities is based on standard errors from the delta method. Asterisks indicate that coefficient is statistically significant at the 1% $***$, 5% $**$, and 10% $*$ levels.

6. Estimating the benefits of the technology

We also try to briefly consider the environmental benefits of AWD. First, AWD reduces groundwater extraction which lowers electricity demand and therefore greenhouse gas emissions from electricity generation. Ideally, electricity should be priced at its marginal social cost, which would include the negative externalities from electricity generation. However, taxing electricity has proven to be elusive in practice. In the absence of a socially optimal electricity price, subsidizing energy efficiency is a second-best alternative to reducing these externalities.

We quantify one part of such a subsidy for AWD by approximating the dollar value of reduced carbon emissions from an installed AWD device. We base our estimate on both the results from the experiment and additional data we collected for this purpose. The remainder of the section describes the different steps of this computation.

Reduced groundwater pumping: We do not have survey measures of pumping hours to compare treatment and control farmers from our first experiment. However, col- umn 1 in Table 12 finds that AWD reduces water costs by 931.1 taka per acre for farmers with hourly irrigation cards. The median plot size is 0.3 acres and the cost per hour of pumping is 120 taka. Combining these three figures delivers an estimated savings of 2.3 hours of pumping per AWD device.

Electricity consumption per hour of pumping: We sent enumerators to 26 random villages in March/April 2018 to observe electricity usage by monitoring electric meters during tube well operation. We use the starting and ending time of operation, combined with electricity consumption, to estimate an electricity usage of 18.1 kilowatt hours (kwh) per hour of operation. As a benchmark, annual household electricity consumption per capita in Bangladesh is about 300 kwh.

Electricity produced per unit of consumption: The ratio of electricity produced to consumed in Bangladesh is 1.14. We adjust this number to allow for 75% of the transmission losses to be attributed to electricity flowing through power lines, while the other 25% are fixed and independent of consumption. We therefore end up with 1.105 kwh of production needed per kwh of consumption.

Marginal CO_2 emissions from electricity production in Bangladesh: A reduction in electricity demand for irrigation reduces CO_2 emissions from generating electricity. Marginal CO_2 emissions from electricity depend on a number of factors, including the type of fuel and the efficiency of power plants. Ideally, we need data from Bangladesh power plants with repeated observations on plant load and emissions. Without this data for Bangladesh, we instead use annual panel data from about 3,900 U.S. power plants to estimate marginal CO_2 emissions as a function of fuel type and thermal efficiency of the plant. We then obtain these two characteristics (fuel type and efficiency) for the universe of Bangladesh power plants and estimate marginal emissions per plant using the regression estimates from U.S. plants. We take the average of plant-level marginal emissions where each plant is weighted by its share of annual electricity generation for the whole country.

This approach delivers a marginal emissions rate of 1.4 lbs of CO_2 per kwh of electricity. This number is roughly on par with CO_2 emissions generated by the electricity grid in the eastern United States. The estimate is also similar to the grid emission factor released by the Bangladesh Department of Environment in 2014 (1.47 lbs per kwh).

Social cost of carbon: We use the standard estimate of 31 US$ per ton of CO_2. Combining these figures, the estimated one-year benefit of AWD on a single rice plot — due to reduced carbon emissions from electricity — is 79.91 taka. This annual benefit represents about 60% of the marginal cost of production. Moreover, these are not the only external benefits of AWD. Agronomic studies find that adopting AWD lowers methane emissions from rice by approximately 50%. We attempted to measure methane gas on a sample of 104 plots from the first experiment. A malfunction in our partner's gas chromatograph delayed analysis of the samples and made these results unreliable.

An additional social benefit of AWD is in valuing the groundwater that is not pumped, and remains in the aquifer for future use, which delivers benefits to other farmers relying on the same groundwater source. To approximate these benefits, we first need to compute the volume of water saved by AWD. The calculations above suggest that AWD reduces pumping times by 2.3 hours per plot. The standard government deep tube well has a capacity of 1 cusec, i.e. 1 ft3/sec or 101.941 m3/hr. Thus, a reasonable estimate of averted pumping by using AWD on a single plot is 234.46 m3 or 0.19 acre feet of water. Column 3 of Table 4 shows water savings of about 18.3%, suggesting total water use of 1.04 acre feet for the rice plots in our sample. A conservative agronomic estimate of the return flow for rice is 25%. That is, 25% of the averted pumping caused by AWD is water that would have returned to the aquifer anyway. Thus, an estimate of the true water savings from AWD is 75% 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.

What is the value of this conserved groundwater? The average value of water in rice farming in our sample can be obtained by multiplying the profit per acre from column 1 of Table 9 (which is 27,133 taka) by plot size (0.3 acres) and dividing by total water use (1.04 acre-ft) which gives 7,827 taka per acre-ft of water. This is approximately $93 per acre-ft, which is high for a developing country, but shows the value of water for dry-season rice in Bangladesh. Our estimate of the value of conserved water from using AWD on a single plot is therefore 1,115 taka per year ($13.9). The estimated benefits from water conservation are an order of magnitude greater than the benefits from reduced CO_2 emissions.

In summary, the technology we study can deliver substantial environmental benefits.

However, farmers valuing the technology, and using it properly, depends on water having a marginal price.

7. Discussion

7.1 Introduction

In our first experiment, we offer rigorous evidence on the causal effect of AWD on water savings, profits and input costs. The average effect of AWD on these outcome variables was small and insignificant. We observed no significant difference between treatment and control plots in the frequency of dry fields or in the level of water in the field. Our results show that a sizable number of farmers dry their fields even without AWD. Thus continuously irrigating the rice plot may not be the correct counterfactual for evaluating AWD.

However, we find that AWD has significant effects only in plots where farmers pay volumetric pricing. There is a 18% decrease in the height of the observed water in the field and a 19% decrease in the probability of the field being dry. These water savings occur in the first 70 days after planting. Our magnitude estimates under volumetric pricing fall at the 25% of existing estimates from laboratory evaluations of AWD. However, the failure to price water seems to explain the divergence between our estimates from the field and those from the laboratory. Most lab experiments are unable to incorporate behavioral elements in their analysis.

A limitation of the first RCT was that volumetric pricing may be correlated with un- observables that affect the heterogeneous impacts of AWD use. Thus in the second experiment, we observe that demand for AWD is elastic, with an elasticity of 1.7 at the midpoint of prices offered. 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, 2018). Moreover, the willingness to pay for the technology was low, compared to the estimated benefits of installing an AWD pipe on a typiocal plot, which is about 533 taka. Our estimate of the marginal cost of production for the pipe is 133 taka, but at this price, demand is close to zero.

There are several limitations of our study. We do not experiment with the level of the hourly irrigation price. Instead, we encourage a switch from a seasonal contract to hourly billing, where the hourly price is set uniformly by the local irrigation authority. Our treatment only approximates volumetric pricing because hours pumped is imperfectly cor- related with the volume of water extracted. Given that electricity accounts for a large share of the pumping cost, our treatment moves the pricing regime towards marginal cost pricing. But we do not necessarily introduce the socially optimal hourly price because that price would need to incorporate the externality costs of electricity generation. Implementing volumetric pricing is difficult due to its high cost and political pressure from farmers, some of whom may lose under the new regime (Tsur and Dinar, 1997). How- ever, our study shows that a simple digital payment technology moves the pricing regime closer to marginal cost pricing and induces farmers to put more value on conservation technology. In essence, encouraging volumetric pricing leads to a perceptible change in the farmer’s attitude towards conservation, as measured by the shift in their demand for the technology.

We also do not measure water use on farmer plots perfectly. We observe whether the field is dry and measure the depth of the water level during randomized visits. These measurement can introduce error in our estimates.

However, there is no field evidence that documents the role seasonal water charges play in discouraging efficient agriculture water use (see Zilberman and Schoengold (2005)). To our knowledge, this is the first paper that randomly introduces volumetric pricing for agricultural water. Fishman et al. (2016) use non-experimental 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.

7.2 Policy and program relevance: evidence uptake and use

In the several workshops we organized, there was intense discussion on the importance of water conservation and specifically AWD in water management. Policy makers and scientists involved in AWD research and extension in Bangladesh accepted our tentative findings and have promised to discuss follow-up in coordination with other agencies.

In the larger literature in development and environmental economics, our study shows that inefficient factor pricing may explain why technologies that are available, proven in the laboratory, and seemingly in reach of farmers continue to exhibit low rates of adoption. Earlier explanations have focused on failures in output markets (Ashraf, Gine´, and Karlan, 2009), behavioral biases (Duflo, Kremer, and Robinson, 2011), frictions in insurance or credit markets (Karlan et al., 2014; Cole, Gine´, and Vickery, 2017), unobservable input quality (Bold et al., 2017), heterogeneity in the net benefits and costs of adoption (Suri, 2011), and learning frictions (Conley and Udry, 2010; Hanna, Mullainathan, and Schwartzstein, 2014; Beaman et al., 2015).[18] We add to this debate by showing that the pricing mechanism for a critical factor of production inhibits technology adoption.[19]

7.3 Challenges and lessons

A key challenge of the study was in understanding why farmers do not use the AWD technology, even after purchasing them. While take up is reasonably high, when measured by purchasing an AWD pipe, installation and use of the pipe is modest. Only 18.4% of purchasing farmers installed the AWD pipes on one of their rice plots.[20] 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."[21] After conferring with

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[18] Jack (2011), de Janvry, Sadoulet, and Suri (2017), and Magruder (2018) provide comprehensive re- views of the literature on technology adoption in developing country agriculture.

[19] Outside of agricultural technology, inefficiently low (marginal) prices for electricity have been shown to reduce development and adoption of energy-efficiency technologies in developed countries. Borenstein and Bushnell (2018) find that electricity is priced below its social marginal cost in many parts of the United States. At the same time, a literature on induced innovation shows a positive association between electricity prices and development of energy-efficiency technologies (Newell, Jaffe, and Stavins, 1999; Popp, 2002). Other studies find that consumers shift to fuel-efficient vehicles when gasoline prices are high (Busse, Knittel, and Zettelmeyer, 2013; Allcott and Wozny, 2014).

[20] A low rate of usage, conditional on purchasing, has been observed for fertilizer trees in Zambia (Jack et al., 2015) 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).

[21] Farmers that purchased pipes were told that AWD should be practiced starting 10 days after transplanting. The date of the verification survey was randomized and survey teams arrived less than 10 days after planting in fewer than 1% of cases. Moreover, the rate of uptake (conditional

others, some farmers suggested that it was not feasible to use AWD individually because of coordination externalities. Two examples were common. Farmers with low-lying land often get water that spills over into their plot when it is being pumped into a nearby higher field. Also, 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.

8. Conclusions and recommendations

We can draw the following conclusions and offer these recommendations:

1. Policy maker, global, national, local: The results obtained from AWD in experiment stations can only be replicated in the field if farmers pay a marginal price for water. When farmers pay a fixed price that is unrelated to the volume of water they use, the water savings from AWD are statistically insignificant. Across the whole country, water and electricity savings from even modest adoption of the technology would be significant.
2. Policy maker, national, local: In villages which are equipped with tube wells that can accept debit cards, facilitating the debit card application process for individual farmers results in a shift in the demand for AWD. More farmers purchased the AWD device, especially at the higher prices. However, even after purchase, installation of the pipe was low. Most farmers did not install the pipe, suggesting that other factors may affect their ability to reduce water use.
3. Policy maker and Researcher, global, national, local: Our findings suggest that the social benefits of AWD are large, mainly in the form of savings of electricity for pumping as well as the value of the water that can be used later. The benefits are an order of magnitude higher than the cost of producing the pipe.
4. Policy maker, Researcher, global, national, local: One key challenge may be to engage in reform of water pricing policies so that farmers face the correct incentives. While changing pricing mechanisms at the local level may be a daunting task, some farmers are likely to lose under the transition and therefore resist change. Our second experiment shows that at least in villages where the infrastructure for digital payment exists, increasing the penetration of the digital payment system can significantly alter water conservation behavior among farmers. In areas where this infrastructure does not exist currently, it may be worthwhile to think of policies that encourage new tubewells to come equipped with a meter than can accept individual debit cards.

on purchasing) is only 20% for the farmers that 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.

Online appendixes

https://www.3ieimpact.org/sites/default/files/2020-03/DPW1.1081-Bangladesh-AWD-Online-appendixes.pdf

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