Marketing and Economics of Harm Reduction: Evidence from Conservation Field Experiments*

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Abstract

This paper extends the canonical harm reduction approach to a wider set of applications, including conservation. We develop an economic model to illustrate the trade-offs inherent to harm reduction, weighing the benefits of reducing harm against the risk of drawing those previously abstaining into consumption. Using sequential campaigns with embedded experimentation that enables measurement, we market a harm reduction solution in the context of water conservation. We show that a smart irrigation controller that efficiently maintains stigmatized ornamental landscapes appeals to the heaviest irrigators and generates large and long-lasting individual and social benefits: cost recovery in six months and water savings covering another household's basic needs. We find no evidence it cannibalizes abstinence (lawn removal) or increases irrigation by conservation prone individuals. Our conceptual and measurement framework provides a foundation for implementing and evaluating harm reduction well beyond the typical drug and public health contexts.

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

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As society confronts social problems such as environmental sustainability, policy-makers and experts face the challenge of persuading people to change behavior. While many people are inherently motivated by calls to act pro-socially (Funk and Hefferon (2019), Bell et al. (2021)), those contributing to the social problem the most are often the least motivated to make a change, since they derive the highest utility from behaviors inconsistent with the pro-social goal. Nevertheless, a common approach to tackling such social challenges is to heavily promote drastic reductions or abstinence. For instance, agencies and conservation proponents often promote walking or taking public transport instead of driving a car (e.g. United Nations (2022), Katz and Daniel (2015)), reducing or eliminating meat and dairy consumption (e.g., United Nations (2022), Katz and Daniel (2015)) and, in our context of water conservation, removing green lawns in favor of native vegetation (e.g., Be Water Wise (2022)). Such solutions allow the most pro-socially motivated to make their biggest impact, but are particularly unappealing or even inaccessible to those who derive the highest value from the "socially undesired behavior."[1]

We consider accepting that the preferences of the most challenging customers will lead to their continued engagement in the socially undesirable behavior and instead shift the focus to decreasing the intensive margin of the "harm" they generate. In other words, we suggest promoting conservation via "harm reduction," a once-controversial approach to public health that avoids stigmatizing socially undesirable behavior (e.g., opioid injections) and provides access to alternative solutions (e.g., oral opioid substitution treatment) without requiring abstinence (Logan and Marlatt (2010),Britton and Edwards (2008),McNeill (2004),Marlatt and Witkiewitz (2002)).

Traditional harm reduction methods for substance use, such as needle exchanges, fentanyl test kits or opioid substitution therapies, work by *reducing harm from consumption.* They retain the private benefits of the behavior while reducing personal and social harm (e.g., HIV transmission from injecting opioid use (Gowing et al. (2008))). However, reduced personal harm may lead to increased consumption or draw those previously abstaining into consumption. Hence, for harm reduction to succeed, the reduction in harm among existing consumers must outweigh any additional harm resulting from increased consumption, including from new, formerly abstinent, consumers.

[1] Allcott et al. (2022) illustrate the potential welfare losses arising from such heterogeneous responses to a call to action or to other non-standard policy instruments.

We propose that harm reducing alternatives also exist in the context of conservation. Although less impactful than abstinence, research suggests that electric vehicles (EPA (2022)) and smart devices (Bollinger and Hartmann (2020); Harding and Sexton (2017); Blonz et al. (2021)) can offer environmental benefits over the behaviors they replace. However, harm reduction alternatives in conservation operate differently than in traditional substance use cases. They work by *reducing harmful consumption*, particularly among the heaviest users, through more efficiently delivering private benefits, such as green landscapes or rapid acceleration in vehicles. The main trade-off remains similar to the *reducing harm from consumption* case: the harm reduced by decreasing consumption must outweigh any additional harm caused by increased consumption among marginal users who are drawn into consumption due to the improved efficiency of private benefit production.

In practice, measuring utility and hence welfare is challenging. We propose that policymakers can evaluate the overall success of a conservation harm reduction approach by focusing on the following metrics, which account for these opposing forces and provide for a more accurate reflection of welfare improvements over a simple aggregate consumption reduction benchmark: (i) the extent to which heavy consumers adopt the solution (ii) the extent to which harmful consumption decreases for heavier consumers, (iii) the extent to which formerly abstaining consumers are drawn into consumption and (iv) whether or not benefits of consumption are decreased.

Notably, the trade-offs that render harm reduction a controversial approach apply only in contexts where abstinence from consumption by certain individuals is socially optimal. Examples include contexts with high social costs of consumption, such as heavy drug use in the canonical case, or watering ornamental landscapes and driving energy-inefficient luxury vehicles in the context of conservation. In contrast, no such trade-off exists in contexts where consumption meets a basic need, such as water for personal hydration or hygiene, or heating or air conditioning during extreme temperatures. In these cases, encouraging previously abstaining consumers to adopt consumption unequivocally improves social welfare by, for example, reducing hospital admissions and deaths from extreme temperatures.

Focusing on a context with high social costs of consumption, we consider a smart irrigation controller as a harm reduction solution that can help heavy irrigators contribute toward the

social goal of water conservation. The device aims to water green landscapes efficiently, thus inherently enabling the maintenance of water-dependent ornamental landscapes, which are increasingly stigmatized in California. Recent work by Brandon et al. (2022) evaluates smart thermostats and raises questions about the impact of smart devices because user adjustments can override potential conservation. The smart irrigation controller used in our study functions more similarly to smart thermostats studied by Harding and Sexton (2017), Bollinger and Hartmann (2020) and Blonz et al. (2021), where the primary feature enables automated response to changing demand and/or supply conditions.[2] The device automatically reduces the use of scarce resources when user preferences, home and landscape characteristics and weather do not justify consumption. Thus, a household could automatically save water without any reduction in the attractiveness of an ornamental landscape. Yet, the device could also increase overall consumption for those previously conserving and for those who expand irrigable area in response to more efficient watering. It could also cannibalize abstinence solutions that have greater potential for conservation.

Recognizing the smart irrigation controller's inherent potential for alignment with the preferences of the heaviest water users, we partnered with a local water utility and a smart irrigation startup to design a marketing plan for this harm reduction solution. In a setting where fairness concerns restrict targeted outreach, we developed a Shopify portal for direct purchase and shipping, avoiding traditional rebates that attract price-sensitive, low-consumption households (Narasimhan (1984)) and aiming to encourage positive self-selection by inframarginal consumers. We then conducted two sequential randomized control trials to evaluate marketing levers and the four criteria described above.[3] The first experiment finds that both communications and heavy discounting is needed to drive adoption, while subsidized professional installation may increase compliance. We use the pricing findings from this 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.

The refined marketing strategy yields treatment effects on device adoption that are twice as large as the largest treatment effect in the first experiment.[4] With the results from the

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

[3] Banerjee et al. (2017) discuss the merits of sequential trials for scalable policy design in the context of schooling.

[4] This result is consistent with past research on pricing incentives (e.g., Cohen and Dupas (2010)).

two experiments in hand, we set out to assess the four metrics defined earlier: (1) whether our harm reduction solution is, indeed, particularly well-aligned with the preferences of the heaviest irrigators and those least likely to conserve, (2) whether device adoption leads to a reduction or increase in water usage, (3) whether the device cannibalizes turf-removal, the abstinence solution in this context, and (4) whether benefits of consumption (greenness of lawns) is decreased.

First, we find that those contributing most to the social problem, heavy irrigators, adopt at the highest rates. These results suggest that the device and its marketing is particularly well-aligned with the preferences of these households.

Second, we find significant reductions in water consumption that persist through our latest data period, nearly four years post-intervention. Specifically, we find negative and statistically significant effects of the marketing intervention on water consumption in the transitional seasons (e.g., September-October) as well as the peak irrigation season (July-August), coming largely from the heavy irrigator households. We interpret these results to mean that two major roles of the smart irrigation controller in facilitating water conservation are i) to more quickly respond to changing environmental conditions during season transitions and ii) reduce peak season irrigation, potentially due to app-based recommended watering times that might better match the true irrigation needs. The persistence of the effects is likely caused by the automation embedded in the durable smart irrigation controller and represents a contrast to "backsliding" observed in energy interventions (Allcott and Rogers (2014)) and interventions fostering pro-social change in developing economies (Caro-Burnett et al. (2021)). Importantly, we see no increases in consumption among non-irrigator households.

To quantify individual and social benefits of the smart irrigation controller, we estimate the local average treatment effect implied by the intent-to-treat effect and the rate of compliance with the treatment. We find that the effect of the smart irrigation controller on water consumption is large: using a household watering 8 sprinkler zones for 15 minutes twice a week as a baseline, the smart irrigation controller can lead to a 26% reduction in water consumption during the September-October time-frame when set it and forget it consumers with traditional controllers do not steadily reduce their water use into winter. For the heaviest irrigators, adoption of the device yields monetary savings that recover the typical cost of the device ($250) in

about half a year,[5] suggesting relatively large investment inefficiencies (Allcott and Greenstone (2012)). The annual water savings of a heavy irrigator household covers the basic (indoor) annual water needs of a local household,[6] suggesting significant social benefits.[7]

Next, we address the question of whether the heavy promotion of a harm reduction alternative cannibalizes abstinence. The case of e-cigarettes' potential for harm reduction is a telling example about the risks of cannibalizing abstinence. Centers of Disease Control and Prevention (2023) suggests that e-cigarettes are a less harmful alternative to traditional cigarettes, and Tuchman (2019) documents that e-cigarette advertising reduces demand for traditional cigarettes. However, Soneji et al. (2018) find e-cigarettes may attract consumers who never would have smoked in the first place. In our smart irrigation controller case, we find that adoption incentives do not lead households to forgo turf removal by documenting no change in measured photosynthetically active vegetation (PSAV).[8] Abstinence thus appears unchanged.

Finally, we consider whether this harm reduction alternative reduces positive surplus realized by those with a high valuation of the private benefit. We therefore measure the greenness of the PSAV and find it to be unaffected by the intervention. This, together with the water reductions, suggests surplus gains for high valuation households.

Our results underscore the importance of promoting solutions that are well-targeted to not only the most pro-socially inclined, but also those most reluctant to change their behaviors.[9] Thus, our findings shed light on how policy-makers and conservation proponents can improve progress towards social goals by recognizing and catering to the inherent heterogeneity in preferences of the households, even when such preferences do not align with their own. Our framework for analysis can be used by policy-makers considering the potential for harm

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

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

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

[8] We quantify turf removal and browning of lawns using supplementary data on the photosynthetically active vegetation area and its greenness (Quesnel et al. (2019)) for a subset of households in the second experiment.

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

reduction in other contexts.

In addition to extending the domain of harm reduction and formalizing its marketing and economics, we also contribute to a growing literature quantifying the pro-social (rather than profit-maximizing) uses of marketing. Studies have measured the role of marketing in the shift to green energy (e.g. Bollinger and Gillingham (2012), consumption of healthier foods (Seiler et al. (2021), Bollinger and Sexton (2023)), promotion of pharmaceuticals for physical and mental health (e.g. Manchanda et al. (2005), Shapiro (2018)), fire arm choice (Moshary et al. (2023)) and consumer and firm behavior in developing countries (Anderson et al. (2018), Anderson et al. (2022), Economides and Jeziorski (2017), Sudhir et al. (2016) and Donati (2023)). We contribute to this literature by evaluating marketing interventions for water conservation.

The rest of the paper proceeds as follows. In Section 1, we outline the *economics* of harm reduction and introduce how conservation contexts such as ours operate by *reducing harmful consumption* rather than *reducing harm from consumption* as is in the canonical drug cases. In Section 2, we introduce the empirical context of our study. In Section 3, we describe our empirical study design, which integrates marketing a harm reduction solution with embedded experimentation to enable measurement and evaluation. In Section 4 we present the effects on adoption and evaluate whether it is concentrated among the heavy irrigators. Section 5, presents the substantial water reductions, concentrated among the heavy users. In Section 6, we evaluate landscape size and greenness to validate that efficient irrigation is neither increasing yard sizes nor diminishing surplus by creating less green landscapes. Section 7 concludes.

1 The Economics of Harm Reduction: Illustrative Model

In this section, we present an illustrative analysis of the economics of harm reduction.[10] We begin with a simple model of a continuous quantity choice based on private costs and benefits. "Harm" arises proportional to consumption because the private costs are lower than the social costs of the behavior. We introduce two forms of harm reduction: (i) reducing harm from consupmtion by lowering both the social and private costs of the behavior (e.g., a needle exchange), or (ii) reducing harmful consumption through a solution such as an efficiency device that delivers the same private benefits with lower consumption. Both harm reduction

[10] For mathematical derivations and model parametrization see Web Appendix A.

solutions yield private and social benefits. The economics of harm reduction involve reduced social costs from existing consumers, particularly high users, but may also result in increased consumption and social costs from previously abstinent consumers. The empirical assessment of harm reduction depends on the relative magnitudes of these effects.

Our analysis also considers a case of abstinence promotion, which typically precedes harm reduction in policy discussions in both the classic case of drug use and the water conservation case we consider. In both cases, price levers are typically unavailable. Drugs are illegal and therefore untaxed and pricing for conservation was ruled illegal when contested during the California drought we consider (Capistrano Taxpayers Association, Inc., v. City Of San Juan Capistrano (2015)). However, in Web Appendix A.5, we illustrate how pricing mechanisms (e.g. a tax) could align social benefits and costs.

1.1 A Baseline Case

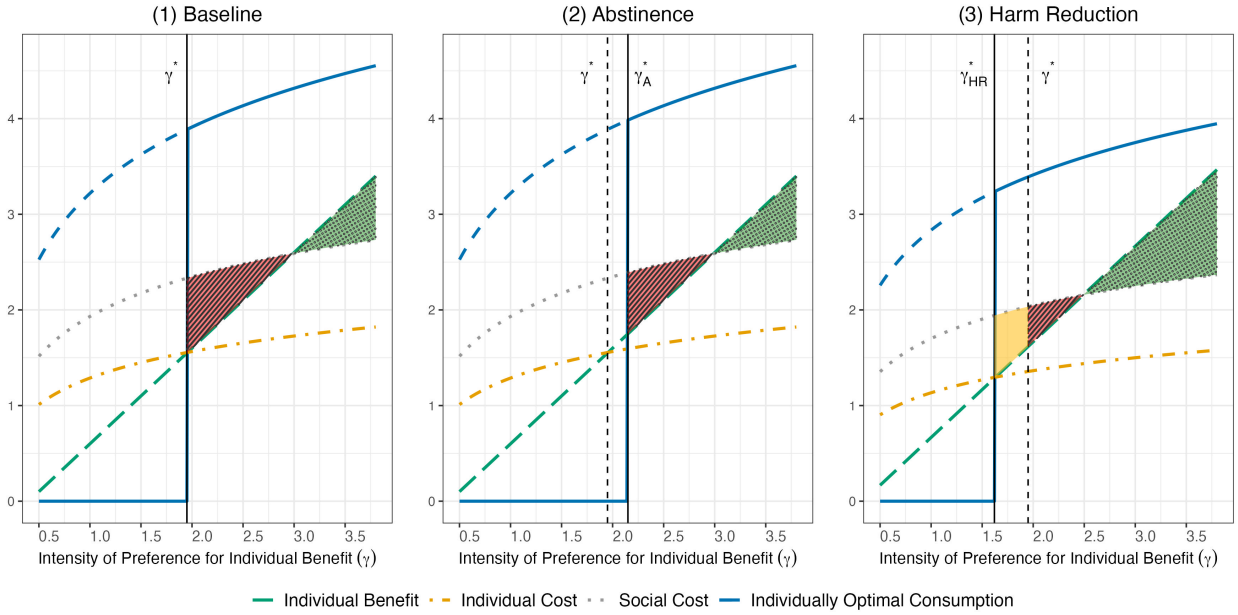
Let Q represent the consumption that produces private benefits and social costs not internalized by consumers. pQ are a consumer's expenditures arising from price, p, and consumption. For simplicity, we consider quasi-linear preferences where the expenditures enter through a numeraire good such that utility can be written as:

$$u(Q|\gamma, \phi, \theta, \eta, p) = v(Q|\gamma, \phi) - \theta Q + \eta(I - pQ) \tag{1}$$

where η is the marginal benefit of the numeraire good (i.e. the constant marginal utility of income) and θ are non-pecuniary harmful effects of consumption that do not fully capture the social harm of consumption. $v(.)$ defines the private benefits of consumption, where γ indicates the intensity of preference generated by Q and ϕ defines the efficiency with which Q produces v. We adopt the standard assumption that the marginal benefit of consumption is positive and diminishing, expressed as $\partial v(Q|\gamma,\phi)/\partial Q > 0$ and $\partial^2 v(Q|\gamma,\phi)/\partial^2 Q < 0$. We further assume that optimal consumption increases with a stronger preference for the private benefit, implying the additional condition $\partial^2 v(Q|\gamma,\phi)/\partial Q \partial \gamma > 0$.

We represent the social costs of consumption as $cQ > \theta Q + \eta pQ$. The condition that social costs exceed private costs applies to contexts like ours in which individuals do not fully internalize the social costs of their consumption – due, for example, to inefficient pricing mechanisms.

Figure 1: Promoting Abstinence vs. Harm Reduction (Illustrative)



This figure illustrates the sources of consumption and welfare changes in response to abstinence promotion (panel (2)) and harm reduction (panel panel(3)). The reference point is the baseline case in which the individual consumption costs do not fully internalize the social costs of consumption (panel (2)). The illustrations are based on the parametrization of the illustrative model presented in full in Web Appendix A.

We depict this baseline case, parametrized in Web Appendix A.3, in Panel 1 of Figure 1. The horizontal axis represents heterogeneous preference for consumption (γ), with the solid vertical line marking the marginal consumer. The blue line shows optimal consumption: it is solid to the right of the vertical line, where individual benefits (depicted by the green long-dashed line) exceed individual costs (depicted by the orange dot-dashed line). To the left of the vertical line, the blue line becomes dashed, reflecting abstinence by those whose individual benefits fall below their individual costs. The red shaded area highlights socially inefficient consumption, where social costs (depicted by the gray dotted line) exceed individual benefits. For consumers with a strong enough preference for the private benefits of consumption (γ), individual benefits also exceed social costs, resulting in positive social surplus, represented by the green shaded area.

1.2 Abstinence

A commonly promoted social alternative to harmful consumption is abstinence from consumption or $Q = 0$. Abstinence arises organically when the net private benefit, accounting for the fixed cost of abstaining, exceeds the private benefit of consumption:

$$u(Q = 0|\gamma, \phi, \theta, \eta, p) + F_A \geq u(Q^* > 0|\gamma, \phi, \theta, \eta, p) \tag{2}$$

F_A can be negative, reflecting fixed costs associated with behavior change, such as removing a lawn and replacing it with a native landscape. Alternatively, it can be positive, representing fixed benefits like the aesthetic appeal of a native landscape over a traditional lawn or the personal satisfaction of abstaining completely from socially undesirable consumption (e.g., avoiding a "sin"). In the baseline case, $F_A = 0$ and abstinence is individually optimal for consumers whose preference for the benefits of consumption falls below that of the marginal consumer, represented by the area to the left of the vertical line.

In Panel 2 of Figure 1, we examine a "nudge" aimed at encouraging more consumers to abstain. This mechanism shifts the marginal consumer to the right, either (1) without changing individual costs or benefits, or (2) by reducing the fixed cost of abstinence (or increasing its fixed benefit). We remain agnostic about the specific mechanism driving the nudge. The dashed vertical line represents the marginal consumer from the baseline case. Under abstinence promotion, the marginal consumer's preference for private benefits is higher than in the baseline case.

The challenge with abstinence is that it primarily appeals to consumers near the margin, as they derive limited benefits from consumption. This is why we depict the abstinence region as narrow. In contrast, other consumers gain substantial individual benefits from consumption and are unlikely to be influenced by an abstinence "nudge."

1.3 Harm Reduction

Harm reduction offers an intermediate alternative to abstinence, mitigating harm while allowing for continued consumption. We consider two pathways for harm reduction:

- Reducing *Harmful Consumption* by improving efficiency of consumption, ϕ.
- Reducing *Harm from Consumption* by decreasing social cost c and/or individual cost θ.

Traditional harm reduction methods, such as needle exchanges or fentanyl test kits, fall in the latter category. In contrast, efficiency devices, such as electric vehicles or smart irrigation controllers, offer an alternative approach by reducing harmful consumption, especially among the heaviest users, through improved efficiency in delivering private benefits. We first focus

on the "Reducing Harmful Consumption," case as it is most relevant to our study, and then compare it to the classic drug case and other scenarios where promotion of efficiency does not qualify as harm reduction.

1.3.1 Reducing Harmful Consumption: Model

Harm reduction through efficiency devices in conservation arises from decreased consumption. This reduction is driven by increased production efficiency ϕ, which lowers optimal consumption by allowing consumers to obtain the same private benefits (e.g., the aesthetics of an ornamental lawn) with less consumption. This relationship holds under the additional condition $\partial^2 v/\partial Q \partial \phi < 0$.

Panel (3) of Figure 1 illustrates harm reduction through efficiency devices. An increase in efficiency (ϕ) reduces optimal consumption, shown by the downward shift of the blue (solid) line. This reduction decreases both private and social costs, expanding social surplus (green shaded area) and reducing social loss (the red shaded area). Notably, the extensive margin may increase due to the more efficient production of private benefits, causing the marginal consumer to shift leftward (new solid vertical line compared to the former marginal consumer, depicted by the dashed vertical line). The yellow shaded area reflects the social loss from consumers who previously abstained but now begin consuming. We detail the additional conditions on $v(.)$ that would lead to such a shift in Web Appendix A.2.

The yellow shaded area may be limited if adopting a harm reduction solution incurs a fixed cost, F_{HR}. Specifically, if the distance between individual benefits and private costs is less than F_{HR}, the consumer will not adopt the harm reduction alternative. If this distance for the marginal consumer from the baseline equals F_{HR}, there will be no change in the marginal consumer.

1.3.2 Reducing Harmful Consumption: Empirical Evaluation

In practice, measuring utility and welfare effects directly is challenging. To address this challenge, we propose the following practical evaluations for *reducing harmful consumption*.

1. **Adoption by Heavy Users**: Harm reduction solutions should primarily be adopted by heavy users, with minimal adoption among marginal consumers, ensuring the yellow

region in Figure 1 remains narrow or nearly zero. See Table 3 in Section 4 of our analysis.

2. **Significant Reductions by Heavy Users**: Consumption reduction should be substantial among heavy users, reducing the social costs (gray dotted line in Figure A.1) and hence shrinking social losses from the top (red area) and expanding the social surplus towards the bottom (green area). See the lower panels in Figures 5 and 6 in Section 5.

3. **Limited Impact on Marginal Consumers**: If marginal consumers adopt the harm reduction alternative, their consumption increases should be small or insignificant, limiting the height of the yellow region in Figure 1. See the upper panels of Figures 5 and 6 in Section 5 as well as Figure 7.

4. **Preserving Private Benefits**: To ensure that reductions in consumption do not diminish private benefits (green long-dashed line in Figure 1), thereby reducing social surplus (green area from the top) and increasing social losses (red area toward the bottom), the output of consumption (e.g., lawn greenness) should not substantially decrease. See Table 4 in Section 6, which evaluates whether water efficiency from adoption affects lawn greenness.

Note the contrast between the evaluation of harm reduction and that of a "nudge" towards abstinence, where the primary prediction is a reduction in consumption at the margin.

1.3.3 Reducing Harm from Consumption

Harm reduction through *reduced harm from consumption* involves similar trade-offs. Reducing private harm lowers the marginal costs of consumption, which can lead to increased usage and potentially encourage individuals to move out of abstinence. As a result, the overall impact becomes an empirical question of balancing the harm reduction for existing consumers against the harm arising from increased consumption, including from new consumers.

Although we do not evaluate the canonical harm reduction case for drugs, it is helpful to consider the similarities and differences in the required empirical analysis. First, a nudge toward abstinence has a similar effect of reducing consumption only at the margin. Second, evaluating this harm reduction approach should align with evaluation criteria 1 and 3 in Section 1.3.2, demonstrating concentrated adoption by heavy users and minimal adoption among marginal consumers.

The primary distinction between evaluating *reduction in harm from consumption* and *reduction in harmful consumption* lies in point 2 of Section 1.3.2. When the policy focuses solely on reducing harm from consumption, overall consumption need not decrease and, theoretically, may increase.[11] In this context, an analysis similar to point 4 in Section 1.3.2, using an alternative welfare indicator, is more appropriate. Instead of focusing on insignificant reductions in utility, researchers should aim to identify significant reductions in disutility. For example, in the drug case, this could include fewer hospital admissions related to drug use or its adverse effects.

1.3.4 Comparison with Other Efficiency Device Policies

The condition above that social costs are always greater than private costs, particularly for the marginal consumer, is what brings us into the realm of tradeoffs between abstinence and harm reduction. Abstinence is optimal for some consumers, especially those at the margin, but the greatest aggregate harm and opportunities to reduce it and increase surplus are for inframarginal consumers who would find abstinence very costly. If the social costs are not greater than private costs for the marginal consumer, abstinence is not optimal and we shift out of this analysis framework. This might occur, for instance, if the social benefits of consuming essentials such as air conditioning on excessively hot days is undervalued, i.e. c is a net social cost and might be negative for those consuming very little. In particular, smart thermostats hopefully enable consumption at the margin and draw people out of abstinence, potentially reducing hospital admissions for heat stroke. The same could go for under-consumption of water, but by focusing on irrigation for ornamental landscapes, this is not the case and is what puts us outside the typical demand reduction framework of the literature on efficiency devices. In that framework, points 1 and 3 from Section 1.3.2 does not apply. Adoption by marginal customers may be particularly important and we do not anticipate surplus loss from drawing consumers out of abstinence.

[11] Consumption could, however, indirectly decrease if, for instance, the improved health from safer drug use (via reductions in θ) enables consumers to retain employment and housing, thereby providing access to formerly inaccessible alternatives to consumption.

2 Empirical Context: The 2013-2016 California Drought

2.1 California Drought

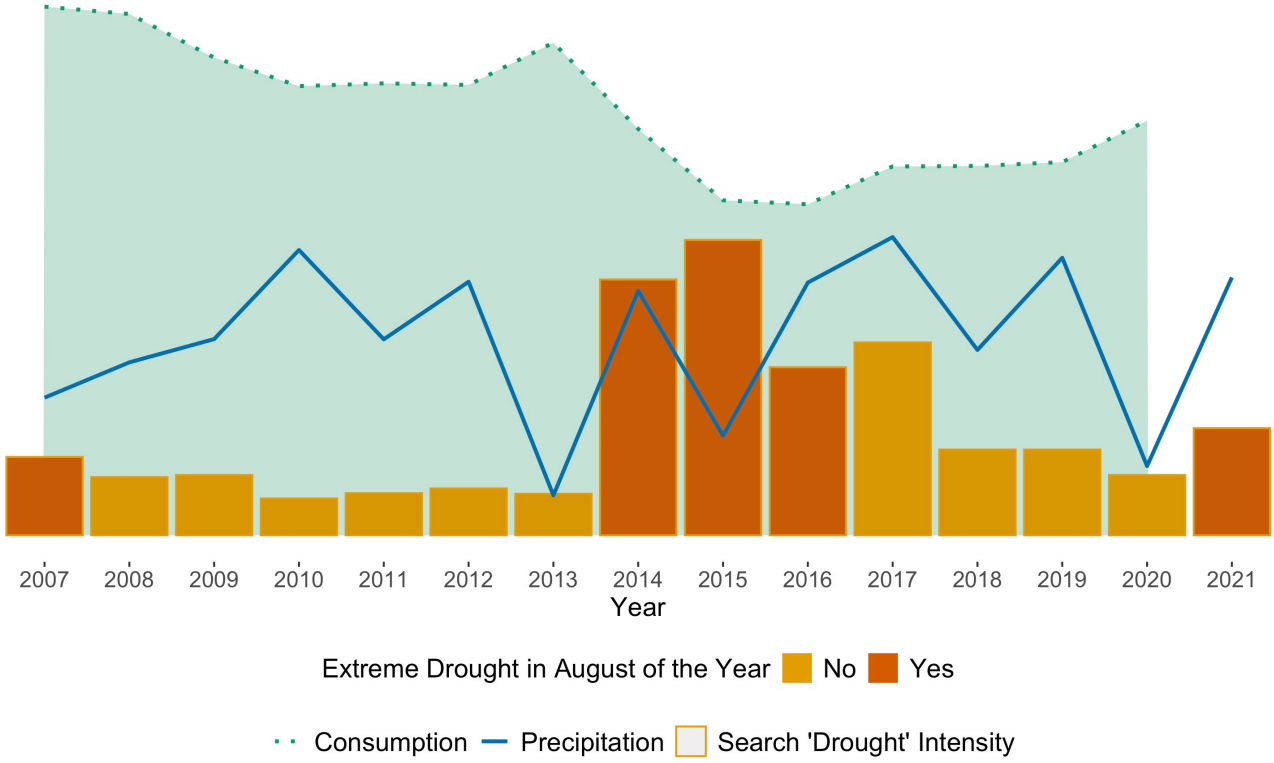
Drought in California is a recurring phenomenon with temporary reprieves that have grown shorter over the past few decades (Figure B.1). Drought arises because the demand for water outpaces supply. This dynamic is illustrated in Figure 2, which compares 2007-2021 residential water consumption in our partner city – Redwood City, California – to annual precipitation levels, incidence of extreme drought, and interest in drought as measured by Google trends (we describe data sources and data set construction for this and subsequent analyses in Web Appendix E). The patterns in 2013 illustrate the tension well: water supply (precipitation, in blue) falls drastically, but water demand (in green) increases, likely due to the increased need to irrigate a dry landscape. These levels could be efficient if reservoirs held sufficient water to smooth such shocks, but the red shading in 2014 reveals that the demand and supply imbalance in 2013 sent California into extreme drought in the following year.

Solving drought in California is a complicated challenge. Proposals to reform water rights, build infrastructure to capture runoff, and other initiatives aim to address 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. This paper, therefore, focuses on residential conservation and the challenge faced by the local water utility in altering the water consumption behavior of 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 occurred without a fully functioning price system, relying instead on a multi-party marketing process. As with other essentials like electricity, there is resistance to raising water prices, despite their potential to balance the supply and demand in the short-run without requiring changes in capacity investment (e.g., Borenstein and Holland (2005) and Fowlie et al. (2021) examine these dynamics in electricity markets, where prices can

Figure 2: Precipitation, Drought and Demand Response in Redwood City, California



"Consumption" refers to the annual water usage of an average residential unit in Redwood City, measured in units (1 unit = 748 gallons). "Search 'Drought' Intensity" represents the intensity of Google searches for the term "drought" in California. "Precipitation" indicates the total annual rainfall (in inches) recorded at the San Francisco AP Station (the nearest station to Redwood City), as reported by the National Weather Service.

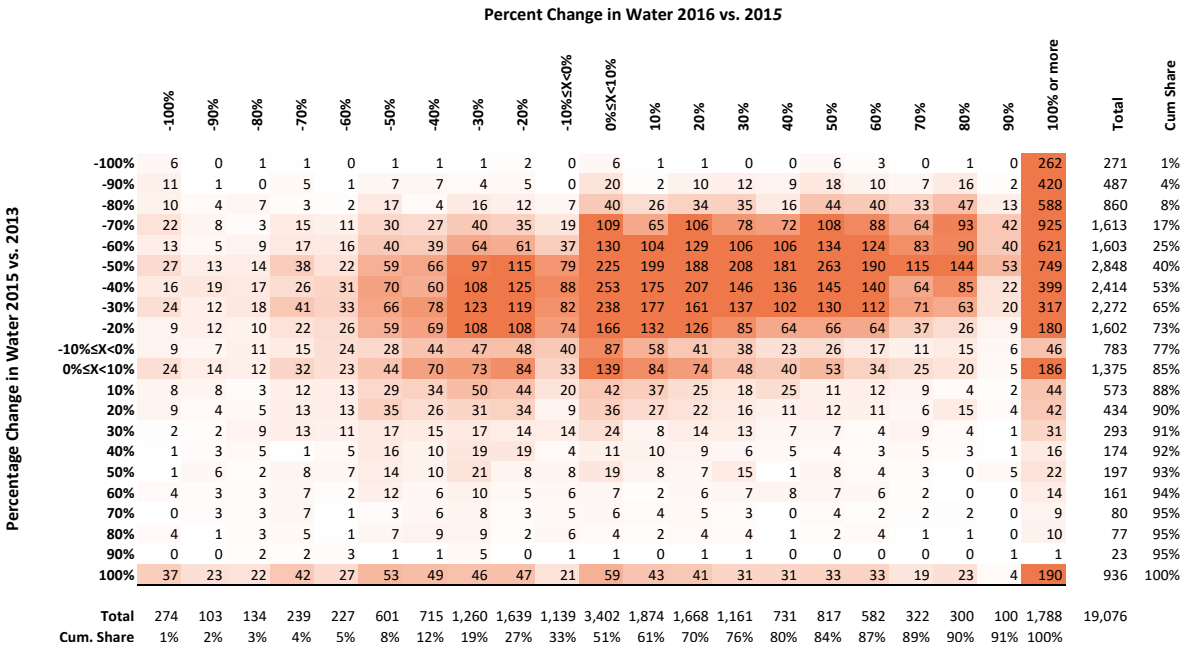
be used to shift consumption from high-cost to low-cost hours within a day). One alternative is a tiered pricing system that drastically raises prices for non-essential or heavy use. However, in 2015, California courts ruled conservation pricing illegal (Capistrano Taxpayers Association, Inc., v. City Of San Juan Capistrano (2015)), prompting many utilities, including our partner, to seek non-price approaches to reduce demand.

2.2 Utility Partner and Residential Response

We partnered with Redwood City Public Works (RWCPW) because of its proximity, their openness to collaboration[12] 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 given

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

Figure 3: Household Water Conservation and Reversion During Drought



Percent Change in Water 2016 vs. 2015

Percentage Change in Water 2015 vs. 2013

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

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

an 8% reduction mandate, likely, because of the low water use per household among its more urban households. RWCPW was therefore representative of the broader challenges in California of motivating behavioral change from a segment of the population where opportunities were large because of lot sizes, yet conservation was still challenging.

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

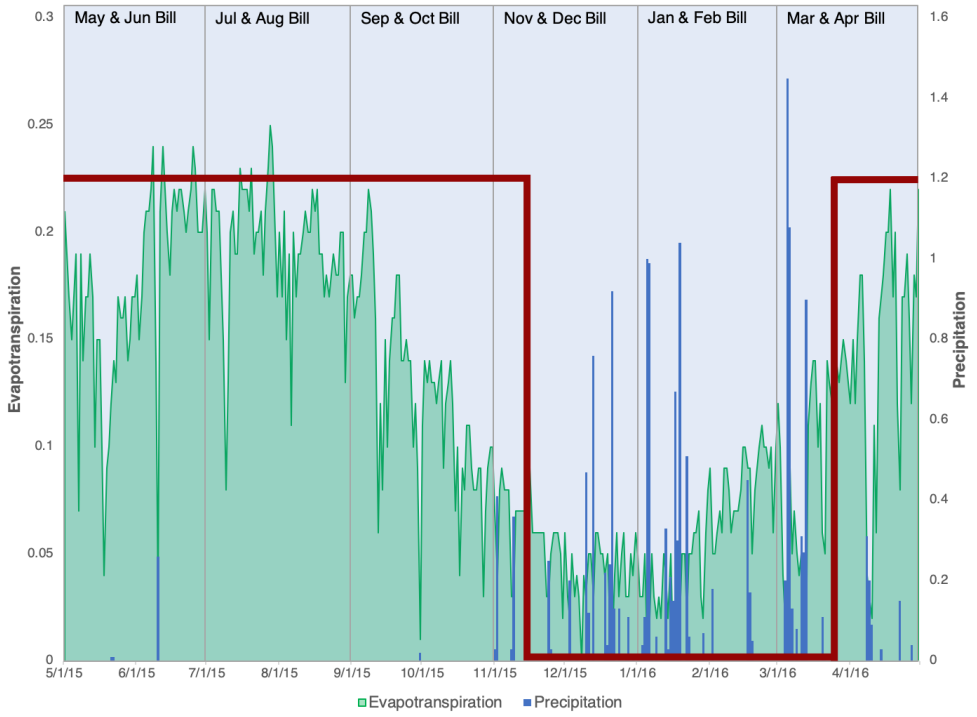
in outdoor irrigation. For example, a typical toilet and shower respectively use 32.6 and 26.9 gallons per household per day (gphd). On the other hand, running a typical 8 zone sprinkler system for 15 minutes in a day uses 1,920 gallons of water (DeOreo et al. and WSSCWater (2022)).

Before our collaboration, RWCPW primarily promoted indoor water use efficiency and conservation and the outdoor water use abstinence solution: turf removal. Figure B.2 displays RWCPW's dashboard tracking uptake of promoted conservation activities from 2013 through May 2016. The pre-drought (pre-2014) focus was on indoor conservation, particularly efficient toilets and clothes washers. Conservation kits, including indoor faucet aerators, faucet leak calculators and dye tablets to detect toilet leaks, were promoted and heavily adopted in 2015. As described in Section 1.3.4 these efficiency devices are not part of our harm reduction framework because these may efficiently enable consumption at the margin. The outdoor water use "abstinence solution" – turf removal – was heavily promoted at the start of the drought, with uptake increasing more than elevenfold between 2013 and 2014 with a further increase of more than 25 percent by mid-2015.

On the other hand, efforts to promote alternatives that reduce harmful outdoor water use without requiring abstinence were minimal. RWCPW began offering free efficient sprinkler nozzles in mid-2014 and introduced rain barrel rebates in 2015. However, from 2013 to 2016, RWCPC did not offer incentives for adopting smart irrigation controllers, which could have helped households better adapt to fluctuating demand and supply conditions for irrigation.

After initially reducing consumption during the drought, many households began to increase consumption in the summer of 2016, before the drought ended. The columns in Figure 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. Within this context, our harm reduction approach of mitigating the water use through a smart irrigation controller provided the potential for ongoing conservation while recognizing that many households would maintain an ornamental landscape despite the heavy push toward turf removal.

Figure 4: Water Demands Throughout the Year



This figure shows 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.

2.3 Smart Irrigation Controllers

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

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

The green area in Figure 4 plots evapotranspiration data, which is a weather metric wa-

ter 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 consumption. Another hypothetical consumer might split the difference and set the red line somewhere between spring and summer watering needs. Such a policy may, however, hinder the ability to realize the desired green landscape by under-watering in summer.

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

Rachio's smart irrigation controller replaces a traditional timer by swapping out the valve wires and setting up schedules using the smartphone app interface. Setup alone can influence irrigation because schedules are based on soil type, slope of the ground, and type of vegetation. While Rachio includes settings that can optimize daily watering based on evapotranspiration measures, its default and most common use involve adjusting watering times on the first of each month based on historical evapotranspiration for the coming month.[14]

[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.

[14]Examples of email notifications of monthly changes and rain / soil saturation skips are in Figures C.1 and C.2.

In Section 1, we developed an illustrative model to motivate the smart irrigation controller as a potential harm reduction solution requiring empirical validation. To empirically validate the use of the smart irrigation controller as the solution at the center of a harm reduction approach to conservation, we conduct a field study.

3 Marketing Harm Reduction: Drought Study Design

Conservation activities that sacrificed green landscapes during the peak of the drought achieved remarkable savings. However, the variability in households' ability to sustain those reductions during and beyond the drought underscores the need for diverse solutions. Turf removal provided a permanent conservation method, but the re-irrigation of previously browned lawns highlighted the need for a harm reducing solution that could enable both the retention of green lawns and conservation.

In what follows we outline a market-based approach to implementing harm reduction with embedded experimentation to evaluate both the effectiveness of the marketing strategies and the harm reduction solution. We focus on marketing with minimal targeting, as the water utility, like many other public agencies, aim to provide equal access to all customers. Consequently, the heterogeneous response we examine, as outlined in Section 1, arise through self selection akin to second degree discrimination.

3.1 A Marketing Process

Marketing helps guide diverse customers along tailored paths toward behavioral change, recognizing that different solutions appeal to different customers and that individuals may encounter varying challenges in adopting and using these solutions. The consumer decision-making process typically includes five stages: (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 focus on steps (2)-(5). Government and media communications surrounding the drought facilitated problem recognition (stage 1). We addressed stage (5) by influencing installation, leaving evaluations that may influence future adoption to our partner, Rachio.

Our marketing process, therefore, began with communications that added the smart irrigation controller into the consumer's consideration set (stage 2), alongside options already promoted by RWCPW (Figure B.2). This approach expanded the set of consumers consider-

ing the smart irrigation controller beyond organic adopters who discovered the device online, in-store, or via targeted display or search advertisements. Notably, we initiated these communications in 2016, after customers had already significantly reduced their consumption and likely adopted an abstinence alternative if they found it acceptable.

We then focused on the evaluation of alternatives (stage 3), during which individuals compare options within their consideration set. Although Rachio's product characteristics were fixed, we tested a range of price and installation discount offers that were supported by reductions in upstream prices. These incentives, represented by F_{HR} in the model in Section 1 aimed to make the smart irrigation controller more appealing compared to other available alternatives.

Next, we streamlined the purchase decision (stage 4) by linking the communications to dedicated portals built by Rachio, allowing verified RWCPW-account holders to quickly and easily purchase their discounted devices (Figure D.5). This reduced friction and encouraged adoption by higher income customers who might have been deterred by the lengthy submission and approval processes of traditional rebates. In fact, had we used the traditional rebates approach it may have, like coupons, concentrated adoption toward marginal consumers Narasimhan (1984) we hope continue to abstain from irrigation.

Finally, Rachio helped us influence (stage 5) by coordinating with a professional installation partner. Experimentation with different installation subsidy levels was aimed to prevent consumers from stalling in the adoption process and leaving purchased devices unused (Lambrecht et al. (2011)). Additionally, professional installation could ensure the device was set up correctly, potentially improving its irrigation effectiveness.

3.2 Field Experiments

We conducted two field experiments in 2016 and 2017, with the collaboration of a smart irrigation controller manufacturer (Rachio) and RWCPW. The first experiment launched in June 2016 with a set of pricing and professional installation incentives for the adoption of the smart irrigation device. The second experiment launched in December 2017 with the offer of free smart irrigation devices and discounted professional installation. In the following subsections, we describe in detail the offered incentives and communication methods in each of the two experiments. We include images of the communications in Web Appendix D.

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 included in experiment 1 were single-family households with sufficiently high average water usage to have a lawn (12 units per billing period).

We communicated offers to treatment households through postcards 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 (Figure D.1). 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 (Figure D.2). 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 (Figure D.3). To address the fairness concerns described above, the 10% discount was also available to all control group households were they to navigate to the study portal and enter their account number; however, the control households did not receive communications informing them about the portal or the availability of a discount.

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

The treated households received an email communication informing them of the offer on December 1st, 2017 (Figure D.4). To further drive adoption relative to the first experiment, we added two additional motivations. First, we communicated the limited number of available

[15] Additional discussion of the randomization and stratification in experiment 1 is in Web Appendix F.

controllers to create a "fear of missing out" element. Second, we conducted randomization at the neighborhood block level to foster a social adoption element. The email therefore included the following additional call to action: "Don't forget to tell your neighbors - only 250 controllers are available through this special program." Although 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 measure the effects of controllers on water usage. Importantly, our data enable us to quantify the magnitude of any spillovers to the control group, and such spillovers would make our measured effect a conservative estimate.

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 investigate the balance of water usage and smart irrigation controller adoption rates across treatment and control arms in each of the experiments. Given the levels of analyses reported in Section 5, we investigate balance in (1) water usage the year prior to the experiment, (2) water usage in all years prior to the experiment for which we have consumption data and (3) water usage by bill period in all years prior to the experiment for which we have consumption data. Tables 5 and 6 report the balance checks for experiments 1 and 2, respectively. For experiment 1 (Table 5) 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 6), where there is only one treatment arm, we rely on the p-value of the estimated coefficient for the treatment group. We fail to reject the null that the treatment and control groups have the same water usage and smart irrigation controller adoption rates prior to each experiment.

4 Device Adoption and Activation

In this section, we first discuss the insights from the average treatment responses in the first and second experiments, highlighting how findings from the first experiment shaped the design of the second. We then explore the heterogeneity in adoption behavior and its implications for our analysis of water usage as it relates to the predictions in Section 1.3.2.

4.1 Treatment Response in the Two Experiments

We focus on two outcome variables.[16] The first measures device adoptions exclusively through the dedicated experiment portals. This metric does not account for organic device adoptions, which is particularly relevant for the control groups that did not receive communications directing them to the experiment portals.[17]

To address this limitation, the second outcome variable includes all observed device activations within the Redwood City water district during the relevant periods: from June 2016 (the start of Experiment 1) to November 2017 (prior to the launch of Experiment 2) for Experiment 1, and from December 2017 (the start of Experiment 2) to December 2018 (the last snapshot capturing newly adopted devices) for Experiment 2. This broader measure serves as a proxy for purchases made through channels outside the experiment portals, enabling a more accurate comparison between treatment and control groups. In Experiment 2, where limited supplies may have prevented some treatment group consumers from claiming a device, this broader measure also captures potential "advertising" effects. The experiment communication may have moved these consumers into the purchase funnel by raising awareness of the Rachio device, encouraging exploration of smart irrigation controllers or other water conservation options, or advancing them further in the purchase funnel with the endorsement of the water district.

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

$$a_i = \beta_0 + \sum_j \beta_1^j T_i^j + \varepsilon_i \tag{3}$$

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

[16] See Web Appendix E for additional details on the construction of these outcome variables and Figure G.2 for the timing and prevalence of device adoptions and activations.

[17] A small number of control households obtained the device through the portal in both experiments (2 out of 86 total adoptions in Experiment 1 and 14 out of 412 total adoptions in Experiment 2.). This occurred because (1) in Experiment 1, control households could learn about the offer from treated households and access the portal to redeem the 10% district-wide discount, and (2) in both experiments, households could use a neighbor's account number to claim the discounted or free device.

j = free controller with discounted installation offer.

4.1.1 Experiment 1: Response to Adoption Incentives

In experiment 1, a total of 86 devices were purchased by 86 Redwood City account holders through the dedicated portal. Purchases occurred between June 13^{th}, 2016 and August 22^{nd}, 2016, with a bulk of purchases shortly after experiment launch and another increase in purchases after the reminder email was sent on July 28^{th}, 2016 (Figure G.1).

Columns 1 and 2 of Table 1 show that only the deeper discounts and deeper discounts paired with installation incentives significantly increase the device adoption rate, while the 10% discount has no measurable effect. After accounting for organic adoption in the control group in Column 2, 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 ($\hat{\beta}_0$)). Although the 80% discount results in the highest effect on device adoption, the incremental effects of the deeper discount and installation offers are not statistically distinguishable from each other. These findings inform our design of the second experiment, which features an even deeper price discount (free device) and a discounted professional installation.

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

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

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

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

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

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

4.1.2 Experiment 2: Broad Roll-Out and Activation

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

Despite a less intensive communication campaign (no postcards and only a single email) and a smaller proportion of households in the treatment group, overall device uptake in Experiment 2 (387/19,131 = 0.02) exceeds that of Experiment 1 (86/7,000 = 0.01). Column 2 in Table 2 shows that the adoption rate in the treatment group (Control ($\hat{\beta}_0$) + Free Controller ($\hat{\beta}_1^{free}$)) in Experiment 2 is 5.2 times higher than in the control group (Control ($\hat{\beta}_0$)), which is double the effect of the 80% discount in Experiment 1. The device activation rate in Experiment 2 (202/387 = 0.52[18]) is slightly lower than in Experiment 1 (57/86 = 0.66), suggesting that the less generous price discounts of Experiment 1 may have attracted earlier adopters with higher intrinsic valuation of the device (Ashraf et al. (2010), Cohen et al. (2015)). Nonetheless, the

[18]Of the 387 households that claimed a free smart irrigation controller during the experiment, 187 activated their devices within the Redwood City service area after the experiment's start. An additional 15 households had previously purchased and activated a device, likely using the free device offer to replace an existing one. As in Experiment 1, 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.

broad roll-out of devices Experiment 2 in absolute terms, allows us to reliably examine the heterogeneity of adoptions and the effect of adoptions on eventual household water usage.

4.2 Heterogeneity in Treatment Response

Irrigation controllers offer the potential to improve watering efficiency, but the magnitude of this potential depends on factors such as parcel size, vegetation type as well as the household's relative preference for green landscape over water conservation. To assess whether our offered incentives successfully encouraged adoption among the households with the largest potential water reduction, we thus examine heterogeneity in offer uptake behavior.

We show that incentives primarily drive adoption among households with significant potential for outdoor water conservation: likely heavy outdoor irrigators. To identify these households, we use a data-driven approach based on the observation that heavy irrigators in Redwood City typically consume more water during warmer summer months than in winter (see Figure 4). For each household, we calculate the difference between summer (May–August) and winter (November–February) water consumption in the year preceding each experiment. We then group households into four quantiles based on this difference, with quantile 4 representing those with the highest summer-to-winter variation and quantile 1 representing those with the lowest. Table B.1 summarizes water consumption by billing period for households categorized by quantile.

Households in quantile 4 ("heavy irrigator" households) are likely to have large lawns requiring intensive watering during the dry summer months to stay green. In contrast, quantile 1 households either have minimal vegetation or exhibit low summer-to-winter variation, possibly due to consistently high overall water usage driven by indoor needs, such as toilets and showers, in larger households. While water meters cannot differentiate between these two types of households in quantile 1, seasonal variation in water use effectively identifies irrigator households in quantile 4. In Web Appendix K, we consider an alternative definition of heavy irrigators.

To examine the heterogeneity in response to treatment, we estimate the following equation, using the rate of adoption and activation as the outcome variable:

$$a_i = \beta_0 + \sum_k \beta_1^k T_i x_{ik} + \sum_k \beta_2^k x_{ik} + \varepsilon_i \tag{4}$$

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

Summer to Winter Use Δ Quantiles		Experiment 1 (1) Adopt or Activate	Experiment 1 (2) Num HH	Experiment 2 (3) Adopt or Activate	Experiment 2 (4) Num HH
Lowest:	Quant 1	0.009	1,895	0.014***	4,533
		(0.008)		(0.005)	
	Quant 2	-0.001	1,614	0.025***	4,749
		(0.009)		(0.005)	
	Quant 3	0.014*	1,799	0.037***	4,326
		(0.008)		(0.005)	
Highest:	Quant 4	0.020**	1,687	0.061***	4,371
	(Heavy Irrigators)	(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 their seasonal water usage variation. Variation quantiles are formed by computing the difference between summer (May-August) and winter (November-February) usage in 2015 (Experiment 1) and 2017 (Experiment 2), with households showing greater summer-to-winter variation assigned to higher quantiles. We distinguish quantile 4 households with the highest seasonal use variation as "irrigator households." The outcome measure is the rate of adoption and activation, as in Column (2) of Tables 1 and 2. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

where T_i indicates household i belongs to any treatment group (combining all treatment households in Experiment 1), and x_{ik} denotes the seasonal water use variation quantile k for household i.

Table 3 reports the coefficient estimates $\hat{\beta}_1^k$ and shows that, in both experiments, device adoption is primarily driven by heavy irrigator households. Column 1 of Table 3 shows a statistically significant treatment effect in Experiment 1 only for households in the 3^{rd} and 4^{th} quantiles. Column 3 reveals that while Experiment 2 incentives drove adoption across all quantiles, the treatment effects are significantly larger for higher-quantile households, consistent with the results from Experiment 1.[19]

Adoption concentrated among high use households helps assure that the solution is reducing harmful consumption among the heavy users, but not substantially drawing low or abstinent consumers into high use. However, given that there is small but statistically significant adoption even among the lowest quartile households, we need to evaluate how that influenced their

[19]In Web Appendix H, we provide additional supporting evidence of stronger treatment effects 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.

consumption in the next section.

5 Water Conservation

In this section, we assess whether our intervention was, in fact, harm reducing; i.e., whether water consumption decreased as a result of the smart irrigation controller promotion.[20] We split our analysis across two dimensions.

First, we distinguish between average effects for the entire population and those we identify as heavy irrigators. This distinction is important because the study population in experiment 2 (the focus of the analysis in this section) included all residential households in the Redwood City service area, many of whom do not have outdoor irrigation needs and/or may be using very little water.[21] Thus, we expect attenuated conservation in the average effects for the entire population and the possibility of irrigation increases among low-consumption households for whom device adoption may lead to increased irrigation. We view the analysis of heavy irrigators as the primary gauge of whether the intervention obtains conservation from those least aligned with the pro-social objective.

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

5.1 Effect of 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:

$$\tilde{w}_{it} = \sum_b \alpha_1^b T_i \mathbb{1}\{t = b\} + \sum_b \alpha_2^b \mathbb{1}\{t = b\} + \varepsilon_{it} \tag{5}$$

[20] In the analysis in this section and in the PSAV analysis in Section 6, we exclude four outlier households in an effort to report conservative estimates. We define an outlier household as having an observation of >2.5K units consumption in a billing period (≈ 11.22M gallons annual consumption). In practice, these four households either have consistently very high water consumption per billing period or have extremely high water consumption in one billing period only. All of the four households are in the treatment group, but none are heavy irrigator quartile 4 households and none adopt a smart irrigation controller. Thus, quartile four results remain exactly the same when the outlier households are included, and average consumption results are directionally very similar.

[21] In Web Appendix I, 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 smaller number of devices adopted in experiment 1.

where $\tilde{w}_{it} = w_{it} - w_{ib(t)}^{\text{pre-exp}}$ represents water consumption in units (1 unit = 100 cubic feet = 748 gallons) at time t, differenced relative to the household's consumption in the same billing period the year prior to the experiment. The variable b indexes billing periods, $b \in \{\text{Nov-Dec 2017}, \ldots, \text{Jul-Aug 2021}\}$ and T_i is the treatment indicator, equal to 1 for treatment households and 0 for control households.[22] We two-way cluster standard errors at the street (i.e., treatment assignment) (Abadie et al. (2017)) and billing period level.

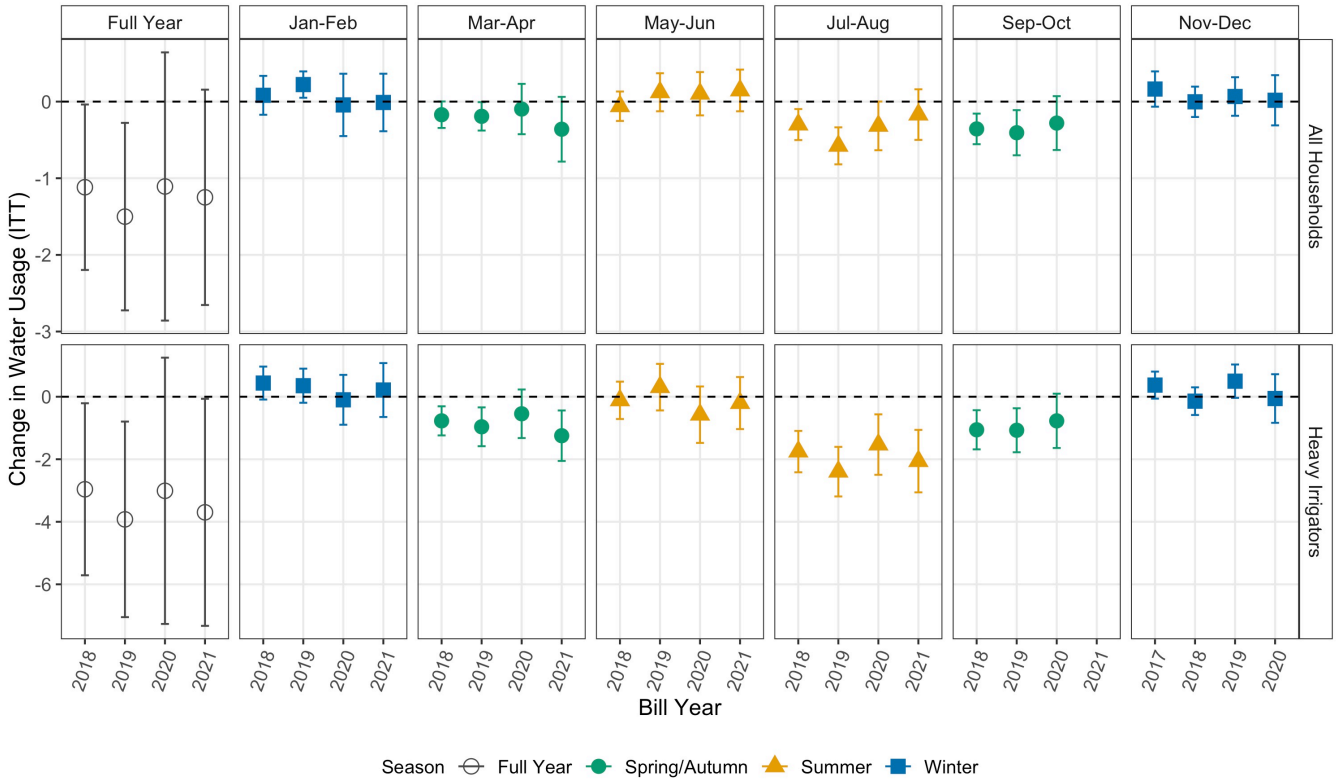
By estimating equation 5, we are effectively estimating year-billing period-specific intent-to-treat effects of interventions on water consumption. We do this to test our hypotheses that smart technology can drive and sustain long-term changes in water consumption behavior and that its effectiveness may vary with seasonal differences in precipitation and irrigation needs (e.g., during the growing season).

In Figure 5, we report coefficient estimates $\hat{\alpha}_1^b$. Column 1 reports aggregate year effects, while columns 2-7 report the results by bill period. Focusing on the treatment effects for all households (upper panels), 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).

We see further evidence of this same force when estimating equation 5 separately by quantile of summer to winter consumption difference (as defined for the analysis in Table 3). The bottom panels of Figure 5 report coefficient estimates $\hat{\alpha}_1^b$ for irrigator households (quantile 4) and show

[22] In Web Appendix J, we present coefficient estimates for two alternative versions of the main specification. In both, the results are similar to the main specification but more noisy.

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



This figure shows the intent-to-treat (ITT) treatment effect on household water consumption (estimates $\hat{\alpha}_1^b$, resulting from estimating equation 5). Each panel displays the estimates for a given billing period across all in-sample years, with seasons distinguished by color and shape. The upper panels present the ITT estimates for all households, while the lower panels focus on ITT estimates for irrigator households (quantile 4). Error bars represent 90% confidence intervals.

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). Figure 5 also shows that in addition to the transitional periods, for quantile 4 households the intervention led to a large negative and statistically significant reduction in water usage in the peak summer period between July and August. We interpret this to mean that a second major role of the smart irrigation controller in facilitating water conservation is to help households set appropriate baseline irrigation needs so as to avoid over-watering even during peak needs.

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.

5.2 Local Average Treatment Effect (LATE)

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

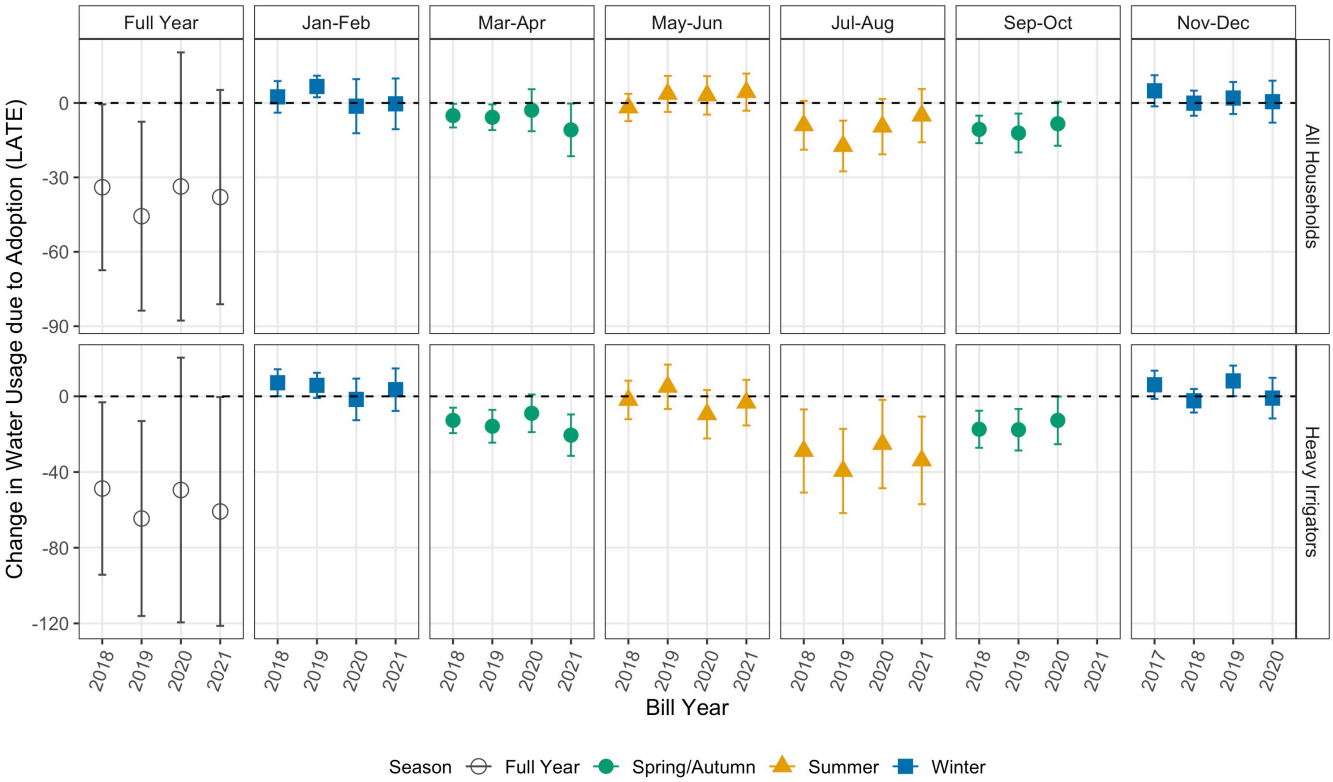
$$\tilde{w}_{it} = \sum_b \delta_1^b p_i \mathbb{1}\{t = b\} + \sum_b \delta_2^b \mathbb{1}\{t = b\} + \varepsilon_{it} \tag{6}$$

where p_i 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)[23]. We further instrument for p_i using random treatment T_i, which is equal to 1 for treatment households and 0 for control households, as in equation 5.

In the top panels of Figure 6, we report coefficient estimates $\hat{\delta}_1^b$. When averaging across

[23]The definition of adoption or activation is the same as in Column 2 of Table 2; i.e., within and out of portal adoption, as proxied by device activation from December 2017 to December 2018.

Figure 6: Local Average Treatment Effect of Adoption By Bill Period and Year (Exp2)



This figure shows the intent-to-treat (ITT) treatment effect on household water consumption (estimates $\hat{\alpha}_1^b$, resulting from estimating equation 5). Each panel displays the estimates for a given billing period across all in-sample years, with seasons distinguished by color and shape. The upper panels present the ITT estimates for all households, while the lower panels focus on ITT estimates for irrigator households (quantile 4). Error bars represent 90% confidence intervals.

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. 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 $10.65/41 = 26\%$ reduction in water consumption against this benchmark in the 2018 September-October billing period.

As in the analyses in sub-section 5.1, for irrigator households, these results are larger and more pervasive (see the bottom panels of Figure 6). A smart irrigation controller in an irrigator household leads to the largest decrease in consumption in the July-August peak consumption months (e.g., 29.0 units in 2018). It also leads to relatively large decreases in usage in the March-April and September-October transitional periods (e.g., 12.7 units and 17.4 units, respectively), when households without the device may have more quickly turned on or more slowly ramped

down the irrigation. For these heaviest irrigators, adoption of the device yields monetary savings that recover the typical cost of the device ($250) in about half a year (based on 2018 reduction - 48.73 units - and a $10.17/unit residential water rate, as described in footnote 5), suggesting relatively large investment inefficiencies among the heavy irrigators (Allcott and Greenstone (2012)). Moreover, the annual water savings of a heavy irrigator household covers the basic (indoor) annual water needs of a local household (based on the top usage of the first pricing tier (0-8 units) and 6 bi-monthly billing periods, as described in footnote 6).

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

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

6 Impact on Abstinence and Adopter Surplus

In this section, we use satellite imagery data to better understand whether our intervention cannibalizes abstinence (i.e., whether lawns would have been removed or left to brown in absence of our harm reduction offer) and whether harm reduction reduces surplus from adopters.

If the monetary incentives for smart controllers were causing consumers to forgo turf removal, we would expect the intervention to lead to an increase in the square footage of the irrigable area in the treatment group relative to the control (as in the illustrative model description in Section 1). Moreover, if this shift was sufficiently high, we would expect to see increased water usage in the treatment relative to the control group. In Section 5, we document a decrease in water usage resulting from the offered smart controller incentives, primarily driven by consumers prone to irrigation. Supplementary data on a subset of Redwood City households' photosynthetically active vegetation (PSAV) and the greenness of this vegetation (% Green PSAV) sheds further light on the extent to which adoption incentives for the smart irrigation controller - the harm reduction alternative - cannibalize adoption of the highest impact solution - turf removal.

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

In Table 4, for this sub-set of households with above-median irrigable areas, we examine the intent-to-treat effect on water consumption (column 1), square footage of green PSAV (column 2) and share of green PSAV in the parcel (column 3), using the same specification as in equation 5, implemented separately for the landscape size and greeness measures and select water consumption billing periods, and 2017 consumption and 2016 PSAV values as a baseline, respectively.

In column 1, we present the effect of treatment on change in water usage in three bill periods leading up to and immediately following the recording of the parcel via the NAIP satellite imagery in August. As in Figure 5, for these larger PSAV households, we observe statistically

Table 4: Effect on Consumption, Landscape Size and Greenness (Exp2)

	(1) Cons	(2) Green PSAV	(3) Share Green PSAV
Mar-Apr 2018	-0.673***	—	—
	(0.198)		
May-Jun 2018	0.0109	—	—
	(0.271)		
Jul-Aug 2018	-0.306	7.174	-0.00228
	(0.320)	(98.97)	(0.00478)
Sep-Oct 2018	-0.456*	—	—
	(0.258)		
HH FE	Yes	Yes	Yes
Clustering	street	street	street
N streets (Jul-Aug 2018)	509	513	513
N HH (Jul-Aug 2018)	8,826	9,157	9,157
N obs (Jul-Aug 2018)	18,118	18,314	18,314

This table shows the effect of treatment on on water consumption (column 1), square footage of green 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 5 and 2017 consumption and 2016 PSAV values as a baseline, respectively. The estimates in column 1 are each a result of a separate regression for the different billing periods. Green PSAV and Share 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

significant reductions in water consumption in the March-April and September-October 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.[24] As discussed in Section 1, this result suggests that the smart controller adoption incentives are mainly increasing uptake among consumers who would otherwise continue to water fully rather than those who would remove turf. This result is also consistent with the overall decrease in water usage resulting from the offered incentives (as shown in column 1 of Table 4 and Figure 5).

In column 3, we examine the effect of the treatment on the change in PSAV greenness from

[24]The median PSAV area for this subset of households is 3,326 square feet. Thus, a 95% confidence interval around the estimate represents a change of about 6% from this median.

2016 to 2018. As in column 2, we see an insignificant effect of treatment on the percentage of the irrigable area that is green.[25][26] This result speaks to both the abstinence cannibalization and the potential for surplus reductions among the heavy users. Because share of green vegetation in the parcel did not increase, it is not the case that devices were adopted by those with browning lawns (as implied by the model in Section 1). It also suggests that treatment group households decreased water consumption without sacrificing landscape greenness. Referring back to Figure 1, the green shaded areas to the right likely expanded since greenness which produces benefits was not reduced, but water usage and its associated costs were.

7 Conclusion

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

We employ two sequential field experiments to evaluate the effectiveness of heavily promoting a smart irrigation controller efficiency device as the harm reducing alternative. We show

[25]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 1.5% from this median.

[26]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 7, 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.

that our marketing interventions induce the highest adoption among the heaviest irrigators and those previously disinclined to conserve. The interventions, in turn, lead to significant reductions in water usage, driven by the heaviest irrigators without a corresponding increase among the non-irrigator households. We find no evidence that treated households forgo turf removal, the highest impact alternative in our context, suggesting that the harm reduction approach expands rather than cannibalizes engagement in conservation.

Overall, our results showcase the importance of considering heterogeneous preferences in designing interventions aimed at fostering pro-social behaviors. Disproportionate focus on the highest impact solution inherently excludes those deriving most value from the socially undesirable behavior; i.e., those who have the potential to make a large impact towards the pro-social goal. A harm reduction approach, on the other hand, can help engage the least pro-socially inclined who would otherwise not contribute towards the pro-social goal.

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

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

Next, we might expect a more preference-aligned alternative to simply 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. We expect this may be due to

the long replacement cycles of irrigation controllers; i.e. communications may increase demand, but without a substantial price decrease there is no obvious reason to replace now rather than later, especially if water and monetary savings are unknown as they were before this study. 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 and, hence, short-run adoption that created sample sizes sufficient 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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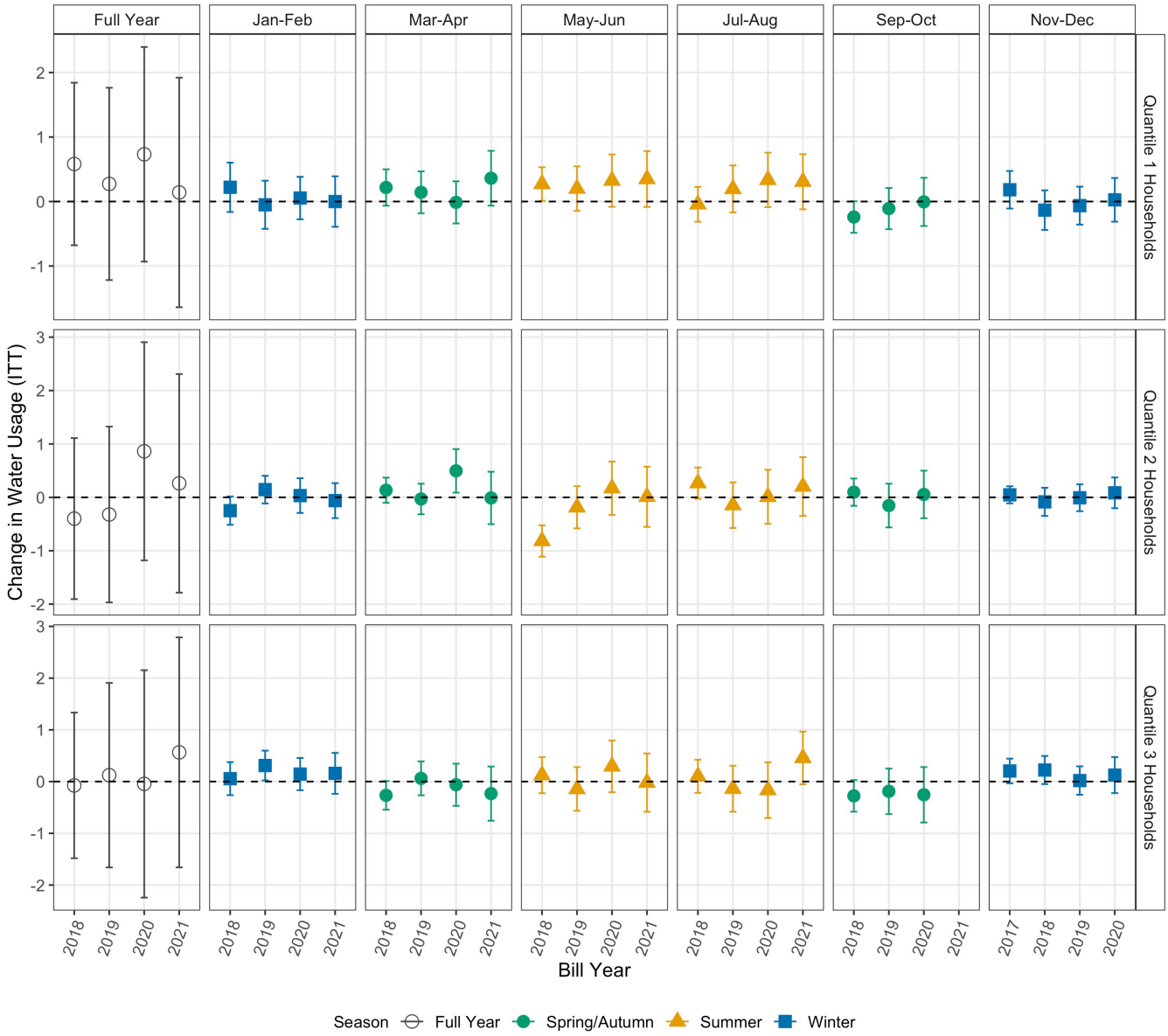
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8 Appendix

Figure 7: Intent-to-Treat Effect By Bill Period, Year (Exp2): Quantile 1-3 Households



This figure shows the intent-to-treat (ITT) treatment effect on household water consumption (estimates $\hat{\alpha}_1^b$, resulting from estimating equation 5), for households with lower seasonal variation in water consumption. Seasonal variation quantiles are calculated as the difference in water consumption between bills 4 and 5 (May–Aug) and bills 1 and 2 (Nov–Feb) in 2017, with quantile 1 representing households with the smallest variation and quantile 4 the largest. Each panel presents the estimates for a specific billing period across all in-sample years, with seasons indicated by different colors and shapes. Error bars denote 90% confidence intervals.

Table 5: 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)	

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

Table 6: Pre-Experiment 2 Characteristics by Treatment Status

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

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

Table 7: Correlation between 2016 to 2018 Change in PSAV & Change in Consumption

	Change in Annual Consumption		Change in Jul-Aug Consumption	
	(1)	(2)	(3)	(4)
	Δ Cons	Δ Cons	Δ Cons	Δ Cons
Δ Green PSAV	0.000837***		0.000233*	
	(0.000307)		(0.000130)	
Δ % Green		45.40***		10.61***
		(3.941)		(1.659)
N	8,691	8,691	8,941	8,941

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

Marketing and Economics of Harm Reduction: Evidence from Conservation Field Experiments

Kristina Brecko and Wesley R. Hartmann

January 15, 2025

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A Illustrative Model

Let Q represent the consumption that produces private benefits and social costs not internalized by consumers. pQ are a consumer's expenditures arising from price, p, and consumption. For simplicity, we consider quasi-linear preferences where the expenditures enter through a numeraire good such that a consumer's utility can be written as:

$$u = v(Q|\gamma, \phi) - \theta Q + \eta(I - pQ) \tag{A.1}$$

where η is the marginal benefit of the numeraire good (i.e. the constant marginal utility of income) and θ are non-pecuniary harmful effects of consumption that do not fully capture the social harm of consumption. $v(.)$ defines the private benefits from consumption where γ indicates the intensity of preference generated by Q and ϕ plays a role through the efficiency in which Q produces v.

We place the following general requirements on the utility u: (1) marginal private benefit of consumption is positive (i.e., the focal product is a *good* from the individual consumer's perspective), (2) optimal consumption is increasing in the preference for the private benefit (i.e., consumers with higher preferences for the private benefit γ will have higher optimal consumption), (3) optimal consumption is decreasing in efficiency of production of the private benefit (i.e., increasing the efficiency of production ϕ leads to lower optimal consumption levels because consumers realize the same benefits with less consumption)[1], (4) optimal consumption is zero below some threshold of the private benefit preference (i.e., there exist consumers with a sufficiently low valuation of the private benefit or sufficiently high monetary or non-monetary disutility of consumption that will choose not to consume at the baseline) and non-zero above this threshold.

A.1 Conditions on Model Primitives

We next express the four requirements above as conditions on the model primitives.

Requirement 1 The marginal private benefit of consumption is positive implies:

[1]This condition is necessary for the harm reduction solution to be in the feasible set of potential alternatives for social change. Although we impose this condition in the model, we test it empirically using our field experiment.

$$\frac{\partial v(Q|\gamma,\phi)}{\partial Q} > 0 \tag{A.2}$$

Requirement 2 To obtain the conditions on model primitives that satisfy requirement 2, we first characterize optimal consumption Q^* determined by the first order condition:

$$\frac{\partial v(Q^* \mid \gamma,\phi)}{\partial Q} = \theta + \eta p \tag{A.3}$$

Equation A.3 implicitly defines Q^* as a function of the model primitives: $\gamma, \phi, \theta, \eta$. To ensure that optimal consumption Q^* increases in the preference for the private benefit γ (i.e., $\frac{\partial Q^*(\gamma)}{\partial \gamma} > 0$), we then differentiate both sides with respect to γ:

$$\begin{aligned}
\frac{d}{d\gamma}\left[\frac{\partial v(Q^* \mid \gamma,\phi)}{\partial Q}\right] &= \frac{d}{d\gamma}\left[\theta - \eta p\right] \\
\frac{\partial^2 v(Q \mid \gamma,\phi)}{\partial Q^2} \cdot \frac{\partial Q^*(\gamma)}{\partial \gamma} + \frac{\partial^2 v(Q \mid \gamma,\phi)}{\partial Q \partial \gamma} &= 0 \\
\frac{\partial Q^*(\gamma)}{\partial \gamma} &= -\frac{\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q \partial \gamma}}{\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q^2}}
\end{aligned} \tag{A.4}$$

For $\frac{\partial Q^*(\gamma)}{\partial \gamma} > 0$:

$$\frac{\partial^2 v(Q \mid \gamma,\phi)}{\partial Q \partial \gamma} > 0 \text{ (higher } \gamma \text{ increases the marginal benefit of } Q) \tag{A.5}$$

$$\frac{\partial^2 v(Q \mid \gamma,\phi)}{\partial Q^2} < 0 \text{ (private benefits are concave in } Q) \tag{A.6}$$

Requirement 3 To ensure that optimal consumption Q^* decreases in efficiency of production of the private benefit ϕ (i.e., $\frac{\partial Q^*(\phi)}{\partial \phi} < 0$), we take the same steps to obtain the expression for $\frac{\partial Q^*(\phi)}{\partial \phi}$:

$$\frac{\partial Q^*(\phi)}{\partial \phi} = -\frac{\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q \partial \phi}}{\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q^2}} \tag{A.7}$$

For $\frac{\partial Q^*(\phi)}{\partial \phi} < 0$:

$$\frac{\partial^2 v(Q \mid \gamma, \phi)}{\partial Q \partial \phi} < 0 \text{ (higher } \phi \text{ diminishes the marginal benefit of Q)} \tag{A.8}$$

$$\frac{\partial^2 v(Q \mid \gamma, \phi)}{\partial Q^2} < 0 \text{ (private benefits are concave in } Q) \tag{A.9}$$

Requirement 4 Requirement 4 implies that for sufficiently low values of the private benefit valuation γ, the cost of consumption exceeds the benefit of consumption and the individual chooses to consume zero. Thus, at some threshold value γ^*, $\max_{Q>0} u(Q|\gamma^*) = u_0$ (i.e., the utility of consuming the optimal amount Q^* equals the utility of taking up the outside option u_0), which implies that:

$$Q^* = \begin{cases} 0, & \text{for } \gamma < \gamma^*, \text{ where } \max_{Q>0}[v(Q \mid \gamma, \phi) - \theta Q + \eta(I - pQ)] < u_0 \\ Q^*(\gamma, \phi, \theta, p), & \text{for } \gamma \geq \gamma^*, \text{ where } \max_{Q>0}[v(Q \mid \gamma, \phi) - \theta Q + \eta(I - pQ)] \geq u_0 \end{cases} \tag{A.10}$$

Equation A.10 implies that consumers with a preference for private benefits (γ) below the threshold γ^* will not consume because the private benefit at $Q = 0$ net of the cost of consumption is below the utility afforded by the outside option. It also implies that a higher disutility (θ) or price (p) raises the threshold γ^*, making consumption less likely for low-γ individuals. Finally, the threshold γ^* will also depends on ϕ. We examine the relationship between the level of the threshold γ^* and the efficiency ϕ in the following sub-section.

We summarize the unique conditions on the model primitives as follows:

$$\frac{\partial v(Q|\gamma, \phi)}{\partial Q} > 0 \text{ (marginal private benefits are positive)} \tag{A.11}$$

$$\frac{\partial^2 v(Q \mid \gamma, \phi)}{\partial Q^2} < 0 \text{ (private benefits are concave in } Q)$$

$$\frac{\partial^2 v(Q \mid \gamma, \phi)}{\partial Q \partial \gamma} > 0 \text{ (higher } \gamma \text{ increases the marginal benefit of } Q)$$

$$\frac{\partial^2 v(Q \mid \gamma, \phi)}{\partial Q \partial \phi} < 0 \text{ (higher } \phi \text{ diminishes the marginal benefit of Q)}$$

$$Q^* = \begin{cases} 0, \text{ for } \gamma < \gamma^*, & \text{where } \max_{Q>0}[v(Q \mid \gamma, \phi) - \theta Q + \eta(I - pQ)] < u_0 \\ Q^*(\gamma, \phi, \theta, p), \text{ for } \gamma \geq \gamma^*, & \text{where } \max_{Q>0}[v(Q \mid \gamma, \phi) - \theta Q + \eta(I - pQ)] \geq u_0 \end{cases}$$

A.2 Changes in Consumption Threshold with Changes in Efficiency

We next consider how the threshold of consumption γ^* changes with changes in the efficiency of production of Q into v. In particular, we may be concerned that improving the efficiency of production to $\phi' > \phi$ may lower the threshold for consumption to $\gamma^{*\prime} < \gamma^*$ and draw more individuals into consumption for whom previously $\max_{Q>0} u(Q|\gamma^*) < u_0$, but is now $\max_{Q>0} u(Q|\gamma^{*\prime}) > u_0$. This concern is typically what makes harm reduction solutions controversial from the policy perspective.

To characterize the conditions under which this may be the case we consider the sign of $\frac{\partial \gamma^*(\phi)}{\partial \phi}$ by differentiating the threshold condition in equation A.10, which implicitly defines γ^* with respect to ϕ, assuming that the utility of the outside option u_0 is independent of the efficiency of production ϕ:

$$\begin{aligned} \frac{d}{d\phi}\left[\max_{Q>0}\left[v\left(Q \mid \gamma^*, \phi\right) - \theta Q + \eta(I - pQ)\right]\right] &= \frac{du_0}{d\phi} \\ \frac{\partial v\left(Q \mid \gamma^*, \phi\right)}{\partial \phi} + \frac{\partial v\left(Q \mid \gamma^*, \phi\right)}{\partial \gamma} \cdot \frac{\partial \gamma^*}{\partial \phi} &= 0 \\ \frac{\partial \gamma^*}{\partial \phi} &= -\frac{\frac{\partial v(Q|\gamma^*,\phi)}{\partial \phi}}{\frac{\partial v(Q|\gamma^*,\phi)}{\partial \gamma}} \end{aligned} \tag{A.12}$$

Equation A.12 implies that if $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \gamma} > 0$ and $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \phi} > 0$, the consumption threshold decreases in production efficiency $\frac{\partial \gamma^*}{\partial \phi} < 0$. In our context, as in many similar contexts, it is plausible that these two additional conditions would hold: (1) consumers with higher preferences for private benefits will derive more value from consumption and (2) more efficient production will generate higher private value. Together, these conditions suggest that promoting a more efficient solution could lower the consumption threshold, thereby encouraging more individuals to consume.

It is important to distinguish these two conditions from the set of conditions in equations A.11. Whereas the latter are required for harm reduction to be in the feasible set of potential solutions to social change, the former represent a case where marketing a harm reduction solution may have

one type of negative impact on the desired social outcome, which may still be outweighed by its positive impact. For the purposes of illustration of the potential negative as well as positive effects of marketing a harm reduction solution, we focus on a parametrization of the model that both satisfies conditions in equations A.11 and allows for the consumption threshold to decrease with production efficiency (i.e., $\frac{\partial \gamma^*}{\partial \phi} < 0$ because $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \gamma} > 0$ and $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \phi} > 0$).

A.3 Parametrization of the Baseline Model for Illustration

For the purposes of illustration, we parametrize the private benefits function $v(Q \mid \gamma, \phi)$ as $\gamma\left(1 - 10e^{-Q\phi}\right)$, leading to the following utility function:

$$u(Q \mid \gamma, \phi) = \gamma\left(1 - 10e^{-Q\phi}\right) - \theta Q + \eta(I - pQ) \tag{A.13}$$

where, as before, γ is the preference for private benefits, ϕ is the efficiency of generating the private benefit, θQ is the non-monetary disutility of consumption and $\eta(I - pQ)$ is the utility from income after spending on Q. We normalize the outside utility $u_0 = \eta I$ and set the parameter values and ranges to $\theta = 0.1, \eta = 1, p = 0.3, \phi = 1, \beta = 10, \gamma \in [0.5, 4]$.

We next confirm that this parametrization of the utility function satisfies each of the conditions laid out in equation A.11.

Marginal private benefits are positive: Satisfied $\forall\ \gamma \in [0.5, 4]$

$$\frac{\partial v(Q|\gamma,\phi)}{\partial Q} = \gamma\phi 10e^{-Q\phi} = \gamma 10e^{-Q} > 0, \quad \forall\ \gamma \in [0.5, 4] \tag{A.14}$$

Private benefits are concave in Q: Satisfied $\forall\ \gamma \in [0.5, 4]$

$$\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q^2} = -\gamma\phi^2 10e^{-Q\phi} = -\gamma 10e^{-Q} < 0, \quad \forall\ \gamma \in [0.5, 4] \tag{A.15}$$

Higher γ increases the marginal benefit of Q: Satisfied

$$\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q \partial \gamma} = \phi 10 e^{-Q\phi} = 10e^{-Q} > 0 \tag{A.16}$$

Higher ϕ diminishes the marginal benefit of Q: Satisfied $\forall\ Q > 1$.[2]

$$\frac{\partial^2 v(Q|\gamma,\phi)}{\partial Q \partial \phi} = 10\gamma(e^{-Q\phi} - Q\phi e^{-Q\phi}) = 10\gamma(1-Q)e^{-Q} < 0, \quad \forall Q > 1 \tag{A.17}$$

There exists a threshold γ^* below which optimal consumption is 0: Satisfied and $\gamma^* \approx 1.956$, given the parametrization of the model.

We first derive the optimal consumption from the first order condition in equation A.3 under the given model parametrization:

$$\begin{aligned} \frac{\partial v(Q^* \mid \gamma,\phi)}{\partial Q} &= \theta + \eta p \\ \gamma 10 e^{-Q^*} &= 0.4 \\ Q^* &= \ln\left(\frac{\gamma}{0.04}\right) \end{aligned} \tag{A.18}$$

We then determine the threshold γ^*, where $\max_{Q>0}[v(Q \mid \gamma,\phi) - \theta Q + \eta(I - pQ)] = u_0$:

$$\begin{aligned} \gamma^*\left(1 - 10e^{-Q^*\phi}\right) - \theta Q^* + \eta(I - pQ^*) &= u_0 \\ \gamma^*\left(1 - 10 \cdot \frac{0.04}{\gamma^*}\right) - \theta \ln\left(\frac{\gamma^*}{0.04}\right) + \eta\left(I - p\ln\left(\frac{\gamma^*}{0.04}\right)\right) &= \eta I \\ \gamma^* - 0.4 - (\theta + \eta p)\ln\left(\frac{\gamma^*}{0.04}\right) &= 0 \\ \gamma^* - 0.4 - 0.4\ln\left(\frac{\gamma^*}{0.04}\right) &= 0 \\ \gamma^* &\approx 1.956 \end{aligned} \tag{A.19}$$

[2] Under the current model parametrization, this condition is satisfied because the consumption threshold is $\gamma^* \approx 1.956$ (see the threshold condition below), so optimal consumption is $Q^* > \ln\left(\frac{\gamma^*}{0.04}\right) \approx 3.890$.

We next show that the two conditions ensuring that the consumption threshold decreases in production efficiency, $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \gamma} > 0$ and $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \phi} > 0$ also hold under the current model parametrization:

$$\frac{\partial v\left(Q \mid \gamma^*, \phi\right)}{\partial \gamma} = 1 - 10e^{-Q\phi} > 0$$

$$Q > \ln(10) \approx 2.302 \tag{A.20}$$

$$\frac{\partial v\left(Q \mid \gamma^*, \phi\right)}{\partial \phi} = \gamma 10 Q e^{-Q\phi} > 0 \tag{A.21}$$

Equation A.20 shows that $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \gamma} > 0$ for $Q > 2.302$, which is true for all levels of optimal consumption because equations A.18 and A.19 put together imply that $Q^* > \ln\left(\frac{\gamma^*}{0.04}\right) \approx 3.890$. Further, equation A.21 implies that, in the given range of γ, $\frac{\partial v(Q|\gamma^*,\phi)}{\partial \phi} > 0 \quad \forall Q > 0$. Taken together, equations A.20 and A.21 imply that under this model parametrization the consumption threshold decreases in production efficiency.

A.4 Parametrization of Harm Reduction and Abstinence Solutions for Illustration

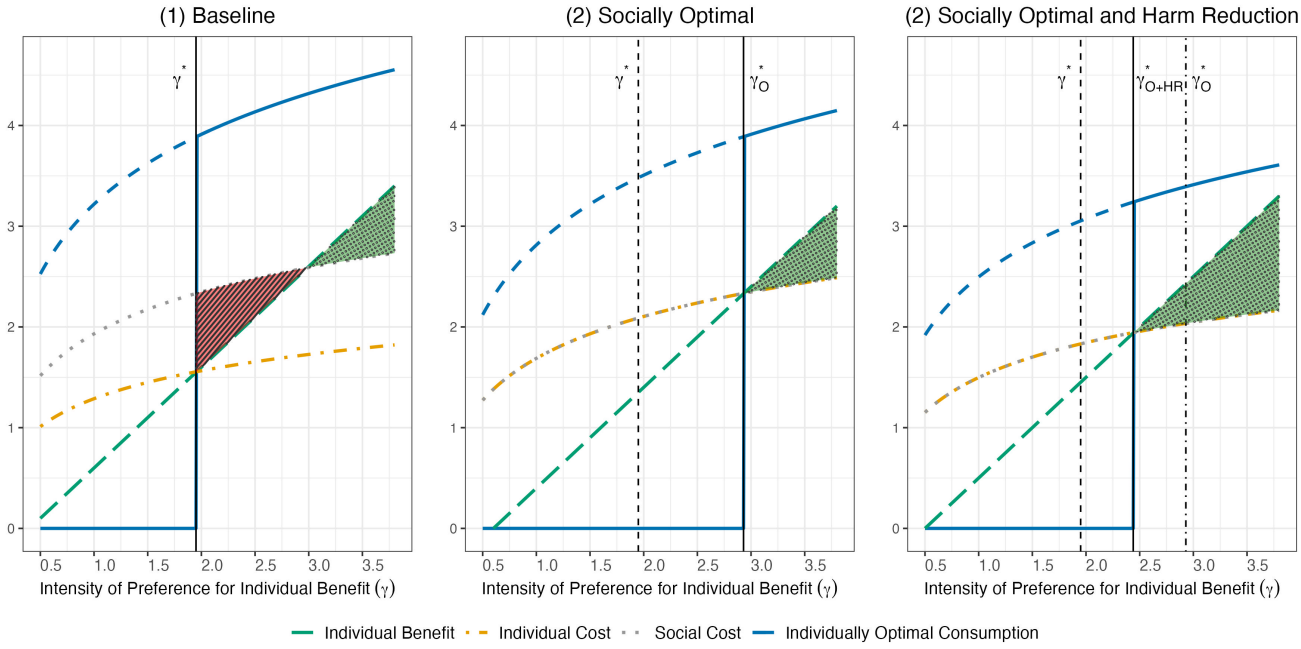
We parameterize a harm reduction solution as one that increases the production efficiency ϕ. Specifically, given the baseline model parametrization, $\phi = 1$, we parametrize the harm reduction solution as $\phi_{HR} = 1.2$. In this case, the consumption threshold becomes $\gamma^*_{HR} \approx 1.63 < 1.96 \approx \gamma^*$ and optimal consumption is lower than in the baseline case within the range of γ: $Q^*_{HR} = \frac{1}{1.2}\ln\left(\frac{12\gamma}{0.4}\right) < \ln\left(\frac{\gamma}{0.04}\right) = Q^*$. Thus, the harm reduction solution draws more individuals into consumption, but lowers consumption for all individual utility preference levels.

We parametrize an abstinence solution as one that increases the consumption threshold. In contexts such as ours, this is typically achieved by highlighting benefits of abstinence or offering incentives R to abstain from consumption, such that $\eta I + R > \eta I$. We parametrize the promotion of an abstinence solution as increasing the consumption threshold by 0.15; that is, $\gamma^*_A = \gamma^* + 0.15$. Ultimately the extent to which the consumption threshold shifts would depend on the magnitude of such incentives relative to that of the individual consumption benefits. Importantly, promoting

abstinence only shifts the marginal consumer and leaves unaffected the consumption, consumption utility and social costs produced by those consuming.

A.5 Parametrization of Socially Optimal Pricing and Harm Reduction

Figure A.1: Socially Optimal Pricing and Harm Reduction



This figure illustrates the sources of consumption and welfare changes in response to socially optimal pricing (panel (2)) and socially optimal pricing with a harm reducing solution (panel (3)). The reference point is the baseline case in which the individual consumption costs do not fully internalize the social costs of consumption (panel (1)). The illustrations are based on the illustrative model presented in full in Web Appendix A.

In Figure A.1, we also consider a case in which price can be used to align individual and social incentives. We show that although socially optimal pricing can increase social welfare relative to the baseline case, the addition of a harm reducing alternative at socially optimal prices may increase social welfare even further. Pricing and taxation is infeasible for illegal consumption such as drugs but are the standard tools that may help the policy-maker make progress toward pro-social goals. However, pricing or taxation may need to be extremely progressive in order to influence the inframarginal consumer without adversely affecting the consumption of marginal consumers who may have high basic water needs (e.g., those with large families). Such complexities help explain the lack of efficient pricing in resource markets and may explain legal rulings against using price to

adapt to drought in California. For example, 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.

B Temporal Trends in Drought Prevalence and Conservation Efforts

Figure B.1: Prevalence of Drought in California 1985 to Present

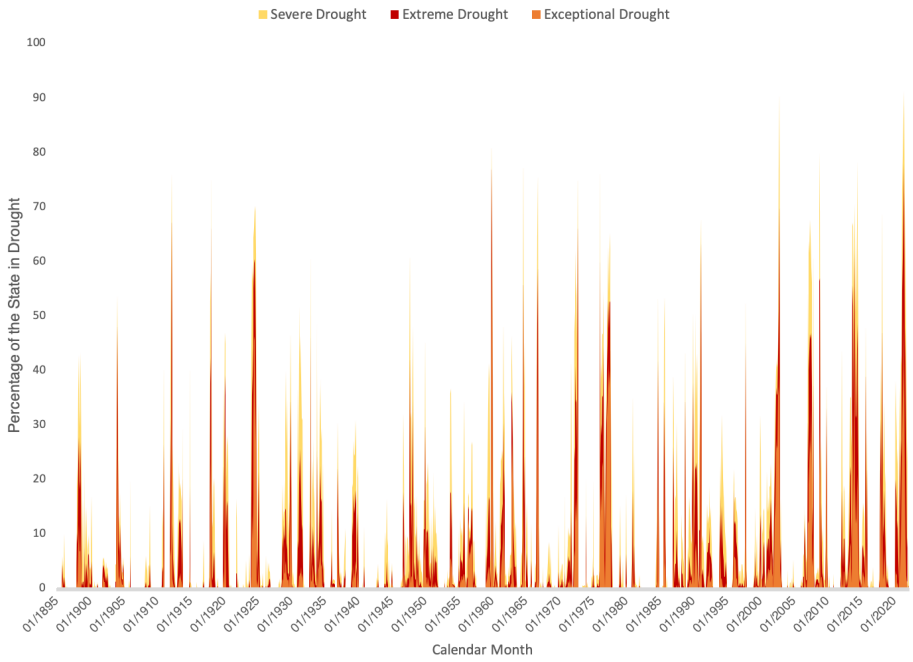


Figure B.2: Redwood City Conservation Programs and Participation 2013-2015

Water Conservation Activities Dashboard

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

C Smart Irrigation Controller Notification Examples

Figure C.1: Email Notification for a Seasonal Shift in Irrigation Durations

rachio



Front Grass on 813 Allardice adjusted.

Seasonal Shift automatically adjusts your schedule durations to offset seasonal weather changes.

In September, this schedule ran for 20 minutes. In October, this schedule will run for 14 minutes.

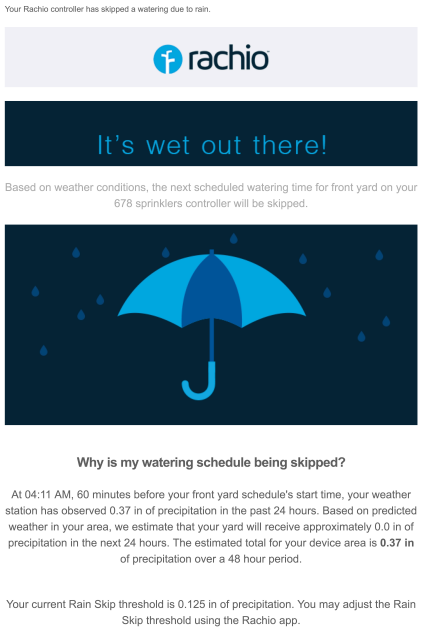
How does Seasonal Shift work?

Seasonal Shift uses historical weather data to automatically optimize schedules - watering more during the summer and less during fall, for instance. Shifts will be applied even when schedules are disabled or the controller is on Standby Mode.

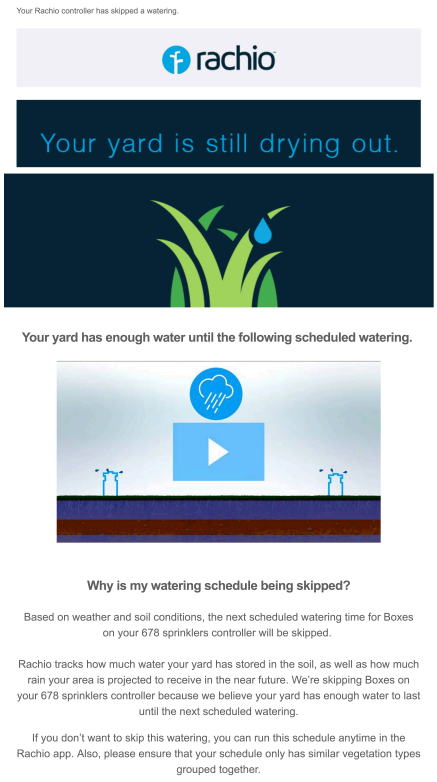
If you do not want your schedule to make monthly seasonal adjustments, disable Seasonal Shift for this schedule.

Click here to learn more about Seasonal Shift.

Figure C.2: Email Notification of Schedule Skips



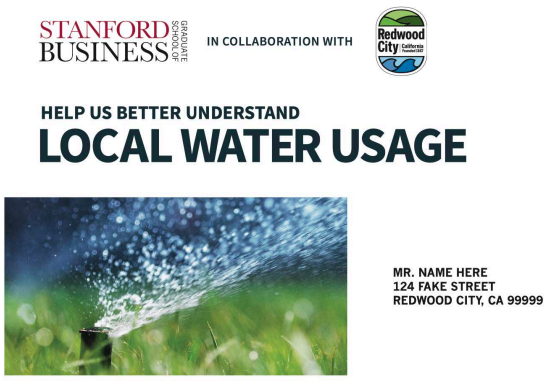
Rain Skip



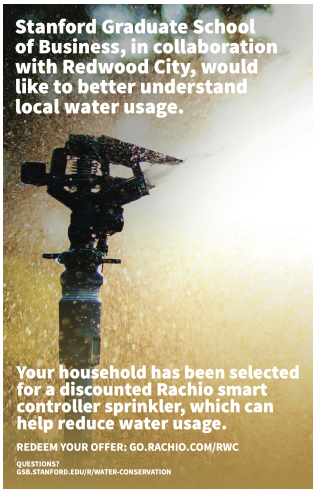
Soil Saturation Skip

D Field Experiment Communications and Portal

Figure D.1: Treatment Group Post Card (Experiment 1)



Address Side



Message Side

Figure D.2: Treatment Group Email (Experiment 1)



STANFORD BUSINESS

Redwood City

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

Your household has been selected for a 10% discount on a Rachio smart sprinkler controller that can help reduce water usage.

Redeem your offer: go.rachio.com/rwc

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

Redwood City California Founded 1867

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

myRWC

Figure D.3: 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 BUSINESS

Redwood City

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

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

Thank you for your participation.

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

Redwood City California Founded 1867

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

myRWC

Email

Figure D.4: Treatment Group Email (Experiment 2)

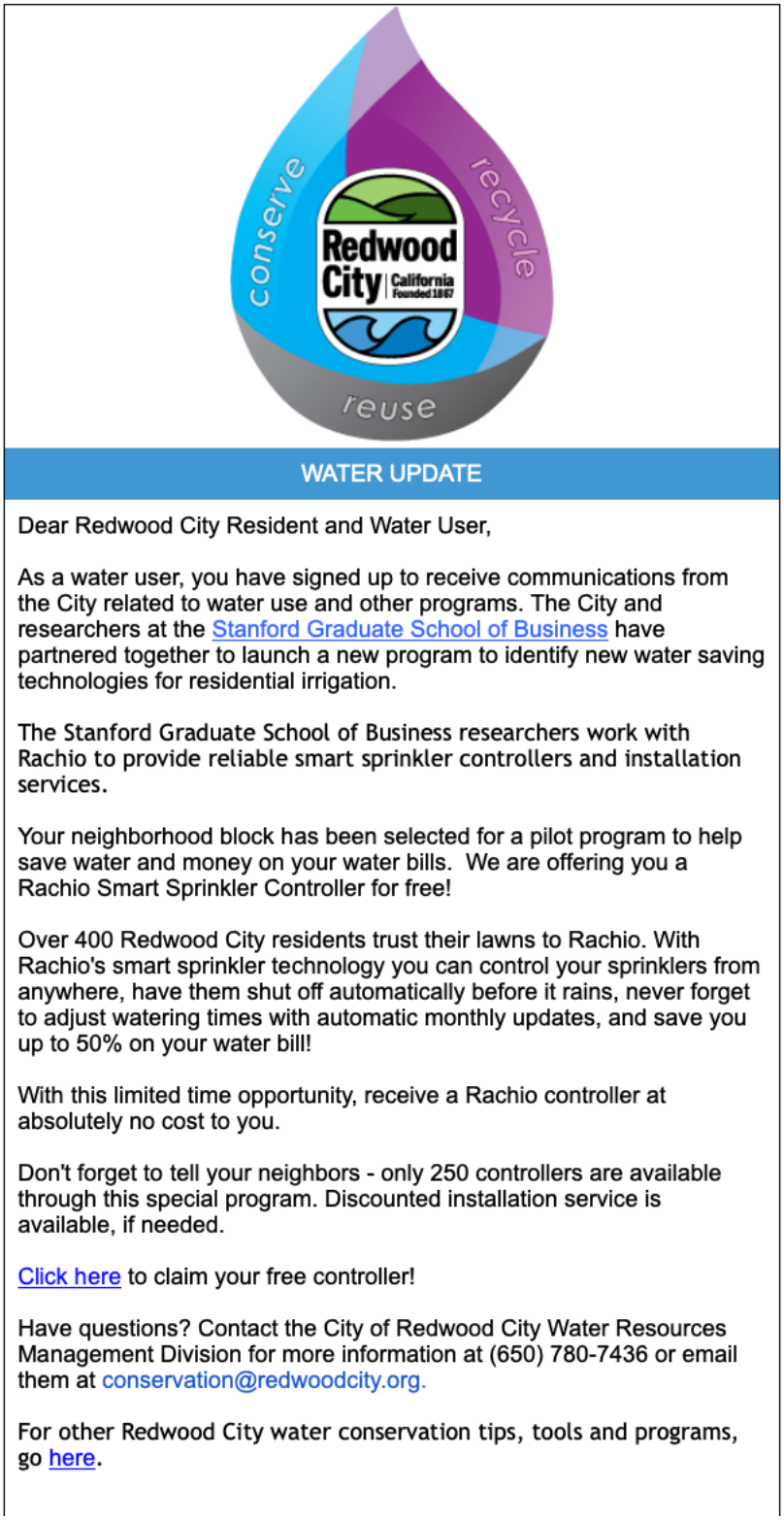


Figure D.5: Rachio's Portal for Redwood City Public Works Account Holders

How to Get Your Discounted Rachio Controller

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

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

(Only 1 offer per household)

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

Redwood City Water Account Number *

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

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

☐ I Agree to the Below Terms and Conditions

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

Read Full Terms & Conditions

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

Submit

E Data Description

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

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

The third data set contains 9 snapshots of all active Rachio devices in the RWCPW service area from 2015 through 2020: September 2015, February 2016, August 2016, October 2016, March 2017, September 2017, October 2018, December 2018, February 2020. Within this panel, we identify all the devices that were adopted as a result of the two experiments and match the organically adopted devices to the RWCPW accounts via common data fields. Thus, in the account-year-bill panel, we can identify accounts which adopted a device within each of the experiments or activated a device organically as well as the date of adoption or activation. From these data, we create an indicator of device adoption or activation in the year following each experiment, which is the primary variable used in the adoption and local average treatment effects analyses[3].

The fourth data set used in our empirical analysis tracks two snapshots (August 2016 and August 2018) of photosynthetically active vegetation (PSAV) and percentage of this vegetation that is

[3]Our data do not allow us to account for devices adopted but not activated by control households; however, given that such devices would have been purchased at full price by households seeking them out, 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 snapshots of active devices that we observe. To the extent that such unobserved activations occur at similar rates in treatment and control groups, they would affect the baseline rate of adoption ("Control") rather than the incremental rate due to the experimental manipulation ("Discount").

Table B.1: Water Consumption Summary by Summer to Winter Change Quantiles in Year Pre-Experiment

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

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

green (% green) for each parcel in the RWCPW service area. The PSAV and share green vegetation measures are generated from National Agricultural Imagery Program (NAIP) multispectral satellite imagery data using the proprietary California Irrigable Landscape Algorithm (CILA) (Quesnel et al. (2019)). We use publicly available data on parcels in San Mateo county[4] to match the Redwood City accounts to parcel photosynthetically active vegetation and greenness data via common data

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

fields. Although 93% of all accounts in our study can be matched, for our analysis we use above-median PSAV households because (1) CILA classification accuracy is higher for larger areas and (2) we note from initial analysis that in both years mean water use is significantly increasing across above-median deciles of PSAV parcels, but not across below-median deciles of PSAV parcels. We interpret this observation as indicative that PSAV measures are more reliable and less noisy for parcels of above-median size.

F 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[5]. 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.

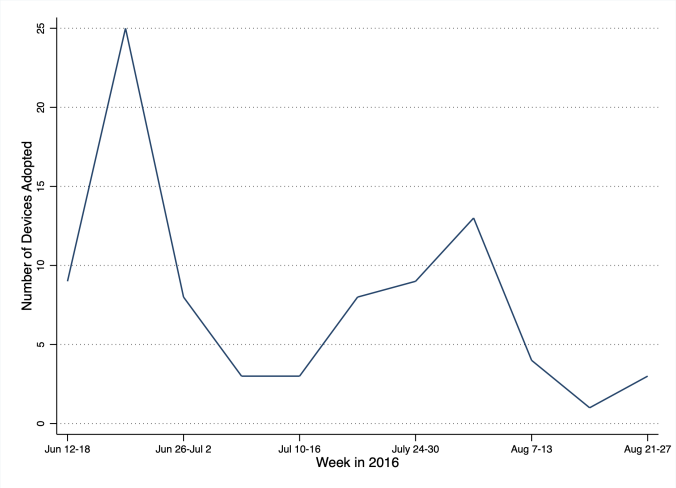
The sample size of 7,000 was initially chosen to retain a random group of households that would neither be assigned to control or treatment. For instance, these excluded households could be exposed in the second experiment without having ever received a control or treatment communication from the first experiment. A total of 9,590 households had water consumption potentially consistent

[5]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.

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.

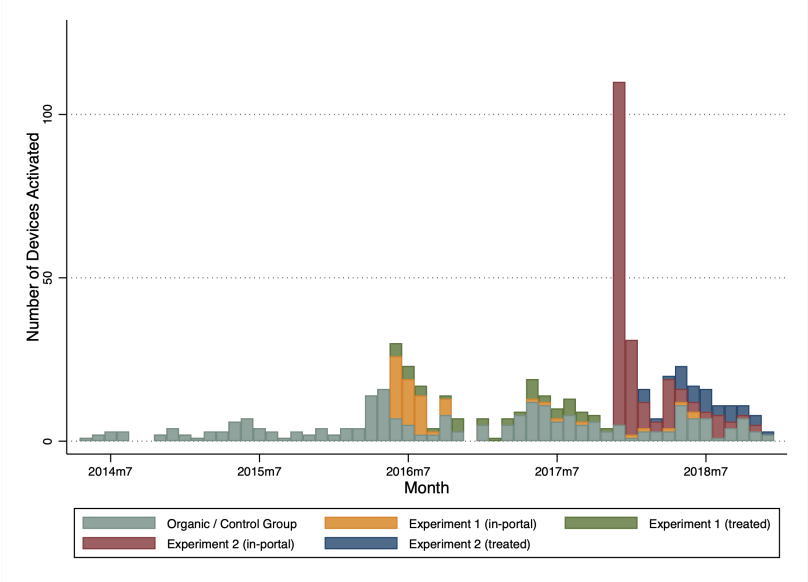
G Device Adoption and Activation Patterns Over Time

Figure G.1: Within Experiment 1 Device Adoptions



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

Figure G.2: Device Activation Timeline by Adoption Type



H Supplementary Analysis of Heterogeneity in Treatment Response

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 (Figure 2). As a result, we are able to examine heterogeneity in experiment 2 offer uptake based on responsiveness to the previous drought. Using the 2014-2016 summer (May-August) water consumption, we thus form 16 mutually exclusive groups of households, based on change in water usage between 2014 and 2015 when the drought was intensifying and between 2015 to 2016 when the drought was showing first signs of abating. For reference, households in quantile 1 of the 2014 to 2015 change in consumption are households that conserve the most in response to worsening drought conditions, and households of quantile 4 of the 2015 to 2016 change in consumption are households that increase their water usage the most as the drought conditions begin to improve.

We estimate equation 4 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 B.2. 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) (i.e., the upper-left, upper-right and lower-right cells of the table).

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

Table B.2: Effect on Adoption by Past Drought Responsiveness (Exp2)

2014 ⇒ 2015 Usage Decrease (Conservation)		2015 ⇒ 2016 Usage Increase (Backslide)			
		Smallest Increase			**Largest Increase**
		Quant 1	Quant 2	Quant 3	Quant 4
Largest Decrease	Quant 1	**0.061*** (0.010)**	0.032** (0.013)	**0.051*** (0.009)**	**0.057*** (0.007)**
	Quant 2	**0.037*** (0.010)**	0.016 (0.010)	0.029*** (0.008)	**0.047*** (0.009)**
	Quant 3	0.015 (0.009)	0.021*** (0.008)	0.029*** (0.008)	0.018 (0.014)
Smallest Decrease	Quant 4	0.024*** (0.007)	0.020** (0.009)	0.015 (0.011)	**0.042*** (0.013)**

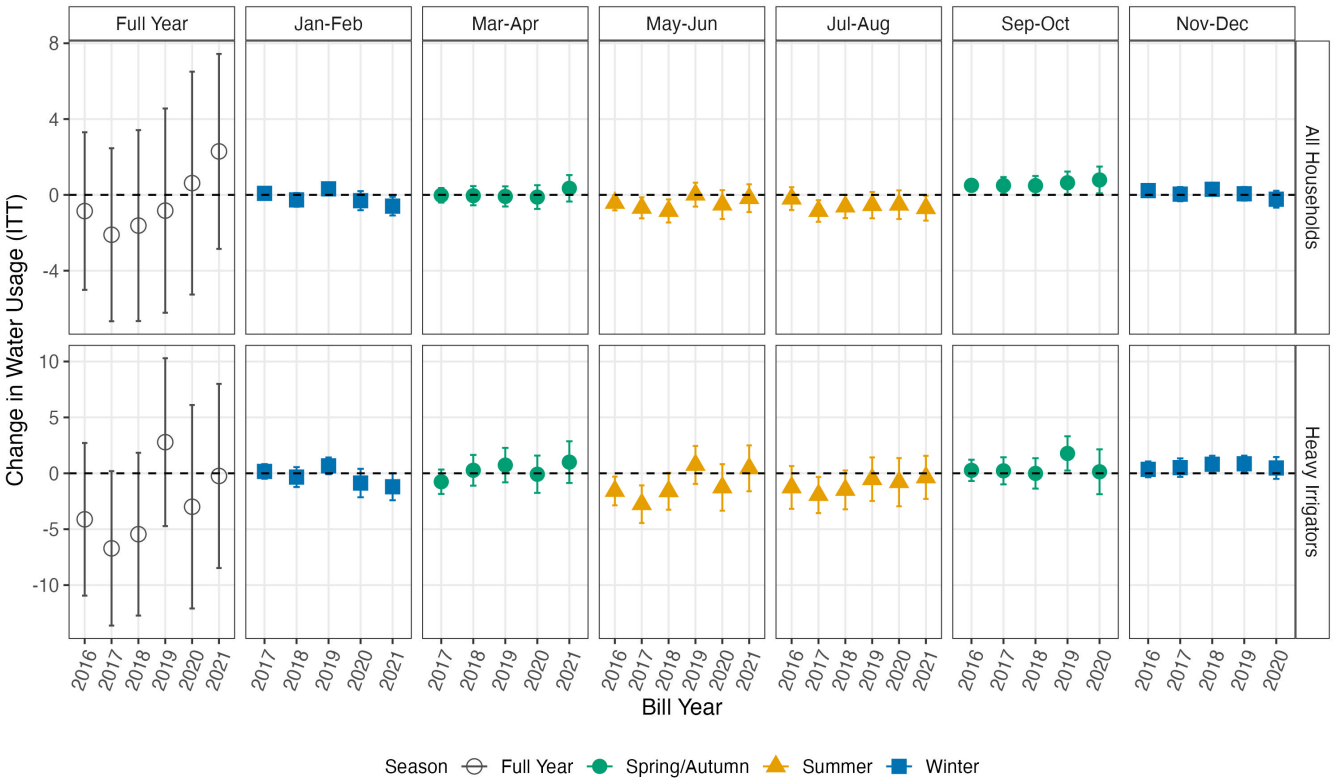
This table shows the effect of treatment on device adoption in households grouped by drought responsiveness and water usage reversion post-drought. Quantiles for 2014-2015 changes are based on the difference in water consumption between May-August of 2015 and 2014, where smaller decreases are assigned to higher quantiles. 2015–2016 change quantiles are constructed similarly. The outcome measure is the rate of adoption and activation, as in Column (2) of Table 2. Shading highlights treatment effects that fall above the average (Table 2, Column (2)) by household type: from lightest to darkest - conserver, backslider, and non-conserver households. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.

I Experiment 1 Intent-To-Treat Results

The experiment 1 intent-to-treat results are directionally similar to experiment 2 intent-to-treat results, though they are less consistently statistically significant. There are three differences worth noting: (1) The effects for the full population in experiment 1 appear to be consistently negative in the peak summer period (May-August), rather than in the peak and shoulder seasons (March-October), as in experiment 2. (2) For the higher variation households, the effect in experiment 1 is strongest in the first few years (2016-2018) post experiment. And (3) the experimental manipulation appears to have caused a small, but consistent increase in watering in the autumn shoulder season,

Figure G.3: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp1)



This figure shows the intent-to-treat (ITT) treatment effect (treatment = any of the 4 treatment arms) on household water consumption (estimates $\hat{\alpha}_1^b$, resulting from estimating equation 5). Each panel displays the estimates for a given billing period across all in-sample years, with seasons distinguished by color and shape. The upper panels present the ITT estimates for all households in experiment 1, while the lower panels focus on ITT estimates for heavy irrigator households (quantile 4), defined by the difference between water consumption in bills 4 and 5 (May-Aug) and bills 1 and 2 (Nov-Feb) in 2015. Error bars represent 90% confidence intervals.

largely driven by quartile 3 households (not shown in the Figure G.3). We hypothesize that such 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.

J Alternative Empirical Specifications

In Tables E.1 and E.2 we report coefficient estimates of two other variations on our main intent-to-treat specification in equation 5: (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 differencing relative to the pre-experiment year (see Table E.1) and (2) $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + X_{it} + \varepsilon_{it}$, where specification is as in (1), but with additional controls X_{it} for all past water consumption (2007-2016) in the same billing period (see Table E.2). We estimate these regressions separately by billing period or at the annual level. The results are similar to the main specification but more noisy in both these alternative specifications.

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

	(1) Jan-Feb	(2) Mar-Apr	(3) May-Jun	(4) Jul-Aug	(5) Sep-Oct	(6) Nov-Dec
2017						0.241
						(0.275)
2018	0.179	0.0266	-0.371	-0.301	-0.312	0.0748
	(0.250)	(0.598)	(0.884)	(0.820)	(0.540)	(0.237)
2019	0.318	-0.00244	-0.275	-0.542	-0.324	0.134
	(0.224)	(0.568)	(0.849)	(0.872)	(0.619)	(0.271)
2020	0.0588	0.0823	-0.208	-0.238	-0.235	0.0702
	(0.361)	(0.677)	(0.925)	(0.907)	(0.654)	(0.302)
2021	0.0822	-0.166	-0.273	-0.204		
	(0.355)	(0.701)	(0.896)	(0.832)		
Clustering	street	street	street	street	street	street
N	75,805	75,867	75,942	76,032	57,050	75,731

This table shows coefficient estimates of an alternative specification to that in equation 5: $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + \varepsilon_{it}$, using only post-experiment 2 data, where $y \in \{2018, 2019, 2020, 2021\}$ and no household street fixed effects (ξ_i). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: 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						0.173
						(0.138)
2018	0.128	-0.0270	-0.0381	-0.00654	-0.165	0.00184
	(0.114)	(0.140)	(0.235)	(0.184)	(0.192)	(0.127)
2019	0.217*	-0.00370	0.168	-0.218	-0.158	0.0290
	(0.124)	(0.132)	(0.190)	(0.221)	(0.238)	(0.151)
2020	-0.0463	0.0747	0.168	0.0749	-0.0641	0.0325
	(0.206)	(0.216)	(0.243)	(0.263)	(0.280)	(0.180)
2021	0.0171	-0.160	0.174	0.241		
	(0.201)	(0.269)	(0.277)	(0.274)		
Usage Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	street	street	street	street	street	street
N	69,950	70,140	68,381	68,931	53,698	69,702

This table shows coefficient estimates of an alternative specification to that in equation 5: $w_{it} = \alpha_0 + \sum_y \alpha_1^y T_i \mathbb{1}\{t = y\} + \sum_y \alpha_2^y \mathbb{1}\{t = y\} + X_{it} + \varepsilon_{it}$, where specification is as in Table E.1, but with additional controls X_{it} for all past water consumption (2007-2016) in the same billing period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

K Robustness to Alternative Definitions of Irrigation and Conservation

In this sub-section, we examine the robustness of the results showing heterogeneity in incentive responsiveness (Tables F.1 and F.2) and intent-to-treat effects (Figure F.1) to alternative definitions of irrigator households and households' conservation motivation.

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

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

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

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

In Figure F.1 we examine the robustness of the intent-to-treat results to the definition of irrigator households. Comparison of Figure F.1 to Figures 5 and 7 shows that the results are largely robust to this definition.

Table F.1: Effect on Adoption by Irrigator Quantiles

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

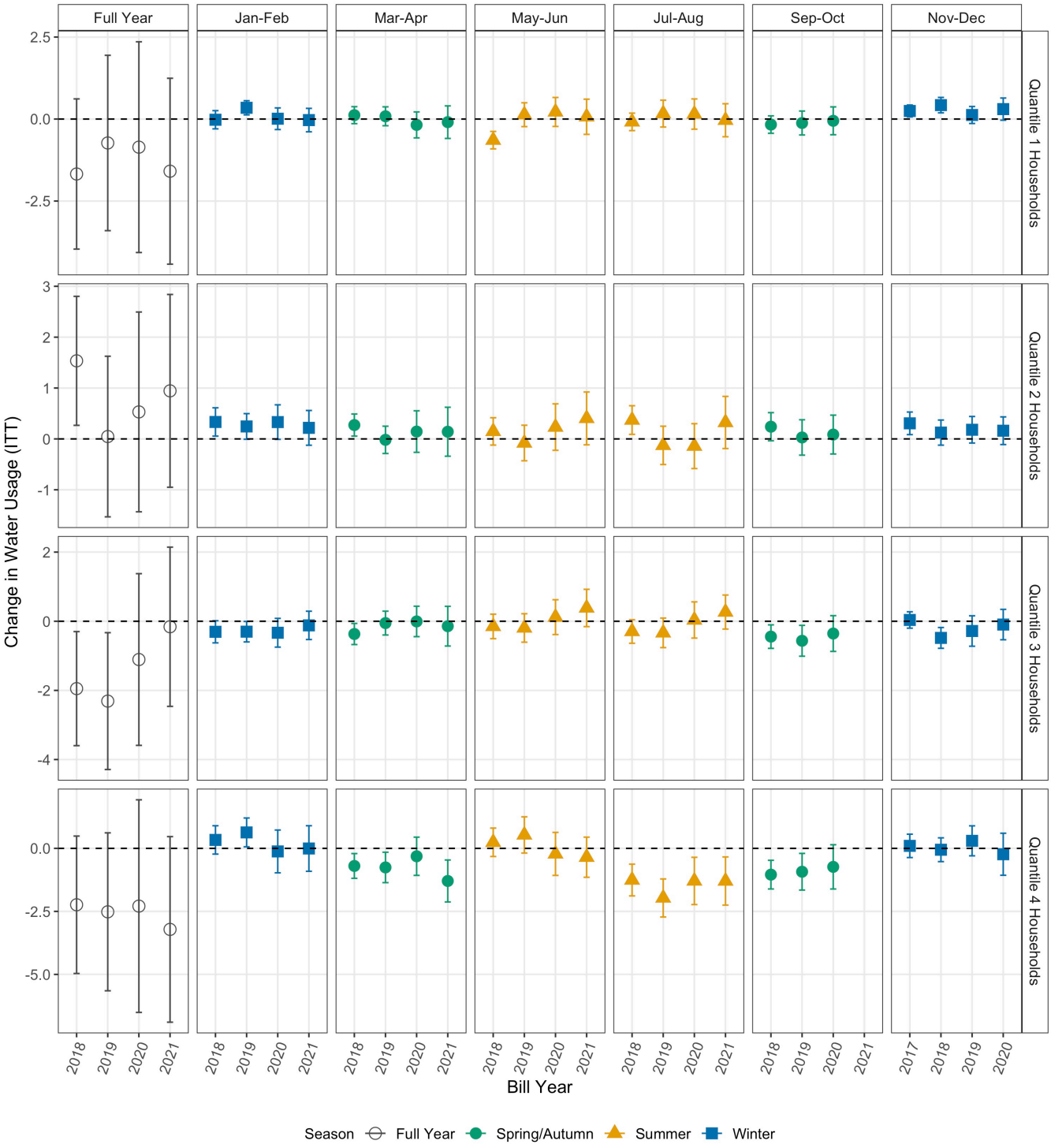
This table examines the robustness of the results in Table 3 to the definition of irrigator households. The table shows the effect of treatment on device adoption in households grouped by either Change Quantiles: summer to winter water usage variation or Peak Quantiles: summer usage. Change Quantiles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

Table F.2: Effect on Adoption by Alternative Definition of Past Drought Responsiveness (Exp2)

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

This table examines the robustness of the results in Table B.2 to the definition of drought responsiveness. Table B.2 defines drought responsiveness as change in peak consumption across three consecutive years when drought is deepening and then easing up. This table defines drought responsiveness as peak consumption at the worst point in the drought (2015) and after the state is out of drought (2017). Peak 2015 and 2017 usage quantiles are formed based on consumption in bills 4 and 5 (May-Aug) in 2015 and 2017, respectively. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure F.1: Intent-to-Treat Effect on Water Usage By Bill Period and Year (Exp2, Alternative Definition of Irrigator Quantiles)



This figure examines the robustness of the results in Figure 5 to the definition of heavy irrigators. It shows the intent-to-treat (ITT) effect on household consumption (estimates $\hat{\alpha}_1^b$, resulting from estimating equation 5), by household peak usage as a proxy for irrigation intensity. Peak usage quantiles are based on May-Aug 2017 water consumption, with quantile 1 representing households with the lowest peak usage and quantile 4 those with the highest. Each panel presents the estimates for a specific billing period across all in-sample years, with seasons indicated by different colors and shapes. Error bars denote 90% confidence intervals.

References

Kimberly J Quesnel, Newshaw Ajami, and Andrew Marx. Shifting landscapes: Decoupled urban irrigation and greenness patterns during severe drought. *Environmental Research Letters*, 14(6), 2019.