Pro-Social Change for the Most Challenging: Marketing and Testing Harm Reduction for Conservation*

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Abstract

This paper investigates the effectiveness of pursuing conservation goals by promoting harm reduction, a once controversial approach to health care that aims to reduce the harmful impacts of unhealthy behaviors without promoting full abstinence or stigmatizing said behaviors. Conservation proponents often heavily promote solutions more akin to full abstinence, which do not recognize the inherent preference trade-off the heaviest users face when giving up a behavior that may be harmful to the environment, such as driving a car, eating meat and dairy or watering a lawn. We employ two sequential field experiments to market and test effectiveness of a smart irrigation controller, a lawn watering efficiency device. This solution has an ex-ante lower expected impact on conservation than turf removal, the highest impact solution in this context, but is nevertheless more aligned with the preferences of the heaviest users. We show that marketing this preference-aligned solution induces the highest adoption among the heaviest irrigators and those previously disinclined to conserve. Given these compliance patterns, our interventions lead to large and long-lasting individual and social benefits: water savings from the device recover its cost in half a year and are of the magnitude of one household's basic (indoor) water needs. We find no meaningful increase in water usage among those irrigating less and no evidence of reduced turf removal, suggesting that the harm reduction intervention grows, rather than cannibalizes, the adoption of water conservation alternatives. Our results underscore the importance of considering heterogeneous preferences when designing interventions aimed at fostering pro-social behaviors such as conservation and shed light on how to use marketing to engage the least pro-socially inclined.

Keywords: field experiments, smart technology, pro-social marketing, environmental conservation, harm reduction

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1 Introduction

As society confronts social problems such as environmental sustainability, policy-makers and experts face the challenge of persuading people to change their behaviors towards a pro-social goal. While many people are inherently motivated by calls to act pro-socially (Funk and Hefferon (2019), Bell, Poushter, Fagan, and Huang (2021)), those contributing to the social problem the most are often the least motivated to make a change, since they derive the highest utility from behaviors inconsistent with the pro-social goal. Nevertheless, a common approach to tackling such social challenges is to heavily promote solutions identified as having the highest impact towards the given social goal. For instance, agencies and conservation proponents often promote walking or taking public transport instead of driving a car (e.g. United Nations (2022), Katz and Daniel (2015)), reducing or eliminating meat and dairy consumption (e.g., United Nations (2022), Katz and Daniel (2015)) and removing green lawns in favor of native vegetation (e.g., Be Water Wise (2022)). Such solutions allow the most pro-socially motivated to make their biggest social impact, but are particularly unappealing or even inaccessible to those who derive the highest value from the socially undesired behavior.

An alternative is a harm reduction approach, a once-controversial approach to public health that originated in response to rising concern about the social costs of illicit drug use at the end of twentieth century (Marlatt (1996)). Its proponents argue that although the best alternative is for an individual to abstain from harmful behaviors, if this outcome is unlikely, the next best alternative is to promote behaviors that reduce the harm of unhealthy behaviors (Marlatt (1996)). Consistent with core principles of marketing, which emphasize the role of underlying preference heterogeneity among consumers (Rossi, Berry, and Allenby (1996)), this approach recognizes the importance of individualized interventions in assisting different people towards positive behavior change (Marlatt and Witkiewitz (2002)) without stigmatizing the socially undesirable behavior (Marlatt (1996)). Such solutions have shown to be effective in reducing harm associated with behaviors such as injecting drug use (Gowing, Farrell, Bornemann, Sullivan, and Ali (2008)), adolescent substance use (Toumbourou, Stockwell, Neighbors, Marlatt, Sturge, and Rehm (2007)) and alcohol use (Marlatt and Witkiewitz (2002)), among others (Logan and Marlatt (2010)[1]), and emphasize the importance of developing solutions most effective for *and* appealing to those least motivated to engage in pro-social behavior (Britton and Edwards (2008), McNeill (2004)). Thus, an effective alternative solution will not only reduce harm, it will also not require the least-prosocial to abstain from the socially undesirable activity to which they assign high value (Logan and Marlatt (2010)).

Such potentially preference-aligned and harm reducing alternatives also exist in the context of conservation. For example, in transportation, electric car companies (e.g., Tesla, Rivian) offer alternatives

[1]More recently, Arnold (2021) and Kutscher and Greene (2020) also propose a harm reduction approach to mitigating the harms of COVID-19.

that retain many of the benefits of gas guzzling SUVs or sports cars, but could cannibalize even higher impact solutions such as using public transport. In the home, a smart thermostat (e.g., Ecobee) or irrigation controller (e.g., Rachio) may help households with strong preferences for in-home comfort or ornamental landscapes to avoid wasting resources without giving up these non-essentials. Similarly, plant-based meats avoid the environmental and animal welfare externalities of a tasty burger, while potentially cannibalizing a move to healthier fruits and vegetables.

Research suggests that electric vehicles (EPA (2022)), smart devices (Bollinger and Hartmann (2020); Harding and Sexton (2017); Blonz, Palmer, Wichman, and Wietelman (2021)) and plant-based meat alternatives (Bryant (2022)) can be better for the environment than what they replace; however, the success of the harm reduction approach depends on three factors. First is the question of whether or not the less pro-socially inclined indeed respond to the incentives to adopt the alternative. Second, the sign and magnitude of the solution's impact on the adopting population can be ambiguous (i.e., one may be concerned that harm reduction solutions may foster rather than decrease socially undesirable behaviors Logan and Marlatt (2010)). Third, if the harm reduction alternative appeals more broadly it may cannibalize more efficient alternatives those consumers might have otherwise chosen.[2] The theoretical ambiguity generated by these factors, together with conservationists potentially holding their moral convictions as universally applicable (Feinberg, Kovacheff, Teper, and Inbar (2019), Skitka, Bauman, and Sargis (2005)), may explain why harm reducing conservation alternatives are often not promoted on equal footing with higher impact solutions.[3]

This paper investigates the viability of a harm reduction approach to fostering conservation. We focus on the marketing challenges in California's drought response, where pricing for conservation goals is restricted[4] and regulation and enforcement depend directly on the effectiveness of voluntary conservation.[5] Notably, most messaging campaigns and incentives for voluntary conservation in this setting focus on high-impact solutions such as brown lawns, turf removal or outdoor water reductions,[6] effectively helping those most motivated by the conservation objective to maximize their impact. Incentives for these high

[2]For instance, marketing a smart irrigation controller would have a net negative effect on the conservation objective if the device cannibalizes adoption of high-impact solutions such as turf removal and counters associated peer effects (Bollinger, Burkhardt, Chan, and Gillingham (2021).

[3]For example, United Nations (2022) lists adoption of electric cars as the seventh out of ten actions to help climate change (cautioning that electric cars still have significant harmful effects on the environment), but does not mention plant-based meat alternatives as helpful substitutes to meat-eating. Similarly, the front pages of Be Water Wise (2022) and Save Our Water (2022) heavily promote turf removal and replacement as well as indoor conservation without mentioning more efficient outdoor irrigation.

[4]California's Proposition 218 mandates that the price of water has to reflect the cost of water provision. The court's ruling in the case of Capistrano Taxpayers Association, Inc., v. City Of San Juan Capistrano, 235 Cal. App. 4th 1493 (4th Dist. App. 2015) found the City of San Juan Capistrano's tiered rate schedule adopted to be in violation of Proposition 218, thus, upholding the mandate to price water to recover cost.

[5]For example, when the State Water Resources Control Board introduced emergency regulation to respond to drought in May 2015, community water suppliers faced different thresholds for cease and desist orders and resulting fines depending on the voluntary reductions they had achieved up to that date (California Water Boards (2015)).

[6]See, for instance, the home pages of Save Our Water (2022), a state-wide resource, and Be Water Wise (2022), a resource provided by the Metropolitan Water District of Southern California.

impact solutions can even exceed the individual costs of their adoption (Stratecon Inc. (2015)), thereby attracting households who are motivated by the conservation goals as well as the monetary incentives. Such marketing efforts, however, are in direct conflict with the preferences of the heaviest consumers of residential water supplies who place high value on lawn aesthetics and less weight on the consequences of their heavy irrigation on water scarcity or the size of their water bill.[7]

We consider a smart irrigation controller as a harm reduction solution that can help heavy irrigators contribute toward the social goal of water conservation. The device aims to water green landscapes efficiently, thus inherently enabling the maintenance of water-dependent ornamental landscapes, which are increasingly stigmatized in California. Recent work by Brandon, Clapp, List, Metcalfe, and Price (2021) evaluates smart thermostats and raises questions about the impact of smart devices because user adjustments can override potential conservation. The smart irrigation controller used in our study functions more similarly to smart thermostats studied by Harding and Sexton (2017), Bollinger and Hartmann (2020) and Blonz et al. (2021), where the primary feature enables automated response to changing demand and/or supply conditions.[8] The device automatically reduces the use of scarce resources when user preferences, home and landscape characteristics and weather do not justify consumption. Thus, a household could automatically save water without any reduction in the attractiveness of an ornamental landscape. Yet, the device could also increase overall consumption for those previously underwatering and for those who expand irrigable area in response to more efficient watering. It could also cannibalize abstinence solutions that have greater potential for conservation.

We partnered with a local utility willing to evaluate the effectiveness of this solution and conduct two sequential randomized control trials that first focus on the marketing variables to drive adoption, then test the effects of the device on water consumption.[9] Both experiments employ an encouragement design: although the device is readily available for purchase to all households, a randomly selected set of households receive messaging or incentives to encourage adoption.[10]

The first experiment tests different marketing strategies for driving adoption, focusing on single-family households with average water usage above typical indoor needs. We vary the price discount at which consumers can purchase a smart irrigation controller from a shallow 10% discount to a deep 80% discount. We additionally pair a moderately deep 60% discount with a free installation incentive

[7] Allcott, Cohen, Morrison, and Taubinsky (2022) show that the welfare effects of "nudges" depend not only on whether they increase desired behaviors on average but also on whether they decrease the variance of distortions. In our context, the typical approach to messaging and incentives would likely increase the variance of distortions, since those are likely to appeal to those already motivated by conservation.

[8] In water, the supply is precipitation and retained soil moisture and the primary demand input is evapotranspiration, a local weather-based metric reflecting rate of evaporation from the soil and transpiration from plants.

[9] Banerjee, Banerji, Berry, Duflo, Kannan, Mukerji, Shotland, and Walton (2017) discuss the merits of sequential trials for scalable policy design in the context of schooling.

[10] Similar encouragement designs have been used in the energy economics literature (e.g., Fowlie, Greenstone, and Wolfram (2015) and Blonz et al. (2021)) and health and development economics literature (e.g., Cohen and Dupas (2010) and Cohen, Dupas, and Schaner (2015)).

to investigate the extent to which professional installation can aid adoption and use of the device.[11] In parallel, we run a communication campaign to (1) increase awareness of available monetary and installation incentives among treated households and to (2) collect information about households in the control group. We find that only moderate to deep discounts are able to increase the adoption rate of the devices over the control group.[12] We also find suggestive evidence that the rate at which households activate the device (an action necessary for usage of the device and, thus, conservation) depends, in part, on installation incentives. Nevertheless, as is the case for most marketed products, adoption rates in our first experiment are overall low, which presents a statistical challenge for inferring the effects of the device on water consumption.[13]

We therefore use the pricing findings from the first experiment to design a second study, in which we offer free devices and discounted professional installation to a randomly selected set of households in the same water district. To foster broad adoption, all households in the water district, regardless of past water consumption, are eligible for the treatment in this second experiment. Despite reduced targeting in this second communication campaign, the refined marketing strategy yields treatment effects on device adoption that are twice as large as the largest treatment effect in experiment 1.[14][15] With the results from the two experiments in hand, we set out to answer our three key empirical questions: (1) whether our harm reduction solution is, indeed, particularly well-aligned with the preferences of the heaviest irrigators and those least likely to conserve, (2) whether device adoption leads to a reduction or increase in water usage, and (3) whether the device cannibalizes turf-removal, the highest impact solution in this context.

First, we find that those contributing most to the social problem, heavy irrigators,[16] adopt at the highest rates. In the first experiment, we find no evidence of adoption (or activation) by households unlikely to be irrigators, a 0.014 increase in adoption rate for the upper third quartile of irrigators and a 0.02 increase in adoption rate for the highest quartile of irrigators.[17] In the second experiment, all quar-

[11] Our design in the first experiment parallels those previously employed in developmental economics to study the impact of incentives on individually and socially desirable outcomes, such as anti-malarial bed net and medication uptake and usage (Cohen and Dupas (2010) and Cohen et al. (2015)) and immunisation (Banerjee, Duflo, Glennerster, and Kothari (2010)).

[12] On the contrary, Banerjee et al. (2010) find that small incentives have significant effects on immunisation behavior.

[13] Lewis and Rao (2015) illustrate statistical power challenges in advertising where response rates are very low. In our context, the first experiment illustrates the ability to find significant adoption with our communications, but we face the further challenge of inferring effects on outcomes that are conditional on low adoption. In short, while our adoption rates are statistically significant, there are simply too few adopted controllers in the first experiment to shift the aggregate outcomes of the intended treatment group relative to control.

[14] This result is consistent with past research on pricing incentives (e.g., Cohen and Dupas (2010)) and the power of a zero price (e.g., Shampanier, Mazar, and Ariely (2007)).

[15] Conversely, the conversion from adoption to device activation is somewhat higher in experiment 1 than in experiment 2, indicating that households obtaining devices for free in experiment 2 are less likely to ultimately use their devices. Past literature on the role of incentives in promoting adoption and usage of public health solutions finds similar results and argues that this pattern is driven by a screening effect, whereby households with higher anticipated use-value purchase the device earlier and at higher prices (Ashraf, Berry, and Shapiro (2010), Cohen et al. (2015)) rather than a sunk cost effect, whereby households assign higher value to devices obtained for a higher price (Cohen and Dupas (2010), Ashraf et al. (2010)).

[16] We proxy for the extent of irrigation by measuring the difference in water consumption during the summer from that in the winter when most irrigation is turned off. We measure this difference in the year prior to each experiment.

[17] These increases in adoption rates represent about 2.3 times and 2.1 times increase over the corresponding control groups

tiles of irrigators exhibit significant adoption in response to the incentives; however, adoption increases significantly with irrigation levels, reaching an increase of 0.06 in adoption rate for the upper quartile.[18] We then utilize the timing of the second experiment to investigate heterogeneity in incentive responsiveness based on households' behavior during the preceding drought (2012-2017). We find that treatment responsiveness is highest among conservation-prone households, conservation-prone households looking to return to "normal" after extreme drought conditions and households not inclined to conserve at all. Thus, incentives to adopt the smart irrigation controller successfully target not only households with large potential for conservation, but also households with strong preferences for green vegetation despite existing drought.[19] These results suggest that the device is particularly well-aligned with the preferences of these households.

Second, we find significant reductions in water consumption that persist through our latest data period, nearly four years post-intervention. Specifically, we find negative and statistically significant effects of the marketing intervention on water consumption in the transitional seasons (e.g., September-October) as well as the peak irrigation season (July-August). Both of these effects are particularly pronounced and long-lasting for heavy irrigators. We interpret these results to mean that two major roles of the smart irrigation controller in facilitating water conservation are i) to more quickly respond to changing environmental conditions during season transitions and ii) reduce peak season irrigation, potentially due to app-based recommended watering times that might better match the true irrigation needs. The persistence of these effects is likely caused by the automation embedded in the durable smart irrigation controller and represents a contrast to "backsliding" that has been observed in energy interventions (Allcott and Rogers (2014)) and interventions fostering pro-social change in developing economies (Caro-Burnett, Chevalier, and Mobarak (2021)).

To better understand the effect of the smart irrigation controller on water consumption in households who adopted the device, we estimate the local average treatment effect implied by the intent-to-treat effect and the rate of compliance with the treatment. We find that the effect of the smart irrigation controller on water consumption is large: using a household watering 8 sprinkler zones for 15 minutes twice a week as a baseline, the smart irrigation controller can lead to a 27% reduction in water consumption during the September-October time-frame when set it and forget it consumers with traditional controllers do not steadily reduce their water use into winter. For the heaviest irrigators, adoption of the device yields monetary savings that recover the typical cost of the device ($250) in about half a

for the third and fourth quartiles of irrigators, respectively.

[18] This increase in represents about 6.1 increase over the corresponding control group of the upper quartile of irrigators.

[19] Our finding of above average adoption rates by conservation-prone households mirrors some of the the findings in Allcott, Knittel, and Taubinsky (2015), who document that energy efficiency subsidies have the highest uptake rate among wealthy environmentalist households. Our study contributes in two ways: (1) we find that the adoption incentives for this smart IOT device are also particularly appealing to (likely wealthy) households with large conservation potential who would not otherwise conserve and (2) unlike in Allcott et al. (2015), the effect in (1) is likely to be the main driver of social welfare, since due to the discretionary (rather than necessary) nature of lawn watering, lower income households and environmentally conscious households are less likely to over-water in the first place.

year,[20] suggesting relatively large investment inefficiencies (Allcott and Greenstone (2012)). The annual water savings of a heavy irrigator household covers the basic (indoor) annual water needs of a local household,[21] suggesting significant social benefits.[22]

Finally, we address the question of whether the heavy promotion of a harm reduction alternative cannibalizes abstinence alternatives such as turf removal or brown lawns. Armitage (2022) documents cannibalization concerns in conservation by showing that the durability of early energy efficient lighting (e.g., halogens) can cannibalize adoption of subsequent more efficient solutions (e.g., LEDs). In harm reduction, the higher impact alternative exists contemporaneously with the alternative harm reducing solution, but does not appeal to the least pro-socially inclined. Thus, one key question is whether promoting the harm reducing solution can engage these households in conservation. In a public health context, Cohen et al. (2015) show that cannibalization induced by the marketing of an alternative health care solution (e.g., rapid diagnostic malaria tests) can be beneficial when the solution with the highest immediate impact (e.g., antimalarial medication) has potential negative long-run effects if poorly targeted. In our case, the alternative harm reducing solution has more potential negative long-run effects compared to the higher impact alternative, making its promotion ex-ante more risky and controversial.

We quantify turf removal and browning of lawns by using supplementary data on the photosynthetically active vegetation (PSAV) area and its greenness (Quesnel, Ajami, and Marx (2019)) for a subset of the households in the second experiment. We find that smart controller adoption incentives do not lead households to forgo turf removal by documenting no change in PSAV area in the treatment group relative to the control group. This result suggests that device adoption is driven by consumers who would otherwise continue to maintain a green lawn rather than those who would remove turf absent adoption incentives. We further show that the adoption incentives do not lead to a change in the percentage of the irrigable area that is green, suggesting that households in the treatment group decrease water consumption without sacrificing landscape greenness and device adoptions and subsequent water reductions come largely from consumers who were maintaining a green lawn prior to adoption.

In short, we find that the harm reduction approach - heavily marketing a smart irrigation controller that improves watering efficiency alongside the heavily promoted turf removal alternative - is effective at fostering water conservation. The controller appeals most to heavy irrigators and those reverting from previous conservation and yields significant long-run water reductions. Our results underscore

[20]We compute the time to cost recovery using the annual local average treatment effect for the heaviest irrigators in 2018 (48.73 units) and the mid-point rate ($10.17/unit) between third tier ($8.77/unit for 21-40 units) and fourth and highest tier ($11.57/unit for 41+ units) residential water rates in Redwood City in 2018, thus assuming that half of the reduction comes from the highest tier and half from the second highest; i.e., 12 months * $250/device / (48.73 units * $10.17 units) = 5.3 months.

[21]We compute the basic (indoor) annual water needs using the top value of the first tier (0-8 units) of bi-monthly residential water rates in Redwood City in 2018; i.e., 8 units * 6 bi-monthly periods in a year = 48 units/year.

[22]We caution that this reduction may represent an upper bound because some of the intent-to-treat effect could have been driven by unaccounted for actions, such as adoption of devices of other brands or other conservation actions. One potential cause of such unaccounted for actions derives from our inability to fulfill all of the smart controller demand requested by the treatment group through our portal and associated offer.

the importance of using various marketing elements to ensure that interventions aimed at fostering conservation are well-targeted.[23] In our case, the financial incentives for turf removal are not enough to engage the least pro-socially inclined. On the other hand, adding financial incentives for a solution that is aligned with the preferences of these households allows them to conserve without cannibalizing the other more pro-social solution. Our findings shed light on how policy makers and conservation proponents can improve progress towards social goals by marketing harm reducing solutions likely to appeal to those least motivated by the social goal alongside the highest impact solutions most inherently appealing to the conservation-inclined.

The rest of the paper proceeds as follows. In Section 2, we introduce the empirical context of our study. In Section 3, we discuss the design of the two randomized trials. In Sections 4 and 5, we discuss the results of the interventions on smart irrigation controller adoption and resultant effects on water usage, respectively. In Section 6, we discuss indirect effects of the treatment on landscape size and greenness. And in Section 7, we conclude.

2 Empirical Context

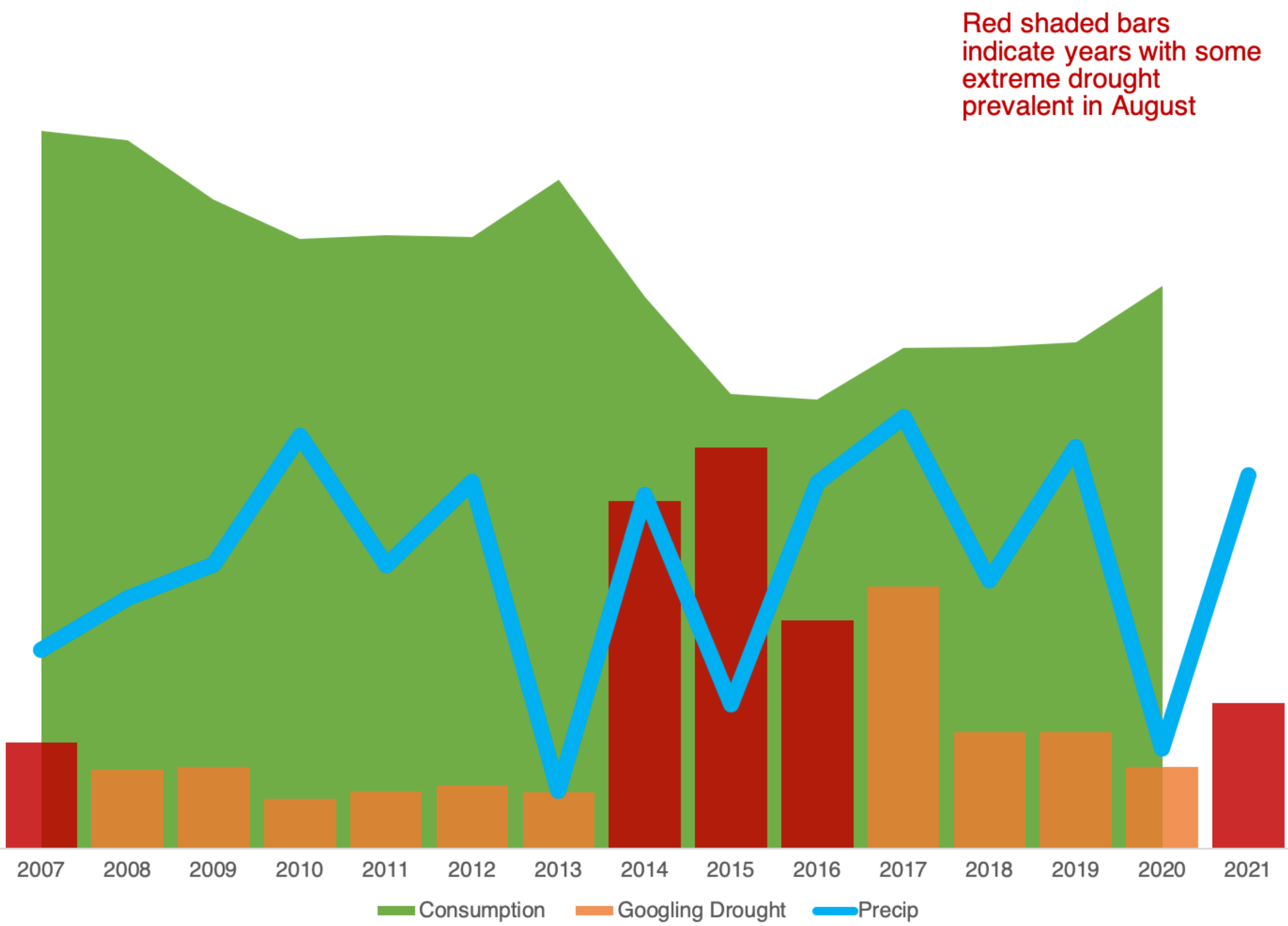
2.1 California Drought

Drought in California is a recurring phenomenon with temporary reprieves that have been decreasing in length over the past few decades (Figure 5). Drought arises because the demand for water outpaces supply. Demand and supply dynamics are visible in Figure 1, which compares 2007-2021 residential water consumption in our partner city of Redwood City, California to annual precipitation levels, incidence of extreme drought and interest in drought as measured through Google trends (we describe the sources and construction of data sets for this and subsequent summaries and analysis in Appendix Section A). The patterns in 2013 illustrate the tension well: we see precipitation (water supply, in blue) fall drastically, but water demand (in green) increases, likely due to the increased need to irrigate a dry landscape. These levels could be efficient if enough water supply existed in reservoirs to smooth such shocks, but from the red shaded bar in 2014, we see the demand and supply imbalance in 2013 sent California into extreme drought in the following year.

Solving drought in California is a complicated problem. Proposals to change water rights, build infrastructure to capture runoff, and many other proposals can affect the long-run aggregate supply and demand problems. In the short-run, much of the adaptation to drought emphasizes residential conservation because water rights limit the ability to affect consumption by those with strategic land holdings. The focus of this paper is therefore residential conservation and the challenge faced by the

[23] Studies in other contexts have found heterogeneity in effectiveness of messaging on socially desirable behavior (e.g., Costa and Kahn (2013) in the context of "nudges" towards energy efficiency) and underscored the importance of well-targeted campaigns to engage the most reluctant (e.g., Kessler, Milkman, and Zhang (2019) in the context of donations).

Figure 1: Precipitation, Drought and Demand Response in Redwood City, California



"Consumption" (in green) is the unit consumption (in units = 748 gallons) in a given year of an average residential consumer in Redwood City. "Googling Drought" (in orange and red) is the number of searches for the word "drought" in California in a given year. "Precip" (in blue) is the number of inches of precipitation in a given year at the San Francisco AP Station (closest to Redwood City), as reported by the National Weather Service.

local water utility to change the water consumption behavior in the many households they serve.

Figure 1 shows that Redwood City managed to realize a large residential demand reduction in 2014 and even further reductions into 2015. California remained in drought through 2016, with the end announced at the beginning of 2017. The uptick in search activity for drought in 2017 therefore likely reflects interest in the announced end of the drought.

The observed water reductions came in the absence of a fully functioning price system, thereby relying heavily on a multi-party marketing process. Like other essentials such as electricity, there is resistance to raising water prices, despite their potential to balance the supply and demand in the short-run without necessarily changing capacity investment (e.g., Borenstein and Holland (2005) and Fowlie, Wolfram, Baylis, Spurlock, Todd-Blick, and Cappers (2021) study these questions in the context of electricity markets, where the prices can be used to shift consumption from high-cost to low-cost hours within a day). One mechanism to circumvent this is a tiered pricing system that drastically raises prices for non-essential or heavy use. However, in 2015, California courts ruled conservation pricing to be illegal (Mintz (2015)), thereby leading many utilities, such as our partner, to seek non-price approaches for reducing demand.

2.2 Utility Partner and Residential Response

To mitigate the effects of the drought, the California Governor first issued a call for a voluntary 20% reduction in residential water consumption in January 2014 (Office of Governor Edmund G. Brown Jr. (2014)). When that failed to alleviate the shortage, in May 2015 the State Water Resources Control Board adopted emergency regulations that (1) assigned each utility to a residential conservation tier, based on existing water use and conservation success to date and (2) threatened a $10,000 per day fine if the utility failed to comply (California Water Boards (2015)). Conservation targets ranged from 8% in the lowest tier to 36% in the highest tier. The highest tier included wealthy cities such as Beverly Hills in Southern California and Woodside in Northern California, which had previously reduced consumption by only 3% and 11% respectively relative to 2013. Such cities were noted in the press because consumption was predominantly from non-essential outdoor uses for large landscapes, whereas reductions from more densely populated areas would have greater impacts on human needs for toilets, showers, laundry etc.[24]

We partnered with Redwood City Public Works (RWCPW) because of its proximity, their openness to collaboration[25] and residential mix that reflected a wide range of lots and water use levels. Specifically, it includes some parts of Woodside and nearby areas, where lots are large, denser areas with much smaller lots closer to downtown Redwood City, as well as multifamily homes. Redwood City had saved 14% at the time of the emergency regulation, but was placed in the 8% tier, likely, because of the low water use per household among its more urban households. RWCPW was therefore representative of the broader challenges in California of motivating behavioral change from a segment of the population where opportunities were large because of lot sizes, yet conservation was still challenging.

Most RWCPW households had engaged in some degree of water reduction by 2015. The rows in Figure 2 document the distribution of households in Redwood City based on their percentage reduction in peak water consumption (July-August) from 2013 to 2015. 77% of households exhibited some reduction with the most common change in consumption being a 40-50% reduction. Households achieved this reduction by engaging in a variety of conservation measures. As a part of our later described control condition, we surveyed RWCPW households with water use potentially indicative of an irrigable landscape and found the following conservation activities: 4 of 172 reported doing nothing to reduce water

[24] See for example Krieger (2015) discuss this tension in the San Jose Mercury News.

[25] Some other utilities with which we had discussed interventions aimed at promoting adoption of smart irrigation controllers were resistant to such collaboration because of a concern that smart controllers might increase water use and/or detract from their turf removal goals.

Figure 2: Household Water Conservation and Reversion During Drought

Percent Change in Water 2016 vs. 2015

Rows: Percentage Change in Water 2015 vs. 2013

	-100%	-90%	-80%	-70%	-60%	-50%	-40%	-30%	-20%	-10%≤X<0%	0%≤X<10%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100% or more	Total	Cum Share
-100%	6	0	1	1	0	1	1	1	2	0	6	1	1	0	0	6	3	0	1	0	262	271	1%
-90%	11	1	0	5	1	7	7	4	5	0	20	2	10	12	9	18	10	7	16	2	420	487	4%
-80%	10	4	7	3	2	17	4	16	12	7	40	26	34	35	16	44	40	33	47	13	588	860	8%
-70%	22	8	3	15	11	30	27	40	35	19	109	65	106	78	72	108	88	64	93	42	925	1,613	17%
-60%	13	5	9	17	16	40	39	64	61	37	130	104	129	106	106	134	124	83	90	40	621	1,603	25%
-50%	27	13	14	38	22	59	66	97	115	79	225	199	188	208	181	263	190	115	144	53	749	2,848	40%
-40%	16	19	17	26	31	70	60	108	125	88	253	175	207	146	136	145	140	64	85	22	399	2,414	53%
-30%	24	12	18	41	33	66	78	123	119	82	238	177	161	137	102	130	112	71	63	20	317	2,272	65%
-20%	9	12	10	22	26	59	69	108	108	74	166	132	126	85	64	66	64	37	26	9	180	1,602	73%
-10%≤X<0%	9	7	11	15	24	28	44	47	48	40	87	58	41	38	23	26	17	11	15	6	46	783	77%
0%≤X<10%	24	14	12	32	23	44	70	73	84	33	139	84	74	48	40	53	34	25	20	5	186	1,375	85%
10%	8	8	3	12	13	29	34	50	44	20	42	37	25	18	25	11	12	9	4	2	44	573	88%
20%	9	4	5	13	13	35	26	31	34	9	36	27	22	16	11	12	11	6	15	4	42	434	90%
30%	2	2	9	13	11	17	15	17	14	14	24	8	14	13	7	7	4	9	4	1	31	293	91%
40%	1	3	5	1	5	16	10	19	19	4	11	10	9	6	5	4	3	5	3	1	16	174	92%
50%	1	6	2	8	7	14	10	21	8	8	19	8	7	15	1	8	4	3	0	5	22	197	93%
60%	4	3	3	7	2	12	6	10	5	6	7	2	6	7	8	7	6	2	0	0	14	161	94%
70%	0	3	3	7	1	3	6	8	3	5	6	4	5	3	0	4	2	2	2	0	9	80	95%
80%	4	1	3	5	1	7	9	9	2	6	4	2	4	4	1	2	4	1	1	0	10	77	95%
90%	0	0	2	2	3	1	1	5	0	1	1	0	1	1	0	0	0	0	0	1	1	23	95%
100%	37	23	22	42	27	53	49	46	47	21	59	43	41	31	31	33	33	19	23	4	190	936	100%
Total	274	103	134	239	227	601	715	1,260	1,639	1,139	3,402	1,874	1,668	1,161	731	817	582	322	300	100	1,788	19,076	
Cum. Share	1%	2%	3%	4%	5%	8%	12%	19%	27%	33%	51%	61%	70%	76%	80%	84%	87%	89%	90%	91%	100%		

This figure shows the number of residential households in Redwood City who (y-axis) effect a particular percentage change in water usage from 2013 to 2015 and then (x-axis) effect a particular percentage change in water usage from 2015 to 2015. The higher number of households in a particular cell, the deeper the red shading. Water usage and, thus, change in usage measured at the annual level.

consumption, 52% let their lawn turn brown, 23% removed turf, 13% used a smart irrigation controller and 49% did something else which was typically described as indoor conservation. While many attempts at conservation focused on indoor savings, the biggest residential opportunities to save water exist in outdoor irrigation. For example, a typical toilet and shower respectively use 32.6 and 26.9 gallons per household per day (gphd). On the other hand, running a typical 8 zone sprinkler system for 15 minutes in a day uses 1,920 gallons of water (Water Research Foundation (2016) and WSSCWater (2022)).

The conservation activities promoted by RWCPW before our collaboration were primarily focused on indoor water and the abstinence solution of turf removal. Figure 6 displays the dashboard from RWCPW's website on uptake of promoted conservation activities from 2013 through end of May 2016. The pre-drought (pre-2014) focus was on indoor conservation, particularly efficient toilets and clothes washers. Conservation kits, including indoor faucet aerators, faucet leak calculators and dye tablets to detect toilet leaks, were promoted and heavily adopted in 2015. The highest impact outdoor solution - turf removal - was heavily promoted and its uptake grew by more than eleven times between 2013 and 2014 with a further increase of more than 25 percent by mid-2015.

On the other hand, promotion of harm reduction alternatives was minimal. Setting the smaller impacts of indoor water conservation aside, solutions such as efficient toilets, clothes washers and conservation kits would not be viewed as harm reduction alternatives because they are the highest impact solutions for their use case and their use is a basic need rather than an aesthetic pleasure that may be stigmatized during times of scarcity. To reduce harm of outdoor water use, RWCPW started offering free efficient sprinkler nozzles in mid-2014 and rain barrel rebates in 2015. Throughout the 2013-2016 period RWCPC did not offer incentives to adopt smart irrigation controllers, which could help adapt to changing demand and supply conditions for irrigation.

After initially reducing consumption during the drought, many households began to increase consumption in the summer of 2016, before the drought ended. The columns in Figure 2 illustrate the 2016 vs 2015 percent change in water consumption for the July-August billing period, and we see nearly 40 percent of households increase consumption by 10% or more. Almost 10% of households increased their consumption by 100% or more between 2015 and 2016. Within this context, our harm reduction approach of mitigating the water use through a smart irrigation controller provided the potential for ongoing conservation while recognizing that many households would maintain an ornamental landscape despite the heavy push toward turf removal.

2.3 Smart Irrigation Controllers

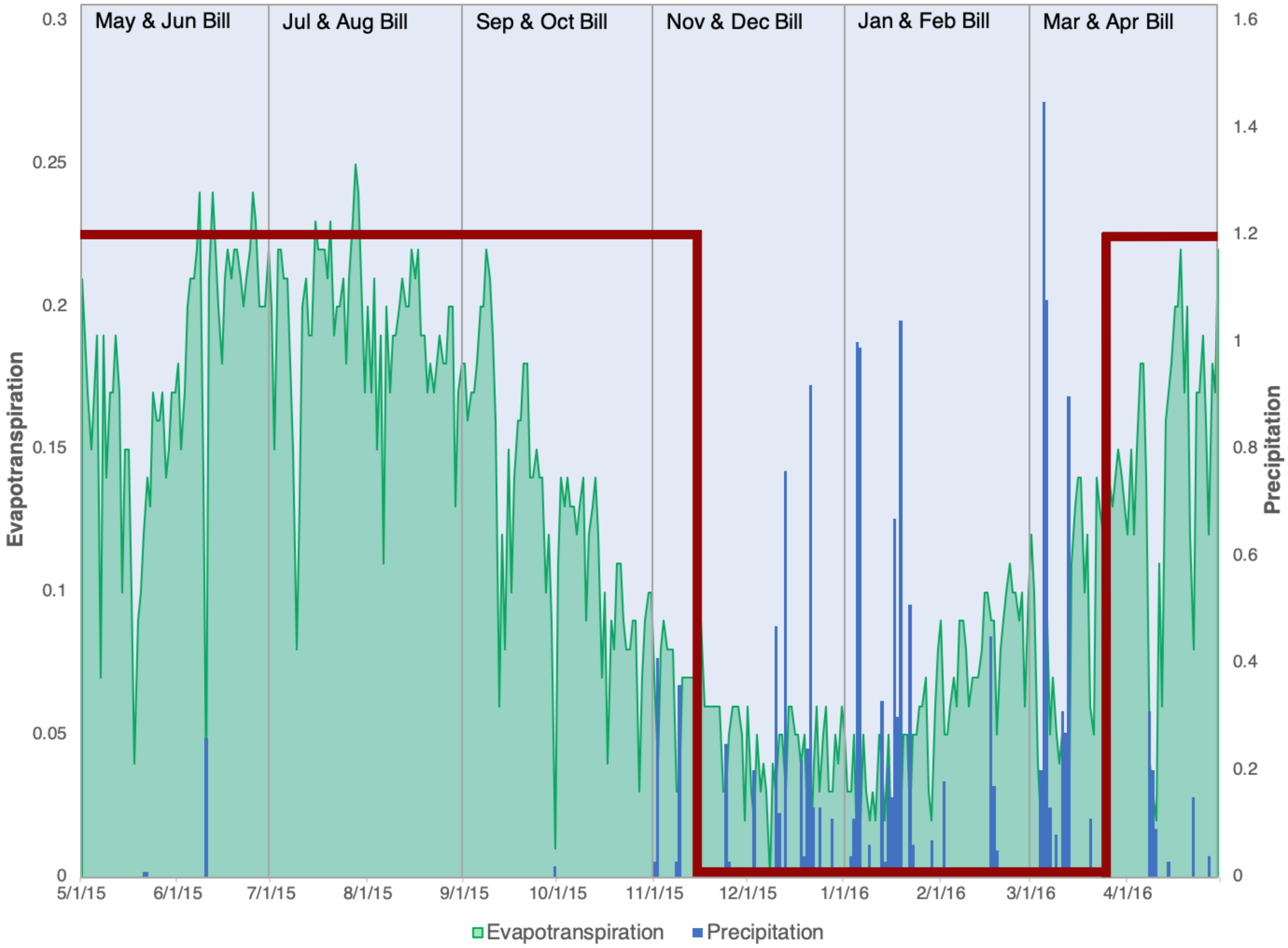
Irrigation controllers are automation devices that followed a line of household convenience products introduced in the mid-20th century. In fact, upon introduction in 1968, the Rain Clox was marketed as the "World's First Appliance for the Garden" with benefits such as "Set it and forget it" and "Saves time too. No more dragging hose around; no more hand-watering. Gives you a couple of extra hours each weekend." The device was a simple timer wired to valves that turned on and off sprinklers at pre-specified start times, days and durations.

Like many convenience devices, automation created default consumption of resources that was "inelastic" to changing consumer needs and supply conditions, thereby unnecessarily using resources when not needed (watering during the rain as an obvious example). The focal value proposition of the smart irrigation device we use in our study is avoiding such water waste, but the benefits of smart devices are potentially much greater, especially in drought-prone areas with little rain.

The green area in Figure 3 plots evapotranspiration data, which is a weather metric water utilities such as RWCPW use to set recommended watering budgets because it measures daily consumption needs for landscapes[26]. Precipitation is depicted in blue columns. Notably, outdoor watering needs in Redwood City vary throughout the year with peaks in the summer months and a steady decline through fall into winter when most needs disappear and/or may be covered by recent precipitation. Watering needs steadily increase in spring until again reaching peak summer needs.

[26]Evapotranspiration is a process by which water is transferred from the land to the atmosphere by evaporation from the soil and other surfaces and by transpiration from plants. Thus, high evapotranspiration implies high irrigation needs and low evapotranspiration implies low irrigation needs.

Figure 3: Water demands throughout the year



This figure shows the daily evapotranspiration (in green) and precipitation (in blue) in inches in Redwood City for a reference time period. The data used here were provided by RWCPW. The dark red line represents scheduled irrigation via a hypothetical traditional controller, active in the dry season and inactive in the rainy season.

The potential water waste from a typical "set it and forget it" approach becomes apparent by comparing the red line with the evapotranspiration and precipitation patterns in green and blue, respectively. The red line depicts a hypothetical irrigator who turns on their fixed outdoor irrigation schedule in the spring and shuts it off in early winter. Such a schedule would be prone to over-watering in the fall, when even in absence of significant precipitation, lower evapotranspiration implies lower irrigation needs. By the same reasoning, such a schedule may also prompt over-watering in the spring. On the other hand, a delay in turning the irrigation schedule back on might instead lead to savings in spring water consumption. Another hypothetical consumer might split the difference and set the red line somewhere between spring and summer watering needs. Such a policy may, however, hinder the ability to realize the desired green landscape by under-watering in summer.

A smart irrigation controller can efficiently adapt to watering needs throughout the year, as well as temporarily shut off irrigation when it has rained, will rain, or the soil is saturated enough from rain or past irrigation that the next cycle is not needed. We analyze such a device - the Rachio smart controller - which had achieved early penetration in Redwood City, with nearly 100 devices activated prior to our first experiment.

Rachio's smart irrigation controller replaces a traditional timer by swapping out the valve wires and setting up schedules using the smartphone app interface. Setup alone can influence irrigation because schedules are based on soil type, slope of the ground, and type of vegetation. While Rachio includes settings that can optimize daily watering based on evapotranspiration measures, its default and most common use involve adjusting watering times on the first of each month based on historical evapotranspiration for the coming month.[27]

2.4 Harm Reduction in the Residential Water Conservation Context

The smart irrigation controller represents a potential harm reduction solution requiring empirical validation. To motivate an empirical study of our research question, in Appendix Section B, we write down and discuss an illustrative model that integrates preferences for the outputs of scarce resource consumption and conservation of said scarce resources. While this model is applicable more broadly to other conservation contexts (e.g., energy), we focus the discussion on preferences for a green landscape (an output of water consumption) on the one hand and water conservation on the other.

We first use the model to show that in a setting in which the heavily promoted highest impact solution - turf removal - works directly against strong preferences for green lawns, marketing of a smart irrigation controller may be particularly appealing to the heaviest water consumers without stigmatizing their preferences for ornamental landscapes. In other words, it may reduce the environmental harm from the heaviest users who would otherwise not engage in conservation via the highest impact approach. On the other hand, we also show that i) the device could increase water consumption for households previously not noticing or ignoring some brownness in their lawn and ii) the device could increase water use through cannibalization of the higher impact turf removal (if households infer promotion of the solution as condoning ornamental landscapes, for instance).

Our analysis of the illustrative model lays out the determinants of success of a harm reduction approach. That is, we show that the viability of this approach depends on three factors: (1) who responds to the incentives to adopt the smart irrigation controller, (2) how the device impacts their water consumption and (3) whether households that respond to the smart irrigation adoption incentives forgo adoption of the higher impact turf removal alternative. To empirically validate the use of the smart irrigation controller as the solution at the center of a harm reduction approach to conservation we conduct an field study.

[27] An example of an email notification of such a change is included in Figure 8. Email notifications for rain skips and saturated soil are depicted in Figure 9.

3 Study Design

3.1 A Marketing Process

Conservation activities that sacrificed green landscapes during the peak of the drought created incredible savings, but the heterogeneity in households' abilities to maintain that throughout and beyond the drought makes the needs for diverse solutions clear. Turf removal permanently conserved water, but the irrigation of previously browned lawns generated a need for a harm reducing solution that could enable the retention of both green lawns and conservation.

Marketing helps guide heterogeneous customers down paths towards behavioral change and addresses the specific challenges they may face along the way. Different solutions will work for different customers, and different customers may require different paths to adopt and use them. The full consumer decision-making process typically includes (1) need or problem recognition, (2) consideration set formation, (3) evaluation of alternatives, (4) purchase decision and (5) use and evaluation. In this study, we pay particular attention to steps (2)-(4)[28], starting with consideration set formation, as consumers seek out information about available alternatives.

Our marketing process therefore began with communications that added the smart irrigation controller into the consumer's consideration set alongside the options from Figure 6 that RWCPW had been promoting. This approach expanded the set of consumers considering the smart irrigation device alternative beyond organic adopters who found out about the device online, in-store, or via a search or targeted display advertisement. It is important to note that we began these communications in 2016 after customers had already heavily reduced consumption and likely chosen a higher impact alternative if it was acceptable to them. We then focused on the evaluation of alternatives stage, where customers compare alternatives within the consideration set. While Rachio's product characteristics were fixed, we tested a range of offers with price and installation discounts that were supported by reductions in upstream prices. These incentives would have made the smart irrigation device more appealing relative to other available alternatives. Finally, we streamlined the purchase decision by linking the communications to dedicated portals built by Rachio, where verified RWCPW-account holders could easily and immediately purchase their discounted devices (see Figure 7. This process contrasted with a traditional rebate/reimbursement approach, which includes barriers to redemption and hence adoption.

3.2 Field Experiments

We conducted two field experiments in 2016 and 2017, with the collaboration of a smart irrigation controller manufacturer, Rachio) and RWCPW. The first experiment launched in June 2016 with a set of pricing and professional installation incentives for the adoption of the smart irrigation device.

[28]Note that the Governor's office and associated reporting had already established need recognition, and Rachio was handling consumer use and evaluation of the device.

The second experiment launched in November 2017 with the offer of free smart irrigation devices and discounted professional installation. The number of devices available for adoption in-experiment was capped at 600, a number that was determined based on budget limitations and limits on discounted devices available from the smart irrigation controller manufacturer. In the following sub-sections, we describe in detail the offered incentives and communication methods in each of the two experiments.

Experiment 1 In the first experiment, we randomly assigned a total of 7,000 households to either one of four treatment arms or the control group. We varied the discount and professional installation incentives across four treatment arms: (1) 10% discount, (2) 80% discount, (3) 60% discount, or (4) 60% discount plus free professional installation[29]. The 7,000 households selected into experiment 1 were all single-family households with sufficiently high average water usage to have a lawn (12 units per billing period).

We communicated the offers to the households in the treatment groups via a postcard and emails. The postcard was sent on June 9th, 2016 and provided a link to a portal where customers could uncover and redeem their discount (see Figure 10). To observe the discount, customers would input their water district account number on the landing page. To redeem the discount, customers would then execute the purchase through a Shopify portal designed for the study. Customers who had an email on file with the water agency also received an email notification on either June 17th, 2016 or June 18th, 2016 that included their discount or installation offer (see Figure 11). These same customers received an offer reminder email on July 28th, 2016.

The control group received comparable communications that, instead of communicating an irrigation controller offer, asked customers to answer a few short questions about household characteristics relevant to the potential for installing a controller, (e.g. presence of WiFi) and actions taken to adapt to the ongoing drought (see Figure 12). For fairness reasons, the 10% discount was also available to all control group households were they to navigate to the study portal and enter their account number; however, the control households did not receive communications informing them about the portal or the availability of a discount.

Experiment 2 In the second experiment, we randomized at the street level and assigned all households (a total of 19,131) to either a treatment or control group, depending on their street-level assignment. The treatment in this experiment included a free controller with discounted installation. The households in experiment 2 included all households (single and multi-family) residing in the water district.

The treated households received an email communication informing them of the offer on December 1st, 2017 (see Figure 14). To further drive adoption relative to the first experiment, we added two additional motivations. First, we communicated the limited number of available controllers to create a

[29] Additional discussion of the randomization and stratification approach in experiment 1 is in Online Appendix Section O.1

"fear of missing out" element. Second, we conducted randomization at the neighborhood block level and tried to initiate a social adoption element. The email therefore included the following: "Don't forget to tell your neighbors - only 250 controllers are available through this special program." Note however that while we used the social communications to drive adoption, the goal of this paper is not to evaluate the peer effects on adoption. It simply helped assure we get enough controllers into the market to try to measure the effects of controllers on water usage.

The control group did not receive any communications. This allowed us to increase power for measuring the device effects by not creating a communications arm without a device offer. Though not exactly transferable, the separation of a pure communication effect on adoption is measured in the first experiment.

Randomization and Household Characteristics We conduct randomization checks for each of the experiments. In particular, we investigate the balance of water usage and smart irrigation controller adoption rates across the different treatment arms. Given the levels of analyses reported in Section 5, we investigate balance in (1) water usage the year prior to the experiment, (2) water usage in all years prior to the experiment for which we have consumption data and (3) water usage by bill period in all years prior to the experiment for which we have consumption data. Tables 10 and 11 report the balance checks for experiments 1 and 2, respectively. For experiment 1 (Table 10) we report the F-stat of a joint hypothesis test that the coefficients in each of the treatment arms are equal to the control coefficient. For experiment 2 (Table 11), where there is only one treatment arm, we rely on the p-value of the estimated coefficient for the treatment group. We fail to reject the null that the treatment and control groups have the same water usage and smart irrigation controller adoption rates prior to each experiment.

4 Device Adoption and Activation

In this section, we discuss the impact of the two experiments on Rachio device adoption and activation. We first discuss the insights from the first experiment and how we used this learning to design the second experiment. We then compare the insights from the first and second experiments and discuss heterogeneity in adoption behavior.

4.1 Experiment 1: Response to Adoption Incentives

In each experiment, we provided a portal through which customers could purchase or claim the device. In experiment 1, a total of 86 of the 600 available devices were purchased by 86 Redwood City account holders through the dedicated portal. Purchases occurred between June 13^{th}, 2016 and August

Table 1: Adoption and Activation of Rachio Devices (Exp1)

	(1) Adopt	(2) Adopt or Activate	(3) Num HH
10% Discount	0.001	-0.004	1,416
	(0.004)	(0.005)	
80% Discount	0.019***	0.019***	1,388
	(0.004)	(0.005)	
60% Discount	0.019***	0.016***	1,397
	(0.004)	(0.005)	
60% Discount + Install	0.018***	0.013**	1,398
	(0.004)	(0.005)	
Intercept (Control)	0.001	0.012***	1,401
	(0.003)	(0.004)	
N	7,000	7,000	7,000

Column (1) compares within-portal adoption rates. Column (2) compares rates of within and out of portal adoption, as proxied by device activation from June 2016 to November 2017. Column (3) shows the number of residences in each treatment group and the control group. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

22^{nd}, 2016, with a bulk of purchases shortly after experiment launch and another increase in purchases after the reminder email was sent on July 28^{th}, 2016 (see Figure 13).

To evaluate the effect of a particular program and incentive on adoption, we estimate the following equation:

$$a_i = \beta_0 + \sum_j \beta_1^j T_i^j + \varepsilon_i \tag{1}$$

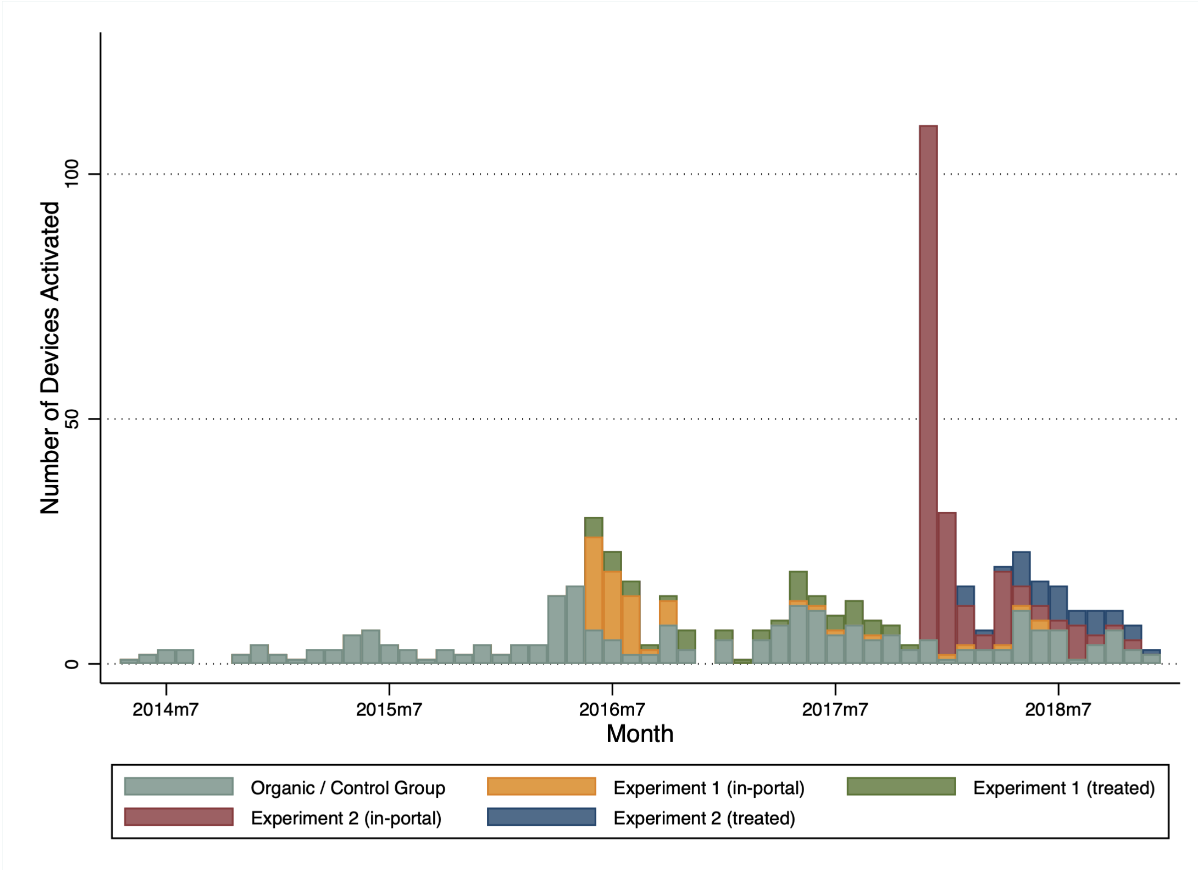
where a_i is an indicator for an individual household i's device adoption and T_i^j is an indicator of an individual household i's treatment group j. As in the description above, in experiment 1, there are four treatment groups such that $j \in \{$10% discount, 80% discount, 60% discount & install, 60% discount$\}$, while in experiment 2, there is just one treatment group such that $j =$ free controller offer.

Column 1 in Table 1 shows that the deeper discounts and deeper discounts paired with installation incentives significantly increase the device adoption rate, while the 10% discount does not have an effect on device adoption. There is no statistically significant difference in adoption rates across the three deeper discount treatment arms.

It is important to note that this analysis in Column 1 does not allow us to fully capture device adoption in the control group, since control households did not receive communications directing them to the experiment portals[30]. In Column 2 of Table 1, we thus supplement the in-portal adoptions with

[30] Nevertheless, we observe some control households purchase the device at a discounted price in experiment 1 and claim it for free in experiment 2. This is possible because (1) in experiment 1, any household that learns about the offer from a

Figure 4: Device Activation Timeline by Adoption Type



all other observed device activations within the Redwood City water district in the period between June 2016 (start of the first experiment) and November 2017 (before the launch of the second experiment). See Figure 4 for the timing and prevalence of such device activations. This additional activation data allow us to proxy for purchases of Rachio devices through channels other than the experiment portal and thus draw a more fair comparison between the treatment and control groups[31]

Similar results emerge: while there is a higher rate of adoption in the control group than in Column 1, incentives, specifically the deeper discounts and installation, increase device adoption. In particular, the adoption rate in the 80% discount group (Control ($\hat{\beta}_0$) + 80% Discount ($\hat{\beta}_1^{80\%}$)) is 2.6 times higher than in the control group (Control ($\hat{\beta}_0$)). While the deepest price discount (80% discount) leads to the highest effect on device adoption, the incremental effects of the deeper discount and installation offers

household in one of the treatment arms can navigate to the experiment portal and redeem the 10% discount available to all water district households and (2) in both experiments, a household could technically use a neighbor's account number to claim the discounted or free device. There are few such adoptions by control group households: 2 out of 86 total adoptions in experiment 1 and 14 out of 412 total adoptions in experiment 2.

[31]Note that even in this specification, we are not accounting for the devices adopted but not activated by control group households; however, given that these devices would have been purchased at the full price by households seeking them out, rather than a part of the experiment, we expect few households outside of the treatment groups to adopt but not to activate their devices. Another possible concern is that some devices may have been activated and deactivated between the snapshots of active devices that we observe. To the extent that such unobserved activations have the same likelihood of occurring in treatment and control groups, they would bias the estimate of the baseline rate of adoption ("Control") rather than the incremental rate due to the incentives introduced via the experimental manipulation ("Discount").

are not statistically distinguishable from each other.

To fully understand the role of the professional installation offer, we separately investigate the activation rates for the in-portal adopted devices for which we observe the full adoption and activation information. Of the 86 households who purchased a smart irrigation controller within the experiment portal, 57 then activated their devices within the Redwood City service area after the start of the first experiment and before the start of the second experiment[32]. The conversion from in-portal adoption to device activation differs by treatment arm: 100% in the 10% discount group, 50% in the 60% discount group, 70% in the 80% discount group and 77% in the 60% discount plus free professional installation group. Given the modest number of adoptions, these differences in activation rates are not statistically significant for all but the 10% discount group; however, we take it as suggestive that the activation rates are highest with a very deep discount (e.g., compare 80% discount to 60% discount) and with a moderate discount paired with installation (e.g., compare 60% discount plus free professional and 60% discount-only). These observations inform our design of the second experiment in which the offer entails an ever deeper price discount (free device) and a discounted professional installation.

4.2 Experiment 2: Broad Roll-Out and Activation

In experiment 2, a total of 412 devices were claimed by 387 water district account holders through the dedicated portal. 200 of the 250 pre-committed devices were claimed by the end of the launch day (December 1^{st}, 2017). Given the lower than anticipated uptake of discounted professional installation among these 200 devices, budget was freed for the smart irrigation controller manufacturer to raise the number of devices available for adoption within the experiment. All available devices were claimed by December 3^{rd}, 2017, and the portal was closed down.

Even with a less intensive communication campaign (no postcards and single email) and a smaller proportion of households in the treatment group, we see a higher overall uptake of devices in experiment 2 (387/19,131 = 0.02) than in experiment 1 (86/7,000 = 0.01). Moreover, Column 1 in Table 2 shows that the vast majority of adoptions through the experiment portal (all but 14) come from households in the treatment group.

We further supplement the in-portal adoptions with all other observed device activations within the Redwood City water district in the period between December 2017 (start of the first experiment) and December 2018 (last snapshot in which we observe newly adopted devices). As in experiment 1, we do so in order to account for organic device adoptions in the control group. A second reason to account for out of portal adoptions is to capture any "advertising" effect of the second experiment. Given the

[32] An additional 2 households had purchased and activated a device prior to the experiment, indicating that they used the experimental offer to replace an existing device, and an additional 6 households activated their device after the start of the second experiment. The remaining 21 households either did not activate their devices or activated them outside of the service area (as a result of a move or transfer of device to another household).

Table 2: Adoption and Activation of Rachio Devices (Exp2)

	(1) Adopt	(2) Adopt or Activate	(3) Num HH
Free Controller Group	0.035***	0.033***	10,224
	(0.002)	(0.002)	
Intercept (Control)	0.002	0.008***	8,907
	(0.001)	(0.002)	
N	19,131	19,131	19,131

Column (1) compares within-portal adoption rates. Column (2) compares rates of within and out of portal adoption, as proxied by device activation from December 2017 to December 2018. Column (3) shows the number of residences in each treatment group and the control group. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

rapid uptake in the second experiment, there may have been consumers in the treatment group who viewed the experiment communication, but were unable to claim a device because of the limited supplies. The experiment message may have either moved such consumers into the purchase funnel by informing them of the existence of the Rachio device or moved them along the purchase funnel towards purchase with the endorsement by the water district.[33] In both cases, by considering all in-portal adoptions and out-of-portal activations in the course of a year, we capture both the price incentive effect as well as the advertising effect on adoption.

Column 2 in Table 2 shows that taking these two forces into account, the adoption rate in the treatment group (Control ($\hat{\beta}_0$) + Free Controller ($\hat{\beta}_1^{free}$)) is 5.2 times higher than in the control group (Control ($\hat{\beta}_0$)), an effect that is twice as large as the effect of the 80% discount in experiment 1. Conversely, for the devices adopted via experiment portal for which we observe both adoption and activation, we see a lower conversion from adoption to activation in experiment 2 (187/387 = 48%[34]) than in experiment 1 (57/86 = 66%), indicating that households are less likely to use devices obtained for free than devices for which they paid a discounted amount. Nevertheless, some device activations are likely unobserved due to the nature of our data (see the description of the data in Appendix Section A), so we use all device adoptions and activations in the analysis that follows.

Although the experiment 2 activation rate is lower than the experiment 1 activation rate, given the broad uptake in experiment 2, the absolute numbers of both adoptions and activations in experiment 2

[33]This same force may have caused some consumers to explore the broader category of smart irrigation controllers or water conservation activities and ultimately undertake another path towards water conservation. We discuss the implications of such actions in the context of a model in Appendix Section B and in the context of our empirical results in Sections 5 and 6.

[34]Of the 387 households who claimed a free smart irrigation controller within the experiment, 187 then activated their devices within the Redwood City service area after the start of the second experiment. An additional 15 households had purchased and activated a device prior to the experiment, suggesting that they used the free device offer to replace an existing device. As in the first experiment, the remaining devices were either never activated (the vast majority of the remaining devices) or activated outside of the service area by the adopting household or a household to whom the device was transferred.

are higher. This broad roll-out of devices allows us to reliably examine the heterogeneity of adoptions and the effect of adoptions on eventual household water usage.

4.3 Heterogeneity in Treatment Response

Irrigation controllers offer the potential to improve watering efficiency, but the magnitude of this potential will depend on the size and vegetation of the parcel as well as the household's relative preference for green landscape over water conservation (see the illustrative model in Appendix Section B). To better understand whether our offered incentives were able to drive adoption among the households with the largest potential water reduction, we thus examine heterogeneity in offer uptake behavior.

We first show that incentives drive adoption mostly among households with the potential for outdoor water conservation. Such households would consume substantially more water in warmer summer months than in the winter. We therefore estimate the following equation

$$a_i = \beta_0 + \sum_k \beta_1^k T_i x_{ik} + \sum_k \beta_2^k x_{ik} + \varepsilon_i \tag{2}$$

where T_i is now an indicator for whether an individual household i is in any treatment group[35], and x_{ik} is an indicator of whether household i belongs to one of the k mutually exclusive groups based on previous household water consumption.

To form the groups of households likely to be irrigators, we first compute the difference between summer (May-August) and winter (November-February) water consumption in the year preceding each experiment. We then split the households into four groups, depending on this difference, with quantile 4 households and quantile 1 households having the highest and lowest summer to winter difference, respectively.[36] That is, quantile 4 households are more likely to have large lawns that need intensive watering in the dry summer season to stay green, and quantile 1 households either do not have much vegetation or have low summer to winter variation due to high overall water consumption. Table 12 summarizes the water consumption by billing period for experiment 1 and experiment 2 households, grouped by quantile, in the year preceding the experiment.

Table 3 reports the coefficient estimates $\hat{\beta}_1^k$ and shows that in both experiments, the device adoptions are driven by households with higher summer to winter consumption variation. Column 1 of Table 3 shows a statistically significant treatment effect in experiment 1 for 3^{rd} and 4^{th} quantile households only. Column 3 of Table 3 shows that while experiment 2 incentives drove adoption in all summer to winter consumption quantiles, the treatment effects on adoption are significantly larger for the higher quantile households, as in experiment 1[37].

[35] For ease of exposition, in this analysis, we group together all households in any experiment 1 treatment group.

[36] In the quantile 1 groups in experiments 1 and 2, the mean difference between summer and winter water consumption is negative, meaning that on average households in these groups increased their usage in the winter relative to the summer.

[37] We note that the quantile definitions are different for the two experiments because (1) households in experiment 1 are

Table 3: Effect on Adoption by Summer to Winter Consumption Difference

	Experiment 1		Experiment 2	
	(1) Adopt or Activate	(2) Num HH	(3) Adopt or Activate	(4) Num HH
Change Q1	0.009	1,895	0.014***	4,533
	(0.008)		(0.005)	
Change Q2	-0.001	1,614	0.025***	4,749
	(0.009)		(0.005)	
Change Q3	0.014*	1,799	0.037***	4,326
	(0.008)		(0.005)	
Change Q4	0.020**	1,687	0.061***	4,371
	(0.009)		(0.005)	
N	6,995	6,995	17,979	17,979

This table shows the effect of treatment on device adoption in households grouped by summer to winter water usage variation. For ease of exposition, we group together all households in any experiment 1 treatment group. Change quantiles are formed by computing the the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2015 (exp 1) and 2017 (exp 2). Households with higher summer to winter change fall into higher quantiles. Column (1) compares rates of within and out of portal adoption, as proxied by device activation from June 2016 to November 2017 (exp 1) and December 2017 to December 2018 (exp 2). Column (2) shows the number of residences in each quantiles group. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We next provide evidence that device adoption is more prevalent among (1) conservation-prone households, (2) conservation-prone households looking to return to "normal" after extreme drought conditions and (3) households not inclined to conserve at all. The timing of experiment 2 is particularly helpful because by the end of 2017 when experiment 2 launches, we have observed the households' water consumption in 2015 at the peak of the drought as well as in 2016 when the state starts to come out of the drought (see Figure 1). As a result, we are able to examine the heterogeneity in experiment 2 offer uptake based on the responsiveness to the previous drought. Using the 2014-2016 summer (May-August) water consumption, we thus form 16 mutually exclusive groups of households, based on change in water usage between 2014 and 2015 when the drought was intensifying and between 2015 to 2016 when the drought was showing first signs of abating. For reference, households in quantile 1 of the 2014 to 2015 change in consumption are households that conserve the most in response to worsening drought conditions, and households of quantile 4 of the 2015 to 2016 change in consumption are households that increase their water usage the most as the drought conditions begin to improve.

We estimate equation 2 with x_{ik} as the indicators for whether household i belongs to one of the 16 household groups based on 2014-15 and 2015-16 summer water consumption changes and report the

single-family residences with at least 12 units average consumption and households in experiment 2 comprise all Redwood City residences and (2) overall water consumption and summer to winter variation differed between 2015 and 2017 due to different drought status and precipitation levels. As a result of these differences, all quantiles have higher mean summer to winter consumption differences in 2017 (exp 2) relative to 2015 (exp 1).

Table 4: Effect on Adoption by Past Drought Responsiveness (Exp2)

	'15-'16 Change			
	Q1	Q2	Q3	Q4
'14-'15 Change				
Q1	0.061***	0.032**	0.051***	0.057***
	(0.010)	(0.013)	(0.009)	(0.007)
Q2	0.037***	0.016	0.029***	0.047***
	(0.010)	(0.010)	(0.008)	(0.009)
Q3	0.015	0.021***	0.029***	0.018
	(0.009)	(0.008)	(0.008)	(0.014)
Q4	0.024***	0.020**	0.015	0.042***
	(0.007)	(0.009)	(0.011)	(0.013)

This table shows the effect of treatment on device adoption in households grouped by drought responsiveness and water usage reversion post-drought. '14-'15 change quantiles are formed from the difference between water consumption in bills 4 and 5 (May-Aug) in 2015 and bills 4 and 5 in 2014. Households with smaller decrease (or increase) in usage change fall into higher quantiles. '15-'16 change quantiles are formed using the same approach. The outcome measure is the rate of within and out of portal adoption, as proxied by device activation from December 2017 to December 2018. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

coefficient estimates $\hat{\beta}_1^k$ in Table 4. This table shows that the treatment effect is particularly strong among households that continue to conserve even as precipitation returns (Q1 '14-'15 / Q1 '15-'16), households that return to higher water usage as drought conditions abate (Q1-Q2 '14-'15 / Q4 '15-'16) and households that did not conserve in either time period (Q4 '14-'15 / Q4 '15-'16). These are the upper-left, upper-right and lower-right cells of the table.

We note that the analysis of experiment 1 in Table 3 provides additional suggestive evidence for the latter point. Given that 2015 was a particularly dry year (see Figure 1), even compared to the neighboring drought years, households with large summer to winter usage variation in 2015 are those who had not responded to drought messaging and water conservation incentives even at the point when they were at their peak in 2015. In Column 1 of Table 3 we see that even more than in experiment 2, these are the households with the highest responsiveness to treatment in experiment.

From this set of analyses, we take away that with the set of incentives across the two experiments we have been able to drive compliance among a group of households that (1) have a large water reduction potential and (2) are perhaps least compliant with the objective of water conservation. In the following section, we report the effect of adoption on water consumption and the heterogeneity therein.

5 Water Conservation Behavior

In this section, we assess whether our intervention was, in fact, harm reducing; i.e., whether water consumption decreased as a result of the smart irrigation controller promotion. We split our analysis across two dimensions.

First, we distinguish between average effects for the entire population and those we identify as heavy irrigators. This distinction is important because the study population in experiment 2 (the focus of the analysis in this section) included all residential households in the Redwood City service area, many of whom do not have outdoor irrigation needs and/or may be using very little water.[38] Thus, we expect attenuated conservation in the average effects for the entire population and the possibility of irrigation increases among low-consumption households for whom device adoption may lead to increased irrigation (as in the discussion in Appendix Section B). We view the analysis of heavy irrigators as the primary gauge of whether the intervention obtains conservation from those least aligned with the pro-social objective.

Second, we consider intent-to-treat effects as well as local average treatment effects, which give a better sense of the water savings associated with an installed device. The latter allows us to assess the economic viability of the device and to quantify adopting households' potential progress toward the conservation goal.

5.1 Effect of Marketing Intervention on Water Consumption (ITT)

We use the following as the main specification for evaluating the average effect of smart irrigation controller incentives on water consumption:

$$w_{it} = \alpha_0 + \sum_y \alpha_1^y \tilde{T}_{it} \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + \xi_i + \varepsilon_{it} \tag{3}$$

where w_{it} measures water consumption in units (1 unit = 100 cubic feet = 748 gallons) at time t, y represents years $y \in \{2017, 2018, 2019, 2020, 2021\}$[39], treatment $\tilde{T}_{it}$ takes on values 0 before the start of the experiment (December 2017) and treatment assignment T_i after the start of the experiment, and ξ_i is a household street fixed effect[40]. We cluster standard errors at the street (i.e., treatment assignment)

[38] In Tables 13 and 14, we also present the results for experiment 1, using the same main specification as for experiment 2. The effects are directionally similar, though not consistently statistically significant due to the much smaller number of devices adopted in experiment 1.

[39] The water consumption data span November 2006 through August 2021; thus we analyze September-October and November-December consumption data through 2020 only.

[40] We use the fixed effects specification in order to shrink the standard errors around the estimated treatment effects. In Online Appendix Section O.2, we report coefficient estimates of two other variations on this main specification: (1) $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + \varepsilon_{it}$, using only post-experiment 2 data, where $y \in \{2018, 2019, 2020, 2021\}$ and no household street fixed effects (ξ_i) (see Table O.1) and (2) $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + X_{it} + \varepsilon_{it}$, where specification is as in (1), but with additional controls X_{it} for all past water consumption (2007-2016) in the same billing period (see Table O.2). The results are similar to the main specification but more noisy in both these alternate specifications.

Table 5: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp2)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							0.151
							(0.156)
2018	-2.051*	0.0516	-0.186	-1.110	-0.350	-0.371**	-0.0088
	(1.079)	(0.159)	(0.141)	(1.007)	(0.254)	(0.158)	(0.142)
2019	-1.458	1.132	-0.217	-1.000	-0.581**	-0.381**	0.0583
	(1.470)	(0.932)	(0.150)	(1.016)	(0.258)	(0.189)	(0.169)
2020	-2.024	-0.0604	-0.124	-0.939	-0.287	-0.296	-0.0122
	(1.437)	(0.259)	(0.205)	(1.029)	(0.283)	(0.224)	(0.202)
2021	-2.158*	-0.0404	-0.376	-1.004	-0.238		
	(1.207)	(0.252)	(0.279)	(1.042)	(0.318)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N streets	659	659	659	658	658	658	659
N HH	19,116	19,112	19,114	19,109	19,113	19,087	19,114
N obs	95,554	94,678	94,740	94,169	94,416	75,577	94,604

This table shows the effect of treatment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3). Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

level (Abadie, Athey, Imbens, and Wooldridge (2017)).

By estimating equation 3, we are effectively estimating year-specific intent-to-treat effects of interventions on water consumption. We do this to test our hypothesis that smart technology has the potential to lead to and sustain a long-run change in water consumption behaviors. Additionally, we estimate this equation separately for each bill period to account for the fact that both precipitation and irrigation requirements can differ by season (e.g., growing season).

In Table 5, we report coefficient estimates $\hat{\alpha}_1^y$. Column 1 reports aggregate year effects, while columns 2-7 report the results by bill period. Results in Column 1 reveal decreases in water consumption by treated households in 2018-2021. From results in Columns 2-7, we see that these decreases are driven by larger reductions in particular seasons. While the water consumption in the treatment group is lower March through October in all the years, this difference is statistically significant for 2018-2019 September-October and 2019 July-August bill periods only. We interpret this result to mean that one major role of the smart irrigation controller in facilitating water conservation is to more quickly respond to changing environmental conditions (e.g., precipitation and evapotranspiration) between seasons (i.e, in the transition between the arid and warm summers and wet and cloudy winters). That is, households with the smart controller will continuously adjust water usage in response to the changing precipitation and evapotranspiration conditions in the border seasons, while households without the device may be

Table 6: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp2, Quantile 4 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							0.371
							(0.372)
2018	-2.960*	0.437	-0.779**	-0.114	-1.751*	-1.065**	-0.130
	(1.669)	(0.326)	(0.390)	(0.520)	(0.963)	(0.477)	(0.335)
2019	-3.923**	0.361	-0.944**	0.282	-2.373**	-1.061**	0.489
	(1.898)	(0.415)	(0.463)	(0.627)	(0.957)	(0.517)	(0.420)
2020	-2.968	-0.101	-0.559	-0.585	-1.526	-0.765	-0.0676
	(2.590)	(0.522)	(0.511)	(0.674)	(1.019)	(0.626)	(0.502)
2021	-3.665*	0.212	-1.249*	-0.220	-2.034*		
	(2.213)	(0.538)	(0.637)	(0.710)	(1.086)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N streets	497	497	497	497	497	497	497
N HH	4,371	4,371	4,371	4,371	4,371	4,371	4,371
N obs	21,852	21,842	21,842	21,844	21,843	17,473	21,835

This table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households with the highest summer to winter water consumption variation in 2017. Change quantiles are formed by computing the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

slower to decrease water consumption, especially if the environmental condition change is not salient (e.g., more cloud cover rather than a large amount of precipitation)[41]

We see further evidence of this same force when estimating equation 5 separately by quantile of summer to winter consumption difference (as defined for the analysis in Table 3). Table 6 reports coefficient estimates $\hat{\alpha}_1^y$ for quantile 4 households and shows persistent, large, negative and statistically significant effects in the March-April, July-August as well as September-October bill periods. Similarly to the September-October bill period in the fall, March-April is the transitional spring period, where more gradual adjustments based on environmental conditions may lead to lower water consumption than a more discrete change in irrigation (e.g., turning on irrigation for the summer). Table 6 also shows that in addition to the transitional periods, for quantile 4 households the intervention led to a large negative and statistically significant reduction in water usage in the peak summer period between July and August. We interpret this to mean that a second major role of the smart irrigation controller in facilitating water conservation is to help households set appropriate baseline irrigation needs so as to avoid over-watering even during peak needs.

[41] We plan to test this more directly in future work by supplementing the analysis with information on over-time changes in evapotranspiration and precipitation in Redwood City.

Finally, in all three bill periods that see a water consumption reduction in the treatment group, we observe a change that persists after 2018, especially among the quantile 4 households. Even as California entered yet another drought period in 2021, we see continued reduced consumption in the group of households that received the offer.

Moreover, this reduction is directionally largest (though the difference is not statistically significant) in years with higher precipitation. As shown in Figure 1, 2019 and 2021 were high-precipitation years, while 2018 and 2020 were relatively lower-precipitation years. Correspondingly, across Mar-Apr, Jul-Aug and Sept-0ct, the water reduction is higher in 2019 and 2021 than in 2018 and 2020 for each respective bill period. We note that this difference suggests that smart irrigation controllers could be particularly well-suited to drive water consumption reductions in years with significant precipitation. This is important, as Figure 1 shows high-precipitation years even at the peak of the 2011-2017 drought. More efficient water usage in such high-precipitation years could help smooth out water availability by more quickly replenishing reservoir supply after particularly dry years. We are careful not to over-emphasize this set of conclusions, however, due to lack of statistical significance in the differences as well as due to the likely abnormal water consumption patterns resulting from the 2020 pandemic[42].

5.2 Local Average Treatment Effect (LATE)

The average intent-to-treat effects estimated in sub-section 5.1 average changes in water consumption across households who claimed the free irrigation controller (387 households) as well as households who did not (18,744 households). To provide a better representation of the effect of the smart irrigation controller on water consumption in households who adopted the device, we thus estimate the local average treatment effect implied by the intent-to-treat effect and the rate of compliance with the treatment. We estimate the following equation:

$$w_{it} = \delta_0 + \sum_y \delta_1^y p_{it} \mathbb{1}\{t = y\} + \sum_y \delta_2^y \mathbb{1}\{t = y\} + \xi_i + \varepsilon_{it} \tag{4}$$

where p_{it} is an indicator of whether the household adopts or activates the smart irrigation controller in the year following the second experiment (December 2017-December 2018)[43]. We further instrument

[42]The intent-to-treat results from experiment 1 are directionally similar to the experiment 2 intent-to-treat results, though they are not consistently statistically significant. There are a two differences worth noting: (1) The effects for the full population appear to be consistently negative in the March-August period, rather than in the March-October period, as in experiment 1. And (2) for the higher variation households, the effect is strongest in years 2017, 2018, and 2020 rather than in years 2019 and 2020, as in experiment 1. While these differences are not statistically significant, we hypothesize that any observed differences could be due to differences in the study population in experiments 1 and 2. For one, experiment 1 was conducted a year and a half before experiment 2, at a time when California was still in exceptional drought and the smart irrigation controller was a less established product. The households adopting at this time might be (1) earlier adopters and (2) better-attuned to conservation needs than those that had not undertaken conservation activities by the end of the drought when experiment 2 takes place. Secondly, experiment 1 selected on high-usage households, while experiment 2 included all residential consumers in the RWCPW service area. Experiment 1 households might thus have specific needs and irrigation behaviors that are not fully reflective of the broader population.

[43]The definition of adoption or activation is the same as in Column 1 of Table 2; i.e., within and out of portal adoption, as

Table 7: Local Average Treatment Effect By Bill Period and Year (Exp2)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							4.565
							(4.640)
2018	-62.44*	1.563	-5.610	-33.68	-10.62	-11.21**	-0.267
	(33.72)	(4.791)	(4.289)	(30.79)	(7.726)	(4.939)	(4.316)
2019	-44.39	34.17	-6.556	-30.32	-17.56**	-11.52*	1.764
	(44.99)	(28.41)	(4.607)	(31.03)	(7.916)	(5.895)	(5.099)
2020	-61.58	-1.835	-3.741	-28.41	-8.721	-8.965	-0.372
	(44.77)	(7.888)	(6.277)	(31.40)	(8.681)	(6.955)	(6.123)
2021	-65.62*	-1.234	-11.41	-30.67	-7.200		
	(37.53)	(7.681)	(8.625)	(32.10)	(9.675)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N streets	659	659	659	658	658	658	659
N HH	19,116	19,112	19,114	19,109	19,113	19,087	19,114
N obs	95,554	94,678	94,740	94,169	94,416	75,577	94,604

This table shows the effect of adoption (instrumented for by the random treatment assignment) on household water consumption in subsequent years (estimates $\hat{\delta}_1^y$, resulting from estimating equation 4). Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for p_i using random treatment $\tilde{T}_{it}$, which takes on values 0 before the start of the experiment (December 2017) and treatment assignment T_i after the start of the experiment, as in equation 3.

In Table 7, we report coefficient estimates $\hat{\delta}_1^y$. When averaging across all households who claim the device, the effect of the smart irrigation controller on the water consumption of those who adopt it is negative and statistically significant in the July-August and September-October bill periods. These effects are economically significant. To interpret the magnitude, we note that watering 8 sprinkler zones for 15 minutes twice a week typically leads to 41 units of water consumption in a 60 day billing period. Thus, a smart irrigation controller leads to a $11.21/41 = 27\%$ reduction in water consumption against this benchmark in the 2018 September-October billing period.

As in the analyses in sub-section 5.1, for households in quantile 4 of summer to winter water consumption variation, these results are larger and more pervasive (see Table 8). A smart irrigation controller in a quantile 4 household leads to the largest decrease in consumption in the July-August peak consumption months (e.g., 28.8 units in 2018). It also leads to relatively large decreases in usage in the March-April and September-October transitional periods (e.g., 12.8 units and 17.5 units, respectively), when households without the device may have more quickly turned on or more slowly ramped down the irrigation.

proxied by device activation from December 2017 to December 2018.

Table 8: Local Average Treatment Effect By Bill Period and Year (Exp2, Quantile 4 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							6.098
							(6.118)
2018	-48.73*	7.185	-12.82**	-1.877	-28.80*	-17.51**	-2.132
	(27.65)	(5.480)	(6.459)	(8.545)	(15.99)	(8.215)	(5.477)
2019	-64.57**	5.942	-15.53**	4.632	-39.06**	-17.46**	8.034
	(31.26)	(6.957)	(7.653)	(10.32)	(16.11)	(8.647)	(7.015)
2020	-48.84	-1.656	-9.190	-9.620	-25.11	-12.59	-1.110
	(42.54)	(8.580)	(8.355)	(11.06)	(16.86)	(10.41)	(8.249)
2021	-60.32	3.483	-20.55**	-3.617	-33.45*		
	(36.81)	(8.858)	(10.34)	(11.69)	(18.18)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N streets	497	497	497	497	497	497	497
N HH	4,371	4,371	4,371	4,371	4,371	4,371	4,371
N obs	21,852	21,842	21,842	21,844	21,843	17,473	21,835

This table shows the effect of adoption (instrumented for by the random treatment assignment) on household water consumption in subsequent years (estimates $\hat{\delta}_1^y$, resulting from estimating equation 4) for households with the highest summer to winter water consumption variation in 2017. Change quantiles are formed by computing the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

It is important to note that while we report the results for all years for which we observe water consumption behavior, our device adoption data span May 2014 through December 2018. It is likely that years after 2018 saw additional device adoptions; however, the local average treatment effect estimates attribute any changes in water consumption in years 2019-2021 to the devices adopted through 2018 only. Since the 2019-2021 reduction in water consumption in adopting households is likely overstated as a result, in what follows, we focus on the 2018 water reduction numbers.

In addition, we recognize that the experimental manipulation may have have also caused some consumers in the treatment group to explore the broader category of smart irrigation controllers or other water conservation solutions and activities. This may be especially true if households perceive that an offer of a free device conveys an urgent need on the part of the water agency to reduce water consumption in their district. Such broader search may have, in turn, caused some households to ultimately undertake a path towards conservation other than the smart irrigation controller. If this were the case, then we would be attributing more of the water reduction to the smart irrigation controller than is appropriate. We note that one email communication in 2017 is unlikely to cause effects on water consumption that persist into 2021; however, keeping in mind these potential joint effects, we take even the 2018 reductions in water consumption as an upper bound of the direct effect of the smart irrigation controller.

6 Does the Harm Reduction Alternative Cannibalize the Highest Impact Alternative?

If the monetary incentives for smart controllers were causing consumers to forgo turf removal, we would expect the intervention to lead to an increase in the square footage of the irrigable area in the treatment group relative to the control (as in the illustrative model description in Online Appendix Section B). Moreover, if this shift was sufficiently high, we would expect to see increased water usage in the treatment relative to the control group. In Section 5, we document a decrease in water usage resulting from the offered smart controller incentives, primarily driven by consumers prone to irrigation. In this section, we use supplementary data on a subset of Redwood City households' photosynthetically active vegetation (PSAV) and the greenness of this vegetation (% Green PSAV) to shed further light on the extent to which adoption incentives for the smart irrigation controller - the harm reduction alternative - cannibalize adoption of the highest impact solution - turf removal.

The PSAV and greenness measures we use in the analysis are based on 2016 and 2018 National Agricultural Imagery Program (NAIP) multispectral satellite imagery of Redwood City parcels (typically recorded in August) and the California Irrigable Landscape Algorithm (CILA) classification thereof. The CILA classifies PSAV (in square feet) as distinct from impervious surfaces (e.g., roofs, asphalt, etc.), non-PSAV (e.g., dead grass) and soil. Within the PSAV area, the CILA further classifies green vegetation, which we then convert to % Green PSAV. The reliability of the CILA classification increases with the size of the parcel. As a result, we limit our analysis to parcels that are above median for photosynthetically active vegetation in 2016, the year before the second experiment.

In Table 9, for this sub-set of households with above-median irrigable areas, we examine the intent-to-treat effect on water consumption (column 1), size of PSAV (column 2) and percentage of green PSAV in the parcel (column 3), using the same specification as in equation 3 and 2016 values as a baseline.

In column 1, we present the effect of treatment on change in water usage in three bill periods leading up to the recording of the parcel via the NAIP satellite imagery in August. As in Table 6, for these larger PSAV households, we observe statistically significant reductions in water consumption in the March-April and July-August billing periods.

In column 2, we present the effect of the treatment on the change in PSAV area from 2016 to 2018. Using the 2016 PSAV measure as a baseline, we find an insignificant effect of treatment on 2018 PSAV measure, suggesting that the treatment group did not see significantly different levels of turf removal

Table 9: Effect on Consumption, Landscape Size and Greenness (Exp2)

	(1) Cons	(2) PSAV	(3) Share Green PSAV
Mar-Apr 2018	-0.811*	—	—
	(0.440)		
May-Jun 2018	-0.791	—	—
	(0.493)		
Jul-Aug 2018	-0.962*	6.647	-0.00239
	(0.525)	(82.44)	(0.00480)
Street FE	Yes	Yes	Yes
Clustering	street	street	street
N streets (Jul-Aug 2018)	513	514	514
N HH (Jul-Aug 2018)	8,946	9,159	9,159
N obs (Jul-Aug 2018)	18,118	18,335	18,335

This table shows the effect of treatment on on water consumption (column 1), size of PSAV (column 2) and percentage of green PSAV in the parcel (column 3) for households with above-median irrigable area, using the same specification as in equation 3 and 2016 values as a baseline. The estimates in column 1 are each a result of a separate regression for the different billing periods. PSAV and % Green PSAV measures are based on National Agricultural Imagery Program (NAIP) multispectral satellite imagery of Redwood City parcels and the California Irrigable Landscape Algorithm (CILA) classification thereof. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

from the control group.[44] As discussed in more depth in Appendix Section B, this result suggests that the smart controller adoption incentives are mainly increasing uptake among consumers who would otherwise continue to water fully rather than those who would remove turf. This result is also consistent with the overall decrease in water usage resulting from the offered incentives (as shown in column 1 of Table 9 and Table 6.

In column 3, we examine the effect of the treatment on the change in PSAV greenness from 2016 to 2018. As in column 2, we see an insignificant effect of treatment on the percentage of the irrigable area that is green, suggesting that (1) the households in the treatment group decreased water consumption without sacrificing landscape greenness and (2) device adoptions and subsequent water reductions come largely from consumers watering fully at the baseline.[45] To see this second point, note from Table B.1 and the discussion in Appendix Section B that consumers with previously brown lawns would necessarily increase the greenness of their landscape upon adoption of the smart irrigation controller[46],

[44] To interpret the magnitude of the result, note that the median PSAV area for this subset of households is $3,326$ square feet. Thus, a 95% confidence interval around the estimate represents a change of about 5% from this median.

[45] To interpret the magnitude of the result, note that the median percentage of green vegetation for this subset of households is 76%. Thus, a 95% confidence interval around the estimate represents a change of about 1% from this median.

[46] This is because for consumers with previously brown lawns optimal water usage remains the same ($w^* = w^{*\prime} = \frac{\kappa\gamma}{A(\theta c + \eta p)}$), but the required amount of water to achieve full greenness decreases to $\underline{w}$. Thus, for consumers previously under-watering, $\frac{w^*}{\overline{w}} < \frac{w^{*\prime}}{\underline{w}}$.

while consumers with previously green lawns would see no change in greenness.[47] Thus, the lack of a positive effect of treatment on landscape greenness suggests that adoption is driven by the latter group.[48]

7 Conclusion

This paper illustrates the effectiveness of a harm reduction approach to fostering long-run conservation. In the context of residential water use, where the focus had been on heavy promotion of solutions akin to full abstinence (e.g., letting a lawn go brown or removing turf altogether) and increased stigmatization of ornamental landscapes, we heavily market a solution to more efficiently keep a green lawn. While the highest impact solutions save more water if adopted, their adoption entails the largest trade-off for those who value the green landscapes the most (i.e., some of the heaviest consumers of the scarce resource). The smart irrigation controller, on the other hand, is ex-ante more likely to be aligned with the preferences of the heaviest consumers of water and those disinclined to conserve; however, it has an uncertain impact on consumption, especially among those who may otherwise conserve or remove their turf altogether. The effectiveness of the harm reduction approach with the smart irrigation controller as the alternative solution in focus thus depends on (1) who responds to the adoption incentives, (2) how the device affects water consumption of the adopting households and (3) whether promotion of the alternative solution cannibalizes higher impact solutions.

We employ two sequential field experiments to evaluate the effectiveness of heavily promoting an efficiency device such as the smart irrigation controller as the harm reducing alternative. We show that our marketing interventions induce the highest adoption among the heaviest irrigators and those previously disinclined to conserve. The interventions, in turn, lead to significant reductions in water usage, driven by the heaviest irrigators without a corresponding increase among the non-irrigator households. We find no evidence that treated households forgo turf removal, the highest impact alternative in our context, suggesting that the harm reduction approach expands rather than cannibalizes engagement in conservation.

Overall, our results showcase the importance of considering heterogeneous preferences in designing interventions aimed at fostering pro-social behaviors. Even when the prevailing consensus recognizes full abstinence as the best social outcome, disproportionate focus on the highest impact solution inherently excludes those deriving most value from the socially undesirable behavior; i.e., those who have the potential to make a large impact towards the pro-social goal. A harm reduction approach, on the other

[47] This is because consumers with previously green lawns continue to water fully after the adoption of the smart irrigation controller; i.e., because $\kappa\gamma > \overline{w}A(\theta c + \eta p)$, it must be that $\kappa\gamma > \underline{w}A(\theta c + \eta p)$.

[48] Although the measured effects on the PSAV and greenness outcomes are small relative to the median values, we might still be concerned that insignificance of these effects reflects the inherent noise in these measures rather than a null effect of the intervention. In Table 18, we show that changes in PSAV and percent green PSAV measures are associated with changes in water consumption between 2016 and 2018, giving additional evidence that PSAV measures are meaningful and the null effect is unlikely to be due to noise.

hand, can help engage the least pro-socially inclined who would otherwise not contribute towards the pro-social goal.

It is important to recognize that different timing of the harm reduction intervention may lead to different results. By delaying public promotion until after the 2011-2017 drought conditions had already started to improve, those willing to comply with the government's preferred alternatives did so before being introduced to a device that might have cannibalized more socially beneficial choices. In fact, the delayed (relative to peak of the drought) promotion of the device allowed us the opportunity to find that adoption was highest among those who were already reverting toward past consumption behavior before the drought was declared over.

A common note of caution about interventions such as ours is that they could substitute for the adoption of later-developed solutions that better advance the social objective (Armitage (2022)). In our case, the preference alignment problems of the existing solutions such as turf removal make them poor substitutes for consumers with high preferences for green vegetation. While unknown future developments could both be more efficient and a good fit for these customers less aligned with the objective of reducing vegetation or other outputs of water use, acute needs for water conservation during drought can rationalize favoring current vs unknown future solutions.

Next, we might expect a more preference-aligned alternative to only require communications rather than monetary promotions. We therefore tested a range of price and installation discounts on the device and found that awareness alone was insufficient to deeply penetrate the consumer market beyond what might be organically adopted. Experimenting with such variables that are critical to adoption is important for guiding subsequent roll-out, but statistically, it may also be advantageous to test these incentives separately, up front, as we have done here. Since compliance may be very low if some adoption treatments are ineffective, it may be particularly challenging to achieve sufficient penetration to measure post-adoption outcomes such as conservation. We were able to use the insights from the first test of price and installation incentives to design an offer with much greater compliance that allowed us to measure the effects on water use.

We hope that the design and findings are helpful for future researchers confronting the challenges of social change and for decision-makers in the water industry and beyond. There are some caveats to the analysis. Our estimates of water reductions for devices specifically may be overstated because the communications campaign could have motivated other changes in behavior that we cannot quantify and separate from the effect attributed to the activation of devices. Further, if this utility were to offer smart controllers to more households now, conservation could be lower if households with the potential to gain the most from the devices already adopted during our experiments.

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8 Supplementary Figures

Figure 5: Prevalence of Drought in California 1985 to Present

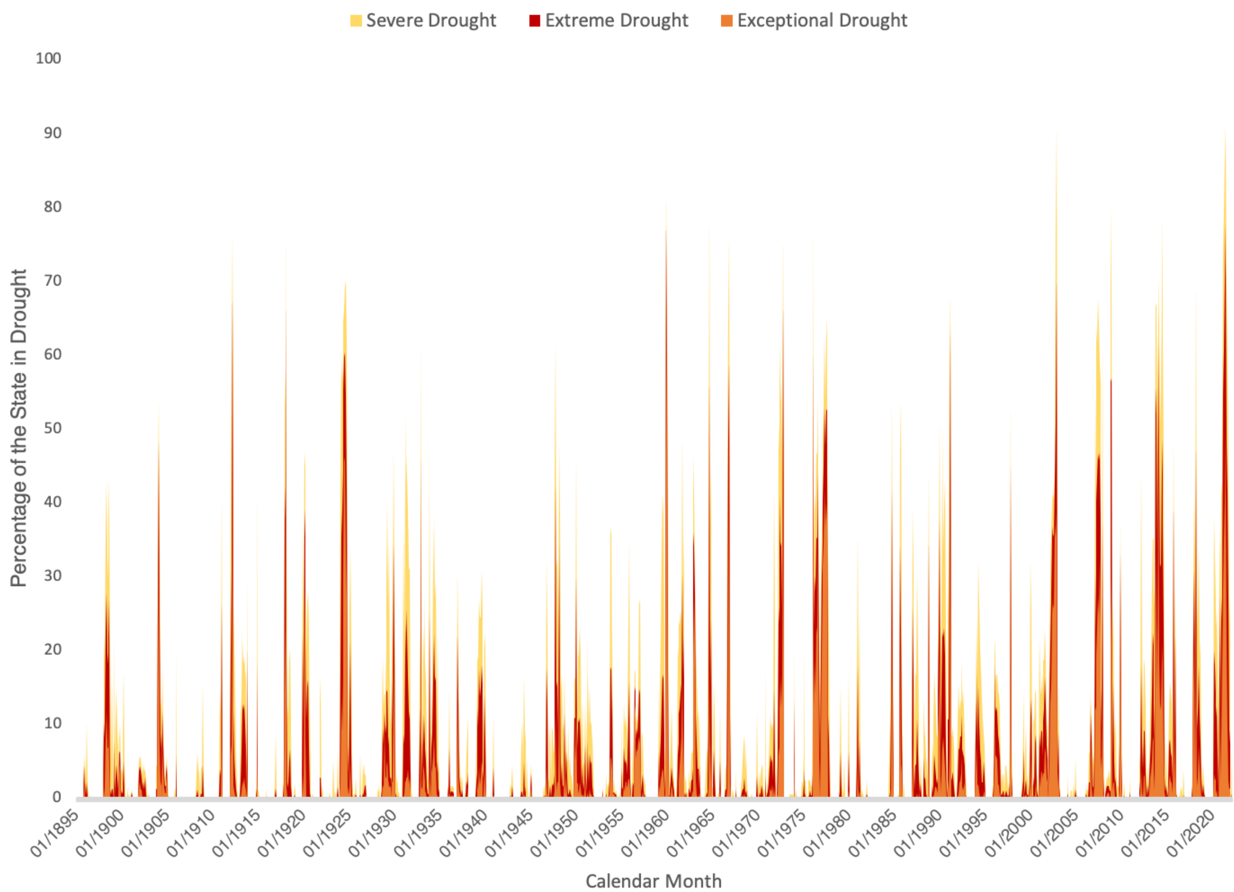
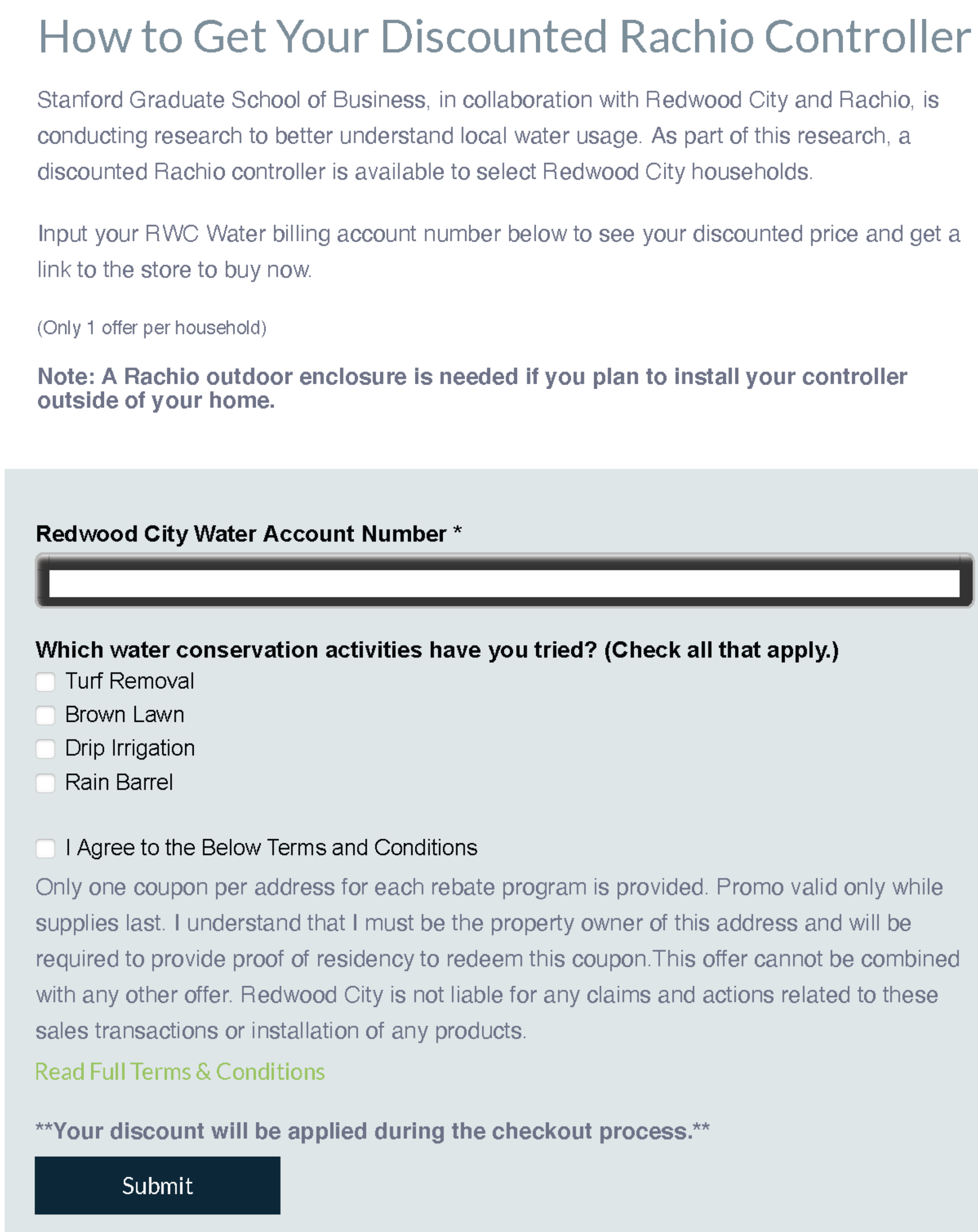


Figure 6: Redwood City Conservation Programs and Participation 2013-2015

Water Conservation Activities Dashboard

CITY CONSERVATION ACTIVITIES (5/31/16)	2016	2015	2014	2013
High Efficiency Toilet Rebates Issued	80	191	139	145
High Efficiency Clothes Washer Rebates Issued	62	231	384	487
Rain Barrel Rebates Issued	30	61	N/A	N/A
Free Sprinkler Nozzles	25	560	N/A	N/A
Lawn Be Gone [Square Ft. grass removed]	10,848	38,073	30,222	2,590
Conservation Kits and Fixture Giveaways	102	776	45	10
Outreach & Education Events	16	53	8	8
Drought Related Resident Requests Fulfilled	440	896	22	N/A
Water Audits Performed	0	13	18	26
School Education (students reached)	2,266	8,032	N/A	N/A

Figure 7: Rachio's Portal for Redwood City Public Works Account Holders



How to Get Your Discounted Rachio Controller

Stanford Graduate School of Business, in collaboration with Redwood City and Rachio, is conducting research to better understand local water usage. As part of this research, a discounted Rachio controller is available to select Redwood City households.

Input your RWC Water billing account number below to see your discounted price and get a link to the store to buy now.

(Only 1 offer per household)

Note: A Rachio outdoor enclosure is needed if you plan to install your controller outside of your home.

Redwood City Water Account Number *

Which water conservation activities have you tried? (Check all that apply.)

- Turf Removal
- Brown Lawn
- Drip Irrigation
- Rain Barrel

I Agree to the Below Terms and Conditions

Only one coupon per address for each rebate program is provided. Promo valid only while supplies last. I understand that I must be the property owner of this address and will be required to provide proof of residency to redeem this coupon.This offer cannot be combined with any other offer. Redwood City is not liable for any claims and actions related to these sales transactions or installation of any products.

Read Full Terms & Conditions

****Your discount will be applied during the checkout process.****

Submit

Figure 8: Email Notification for a Seasonal Shift in Irrigation Durations

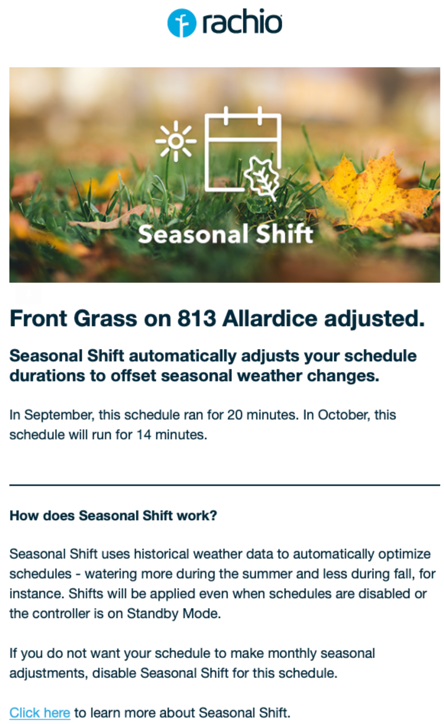
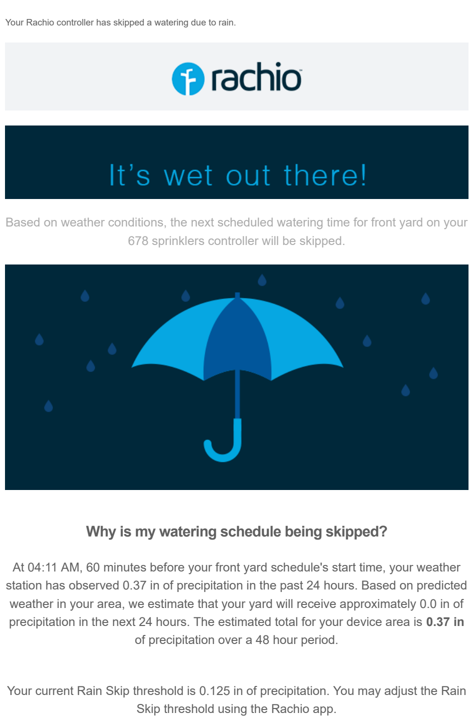
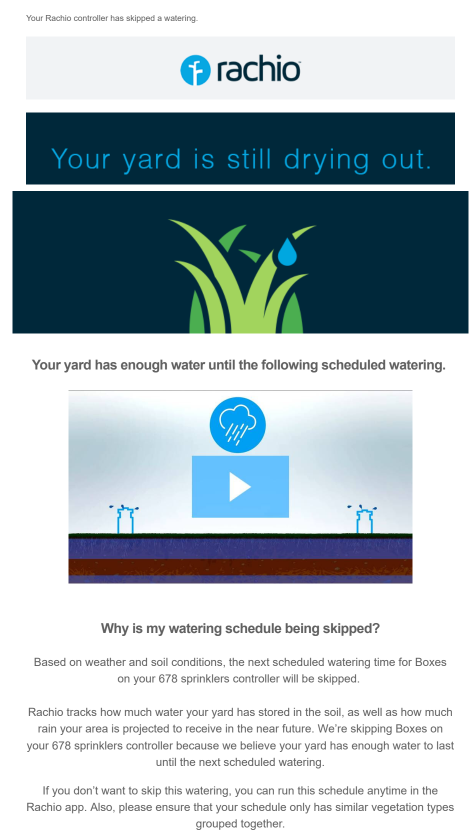


Figure 9: Email Notification of Schedule Skips



Rain Skip



Soil Saturation Skip

Figure 10: Treatment Group Post Card (Experiment 1)

Address Side

Message Side

Figure 11: Treatment Group Email (Experiment 1)

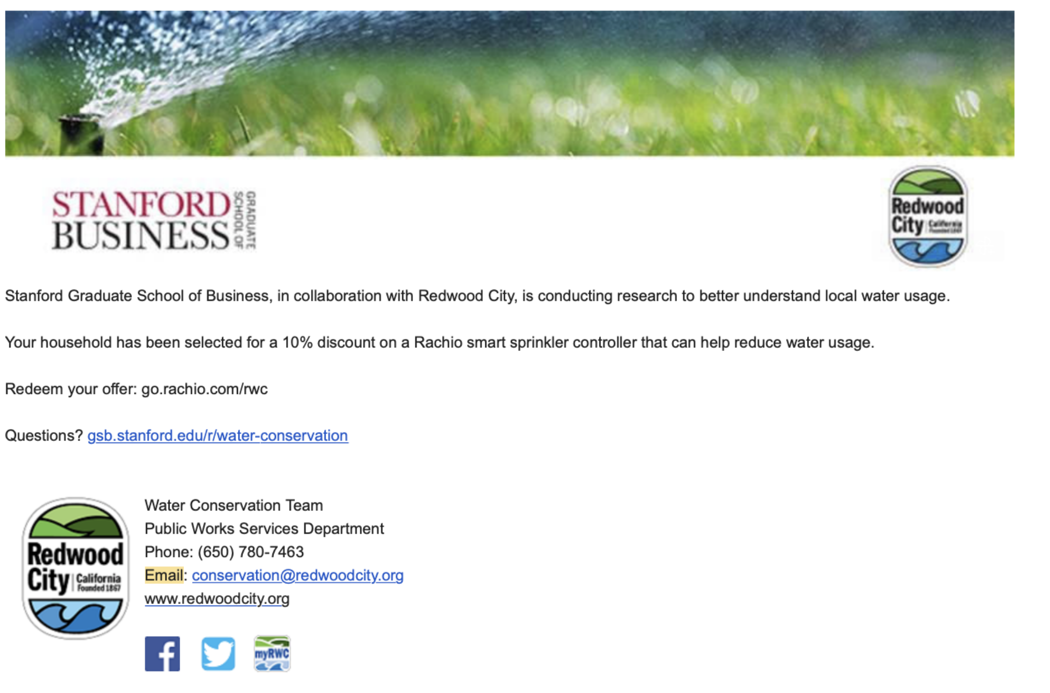
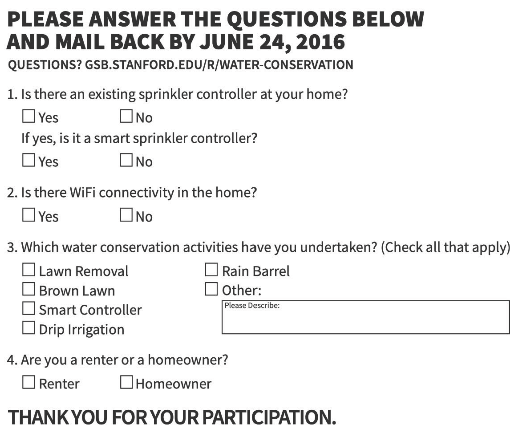


Figure 12: Control Group Communications (Experiment 1)

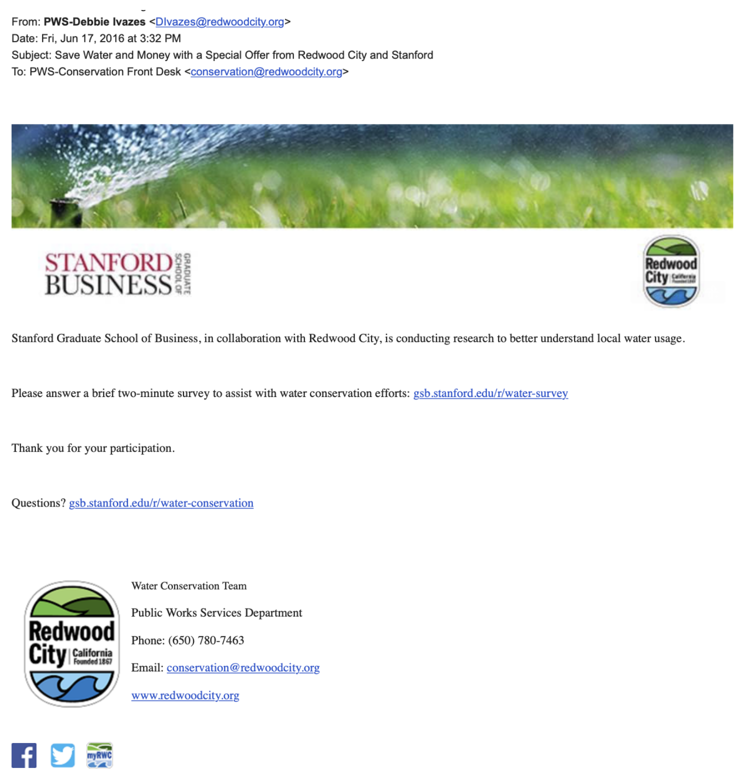


PLEASE ANSWER THE QUESTIONS BELOW AND MAIL BACK BY JUNE 24, 2016

QUESTIONS? GSB.STANFORD.EDU/R/WATER-CONSERVATION

1. Is there an existing sprinkler controller at your home?
   ☐ Yes ☐ No
   If yes, is it a smart sprinkler controller?
   ☐ Yes ☐ No
2. Is there WiFi connectivity in the home?
   ☐ Yes ☐ No
3. Which water conservation activities have you undertaken? (Check all that apply)
   ☐ Lawn Removal ☐ Rain Barrel
   ☐ Brown Lawn ☐ Other: Please Describe:
   ☐ Smart Controller
   ☐ Drip Irrigation
4. Are you a renter or a homeowner?
   ☐ Renter ☐ Homeowner

THANK YOU FOR YOUR PARTICIPATION.



From: **PWS-Debbie Ivazes** <DIvazes@redwoodcity.org>
Date: Fri, Jun 17, 2016 at 3:32 PM
Subject: Save Water and Money with a Special Offer from Redwood City and Stanford
To: PWS-Conservation Front Desk <conservation@redwoodcity.org>

STANFORD GRADUATE SCHOOL OF BUSINESS

Redwood City

Stanford Graduate School of Business, in collaboration with Redwood City, is conducting research to better understand local water usage.

Please answer a brief two-minute survey to assist with water conservation efforts: gsb.stanford.edu/r/water-survey

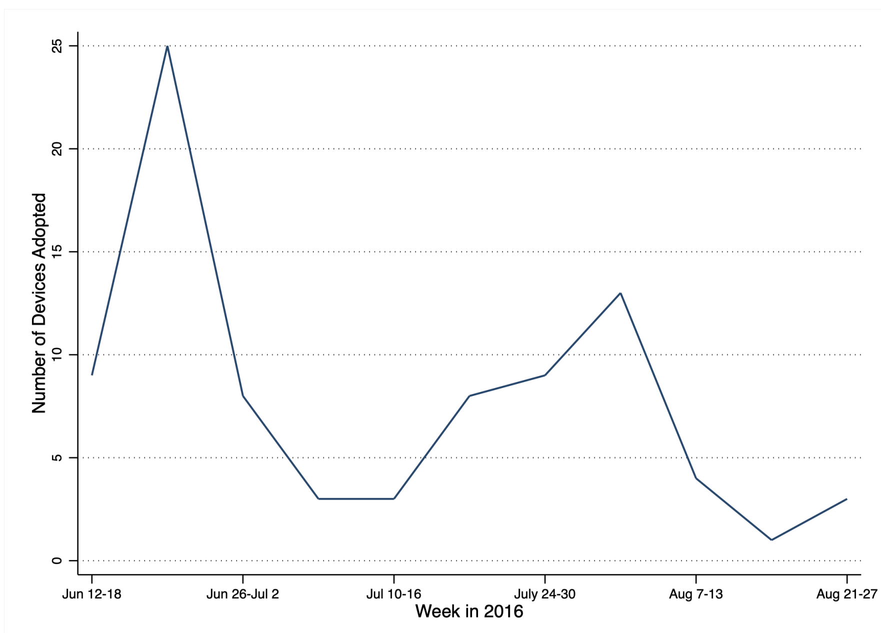
Thank you for your participation.

Questions? gsb.stanford.edu/r/water-conservation

Water Conservation Team
Public Works Services Department
Phone: (650) 780-7463
Email: conservation@redwoodcity.org
www.redwoodcity.org

Post Card Email

Figure 13: Within Experiment 1 Device Adoptions



The figure shows the week of purchase of the 86 smart irrigation controllers purchased via the dedicated portal in experiment 1.

Figure 14: Treatment Group Email (Experiment 2)

WATER UPDATE

Dear Redwood City Resident and Water User,

As a water user, you have signed up to receive communications from the City related to water use and other programs. The City and researchers at the Stanford Graduate School of Business have partnered together to launch a new program to identify new water saving technologies for residential irrigation.

The Stanford Graduate School of Business researchers work with Rachio to provide reliable smart sprinkler controllers and installation services.

Your neighborhood block has been selected for a pilot program to help save water and money on your water bills. We are offering you a Rachio Smart Sprinkler Controller for free!

Over 400 Redwood City residents trust their lawns to Rachio. With Rachio's smart sprinkler technology you can control your sprinklers from anywhere, have them shut off automatically before it rains, never forget to adjust watering times with automatic monthly updates, and save you up to 50% on your water bill!

With this limited time opportunity, receive a Rachio controller at absolutely no cost to you.

Don't forget to tell your neighbors - only 250 controllers are available through this special program. Discounted installation service is available, if needed.

Click here to claim your free controller!

Have questions? Contact the City of Redwood City Water Resources Management Division for more information at (650) 780-7436 or email them at conservation@redwoodcity.org.

For other Redwood City water conservation tips, tools and programs, go here.

9 Supplementary Tables

Table 10: Pre-Experiment 1 Characteristics by Treatment Status

	Control	Comparison By Treatment					Obs
		10% Disc	80% Disc	60% Disc	60% Disc + Install	F-Stat all=contr	
Year Prior to Exp 1							
Avg Bill Water Use	20.36***	-0.000210	0.0489	-0.0420	0.161	0.0464	48,861
	(0.287)	(0.444)	(0.464)	(0.409)	(0.491)	(0.996)	
Jan '07 - April '16							
Avg Bill Water Use	26.87***	0.212	-0.00388	-0.275	0.272	0.177	388,564
	(0.372)	(0.646)	(0.622)	(0.624)	(0.650)	(0.950)	
Jan '07 - April '16: Avg Bill Water Use							
Bill 1	18.74***	0.284	0.0501	0.230	0.535	0.291	69,305
	(0.317)	(0.507)	(0.451)	(0.592)	(0.556)	(0.884)	
Bill 2	18.20***	0.148	0.0832	0.156	0.417	0.164	69,352
	(0.299)	(0.488)	(0.442)	(0.538)	(0.525)	(0.957)	
Bill 3	28.21***	0.0420	0.287	-0.198	0.386	0.155	62,432
	(0.442)	(0.778)	(0.853)	(0.715)	(0.744)	(0.961)	
Bill 4	36.72***	0.205	-0.248	-0.889	0.0726	0.438	62,468
	(0.559)	(1.028)	(0.968)	(0.830)	(0.904)	(0.781)	
Bill 5	35.94***	0.292	-0.195	-0.962	-0.220	0.518	62,491
	(0.523)	(0.955)	(0.923)	(0.802)	(0.858)	(0.723)	
Bill 6	25.22***	0.314	-0.0000881	-0.0861	0.416	0.230	62,516
	(0.355)	(0.554)	(0.540)	(0.588)	(0.627)	(0.922)	
Rachio Adoption Rate							
Rate Prior to Exp 1	0.00211*	0.000754	0.0000502	-0.00140	-0.00211	1.228	7,000
	(0.00105)	(0.00149)	(0.00149)	(0.00149)	(0.00149)	(0.296)	

This table shows randomization checks for experiment 1 households. Bill numbers 1, 2, 3, 4, 5, 6 reflect water usage in the Nov-Dec, Jan-Feb, Mar-Apr, May-Jun, Jul-Aug, and Sep-Oct time periods, respectively. Standard errors in parentheses (clustered at household level for water usage variables). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Pre-Experiment 2 Characteristics by Treatment Status

	Control	Treatment	Obs
Year Prior to Exp 2			
Avg Bill Water Use	14.70***	0.305	112,097
	(0.114)	(0.236)	
Jan '07 - Oct '17			
Avg Bill Water Use	18.87***	0.0384	1,215,366
	(0.156)	(0.297)	
Jan '07 - Oct '17: Avg Bill Water Use			
Bill 1	13.25***	0.226	205,574
	(0.0821)	(0.163)	
Bill 2	12.77***	0.249	205,691
	(0.0889)	(0.179)	
Bill 3	19.19***	0.174	205,809
	(0.208)	(0.378)	
Bill 4	25.39***	-0.100	205,292
	(0.260)	(0.462)	
Bill 5	24.84***	-0.264	205,585
	(0.239)	(0.427)	
Bill 6	17.67***	-0.0781	187,415
	(0.125)	(0.241)	
Rachio Adoption Rate			
Rate Prior to Exp 2	0.00808***	-0.000942	19,129
	(0.000919)	(0.00126)	

This table shows randomization checks for experiment 2 households. Bill numbers 1, 2, 3, 4, 5, 6 reflect water usage in the Nov-Dec, Jan-Feb, Mar-Apr, May-Jun, Jul-Aug, and Sep-Oct time periods, respectively. Standard errors in parentheses (clustered at household level for water usage variables). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Water Consumption Summary by Summer to Winter Change Quantiles in Year Pre-Experiment

	Water Consumption: Mean / (SD) / 25^{th} percentile / 75^{th} percentile									
	Experiment 1					Experiment 2				
	All HH	Q1 HH	Q2 HH	Q3 HH	Q4 HH	All HH	Q1 HH	Q2 HH	Q3 HH	Q4 HH
Nov-Dec	14.69	17.44	14.82	12.69	13.59	10.05	10.91	9.22	9.70	10.73
	(12.24)	(13.31)	(10.04)	(9.54)	(14.66)	(8.67)	(11.04)	(6.28)	(6.65)	(9.93)
	9	12	10	8	7	5	5	5	5	6
	17	20	17	15	16	13	13	12	13	13
Jan-Feb	14.38	16.88	14.27	12.46	13.66	9.60	10.35	8.85	9.17	10.41
	(11.68)	(12.97)	(8.92)	(9.15)	(13.99)	(8.55)	(11.42)	(5.90)	(6.16)	(9.65)
	9	11	10	8	7	5	5	5	5	6
	17	19	17	15	16	12	13	12	12	13
Mar-Apr	20.29	19.22	17.81	18.50	25.73	14.37	9.99	10.58	13.80	24.29
	(15.37)	(13.56)	(9.84)	(11.48)	(22.28)	(12.98)	(9.82)	(6.89)	(7.86)	(18.96)
	13	13	13	12	14	7	5	6	9	13
	23	22	20	22	32	18	13	14	17	30
May-Jun	24.82	19.81	19.36	22.45	38.18	21.63	9.54	12.65	20.66	43.05
	(18.70)	(12.95)	(8.40)	(8.81)	(29.50)	(76.04)	(7.81)	(6.54)	(7.50)	(23.54)
	16	13	15	17	25	9	5	8	16	29
	28	22	22	26	43	27	12	16	25	50
Jul-Aug	25.93	19.57	20.15	23.96	40.66	20.80	9.18	12.58	20.75	42.16
	(18.33)	(12.44)	(8.83)	(9.12)	(27.52)	(21.63)	(8.16)	(6.40)	(7.31)	(33.24)
	16	13	15	19	27	9	5	8	16	29
	30	22	22	27	46	27	12	16	25	48
Sep-Oct	20.69	19.25	17.84	19.04	26.77	15.80	9.30	11.34	16.43	26.96
	(13.78)	(13.70)	(8.94)	(10.28)	(18.37)	(12.69)	(8.89)	(6.58)	(8.27)	(16.68)
	14	13	13	13	16	8	5	7	11	17
	23	21	20	22	32	20	12	15	20	33

This table shows the mean, standard deviation, 25^{th} percentile and 75^{th} percentile of water consumption by billing period for experiment 1 and experiment 2 households, overall and grouped by summer to winter water usage variation, in the year preceding the experiment. Change quantiles are formed by computing the the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2015 (exp 1) and 2017 (exp 2). Households with higher summer to winter change fall into higher quantiles. The year prior to experiment 1 spans May 2015 through April 2016. The year prior to experiment 2 spans Nov 2016 through Oct 2017.

Table 13: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp1)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2016	-0.553			-0.380	-0.134	0.483	0.186
	(1.410)			(0.407)	(0.401)	(0.340)	(0.237)
2017	-1.589	0.0841	-0.0487	-0.661	-0.710	0.400	0.00426
	(1.526)	(0.239)	(0.307)	(0.460)	(0.436)	(0.369)	(0.278)
2018	-1.766	-0.295	-0.0983	-0.857*	-0.588	0.390	0.273
	(1.679)	(0.261)	(0.339)	(0.474)	(0.490)	(0.391)	(0.274)
2019	0.0365	0.298	-0.0965	-0.0932	-0.515	0.511	0.0422
	(1.732)	(0.260)	(0.379)	(0.496)	(0.506)	(0.431)	(0.398)
2020	-0.983	-0.311	-0.116	-0.595	-0.473	0.672	-0.245
	(2.059)	(0.330)	(0.410)	(0.526)	(0.549)	(0.502)	(0.328)
2021	-1.077	-0.596*	0.357	-0.267	-0.652		
	(1.809)	(0.324)	(0.434)	(0.530)	(0.508)		
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	siteid	siteid	siteid	siteid	siteid	siteid	siteid
N	46,283	38,453	38,467	45,826	45,890	38,898	38,425

This table shows the effect of experiment 1 treatment (any of the 4 treatment arms) on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3). Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp1, Quantile 4 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2016	-4.116			-1.553	-1.138	0.267	0.339
	(4.148)			(1.275)	(1.344)	(0.847)	(0.528)
2017	-7.288*	0.175	-0.740	-2.871**	-1.703	0.124	0.476
	(4.300)	(0.502)	(0.883)	(1.357)	(1.352)	(0.903)	(0.628)
2018	-6.021	-0.442	0.0641	-1.754	-1.510	-0.109	0.839
	(4.526)	(0.627)	(0.958)	(1.334)	(1.557)	(0.983)	(0.573)
2019	2.211	0.701	0.743	0.489	-0.556	1.668	0.847
	(4.660)	(0.661)	(1.119)	(1.429)	(1.484)	(1.086)	(0.604)
2020	-3.567	-0.864	-0.0644	-1.493	-0.785	0.0271	0.479
	(5.609)	(0.821)	(1.148)	(1.512)	(1.636)	(1.385)	(0.738)
2021	-0.951	-1.149	1.031	0.208	-0.358		
	(5.087)	(0.801)	(1.197)	(1.496)	(1.494)		
HH FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	siteid	siteid	siteid	siteid	siteid	siteid	siteid
N	11,512	9,714	9,716	11,411	11,430	9,771	9,708

This table shows the effect of experiment 1 treatment (any of the 4 treatment arms) on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households with the highest summer to winter water consumption variation in 2015. Change quantiles are formed by computing the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2015. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp2, Quantile 1 Households)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						0.166
						(0.236)
2018	0.218	0.175	0.278	-0.0460	-0.242	-0.154
	(0.271)	(0.180)	(0.191)	(0.206)	(0.178)	(0.253)
2019	-0.0568	0.0998	0.208	0.249	-0.0766	-0.0559
	(0.285)	(0.211)	(0.235)	(0.261)	(0.200)	(0.246)
2020	0.0666	-0.0163	0.345	0.358	0.00276	0.00639
	(0.276)	(0.214)	(0.255)	(0.284)	(0.224)	(0.269)
2021	-0.00783	0.350	0.362	0.312		
	(0.306)	(0.267)	(0.298)	(0.334)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	22,566	22,551	22,543	22,548	18,050	22,571

This table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households with the lowest summer to winter water consumption variation in 2017. Change quantiles are formed by computing the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp2, Quantile 2 Households)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						0.0587
						(0.145)
2018	-0.246	0.149	-0.807	0.265	0.101	-0.0683
	(0.204)	(0.179)	(0.625)	(0.228)	(0.180)	(0.183)
2019	3.825	-0.0311	-0.171	-0.147	-0.147	-0.0180
	(3.659)	(0.222)	(0.269)	(0.318)	(0.240)	(0.186)
2020	0.0297	0.498*	0.166	0.0162	0.0458	0.0870
	(0.196)	(0.262)	(0.315)	(0.332)	(0.265)	(0.215)
2021	-0.0654	-0.00677	0.00179	0.205		
	(0.213)	(0.277)	(0.381)	(0.396)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	23,694	23,698	23,692	23,704	18,966	23,698

This table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for quantile 2 irrigator households. Change quantiles are formed by computing the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp2, Quantile 3 Households)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						0.184
						(0.201)
2018	0.0493	-0.263	0.131	0.0996	-0.255	0.212
	(0.197)	(0.243)	(0.330)	(0.255)	(0.273)	(0.236)
2019	0.337	0.0626	-0.113	-0.121	-0.158	0.0489
	(0.223)	(0.257)	(0.342)	(0.323)	(0.296)	(0.295)
2020	0.187	-0.0275	0.319	-0.156	-0.239	0.127
	(0.220)	(0.293)	(0.343)	(0.389)	(0.358)	(0.274)
2021	0.180	-0.211	0.00160	0.484		
	(0.250)	(0.356)	(0.437)	(0.401)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	21,613	21,615	21,609	21,613	17,297	21,614

This table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for quantile 3 irrigator households. Change quantiles are formed by computing the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Correlation between 2016 to 2018 Change in PSAV & Change in Consumption

	Change in Annual Consumption			Change in Jul-Aug Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Cons	Δ Cons	Δ Cons	Δ Cons	Δ Cons	Δ Cons
Δ PSAV	0.00660***		0.00641***	0.00120***		0.00115***
	(0.000720)		(0.000721)	(0.000191)		(0.000191)
Δ % Green		34.30***	29.32***		8.576***	7.681***
		(7.932)	(7.917)		(2.085)	(2.086)
N	8,693	8,693	8,693	8,943	8,943	8,943

This table shows the result of a first-differences regression of 2016 to 2018 change in PSAV and share PSAV greenness measures on 2016 to 2018 change in annual (columns 1-3) and July-August (columns 4-6) water consumption for households with above-median irrigable area. PSAV and % Green PSAV measures are based on National Agricultural Imagery Program (NAIP) multispectral satellite imagery of Redwood City parcels and the California Irrigable Landscape Algorithm (CILA) classification thereof. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Data Description Appendix

The data used in the empirical analysis come primarily from four sources. The first data set contains Redwood City Public Works household account and water billing data from January 2007 to August 2021. Most households within the RWCPW service area receive bi-monthly bills for their water consumption. Thus, we analyze water usage at the account-year-bill level. Bill numbers 1, 2, 3, 4, 5, 6 reflect water usage in the Nov-Dec, Jan-Feb, Mar-Apr, May-Jun, Jul-Aug, and Sep-Oct time periods, respectively. Columns 1 and 6 in Table 12 show the variation in water consumption across bill periods for experiment 1 and experiment 2 households, respectively, in the year prior to each experiment. Our main specifications use 2017-2021 water consumption data, and some of the robustness checks incorporate water consumption data from 2007 onward.

The second data set is generated from the two experiments described in Section 3. This data set records all the Rachio devices adopted within the two experiments through the dedicated portals. All within-experiment adoptions can be linked directly to the RWCPW account because an account number is required in order to redeem all device and professional installation discount offers.

The third data set contains 9 snapshots of all active Rachio devices in the RWCPW service area from 2015 through 2020: September 2015, February 2016, August 2016, October 2016, March 2017, September 2017, October 2018, December 2018, February 2020. Within this panel, we identify all the devices that were adopted as a result of the two experiments and match the organically adopted devices to the RWCPW accounts via common data fields. Thus, in the account-year-bill panel, we can identify accounts which adopted a device within each of the experiments or activated a device organically as well as the date of adoption or activation. From these data, we create an indicator of device adoption or activation in the year following each experiment, which is the primary variable used in the adoption and local average treatment effects analyses.

The fourth data set used in our empirical analysis tracks two snapshots (August 2016 and August 2018) of photosynthetically active vegetation (PSAV) and percentage of this vegetation that is green (% green) for each parcel in the RWCPW service area. The PSAV and share green vegetation measures are generated from National Agricultural Imagery Program (NAIP) multispectral satellite imagery data using the proprietary California Irrigable Landscape Algorithm (CILA) (Quesnel et al. (2019)). We use publicly available data on parcels in San Mateo county[49] to match the Redwood City accounts to parcel photosynthetically active vegetation and greenness data via common data fields. Although 93% of all accounts in our study can be matched, for our analysis we use above-median PSAV households because (1) CILA classification accuracy is higher for larger areas and (2) we note from initial analysis that in both years mean water use is significantly increasing across above-median deciles of PSAV parcels, but not across below-median deciles of PSAV parcels. We interpret this observation as indicative that PSAV

[49] https://www.smcgov.org/isd/gis-data-download

measures are more reliable and less noisy for parcels of above-median size.

B Illustrative Model

In this section, we first present an illustrative model integrating preferences for scarce resource consumption and conservation. We then discuss the implications of the model on the effectiveness of non-regulatory incentives of promoting more socially aligned conservation behavior.

Let W represent a consumable resource, for which the price system does not efficiently align supply and demand. W produces a good g, over which the consumer has utility. In the present context, W represents water and g represents the size of a green landscape. In a different context, W might represent gas or electricity and g internal temperature in the home or other outputs of energy consumption. Let $h(W, p)$ be household expenditures arising from the amount of the resource used and the price schedule, p. Finally, let c represent the social costs of the resource beyond the price the consumer pays.

The following is an additively separable utility function in these components, with $\gamma \ln g$ specifying the benefits of consumption, η representing the marginal utility of income and $-\theta$ a preference for conservation or, more precisely, the disutility of the added social costs of consumption:

$$u = \gamma \ln g(W) - \theta c W - \eta h(W, p) \tag{B.1}$$

To stylize the production function to our example of water use, define the area to be irrigated as A, and the greenness of that area to be determined by the ratio of water used relative to water needed per unit of the area, i.e. $g = \left(A\left(\frac{w}{\overline{w}}\right)^{\kappa}\right)$, with κ representing the relative weighting of the greenness to the size of the irrigable area A in producing a desirable landscape, and total water consumption $W = wA$. Assuming a linear price schedule, we then obtain:

$$u = \gamma \ln \left(A\left(\frac{w}{\overline{w}}\right)^{\kappa}\right) - wA(\theta c + \eta p) \tag{B.2}$$

We constrain the consumption of the resource to be $0 \leq w \leq \overline{w}$. In other words, consuming w at the threshold produces a fully green lawn and there are no additional returns to watering above $\overline{w}$. On the other hand, consuming below the threshold produces a brown lawn, and the consumer has room to improve the greenness of the landscape $\frac{w}{\overline{w}}$ by watering closer to $\overline{w}$. We further constrain $\kappa > 1$; i.e., all residential consumers ascribe at least a somewhat higher importance to landscape greenness relative to the (photosynthetically active) landscape area that may otherwise be a brown lawn.

Given this utility function, the optimal (interior) consumption of w is given by:

$$w^* = \frac{\kappa\gamma}{A(\theta c + \eta p)} \tag{B.3}$$

B.1 Brown Lawn ($w^* \leq \overline{w}$)

Given the constraint on resource consumption w, consumers fall below the corner solution of a fully green lawn to some degree of brownness ($w^* < \overline{w}$) if:

$$\gamma\kappa < \overline{w}A(\theta c + \eta p) \tag{B.4}$$

That is, brown lawns arise when consumers have relatively low preferences for aesthetics (γ and the relative weighting of landscape greenness κ) and/or high preferences for conservation θ and price sensitivity η. Consumers with larger irrigable areas, A, are also more prone to brown the lawn; however, it is worth noting that optimal choice of A is increasing in γ: ($A^* = \frac{\gamma}{w(\theta c+\eta p)}$). That is, if consumers were choosing the size of their irrigable landscape optimally, larger A would be associated with larger preferences of aesthetics γ and smaller preferences for conservation θ and and price sensitivity η.

In the short run, messaging (as is common during droughts) can inform consumers of an increased social cost of water c and, thus, shift previously unwilling consumers to let their lawn go brown. Of the set of consumers who are watering fully, however, it is those with relatively low γ and high θ and η that will be convinced by this type of messaging. Such actions are typically temporary because it is practically cost-less to revert to higher consumption levels once the drought is over and conservation issues appear less pressing.

In the long run, changes to preferences for green vegetation aesthetics, preferences for conservation or price sensitivity are necessary to shift consumers more permanently towards brown lawns.

B.2 Turf Removal (A')

One common proposal aimed at long-run conservation is to encourage consumers to reduce the size of their photosynthetically active landscape to ultimately achieve irrigable area $A' < A$. A consumer will uptake this solution if the gain in utility outweighs the cost of turf removal F_A:

$$u(w^{*\prime}|A') - u(w^*|A) > F_A \tag{B.5}$$

We further decompose the change in utility $u(w^{*\prime}|A') - u(w^*|A)$ caused by removing turf into (1) a change in landscape aesthetics utility and (2) a change in monetary and social costs disutility. In column 1 of Table B.1, we examine the effect of turf removal on the aesthetics utility and change in water usage, which can further be translated to the change in monetary and social costs disutility by multiplying by $(\theta c + \eta p)$. We do so for three groups of consumers: (1) those who maintain green lawns before and after turf removal[50], (2) those who had brown lawns prior to removal, but water the reduced

[50]Note that consumers who had green lawns before removing turf would necessarily continue to maintain green lawns after turf removal because for these consumers $\gamma\kappa > \overline{w}A(\theta c + \eta p)$ and, thus, $\gamma\kappa > \overline{w}A'(\theta c + \eta p)$, since $A' < A$.

Table B.1: Effect of Turf Removal and Smart Controller on Consumer Utility and Water Usage

	Turf Removal	Smart Controller
Green Before and After (Non-Conservers)		
Δ Aesthetics u	$\gamma \ln(\frac{A'}{A}) < 0$	None ($\frac{w^*}{\overline{w}} = \frac{w^{*\prime}}{\underline{w}} = 1$)
Δ Water Use	$\overline{w}(A' - A) < 0$	$(\underline{w} - \overline{w})A < 0$
Brown Before, Green After (Conservers to Fully Green)		
Δ Aesthetics u	$\gamma\left(\ln(\frac{A'}{A}) - \kappa \ln(\frac{w^*}{\overline{w}})\right) \lesseqgtr 0$	$-\gamma\kappa \ln(\frac{w^*}{\overline{w}}) > 0$
Δ Water Use	$(\overline{w}A' - w^*A) < 0$	$(\underline{w} - w^*)A < 0$
Brown Before and After (Conservers)		
Δ Aesthetics u	$\gamma\left(\ln(\frac{A'}{A}) + \kappa \ln(\frac{w^{*\prime}}{w^*})\right) \lesseqgtr 0$	$\gamma\kappa \ln(\frac{\overline{w}}{\underline{w}}) > 0$
Δ Water Use	None ($w^{*\prime}A' = w^*A$)	None ($w^{*\prime} = w^* < \underline{w} < \overline{w}$)

This table presents the change in aesthetics utility and total water usage induced by two possible long-run solutions: removing turf and adopting a smart irrigation controller. Because of the differing effects, we present these changes separately for consumers who (1) maintain green lawns before and after solution adoption, (2) have brown lawns before solution adoption and green lawns afterwards and (3) consumers who maintain brown lawns before and after solution adoption.

photosynthetically active area fully and (3) those who continue to maintain brown lawns after turf removal.

Several observations emerge. First, the water conservation potential with turf removal is highest for non-conservers who value green lawns (because $\overline{w}(A' - A) < (\overline{w}A' - w^*A) < 0$); however, for these same consumers, turf removal entails an aesthetics utility trade-off ($\gamma \ln(\frac{A'}{A}) < 0$). On the other hand, consumers who organically let their lawns go brown have lower water conservation potential with turf removal, but may even experience an improvement in their aesthetics utility if their valuation of green landscape is sufficiently high (i.e, they water their reduced turf area more and thereby enjoy a smaller, but fully green landscape).

Monetary incentives can further lower F_A, thus, making the turf removal solution more appealing to consumers with higher potential for conservation. Importantly, any monetary incentives have to be sufficiently large to overcome the preference for aesthetics γ. In particular, consumers for whom $\gamma \ln\left(\frac{A}{A'}\right) > \overline{w}(\theta c + \eta p)(A - A')$ will only adopt if they are paid a subsidy beyond F_A to remove turf area.

B.3 Smart Irrigation Controller ($\underline{w}$)

Another solution with long-run water conservation potential is smart irrigation technology $\underline{w} < \overline{w}$, which improves the efficiency of watering and, thus, requires less water to achieve full landscape greenness. A consumer will uptake the solution if the gain in utility outweighs the cost of adopting F_W:

$$u(w^{*\prime}|\underline{w}) - u(w^*|\overline{w}) > F_W \tag{B.6}$$

As before, we further decompose $u(w^{*\prime}|\underline{w}) - u(w^*|\overline{w})$ into (1) a change in landscape aesthetics utility and (2) a change in monetary and social costs disutility. In column 2 of Table B.1, we present the effect of smart irrigation controller adoption on the aesthetics utility and change in water usage.

As with turf removal, smart irrigation technology presents the highest potential for water conservation for consumers who choose green lawns (because $(\underline{w} - \overline{w})A < (\underline{w} - w^*)A < 0$). Unlike with turf removal, however, smart irrigation controller adoption does not require these consumers to trade-off their preference for green landscapes against water conserved. In fact, these consumers see no change in their aesthetics utility in addition to gaining the savings from reduced usage.

As in the turf removal case, consumers who organically let their lawns go brown have lower water conservation potential with smart irrigation technology. Moreover, these consumers see aesthetic gains upon adoption of the device because it allows them to maintain a greener lawn for the same level of water usage. Thus, of those with brown lawns at the baseline, consumers with higher aesthetic preferences may choose to adopt the smart irrigation controller organically.

Importantly, unlike the brown lawn and turf removal options, the decision to adopt the irrigation controller no longer involves a trade-off with the preference for aesthetics γ, and can provide an increase in aesthetic utility for those with brown lawns at baseline because of the lower threshold to reach a green lawn. This makes it appealing to consumers with high preferences for aesthetics who also care about conservation[51][52]. While such consumers may prefer to continue to water fully rather than remove their turf or let their lawn go brown, they may instead be willing to adopt the technology $\underline{w}$ that would allow them to water more efficiently. Finally, assuming all consumers have at least some price sensitivity, there are no consumers who would need to be paid a subsidy to adopt such a technology unless F_W also includes non-pecuniary costs of adoption.

[51] Note that because optimal irrigable area A^* is increasing in γ, it is possible that γ additionally enters this condition indirectly through A. In our context, we treat A as endowed rather than an outcome of optimization. This is because, while the irrigable area size (as distinct from overall outdoor square footage) is an important input, it is only one of the factors that enters the decision to purchase a home. This is particularly true in competitive housing markets like Redwood City, where the buyers are more likely to compromise on such features.

[52] It is also worth noting that the "smart" features of the irrigation controller might be particularly appealing to those interested in Internet of Things (IOT) technologies (e.g., Nest smart thermostat). For these consumers, F_W could be particularly low or even negative, making adoption more likely even for lower irrigable areas, conservation preferences or price sensitivity.

B.4 Discussion and Empirical Motivation

As we detail in Section 3, our experimental manipulation involves varying the incentives to adopt a smart irrigation technology. In this sub-section, we consider the effect of the incentives on adoption behavior and water usage in the context of the model and form empirical predictions to be tested in Sections 4, 5 and 6.

For the purposes of this discussion and most of the empirical analysis, we treat the level of landscape greenness as unobserved. That is, in our main data set, we do not observe whether a consumer maintains a green or brown lawn prior to the experiment. We later supplement our empirical analysis with satellite data on irrigable area and landscape greenness for a portion of the observed households to more directly test for changes in irrigable area and its greenness.

B.4.1 Heterogeneity in Adoption Rates

As given by the condition on preferences and irrigable area A in equation B.4, consumers with brown lawns have relatively low preferences for aesthetics γ or κ and / or relatively high preferences for conservation θ and price sensitivity η. Due to the restrictions on pricing in our context (discussed in more detail in Section 2), we focus only on the aesthetics and conservation preferences in what follows.

Thus, if for a given level of monetary incentive $\tilde{F}_W$ technology adoption rates are increasing in irrigable area and preference for conservation, we can infer a higher uptake among those previously under-watering ("Conservers" and "Conservers to Fully Green" in Table B.1). On the other hand, adoption rates increasing in preference for lawn aesthetics γ or κ would likely indicate adoption by those maintaining green lawns ("Non-Conservers" in Table B.1).

To test for adoption by these different household types in our empirical analysis in Section 4, we characterize consumers by their likely irrigable area and propensity to conserve. We then examine heterogeneity in incentive responsiveness to determine whether response comes mainly from consumers watering fully or under-watering at the baseline.

B.4.2 Effect of Adoption on Water Usage

In the following paragraphs we focus on outlining the possible effects of the experimental intervention on total water usage wA. We show that the largest potential for water reduction resulting from smart irrigation controller adoption incentives comes from consumers who are watering fully at the baseline; however, any water reductions could be dampened and even reversed if the monetary incentives to adopt the smart irrigation controller significantly lower the probability of turf removal uptake among these consumers.

Among the consumers who chose brown lawns, water reduction potential depends on whether the consumer would continue to under-water after adopting the device. Those consumers whose optimal watering level is below the technology threshold will see no water savings from adopting the device, while those for whom the device can improve production of greenness will conserve water with the device. On the other hand, if consumers who under-water at the baseline have an incorrect understanding of their watering needs or if the device increases their usage above their optimum, the monetary incentives to adopt the smart irrigation controller will increase water usage among these consumers[53].

Direct Effect, Full Information As shown in Table B.1, adoption of the device should lead to the maximum decrease in total water usage among those who have green lawns before technology adoption. This is because consumers who water fully without the device continue to do so with the device with greater efficiency. Thus, consumers save a maximum $\underline{w}A - \overline{w}A$ units of water. On the other hand, the model predicts those under-watering prior to adoption will have smaller or no change in water usage depending on whether the technology reduces watering needs below their previous watering level or leaves them with the same watering but at a higher level of greenness.

Thus, any observed decrease in water usage due to the technology adoption incentives has to come from consumers who are watering fully after device adoption. Moreover, higher rates of adoption among consumers who were previously watering fully lead to higher overall water reductions.

Substitution from Turf Removal Consumers with green lawns have the highest potential to reduce water consumption with a smart irrigation controller, these same consumers also have the highest potential to reduce consumption by removing turf. Thus, one potential indirect effect of adopting a smart controller is substitution away from turf removal. We focus on consumers who water fully at the baseline, where this potential loss is the largest.

Let's assume that total usage without either solution is the highest, followed by total usage with the smart controller and total usage when turf is removed; i.e., $\overline{w}A > \underline{w}A > \overline{w}A'$. Let $\mathbb{P}[a_W|\tilde{F}_W]$ and $\mathbb{P}[a_W|F_W]$ represent the probability of adopting the smart irrigation controller when the price of the controller is $\tilde{F}_W$, and F_W, respectively, and $\mathbb{P}[a_A|\tilde{F}_W]$ and $\mathbb{P}[a_A|F_W]$ represent the probability of tearing out turf when the price of the controller is $\tilde{F}_W$, and F_W, respectively.

By offering a smart controller adoption incentive $\tilde{F}_W$, we increase the probability of smart controller adoption relative to continued full consumption and turf removal. If the incentive draws more from those who would have otherwise removed turf, we will see two effects: (1) decrease in probability of turf removal in the treatment group ($\mathbb{P}[a_A|\tilde{F}_W] - \mathbb{P}[a_A|F_W] < 0$), leading to larger irrigable areas in the treatment group and (2) if the effect on probability of turf removal is sufficiently high, an increase in water usage in the treated group. To see this second point, we can write the total effect of incentives on water savings (including substitution from turf removal) as:

[53]This undesired effect of adoption incentives on the consumption of those previously under-watering is similar in spirit to the boomerang effect described in Allcott (2011), albeit in the context of solution adoption incentives rather than messaging interventions. As in the present work, Allcott (2011) finds no boomerang effect on low users.

$$\left(\mathbb{P}[a_W|\tilde{F}_W] - \mathbb{P}[a_W|F_W]\right)(\overline{w} - \underline{w})A + \left(\mathbb{P}[a_A|\tilde{F}_W] - \mathbb{P}[a_A|F_W]\right)\overline{w}(A - A') \tag{B.7}$$

The first term is necessarily positive due to own price-sensitivity, leading to water reductions. The second term is negative if $\mathbb{P}[a_A|\tilde{F}_W] - \mathbb{P}[a_A|F_W] < 0$ as described above. Moreover, small decreases in probability of turf removal will lead to disproportionately large increases in water usage (alternatively, large decreases in water savings) because $(\overline{w} - \underline{w})A < \overline{w}(A - A')$.

Thus, to test for meaningful substitution away from turf removal, we examine the change in square footage of irrigable area as well as the overall water consumption change.

Incorrect Understanding of Watering Needs The goal of the smart controller is to achieve full greenness of the landscape with greater efficiency. As a result, with incorrect understanding of watering needs, adoption of the smart irrigation controller could increase water consumption for consumers who desire full greenness (see Allcott (2016) for a discussion of consumer "mistakes" arising from biased beliefs in the context of energy efficiency).

To see this, assume that a consumer who is currently under-watering believes that the baseline technology helps achieve full greenness with $\tilde{\overline{w}} = \zeta\overline{w} < \overline{w}$ and the smart irrigation controller lowers this required amount to $\tilde{\underline{w}} = \zeta\underline{w} < \underline{w}$. If this belief is sufficiently incorrect, such that $\zeta\overline{w} < \underline{w}$, adoption of the smart irrigation controller would lead to an increase of $A\overline{w} - A\zeta\underline{w}$ in total water usage.

While this scenario may be less likely in applications where the smart controller leads to immediately observable effects (e.g., temperature in a home), it may be more likely in contexts, such as ours, where the effect of the input (water) on the outcome (e.g., aesthetics of the lawn) accumulates over time and is only apparent when the consumer is outdoors.

To test for this undesirable effect on water usage, we consider the effect of incentives on consumers who are likely to have been under-watering prior to the intervention.

Inattention to Sub-Optimally High Watering Finally, because the smart irrigation controller is a convenience-enhancing device, it can alter usage to sub-optimal levels due to consumer inattention after installation (as in Allcott (2016), consumers can be exogenously inattentive or endogenously inattentive to attributes which they perceive to matter less.). This is particularly relevant for consumers under-watering at the baseline for whom under-watering is optimal even upon adoption of the device ($w^{*\prime} < \underline{w}$). If these consumers install the device, but do not pay attention to the ultimate watering levels, the device may increase their usage to $\underline{w}$. As a result, the adoption of the smart irrigation controller would lead to an increase of $A(\underline{w} - w^{*\prime})$ in total water usage. It is worth noting that such controller-caused over-consumption is likely to be a short-run rather than long-run outcome, which is likely to erode once the consumer receives sufficiently many high water bills or observes the lawn greener than intended.

As before, to test for this undesirable effect on water usage, we consider the effect of incentives on consumers who are likely to have been under-watering prior to the intervention. To additionally test for this likely shorter-run effect, we examine change in water usage over time.

O Online Appendix

O.1 Randomization and Stratification in Experiment 1

We stratified our randomization in two dimensions. First, we created four groups of households based on (1) whether or not they had an email on file with the water agency and (2) whether or not their residence had a smart-meter, which allows the customer to log into an online portal to view historical water consumption at the hourly level[54]. Second, we stratified customers based on water usage. Specifically, we created matched groups with two members per treatment arm (i.e., group size was 10 with 2 households in the control group and 2 in each of the four treatment arms). This approach would allow each group to be analyzed as a separate experiment where a mean and variance for each outcome could be measured. Then statistical power would come from pooling across these experiments.

Ultimately, we choose to ignore this stratification in calculating the standard errors for two reasons: (1) the statistical power in evaluating the treatment effects on adoption is sufficiently strong without exploiting the tight within group variances and (2) an execution error at the portal led to early visitors being randomly re-assigned to a treatment, such that neither the small grouping nor the aggregate sample is perfectly balanced across treatments. That is, 7,000 accounts were initially divided into 5 groups of 1,400; however, with the random reassignments, the size of treatment and control groups varies from as few as 1,388 to 1,416.

The sample size of 7,000 was initially chosen to retain a random group of households that would neither be assigned to control or treatment. For instance, these excluded households could be exposed in the second experiment without having ever received a control or treatment communication from the first experiment. A total of 9,590 households had water consumption potentially consistent with irrigation (i.e., we followed our partners suggestion of using an average of 12 units), and we randomly selected 73 percent of the small groupings from each of the 4 larger stratification criteria to form the final sample of 7,000.

O.2 Specifications without Household Street Fixed Effects

In Tables O.1 and O.2 we report coefficient estimates of two other variations on our main intent-to-treat specification in equation 3: (1) $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + \varepsilon_{it}$, using only post-experiment 2 data, where $y \in \{2018, 2019, 2020, 2021\}$ and no household street fixed effects (ξ_i) (see Table O.1) and (2) $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + X_{it} + \varepsilon_{it}$, where specification is as in (1), but with additional controls X_{it} for all past water consumption (2007-2016) in the same billing period (see Table O.2). The results are similar to the main specification but more noisy in both these alternate specifications.

[54]Households without smart-meters can only observe their consumption at the level of a billing period, which is typically two months long and determined based on when an employee of the water district manually reads the meter.

Table O.1: Treatment Effect on Water Usage By Bill Period and Year (Exp2, No Usage Controls)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						0.240
						(0.275)
2018	0.179	0.0271	-0.371	-0.298	-0.305	0.0796
	(0.250)	(0.598)	(0.884)	(0.820)	(0.540)	(0.236)
2019	1.260	-0.00393	-0.271	-0.526	-0.312	0.143
	(0.950)	(0.568)	(0.849)	(0.872)	(0.619)	(0.271)
2020	0.0659	0.0889	-0.205	-0.234	-0.230	0.0750
	(0.361)	(0.677)	(0.925)	(0.907)	(0.654)	(0.302)
2021	0.0870	-0.162	-0.269	-0.196		
	(0.356)	(0.701)	(0.896)	(0.832)		
Clustering	street	street	street	street	street	street
N	75,821	75,883	75,958	76,048	57,062	75,747

This table shows coefficient estimates of an alternative specification to that in equation 3: $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + \varepsilon_{it}$, using only post-experiment 2 data, where $y \in \{2018, 2019, 2020, 2021\}$ and no household street fixed effects (ξ_i). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.2: Treatment Effect on Water Usage By Bill Period and Year (Exp2, Usage Controls)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						0.206
						(0.155)
2018	0.0875	-0.0657	-0.0791	-0.126	-0.321	0.0410
	(0.134)	(0.154)	(0.344)	(0.207)	(0.269)	(0.132)
2019	1.207	-0.0424	0.133	-0.326	-0.305	0.0742
	(1.018)	(0.142)	(0.291)	(0.249)	(0.331)	(0.160)
2020	-0.0765	0.0467	0.134	-0.0433	-0.216	0.0719
	(0.223)	(0.234)	(0.366)	(0.287)	(0.374)	(0.192)
2021	-0.0161	-0.194	0.143	0.123		
	(0.212)	(0.287)	(0.377)	(0.285)		
Usage Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	69,962	70,152	68,393	68,947	53,710	69,714

This table shows coefficient estimates of an alternative specification to that in equation 3: $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + X_{it} + \varepsilon_{it}$, where specification is as in Table O.1, but with additional controls X_{it} for all past water consumption (2007-2016) in the same billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

O.3 Robustness to Alternative Definitions of Irrigation and Conservation Motivation

In this sub-section, we examine the robustness of the results showing heterogeneity in incentive responsiveness (Tables O.3 and O.4) and intent-to-treat effects (Tables O.5, O.6, O.7 and O.8) to alternative definitions of irrigator households and households' conservation motivation.

To form our preferred definition of irrigators, we first compute the difference between summer (May-August) and winter (November-February) water consumption in the year preceding each experiment. We then split the households into four groups, depending on this difference, with quantile 4 households and quantile 1 households having the highest and lowest summer to winter difference, respectively. While we believe these quantiles are better able to separate irrigator households from households who may have overall high water needs (due to a large house with many residents, for instance), we also recognize that an alternative definition of irrigators would focus on peak usage only. As a result, we form an alternative definition of irrigator households based on summer water consumption in bills 4 and 5 (May-Aug) in 2015 (exp 1) and 2017 (exp 2). Households with higher summer usage fall into higher peak quantiles.

To investigate heterogeneity in adoption behavior based on past responsiveness to drought conditions, we form drought responsiveness and backsliding quantiles based on year over year change in peak summer consumption between 2014-2015 and 2015-2016, respectively. Our alternative definition of drought responsiveness characterizes drought responsiveness as consumption at the worst point in the drought (summer of 2015) and after the state is out of drought (summer 2017). Peak 2015 and 2017 usage quantiles are formed based on consumption in bills 4 and 5 (May-Aug) in 2015 and 2017, respectively.

Table O.3 shows that our finding of increased responsiveness to adoption incentives among likely irrigator households is robust to the definition of irrigation. Experiment 2 results are very similar across the two definitions (columns 3 and 4). Experiment 1 results are largely similar, with a discrepancy for quantile 1 households, which may be driven by the higher overall pre-experiment water consumption of households in experiment 1 (i.e., 12 units per billing period selection criterion for experiment 1).

Table O.4 shows that our finding of above average responsiveness to adoption incentives among (1) households who are eager to get back to high usage after drought, (2) households unlikely to be motivated by conservation and (3) conservers are largely robust to the definition of conservation motivation. The slight qualitative difference between the results in Table O.4 and Table 4 is the relatively low responsiveness among households with low usage in both 2015 and 2017 and the relatively higher responsiveness among households with high usage in 2015 and low usage in 2017. The latter group can be interpreted as households late to the decision to conserve.

In Tables O.5-O.8 we examine the robustness of the intent-to-treat results to the definition of irrigator households. Comparison of Tables O.5-O.8 to Tables 15-17 and Table 6 shows that the results are largely robust to this definition.

Table O.3: Effect on Adoption by Irrigator Quantiles

	Experiment 1		Experiment 2	
	(1)	(2)	(3)	(4)
	Adopt or Activate [Change Q]	Adopt or Activate [Peak Q]	Adopt or Activate [Change Q]	Adopt or Activate [Peak Q]
Quantile 1	0.009	0.016*	0.014***	0.015***
	(0.008)	(0.008)	(0.005)	(0.004)
Quantile 2	-0.001	0.007	0.025***	0.028***
	(0.009)	(0.009)	(0.005)	(0.004)
Quantile 3	0.014*	0.005	0.037***	0.035***
	(0.008)	(0.009)	(0.005)	(0.005)
Quantile 4	0.020**	0.016*	0.061***	0.054***
	(0.009)	(0.009)	(0.005)	(0.005)
N	6,995	7,000	17,979	19,110

This table examines the robustness of the results in Table 3 to the definition of irrigator households. The table shows the effect of treatment on device adoption in households grouped by either Change Quantiles: summer to winter water usage variation or Peak Quantiles: summer usage. Change Quantiles are formed as described in Table 3, while Peak Quantiles are formed based on water consumption in bills 4 and 5 (May-Aug) in 2015 (exp 1) and 2017 (exp 2). Households with higher summer usage fall into higher Peak Quantiles. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.4: Effect on Adoption by Alternative Definition of Past Drought Responsiveness (Exp2)

	Peak 2017 Usage (May-August)			
	Q1	Q2	Q3	Q4
Peak 2015 Usage (May-August)				
Q1	0.010*	0.021***	0.020	0.056**
	(0.006)	(0.007)	(0.015)	(0.025)
Q2	0.004	0.031***	0.036***	0.050***
	(0.013)	(0.006)	(0.008)	(0.016)
Q3	0.010	0.033***	0.034***	0.042***
	(0.019)	(0.013)	(0.007)	(0.008)
Q4	0.062***	0.066**	0.035***	0.057***
	(0.023)	(0.027)	(0.012)	(0.006)

This table examines the robustness of the results in Table 4 to the definition of drought responsiveness. Table 4 defines drought responsiveness as change in peak consumption across three consecutive years when drought is deepening and then easing up. This table defines drought responsiveness as peak consumption at the worst point in the drought (2015) and after the state is out of drought (2017). Peak 2015 and 2017 usage quantiles are formed based on consumption in bills 4 and 5 (May-Aug) in 2015 and 2017, respectively. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.5: Effect on Water Usage By Bill Period and Year (Exp2, Alternative Quantile 1 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							0.0835
							(0.183)
2018	-1.551	-0.0229	0.0470	-0.0572	-0.315	-0.320	0.394^{**}
	(1.571)	(0.187)	(0.223)	(0.362)	(0.404)	(0.296)	(0.197)
2019	-0.542	0.345^{*}	0.0731	-0.0762	0.291	0.0552	0.0906
	(1.925)	(0.193)	(0.238)	(0.423)	(0.485)	(0.350)	(0.194)
2020	-1.279	-0.0951	-0.277	0.327	0.297	-0.0649	0.236
	(2.311)	(0.236)	(0.335)	(0.490)	(0.521)	(0.422)	(0.237)
2021	-1.826	-0.0844	-0.211	-0.319	-0.179		
	(1.983)	(0.288)	(0.340)	(0.513)	(0.550)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N	19,303	18,643	18,708	18,100	18,240	14,626	18,577

This table examines the robustness of the results in Table 15 to the definition of irrigator households. The table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households falling into quantile 1 of peak 2017 consumption. Peak Quantiles are formed based on water consumption in bills 4 and 5 (May-Aug) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.6: Effect on Water Usage By Bill Period and Year (Exp2, Alternative Quantile 2 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							0.324^{**}
							(0.163)
2018	0.912	0.282	0.233	-0.279	0.281	0.126	0.110
	(0.836)	(0.215)	(0.166)	(0.586)	(0.199)	(0.156)	(0.188)
2019	-0.146	0.306^{*}	-0.0429	-0.0898	-0.259	-0.0778	0.125
	(0.941)	(0.161)	(0.198)	(0.235)	(0.253)	(0.207)	(0.183)
2020	0.893	0.336	0.0475	0.266	0.0681	0.184	0.192
	(1.124)	(0.206)	(0.241)	(0.277)	(0.283)	(0.230)	(0.199)
2021	0.879	0.302	0.206	0.407	0.0794		
	(1.021)	(0.202)	(0.255)	(0.311)	(0.305)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N	25,333	25,236	25,234	25,235	25,297	20,243	25,236

This table examines the robustness of the results in Table 16 to the definition of irrigator households. The table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households falling into quantile 2 of peak 2017 consumption. Peak Quantiles are formed based on water consumption in bills 4 and 5 (May-Aug) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.7: Effect on Water Usage By Bill Period and Year (Exp2, Alternative Quantile 3 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							0.0487
							(0.180)
2018	-1.468	-0.456**	-0.295	-0.253	-0.114	-0.200	-0.355
	(0.926)	(0.207)	(0.213)	(0.277)	(0.246)	(0.240)	(0.227)
2019	1.634	2.954	-0.0664	-0.286	-0.184	-0.318	-0.158
	(3.608)	(3.387)	(0.233)	(0.293)	(0.279)	(0.278)	(0.299)
2020	-0.858	-0.325	0.0511	0.0728	-0.0971	-0.301	-0.105
	(1.381)	(0.271)	(0.267)	(0.331)	(0.326)	(0.303)	(0.271)
2021	0.243	-0.289	-0.0560	0.307	0.517		
	(1.338)	(0.260)	(0.345)	(0.419)	(0.407)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N	25,589	25,521	25,519	25,525	25,566	20,457	25,515

This table examines the robustness of the results in Table 17 to the definition of irrigator households. The table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households falling into quantile 3 of peak 2017 consumption. Peak Quantiles are formed based on water consumption in bills 4 and 5 (May-Aug) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.8: Effect on Water Usage By Bill Period and Year (Exp2, Alternative Quantile 4 Households)

	(1) All Year	(2) Jan-Feb	(3) Mar-Apr	(4) May-Jun	(5) Jul-Aug	(6) Sep-Oct	(7) Nov-Dec
2017							0.0977
							(0.366)
2018	-5.950	0.350	-0.682*	-3.512	-1.236	-1.051**	-0.0993
	(4.069)	(0.354)	(0.366)	(3.767)	(0.833)	(0.439)	(0.338)
2019	-6.217	0.623	-0.742*	-3.214	-1.865**	-0.971**	0.229
	(4.203)	(0.408)	(0.430)	(3.793)	(0.839)	(0.484)	(0.419)
2020	-5.925	-0.111	-0.330	-3.964	-1.193	-0.769	-0.243
	(4.580)	(0.532)	(0.473)	(3.790)	(0.904)	(0.588)	(0.508)
2021	-6.972	-0.0103	-1.334**	-4.056	-1.266		
	(4.379)	(0.563)	(0.600)	(3.821)	(0.956)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street	street
N	25,327	25,276	25,277	25,309	25,313	20,250	25,274

This table examines the robustness of the results in Table 6 to the definition of irrigator households. The table shows the effect of treatment assignment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 3) for households falling into quantile 4 of peak 2017 consumption. Peak Quantiles are formed based on water consumption in bills 4 and 5 (May-Aug) in 2017. Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$