Marketing & Experimentation for Social Change: Adapting to Drought in California*

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Abstract

In social change contexts such as conservation or public health, marketing can communicate information, nudge people toward more socially aligned behavior, or encourage adoption of long-run solutions that permanently shift personal outcomes and/or social spillovers. These marketing options, if effective, can substitute for regulatory change to address the respective social issue. In this paper, we focus on California's drought response, where cease and desist orders and community level fines are contingent on the effectiveness of local level voluntary change. We illustrate that a marketing challenge for the favored voluntary conservation approach of turf removal is that it ignores the preference trade-offs of those who consume the most and/or are least motivated by the social objective of conservation. We conduct sequential randomized control trials to evaluate the marketing and effectiveness of an Internet of Things (IOT) irrigation controller that helps consumers more efficiently irrigate and grow their lawns. We find that our marketing interventions for this "preference aligned" solution have higher response rates among heavy irrigators who would not otherwise conserve. Rather than cannibalizing other solutions with greater potential water savings, as some conservationists worry, our interventions lead to large persistent reductions in water usage.

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

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1 Introduction

As society confronts problems such as environmental sustainability or public health challenges, there are a mix of regulatory and non-regulatory options available. The margin between regulating or not depends on the effectiveness of non-regulatory options and the consequences of non-socially compliant behavior by those resistant to change. Stated differently, ineffectiveness in "marketing" socially compliant behavior can increase the likelihood of regulation.

We consider marketing challenges in California's drought response, where regulation and enforcement directly depends on the effectiveness of voluntary conservation[1] and pricing for conservation goals is restricted.[2] Notably, most marketing efforts for voluntary conservation suffer from a design that appeals to those motivated by the social objective, but works in conflict with the preferences of those who (i) contribute most to the social problem and/or (ii) are least motivated by the social objective. Consumers who highly value the aesthetics of lawns and do not place much weight on the consequences of their consumption for water scarcity are the heaviest consumers of scarce residential water supplies. Yet, focal messaging campaigns and incentives that encourage brown lawns, turf removal or outdoor water reductions are particularly unattractive given their preferences.

Given these challenges, we evaluate the marketing and effectiveness of a "preference aligned" solution focused on efficiently maintaining the health of landscape vegetation. The "smart" irrigation controller we evaluate faces reservations from some conservationists because of its potential to increase watering and counter peer effects that reduce turf and consequently watering in neighborhoods (Bollinger, Burkhardt, Chan, and Gillingham (2021)). Working with a local utility willing to evaluate the effectiveness of this preference aligned solution, we conducted sequential randomized control trials that first focused on the marketing variables to drive adoption, then tested the effects on water consumption.[3] We find that it appeals most to heavy irrigators and those reverting from previous conservation and yields significant long-run water reductions on top of the other solutions marketed to and adopted by households in both treatment and control groups.

To describe how different policies appeal to different groups and highlight the misalignment of typical conservation programs, we analyze an illustrative consumer utility model where the scarce resource produces a valuable output such as a green lawn. Production of the output comes at the personal cost of the resource as well as any disutility arising from consuming a resource that may have higher social

[1] 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 (State Water Resources Control Board (2015)).

[2] 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.

[3] 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.

costs than the price paid. If the social cost of the resource suddenly rises, as in the case of drought, individuals informed about the scarcity will endogenously reduce consumption (e.g. letting their lawn turn brown and/or removing it) if they incur this disutility. Yet, if some scarcity has existed in the past, these conservers consume systematically less of the resource to begin with because they would have chosen smaller irrigable areas. Further, marketing campaigns pushing for reductions in resource consuming outputs such as green lawns will present greater utility trade-offs for those that highly value the output produced by the scarce resource. We consider a conservation option that might produce the same output with fewer resources, but empirical questions exist about its efficacy and potential cannibalization of alternatives that conserve more, both of which could increase water use.

Our first experiment tests different marketing strategies for driving adoption and whether this solution appeals more to heavy irrigators.[4] 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 to investigate the extent to which professional installation can aid adoption and use of the device. In doing so, we take an approach 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, Dupas, and Schaner (2015)) and immunisation (Banerjee, Duflo, Glennerster, and Kothari (2010)). In parallel, we run a communication campaign to increase awareness of available monetary and installation incentives among treated households and collect information about households in the control group. As a result, the low discount intervention more closely resembles encouragement interventions used in randomized control trials in the energy literature (e.g., Fowlie, Greenstone, and Wolfram (2015) and Blonz, Palmer, Wichman, and Wietelman (2021)).

We find that only moderate to deep discounts are able to increase the adoption rate of the devices over the control group[5]. 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. To the question of heterogeneous adoption, we find no evidence of adoption (or activation) by the bottom half of irrigators, a 0.014 increase in adoption rate over control for the upper third quartile of irrigators and a 0.02 increase in adoption rate over control for the highest quartile of irrigators. Thus, marketing of this solution does capture the heavy users who may be less motivated by alternative solutions.

As is the case for most marketed products, adoption rates in our first experiment are rather low, which presents a statistical challenge for inferring the effects of the device on water consumption.[6] We

[4]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.

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

[6]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

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 roll-out and not to discriminately exclude any residents from the free offer, 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. 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)). Conversely, the conversion from adoption to device activation is higher in experiment 1 than in experiment 2, indicating that households obtaining their devices for free in experiment 2 are less likely to ultimately use their devices. This result is suggestive of either a screening effect, whereby households with higher anticipated use-value purchase the device earlier and at higher prices, or a sunk cost effect, whereby households assign higher value to devices obtained for a higher price[7].

Adoption rates by irrigation levels in the second experiment are similar to the first experiment, and we further examine heterogeneous adoption by pre-experimental drought response. In this experiment, all quartiles of irrigators exhibit significant adoption. Adoption is still increasing with irrigation levels: reaching an increase of 0.06 in adoption rate over control for the upper quartile. We also 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.

To evaluate the campaign's impact on water consumption, we examine the direct impact of the experimental intervention on water consumption (intention-to-treat effect) as well as the effect of device adoption on water consumption (local average treatment effect), focusing on experiment 2 which induced a broad adoption of the devices. We find negative and statistically significant effects of the marketing intervention on water consumption in the transitional seasons (e.g., September-October and March-April) as well as 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

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

[7]Past work in developmental economics has found economically important screening effects (Ashraf, Berry, and Shapiro (2010), Cohen et al. (2015)) and no consistent evidence of sunk cost effects (Cohen and Dupas (2010), Ashraf et al. (2010)) in the contexts of water purification solution, anti-malarial medication and bed net provision, respectively.

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.

Water consumption data spanning 2007-2021 allow us to estimate long-run effects of the intervention. We find that, particularly for heavy irrigators, the effects of the intervention in 2017 persist through 2021. The persistence of the effect on consumption differs from the "backsliding" that can occur in the long-run responsiveness to behavioral interventions (Allcott and Rogers (2014)) and is likely caused by the automation embedded in the smart irrigation controller. We also see suggestive evidence of larger reductions in consumption in years with significant precipitation, which can allow for the smoothing out of shocks to water supply after particularly dry years.

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 intention-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. We caution that this reduction may represent an upper bound because some of the intention-to-treat effect could have been driven by unaccounted for devices installations or other actions. One potential source of these 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.

Finally, we use supplementary data on the photosynthetically active vegetation (PSAV) area and its greenness for a subset of the households in the second experiment to shed further light on the direct and indirect effects of the smart controller adoption incentives on the ultimate water usage. 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.

This paper contributes to the literature on the effect of incentives and other non-regulatory interventions on the use of scarce resources. Related questions have been studied in particular depth in the context of electricity and energy efficiency. Fowlie et al. (2015) find that an aggressive encouragement intervention increased participation in a weatherization assistance program, but the realized energy

savings from the program were about half the investment costs. Allcott and Rogers (2014) find that social comparison messages have a significant effect on electricity usage that, nevertheless diminishes over time. Houde and Aldy (2017) find that energy efficiency rebates for appliances led to significant adoptions by inframarginal (non-additional) consumers and increased upgrades to higher quality, but less energy-efficient models.

Relative to these studies, the present work focuses on the inherent trade-off consumers often face when engaging in socially compliant behavior: that of weighing the benefits of conserving a scarce resource versus the benefits of consuming a valued output of said resource. We show that marketing a solution that allows more efficient production of a valued output of a scarce resource leads to adoptions by consumers with a large conservation potential that are nevertheless reluctant to engage in conservation behaviors. As a result, the marketing campaign leads to overall reductions in the usage of the scarce resource. Another study that explicitly addresses this trade-off is Blonz et al. (2021) who examine the effect of automated thermostat features on in-home comfort; however, unlike in the present study, where adoption of the smart irrigation controller leads to more efficient production of a green lawn, adoption of the automated thermostat features studied in Blonz et al. (2021) leads to a loss in in-home comfort.

This paper also contributes to recent work on the effects of smart technology on scarce resource consumption. As before, this work mostly focuses on energy efficiency, and the effects of automation on consumption in these other settings are mixed, though suggestive of the potential for automation to increase short-run elasticity (Harding and Sexton (2017)). Bollinger and Hartmann (2020) find that the smart automation feature in a thermostat can enable elastic response to short-term price changes that would otherwise be limited if a utility relied only on communication of price changes. Similarly, Blonz et al. (2021) find that automated thermostat features paired with dynamic pricing lead to a reduction in compressor usage during the peak period and household-level savings. On the other hand, Brandon, Clapp, List, Metcalfe, and Price (2021) find little evidence of energy savings for a smart thermostat because of user adjustments to settings. Our findings, and the device used, are more similar to Bollinger and Hartmann (2020) and Blonz et al. (2021) in that relevant demand information is digitally transferred to a device which can automatically respond based on pre-specified consumer preferences or household characteristics. Specifically, the smart irrigation controller used in our application adjusts irrigation based on historical and real-time local evapotranspiration levels as well as local precipitation and irrigation which may saturate the soil. The irrigation context is also unique from thermostats in two ways. First, the focus of the irrigation device is efficiency so should not impose trade-offs in utility that might generally be associated with conservation. Second, even if conservation produced undesired outcomes, they would be realized through a delayed reduction is landscape aesthetics which is less personal and immediate than a change in indoor temperature.

The rest of the paper proceeds as follows. In Section 2, we introduce an illustrative utility model of

consumption and conservation of a scarce resource to illustrate the trade-offs consumers face and form predictions for our empirical analysis. In Section 3, we introduce the empirical context of our study. In Section 4, we discuss the design of the two randomized trials. In Sections 5 and 6, we discuss the results of the interventions on smart irrigation controller adoption and resultant effects on water usage, respectively. In Section 7, we discuss indirect effects of the treatment on landscape size and greenness. And in Section 8, we conclude.

2 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:

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

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:

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

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:

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

2.1 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:

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

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.

2.2 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:

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

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 1, we examine the effect of turf removal on the aesthetics utility and change in water usage,

Table 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.

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[8], (2) those who had brown lawns prior to removal, but water the reduced 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

[8]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 $A' < A$.

$\gamma \ln\left(\frac{A}{A'}\right) > \overline{w}(\theta c + \eta p)(A - A')$ will only adopt if they are paid a subsidy beyond F_A to remove turf area.

2.3 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:

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

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 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 for reach a green lawn. This makes it appealing to consumers with high preferences for aesthetics who also care about conservation[9][10]. 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,

[9]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.

[10]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.

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.

2.4 Discussion and Empirical Motivation

As we detail in Section 4, 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 the following sections.

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.

2.4.1 Heterogeneity in Adoption Rates

As given by the condition on preferences and irrigable area A in equation 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 3), 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 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 1).

To test for adoption by these different household types in our empirical analysis in Section 5, 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.

2.4.2 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.[11]

Direct Effect, Full Information As shown in Table 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

[11] 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.

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:

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

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.

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. 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.

3 Empirical Context

3.1 California Drought

In Figure 1, we plot drought.gov data on the prevalence of drought across California since 1895. The patterns in the figure clearly illustrate a persistent problem with temporary reprieves that are decreasing in length over the last couple decades.

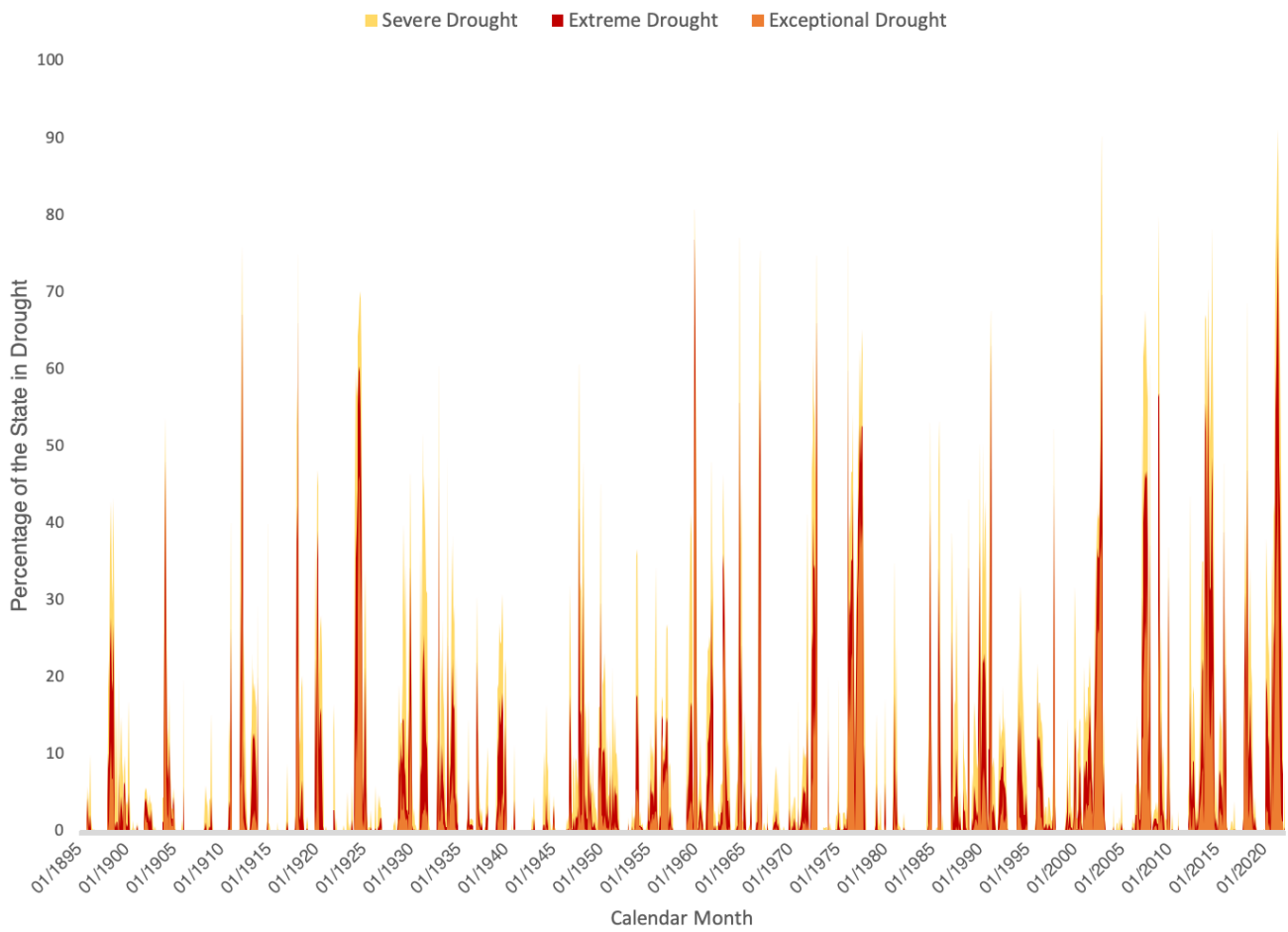
Drought arises because the demand for water outpaces supply. Demand and supply dynamics are visible in Figure 2, which compares 2007-2021 residential water consumption in our partner city of Redwood City, California to annual precipitation levels, incidence of extreme drought and interest in drought as measured through Google trends. 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 local water utility to change the water consumption behavior in the many households they serve.

Figure 2 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

Figure 1: Prevalence of Drought in California 1985 to Present

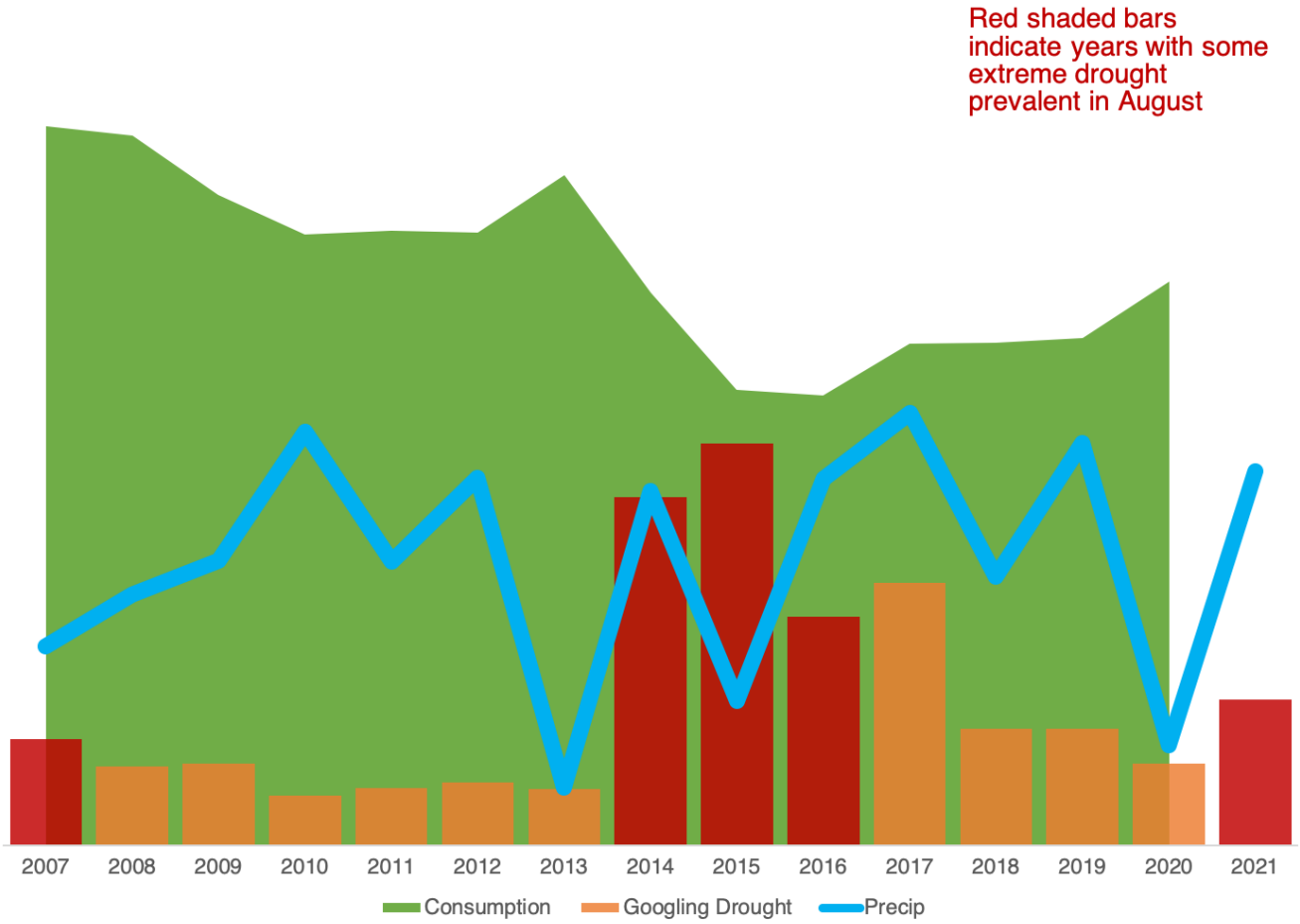


markets, where the prices can be used to shift consumption from high-cost to low-cost hours within a day). One mechanism to circumvent this is a tiered system that drastically raises prices for non-essential or heavy use. However, in 2015, California courts ruled conservation pricing to be illegal (Mintz (2015)), thereby leading many utilities, such as our partner, to seek non-price approaches for reducing demand.

3.2 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. 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. 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

Figure 2: 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.

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.[12]

We partnered with Redwood City Public Works (RWCPW) because of its proximity, their openness to collaboration 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

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

Figure 3: Household Water Conservation and Reversion During Drought

Percentage Change in Water 2015 vs. 2013 \ Percent Change in Water 2016 vs. 2015	-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.

where opportunities were large because of lot sizes, yet conservation was still challenging.

Most RWCPW households engaged in some degree of water reduction by 2015. The rows in Figure 3 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 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).

After initially reducing consumption during the drought, many households began to increase con-

sumption in the summer of 2016, before the drought ended. The columns in Figure 3 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.

As we collaborated with RWCPW and recognized that some consumer preferences would imply retention or resumption of their irrigated landscapes, our focus became mechanisms to help consumers with stronger preferences for continued outdoor water consumption to use it more efficiently.

3.3 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.

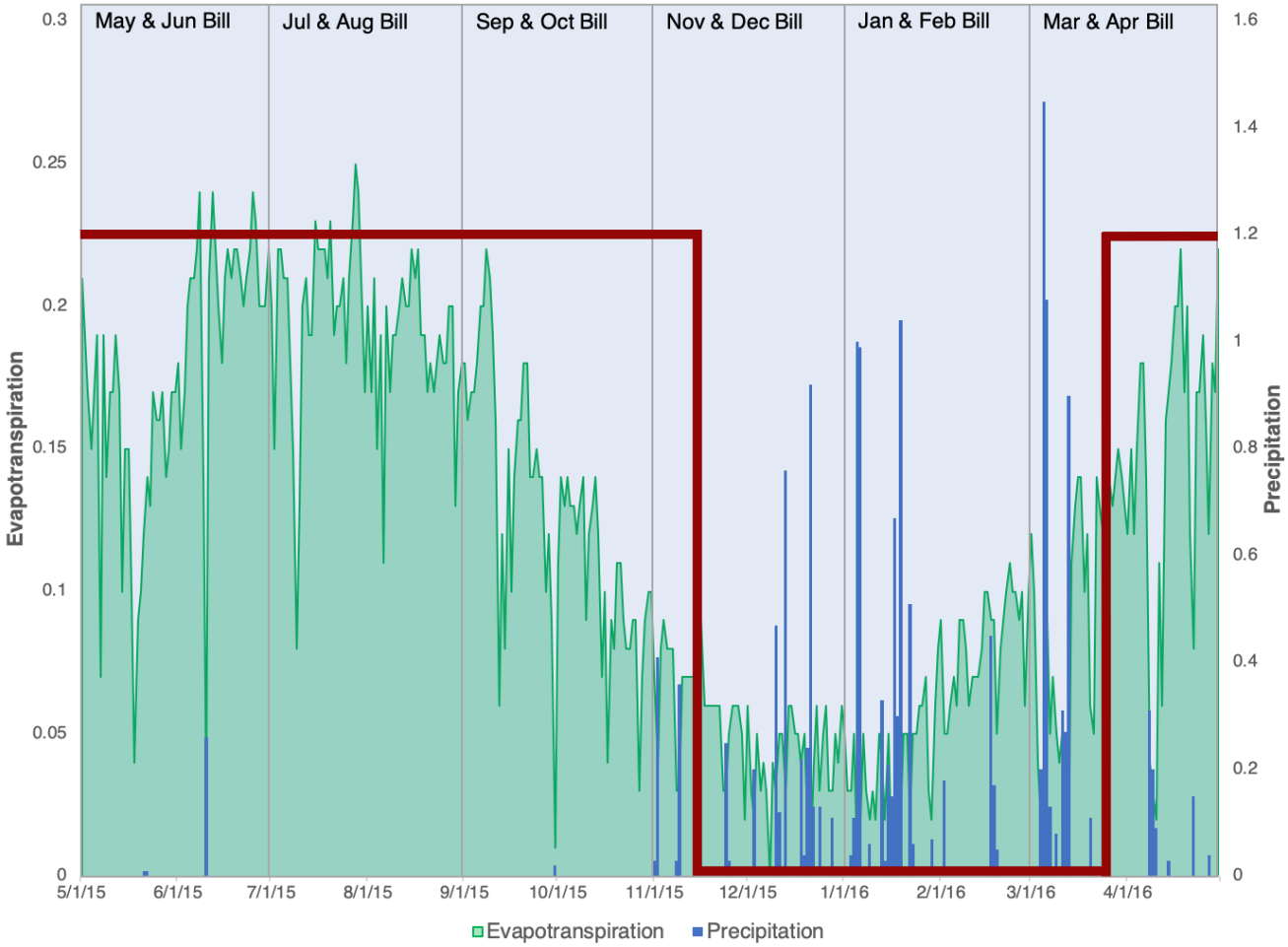
Like many convenience devices, automation created default consumption of resources that was "inelastic" to consumer needs, thereby unnecessarily using resources when not needed (watering during the rain as an obvious example). The focal value proposition of the smart irrigation device we use in our study 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 4 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[13]. 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.

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 consump-

[13]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 4: 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.

tion. 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. An example of an email notification of such a change is included in Figure 6. Email notifications for rain skips and saturated soil are depicted in Figure 7.

4 Study Design

4.1 A Marketing Process

The diversity of drought response is indicative of the role of marketing in such social change examples. There are multiple ways of changing behavior in a way that aligns with the social objective, and consumers are likely to find those that best align with their preferences and needs.

Marketing helps guide these potentially heterogeneous customers down paths towards behavioral change and address 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 process is often referred to as a funnel because, at the top, customers may still choose among many options, but as they progress through the process, their focus often narrows to one alternative and the steps needed to adopt it. In our context, customers are heterogeneous because of i) variation in seasonal water needs (e.g. outdoor/summer vs. indoor/winter), ii) the extent to which they are willing to accept the trade-offs of reduced water consumption, and iii) their preferences for different conservation solutions. Policy makers at the state and local levels need to guide these heterogeneous consumers towards conservation, while retaining support of their constituents and customers.

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)[14], starting with consideration set formation, as consumers seek out information about available alternatives, such as those discussed in Section 2.

Our marketing process therefore began with communications that added the smart irrigation controller into the consumer's consideration set, while acknowledging uncertainty about its effectiveness by describing the campaign as a "study". 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 an acceptable water conservation alternative. We then focused on the evaluation of alternatives stage, where customers compare alternatives within the consideration set. While Rachio's characteristics were

[14]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.

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 purchase their discounted devices.

4.2 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. 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[15]. The 7,000 households selected into experiment 1 were all single-family households with sufficiently high average water usage (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 8). 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 9). 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 10). 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

[15] Additional discussion of the randomization and stratification approach in experiment 1 is in Appendix Section A.1

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 11). 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 "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 6, 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 11 and 12 report the balance checks for experiments 1 and 2, respectively. For experiment 1 (Table 11) 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 12), 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.

5 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.

5.1 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 13th, 2016 and August 22nd, 2016, with a bulk of purchases shortly after experiment launch and another increase in purchases after the reminder email was sent on July 28th, 2016 (see Figure 12).

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

$$a_i = \beta_0 + \sum_j \beta_1^j T_i^j + \varepsilon_i \tag{8}$$

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 2 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[16]. In Column 2 of Table 2, we thus supplement the in-portal adoptions with 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 5 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

[16]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 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.

Table 2: 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)	
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and thus draw a more fair comparison between the treatment and control groups[17]

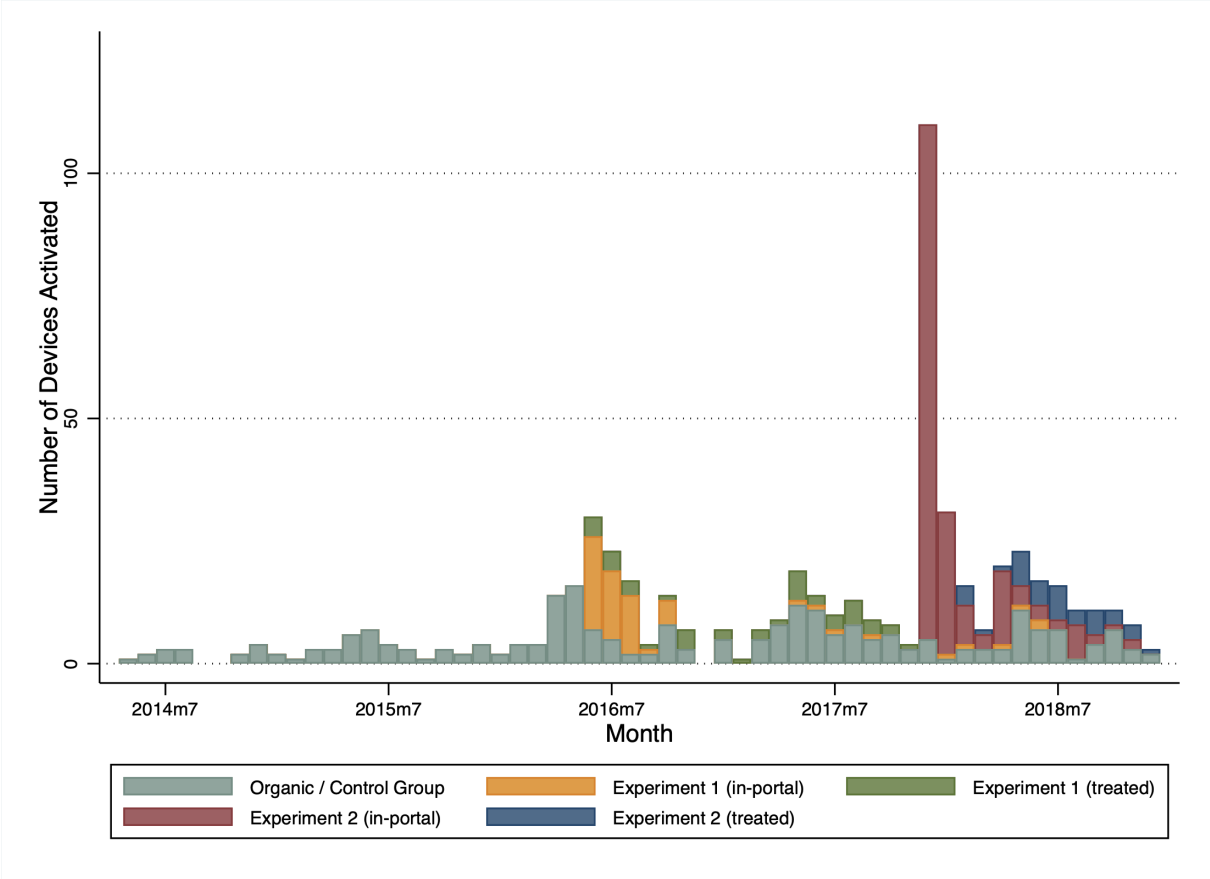
Similar results emerge: while there is a higher rate of adoption in the control group than in Column 1, incentives, specifically the deeper discounts and installation, increase device adoption. In particular, the adoption rate in the 80% discount group (Control ($\hat{\beta}_0$) + 80% Discount ($\hat{\beta}_1^{80\%}$)) 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 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[18]. The conversion from in-portal adoption to

[17]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").

[18]An additional 2 households had purchased and activated a device prior to the experiment, indicating that they used the

Figure 5: Device Activation Timeline by Adoption Type



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.

5.2 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 1st, 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

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 3: 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)	
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

number of devices available for adoption within the experiment. All available devices were claimed by December 3rd, 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 3 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 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.[19] 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 3 shows that taking these two forces into account, the adoption rate in the treat-

[19]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 Section 2 and in the context of our empirical results in Sections 6 and 7

ment 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%[20]) 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. The difference is suggestive of either (1) lower price discounts attracting households with higher anticipated use-value who are, thus, more likely to activate the device (screening effects) or (2) households assigning higher value to devices for which they have paid some amount relative to free devices (sunk cost effects). The former effect might be particularly relevant in this durable good context, where early adopters have a higher expected value of use than those left in the market later down the line.

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 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.

5.3 Heterogeneity in Treatment Response

As described in Section 2, while irrigation controllers offer the potential to improve watering efficiency, 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. To better understand whether our offered incentives were able to drive adoption among the households with the largest potential water reduction (i.e., those watering fully at the baseline), 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

$$a_i = \beta_0 + \sum_k \beta_1^k T_i x_{ik} + \sum_k \beta_2^k x_{ik} + \varepsilon_i \tag{9}$$

where T_i is now an indicator for whether an individual household i is in any treatment group[21], and x_{ik} is an indicator of whether household i belongs to one of the k mutually exclusive groups based on

[20] 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.

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

Table 4: Effect on Adoption by Summer to Winter Consumption Difference

	Experiment 1		Experiment 2	
	(1)	(2)	(3)	(4)
	Adopt or Activate	Num HH	Adopt or Activate	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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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[22]. 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 4 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 4 shows a statistically significant treatment effect in experiment 1 for 3rd and 4th quantile households only. Column 3 of Table 4 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

[22]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.

Table 5: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

households, as in experiment 1[23].

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 2). 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.

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

We estimate equation 9 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 coefficient estimates $\hat{\beta}_1^k$ in Table 5. 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 4 provides additional suggestive evidence for the latter point. Given that 2015 was a particularly dry year (see Figure 2), 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 4 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.

6 Water Conservation Behavior

Ultimately, whether or not the program was successful in driving changes in long-run water conservation behavior will depend on the extent to which it drives water consumption reduction. In the first part of this section, we investigate the intention-to-treat effect of the experimental manipulation on water consumption, focusing on experiment 2 where we saw broad smart irrigation controller adoption[24]. In the second part of the section, we evaluate the effect of the smart irrigation controller device on water consumption behavior and discuss the implications of our results.

6.1 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:

$$w_{it} = \alpha_0 + \sum_y \alpha_1^y \tilde{T}_{it} \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + \xi_i + \varepsilon_{it} \tag{10}$$

[24]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.

Table 6: 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	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 10). Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

where w_{it} measures water consumption in units (1 unit = 100 cubic feet = 748 gallons) at time t, y represents years $y \in \{2017, 2018, 2019, 2020, 2021\}$[25], 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[26]. We cluster standard errors at the street (i.e., treatment assignment) level (Abadie, Athey, Imbens, and Wooldridge (2017)).

By estimating equation 10, we are effectively estimating year-specific intention-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 6, we report coefficient estimates $\hat{\alpha}_1^y$. Column 1 reports aggregate year effects, while columns

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

[26]We use the fixed effects specification in order to shrink the standard errors around the estimated treatment effects. In Section 10, 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 15) 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 16). The results are similar to the main specification but more noisy in both these alternate specifications.

Table 7: 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	21,852	21,842	21,842	21,844	21,843	17,473	21,835

This table shows the effect of treatment on household water consumption in subsequent years (estimates $\hat{\alpha}_1^y$, resulting from estimating equation 10) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 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)[27]

We see further evidence of this same force when estimating equation 6 separately by quantile of summer to winter consumption difference (as defined for the analysis in Table 4). Table 7 reports

[27] 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.

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 7 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 improve efficiency of watering in peak seasons for households with significant preference for summer irrigation.

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 2, 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 2 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[28].

[28]The intention-to-treat results from experiment 1 are directionally similar to the experiment 2 intention-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.

6.2 Local Average Treatment Effect (LATE)

The average intention-to-treat effects estimated in sub-section 6.1 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 intention-to-treat effect and the rate of compliance with the treatment. We estimate the following equation:

$$w_{it} = \delta_0 + \sum_y \delta_1^y p_{it} \mathbb{1}\{t = y\} + \sum_y \delta_2^y \mathbb{1}\{t = y\} + \xi_i + \varepsilon_{it} \tag{11}$$

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)[29]. We further instrument 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 10.

Table 8: Local Average Treatment Effect By Bill Period and Year (Exp2)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						4.565
						(4.640)
2018	1.563	-5.610	-33.68	-10.62	-11.21**	-0.267
	(4.791)	(4.289)	(30.79)	(7.726)	(4.939)	(4.316)
2019	34.17	-6.556	-30.32	-17.56**	-11.52*	1.764
	(28.41)	(4.607)	(31.03)	(7.916)	(5.895)	(5.099)
2020	-1.835	-3.741	-28.41	-8.721	-8.965	-0.372
	(7.888)	(6.277)	(31.40)	(8.681)	(6.955)	(6.123)
2021	-1.234	-11.41	-30.67	-7.200		
	(7.681)	(8.625)	(32.10)	(9.675)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	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 11). Each column represents a regression for the given billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[29]The definition of adoption or activation is the same as in Column 1 of Table 3; i.e., within and out of portal adoption, as proxied by device activation from December 2017 to December 2018.

Table 9: Local Average Treatment Effect By Bill Period and Year (Exp2, Quantile 4 Households)

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						6.098
						(6.118)
2018	7.185	-12.82**	-1.877	-28.80*	-17.51**	-2.132
	(5.480)	(6.459)	(8.545)	(15.99)	(8.215)	(5.477)
2019	5.942	-15.53**	4.632	-39.06**	-17.46**	8.034
	(6.957)	(7.653)	(10.32)	(16.11)	(8.647)	(7.015)
2020	-1.656	-9.190	-9.620	-25.11	-12.59	-1.110
	(8.580)	(8.355)	(11.06)	(16.86)	(10.41)	(8.249)
2021	3.483	-20.55**	-3.617	-33.45*		
	(8.858)	(10.34)	(11.69)	(18.18)		
Street FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	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 11) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 8, 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 6.1, for households in quantile 4 of summer to winter water consumption variation, these results are larger and more pervasive (see Table 9). 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.

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.

7 Landscape Size and Greenness

As discussed in Section 2, 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. 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 6, 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 direct and indirect effect of smart controller adoption incentives on water usage.

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

Table 10: Effect on Consumption, Landscape Size and Greenness (Exp2)

	(1) Cons	(2) PSAV	(3) % Green PSAV
Mar-Apr 2018	-0.631*	—	—
	(0.363)		
May-Jun 2018	-0.563	—	—
	(0.418)		
Jul-Aug 2018	-0.807*	-1.977	-0.00166
	(0.441)	(84.20)	(0.00486)
Street FE	Yes	Yes	Yes
Clustering	street	street	street
N (Jul-Aug 2018)	17,452	17,664	17,664

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 10 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

active vegetation in 2016, the year before the second experiment.

In Table 10, for this sub-set of households with above-median irrigable areas, we examine the intention-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 10 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 7, 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 from the control group.[30] As discussed in more depth in Section 2, 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

[30]To interpret the magnitude of the result, note that the median PSAV area for this subset of households is $3,310$ square feet. Thus, a 95% confidence interval around the estimate represents a change of about 5% from this median.

overall decrease in water usage resulting from the offered incentives (as shown in column 1 of Table 10 and Table 7.

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.[31] To see this second point, recall from Table 1 and the discussion in Section 2 that consumers with previously brown lawns would necessarily increase the greenness of their landscape upon adoption of the smart irrigation controller[32], while consumers with previously green lawns would see no change in greenness.[33] Thus, the lack of a positive effect of treatment on landscape greenness suggests that adoption is driven by the latter group.[34]

8 Conclusion

This paper illustrates the potential for marketing and experimentation to make long-run changes to the behavior of those whose preferences are least aligned with a social objective.

The process involves identifying an alternative that caters to the preferences of those incurring substantial trade-offs of the socially desired behavior. In our case, this alternative is a smart irrigation controller designed to efficiently produce a healthy irrigable landscape. While other alternatives such as turf removal may have saved more water, the heaviest consumers of the scarce resource might be least likely to take up such conservation alternatives. On the other hand, we show that marketing a conservation solution specifically targeted to the needs of these heavy consumers, can induce conservation behaviors among those who would not have otherwise conserved.

The timing of introduction of a preference-aligned alternative may be important. By delaying public promotion, 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 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.

[31] 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.

[32] 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, $\frac{w^*}{\overline{w}} < \frac{w^{*\prime}}{\underline{w}}$.

[33] 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 $\kappa\gamma > \underline{w}A(\theta c + \eta p)$.

[34] 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 20, 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.

It is also important to note for long-run conservation goals, interventions such as ours are likely most helpful in concert with (and not instead of) communication initiatives that normalize native landscapes and reduced outdoor water usage in California and other places battling recurring and worsening droughts. Such communication can decrease preferences for large grassy areas in favor of more conservation-friendly landscapes, thus, allowing for another avenue for long-run water use reductions. Because preferences are persistent and difficult to move, preference-aligned solutions such as the one considered here can provide a conservation solution for those reluctant to conserve in the medium-run.

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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9 Supplementary Figures

Figure 6: Email Notification for a Seasonal Shift in Irrigation Durations

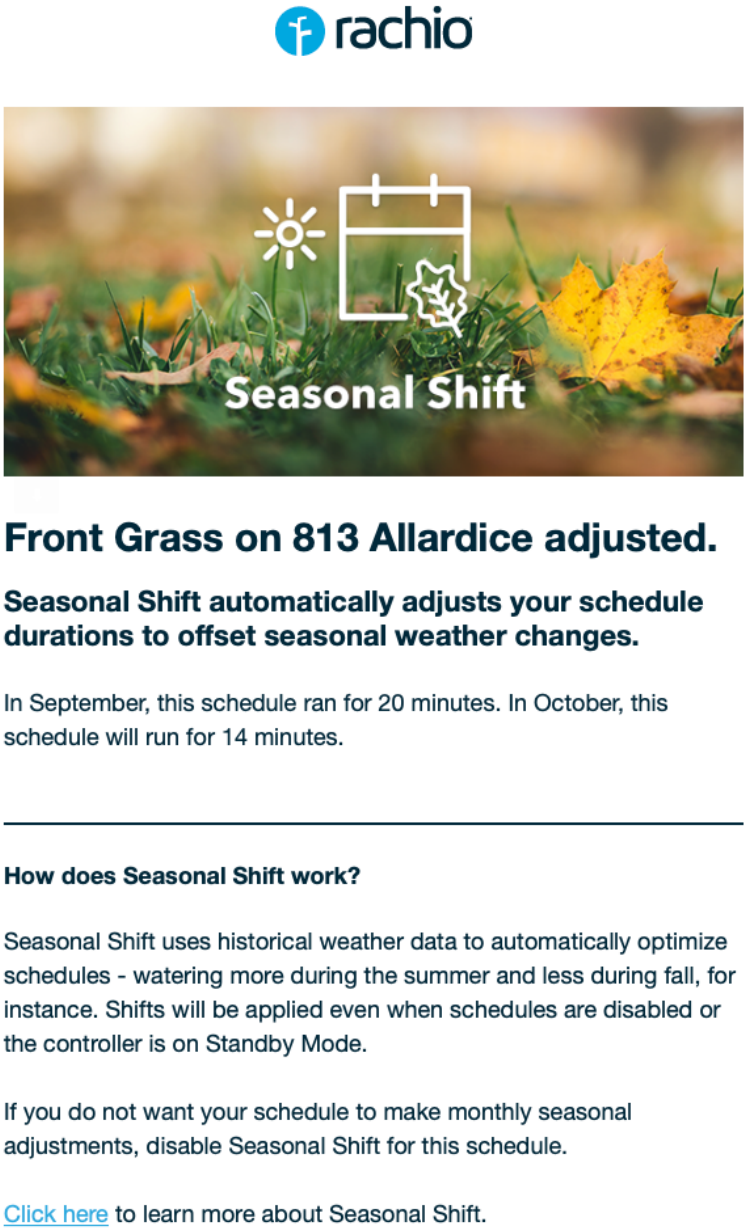
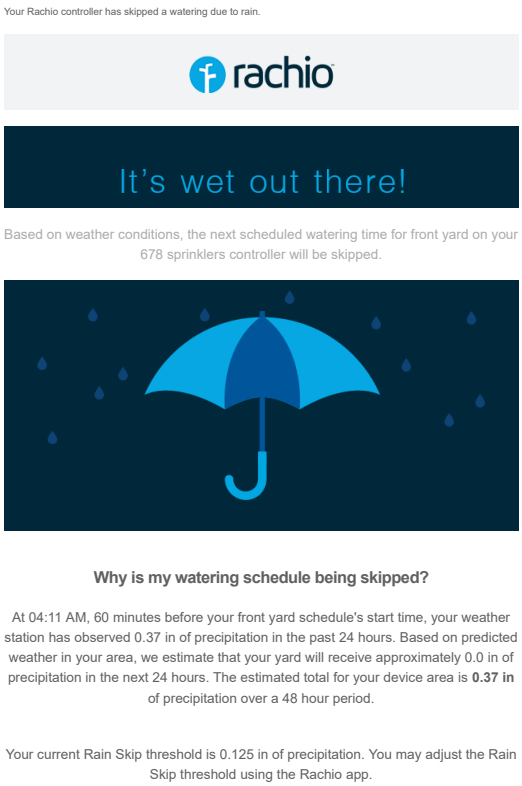
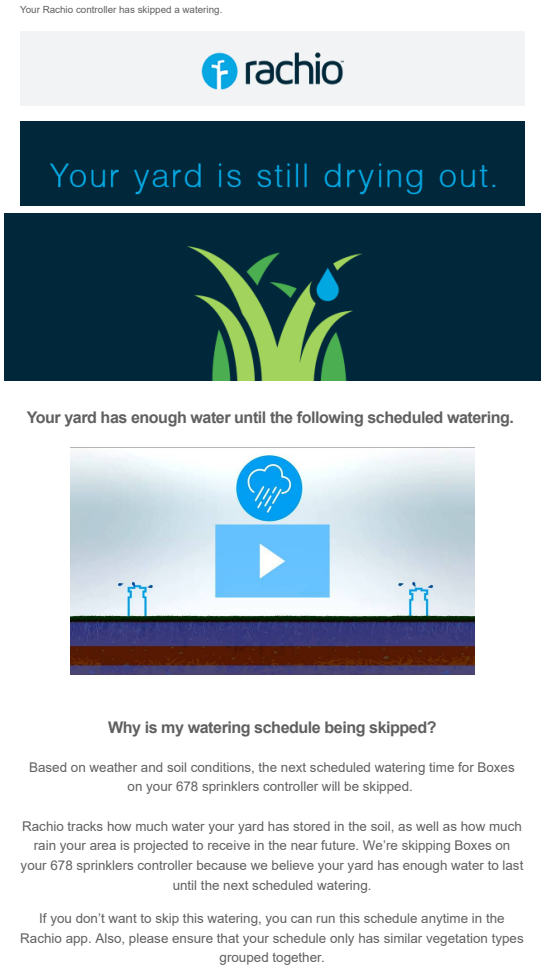


Figure 7: Email Notification of Schedule Skips

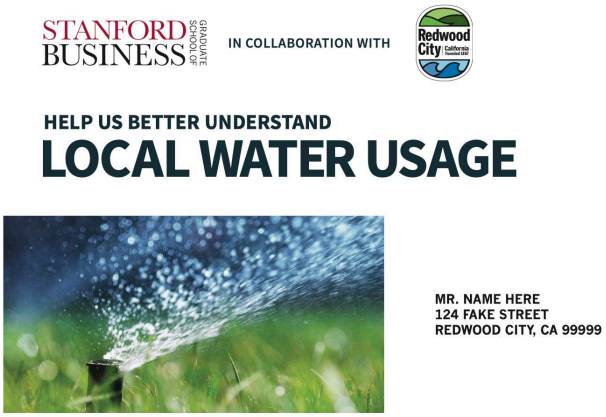


Rain Skip

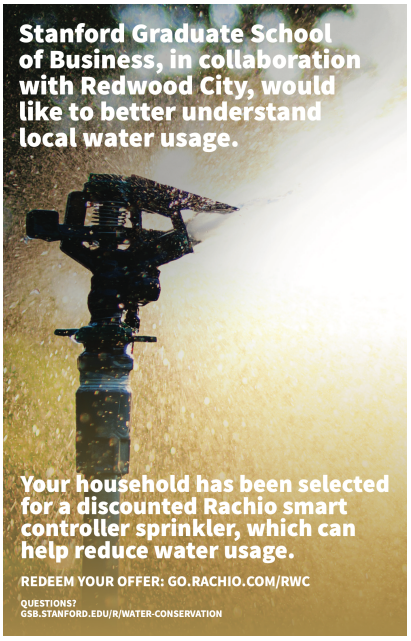


Soil Saturation Skip

Figure 8: Treatment Group Post Card (Experiment 1)



Address Side



Message Side

Figure 9: Treatment Group Email (Experiment 1)

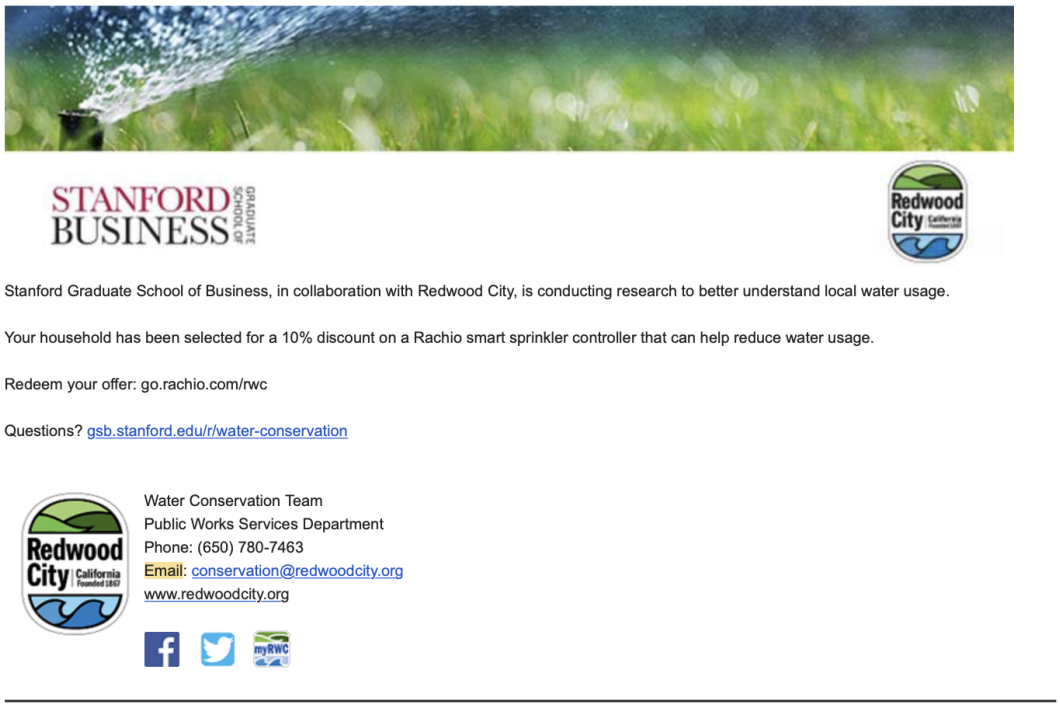


Figure 10: Control Group Communications (Experiment 1)

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:
   ☐ Smart Controller Please Describe:
   ☐ Drip Irrigation
4. Are you a renter or a homeowner?
   ☐ Renter ☐ Homeowner

THANK YOU FOR YOUR PARTICIPATION.

Post Card

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, 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

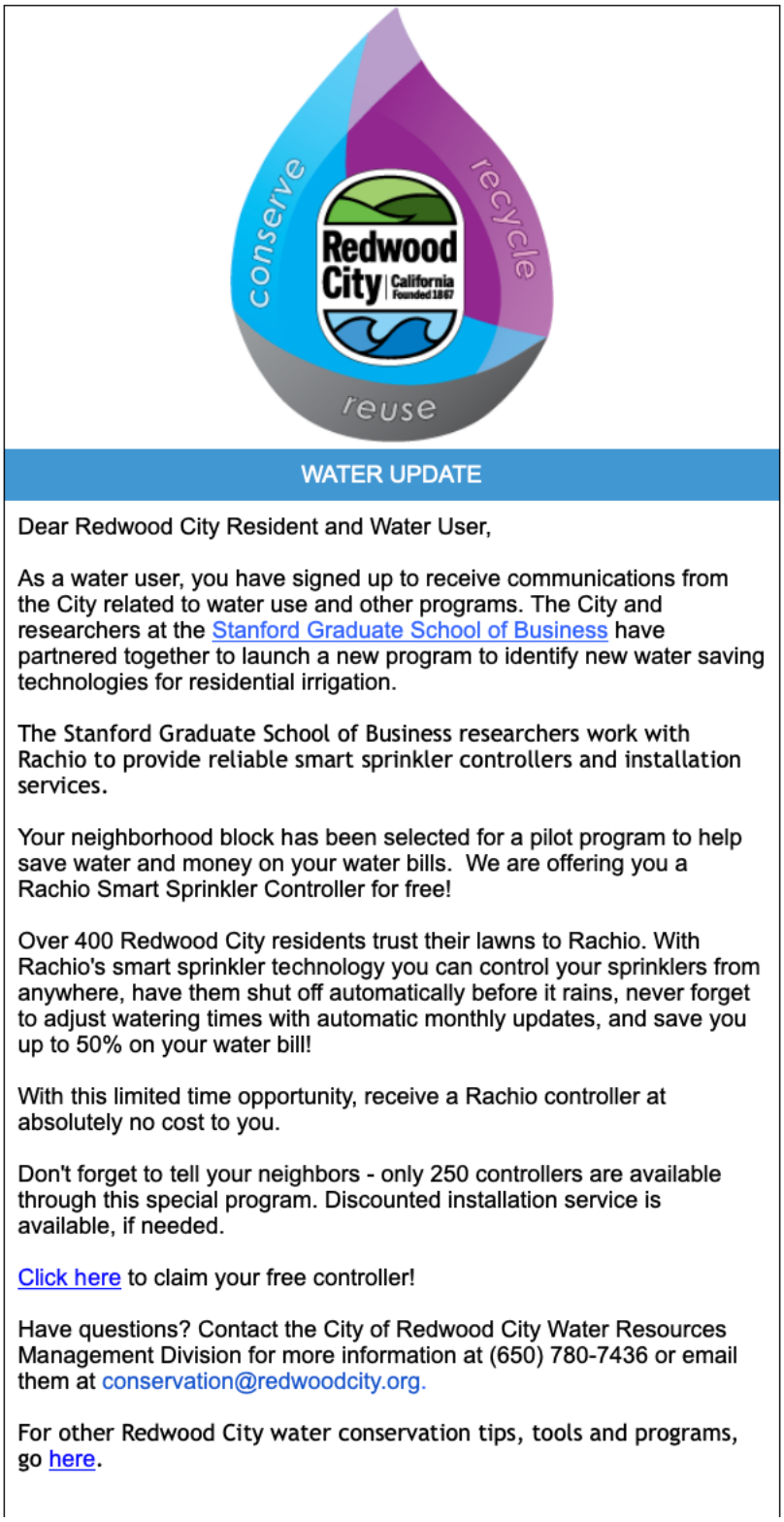
Thank you for your participation.

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

Email

Figure 11: 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.

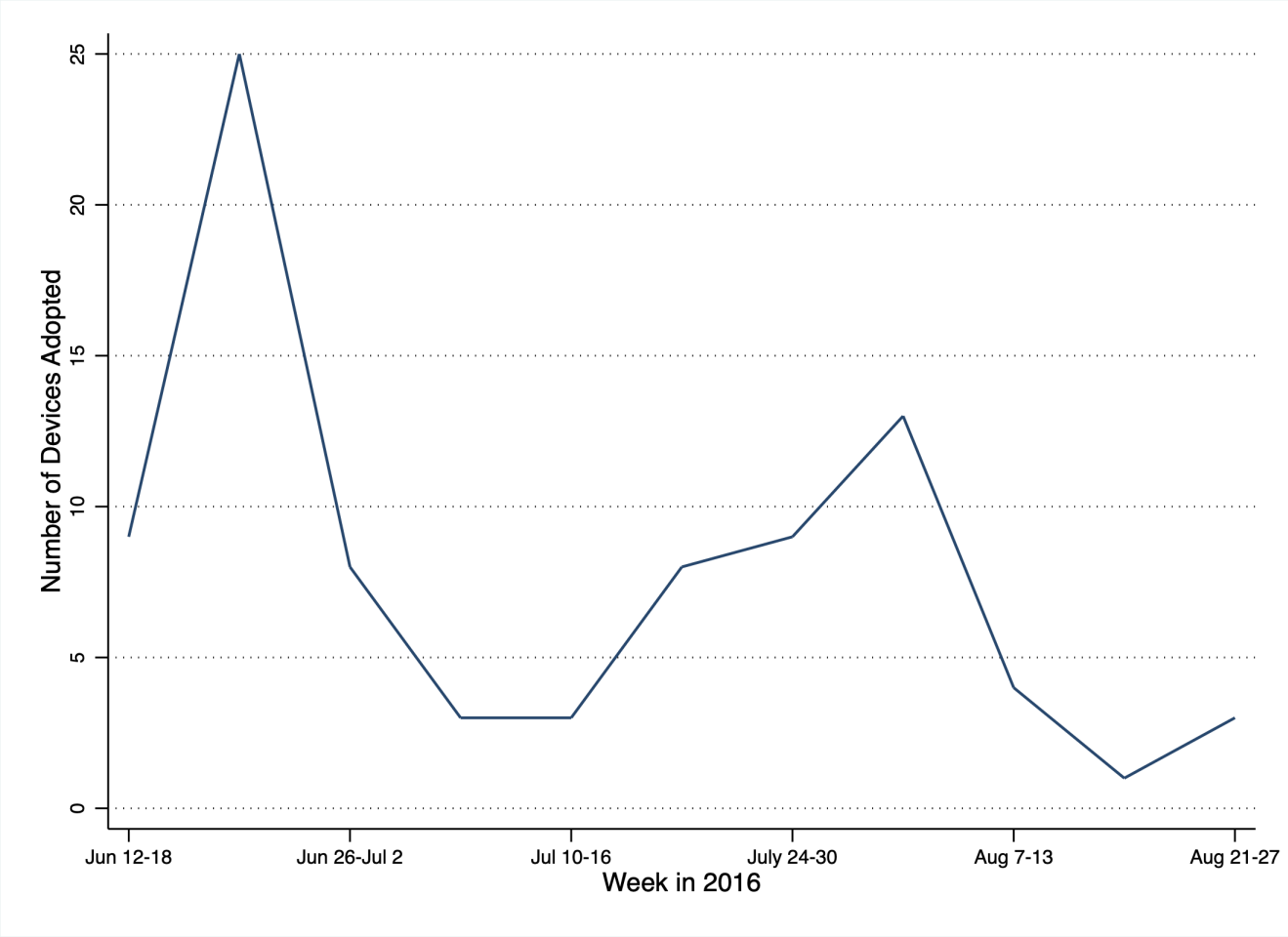
Don't forget to tell your neighbors - only 250 controllers are available through this special program. Discounted installation service is available, if needed.

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.

Figure 12: 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.

10 Supplementary Tables

Table 11: Pre-Experiment 1 Characteristics by Treatment Status

		Comparison By Treatment					
	Control	10% Disc	80% Disc	60% Disc	60% Disc + Install	F-Stat all=contr	Obs
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)	

Standard errors in parentheses (clustered at residence level for water usage variables)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: 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)	

Standard errors in parentheses (clustered at residence level for water usage variables). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Treatment Effect on Water Usage By Bill Period and Year (Exp1, SiteID Fixed Effects)

	(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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Treatment Effect of Water Usage By Bill Period and Year (Exp1, SiteID Fixed Effects: 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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: 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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: 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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Treatment Effect of 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 Fixed Effects	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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Treatment Effect of 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 Fixed Effects	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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Treatment Effect of 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 Fixed Effects	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

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Correlation between 2016 to 2018 Change in PSAV & Change in Consumption

	Change in Annual Consumption			Change in Jul-Aug Consumption		
	(1) Δ Cons	(2) Δ Cons	(3) Δ Cons	(4) Δ Cons	(5) Δ Cons	(6) Δ Cons
Δ PSAV	0.000645*	—	0.000297	0.000101	—	0.0000154
	(0.000379)		(0.000378)	(0.000162)		(0.000162)
Δ Green PSAV	—	0.000893***	—	—	0.000252*	—
		(0.000312)			(0.000134)	
Δ % Green	—	—	44.31***	—	—	10.66***
			(3.994)			(1.700)
N	8,383	8,383	8,383	8,623	8,623	8,623

This table shows the result of a first-differences regression of 2016 to 2018 change in PSAV and 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

11 Appendix

A.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[35]. 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.

[35] 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.