Online Appendix for Inefficient Water Pricing and Incentives for Conservation

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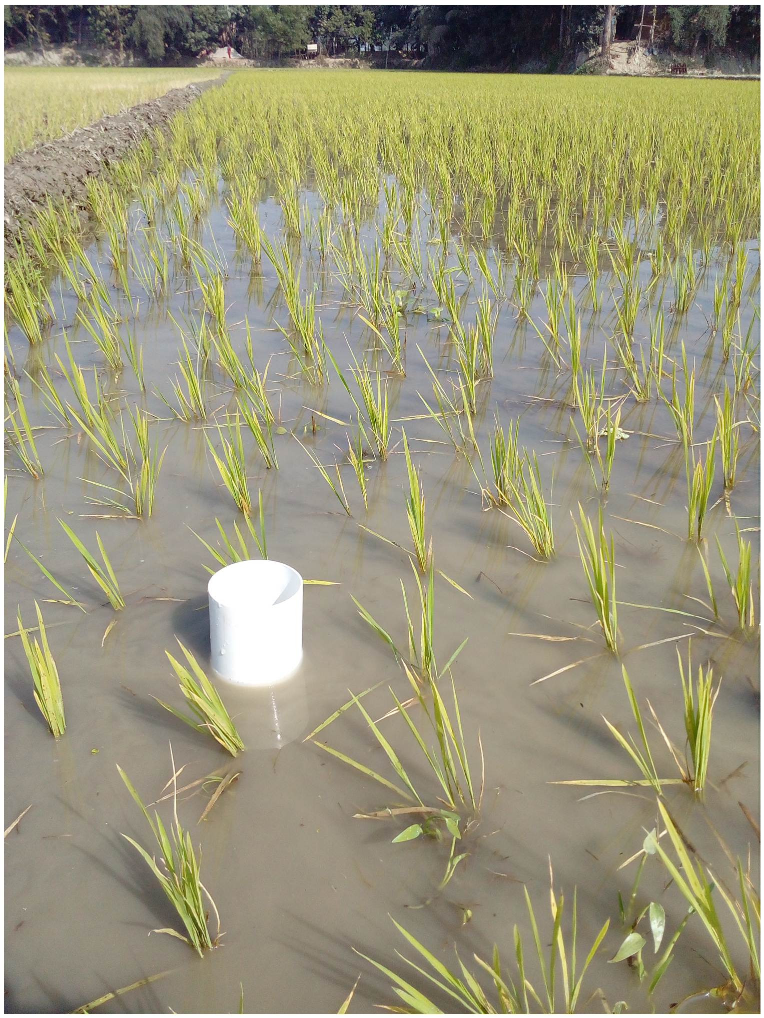
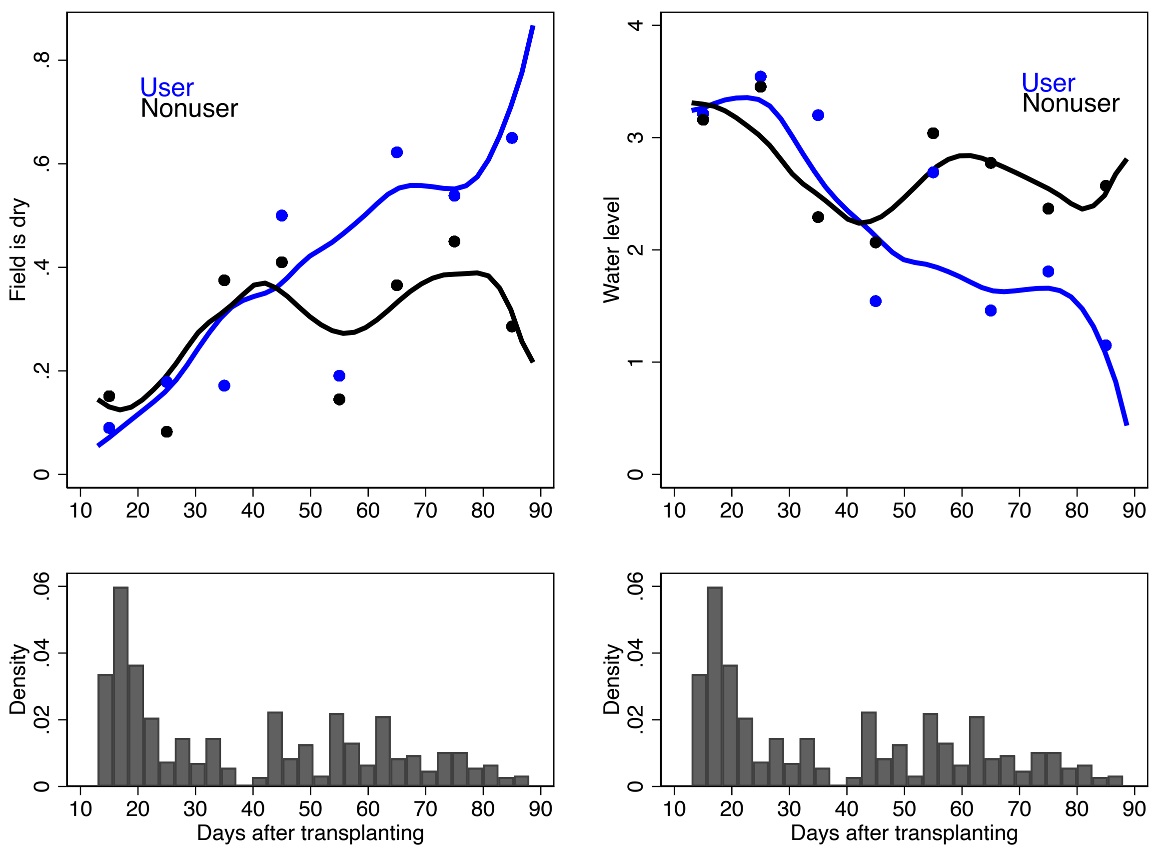
Figure A1: Image of AWD pipe installed in a farmer's field



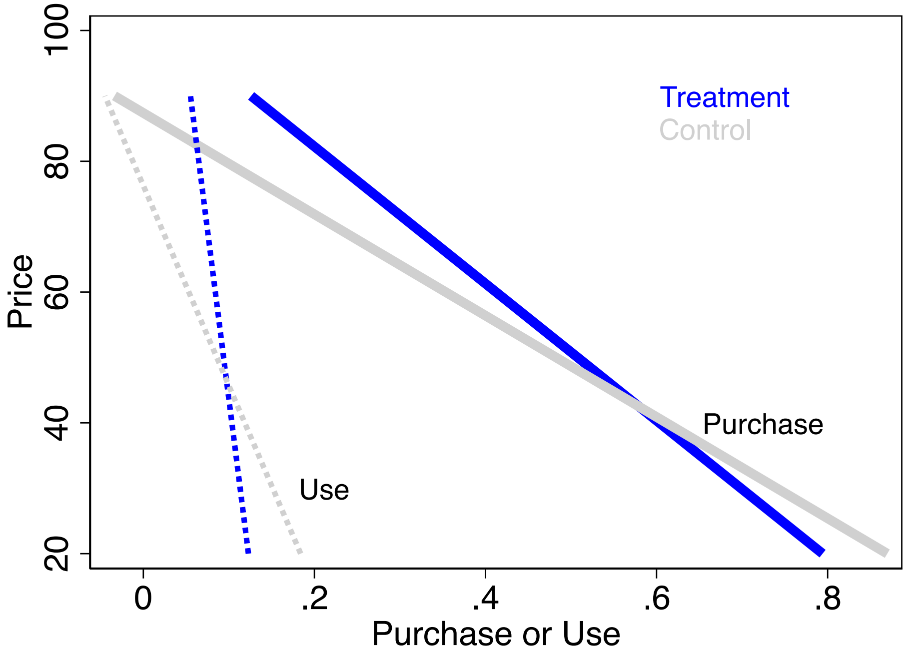
Notes: Figure shows an image of an AWD pipe installed in the farmer's field. The pipe is inserted to a level more than 15 cm below the soil surface. Holes are drilled into the plastic pipe, allowing the farmer to monitor soil moisture below the surface. A small net is wrapped around the bottom of the pipe to prevent mud from clogging the pipe. The farmer uses the pipe to monitor soil moisture. The field can be dried until the water level falls below 15 cm below the surface, marked with a line in the pipe. The field is then re-irrigated, hence the name "Alternate Wetting and Drying." This procedure should be used during the period up until the crop starts to reproduce (flower), when water should be kept in the field.

Figure A2: Correlation between water management and use of the hourly irrigation card



Notes: The figure shows non-parametric fan regressions of an indicator for fields with no standing water (top left) and water levels in centimeters (top right) on the days after transplanting. Observations were taken for one plot per farmer. The blue lines are for the 323 farmers that used the cards while the black lines are for the 477 farmers that did not. 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. The figure is for the one upazila where we received data on card usage.

Figure A3: Usage of conservation technology as a function of price and hourly 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 5. 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. The sample in each village is the 25 farmers that were identified at the start of the experiment.

Table A1: Summary Statistics and Covariate Balance by Treatment for places with volumetric water pricing

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

The table shows mean values of baseline characteristics for control and AWD treatment households in columns 1 and 2, respectively. Column 3 shows the p-value from the regression of each characteristic on the treatment indicator and strata (Upazila) fixed effects. Panel A contains household-level variables and Panel B contains variables specific to the study plot nearest the irrigation tubewell. "Boro" is the dry-season from January to May and "Aman" is the wet season from June to November. All data are based on the baseline survey from November-December 2016 and only include households that reported volumetric water pricing at baseline.

Table A2: Effects of conservation technology when omitting strata fixed effects

	(1) Water Level	(2) Dry	(3) Water Level	(4) Dry
Volumetric Pricing	-0.621***	0.061**	-0.363**	0.018
	(0.147)	(0.026)	(0.183)	(0.035)
Treatment			0.109	-0.009
			(0.229)	(0.029)
Treatment * Volumetric Pricing			-0.510*	0.085
			(0.293)	(0.052)
Mean in Control	2.32	0.45	2.32	0.45
p-Value: Treat+Treat*Volumetric			0.031	0.078
Number of Observations	7596	7596	7596	7596
R squared	0.009	0.003	0.011	0.005

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.

Table A3: Effects of conservation technology on the probability of fields being dried

	Overall		0-70 Days After Planting		70+ Days After Planting	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0191	-0.0122	0.0590**	-0.0120	-0.0211	-0.00329
	(0.0228)	(0.0265)	(0.0265)	(0.0325)	(0.0334)	(0.0390)
Treatment * Volumetric Pricing		0.0960*		0.185***		-0.0708
		(0.0495)		(0.0540)		(0.0746)
		[0.0841]		[0.00701]		[0.266]
Volumetric Pricing		-0.0583		-0.0824		0.0228
		(0.0605)		(0.0650)		(0.0660)
Upazila Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	0.45	0.45	0.32	0.32	0.59	0.59
p-Value: Treat+Treat*Volumetric		0.047		0.000		0.244
Number of Observations	7598	7596	4188	4187	3410	3409
R squared	0.035	0.037	0.035	0.043	0.113	0.114

The data are from random unannounced visits to the study plots of sample farmers during the 2017 boro (dry) growing season. The dependent variable in all columns is 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. The numbers in brackets in columns 2, 4, and 6 are p-values when standard errors are clustered at the *upazila level* using the wild-cluster bootstrapping method of Cameron, Gelbach and Miller (2008).

Table A4: Separate effects by time of growing season, 0-60 and 60+ days after planting

	0-60 Days After Planting		60+ Days After Planting	
	(1) Water Level	(2) Dry	(3) Water Level	(4) Dry
Treatment	-0.357**	0.071**	0.094	0.001
	(0.149)	(0.030)	(0.248)	(0.030)
Upazila 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.

Table A5: Separate effects by time of growing season, 0-80 and 80+ days after planting

	0-80 Days After Planting		80+ Days After Planting	
	(1)	(2)	(3)	(4)
	Water Level	Dry	Water Level	Dry
Treatment	-0.213	0.045*	0.251	-0.029
	(0.152)	(0.025)	(0.334)	(0.039)
Upazila 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.

Table A6: Heterogeneous effects by first 60 days of the growing season

	0-60 Days After Planting		60+ Days After Planting	
	(1) Water Level	(2) Dry	(3) Water Level	(4) Dry
Treatment	-0.103	0.008	0.219	-0.001
	(0.188)	(0.035)	(0.335)	(0.035)
Treatment * Volumetric Pricing	-0.670**	0.164***	-0.386	0.008
	(0.298)	(0.062)	(0.429)	(0.068)
Volumetric Pricing	-0.035	-0.038	-0.365	-0.011
	(0.363)	(0.074)	(0.418)	(0.072)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.65	0.31	2.11	0.54
p-Value: Treat+Treat*Volumetric	0.001	0.001	0.519	0.916
Number of Observations	3147	3147	4449	4449
R squared	0.043	0.043	0.059	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. 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.

Table A7: Heterogeneous effects by first 80 days of the growing season

	0-80 Days After Planting		80+ Days After Planting	
	(1) Water Level	(2) Dry	(3) Water Level	(4) Dry
Treatment	0.049	-0.007	0.294	-0.020
	(0.209)	(0.030)	(0.442)	(0.049)
Treatment * Volumetric Pricing	-0.719**	0.144***	-0.055	-0.037
	(0.279)	(0.052)	(0.514)	(0.071)
Volumetric Pricing	0.097	-0.087	-0.718	0.023
	(0.345)	(0.063)	(0.522)	(0.070)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.55	0.36	1.80	0.63
p-Value: Treat+Treat*Volumetric	0.000	0.001	0.346	0.264
Number of Observations	5315	5315	2281	2281
R squared	0.037	0.057	0.102	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. 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.

Table A8: Effects of conservation technology 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)
Upazila 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 follow-up 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 A9: Effects on material input expenditure

	Fertilizer					Chemicals	
	(1) N apps	(2) Urea	(3) TSP	(4) Potash	(5) Other	(6) Pesticide	(7) 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)
Upazila 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 follow-up 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 A10: Effects on labor expenditure

	Hired			Family		
	(1) Plant	(2) Weed	(3) Harvest	(4) Plant	(5) Weed	(6) 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)
Upazila 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 follow-up 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 A11: Heterogeneous effects on material input expenditure

	Fertilizer					Chemicals	
	(1) N apps	(2) Urea	(3) TSP	(4) Potash	(5) Other	(6) Pesticide	(7) Herbicide
Treatment	-0.019	37.135	14.264	16.740	-38.196**	-49.034	51.928***
	(0.052)	(37.960)	(39.172)	(23.173)	(17.651)	(60.291)	(17.250)
Treatment * Volumetric Pricing	0.041	-124.456*	-30.126	-30.644	40.721	-167.998	-50.193**
	(0.095)	(69.209)	(82.734)	(38.796)	(26.707)	(132.486)	(21.988)
Volumetric Pricing	0.028	77.670	-53.716	-35.319	-49.417**	199.235**	25.228
	(0.075)	(49.332)	(72.425)	(34.355)	(24.619)	(93.076)	(20.514)
Upazila 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
p-Value: Treat+Treat*Volumetric	0.776	0.131	0.828	0.655	0.901	0.067	0.899
Number of Observations	3985	3982	3982	3982	3982	3982	3982
R squared	0.188	0.273	0.216	0.189	0.155	0.395	0.134

The data are taken from the follow-up 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 A12: Heterogeneous effects on labor expenditure

	Hired			Family		
	(1) Plant	(2) Weed	(3) Harvest	(4) Plant	(5) Weed	(6) Harvest
Treatment	121.638	96.450	214.949	-12.322	-78.577	-1.534
	(117.075)	(94.393)	(225.466)	(56.321)	(84.846)	(77.506)
Treatment * Volumetric Pricing	-43.480	213.977	-279.576	112.744	-43.809	-134.140
	(141.671)	(185.537)	(352.897)	(147.297)	(162.296)	(179.529)
Volumetric Pricing	215.358	211.368	671.095**	-198.722	-212.623	-173.712
	(153.256)	(170.082)	(269.756)	(125.856)	(233.701)	(197.290)
Upazila Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	3706.13	1907.60	6605.49	862.73	1298.77	1160.69
p-Value: Treat+Treat*Volumetric	0.341	0.053	0.811	0.460	0.372	0.401
Number of Observations	3982	3980	3982	3977	3982	3981
R squared	0.235	0.142	0.219	0.260	0.205	0.273

The data are taken from the follow-up survey after harvesting. The dependent variables are expenditure per acre on hired labor (columns 1-3), and imputed value of family labor (columns 4-6). 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 A13: Effects of conservation technology on revenues and profit

				Log:		
	(1) Yield	(2) Revenue	(3) Profit	(4) Yield	(5) Revenue	(6) Profit
Treatment	7.736	604.360	425.276	0.002	0.011	0.007
	(21.221)	(614.012)	(681.853)	(0.010)	(0.012)	(0.034)
Upazila Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Control	2269.16	52696.04	27133.39	7.71	10.85	10.12
Number of Observations	3983	3983	3983	3983	3983	3933
R squared	0.352	0.389	0.296	0.328	0.349	0.270

The data are taken from the follow-up survey after harvesting. The dependent variables are crop yield in kilograms per acre (column 1), revenue in Bangladeshi taka per acre (column 2) and profit in Bangladeshi taka per acre (column 3). Columns 4 through 6 show the same regressions with log yields, revenue, and profits, respectively. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Table A14: Treatment effects on a randomly selected non-study plot

	(1) Profit	(2) Revenue	(3) Water Cost	(4) Other Input Cost
Treatment	-338.428	223.523	175.130	384.935
	(889.866)	(805.980)	(125.225)	(449.143)
Treatment * Volumetric Pricing	2046.941	1206.193	-451.348	-387.501
	(1487.757)	(1425.549)	(287.409)	(722.794)
Volumetric Pricing	-1751.422	-815.267	343.016	592.198
	(1512.624)	(1500.246)	(249.677)	(741.170)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	26900.72	52917.74	4927.41	21093.57
p-Value: Treat+Treat*Volumetric	0.156	0.229	0.284	0.996
Number of Observations	3463	3463	3462	3461
R squared	0.189	0.235	0.377	0.175

The data are taken from the follow-up survey after harvesting for the 3,463 farmers that cultivated more than one plot. Each regression shows effects on a randomly selected plot *other than the study plot* for each farmer. The dependent variables are profit per acre (column 1), revenue in taka per acre (column 2), water cost in taka per acre (column 3), and total cost of other inputs in taka per acre (column 4). Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Table A15: Multiple inference corrections for effects of conservation technology with volumetric pricing

	Effect	Unadjusted p-value	FDR q value Anderson (2008)	FWER adjusted List et al. (2016)
Irrigations	-3.61	0.000	0.001	0.078
Times Dried	2.81	0.000	0.001	0.000
Water Level	-0.42	0.021	0.043	0.406
Dry Field	0.08	0.047	0.071	0.393
Water Level 0-70 days	-0.84	0.000	0.001	0.022
Dry Field 0-70 days	0.17	0.000	0.001	0.018
Water Cost	-302.38	0.226	0.252	0.520
Other Input Cost	-163.06	0.780	0.780	0.685
Revenue	1,401.58	0.091	0.115	0.623
Profit	1,866.86	0.049	0.071	0.419

The table shows p-values adjusted for multiple inference. For each of the outcomes, the second column provides the estimated treatment effect for farmers facing volumetric prices, i.e. $\beta_1 + \beta_3$ in equation 1. The third column shows the unadjusted p-value. The fourth column adjusts the p-values to control the false discovery rate, following Anderson (2008). The fifth column uses the method in List, Shaikh and Xu (2016), which more conservatively controls the familywise error rate (the probability of at lease one false rejection).

Table A16: 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 A17: Complier Characteristics for Prepaid Card Usage

	Share of Sample w/ Characteristic	Share that Used Card	Ratio of Usage to Overall Usage
Younger than 40	0.479	0.449	1.112
More than 30 irrigations	0.230	0.668	1.656
Water Price at least 2000 BDT	0.281	0.329	0.815
Dry-season area 1.33 acres or more	0.370	0.486	1.205

The table shows characteristics of treatment farmers that used the prepaid cards in the Paba upazila, for which we obtained data on card usage. The first column shows the share of the sample that had the baseline characteristic of each row. For instance, 47.9 percent of farmers were younger than 40. The second column shows the share of farmers with that characteristic that used the prepaid card. For example, 44.9 percent of farmers younger than 40 used the prepaid cards. The third column shows the ratio of card usage in each group to overall card usage (40.4 percent).

Table A18: Impacts of hourly irrigation cards on demand with log functional form

	Purchase		Usage	
	(1)	(2)	(3)	(4)
Card Treatment	0.0353	-0.5510**	0.0187	-0.4848
	(0.0428)	(0.2622)	(0.0279)	(0.3321)
Log Pipe Price	-0.5084***	-0.6123***	-0.0763**	-0.1665**
	(0.0351)	(0.0489)	(0.0307)	(0.0739)
Log Pipe Price * Card Treatment		0.1497**		0.1287
		(0.0654)		(0.0795)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	0.413	0.413	0.068	0.068
Elasticity at Price=55 Treat	-1.25	-1.13	-0.95	-0.45
Elasticity at Price=55 Control	-1.37	-1.70	-1.23	-3.08
P-value: Equal Elasticities		0.025		0.005
Number Obs	3569	3569	3600	3600
R squared	0.256	0.260	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 columns 1 and 2 is an indicator if the farmer purchased the AWD pipe at the randomly set price. The dependent variable in columns 3 and 4 is an indicator for installing the pipe. 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.

Table A19: Relationship between price and usage conditional on purchase of conservation technology

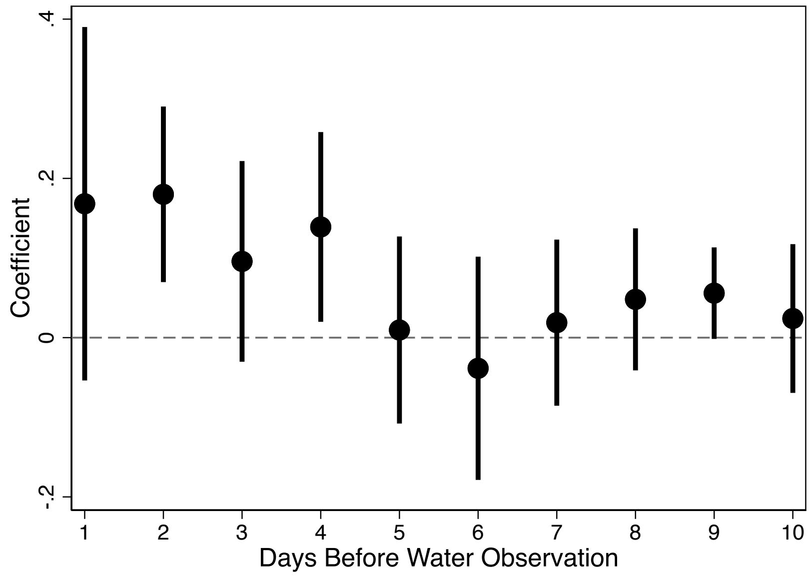
	(1)	(2)
Card Treatment	-0.2501	-1.0292**
	(0.1522)	(0.4638)
Pipe Price	-0.0044*	
	(0.0024)	
Pipe Price * Card Treatment	0.0066**	
	(0.0027)	
Log Pipe Price		-0.1910*
		(0.1067)
Log Pipe Price * Card Treatment		0.2904**
		(0.1193)
Upazila Fixed Effects	Yes	Yes
Mean in Control	0.162	0.162
P-value: Price+Price*Volumetric	0.086	0.058
Number Obs	1580	1580
R squared	0.046	0.049

The data are from the 144 villages that were part of the second-year experiment. The sample is limited to the farmers that bought AWD pipes during the demand experiment. The dependent variable in all regressions is an indicator 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. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Appendix B: The relationship between observed water management and recent pumping behavior

Observed water levels serve as a proxy for actual water use. We chose this method because meters do not exist on most plots in our sample. Yet, a reasonable question to ask is whether observed water levels correlate with actual water use. A subset of 125 of the water-level observations were taken for farmers where we have data on daily pumping times on the prepaid cards. For this sample, Figure B1 shows the relationship between the water level and 10 daily lags of hours pumped using the prepaid card. Regressing the water level on total hours pumped in the previous four days yields a point estimate of 0.15 and a t-statistic of 4.08. Hours pumped during the previous four days — an objective measure of actual usage — is positively correlated with water levels. The correlation coefficient is 0.4. These results suggest that our water-level observations do partly measure water usage during the previous few days.

Figure B1: Relationship between observed water levels and daily pumping hours



Notes: Figure shows the coefficient estimates from a distributed lag model where the observed water level in the field (in cm) is regressed on the number of hours pumped for each of the previous 10 days. The dots show coefficient estimates for each of the 10 variables and the vertical lines display 95 percent confidence intervals. The data on pumping activity — for the upazila which we have data — were matched to the water-level observations for 125 farmers who started using their prepaid cards before the water-level observation and stopped using their cards after the observation. Focusing on this sample ensures that the estimation is only relying on farmers who were actively using their cards during the time when the enumerator observed the water level.

Appendix C: Additional Analysis of Volumetric Pricing Heterogeneity

This appendix examines the robustness of volumetric pricing as a source of heterogeneity in our first experiment. We start by looking at mean characteristics for farmers by either volumetric pricing (Table C1) or having their own prepaid card in Rajshahi (Table C2). The two groups differ on some observable characteristics — owing to volumetric pricing not being randomized.

As a first test, we interact the full set of covariates with the AWD treatment. The purpose of this test is to investigate whether the estimated heterogeneity might instead be driven by a correlate of volumetric pricing. We consider all of the variables in the above summary statistics tables. These include the household- and plot-level variables and the five geographic variables: elevation, soil clay content, soil sand content, soil organic carbon content, and soil water content. We measure these variables by matching plot locations to various remote sensing datasets. Their inclusion helps test robustness to a scenario where volumetric pricing is more likely in places with different types of soil, and returns of AWD are correlated with soil characteristics.

Table 5 in the main text shows the heterogeneous effects when interacting all of these covariates with the AWD treatment. We continue to find large interaction effects on water usage even when interacting the AWD treatment with this large set of 23 covariates. This offers a first piece of suggestive evidence that volumetric pricing — rather than an unobserved covariate — is responsible for the observed heterogeneity.

We perform the same robustness exercise with our analysis of individual card ownership within Rajshahi in Table C3 below. The coefficients on the interactions between the AWD treatment and card ownership are nearly identical to those in Table 3 of the main text. Paying for water by the hour with an individual card is a robust determinant of heterogeneous cost savings from the AWD technology.

As mentioned in the main text, volumetric pricing varies both between and within upazilas, but much of the variation is across upazilas. The map in Figure 2 shows that the more local variation in volumetric pricing exists in parts of Rajshahi and Mymensingh districts. We investigate heterogeneity within these districts separately. Table C4 limits the data to Rajshahi and shows that we do not find any interaction effects between the treatment and volumetric pricing in that part of the sample. About 15 percent of farmers in Mymensingh face marginal prices. This is driven by variation in the northern part of the district where contracts with the tube well owners include pass through of fuel costs to farmers. Table C5 shows that the interaction between treatment and volumetric pricing within Mymensingh is negative for water levels and positive for dry fields (columns 1 and 2). These effects are strongest during the first 70 days of the season when AWD should be practiced. While the sample is small, this gives another source of finer geographic variation.

Panel B of Table 2 showed that across-upazila variation in volumetric pricing is a strong predictor of water savings from AWD. We further investigate whether this result could be driven by and interaction effect between the treatment and an upazila-level average of 16 covariates. For each covariate, we take it's upazila-level average, interact that variable with the treatment, and include the interaction between the upazila-level volumetric pricing and the treatment. We do this covariate by covariate since the small number of upazilas reduces degrees of freedom, reducing any power to detect effects when including multiple interactions between the treatment and upazila-level variables. The results are shown for dry fields in Figure C1 and for water levels in Figure C2. The interaction between the treatment and the upazila-level characteristic is statistically significant at the 5 percent level in only one of the 16 regressions for dry fields. It is significant in two of the 16 regressions for water levels. The interaction effects between volumetric pricing and the AWD treatment are similar in magnitude and mostly remain significant in each of these regressions.

As a last test, we compare volumetric pricing and individual card ownership to the other covariates in terms of their ability to predict treatment-effect heterogeneity. We implement recent machine-learning techniques to predict AWD's treatment effect as a function of observable covariates (Chernozhukov et al., 2018). Using these predictions, we then ask which of the covariates explain most of the variation in the heterogeneous effects of AWD.

This method involves looping through our dataset 100 times. For each iteration, we randomly divide the data into two equal-sized groups: an estimation and validation dataset. For the estimation dataset, we estimate separate conditional expectation functions of the outcome (water use) for the treatment and control villages. We do so by using LASSO to select the covariates from the vector z_i that best predict measured water levels. The difference between the conditional expectation functions for the treatment and control groups delivers a "heterogeneity score", i.e. a predicted treatment effect as a function of the farmer characteristics z_i.

Figure C3 shows that the predicted heterogeneity accurately predicts the actual heterogeneity across the 100 validation datasets. Put differently, water savings from the AWD treatment are larger for the farmers with the most negative values (bottom quartile) of the heterogeneity score. Table 6 in the main text showed that being in a village with volumetric pricing is one of the most important determinants of the predicted heterogeneity. Ninety three percent of farmers in the first quintile of the heterogeneity score (those predicted to save the most water with the technology) have volumetric water pricing. In contrast, only

5 percent of the least affected farmers do. Of the covariates included, volumetric pricing explains the most variation in the predicted treatment effect. Using the same procedure with the heterogeneity on card ownership from Table C3 above, Table C6 shows that owning an individual prepaid card is one of the most significant determinants of the heterogeneous cost savings from using AWD. Paying for water with volumetric pricing shows up as one of the most predictive variables for the ability of the AWD technique to conserve water and lower water costs for farmers.

Table C1: Household, plot, and geographic characteristics by volumetric pricing

	(1) Mean No Volumetric	(2) Coef. Volumetric	(3) Coef. Volumetric, Upazila FE
Panel A: Household Characteristics			
Age	42.528	0.264	1.700*
		(0.577)	(1.004)
Years Education	6.429	0.171	-0.469
		(0.224)	(0.387)
Household Size	4.884	-0.109	-0.065
		(0.111)	(0.254)
Number Livestock Owned	2.964	-0.494***	0.058
		(0.128)	(0.262)
Landholdings in Acres	1.823	0.555***	-0.127
		(0.114)	(0.197)
Owns Television	0.580	0.132***	-0.075*
		(0.032)	(0.044)
Owns Refrigerator	0.149	-0.043**	-0.062**
		(0.018)	(0.031)
Owns Irrigation Shallow Tubewell	0.061	0.005	0.024
		(0.012)	(0.028)
Heard of AWD?	0.196	-0.069***	0.026
		(0.022)	(0.051)
Panel B: Characteristics of Study Plot			
Plot is Rented or Sharecropped	0.077	0.003	-0.019
		(0.016)	(0.025)
Area in Acres	0.437	-0.061**	-0.015
		(0.031)	(0.044)
Number Crops Grown	2.084	0.290***	-0.099
		(0.052)	(0.077)
Rice-Rice Cropping System	0.858	-0.467***	-0.061
		(0.043)	(0.040)
Number Irrigations in Boro	20.835	-0.439	0.183
		(0.884)	(0.874)
Revenue per Acre in Boro	36841.929	9139.360***	855.722
		(776.943)	(1915.412)
Cost per Acre in Boro	21143.547	4765.725***	5533.027**
		(948.821)	(2696.357)
Water Cost per Acre in Boro	5112.937	3838.577***	3485.787
		(799.495)	(2734.064)
Revenue per Acre in Aman	26376.797	3784.064***	44.022
		(1256.348)	(2837.414)
Panel C: Geographic Variables			
Elevation (m)	22.985	-3.675***	-0.630
		(0.629)	(0.587)
Soil Clay Content (%) at 10 cm	27.279	3.211***	-0.217
		(0.314)	(0.558)
Soil Sand Content (%) at 10 cm	43.732	-5.855***	0.570
		(0.566)	(0.748)
Soil Carbon Content at 10cm (g/kg)	3.636	-0.927***	0.149
		(0.106)	(0.210)
Soil Water Content (%) at 10 cm	31.337	-0.945***	0.525
		(0.340)	(0.489)

Column 1 shows the mean value of each of the 23 characteristics among the farmers without volumetric pricing at baseline. Columns 2 and 3 show the coefficient and standard error from a regression where each characteristic is regressed on the volumetric pricing indicator, with upazila fixed effects included in column 3. Standard errors in each regression are clustered at the village level. The plot-level geographic variables are measured by matching plot locations to remote sensing datasets. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Table C2: Household, plot, and geographic characteristics by individual card ownership

	(1) No Card Mean	(2) Own Card	(3) Own Card, Upazila FE
Panel A: Household Characteristics			
Age	41.029	1.949**	1.971**
		(0.911)	(0.973)
Years Education	6.918	0.188	0.041
		(0.349)	(0.423)
Household Size	4.633	0.137	0.389**
		(0.135)	(0.163)
Number Livestock Owned	2.034	0.744***	0.453**
		(0.198)	(0.217)
Landholdings in Acres	1.996	0.826***	0.273
		(0.192)	(0.196)
Owns Television	0.827	-0.081*	-0.027
		(0.042)	(0.053)
Owns Refrigerator	0.081	0.062**	0.042
		(0.028)	(0.039)
Owns Irrigation Shallow Tubewell	0.095	-0.064***	-0.066***
		(0.018)	(0.022)
Heard of AWD?	0.118	-0.001	0.000
		(0.030)	(0.020)
Panel B: Characteristics of Study Plot			
Plot is Rented or Sharecropped	0.063	0.050*	0.014
		(0.029)	(0.022)
Area in Acres	0.259	0.129***	-0.019
		(0.044)	(0.035)
Number Crops Grown	2.552	-0.213**	-0.062
		(0.095)	(0.121)
Rice-Rice Cropping System	0.177	0.289***	0.026
		(0.070)	(0.067)
Number Irrigations in Boro	21.678	-1.821	3.452***
		(1.562)	(1.221)
Revenue per Acre in Boro	46736.926	271.275	1177.190
		(1106.127)	(1299.242)
Cost per Acre in Boro	25133.474	929.293	3726.009**
		(1599.412)	(1489.960)
Water Cost per Acre in Boro	9280.668	-1180.362	746.532
		(1332.266)	(1292.812)
Revenue per Acre in Aman	28601.304	3102.953	3306.767
		(2202.008)	(2888.726)
Panel C: Geographic Variables			
Elevation (m)	17.424	4.865***	2.391***
		(0.939)	(0.773)
Soil Clay Content (%) at 10 cm	32.659	-2.940***	-1.022**
		(0.477)	(0.436)
Soil Sand Content (%) at 10 cm	33.732	4.950***	0.456
		(0.810)	(0.600)
Soil Carbon Content at 10cm (g/kg)	2.615	-0.213*	-0.144
		(0.123)	(0.136)
Soil Water Content (%) at 10 cm	30.334	-1.437***	-1.291**
		(0.506)	(0.603)

Column 1 shows the mean value of each of the 23 characteristics among the farmers not using their own irrigation cards. Columns 2 and 3 show the coefficient and standard error from a regression where each characteristic is regressed on the hourly card indicator, with upazila fixed effects included in column 3. Standard errors in each regression are clustered at the village level. The plot-level geographic variables are measured by matching plot locations to remote sensing datasets. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Table C3: Robustness of card ownership results to interactions between treatment and covariates

	(1) Water Cost	(2) Log Water Cost	(3) Profit	(4) Log Profit
Treatment	404.4	0.0658	1668.9	0.0678
	(786.4)	(0.128)	(1980.1)	(0.0671)
Treatment * Has Card	-1177.4*	-0.211**	2523.8	0.100
	(623.0)	(0.104)	(2103.0)	(0.0714)
Has Card	1100.7**	0.218**	-1895.2	-0.0629
	(484.4)	(0.0871)	(1687.2)	(0.0583)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Treatment*Covariates	Yes	Yes	Yes	Yes
Mean in Control	5527.29	8.55	30473.33	10.29
p-Value: Treat+Treat*Has Card	0.104	0.085	0.023	0.005
Number of observations	1276	1276	1276	1270

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 (column 1), log cost of water per acre (column 2), profit per acre (column 3), and log profit per acre (column 4). All columns included demeaned covariates from baseline as well as geospatial controls for plot characteristics (all the variables in Table C2). Each column also includes interactions between these demeaned covariates and the AWD treatment indicator. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Table C4: Interaction effects for Rajshahi District

	Overall		0-70 Days After Planting	
	(1) Level	(2) Dry	(3) Level	(4) Dry
Treatment	-0.418	0.067	-1.127*	0.225
	(0.592)	(0.149)	(0.578)	(0.142)
Treatment * Volumetric Pricing	-0.059	0.019	0.241	-0.051
	(0.623)	(0.157)	(0.623)	(0.151)
Volumetric Pricing	0.599	-0.147	0.377	-0.093
	(0.517)	(0.126)	(0.542)	(0.131)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.06	0.47	2.81	0.28
p-Value: Treat+Treat*Volumetric	0.015	0.064	0.000	0.000
Number of Observations	2334	2334	1557	1557
R squared	0.025	0.026	0.050	0.052

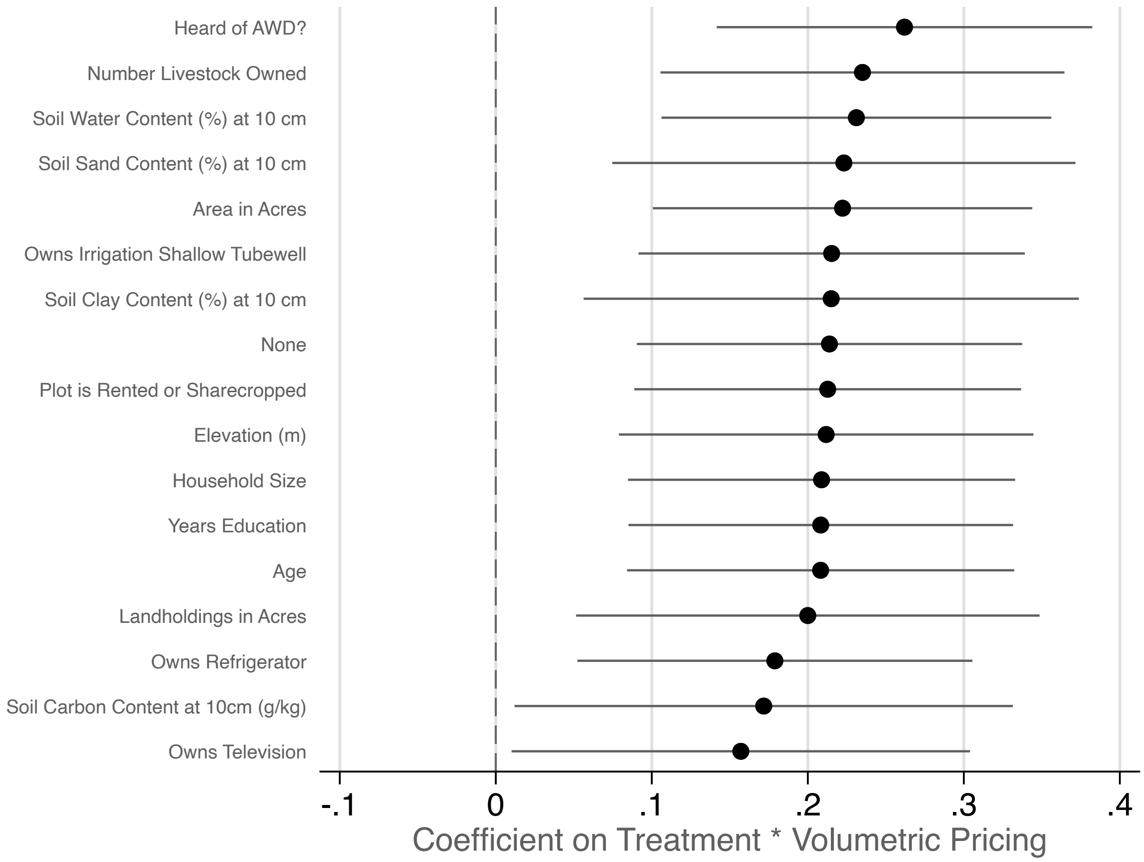
The data in all regressions are limited to Rajshahi district where 89% of farmers in this district face volumetric prices. The variable "Volumetric Pricing" is an indicator variable for these farmers. Columns 1-2 are for the entire season, while columns 3-4 are for measurements taken up to 70 days after 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. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Table C5: Interaction effects for Mymensingh District

	Overall		0-70 Days After Planting	
	(1)	(2)	(3)	(4)
	Level	Dry	Level	Dry
Treatment	0.223	0.015	0.175	-0.031
	(0.368)	(0.044)	(0.364)	(0.053)
Treatment * Volumetric Pricing	-0.505	0.068	-0.949*	0.225**
	(0.637)	(0.108)	(0.547)	(0.106)
Volumetric Pricing	-0.721*	0.039	-0.574	0.003
	(0.425)	(0.063)	(0.499)	(0.068)
Upazila Fixed Effects	Yes	Yes	Yes	Yes
Mean in Control	2.33	0.48	2.42	0.40
p-Value: Treat+Treat*Volumetric	0.587	0.410	0.085	0.044
Number of Observations	2630	2630	1443	1443
R squared	0.020	0.034	0.026	0.049

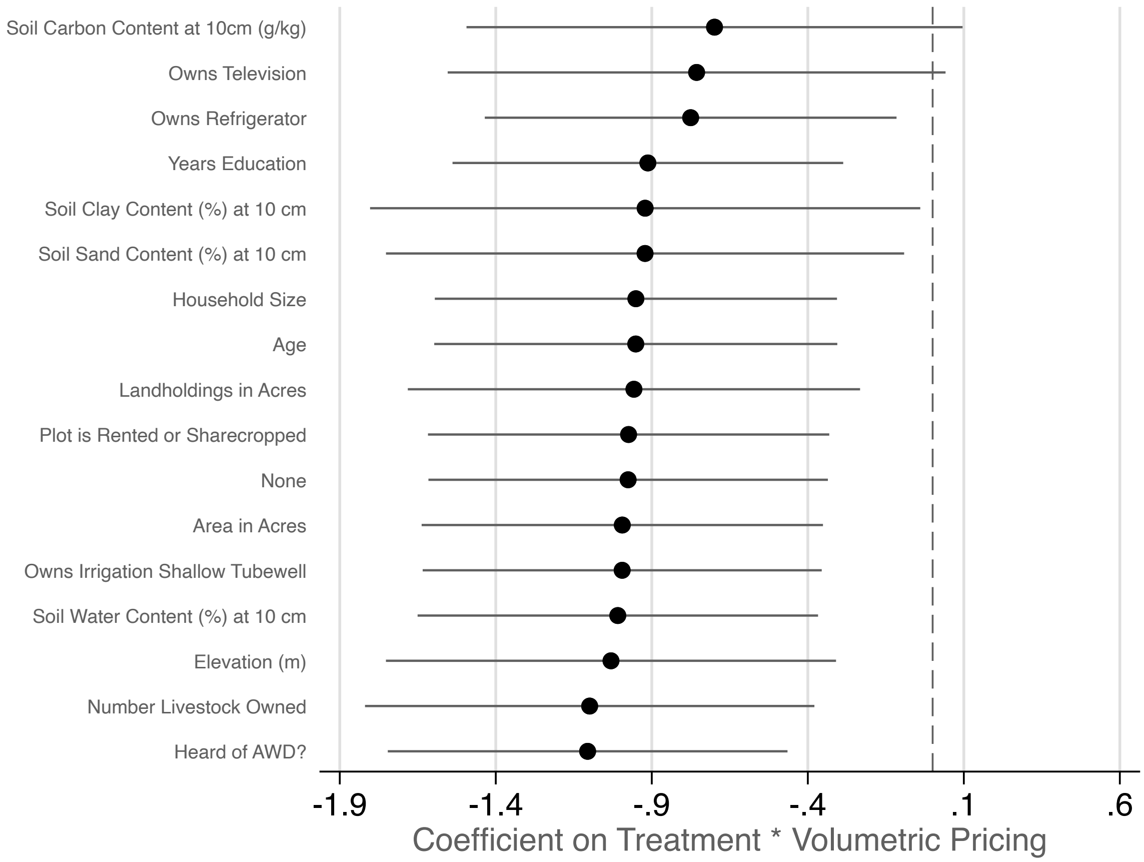
The data in all regressions are limited to Mymensingh district. About 15% of farmers in this district face volumetric prices. The variable "Volumetric Pricing" is an indicator variable for these farmers. Columns 1-2 are for the entire season, while columns 3-4 are for measurements taken up to 70 days 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. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Figure C1: Coefficients on treatment-pricing interaction for dry fields when including upazila-level covariates interacted with treatment



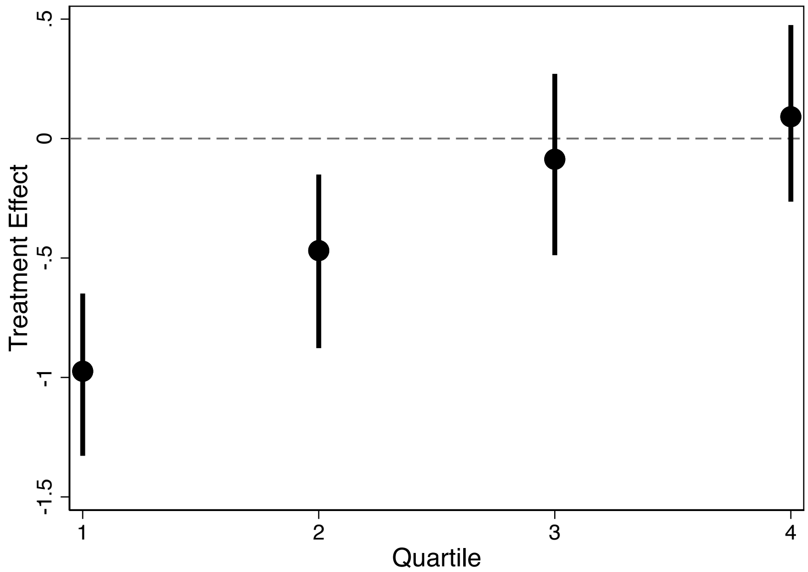
Notes: Each row in the figure represents a separate regression of the indicator for a dry-field on treatment, the interaction of treatment and upazila-level volumetric pricing, the interaction of treatment and the listed upazila-level baseline covariate, and upazila fixed effects. The dots are the coefficients on the treatment-volumetric pricing interaction and the bands show 95% confidence intervals. All regression are from the period 0-70 days after transplanting.

Figure C2: Coefficients on treatment-pricing interaction for water level when including upazila-level covariates interacted with treatment



Notes: Each row in the figure represents a separate regression of the water level (in cm) on treatment, the interaction of treatment and upazila-level volumetric pricing, the interaction of treatment and the listed upazila-level baseline covariate, and upazila fixed effects. The dots are the coefficients on the treatment-volumetric pricing interaction and the bands show 95% confidence intervals. All regression are from the period 0-70 days after transplanting.

Figure C3: Heterogeneous treatment effect by quartiles of predicted heterogeneity score



Notes: Figure shows the treatment effect of AWD across 100 different sample divisions — separately by the quartile of the predicted heterogeneity score. Following the methodology in Chernozhukov et al. (2018), we estimate the predicted heterogeneity score $\hat{s_{0i}}$ as described above. The figure shows the actual treatment effects in the other half of the data (not used to develop the heterogeneity score). The lowest quartile are the farmers predicted to have the *most negative* treatment effect of AWD. Each dot is the mean across the 100 sample divisions, and the vertical lines show the range from the 5th to the 95th percentile.

Table C6: Characteristics of farmers most and least affected by conservation technology for Rajshahi sample only

	Mean Most Affected	Mean Least Affected	Share Variation Explained
Has Card	0.713	0.109	0.158
Age	42.847	41.453	0.001
Years Education	6.414	7.281	0.001
Household Size	4.739	4.693	0.000
Number Livestock Owned	1.828	3.011	0.016
Landholdings in Acres	1.730	2.945	0.022
Owns Television	0.552	0.891	0.063
Owns Refrigerator	0.090	0.146	0.001
Owns Irrigation Shallow Tubewell	0.007	0.221	0.078
Heard of AWD?	0.340	0.015	0.112
Plot is Rented or Sharecropped	0.037	0.184	0.024
Area in Acres	0.310	0.360	0.000
Number Crops Grown	2.341	2.610	0.019
Rice-Rice Cropping System	0.328	0.213	0.006
Number Irrigations in Boro	19.007	24.266	0.041
Revenue per Acre in Boro	41,840.078	53,002.148	0.367
Cost per Acre in Boro	23,921.357	29,440.611	0.035
Water Cost per Acre in Boro	7,128.027	12,498.362	0.046
Revenue per Acre in Aman	23,613.660	36,514.520	0.065

The table classifies farmers according to their predicted treatment effect from AWD, i.e. the predicted decrease in water costs from using AWD. Column 1 shows mean values of characteristics for the 20% of farmers that are predicted to lower costs the most if treated. Similarly, column 2 shows mean values for the 20% of least-affected farmers. Column 3 shows the R^2 of a bivariate regression of the predicted heterogeneity score, s_0, on each characteristic.

Appendix D: Liquidity Constraints as a Possible Mechanism

This appendix investigates whether liquidity constraints explain our result that prepaid cards change the demand for AWD.[1] Our approach is to estimate whether the treatment effect of prepaid cards on demand differs by observable measures of liquidity constraints. The literature commonly proxies for liquidity constraints using income or liquid asset holdings (Zeldes, 1989; Johnson, Parker and Souleles, 2006). Column 1 in Table D1 tests for heterogeneity along three dimensions: landholdings, livestock ownership, and the number of durable assets owned.[2] We find no evidence that prepaid cards increase AWD demand any more for farmers that are smaller, owner fewer livestock, or less durable assets.

We take another approach by proxying liquidity constraint tightness using data on actual card recharging behavior for the 323 treatment farmers for whom we obtained data on card usage. We observe the date, time, and total amount spent for each time the card was charged. Aggregating these data across the entire growing season, we first estimate the regression

$$Nrecharge_i = \beta_0 + \beta_1 TotalSpent_i + u_i, \tag{D1}$$

where $Nrecharge_i$ is the number of times the card was loaded with funds by farmer i and $TotalSpent_i$ is the total amount spent by him throughout the season. We use the fitted residual from this regression, $\hat{u}_i$, as a proxy for liquidity constraint tightness. This is a reasonable proxy because it measures the deviation between the actual and expected number of times a card was recharged, conditional on the total amount spent. In other words, we expect a higher value of $\hat{u}_i$ for a liquidity constrained farmer since he likely needs to load the card more often in order to spend the same amount on water.

We next estimate a function $\hat{u}_i = g(z_i) + \varepsilon_i$, where z_i is a set of baseline observables.[3] We estimate the function g using both a LASSO selection method and a Random forests estimator. The predicted values from each of these models (for all farmers in the sample) generates our measure of liquidity constraint tightness.[4]

[1] We did not pre specify the test of this alternative mechanism in our pre-analysis plan.

[2] The specific assets are a motorbike, indoor toilet, electric fan, television, refrigerator, and washing machine.

[3] z_i consists of age, landholdings, education, number of livestock owned, number of adults in the household, number of children in the household, baseline number of times a field is irrigated during the season, baseline per-acre water price, number of assets owned, access to electricity, tractor ownership, ownership of a shallow tube well for irrigation, and an indicator for whether water fees were paid to the deep driver (as opposed to the water user's committee).

[4] We first randomly divide the 323 observations into training and validation datasets. The training dataset is used to estimate the LASSO or Random forests model. The predictions from the Random forests

The treatment effect of prepaid cards on demand for the pipes should be concentrated on the more liquidity constrained farmers if the liquidity mechanism is important for our estimated demand effect. The results in Table D1 do not line up with the liquidity explanation. The effect of the prepaid cards is no larger for farmers that are predicted to have the tightest liquidity constraint.

are slightly more correlated with the actual $\hat{u}_i$ terms in the validation dataset: the correlations between predicted and actuals are 0.29 for Random forests and 0.23 for LASSO. The covariates selected by LASSO and the signs of their relationship with liquidity constraint tightness are age (+), landholdings (-), baseline seasonal water price (+), number of durable assets (-), and connection to the deep driver (+).

Table D1: Heterogenous effects of the prepaid card treatment by a predicted measure of liquidity constraints

	(1) Interactions	(2) Lasso	(3) Random Forest
Card Treatment	-0.0082	0.0500	0.0348
	(0.1130)	(0.0643)	(0.0616)
Card Treatment * Landholdings	-0.0029		
	(0.0053)		
Card Treatment * Number Livestock	0.0140		
	(0.0146)		
Card Treatment * Number Assets	0.0106		
	(0.0327)		
Landholdings	0.0076**		
	(0.0036)		
Number Livestock	-0.0097		
	(0.0131)		
Number Assets	-0.0035		
	(0.0265)		
Card Treatment * Liquidity Constraint		-0.0013	0.0084
		(0.0231)	(0.0216)
Liquidity Constraint		-0.0268	-0.0423**
		(0.0202)	(0.0184)
Upazila Fixed Effects	Yes	Yes	Yes
Mean in Control	0.415	0.413	0.413
Number Obs	3477	3460	3569
R squared	0.025	0.032	0.034

The data are from the 144 villages that were part of the second-year experiment. The table tests whether the effect of the prepaid card treatment varies as a function of predicted liquidity constraints. The predicted measure of liquidity constraints is from a two step procedure where in the first step the total number of times a prepaid card was recharged (throughout the season) is regressed on the total amount spent. The residual from this regression gives a measure of liquidity constraint tightness since it measures the deviation between the actual and expected number of times a given farmer needed to recharge their card in order to spend a given amount on irrigation water. The second step involves predicting this measure of liquidity constraint as a function of observable characteristics z_i. Columns 1 uses predictions from a LASSO regression, while column 2 uses the prediction from a random forest algorithm. The dependent variable in both regressions is an indicator if the farmer purchased the AWD pipe at the randomly set price. Standard errors are clustered at the village level. Asterisks indicate that coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels.

Appendix E: Calculating an Approximate Subsidy for AWD

This appendix outlines how we arrive at the subsidy estimates in Section 5 of the main text. We follow Allcott, Mullainathan and Taubinsky (2014), who study the combination of taxes on energy and subsidies for energy efficient durables. The optimal combination of these two instruments depends on the share of consumers that "undervalue", or are inattentive to, energy prices. This share is unobservable. Allcott, Mullainathan, and Taubinsky (2014) show that the optimal subsidy for the energy efficient technology can be approximated with three derivatives: the effect of the technology on energy demand, the effect of an energy tax on demand for the technology, and the effect of the technology's own price on its demand. We can approximate all three of this with our data. Formally, applying equation 16 in their paper to our context,

$$\tau_E^* \geq \frac{\left(|Q_{\tau_E}| - D_{\tau_g}\right) p_g + (\tau_g - \phi) Q_{\tau_E}}{D_{\tau_E}}, \tag{E1}$$

where:

τ_E = subsidy for AWD

D_{τ_E} = derivative of AWD demand with respect to the AWD subsidy

Q_{τ_E} = derivative of electricity usage with respect to the AWD subsidy

D_{τ_g} = derivative of AWD demand with respect to the electricity tax

ϕ = marginal damages from electricity generation

p_g = electricity price.

We calculate each of the necessary parameters as follows:

D_{τ_E}: Our second experiment gives an estimate of the slope of AWD demand. The regression estimates in column 8 of Table 7 imply a slope of -0.0033 + 0.0023 = -0.001. Therefore, we set $D_{\tau_E} = 0.001$

Q_{τ_E}: We multiply our estimate of D_{τ_E} by the estimated energy savings from using an AWD device (from the first experiment). We do not have survey measures of pumping hours to compare treatment and control farmers from our first experiment. However, we find 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. 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. This translates to 41.3 kwh per AWD device. Therefore, $Q_{\tau_E} = -0.001 * 41.3 = -.04163$

D_{τ_g}: The ideal estimate of this parameter would be an estimate of how randomly increasing the price of electricity in villages with prepaid pumps affects the demand for AWD. Using an hourly irrigation card in our second experiment represents a transition from no marginal price to a positive marginal price for electricity, similar to that of imposing a tax on electricity. One hour of pumping costs 120 taka and uses 18.1 kwh of electricity, implying a pumping price of 6.63 taka per kwh. Our second experiment found that the prepaid card treatment increased usage of AWD by 16.4 percentage points when its price was 60 taka. Using this figure results in a very conservative estimate of the optimal subsidy because encouraging the prepaid cards had no effect on AWD use at lower prices, which would imply $D_{\tau_g} = 0$. But we use the conservative estimate of $D_{\tau_g} = .164/6.63 = .02473$.

ϕ: The Bangladesh Department of Environment estimates a grid emission factor of 1.47 lbs CO2 per kwh. Using a social cost of carbon of \$51 per ton of CO2, this converts to \$0.034 per kwh, or about 2.72 taka per kwh.

τ_g: We assume that electricity is taxed at marginal damages, i.e. $\tau_g = 2.72$.

p_g: The price of electricity is set to the marginal cost of production plus the tax. We set a marginal cost of 4 taka per kwh, implying that $p_g = 4 + 2.72 = 6.72$.

Applying these parameters to Equation (E1),

$$\tau_E^* \geq 6.72 * \frac{.001 * 41.63 - .02473}{.001} = 113.57. \tag{E2}$$

The subsidy would be over twice as large if every farmer that purchases AWD uses it. Estimating D_{τ_E} with the purchasing regressions in column 7 of Table 7 gives $D_{\tau_E} = 0.0095$, which implies that $Q_{\tau_E} = -.3955$. We obtain $D_{\tau_g} = .02175$ if we using purchasing AWD instead of using it. Using these figures instead would result in $\tau_E^* \geq 264.36$.

Another factor making these estimates conservative is that taxing electricity at its marginal damages is an unlikely policy. Increasing electricity prices for farmers is politically unpopular. The optimal subsidy for AWD becomes even larger when the electricity taxes fall below marginal damages. We obtain an optimal subsidy of $\tau_E^* \geq 180.8$ if $\tau_g = 0$ and $p_g = 4$.

References

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky. 2014. "Energy policy with externalities and internalities." *Journal of Public Economics*, 112: 72–88.

Anderson, Michael L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association*, 103(484): 1481–1495.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller. 2008. "Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics*, 90(3): 414–427.

Chernozhukov, Victor, Mert Demirer, Esther Duflo, and Ivan Fernandez-Val. 2018. "Generic machine learning inference on heterogenous treatment effects in randomized experiments." National Bureau of Economic Research.

Johnson, David S, Jonathan A Parker, and Nicholas S Souleles. 2006. "Household Expenditure and the Income Tax Rebates of 2001." *American Economic Review*, 96(5): 1589–1610.

List, John A, Azeem M Shaikh, and Yang Xu. 2016. "Multiple hypothesis testing in experimental economics." *Experimental Economics*, 1–21.

Zeldes, Stephen P. 1989. "Consumption and Liquidity Constraints: An Empirical Investigation." *Journal of Political Economy*, 97(2): 305–346.