

# Residential Water Conservation During Drought: Experimental Evidence from Three Behavioral Interventions<sup>1</sup>

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## Abstract

This paper deploys a framed field experiment and uses high frequency data to evaluate the short- and long-run effects of three behavioral interventions on residential water use during extreme drought. Our study of the effects of Home Water Reports (HWRs) on hourly water use yields three main results. First, even when layered on top of a 25% drought conservation mandate, HWRs led to conservation effects of 4 to 5%. Second, across all three treatments the profile of water conservation is similar, suggesting that households did not respond to the messaging or recommendations contained in the HWRs. Third, the water conservation effect of all interventions dissipated five months after the intervention ended. In our setting, these behavioral interventions aligned with utility incentives to achieve immediate but temporary water conservation in response to drought.

**Keywords:** Social Norms; Water Use; Long-Run Effects; Randomized Controlled Trial; High-Frequency Data

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# 1 Introduction

The growth in the application of behavioral interventions has been tremendous. Governments and policymakers across the world use default settings, social norms comparisons, commitment devices and salience to encourage retirement savings, college enrollment, vaccinations, and participation in job-training programs (Benartzi et al., 2017). An expansive literature has evaluated the impacts of these nudges on behavior, and in particular the use of social norms comparisons as a tool to influence choice (Allcott, 2011; Beshears et al., 2015; Croson and Shang, 2008; Duflo and Saez, 2003; Frey and Meier, 2013; Gerber and Rogers, 2009). While these studies demonstrate that social norms comparisons alter behavior, the mechanisms underlying the response remain elusive.

This paper deploys a randomized controlled trial and uses high-frequency data to explore potential channels through which agents may respond to social norms comparisons. First, we lean on the experimental design and ask what features of the intervention induce a response? In practice social norms comparisons typically comprise a bundle of treatments, and experiments are rarely designed to map each treatment to a behavioral effect. The behavioral intervention that we study shares this first commonality - it consists of social norms comparisons, informational messaging and personalized recommendations - but by design our experiment directly tests which of these treatments induces a response. Second, we combine granular data on water use with detailed information on longer-run decisions to empirically examine the margins by which agents respond to nudges, and the persistence of these effects. Often, data limitations make it challenging to understand how agents respond to treatment. The availability of high-frequency data spanning eighteen months post-treatment and rich supplemental data on participation in rebate programs allow us to overcome some of these hurdles.

We study these questions in the economically interesting and policy relevant context of residential water use during California’s historic drought. A first distinguishing feature of our setting is the timing of our intervention. Our study coincided with a state-wide policy mandating a 25% reduction in urban water use and a period when numerous conservation policies were already in place (Board, 2015; Browne et al., 2019). The timing of our intervention provides a unique opportunity to test if social norms can induce conservation when layered on top of a suite of existing water conservation policies. A second feature of our setting, and one that generalizes to most urban water utilities, pertains to how urban water is priced. Most urban water districts bundle some fixed costs into volumetric rates

(Mitchell et al., 2017). When urban conservation is required, this pricing structure leads to revenue shortfalls and regulators may respond by raising rates. This was the case following California’s drought, when revenue decreased for more than 70% of urban water suppliers (Mitchell et al., 2017). An implication of this pricing structure is that when conservation is mandated, the utility incentive is for temporary rather than permanent conservation. The time span of our data allows us to examine if nudges provide a conservation instrument that aligns with utility incentives for immediate but temporary water conservation in response to drought.

To evaluate the mechanisms behind the response to nudges, this paper uses a large-scale field experiment that provided popular home water reports (HWR) aimed at urban water conservation to a random sample of households. A distinguishing feature of our experimental design is that we randomly varied the content of HWRs to test what features of the report elicit a conservation response. All treatment households received bi-monthly HWRs that compare own water use to similar and efficient households, offer personalized water conservation recommendations, and share information about utility sponsored programs. Some treatment households were randomly assigned to receive personalized recommendations aimed at indoor water conservation. Given that the only difference across the two treatments is the content of the recommendations, a comparison across them allows us to test if households respond to the recommendations contained within these reports. A third treatment arm provided households with a pecuniary incentive, and informed them of this incentive via the messaging component of the HWR. This treatment offers an opportunity to directly examine if households respond to the messaging portion of HWRs.

We find that across all three treatments, the profile and level of water conservation are similar. The provision of HWRs reduced average hourly water use by 4 to 5%. A look at within day and across day treatment effects highlights that while there is substantial heterogeneity in when water conservation occurs, conservation patterns are similar across all three treatments. In our setting, neither tailored water recommendations targeting indoor water use nor messaging advertising a financial incentive had a differential effect on water conservation. This suggests that households may be responding exclusively to the receipt as opposed to content of HWRs, or to the social comparisons component of the report. This finding adds to recent experimental work in the residential water and energy spaces that examines how the response to these reports differs based on the number of social comparisons, the strength of the normative message, the inclusion of financial or regulatory incentives,

and additional information about energy conservation (Brandon et al., 2019; Brent et al., 2018; Dolan and Metcalfe, 2015; List et al., 2017; West et al., 2019).

The magnitude of the treatment effect adds a critical data point to questions about the external validity of behavioral interventions in the context of residential water conservation. Our study coincides with the most severe drought in California’s history. Residential households throughout the state and in our empirical setting experienced mandatory outdoor watering restrictions, social pressure to conserve water, and a state-wide imposed 25% conservation mandate. These policies translated into large reductions in water use, with control households in our setting engaging in year-on-year water reductions of 26%.<sup>1</sup> HWRs were layered on top of these utility wide conservation policies, and it was unclear ex-ante if any remaining conservation levers existed. Despite the starkly different context, our average treatment effects of 2.8 to 3.5% fit within the range of conservation effects reported from other recent studies, and speak to the generalizability of social norms comparisons as a short-run conservation tool in the residential water setting (Brent et al., 2015; Ferraro and Price, 2013).

Another central finding is the absence of a persistent response, with the water conservation effect of each intervention ending five months after the termination of the experiment. During the treatment period, households respond to HWRs through the channels of indoor water use, outdoor irrigation, and increased compliance with watering restrictions. These conservation behaviors remain for the first four post-treatment months, but decay quickly thereafter. Five months post-intervention the indoor and outdoor watering behaviors of treatment households mirror those of control households, highlighting that households returned to ‘normal’ water use habits. One reason for this short-lived response may be that in our setting households did not respond to treatment through investment in water-efficient capital. Data on the uptake of rebates for water efficient durables highlight that HWRs have no differential effects on participation in water rebate programs. While our results point to the limitations of this intervention as a long-run water conservation policy, this temporary reduction in water use aligns with the pricing model of many utilities.

The short-lived conservation effect detected in our setting is an exception to the persistent impacts typically documented in the residential water and energy space (Allcott and Rogers, 2014; Brandon et al., 2017). In the water space, social norms messaging has led to

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<sup>1</sup>This year-to-year reduction in water use occurred in many other utilities throughout the state, with over 43% of utilities meeting the state wide conservation mandate. The exact policies leading to this reduction are utility specific (Browne et al., 2019).

conservation effects spanning more than two years post-treatment, and increased participation in water conservation and rebate programs (Bernedo et al., 2014; Ferraro et al., 2011; Brent et al., 2015). One reason for the divergence between our finding and that typically found in the literature is the context in which we study HWRs, and specifically the presence of a historic drought. Households may have responded to the drought or drought-related programs via the uptake of water efficient durables and rebates, thus rendering this margin of response unavailable. More broadly, our finding that treatment does not lead to investment in water efficient durables or lasting habit formation suggests that context matters when evaluating the lifespan of treatment effects, and hence the cost-effectiveness of behavioral interventions.

The paper begins by discussing the experimental research design and the data. It then compares treatment effects across the three interventions, as well as the approach used to estimate these effects. The paper then proceeds to evaluate dynamic treatment effects, including the various margins by which households respond to treatment. Lastly, the paper concludes.

## 2 Experimental Design and Data

We deployed a framed field experiment in a service territory with high-frequency water data to evaluate the effect of water conservation instruments on short-run and long-run water use. We implemented the experiment in partnership with WaterSmart and Burbank Water and Power, a municipally owned utility serving roughly 18,500 single family homes in the City of Burbank. The experiment spanned March 2015 to May 2016 and included the summer marked by the worst drought in California’s history. While treatment ended in May 2016, we continued to collect hourly interval data through December 2017, more than eighteen months post-treatment.

### 2.1 Research Design

Our sample consists of 16,900 single family homes that had billing records for at least six months prior to treatment. We randomly assigned households to the control group or one of three treatments: ‘WaterSmart Only’, ‘Hot WaterSmart’, or ‘Hot WaterSmart Plus’. We

describe each treatment below. The 2,967 households assigned to the control group received no notification that they were in a pilot program.

All treatment households received six, bi-monthly HWRs between May 2015 and April 2016.<sup>2</sup> In March 2015, before the arrival of the first report, all treatment households received an introductory letter that explained what HWRs were and when they would be delivered. Both the initial letter and households' first HWR were sent by mail. All subsequent HWRs were sent by mail to households that received their utility bill via mail, and by email to those that paid their utility bill online.

**WaterSmart Only:** The 4,470 accounts randomly assigned to the WaterSmart treatment received HWRs comprised of personalized conservation recommendations, information on utility-sponsored conservation programs and water use, and social comparisons. Figure A.2 provides an example of a report - the social comparison appears on the top left, utility announcements on the top right, and personalized water-saving actions on the bottom of the report. The former compares own water use in the previous billing cycle to water use of similar and efficient households, and contains an injunctive norm comprised of a smiling, indifferent or frowning water drop. Water recommendations include projected water savings and the value of those water savings calculated using utility water rates. The impact of similar HWRs and Home Energy Reports (HERs) on water and electricity use, respectively, has been the focus of several studies (Brent et al., 2015; Ayres et al., 2013; Allcott, 2011; Schultz et al., 2007).

**Hot WaterSmart (HWS):** To test if recommendations aimed at hot water use could reduce indoor water use, we constructed a 'Hot WaterSmart' treatment and assigned 4,709 households to it. This treatment is equivalent to the WaterSmart treatment with two exceptions. First, half of the personalized water-savings recommendations focus on actions that could reduce indoor water use. Second, in addition to quantifying the expected water savings, all recommendations quantified expected natural gas savings and the cumulative dollar value attributable to these savings. Figure A.3 provides an example of a 'Hot' HWR. In this HWR two of the three water-saving recommendations are tailored towards indoor water use (i.e. reduce water heater temperature and fill bathtub three-quarters of the way).<sup>3</sup> Since

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<sup>2</sup>Appendix A.1 and Figure A.1 provide a detailed timeline on the deployment of HWRs. They also include information on coincident utility conservation programs, data availability, and the timing of the mailer.

<sup>3</sup>Figure A.4 shows all hot water saving recommendations used over the treatment year.

the only distinction across this treatment and the ‘Water Smart Only’ treatment is the recommendations contained in the report, our experiment is designed to examine if households respond to the recommendation component of HWRs.

**Hot WaterSmart Plus (HWS+):** The 4,701 households randomly assigned to this treatment had a pecuniary incentive layered on top of the Hot WaterSmart treatment. This incentive took the form of a water and natural gas conservation contest in which a household would win a water or energy efficient durable if (i) it enrolled in the contest and (ii) pre-determined conservation targets were met.<sup>4</sup> To increase program enrollment, we sought to minimize enrollment costs and offer a prize of meaningful value. Enrollment only required visiting the contest website to enter a name and email address, and to agree to the terms of conditions. Conditional on enrollment, all households that met the targets were guaranteed a prize. The twenty-five households with the greatest water use reductions would win a high-efficiency clothes washer (\$850 retail value). The next one hundred enrolled households would win low-flow shower heads (\$30 retail value). All remaining households would win an energy efficiency kit (\$10 retail value).

Importantly, contest information, the enrollment procedure, and progress towards meeting the conservation targets were conveyed exclusively through messages in the HWRs. Households were informed of this contest in the messages of three HWRs - the program was introduced to households in the third HWR (Figure A.5), and households were provided with individualized progress updates in their fourth and sixth HWRs (Figure A.6). Given that the distinguishing feature across this treatment and Hot WaterSmart is the content of the messages, we can directly test if households respond to the messaging component of HWRs.

## 2.2 Data

Hourly water consumption data serve as our primary outcome of interest. BWP provided water use data for all single-family homes in its service territory between April 1, 2014, a year before the intervention, and December 31, 2017, over a year and a half after the experiment ended. We supplement these data with information on customer participation in

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<sup>4</sup>We set two conservation targets: a 27% year-on-year reduction in water use and a 3% year-on-year reduction in natural gas use. The water conservation target corresponded to the conservation mandate imposed by the state of California on BWP. The natural gas conservation target was set based on discussions with our natural gas partner.

BWP’s rebate programs, assessor data on housing characteristics, and hourly temperature and precipitation data from a nearby weather monitor.

Table 1 compares baseline characteristics across control and treatment households, and highlights that prior to the intervention treatment and control households are balanced in seasonal water use, rebate applications and household characteristics.<sup>5</sup> Hourly water use measures at 11.5 and 19.5 gals/hour in the winter and summer months, respectively. As is typical in California, water use exhibits large seasonal fluctuations with use peaking in the dry and warm summer months when outdoor irrigation is most prevalent. To provide additional evidence on the quality of the randomization, we plot out the distribution of average daily water use across control and treatment households. Figure 1 which illustrates these distributions, makes clear that the distribution of daily water use is balanced across treatment and control.

Detailed data on the uptake of utility sponsored water efficient rebates provides an opportunity to test the hypothesis that treatment households respond to WaterSmart by increasing investment in water efficient durables. The utility provided information on the rebate type, rebate amount and rebate date for all utility sponsored water efficiency programs between January 1, 2014 and June 30, 2016. As shown in Table 1, participation in existing water rebate programs is relatively low, with only 3% of households applying for a rebate between January 1, 2014 and June 30, 2016. The value of the rebate is also low, with the mean rebate value amounting to \$2.

### 3 A Comparison Across Interventions

To isolate the impact of each treatment on water use and test for differential effects across the three treatments, we compare average hourly water use across control and treatment households during the twelve month treatment period. We estimate the following regression:

$$y_{iht} = \sum_j \beta_j T_{ij} + \mathbf{X}'_{iht} \gamma + \delta_h + \delta_t + \epsilon_{iht}. \quad (1)$$

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<sup>5</sup>We use the historical water use data to construct three seasonal average water use statistics that are used as controls in some regression specifications. We define two broad seasonal classifications, summer defined as April to October, and winter defined as November to March. These seasonal classifications are also used to construct other variables. These seasonal designations align with BWP’s seasonal outdoor watering restrictions.

The dependent variable  $y_{iht}$  is household  $i$ 's water use in hour  $h$  of calendar date  $t$ . The regressors of interest are  $T_j$ , which equal one if a household is assigned to treatment  $j \in \{\text{WS, HWS, HWS+}\}$ , and zero otherwise. In some specifications, we augment equation (1) to improve the precision of our estimator, conditioning on pre-treatment seasonal water use and weather data ( $\mathbf{X}'_{iht}$ ), as well as hour-of-day ( $\delta_h$ ) and calendar date fixed effects ( $\delta_t$ ).

Our first set of results, reported in Table 2, makes clear that all three HWRs led to a reduction in water use. As shown in columns (1-2), hourly water use reduced by -0.49 to -0.60 gallons, or 3.8% to 4.8% over the course of treatment year.<sup>6</sup> The remainder of this table separately highlights treatment effects in the first six months of the treatment period (columns 3 and 4) and the last six months of the treatment period (columns 5 and 6). The level reductions in water use are similar when we break out the results by the first and second half of the intervention, despite baseline use changing substantially across seasons.

Notably, the first six months of this intervention coincide with the tail end of a historic drought. Mandatory outdoor watering restrictions had been implemented; a state wide 25% conservation mandate was in place; and the utility had introduced a suite of water efficient rebate programs. Perhaps as a result, residential water use was substantially lower than in prior years, with (as shown in Figure 2) control households in our sample exhibiting year-on-year water reductions of 26%. Given the existing conservation efforts, it was unclear ex ante whether HWRs would lead to conservation. We find conservation effects of 2.8 to 3.7%. The magnitude of these treatment effects fits within the range of estimates reported from recent studies on HWRs and residential water conservation, and illustrates the conservation potential of HWRs during times of drought and when layered on top of other conservation instruments (Brent et al., 2015, 2018; Ferraro and Price, 2013).

We find no differential impact of the three treatments on water use despite differences in the content of the HWRs. A comparison of the WaterSmart and HotWaterSmart treatment effects highlights that modifying recommendations to include natural gas conservation and the accompanying financial savings led to no changes in average hourly water use. The addition of recommendations aimed at hot water conservation also did not alter patterns of water use across days of the week and hours of the day (Appendix B.1).

Similarly, we find that altering the content of messages in HWRs to showcase and advertise a financial incentive for water conservation induced no change in average hourly use, or

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<sup>6</sup>A comparison across columns 1 and 2 highlights the stability of our results to the inclusion of controls, and suggests that the addition of these covariates simply increases the precision of our estimates.

patterns of water use. One reason why households may not have responded to the incentive program is that it was conveyed exclusively through messages in HWRs, and households may have been inattentive to these messages. We find that only 68 or 1.4% of customers actively enrolled in the “Conserve and Win” program, though 253 households achieved the water and natural gas targets necessary to receive a durable good. Low enrollment rates, including for those who met the contest requirements, suggest that households may simply have overlooked the messaging portion of HWRs. Collectively, our experimental results provide evidence that households are not responding to the messaging or recommendations components of the HWRs, and are consistent with a framework in which the receipt of or the social norms component of the report alters behavior.

Given the similar response across treatment groups, moving forward we combine all three treatments into a single treatment that we refer to as “WaterSmart”, and focus on the short and long-run impacts of treatment as well as the mechanisms underlying the response to treatment.

## 4 Dynamic Effects

Hourly water data spanning twenty months post-treatment allow us to identify the dynamic effect of Home Water Reports on water use. We first investigate the short and long-run average treatment effects of HWRs. This allows us to evaluate persistence in the response to treatment. We then take advantage of our hourly water use data to study patterns in treatment effects across hours of the day and days of the week. This provides an opportunity to understand the margins along which households respond to treatment, including indoor and outdoor water use behaviors. Lastly, we explore the extent to which households respond to HWRs by investing in water-efficient capital.

### 4.1 Short and Long-Run Effects

To identify the duration of treatment effects, we compare hourly water use across control and treatment households in each calendar-month and use OLS to estimate,

$$y_{iht} = \sum_{\tau} \beta_{\tau} (\mathbf{1}[t_{\tau} = \tau] \times \mathbf{T}_i) + \mathbf{X}'_{iht} \gamma + \delta_h + \delta_t + \epsilon_{iht}. \quad (2)$$

As before, the dependent variable  $y_{iht}$  is household  $i$ 's hourly water use (gals/hour) in hour  $h$  of calendar date  $t$ .  $T_i$  is an indicator for our joint treatment effect, and the indicators  $\mathbf{1}[t_\tau = \tau]$  equal one if date  $t$  is in month  $\tau$ . We also condition on the covariates previously described. We include data from March 2015, two months before the intervention, through December 2017, twenty months after the intervention ended.

The coefficients of interest,  $\beta_\tau$ , measure the effect of assignment to treatment on hourly water use in calendar month  $\tau$ . Figure 3 plots the coefficient estimates and the corresponding 95% confidence intervals. The shaded area A corresponds to the treatment year. We classify the four months post-treatment as the ‘backslide’ period, and label this as shaded area B. The third area, denoted by C and which we refer to as the ‘convergence’ period, corresponds to post-treatment months five to twenty.

This figure illustrates that while HWRs led to a near uniform reduction in levels of water use during the treatment months, this conservation effect quickly decays. In the twelve months during which households received HWRs, water use reduced by 0.5 to 0.6 gals/hour.<sup>7</sup> However, this treatment effect is short-lived. We continue to observe conservation effects of 0.5 to 0.6 gals/hour in the first two post-treatment months, but these effects decay by roughly 1/3 in the third post-treatment month. Five months after treatment ends there is no statistically discernible difference in water use across control and treatment households, and this convergence in water use remains through the end of our sample.

Our finding that HWRs have short-lived impacts stands in contrast to previous experimental work. In the residential water setting, the conservation effects of a similar one-time intervention remained detectable six years after treatment (Bernedo et al., 2014). And the impacts of Home Energy Reports on residential energy use decayed but persisted five to ten years post-treatment (Allcott and Rogers, 2014). One stark difference between our empirical setting and that of others is that our study coincided with extreme drought. During our treatment period, a statewide 25% mandatory conservation mandate was in place, outdoor watering restrictions increased in stringency, and numerous water efficient rebate programs had been deployed. These policies all relaxed following the wet winter of 2016. In June 2016, the regulator removed the statewide conservation mandate and BWP increased the number of allowable outdoor watering days. Looking at Figure 2 we see that water use is higher beginning in June 2016 relative to the corresponding month in the previous year, when stringent drought measures were in place. Given that our treatment period, defined as

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<sup>7</sup>Figure C.5 replicates Figure 3 using the log of water use as the dependent variable. Percentage reductions are largest in winter months when average water use is lower.

May 1, 2015 - May 1, 2016 aligned with a period of extreme conservation measures, and our post-treatment period coincided with the removal of many of these measures, it is possible that the absence of a persistent effect is partly attributable to the end of a historic drought.

## 4.2 Hour-of-Day Treatment Effects

To better understand the absence of a persistent effect in our setting, we take advantage of the temporal granularity in our data and participation in rebate programs to understand the margins by which households respond to treatment. We begin by evaluating the impact of assignment to treatment on the within day profile of water use in the short and long-run. To identify the effect of treatment on water use in each hour of the day, we estimate a fixed effects model in which we interact assignment to treatment with indicator variables for each hour of the day,

$$y_{iht} = \sum_{\eta} \beta_{\eta} (\mathbf{1}[h = \eta] \times T_i) + \mathbf{X}'_{iht} \gamma + \delta_t + \epsilon_{iht} \quad (3)$$

The regression mirrors equation (1) except that assignment to treatment is interacted with a vector of indicators  $\mathbf{1}[h = \eta]$  that equal one when hour-of day  $h$  equals  $\eta$ . We estimate equation (3) for five distinct sub-samples: (i) summer treatment months, (ii) winter treatment months, (iii) the ‘backslide’ months; (iv) summer ‘convergence’ months; and (v) winter ‘convergence’ months. Recall that the treatment months refer to the period when households received bi-monthly HWRs; the ‘backslide’ period defines the first four months post-treatment spanning May 2016 to August 2016; and the ‘convergence’ period characterizes post-treatment months 5 to 20. We estimate separate specifications for summer and winter months to understand household behavior during months when demand for outdoor watering is high.

We first focus on the effects of HWRs during the winter and summer months of the treatment period. Panels A1 and A2 of Figure 4 plot hour-of-day treatment effects for summer and winter months, respectively, and illustrate that treatment is impacting both indoor and outdoor water use. In the summer months, households exhibit the largest water use reductions during early morning and evening hours. On average, households reduce use by 2 gals/hour and 1.3 gals/hour at 6 AM and 7 PM, respectively. The timing of these reductions coincides with the hours when outdoor irrigation peaks, and suggests one margin of response during summer months is outdoor irrigation. We estimate smaller and noisier reductions of around 0.4 gals/hour from 10 AM to 6 PM. During the winter months

(Panel A2), the largest reductions once again occur during the early morning hours though these are relatively smaller than the summertime effects. Mid-day and evening water use reductions are more stable and precise in the winter months. Given that outdoor watering is prohibited during the hours of 9 AM-6 PM in winter of 2016, conservation effects during these hours highlights that households are also responding to treatment through indoor watering. The mid-day winter water use reductions and large, early-morning summertime reductions suggest that households responded to treatment by reducing both indoor and outdoor water use.

The remaining panels in Figure 4 plot treatment effects for the backslide and convergence periods.<sup>8</sup> Consider the backslide period (Panel B). Relative to the previous summer, the treatment effects diminish, most notably in the early morning and evening hours. Standard errors increase appreciably. However, the treatment effect profile remains similar to the one observed in Panel A1, suggesting that household water conservation habits persisted but to a lesser extent in the months following treatment. Little evidence of a treatment impact remains in the convergence period (Panels C1 and C2). Both the winter and summer daytime treatment effects are precisely estimated and indistinguishable from zero, suggesting that indoor water use is nearly identical across control and treatment households. During the summer, some households still appear to conserve water in the early morning and evening hours. However, the standard errors are large, and the point estimates are smaller than those estimated during the treatment period, suggesting that the outdoor watering impacts of HWRs do not persist. Collectively, these results suggest that while HWRs induced meaningful changes in outdoor and indoor watering behaviors during the treatment period, these effects are relatively short-lived with no difference in intraday water use patterns.

### 4.3 Day of Week Treatment Effects

In response to the historic drought, BWP like many other urban water utilities in California, imposed utility-wide outdoor watering restrictions on the days of the week when irrigation was permitted. The deployment of HWRs may have induced systematically different responses on days with and without watering restrictions in place, both during the treatment period and in the post-treatment months. For example, treatment households may have programmed irrigation systems to turn on only on days in which irrigation was permitted, and these settings may have remained in place long after the last HWR was sent. To examine

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<sup>8</sup>Note that all backslide months occurred over the summer of 2016.

whether HWRs induced a differential response across days of the week, we estimate daily treatment effects on days with and without utility-wide outdoor watering restrictions, both during and after the intervention,

$$y_{iht} = \sum_{\delta} \beta_{\delta} (\mathbf{1}[t_{\delta} = \delta] \times T_i) + \mathbf{X}'_{iht} \gamma + \delta_h + \delta_t + \epsilon_{iht}, \quad (4)$$

Figure 5 presents our main results, and plots for each sub-sample the day of week treatment effect as well as the corresponding 95% confidence interval. Blue diamonds display treatment effects during the hours of the day when outdoor watering is permitted, and red circles represent treatment effects during hours when outdoor watering is banned. The shaded gray area designates days when outdoor watering is permitted.<sup>9</sup> Plots A1 and A2 correspond to day of week effects in the summer and winter treatment months; Plot B maps out treatment effects in the ‘backslide’ period; and plot C depicts day of week treatment effects in the convergence period.

Panels A1 and A2 illustrate that during the treatment period the largest conservation effects occur on irrigation days during hours when households are allowed to water their lawns. Summertime treatment effects during these hours are about three times as large as the average treatment effects reported in Table 2. Treatment effects during non-watering hours on watering days are similar to those estimated during all hours on non-irrigation days. We see similar results during winter months (Panel A2). Interestingly, we still estimate a large treatment effect on Tuesdays during early and evening hours, though outdoor watering is now prohibited. The results suggest that treatment caused households to reduce lawn irrigation relative to control households and that these habits persisted throughout the treatment year. As in Section 4.2, we find a steady reduction in water use on days and hours when households were not allowed to irrigate, suggesting that outdoor water use behavior is not the only margin driving our ATE.

The remaining panels illustrate that the conservation patterns developed during treatment persist into the first four post-treatment months, but erode in the convergence period. As shown in Panel B, during the convergence period, we continue to observe large treatment

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<sup>9</sup>A comparison across plots highlights that watering restrictions changed throughout our study period. BWP (mostly) allowed outdoor irrigation on Tuesday and Thursdays in the summer of 2015 and on Saturdays during winter 2015-2016. The utility returned to a Tuesday/Saturday schedule after the experiment ended, and instituted a permanent Tuesday/Thursday/Saturday schedule in August 2016 that remained in effect through the end of our sample. For brevity, we include results for the most prominent watering regimes. We show results for all watering regimes in Appendix B.2.

effects during hours and days when outdoor watering is permitted. The response during hours and days when outdoor watering is prohibited mirrors the response in Panel A1, though estimates are slightly noisier. This panel provides evidence of short-lived behavioral habituation to treatment, both in the daily patterns of water conservation and the magnitude of this conservation effect. These treatment effects are no longer present in the convergence period. We observe minimal differences across control and treatment households for all days and all hours. These results demonstrate that in the short to medium-run treatment households form indoor and outdoor water conservation habits, but that this suite of conservation habits decays entirely five months after treatment ends.

## 4.4 Capital Investments

One reason for this temporary response may be that in our setting households did not respond to treatment through investment in water-efficient capital. To examine this hypothesis, we use rebate application data to test for the effect of assignment to treatment on households durable investments. BWP provided household-level information for all residential rebate applications between July 2014 and June 2016. We focus on rebate applications for water-efficient durables, including clothes washers, dishwashers, outdoor rain-water barrels, and turf replacement, and consider two outcomes. First, we create indicators for whether a household applied for any rebate in a pre-treatment month (July 2014 to February 2015), treatment month (March 2015 to May 2016), or post-treatment month (June 2016). Our second measure aggregates the dollar value of all rebates received by households in each of these three periods.

We estimate a simple difference-in-differences model, comparing rebate outcomes across control and treatment households before and after treatment,

$$r_{ip} = \gamma T_i + \sum_{\rho} \delta_{\rho} (\mathbf{1}[p = \rho]) + \sum_{\rho} \beta_{\rho} (\mathbf{1}[p = \rho] \times T_i) + \mathbf{X}_i' \gamma + \epsilon_{ip}. \quad (5)$$

The dependent variable,  $r_{ip}$ , is either the indicator variable for whether household  $i$  applied for a water efficiency rebate in period  $p$  or the rebate amount (\$) household  $i$  received in period  $p$ . We include an indicator variable,  $T_i$ , that denotes if a household was assigned to the WaterSmart treatment, and indicator variables for the treatment and post-treatment periods,  $\rho$ . Our regressors of interest are the treatment assignment by period interactions,

and our coefficients of interest  $\beta_p$ , measure the effect of WaterSmart in the treatment and post-treatment periods on rebate participation relative to control households in the respective periods.

Table 3 reports our results along with rebate participation summary statistics for control group households. Baseline program participation is low, less than 3% of control households applied for any rebates in the treatment year, and the dollars received is also low, with households receiving just \$5 on average. Most rebates are for appliances (clothes washers or dishwashers).<sup>10</sup> We find that HWRs had no detectable impact on rebate applications or the dollar amount in rebates a household receives. The absence of an effect is notable given that HWRs advertise rebate programs. The results provide another piece of supporting evidence that: (i) households did not respond to the messaging or recommendation components of HWRs; and (ii) assignment to treatment did not increase investment in hard capital.

## 5 Conclusion

This paper uses high frequency data to evaluate the short and long-term effects of three behavioral interventions on household water use during a historic drought. We focus on the impacts of Home Water Reports, an oft-deployed behavioral nudge comprised of social norms comparisons, messaging and individualized conservation recommendations. We first use our experimental design to isolate the extent to which customers respond to each component of this bundled treatment. Neither the content of water recommendations or personalized messaging advertising a financial incentive alters the response to HWRs, suggesting that households respond either to the social comparisons portion of the treatment or the receipt of the HWR.

With climate change, droughts are expected to become more frequent and more severe. Given that our study coincides with the most extreme drought in California’s history, it offers a preview into the potential of social norms comparisons to induce conservation under future weather conditions. We deployed our study during a period when households had already engaged in substantial conservation efforts. Year on year water reductions for control households amounted to 26%, and a statewide conservation mandate of 25% was in place.

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<sup>10</sup>BWP offers generous rebates; the median rebate pays \$70. The largest rebates over this period were for outdoor lawn replacement. Appliance rebates range from \$25 to \$170, while turf rebates range from \$440 to \$2,500.

HWRs delivered average water savings of 2.8 to 3.5% on top of existing conservation efforts, with households reducing both indoor and outdoor water use. The magnitude of the estimated effects are similar to those reported under non-drought conditions, and provide a first data point on the suitability of behavioral interventions as a short-run drought conservation instrument.

These conservation effects of HWRs are short-lived, and fully dissipate five months post-treatment. We find that during the treatment period households change indoor and outdoor water use patterns, and increase compliance with utility-wide watering restrictions. These habits persist in the first four-months post treatment, but consumption patterns across treatment and control households are identical five months post-intervention. One reason for the temporary effect in our setting may be that shortly after our treatment ended, the drought was declared over and conservation policies were removed or relaxed.

The ability of HWRs to quickly illicit a 3 to 4 percent reduction in water use during times of drought may align well with the pricing model used by many urban water utilities. The rules governing the allocation of water in California at times require immediate and large water conservation among urban users. This was the case in the most recent drought. One unintended consequence of the urban water conservation experienced during this drought is that it led to reduced revenues for more than 70% of urban utilities. This is because of how residential water is priced in California: most water utilities bundle some fixed costs into volumetric rates. The degree to which costs exceeded revenues depended in part on the magnitude and duration of water conservation. To cope with reduced revenues, many utilities responded to the end of the drought by raising volumetric rates and scaling back conservation programs. In our setting, HWRs provide an immediate but short-lived reduction in water use that is compatible with the incentive structure of utilities during droughts.

## References

- Allcott, H. (2011). Social Norms and Energy Conservation. *Journal of Public Economics* 95(9), 1082–1095.
- Allcott, H. and T. Rogers (2014). The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation. *American Economic Review* 104(10), 3003–3037.
- Ayres, I., S. Raseman, and A. Shih (2013). Evidence from Two Large Field Experiments that Peer Comparison Feedback can Reduce Residential Energy Usage. *Journal of Law, Economics, and Organization* 29(5), 992–1022.
- Benartzi, S., J. Beshears, K. Milkman, C. Sunstein, R. Thaler, M. Shankar, W. Tucker-Ray, W. Congdon, and S. Galing (2017). Should Governments Invest More in Nudging? *Psychological Science* 28(8), 1041–1055.
- Bernedo, M., P. Ferraro, and M. Price (2014). The Persistent Impacts of Norm-Based Messaging and Their Implications for Water Conservation. *Journal of Consumer Policy* 37, 437–452.
- Beshears, J., J. Choi, D. Laibson, B. Madrian, and K. Milkman (2015). The Effects of Providing Peer Information on Retirement Savings Decisions. *The Journal of Finance* 70(3), 1161–1201.
- Board, S. W. R. C. (2015). Resolution no. 2015-0032 to adopt an emergency regulation for statewide urban water conservation.
- Brandon, A., P. J. Ferraro, J. A. List, R. D. Metcalfe, M. K. Price, and F. Rundhammer (2017). Do The Effects of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments. NBER Working Paper No. 23277.
- Brandon, A., J. A. List, R. D. Metcalfe, M. K. Price, and F. Rundhammer (2019). Testing for crowd out in social nudges: Evidence from a natural field experiment in the market for electricity. *Proceedings of the National Academy of Sciences* 116(12), 5293–5298.
- Brent, D., J. Cook, and S. Olsen (2015). Social Comparisons, Household Water Use, and Participation in Utility Conservation Programs: Evidence from Three Randomized Trials. *Journal of the Association of Environmental and Resource Economists* 2(4), 597–627.

- Brent, D., C. Lott, M. Taylor, J. Cook, K. Rollins, and S. Stoddard (2018). Behavioral motivations behind heterogeneous responses to social comparison messages. Working Paper.
- Browne, O., L. Gazze, and M. Greenstone (2019). Determinants of water conservation: Evidence from a california drought. Working Paper.
- Croson, R. and J. Shang (2008). The Impact of Downward Social Information on Contribution Decisions. *Experimental Economics* 11(3), 221–233.
- Dolan, P. and R. Metcalfe (2015). Neighbors, Knowledge, and Nuggets: Two Natural Field Experiments on the Role of Incentives on Energy Conservation. Becker Friedman Institute for Research in Economics Working Paper No. 2589269.
- Dufló, E. and E. Saez (2003). The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment. *Quarterly Journal of Economics* 118(3), 815–842.
- Ferraro, P., J. J. Miranda, and M. Price (2011). The Persistence of Treatment Effects with Norm-Based Policy Instruments: Evidence from a Randomized Environmental Policy Experiment. *American Economic Review: Papers and Proceedings* 101(3), 318–322.
- Ferraro, P. and M. Price (2013). Using Nonpecuniary Strategies to Influence Behavior: Evidence from a Large-scale Field Experiment. *Review of Economics and Statistics* 95(1), 64–73.
- Frey, B. and S. Meier (2013). Social Comparisons and Pro-Social Behavior: Testing ‘Conditional Cooperation’ in a Field Experiment. *American Economic Review* 94(5), 1717–1722.
- Gerber, A. and T. Rogers (2009). Descriptive Social Norms and Motivation to Vote: Everybody’s Voting and So Should You. *Journal of Politics* 71(1), 1–14.
- List, J. A., R. D. Metcalfe, M. K. Price, and F. Rundhammer (2017). Harnessing policy complementarities to conserve energy: Evidence from a natural field experiment.
- Mitchell, D., E. Hanak, K. Baerenklau, A. Escrivá-Bou, H. McCann, M. Pérez-Urdiales, and K. Schwabe (2017). Building drought resilience in california’s cities and suburbs. Public Policy Institute of California.
- Schultz, P. W., J. M. Nolan, R. B. Cialdini, N. J. Goldstein, and V. Griskevicius (2007). The Constructive, Destructive, and Reconstructive Power of Social Norms. *Psychological Science* 18(5), 429–434.

West, J., R. Fairlie, B. Prat, and L. Rose (2019). Do regulatory policies crowd out social pressure for resource conservation? Working Paper.

Table 1: Balance Tests and Summary Statistics

	Control	WaterSmart	Hot WaterSmart	Hot WaterSmart Plus
Water Use April '14 (gals/hour)	17.00	16.77	17.06	16.92
Difference		-0.22	0.06	-0.08
p-value		(0.38)	(0.82)	(0.75)
Water Use Summer '14 (gals/hour)	19.60	19.39	19.56	19.47
Difference		-0.21	-0.04	-0.13
p-value		(0.44)	(0.89)	(0.62)
Water Use Winter '15 (gals/hour)	11.67	11.76	11.67	11.74
Difference		0.09	-0.00	0.07
p-value		(0.64)	(0.99)	(0.72)
Rebate (Indicator)	0.03	0.03	0.03	0.03
Difference		0.00	0.01	0.00
p-value		(0.94)	(0.10)	(0.58)
Rebate (\$)	1.99	1.96	2.64	2.28
Difference		-0.03	0.65	0.29
p-value		(0.93)	(0.13)	(0.43)
Year Built	1945	1945	1944	1944
Difference		-0.06	-1.05	-0.61
p-value		(0.86)	(0.14)	(0.40)
Square Feet	1630.42	1,634.24	1,634.09	1,643.19
Difference		3.82	3.67	12.77
p-value		(0.82)	(0.82)	(0.44)
Bedrooms	2.91	2.90	2.92	2.92
Difference		-0.01	0.01	0.01
p-value		(0.64)	(0.66)	(0.53)
Bathrooms	1.93	1.93	1.95	1.94
Difference		-0.00	0.01	0.01
p-value		(0.98)	(0.55)	(0.57)
Pool(Indicator)	0.23	0.23	0.23	0.22
Difference		-0.00	0.01	-0.01
p-value		(0.78)	(0.62)	(0.36)

Notes: The table presents average characteristics of control versus treatment households for our three treatments. 'Difference' is the difference in means relative to the control group, and 'p-value' is the p-value from the regression coefficient after running an OLS regression of the outcome on each respective treatment indicator. For water use, standard errors are clustered at the household, while for all other outcomes standard errors are robust to heteroskedasticity in the residuals.

Table 2: Water Intent-to-Treat Effects (Dependent Variable: Water Use (gals/hour))

	Full Sample (5/15-4/16)		First Six Months (5/15-10/15)		Last Six Months (11/15-4/16)	
	(1)	(2)	(3)	(4)	(5)	(6)
	WaterSmart	-0.539*** (0.171)	-0.508*** (0.101)	-0.507*** (0.196)	-0.446*** (0.116)	-0.582*** (0.163)
Hot WaterSmart	-0.603*** (0.167)	-0.591*** (0.097)	-0.524*** (0.192)	-0.497*** (0.113)	-0.701*** (0.158)	-0.684*** (0.108)
Hot WaterSmart Plus	-0.508*** (0.168)	-0.485*** (0.097)	-0.461** (0.194)	-0.401*** (0.114)	-0.571*** (0.159)	-0.567*** (0.106)
H <sub>0</sub> : WS=HWS	0.65	0.34	0.92	0.59	0.39	0.24
H <sub>0</sub> : WS=HWS+	0.83	0.78	0.78	0.64	0.93	0.99
Mean Control Use	12.6	12.6	14.3	14.3	10.9	10.8
Observations	139,470,003	136,932,213	70,545,877	68,894,068	68,924,126	68,038,145
Weather Controls	No	Yes	No	Yes	No	Yes
Date, Month FEs	No	Yes	No	Yes	No	Yes
Pre-Treatment Use Controls	No	Yes	No	Yes	No	Yes

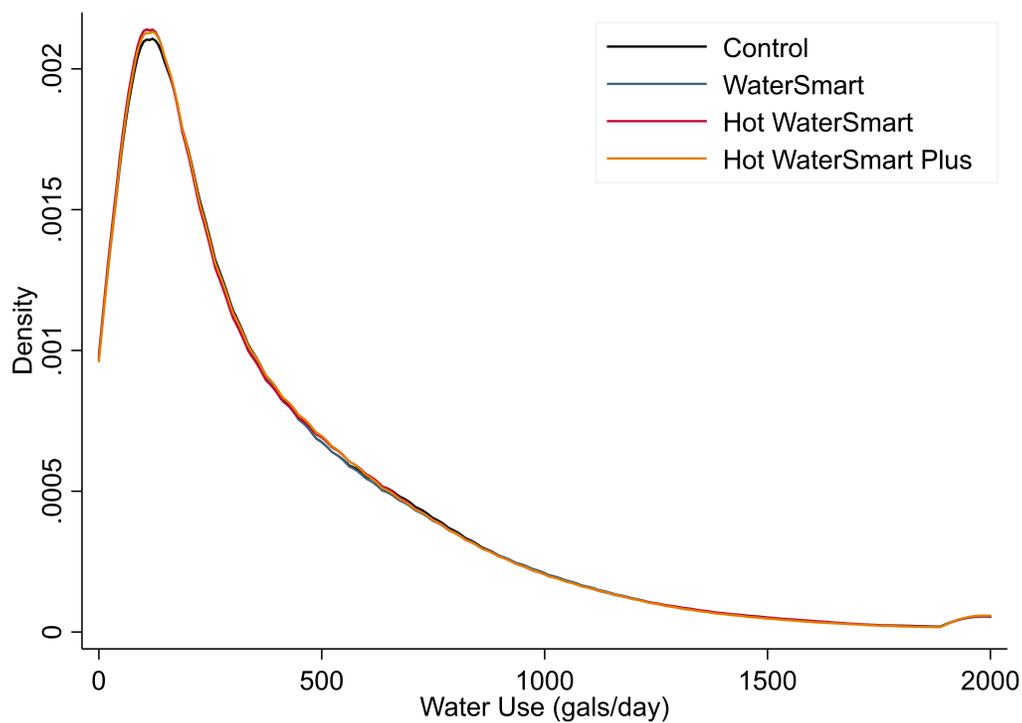
Notes: The table reports intent-to-treat estimates from an OLS regression of hourly water use on assignment to WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus treatments. Columns 1 and 2 include all observations from May 1, 2015 to April 30, 2016. Columns 3 and 4 restrict the sample to the first half of the intervention, and columns 5 and 6 restrict the sample to the second half of the treatment period. H<sub>0</sub>: WS=HWS presents the p-value from a two-sided equivalency test between the WaterSmart and Hot WaterSmart treatments, and similarly for H<sub>0</sub>: WS=HWS+. Standard errors are clustered at the household. \*, \*\*, \*\*\* denote significance at the 10%, 5%, and 1% level.

Table 3: Water-Related Rebate Applications

<b>Panel A: Rebate Application Indicator Outcome</b>						
	<b>Any Rebate</b>		<b>Appliance Rebate</b>		<b>Turf Rebate</b>	
	(1)	(2)	(3)	(4)	(5)	(6)
WaterSmart	-0.002	-0.002	-0.002	-0.002	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
WaterSmart X Post-Treatment	0.001	0.001	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Mean Control Participation (%)	0.028	0.029	0.025	0.026	0.0030	0.0031
<b>Panel B: Rebate Amount Outcome</b>						
	<b>Any Rebate</b>		<b>Appliance Rebate</b>		<b>Turf Rebate</b>	
	(1)	(2)	(3)	(4)	(5)	(6)
WaterSmart	1.608	1.230	-0.008	0.024	1.616	1.206
	(1.406)	(1.477)	(0.243)	(0.250)	(1.386)	(1.458)
WaterSmart X Post-Treatment	-0.480	-0.491	0.067	0.082	-0.547	-0.572
	(0.554)	(0.585)	(0.092)	(0.098)	(0.547)	(0.577)
Mean Control Amount (\$)	4.88	5.07	1.80	1.81	3.08	3.26
Observations	54,441	48,324	54,441	48,324	54,441	48,324
Pre-Treatment Controls	No	Yes	No	Yes	No	Yes

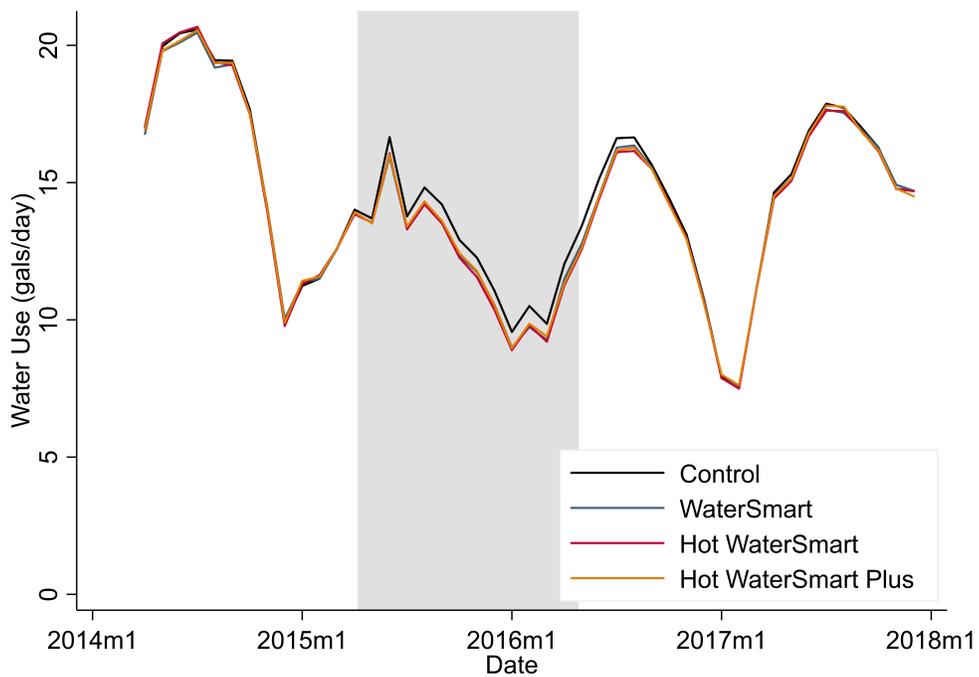
Notes: The table reports intent-to-treat results from an OLS regression of rebate application indicators (Panel A) and rebate payment amounts (Panel B) on assignment to WaterSmart, Hot WaterSmart, or Hot WaterSmart Plus over the treatment and post-treatment periods. The period spans May 2015 through Jun 2016. Pre-Treatment Controls include baseline household average water use for Winter 2014, Summer 2015, and Winter 2015. Standard errors are robust to arbitrary heteroskedasticity. \*, \*\*, \*\*\* denote significance at the 10%, 5%, and 1% level.

Figure 1: Pre-Treatment Water Use Balance



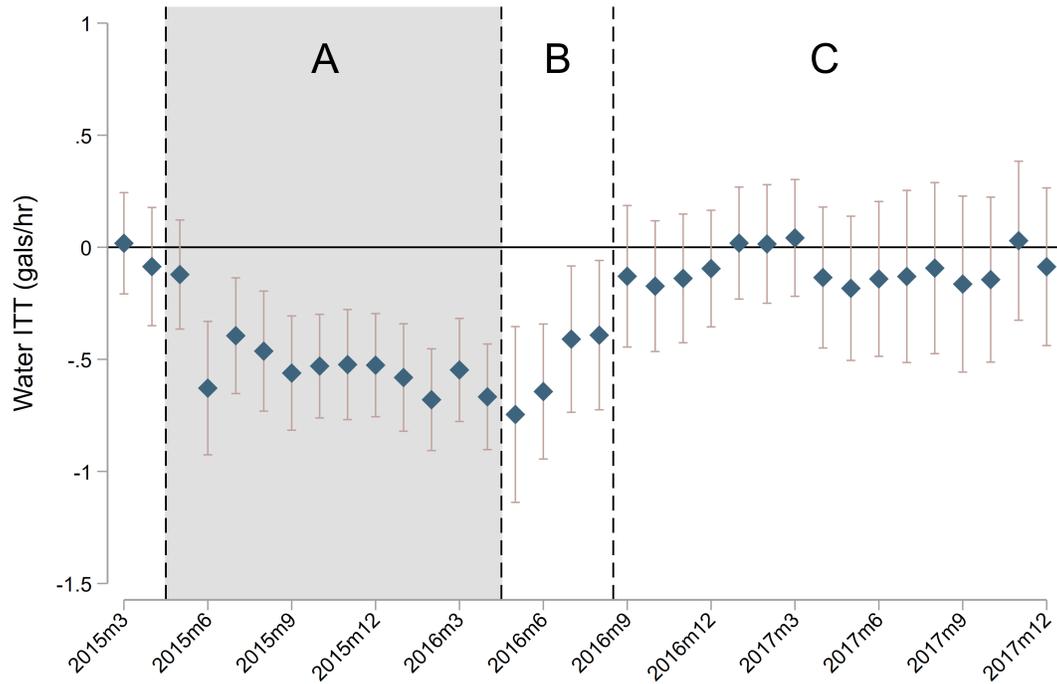
Notes: Figure 1 kernel density functions of daily average, pre-treatment water use for the control and treatment groups. The pre-treatment period includes April 2014 through February 2015. The distribution is truncated at 2,000 gals/day.

Figure 2: Average Water Use By Treatment



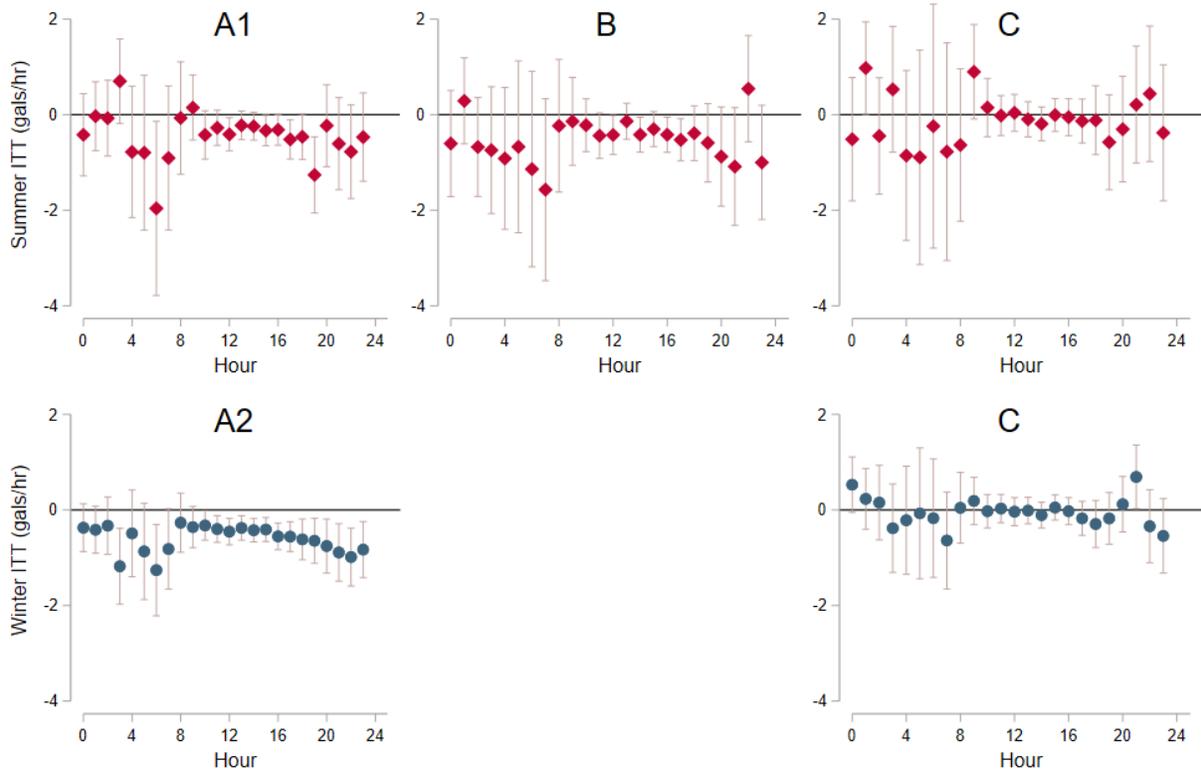
Notes: Figure 2 graphs average hourly water use by month, broken up by control and treatment households. The shaded area is the treatment period.

Figure 3: Intent-to-Treat Effects over Time



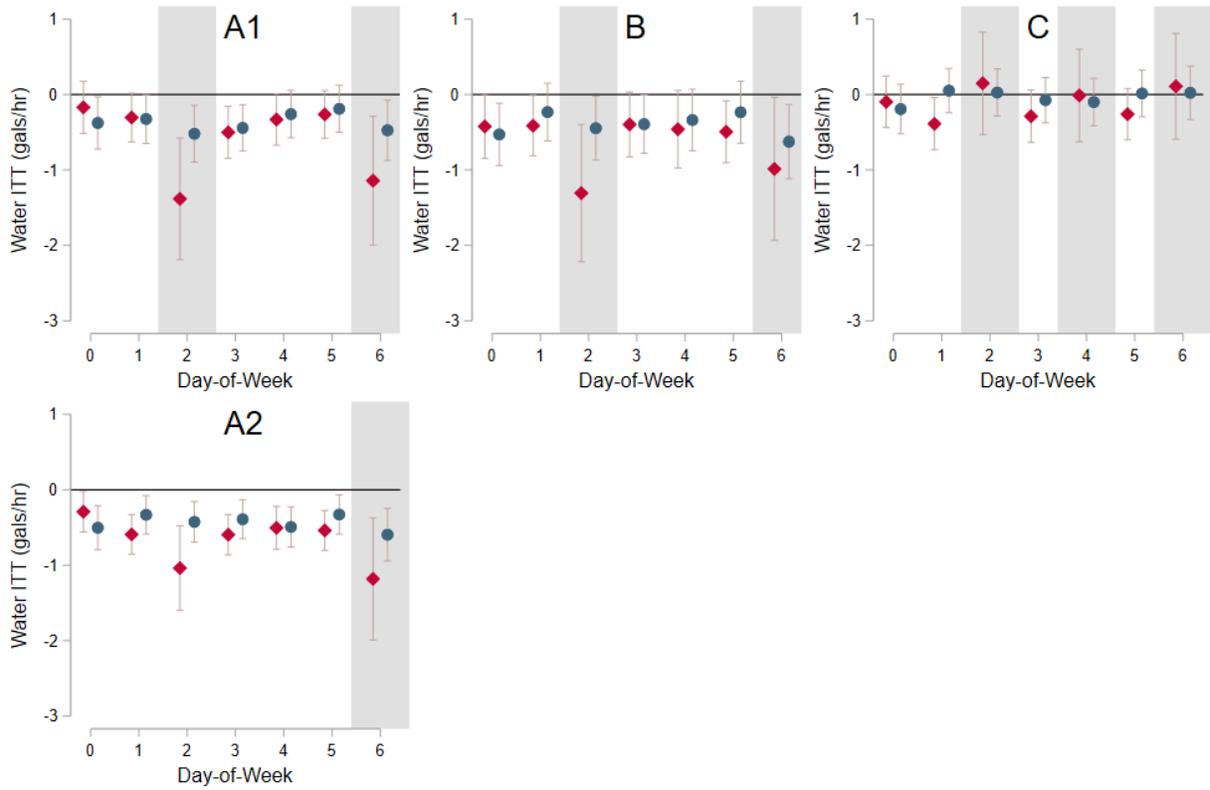
Notes: Figure 3 graphs monthly intent-to-treat effects and 95% confidence intervals over time for the joint treatment indicator (WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus). The shaded area A corresponds to the treatment period, area B corresponds to the ‘backslide’ period, and area C corresponds to the ‘re-convergence’ period. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure 4: Intent-to-Treat Effects by Hour-of-Day



Notes: Figure 4 graphs intent-to-treat effects and 95% confidence intervals over each hour-of-day for the joint treatment indicator (WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus). The top row presents results during summer months (May to October) in red diamonds and the bottom row presents results during winter months (November to April) in blue circles. A is the treatment period, B is the ‘backslide’ period, and C is the ‘re-convergence’ period. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure 5: Intent-to-Treat Effects by Day-of-Week



Notes: Figure 5 graphs intent-to-treat effects and 95% confidence intervals over each day-of-week for the joint treatment indicator (WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus). A1 is the first half of the treatment period (June 2015 to October 2015), A2 is the second half of the treatment period (November 2015 to March 2016), B is the ‘backslide’ period (May 2016 to August 2016), and C is the ‘re-convergence’ period (September 2016 to December 2017). Shaded bars indicate days when BWP permitted outdoor watering. Red circles and blue diamonds denote treatment effects for non-watering and watering hours, respectively. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Online Appendix for  
Residential Water Conservation During Drought: Experimental  
Evidence from Three Behavioral Interventions  
Katrina Jessoe, Gabriel E. Lade, Frank Loge, and Edward Spang  
December 9, 2019

# A Experiment Details

## A.1 Project Timeline and BWP Watering Restrictions

Figure A.1 provides a timeline of our data coverage, treatment, and outdoor watering restriction regimes. Our hourly water use coverage span April 1, 2014, to December 31, 2017. We define the baseline water use period as April 1, 2014 to February 28, 2015. We use these data to construct three baseline measures of water use: April 2014 (April 2014), Summer 2014 (May 2014 to October 2014), and Winter 2015 (November 2014 to February 2015). Each variable is household specific, and measured as average hourly water use.

As shown in the Figure, welcome letters arrived in households' mailboxes the last week of March 2015. Between early May and early June, Water Smart sent the first HWR. Reports were sent on a staggered schedule, and based upon an account's billing cycle. Figure A.1 shows the start date for the first HWR, and each subsequent mailer. The bottom of the figure illustrates BWP's outdoor watering restrictions over this period. BWP had no restrictions before July 2014. The outdoor watering schedule changed with seasons and the severity of the drought. In the earliest and latest dates, households were allowed to water Tuesdays, Thursdays, and Saturdays, though the stringency of the watering restrictions and the enforcement of these restrictions intensified during our treatment period.

Figure A.1: Experiment Timeline - Key Dates and Watering Restrictions

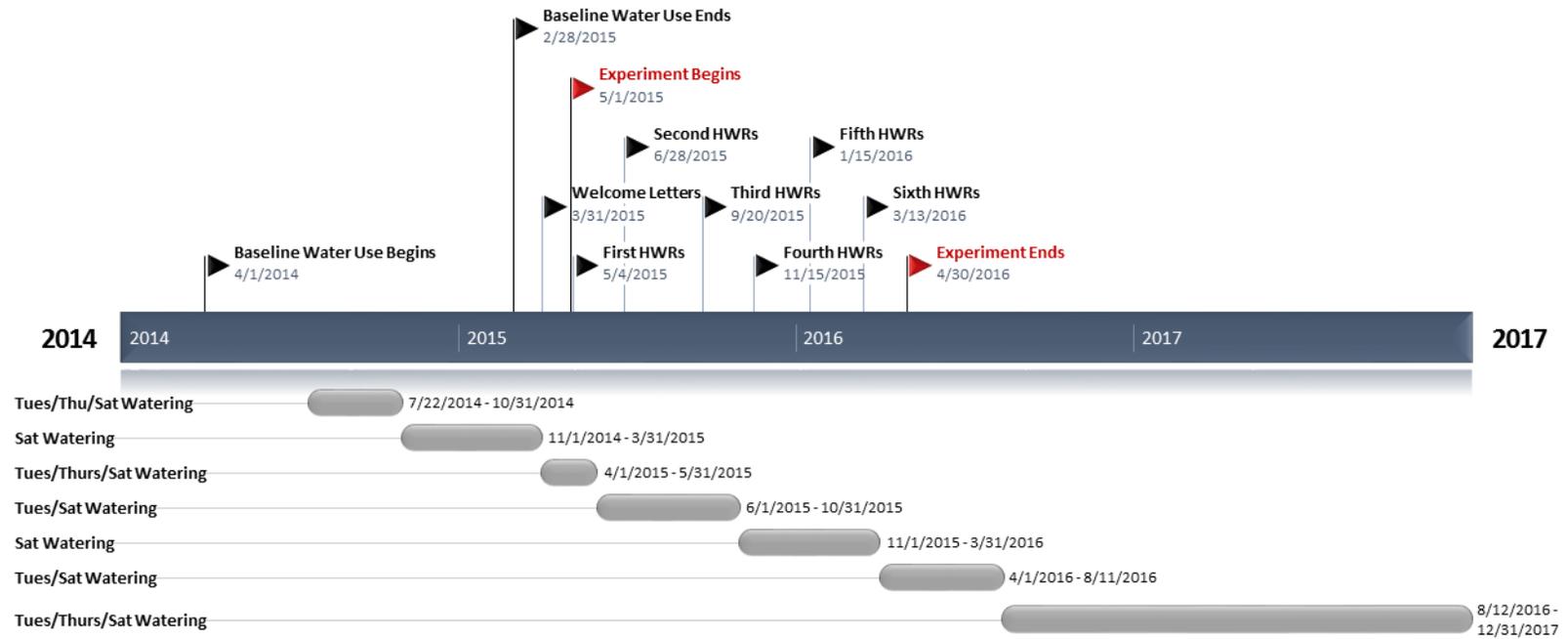


Figure A.2: WaterSmart Home Water Report



WaterInsight Program  
123 Main Street  
Anytown, CA 95875

## YOUR HOME WATER REPORT

THIS IS AN INFORMATIONAL REPORT AND NOT A BILL.

SERVICE ADDRESS: 456 Washington St., Burbank  
ACCOUNT NUMBER: 123456789-02

### TREATMENT 1: TRADITIONAL WATERSMART



SIGN UP TO GET THIS REPORT VIA EMAIL:  
[burbankwaterandpower.com](http://burbankwaterandpower.com)

Blair Jones  
456 Washington St.  
Burbank, CA 91502



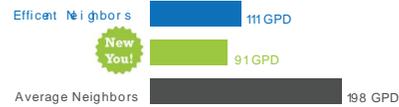
Register online. It works!

"I was alerted to a possible leak. We were trying to be more efficient but each month showed we were using more water...It's eye opening!"  
-Lisa P., resident and user of citywater.com



How much you could be saving

If you took the actions below, you could reduce your use by 83 GPD. That's \$368 per year in potential savings.



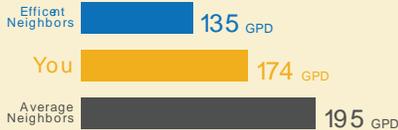
### Your WaterScore

AUG 1 TO SEP 30, 2015



Nice work, WaterSaver.  
Take action to save even more.

Gallons Per Day (GPD)  
14 CCF = 250 GPD



### Water-saving actions just for you

Selected assuming your home has 3 occupants and a 2,000 to 4,000 sq. ft. yard.

Log on to personalize your reports!

Potential savings if you:



Install a faucet aerator

12

GALLONS PER DAY



\$72

DOLLARS PER YEAR



Fill up the clothes washer

9

GALLONS PER DAY



\$55

DOLLARS PER YEAR



Change grass to native plants

62

GALLONS PER DAY



\$241

DOLLARS PER YEAR



Log On

Take the guesswork out of saving water. See:

- Where you're using the most
- All actions relevant to you
- Step-by-step tips and rebates

[burbankwaterandpower.com](http://burbankwaterandpower.com)

Registration Code: XYZYXS  
Zip Code: 98765

A no cost service offered by your water utility and powered by WaterSmart software\*

\*Cost estimates based on Burbank Water & Power and SoCalGas@utility rates.

Figure A.3: Hot WaterSmart Home Water Report



WaterInsight Program  
123 Main Street  
Anytown, CA 95875

**TREATMENT 2: "HOT WATER"  
WATERSMART HWR**

Your WaterScore  
AUG 1 TO SEP 30, 2015



Nice work, WaterSaver.  
Take action to save even more.

Gallons Per Day (GPD)  
14 CCF = 250 GPD



**YOUR HOME WATER REPORT**

THIS IS AN INFORMATIONAL REPORT AND NOT A BILL.

SERVICE ADDRESS: 456 Washington St., Burbank  
ACCOUNT NUMBER: 123456789-02

SIGN UP TO GET THIS REPORT VIA EMAIL:  
[burbankwaterandpower.com](mailto:burbankwaterandpower.com)

Blair Jones  
456 Washington St.  
Burbank, CA 91502

Register online. It works!

"I was alerted to a possible leak. We were trying to be more efficient but each month showed we were using more water...It's eye opening!"  
-Lisa P., resident and user of citywater.com

Did you know?

The second largest use of energy in a home is for heating water. Save water, energy, and money by reducing hot water use. Follow the tips below and log into your WaterSmart account for more information.

**Water-saving actions just for you**

Selected assuming your home has 3 occupants and a 2,000 to 4,000 sq. ft. yard.

Log on to personalize your reports!

Potential savings if you:



\*Cost estimates based on Burbank Water & Power and SoCalGas@utility rates.

Log On

Take the guesswork out of saving water. See:  
•Where you're using the most  
•All actions relevant to you  
•Step-by-step tips and rebates

[burbankwaterandpower.com](http://burbankwaterandpower.com)

Registration Code: XYZYXS  
Zip Code: 98765

A no cost service offered by your water utility and powered by WaterSmart software\*

Figure A.4: Hot WaterSmart Recommendations



WaterInsight Program  
123 Main Street  
Anytown, CA 95875

### YOUR HOME WATER REPORT

THIS IS AN INFORMATIONAL REPORT AND NOT A BILL.

SERVICE ADDRESS: 456 Washington St., Burbank  
ACCOUNT NUMBER: 123456789-02

SIGN UP TO GET THIS REPORT VIA EMAIL:  
[burbankwaterandpower.com](http://burbankwaterandpower.com)

### RECOMMENDATIONS

#### Water-saving actions just for you

Selected assuming your home has 4 occupants.

[Log on to correct us!](#)

Potential savings if you:

Decrease your water heater temp to 120°F or lower.

-	GALLONS PER DAY
73	THERMS PER YEAR
\$66	DOLLARS PER YEAR

**R1**

Install a low flow showerhead

10	GALLONS PER DAY
36	THERMS PER YEAR
\$38	DOLLARS PER YEAR

**R2**

Install low-flow faucet aerators

24	GALLONS PER DAY
59	THERMS PER YEAR
\$66	DOLLARS PER YEAR

**R3**

Take a 5 minute shower

19	GALLONS PER DAY
68	THERMS PER YEAR
\$61	DOLLARS PER YEAR

**R4**

Replace dishwasher with an ENERGY STAR certified model

9	GALLONS PER DAY
46	THERMS PER YEAR
\$41	DOLLARS PER YEAR

**R5**

Decrease pool temp by 2 degrees

-	GALLONS PER DAY
675	THERMS PER YEAR
\$607	DOLLARS PER YEAR

**R6**

Replace gas tank water heater with tankless gas water heater

-	GALLONS PER DAY
115	THERMS PER YEAR
\$103	DOLLARS PER YEAR

**R7**

Replace clothes washer with an ENERGY STAR certified model

11	GALLONS PER DAY
15	THERMS PER YEAR
\$14	DOLLARS PER YEAR

**R8**

Fill up clothes washer

6	GALLONS PER DAY
7	THERMS PER YEAR
\$10	DOLLARS PER YEAR

**R9**

Figure A.5: Hot WaterSmart Plus Home Water Report (Report 1)



Home Water Report Program  
P.O. Box 631  
Burbank, CA 91503-0631

818-238-3700 waterreports@burbankca.gov

## YOUR HOME WATER REPORT

THIS IS AN INFORMATIONAL REPORT AND NOT A BILL.

SERVICE ADDRESS: 20 California, Suite 200  
ACCOUNT NUMBER: 123-4567-89

GO PAPERLESS. SEE ALL INFO & PRODUCTS AT:  
[burbankwaterandpower.com/waterreport](http://burbankwaterandpower.com/waterreport)

<RecipientID>burbank468715</RecipientID>

### Your WaterScore

JUL 21 TO AUG 20, 2015



**53**

**Nice work, WaterSaver.  
Take action to save even more.**

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Gallons Per Day (GPD)  
19 HCF = 460 GPD

Efficient Households	329 GPD
<b>You</b>	<b>460 GPD</b>
Average Households	517 GPD

Your water use is compared to homes in the City of Burbank with 4 occupants and a similar yard size.



### Get leak alerts by email

Not all leaks are easily visible. Protect your property by signing up for alerts. Log on and we'll email you when we spot irregular water use.

[burbankwaterandpower.com/waterreports](http://burbankwaterandpower.com/waterreports)



### Save hot water, win big!

Reduce **water use by 24%** and **gas use by 3%** in the next 7 months and win one of:

- 25 high-efficiency Whirlpool clothes washers
- 100 luxurious, efficient Evolve showerheads
- A hot water efficiency starter kit

**conserveandwin.com**

Use promo code "CONSERVE"

### Water-saving actions just for you

Selected based on your household characteristics, yard size, and historical water use.

[Log on to update your profile](#)

Potential annual savings if you:

 <p>Reduce shower to 5 minutes</p> <div style="background-color: #0070c0; color: white; padding: 5px;"> <p><b>27</b> GALLONS PER DAY</p> <p><b>\$65</b> DOLLARS PER YEAR</p> <p>SAVES GAS! 28 therms/year</p> </div>	 <p>Install high-efficiency showerheads</p> <div style="background-color: #0070c0; color: white; padding: 5px;"> <p><b>13</b> GALLONS PER DAY</p> <p><b>\$33</b> DOLLARS PER YEAR</p> <p>SAVES GAS! 14 therms/year</p> </div>	 <p>Mulch around your plants</p> <div style="background-color: #0070c0; color: white; padding: 5px;"> <p><b>70</b> GALLONS PER DAY</p> <p><b>\$104</b> DOLLARS PER YEAR</p> </div>
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[Log On](#)

Get your full list of recommended actions, and see:

- Where you're using the most
- Your progress over time
- Efficient products for purchase

[burbankwaterandpower.com/waterreports](http://burbankwaterandpower.com/waterreports)

A **free** service offered by your water utility and powered by WaterSmart Software®

Figure A.6: Hot WaterSmart Plus Home Water Report (Report 5)



Home Water Report Program  
P.O. Box 631  
Burbank, CA 91503-0631

818-238-3700 waterreports@burbankca.gov

### Your WaterScore

OCT 18 TO NOV 17, 2015

**You used more water than similar households.**

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**Gallons Per Day (GPD)**  
31 HCF = 752 GPD

Efficient Households	335 GPD
Average Households	513 GPD
<b>You</b>	<b>752 GPD</b>

Your water use is compared to homes in the City of Burbank with 5+ occupants and a similar yard size.

## YOUR HOME WATER REPORT

THIS IS AN INFORMATIONAL REPORT AND NOT A BILL.

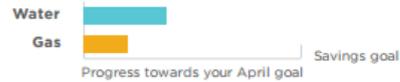
SERVICE ADDRESS: 20 CALIFORNIA, SUITE 200  
ACCOUNT NUMBER: 123-4567-89

GO PAPERLESS. SEE ALL INFO & PRODUCTS AT:  
[burbankwaterandpower.com/waterreports](http://burbankwaterandpower.com/waterreports)

<RecipientID-burbank620120/>RecipientID>

### Keep saving to win!

Reduce water use by 24% and gas use by 3% to win great prizes. Enroll at [conserveandwin.com](http://conserveandwin.com).



### When can you water?

From November to March, outdoor watering is limited to:

- Saturdays only
- 15 minutes per station
- Before 9:00am or after 6:00pm
- Keep sprinklers off when it rains and for at least 2 days after
- Hand watering is fine, as long as the sun is down

### Water-saving actions just for you

Selected based on your household characteristics, yard size, and historical water use.

[Log on to update your profile](#)

Potential annual savings if you:

<p>Mulch around your plants</p> <p><b>61</b> GALLONS PER DAY</p> <p><b>\$90</b> DOLLARS PER YEAR</p>	<p>Minimize fertilizer</p> <p><b>60</b> GALLONS PER DAY</p> <p><b>\$89</b> DOLLARS PER YEAR</p>	<p>Wash your laundry in cold water</p> <p>Washing in cold water uses less energy than hot water and gets your clothes just as clean!</p> <p><b>SAVES GAS! 10 therms/year</b></p>
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### Log On

Get your full list of recommended actions, and see:

- Where you're using the most
- Your progress over time
- Efficient products for purchase

[burbankwaterandpower.com/waterreports](http://burbankwaterandpower.com/waterreports)

A free service offered by your water utility and powered by WaterSmart Software®

## B Additional Results

### B.1 Treatment Comparisons

**Hour-of-Day Treatment Effects.** Figure C.1 graphs point estimates for hour-of-day treatment effects broken out by treatment group. We present results for summer and winter months over the treatment year. The corresponding grouped treatment effects in the main text are Panels A1 and A2 in Figure 4. The treatment effects profiles are nearly identical, and not statistically different, across the three groups. The one exception may be the impact of Hot WaterSmart, where we estimate slightly lower treatment effects in early morning hours (4 AM to 8 AM) and larger treatment effects in evening hours (8 PM to 11 PM) relative to other treatment groups, particularly in the summertime.

**Day-of-Week Treatment Effects.** Figure C.2 graphs point estimates for day-of-week treatment effects by treatment group. We present results for summer (A1) and winter (A2) months, and further break out treatment effects by hours of the day where watering is allowed (left panel) and prohibited (right panel). The corresponding figures in the main text are Panels A1 and A2 in Figure 5. As in the main text, we see that the largest treatment effects occur on days of the week and hours of the day when outdoor watering is allowed. Treatment effects are nearly identical, and not statistically significant, across any specification.

### B.2 All Watering Regimes

BWP had four different outdoor watering regimes in place during the treatment year and two during the backslide period (Figure A.1). BWP allowed outdoor watering on Tuesday, Thursdays, and Saturdays from May 1, 2015 to May 31, 2015. From June 1, 2015 to October 31, 2015, households could water their lawns on Tuesdays and Saturdays. From November 1, 2015 to March 31, 2016, households could water only on Saturdays. From April 1, 2016 to August 11, 2016, Tuesday and Saturday watering resumed. BWP adopted a permanent Tuesday, Thursday, Saturday watering schedule on August 12, 2016. In Section 4.3, we restrict our attention to the Tuesday/Saturday and Saturday regimes during the treatment period, and the Tuesdays/Saturday regime during the backslide period since they covered most of the sample.

Figures C.3 and C.4 compare day-of-week treatment effects across all watering regimes. As in Figure 5, we show treatment effects for hours of the day when outdoor watering

was permitted and those when it was not. We see no discernible difference in households' water use during the first treatment regime (5/1/15 to 5/31/15, Panel A1). The result is unsurprising since we find no treatment effect in May 2015 since households were beginning to receive their first HWRs (Figure 3). The largest treatment effects are on Tuesdays and Thursdays during the remaining treatment regimes (Panels A2 to A4). Even when winter-time restrictions allowed watering on only Saturday (11/1/2015 to 3/31/2016, Panel A3), we continue to find a large treatment effect ( $\approx 1.5$  gals/hour) during morning and evening hours on Tuesdays. The results suggest that habits developed in the first half of the treatment period persisted through the winter months. The treatment effect increased on Tuesday watering hours when BWP returned to a Tuesday/Saturday schedule (April 1, 2016 to April 30, 2016, Panel A4), suggesting treatment households watered their lawns less than control households when they were permitted to water again.

As in Figure 5, we continue to see the largest treatment effects during watering hours on Tuesdays and Thursdays in the backslide period (5/1/2016 to 8/10/2016, Panel B1). The treatment effects are no longer detectable by the time that BWP instituted its Tuesday, Thursday, Saturday schedule mid-August 2016 (Panel B2).

### B.3 Log Results

**Short- and Long-Run Impacts** Figure C.5 reproduces Figure 3 using the log of household water use as our dependent variable.<sup>11</sup> Two differences are apparent. First, the ITT impacts increase over the treatment year, while they are relatively constant after the second treatment month in Figure 3. Second, treatment effects persist 10 months (as opposed to four months) post-treatment. These differences highlight a key distinction between the specifications. Log impacts depend on households' response to treatment and the level of control households water use. A 0.5 gal/hr treatment effect is larger in percentage terms in the wintertime because water use is lower in these months.

**Patterns of Water Use: Hour-of-Day** Figure C.6 presents hour-of-day results using log water use as the dependent variable. Focusing on the treatment period, Column A, we find a flatter response to treatment reflecting changing patterns of water use across hours of the day. The largest treatment effect, around a 4% reduction, is still observed at 7 AM; however,

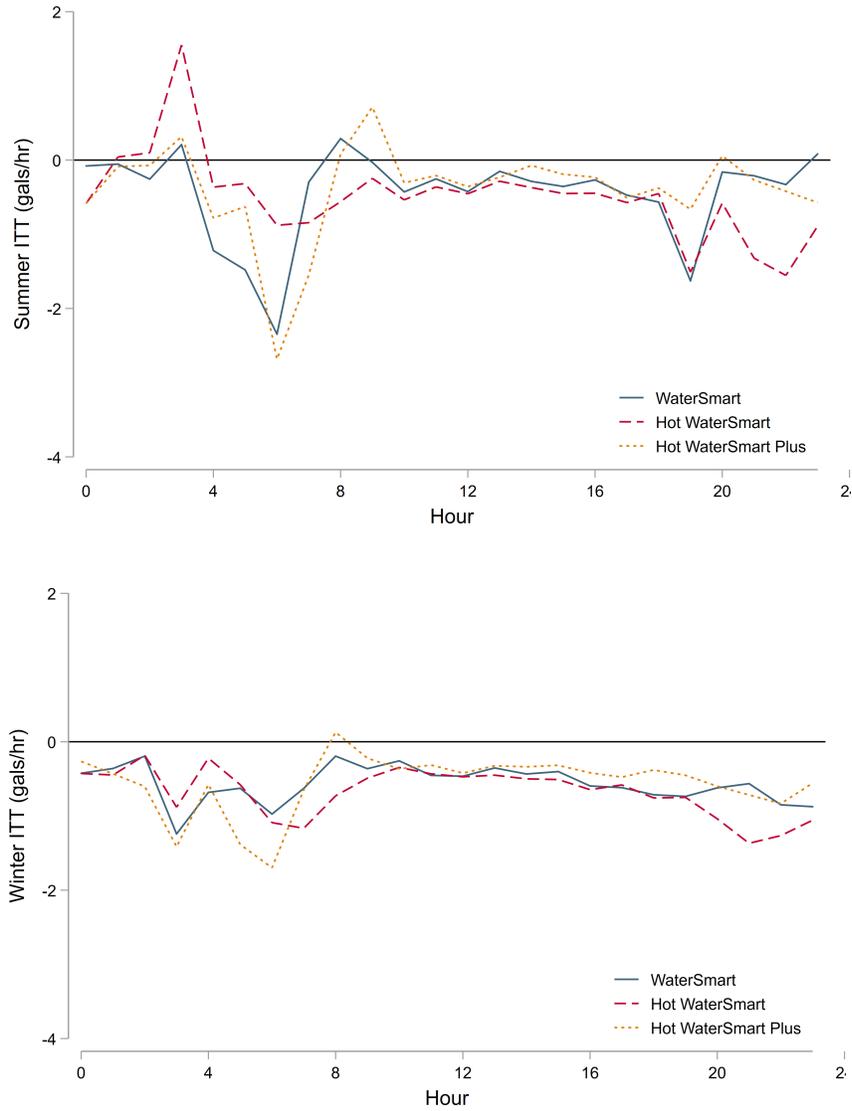
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<sup>11</sup>We transform households hourly water use  $y$  as  $\log(y + 1)$  because there are many observations when households water consumption is zero. Results are similar if we use other transformations like the inverse hyperbolic sine.

middle of the day impacts are larger, around 3%, due to the low baseline water use in those hours. As before, we see that the overall patterns of the treatment effect remain in the ‘backslide’ period (column B), and dissipate in the ‘re-convergence’ period (column C).

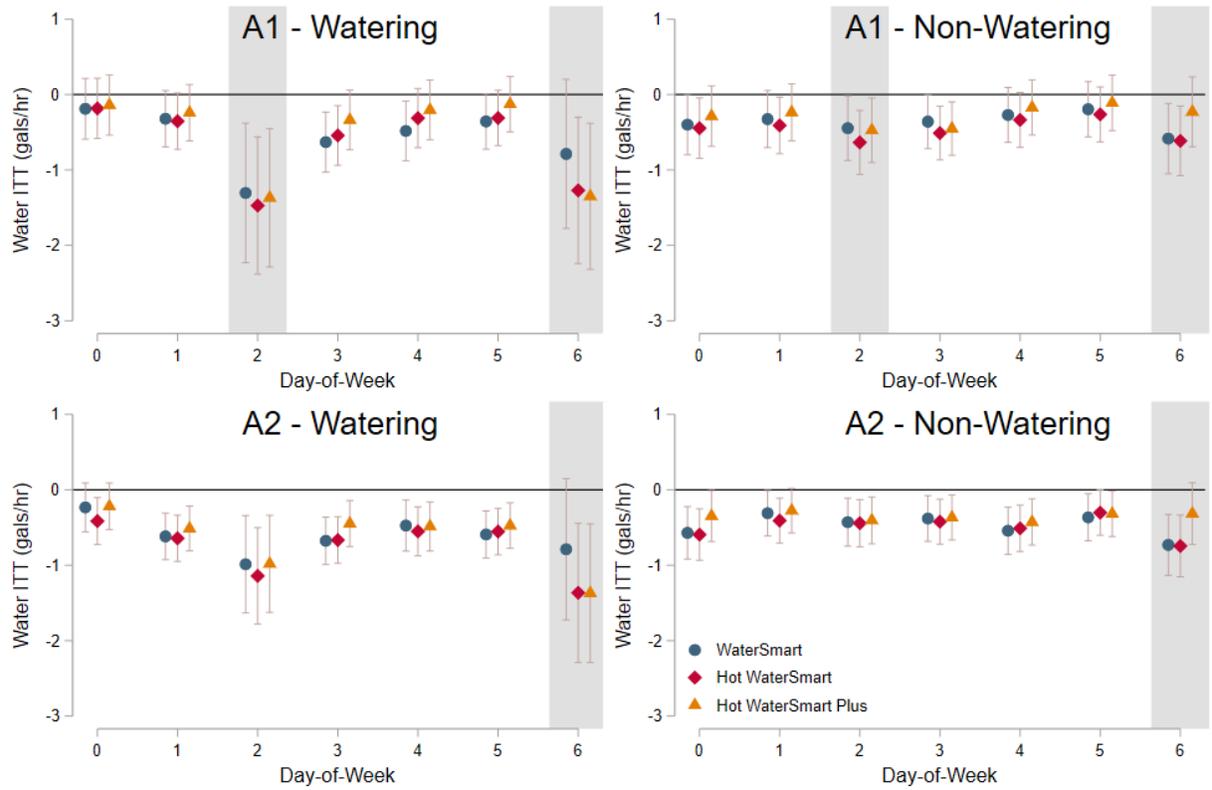
**Patterns of Water Use: Day-of-Week** Figure C.7 presents our day-of-week results using log water use as our dependent variable. Again, we see a flatter treatment response in watering and non-watering hours of the day, reflecting changing baseline water use. We also see a flatter response across days of the week, hiding heterogeneity since average water use increases on Tuesday and Thursdays. We see similar features in panel A2. The treatment effect remains significant and nearly identical in the summer after treatment, panel B. The treatment effect is detectable during watering hours (evening to early morning) for some days of the week even later after treatment ended, panel C, consistent with our findings in Figure C.5.

Figure C.1: Hour-of-Day Results by Treatment Group



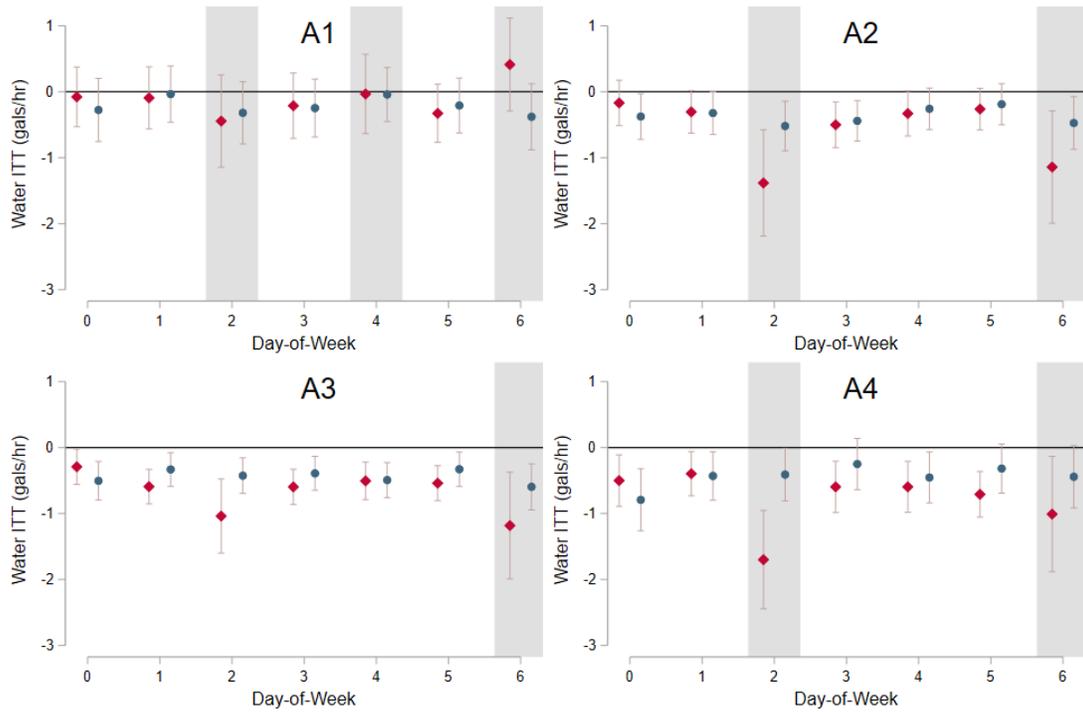
Notes: The figure graphs point estimates for hour-of-day treatment effects by treatment group for the summertime (the top figure) and the wintertime (the bottom figure). The corresponding figures in the main text are Panels A1 and A2 in Figure 4. For simplicity, no 95% confidence intervals are presented. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure C.2: Day-of-Week Results by Treatment Group



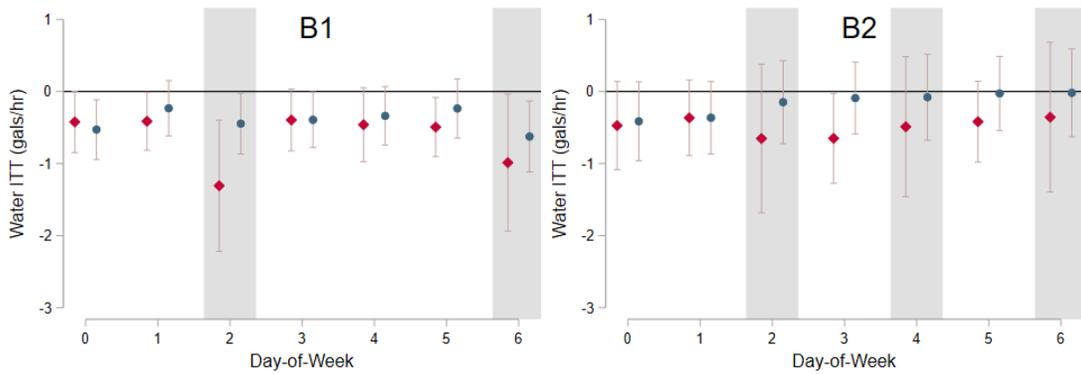
Notes: The figure graphs point estimates for day-of-week treatment effects by treatment group for the summertime (A1) and the wintertime (A2). We further break the treatment effects out by hours of the day where watering is allowed (left panel) and prohibited (right panel). The corresponding figures in the main text are Panels A1 and A2 in Figure 5. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure C.3: Day-of-Week Results: All Watering Regimes (Treatment)



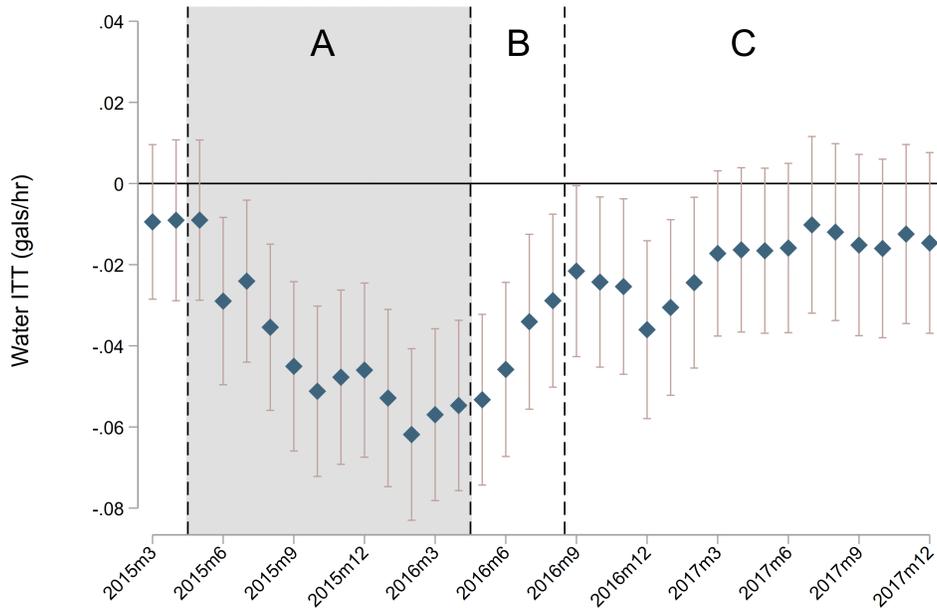
Notes: The figure graphs intent-to-treat effects and 95% confidence intervals for each day-of-week for the joint treatment indicator during the treatment year. A1 is the first outdoor watering regime (May 2015), A2 is the second watering regime (June 2015 to October 2015), A3 is the third watering regime (November 2015 to March 2016), and A4 is the fourth watering regime (April 2016). Shaded bars indicate days when BWP permitted outdoor watering. Red circles and blue diamonds denote treatment effects for non-watering and watering hours, respectively. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure C.4: Day-of-Week Results: All Watering Regimes (Backslide)



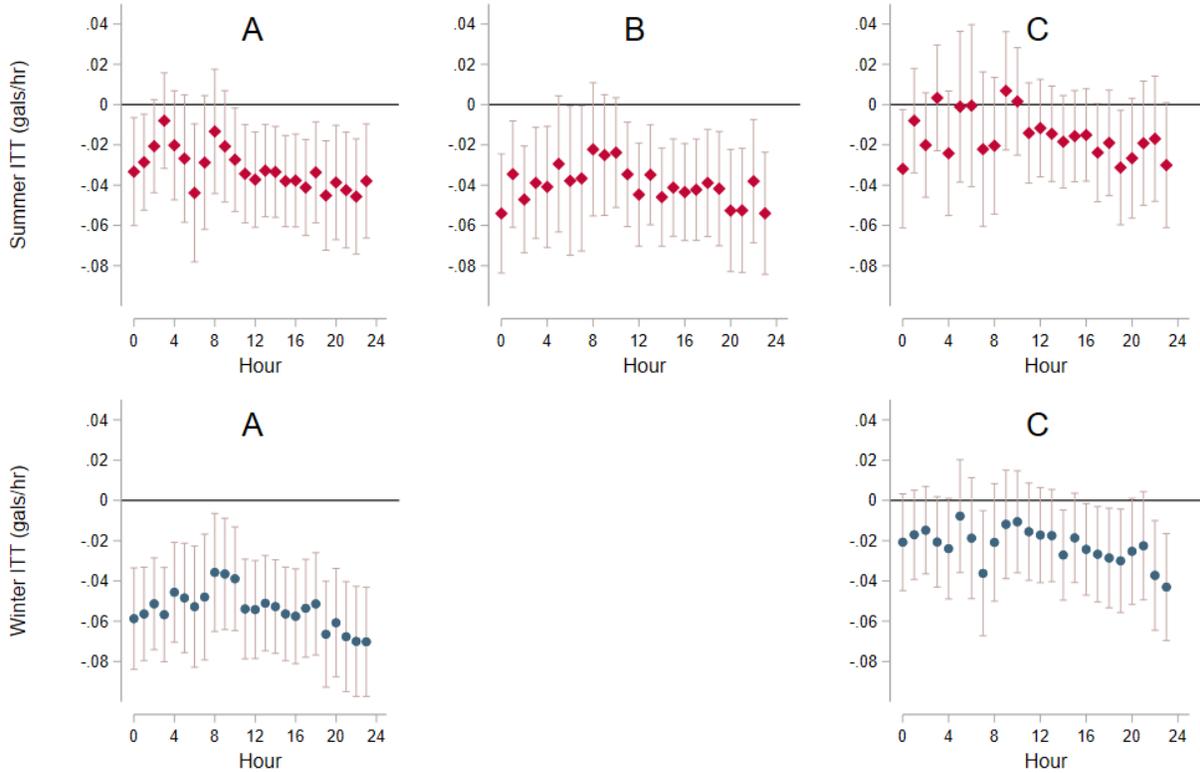
Notes: The figure graphs intent-to-treat effects and 95% confidence intervals for each day-of-week for the joint treatment indicator during the backslide period. B1 is the first outdoor watering regime (May 2016 to August 10, 2016), and B2 is the second watering regime (August 11 2016 to August 31, 2016). Shaded bars indicate days when BWP permitted outdoor watering. Red circles and blue diamonds denote treatment effects for non-watering and watering hours, respectively. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure C.5: Intent-to-Treat Effects over Time  
(Log Water Use)



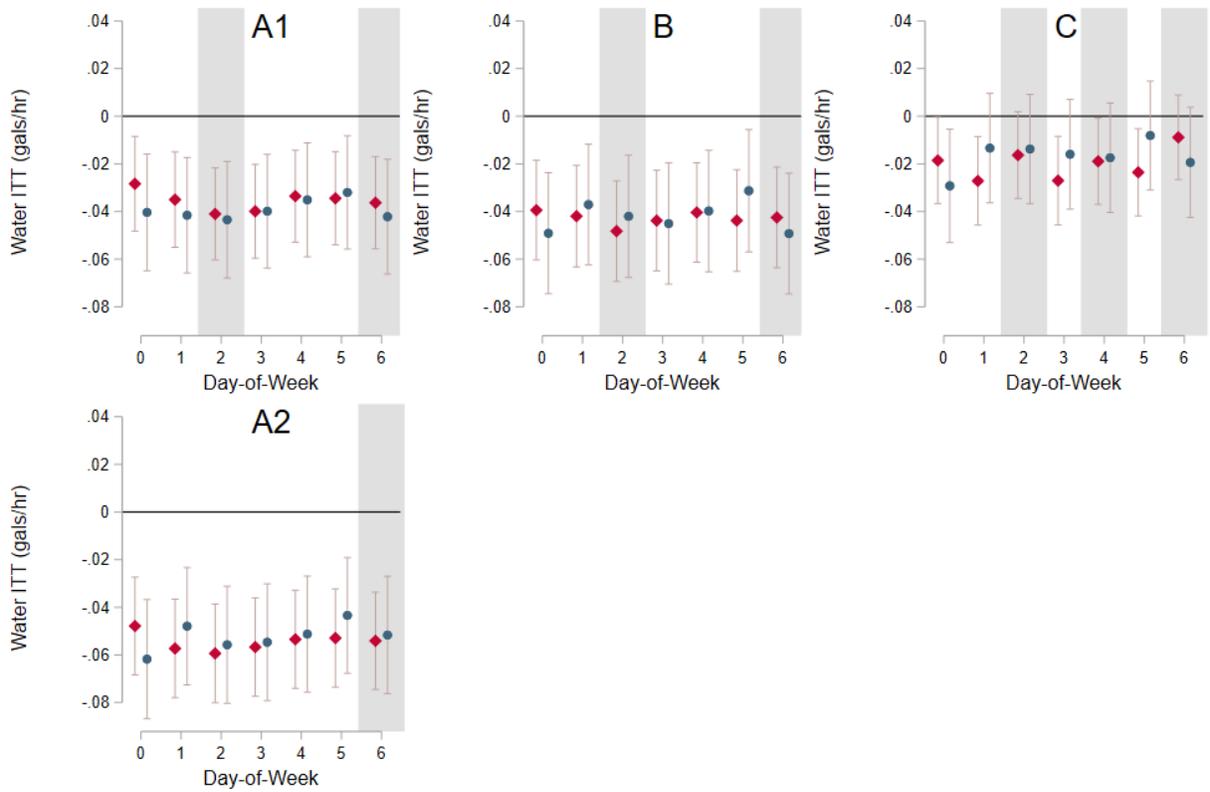
Notes: The figure graphs monthly intent-to-treat effects and 95% confidence intervals over time for the joint treatment indicator (WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus). The shaded area A corresponds to the treatment period, area B corresponds to the ‘backslide’ period, and area C corresponds to the ‘re-convergence’ period. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure C.6: Intent-to-Treat Effects by Hour-of-Day  
(Log Water Use)



Notes: The figure graphs intent-to-treat effects and 95% confidence intervals over each hour-of-day for the joint treatment indicator (WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus). The shaded area A corresponds to the treatment period, area B corresponds to the ‘backslide’ period, and area C corresponds to the ‘re-convergence’ period. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.

Figure C.7: Intent-to-Treat Effects by Day-of-Week  
(Log Water Use)



Notes: The figure graphs intent-to-treat effects and 95% confidence intervals over each day-of-week for the joint treatment indicator (WaterSmart, Hot WaterSmart, and Hot WaterSmart Plus). The shaded area A corresponds to the treatment period, area B corresponds to the ‘backslide’ period, and area C corresponds to the ‘re-convergence’ period. Treatment effects are presented separately for watering hours (red diamonds) and non-watering hours (blue circles), where the shaded days are days where outdoor watering restrictions bind. All regressions include baseline household water use, local weather controls, as well as date and hour-of-day fixed effects.