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Heterogeneous Responses to Social Norms for Water Conservation

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Abstract Utilizing social norms is gaining momentum as a cost-effective mechanism to promote sustainable behavior. We analyze household water data from multiple pilot programs for a company that provides information campaigns containing social comparisons of water use and personalized conservation recommendations in order to reduce household water consumption. We find significant treatment effect heterogeneity across the distribution of consumption and environmental attitudes. In the two pilots with a full year of data one utility achieves savings of 6.5%; while the other in aggregate achieved limited conservation gains. Heterogeneity based on the distribution of consumption is more important in the utility with significant savings, with the highest users saving the most water. In contrast ideology appears to be more important in the utility with an insignificant average treatment effect with dis-savings for those with very low environmental preferences and strong savings for the most environmentally-conscious. Inter-regional ideology may play an critical role since the utility with significant savings is in a much "greener" community, whereas intra-utility ideology is influential in conservative areas. We caution interpretation of the results, particularly for Utility B, as the data are still incomplete.

Keywords: Water demand; Social norms; Behavioral economics; Water conservation.
JEL Classification Numbers: Q21, Q25, Q54.

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1 Introduction

Many water utilities, particularly those in the Western United states, face pressure to reduce water demand as evidenced by California's requirement for utilities to reduce demand by 20% by 2020[1]. Economists tend to favor the price mechanism over other policy tools to reduce consumption for goods with environmental externalities. While we believe that the price mechanism is the most efficient way to reduce consumption other instruments must be used when raising prices or introducing Pigouvian taxes is not feasible. Public utilities that serve most major population centers face barriers to raising rates to reduce demand such as zero profit constraints, concerns over equity[2], and political backlash by constituents of local governments. Command and control interventions, such as imposing mandatory restrictions on outdoor water use, are a common alternative to raising water rates but are shown to reduce consumer welfare (Grafton and Ward, 2008; Mansur and Olmstead, 2012). In this policy climate water managers must seek alternative mechanisms to reduce demand.

An approach that is gaining momentum is the use of information campaigns incorporating social comparisons and arming consumers with additional information about their water use. Stemming from the behavioral economics literature, comparing household water use to a group of peers both establishes a baseline level of conventional consumption and generates civic pressure to refrain from water profligacy. Allcott (2011b) analyzes the impact of Opower, one of the largest and most successful companies applying social norms, in reducing electricity consumption and there are numerous other applications of behavioral economics used for policy initiatives spanning food choice, retirement allocation, utility demand and organ donation (Downs et al., 2009; Johnson and Goldstein, 2003; Benartzi and Thaler, 2007; Ferraro et al., 2011; Dolan and Dolan, 2011). Research on using social norms for water consumption provides insights into how effective non-price instruments can be. Exploring the heterogeneity reveals where the programs are most effective, and provides insights on areas for improvement. Our preliminary results based on the initial data are promising and we will continue to improve our understanding as we receive more data.

[1]See http://www.swrcb.ca.gov/water_issues/hot_topics/20x2020/ for more information.

[2]Raising water rates, while efficient, causes equity concerns since water bills for the poorest households comprise a higher proportion of their disposable income.

We harness a rich dataset from WaterSmart, a clean technology company that is establishing itself as the Opower of water, to analyze the effect of social norms as a water conservation tool. WaterSmart currently has programs running in seven cities in different stages of development - five of which began as randomized pilot programs. This unique dataset allows us to estimate the average treatment effect of their program and to explore heterogeneity within and across pilot. Since the program is still in the early stages in some of the pilots we focus on the two pilots with the most data that also highlight the heterogeneity in program response. We see considerable heterogeneity both within and across the pilots, with different patterns of response across the distribution of consumption for the two pilots. While pilot A achieves a savings of approximately 6.5% over sixteen months, pilot B has small but insignificant savings. Looking deeper at individual billing periods, the time series of savings over the course of the pilot follows divergent paths for the two pilots. While pilot A achieves relatively consistent savings over the course of the program pilot B initially experiences the perverse result of using more water followed by significant savings. It should also be noted that while the pilot program is over for Utility A[3] there are additional treatment periods for Utility B so the results for this utility may change.

Examining the heterogeneity of the treatment effect reveals stark differences between the two pilots. Utility A achieves much of its conservation gains via households with high baseline water consumption, though there appears to be some savings at the low end of the distribution as well. The primary driver of heterogeneity in Utility B is differences in ideology within the service area. Those in the lowest 10% of our green index actually increase consumption by 5% relative to the median due to the treatment. This is in stark contrast to the 19% relative water savings achieved in the 10% most environmentally conscious households. Comparing the effect of ideology across utilities is also revealing since Utility A, which achieved a large average treatment effect, has much stronger environmental preferences than Utility that to date experienced minimal savings. One caveat to this finding is that the income levels of the two service areas are very different, and we will soon test this avenue of heterogeneity as we receive data household level data on home values. Exploring the role of ideology across utilities is an avenue for further research as we receive more data from other pilots.

[3]The program has been expanded to the entire utility.

This paper is organized as follows. The next section presents the relevant literature. Then, Section 3 discusses the background of WaterSmart and describes the data. Section 4 overviews the estimation strategy and presents the empirical results. Section 5 provides plans for future research as we receive more data. Concluding remarks are offered in Section 6.

2 Existing Literature

Using social norms in public policy is a relatively recent development and has spawned a lot of exciting research to determine the efficacy of various programs to achieve policy objectives. Elster (1989) attempts to reconcile the divide between theories in economics, where rational agents are "pulled" by incentives, and sociology where agents are "pushed" by their surrounding environment. Thaler and Sunstein (2003) describe a third route between the two extremes whereby agents still make rational decision, but can be "nudged" by changing seemingly inconsequential elements in the choice environment. Recent research applies behavioral economics to a range of public policy objectives spanning food (Downs et al., 2009), organ donation (Johnson and Goldstein, 2003), retirement savings (Benartzi and Thaler, 2007), and several examples within environmental economics (Allcott, 2011b; Ferraro et al., 2011; Dolan and Dolan, 2011).

A series of papers by Hunt Allcott and coauthors (Allcott and Mullainathan, 2010; Allcott, 2011a,b; Allcott and Rogers, 2012b,a; Allcott and Greenstone, 2012) on various dimensions of energy economics helped establish a role for applied environmental economists to apply techniques from behavioral economics. This avenue is especially important in the context of strong political resistance to direct taxation of environmental externalities. Allcott's work analyzing data from Opower (Allcott, 2011b; Allcott and Rogers, 2012a,b) is the most similar to the research presented here. Allcott (2011b) finds that Opower's program of providing social comparisons along with technical information reduced energy demand by an average of 2%. There is considerable heterogeneity in the treatment effect across the consumption distributions, with the right tail experiencing the largest savings.

Allcott's work on Opower serves as a template for the analysis since water and energy share many common features. However, there are key differences between water and energy that warrant

studying the efficacy of social norms in the water sector. First, while many regions experience seasonal peak demand in the summer for both energy and water, the marginal value of activities driving the peak is likely different. Air conditioning, a major component of energy peak demand, has significant health benefits in combating heat stroke (Semenza et al., 1996). Conversely, research shows that summer demand due to discretionary outdoor use has higher demand elasticity than indoor use (Mansur and Olmstead, 2012; Worthington and Hoffman, 2008; Dalhuisen et al., 2003; Espey et al., 1997) suggesting a lower marginal value for activities shaping peak demand. Second, the externalities of energy are primarily global in terms of reducing greenhouse gas emissions[4]; conversely water consumption externalities such as groundwater exhaustion and reducing in-stream flows for ecosystem services have local impacts. Consumers may be more receptive to limiting externalities whose effects are concentrated within the region as opposed to providing the global public good of emission reductions. Due to both the consumption patterns and environmental impacts, a priori, we may expect to see a different pattern of response to social norms in energy and water.

There exists some applied work using behavioral economics as a tool for water conservation. Ferraro, Miranda and Price (2011) and Ferraro and Miranda (2013) analyze a program in Georgia to reduce consumption during a severe drought. Ferraro et al. (2011) explicitly test the efficacy of different combinations of technical information, an appeal to supporting a public good, and social comparison; and find that social comparison along with technical information is most effective in reducing consumption. In investigations of the heterogeneity to the same program Ferraro and Miranda (2013) find that wealthy high water users are most responsive and Ferraro and Price (2011) find that the effect decreases over time. A major difference between that program and our study area is that WaterSmart continues treatment throughout the year, whereas the Georgia program had only one mailing and one follow-up. Additionally, the program was in the midst of a severe drought during which public perception towards water consumption is likely heightened. Lastly, that project only encompassed one region so while intra-program heterogeneity can be explored it is not possible to compare responses across various service areas.

[4]There are local health benefits due to air quality depending on the type and location of power generation.

3 Background & Data

We analyze the data for WaterSmart Software[5] (henceforth WaterSmart), a clean technology company that provides social comparison and technical advice, to determine the effect of their program on water consumption for two utilities. WaterSmart is a relatively new company that partners with utilities to hep reduce water demand. Additionally, WaterSmart provides technical services to utility companies to help them analyze and interpret metering data. Utility companies often want to reduce demand to offset costly temporary water purchases, delay investments in new supplies, and meet regional or state objectives. Raising rates is often politically infeasible and incentive programs such as toilet rebates are often expensive and may not meet goals of additionality (Bennear et al., 2013). This research analyzes the data for two utilities in pilot programs that will be referred to as Utility A and Utility B for confidentiality reasons[6].

WaterSmart's business model is to send customized Home Water Reports (HWR)[7] to customers that have three sections. The main component is a social comparison that compares a household's water consumption to that of their peers and then ranks them with a WaterScore based on their relative position. The second section is a list of three personalized recommendations for strategies to save water and rebates available from the utility. Lastly, there is a section that offers incentives for signing up for an online account that provides more detailed data on water use and additional water conservation tips. Figure 1 shows an example of the HWR for an above-average home[8], and a sample of the additional information available through the web portal is presented in Figure 2.

As mentioned above in order respect to the wishes of WaterSmart's utility partners we will refer to the utilities by generic names Utility A and Utility B, both of which are in California. Utility A has a small homogeneous service area, and half of the accounts were randomly selected into the treatment group with the remainder representing the control. This element of a randomized field experiment facilitates estimation of the treatment effect by eliminating concerns of endogenous

[5]Additional information on the WaterSmart is available on their website http://www.watersmartsoftware.com/

[6]WaterSmart partners with the utilities and they prefer that there names are kept anonymous when presenting data on consumers water consumption.

[7]Some HWRs are mailed to households, while others are sent via email.

[8]The other categories are "Good" and "Wise" and are very similar to this HWR, and are available upon request.

selection into treatment. Utility A covers a small service area, with 992 households randomly selected into treatment and the remaining 1,630 serve as the control group. Utility B is a larger area with 1,965 treatment households and 19,258 control households. In Utility B the treatment was defined by a specific meter reading route in order to avoid treatment contamination by having neighbors learn about the program. One problem with this strategy is that the treatment group is in a homogeneous geographic area that is wealthier with higher baseline water use than the sample at large. We address this issue in a regression framework by using household level fixed effects[9]. However, we are still working on solutions to deal with the fact that the treatment group is not representative of the overall sample.

We combine several sources of data for the analysis. WaterSmart provides the water metering records at the household level, as well as structural features of the house and treatment status. Weather data is obtained from the National Oceanic and Atmospheric Administrations National Climatic Data Center. Lastly, we gather voting records from the Statewide Database hosted by the University of California, Berkeley[10]. Table 1 displays the summary statistics for the two utilities. Utility B has higher water consumption and is a relatively wealthier area[11] with larger homes, but smaller lots. On average there is less rain and higher temperatures in Utility B[12]. Looking at the raw data is informative for showing the differences in response to the treatment. Figure 3 displays the percentage change in consumption from the same period last year for each of the utilities[13]. There is a very different pattern of consumption after the treatment between the two utilities: Utility A experiences a steady decrease for the duration of the treatment while Utility B stays relatively stable until the end of the sample.

We also expect to see heterogeneity in the response to social norms based on ideology. Costa and Kahn (2010) show that the response to social norms in energy is different for liberals and conservatives. In order to capture the degree to which individuals may sympathize with environ-

[9]We also create a control sample based on finding households with similar pre-treatment water consumption that we use for the graph in Figure 3.

[10]The data are publicly available at http://statewidedatabase.org/.

[11]We have assessor data for Utility B and use the home value as a proxy for income, and we are awaiting this data for Utility A.

[12]cooling degree days is the cumulative sum of daily maximum temperature above 65 degrees Fahrenheit.

[13]In the regression analysis the whole sample is used, but to make the graphs in Figure 3 we restrict the sample to the specified control.

mental concerns, we created the Green Ideology Index (GII). The GII is formed using three census block level measures from the 2010 California election: the percent who voted democrat for Governor, the percent who voted yes on Proposition 21, and the percent who voted no on Proposition 23. Proposition 21 would have increased vehicle license fees in the state by $18 in order to raise $500 million a year dedicated to California State Parks. Proposition 23 would have suspended the Global Warming Solutions Act of 2006 until the state's unemployment rate decreased to 5.5% for four consecutive quarters, a condition not met for decades. For each measure, we categorize census blocks into 100 bins created from the percentile breaks of the given measure, where a score of 100 is allocated to the top 1% of blocks with the greatest percentage of individuals voting along green-friendly lines. Averaging these three scores together yields the GII. Figure 4 presents the maps of the green index for the counties in which Utility A and B reside. It is clear that Utility A is in a much more environmentally friendly county and we expect this influences the response to WaterSmart's program, however large differences in income may also be a contributing factor. In the next section we present our estimation strategy and empirical results.

4 Estimation Strategy

4.1 Average Treatment Effects

The primary goal of this research is to estimate the average treatment effect and explore treatment effect heterogeneity. Unlike many policy interventions we do not need to be concerned with endogeneity due to sample selection because the households are randomly selected into treatment. A simple t-test for difference in means between the treatment group and the control group provides a valid statistical tool for the analysis. However, since we do not have sufficient sample size to generate the statistical power for accepted levels of significance we choose a regression approach in order to reduce the variance of the estimates. A Hausman test that is robust to heteroskedastic and clustered standard errors provides evidence for the fixed effects model written as

$$w_{it} = \alpha_i + \gamma T_i * P_t + \theta P_t + \beta X'_{it} + \xi_{it} \tag{1}$$

where w_{it} is water consumption for household i at time t, T_i is a dummy that identifies the treatment group, P_t is a dummy for treatment period, X_{it} is a set of time-varying covariates, and ξ_{it} is an idiosyncratic error term. In our regressions the covariates include the number of rainy days and cooling degree days; as well as a time trend and year and month fixed effects. We cluster the standard errors at the household level to account for serial correlation within a household over time. The regressions results for each utility using both water consumption and the natural log of consumption are presented in Table 2.

The difference in treatment response between Utility B and Utility A is striking. Utility A has an average treatment effect (ATE) of over 11 gallons per day (GPD), equating to 6.5% of consumption, and is statistically significant at the 1% level. Meanwhile, the average treatment effect for Utility B is a relatively tight zero - close to zero in magnitude with relatively small standard errors. In the next section we explore divergent treatment response to the program by these two utilities by investigating the factors driving the programs efficacy.

4.2 Durability

Our first foray into the heterogeneity involves looking at the treatment effect over time. This is important because ex ante there are several valid hypotheses regarding the durability of the treatment effect. One potential pattern of results is that initially the program increases the salience of water consumption and households make temporary behavioral adjustment to their use. In this setting the treatment effect will wane over the course of the program, after an initial strong response. Another conceivable outcome is that the program induces capital investments or permanent changes in behavior that cause consistent reductions throughout the program. In order to examine the durability of the treatment effect *within* the active administration of the program we run separate regressions for each treatment period. Thus the regression equation is now

$$w_{it} = \alpha_i + \gamma T_i * P_{t,h} + \theta P_{t,h} + \beta X'_{it} + \xi_{it} \tag{2}$$

where $h = 1, ..., H$ is a specific treatment period as opposed to the whole course of the program. In this setting we drop all observations for the other treatment period so that we are only comparing

a single treatment period to all controls as opposed to other treatment periods. The results for both Utility A and Utility B are shown in Figure 5. Utility A shows a relatively stable ATE over the whole course of the program. The slightly lower ATE in period one may be a partially due to the fact that the HWR was sent in the middle of the reading period so only a fraction of the consumption was actually post-treatment. The pattern is drastically different for Utility B, with an initial increase in consumption for the treatment group followed by a decline. This is an intriguing result for two reasons: first what caused the initial increase in consumption, and second, will the treatment group continue to save water? We aim to answer the first question by delving into treatment effect heterogeneity and to address the second question we need to wait until more data are available.

4.3 Treatment Effect Heterogeneity

There are many ways to explore the treatment effect heterogeneity for interventions using social norms to promote sustainable behavior. Allcott (2011b) use quantile regression and interactions with baseline electricity consumption, Ferraro and Miranda (2013) explore the baseline consumption and differences due to home prices, and Costa and Kahn (2010) utilize voting data to examine differences in treatment effect due to ideology. We build on the prior research by combining these approaches in a setting where we observe considerable variation in both ideology and treatment response.

The first set of results present quantile regressions for the conditional quantile treatment effect of Koenker and Basset (1978). We are also exploring unconditional quantile treatment effects in the vein of Fipro (2007) as well as incorporating fixed effects into the quantile regressions (Koenker, 2004) as future work. The current draft does not include fixed effects in the quantile regressions, and therefore in the graphs the average treatment effect is not the same as reported in Table 2. However, we focus on the shape of the distribution and the internal comparison of various quantile treatment effects to the average treatment effect. Figure 6 displays the results for both utilities. It is interesting to note that Utility A has a U-shaped curve for the various quantiles with both the low and high quantiles seeing a greater reduction than the average, depicted by the dashed horizontal line This is different from the traditional monotonically deceasing quantile treatment

effect (Allcott, 2011b; Ferraro and Miranda, 2013) seen in Utility B, and explained by the fact that high-use households have greater financial incentive, and flexibility, to reduce consumption. The quantile treatment effects for Utility A suggests that low-use households in Utility A are more conscious of either costs and/or the environment than users near the median.

In addition to quantile regressions we interact the treatment effect with deciles of baseline water consumption for each utility. Baseline deciles are calculated by taking the average pre-treatment household usage across the whole utility and ordering it into equal groups of ten. We perform a similar technique to create deciles of the GII for each utility. Not that higher deciles of baseline consumption relate to higher baseline usage and higher GII deciles correspond to stronger environmental preferences. The regressions include all the variables as presented in equation (1) in addition to interactions between the treatment effect and the deciles of water and GII. The regressions have the form

$$w_{it} = \alpha_i + \gamma T_i * P_t + \sum_{d=1}^{10} \delta_d (T_i * P_t * D_d) + \theta P_t + \beta X'_{it} + \xi_{it} \tag{3}$$

where D_d is the dth decile of either baseline consumption or the GII. Now the parameters of interest are γ and δ_d. Table 3 displays the results for the two utilities for both sets of interactions; the 5th decile, containing the median household, is the omitted category so the interactions can be interpreted as relative to median baseline consumption.

There are several interesting insights to glean from the empirical results. Examining column (1) of Table (3) shows that for Utility A most of the savings are concentrated around households with high baseline water use. The very lowest users also save more water than the median, though this is not statistically significant. These results match up relatively well with the results from the quantile regressions. Interactions with baseline water are generally not statistically significant for Utility B except for a negative coefficient on the highest decile as seen in column (2). Looking at columns (3) and (4) shows the interaction of the treatment effect with deciles of the GII. None of the coefficient estimates are significant for Utility A, however, it is noteworthy that the lowest two deciles have negative coefficients and the highest has a positive coefficient. With the caveat that the standard errors are large, this suggests that the most conservative households have a greater

response to the program than the most environmentally friendly. This may relate to the results from baseline consumption since the greenest households may already be low users and thus not have much room to make further reductions, and is consistent with the results from column (1). In column (4) we observe that the lowest decile is positive and significant and the highest decile is negative, corresponding to an additional 19% savings relative to the median. This is the pattern of results that we expect to see - environmentally conscious households are most receptive to the program. We also observe that those households least concerned with the environment actually increased consumption, as evidenced by the coefficient on decile 1 in column (4).

The results between the two utilities across the interactions also reveals an important contrast when examining both baseline consumption and ideology. Utility A has lower water consumption, cares more about environmental issues, and exhibits large aggregate savings from the social norms. In this setting it appears that larger users make up the bulk of the savings, and intra-utility ideology is not as important. However, in an area that is more conservative, such as Utility B, ideology does seem to play an important role in explaining the heterogeneity in response to social norms. This highlights the importance of flexibility in adapting policy interventions to meet the needs of the constituents. It suggests that social norms work best in liberal areas, and a different approach is more appropriate in conservative communities. While income may also play a role here, as Utility B is the wealthier community, Ferraro and Miranda (2013) find a high response to social norms in wealthier households.

5 Future Work

As mentioned earlier this work is still very preliminary in nature. We are still receiving additional data for Utility B, and if the trend shown in Figure 5 continues the program may eventually achieve significant average savings. There are three other pilots for which we have data, and adding them to the analysis will increase the sample size and add variation in both demographic variables and ideology. We aim to explore the impact of ideology both across and within pilots to see if the results presented in Table (3) still hold. There are other technical methodologies that we will explore such as estimating the unconditional quantile regressions (Fipro, 2007), and accounting for

fixed effects (Koenker, 2004). We also hope to add in data on home values in order to proxy for income, as this may play a confounding role with ideology.

An additional layer to WaterSmart's program is how the social norms campaign interacts with other policy instruments. We will examine if WaterSmart acts as a complement or a substitute to existing conservation programs. Since WaterSmart provides information about utilities' water conservation programs, and generally increases the awareness of water consumption, we may expect that those in the program participate in utility programs at a higher rate. On the other hand the deluge of information about water conservation may inundate consumers and WaterSmart may crowd out existing conservation. Preliminary analysis suggests that WaterSmart is actually a complement to existing programs, which has important implications for utilities. Additionally, we will analyze the effect of registering for an account on the online web portal and the intensity of use, on water consumption. This is a particularly interesting extension because it allows the exogenous treatment group to self-select into an endogenous sub-treatment group.

The close relationship with WaterSmart also provides opportunities to set up randomized experiments within subgroups of new pilots. This has the same attractive features of WaterSmart's programs since can avoid concerns of endogenous sample selection. The results of this research suggest that there may be conservation gains available by targeting consumers to treatment based on their observables. High water users and households in environmentally conscious areas will likely respond to social norms, whereas in conservative areas a message about potential cost-savings on water bills may be more effective. We hope to explore several of these avenues in future research.

6 Conclusion

We analyze the data from two randomized field experiments that harness social norms as a water conservation tool. There is significant heterogeneity in the treatment effect both within, and across, pilots. There are many dimensions that may impact response to treatment and we select ideology and the distribution of consumption as observable drivers of heterogeneity. At an aggregate level Utility A, that has much stronger environmental preferences, experiences an average treatment effect of 6.5% compared to a relatively minimal insignificant savings in Utility

B. However, pilot data are still coming in for Utility B and the trend over time is towards greater savings. Exploiting intra-utility variation in ideology reveals that the environmental preferences matter more in the relatively less green region. Relative to the median, the most conservative segment of the population in Utility B actually appears to use more water due to the treatment, while the greenest decile saves an additional 19% relative to the median. These results suggest that intra-utility variation in ideology is more important in relatively conservative communities. This adds to the literature on interacting social norms interventions and utility demand initiated by Costa and Kahn (2010) by extending the analysis to water demand and across utilities.

We also estimate quantile treatment effects to study the impact of the program across the distribution of consumption. In Utility A the quantile treatment effect is larger in magnitude than the average treatment effect at both the low and high end of the distribution. This contrasts the traditional monotonically increasing treatment effect (in absolute value) found in the literature (Allcott, 2011b; Ferraro and Miranda, 2013). The interpretation is that low users are likely cost and/or environmentally conscious, whereas high users have a greater financial incentive, as well as the flexibility, to reduce consumption. Interacting the treatment with baseline water consumption produces significant results exclusively for Utility A, with higher users having larger responses to the treatment.

Ideology drives heterogeneity in the conservative utility; and baseline consumption is more important in the green utility. This leads to important policy implications when designing interventions that use social norms. One must consider not only the distribution of the outcome variables, but also the preferences of the constituents. We caution the interpretation of these results as the analysis is still in a preliminary stage. Extensions and future research will incorporate data from additional cities and interact the effect of social norms with other water conservation programs.

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Tables

Table 1: Summary Statistics

	(a) Utility A			**(b)** Utility B		
Variable	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**	**Obs**
Water (GPD)	199.812	193.314	46879	329.579	293.042	412328
Occupants	2.722	1.364	808	2.556	1.295	1590
Sq. ft.	1508.128	554.419	1817	2199.322	1645.799	12083
Floors	1.43	0.592	193	1.325	0.526	40
Lot Size	9419.557	11569.592	1508	7632.438	4536.052	7239
Year Built	1984.907	16.489	2372	1964.474	12.949	12751
Bedrooms	2.917	0.885	1981	3.274	0.947	12380
Bathrooms	2.174	0.697	1962	2.668	0.986	12340
Single Family Home (%)	0.703	0.457	2352	0.537	0.499	21223
# of Rainy Days	14.73	5.563	2612	5.927	2.21	21223
Cooling Degree Days	7.417	72.727	2612	19.322	108.136	21223

Notes: Not all the observations have a full set of covariates, so the number of observations designates the unique households for which that variables is observed.

Table 2: Average Treatment Effect Regressions

VARIABLES	(1) Utility A Levels	(2) Utility B Levels	(3) Utility A Logs	(4) Utility B Logs
Treatment Effect	-11.49***	0.760	-0.0650***	-0.00355
	(2.984)	(2.631)	(0.0146)	(0.00685)
Treat Period	16.57***	-14.47***	0.0414**	-0.0305***
	(3.300)	(1.080)	(0.0192)	(0.00347)
Rainy Days	0.0351	-1.838***	-0.00108	-0.00563***
	(0.136)	(0.0950)	(0.000881)	(0.000295)
Cooling Degree Days	0.0515***	0.00934***	0.000186***	1.21e-05***
	(0.00434)	(0.000675)	(1.81e-05)	(1.83e-06)
Time Trend	-0.981***	-1.873***	-0.00447**	-0.00356***
	(0.249)	(0.112)	(0.00189)	(0.000303)
Constant	1,848***	2,894***	12.54***	10.35***
	(780.7)	(154.2)	(5.918)	(0.418)
Household FE	Yes	Yes	Yes	Yes
Monthly FE	Yes	Yes	Yes	Yes
Yearly FE	Yes	Yes	Yes	Yes
Observations	44,649	394,606	44,649	394,606
Number of id	2,575	21,223	2,575	21,223
R-Squared Overall	0.0721	0.0295	0.0574	0.0233
R-Squared Between	0.00382	0.000574	0.00250	0.00324
R-Squared Within	0.172	0.136	0.157	0.133

Notes: The dependent variable columns (1) and (2) is water consumption in gallons per day and in (3) and (4) it is the natural log of gallons per day. Time is a linear monthly time trend. Robust standard errors clustered at the household level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

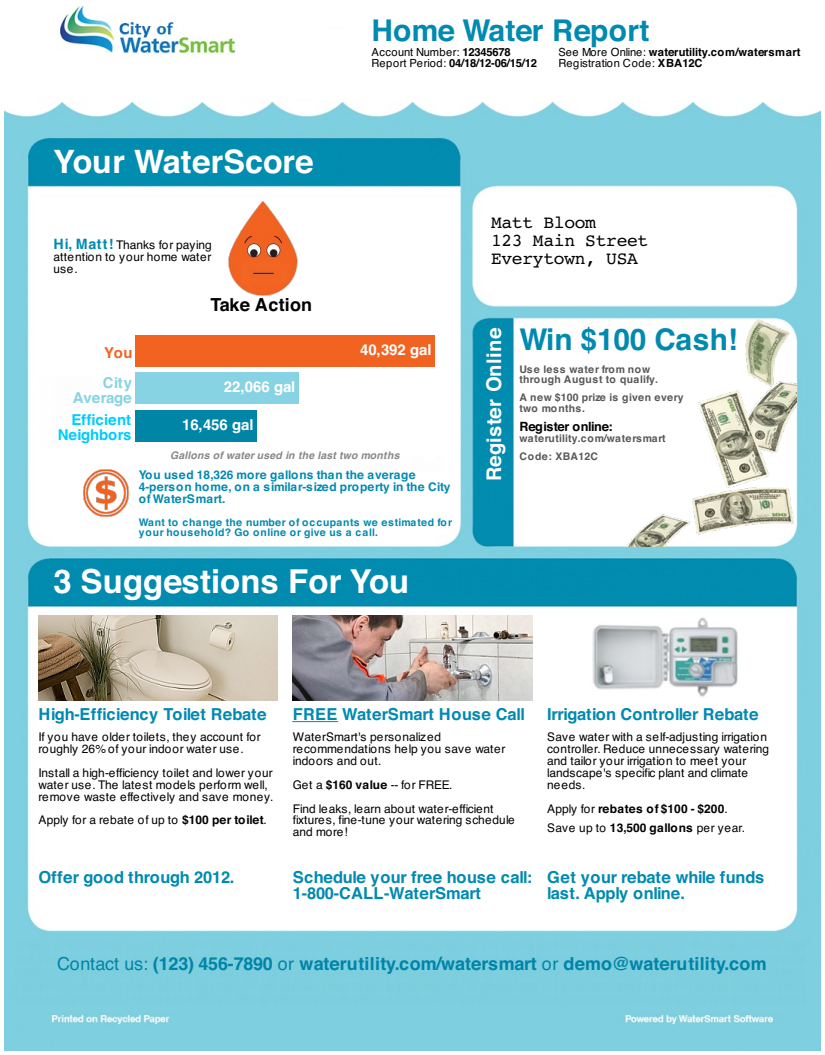
Table 3: Heterogeneous Treatment Effects

VARIABLES	(1) Utility A Water	(2) Utility B Water	(3) Utility A Green	(4) Utility B Green
Treatment Effect	-0.0435	0.0305	-0.0569	0.0268
	(0.0313)	(0.0275)	(0.0634)	(0.0173)
Treatment Effect*Decile 1	-0.0163	-0.0558	-0.0413	0.0493*
	(0.0567)	(0.0537)	(0.0680)	(0.0285)
Treatment Effect*Decile 2	0.0737*	-0.0359	-0.0349	0.00105
	(0.0401)	(0.0590)	(0.0703)	(0.0258)
Treatment Effect*Decile 3	0.0606	0.0110	0.0328	-0.00172
	(0.0445)	(0.0396)	(0.0708)	(0.0224)
Treatment Effect*Decile 4	0.00951	0.0285	0.0297	-0.0558**
	(0.0387)	(0.0394)	(0.0681)	(0.0236)
Treatment Effect*Decile 6	-0.0161	0.0492	0.0492	0.00458
	(0.0432)	(0.0333)	(0.0684)	(0.0278)
Treatment Effect*Decile 7	-0.0269	-0.00416	-0.00975	-0.00232
	(0.0376)	(0.0319)	(0.0784)	(0.0229)
Treatment Effect*Decile 8	-0.0964**	0.000957	0.0185	-0.0303
	(0.0381)	(0.0301)	(0.0703)	(0.0381)
Treatment Effect*Decile 9	-0.0747**	-0.0127	-0.0214	0.0603
	(0.0356)	(0.0299)	(0.0721)	(0.0446)
Treatment Effect*Decile 10	-0.127***	-0.0553*	0.0479	-0.191***
	(0.0379)	(0.0316)	(0.0807)	(0.0325)
Treat Period	0.0556***	-0.0324***	0.0248	-0.0478***
	(0.0191)	(0.00349)	(0.0197)	(0.00892)
Rainy Days	-0.00170*	-0.00539***	-0.00302***	-0.0100***
	(0.000882)	(0.000293)	(0.000937)	(0.000576)
Cooling Degree Days	0.000193***	1.24e-05***	0.000191***	1.23e-05***
	(1.79e-05)	(1.82e-06)	(2.03e-05)	(3.43e-06)
Time Trend	-0.00464**	-0.00304***	-0.00629***	-0.00434***
	(0.00190)	(0.000301)	(0.00181)	(0.000578)
Constant	12.82***	9.631***	15.69***	11.85***
	(3.263)	(0.415)	(3.103)	(0.797)
Household FE	Yes	Yes	Yes	Yes
Monthly FE	Yes	Yes	Yes	Yes
Yearly FE	Yes	Yes	Yes	Yes
Observations	43,590	363,284	28,831	67,966
Number of Households	2,255	18,609	1,366	2,886
R-Squared Overall	0.0489	0.0230	0.0668	0.0527

Notes: The dependent variable is the natural log of gallons per day. Time is a linear monthly time trend. Deciles in columns (1) and (2) refer to baseline water consumption and are calculated by average pre-treatment water consumption for each utility. In columns (3) and (4) deciles relate to ideology are calculated by the green index score for each utility. The 5th decile is used as the baseline in each case. Robust standard errors clustered at the household level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

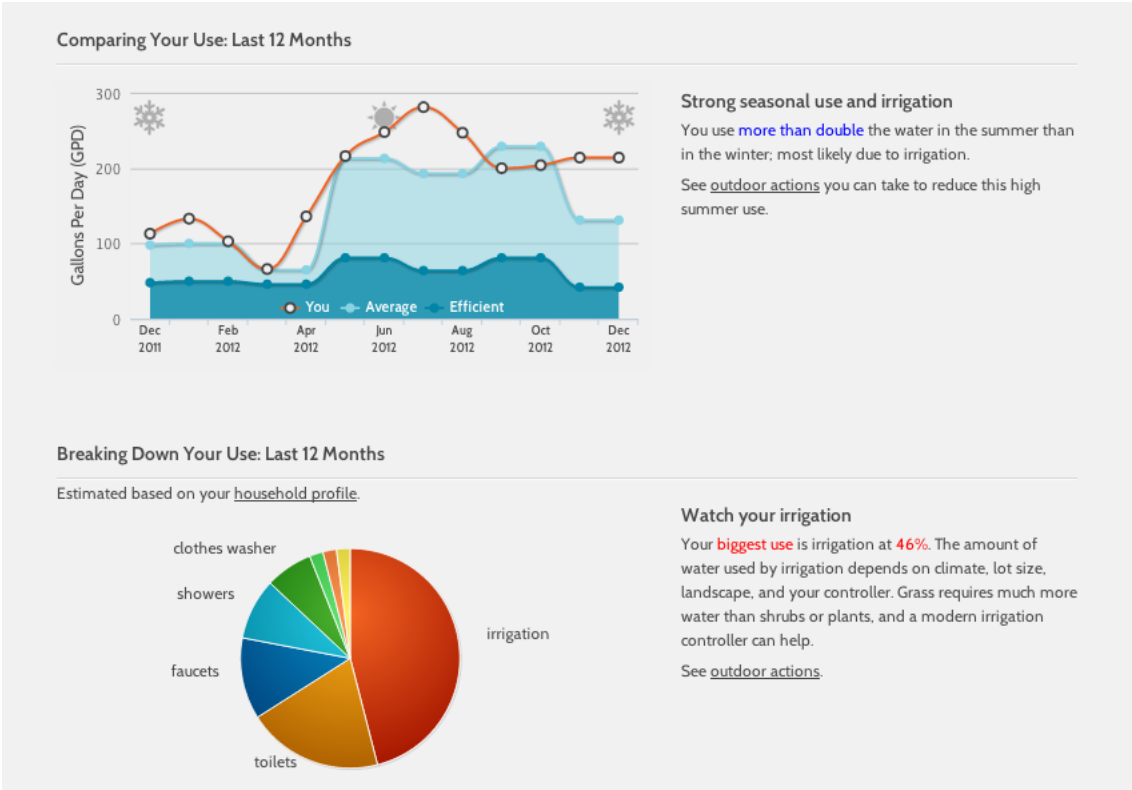
Figures

Figure 1: Home Water Report



Notes: Home Water Reports have WaterScores of "Wise", "Good", or "Take Action". The other HWRs are in the Appendix. The bottom suggestions are customized, and the right "Win $100" offers different incentives or messages

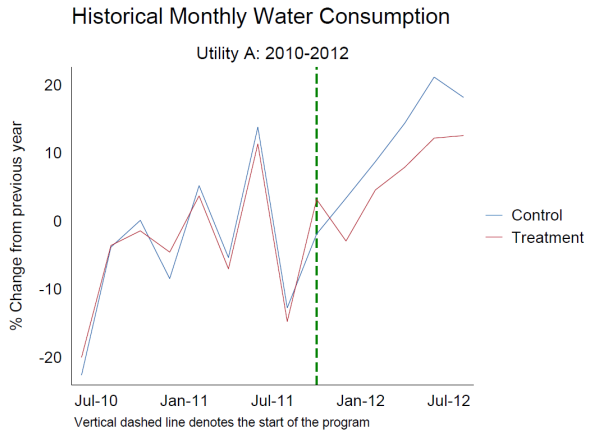
Figure 2: Online Web Portal



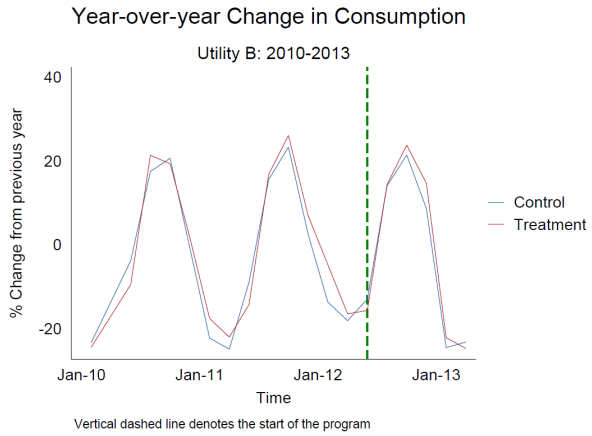
Notes: Online web portal is available to the treatment group and can be viewed as an additional "opt-in" treatment over the base treatment. It offers additional data on consumption, utility rebates, and technical information to help reduce water consumption.

Figure 3: Year-on-Year Change in Consumption

Utilty A



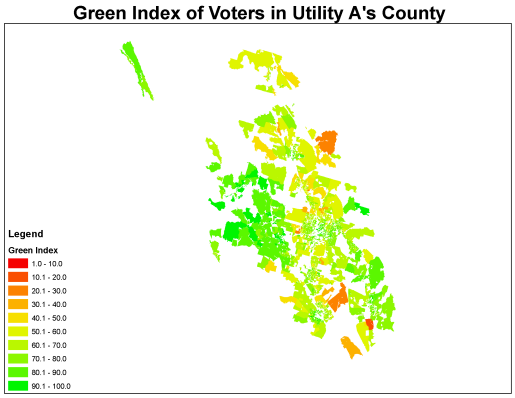
Utility B



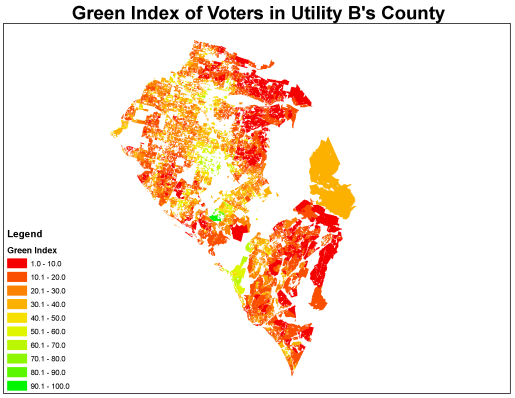
Notes: Year-on-Year consumption is the change in consumption in percentage terms from the same period last year. Vertical dashed line designates the start of the treatment.

Figure 4: Ideology Data

Utilty A

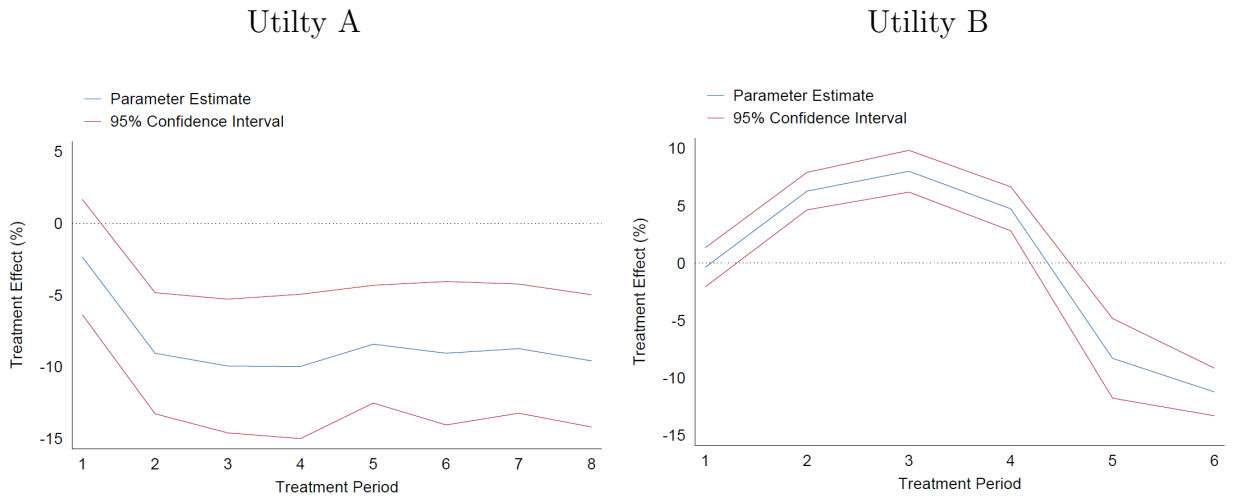


Utility B



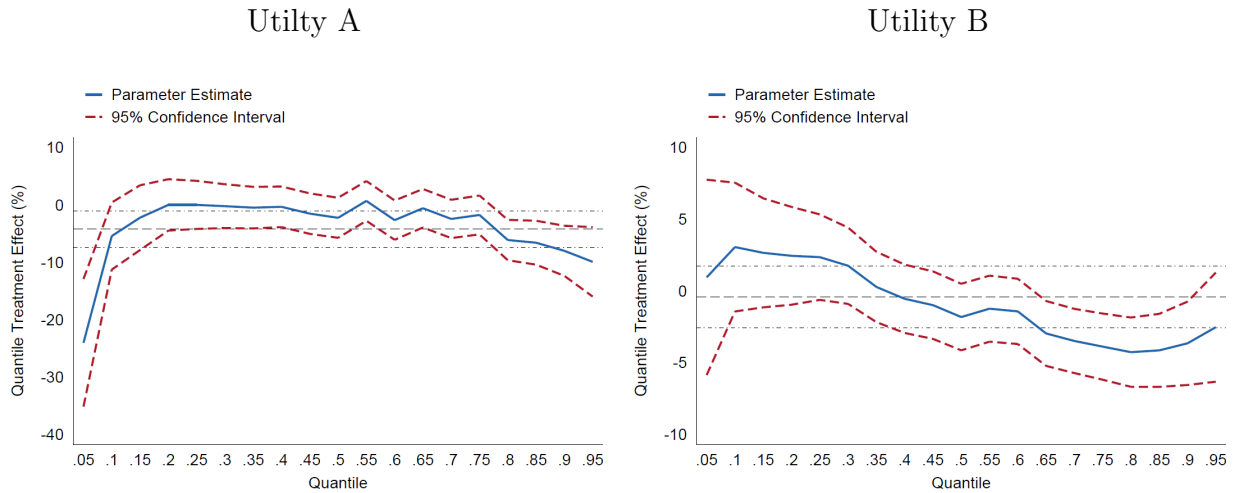
Notes: Green index is calculated at the census block level based on data on several environmental referenda in California. We observe the total number of yes and no votes at the census block level excluding blocks with less than 20 votes over concerns with sample size. The index ranges from 0-100. All valid census blocks for the county that the utilities lies are shown.

Figure 5: Durability of Treatment Effect



Notes: Independent variable is natural log of water consumption in each regression. The line is the series of estimates for the individual treatment effects and their confidence intervals. Confidence intervals are created from cluster-robust standard errors.

Figure 6: Quantile Treatment Effects



Notes: Conditional quantile treatment effects with 95% confidence based on heteroskedastic-robust standard errors. The OLS regression and 95% confidence intervals are the horizontal dashed and dotted lines respectively. Pooled OLS is used for comparison because the quantile regressions do not account for the panel structure of the data.