Smart Water-Energy Savings

Final Report

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EXECUTIVE SUMMARY

The Smart Water-Energy Savings (SWES) Project aimed to maximize and quantify the life-cycle energy savings secured through behavior-based residential water conservation in the cities of Modesto and Riverside in California. The UC Davis Center for Water-Energy Efficiency (CWEE) worked with WaterSmart Software, Inc. to (1) research and develop conservation messages targeted at decreasing residential hot water use and energy related to water use (both methods of water-energy reductions will be referred to as “hot water conservation”), (2) design and deploy the WaterSmart technology in a randomized control trial (RCT) in Modesto and Riverside, and (3) measure and monitor the impact of the technology on reducing residential water use and water-related energy consumption. We then designed and deployed pre-, mid-term, and post-treatment surveys to collect data on consumer response to water conservation messaging. These surveys provided a deeper understanding of the consumer response to the WaterSmart program. Last, we applied our methodology for monitoring and measuring the infrastructure-related energy savings of water conservation as it applies to water delivery.

In partnership with WaterSmart Software, Inc., we deployed the WaterSmart software to 30,132 households in Modesto and 14,359 households in Riverside between September 2016 and November 2017. We set up two treatment experiments to evaluate, compared to a control group. The treatments included evaluating (1) the effect of the WaterSmart Home Water Reports messaging on household water consumption, and (2) the effect of WaterSmart Home Water Reports with additional hot-water specific messages aimed to reduce both household water and water related energy use.

To calculate the impact of WaterSmart, we carried out a retrospective analysis of water and energy use by residential customers in the two study areas before and after the technology deployment. Using a difference-in-difference approach with a log-linear regression in the statistical program Stata, we compared average daily water use during the treatment period to baseline water usage for each treatment group to the control group. Our control group consisted of 16,368 households in Modesto and 38,751 households in Riverside. Comparing the treatment period to the baseline period, WaterSmart reduced household water use by approximately 1.5% in Modesto and 2.2% in Riverside after controlling for weather and aggregate shocks. Hot water-specific messages had no additional observable impact on water savings in either city. However, in Riverside, we observed a 0.7% decrease in electricity use for households with the hot water-specific messaging but not for those receiving only the WaterSmart treatment. This difference suggests that targeted hot-water messaging can provide spillover electricity savings as well as water savings.

To estimate infrastructure energy savings that occurred as a result of water savings, we developed estimations of the energy intensity of the Modesto and Riverside water systems. The city of Modesto has a single pressure zone, which allowed us to simply divide total monthly infrastructure energy use by total water delivered. While the energy intensity of water delivered in Modesto varies depending on the time of year, the aggregate average energy intensity over the study period is 746 kilowatt hours per million gallons (kWh/MG) of water delivered. The city of Riverside's water system includes significant variation in elevation throughout the service territory and 41 different pressure zones. A more complex asset framework model was used to calculate the embedded energy of water throughout the system. Pressure zones at lower elevation were found to have energy intensities of as low as 400 kWh/MG, while those at higher elevation have energy intensities of over 1000 kWh/MG. The aggregate average energy intensity of water in the Riverside distribution system over the study period is 607 kWh/MG.

We conducted extensive household survey research in conjunction with the WaterSmart program in order to evaluate households' response to Home Water Reports in terms of specific water-saving measures adopted, and to explore behavioral spillover from water- to energy-saving measures. Our Post-treatment Survey focused in on responsive households (i.e., Riverside households who remembered receiving and viewing the home water reports and whose consumption data indicated water savings) to hone in on specific behavior changes that occurred when the program was effective. Spillover analyses revealed nine classes of related water- and energy-saving measures, within which behavioral spillover is likely to occur: Water Curtailment and Conservation; Energy Curtailment and Conservation; Efficient Envelope; Efficient Appliance; Edge of Efficiency; Efficient Irrigation; Green Gardening; Green Landscape Foundations; and Efficient Pool and Spa. The WaterSmart program encouraged households to adopt a variety of Efficient Irrigation practices and invest in low-flow faucet aerators, high-efficiency showerheads, and high-efficiency toilets. Survey analysis also provided evidence of behavioral spillover from water- to energy-saving measures within the categories of Efficient Envelope, Efficient Appliance, and Edge of Efficiency.

Overall, the WaterSmart program generated approximately 79,477 CCF of residential water savings in Modesto and 88,385 CCF in Riverside. The Hot WaterSmart program generated an additional 477,004 kWh of direct electricity savings in the residential sector in Riverside. The residential water savings resulted in an additional electricity savings of 44,343 kWh in Modesto's water network and 39,410 kWh in Riverside's water network. WaterSmart produced greater water savings in Riverside than in Modesto, but the reasons are unknown. Riverside baseline household water usage was 41% higher than Modesto, which indicates there may have been a larger margin for households to act upon. However, more research is needed to ascertain exactly what drivers predict how different communities will respond to behavioral conservation programs such as WaterSmart.

INTRODUCTION

The Smart Water-Energy Savings (SWES) Project aimed to maximize and quantify the life-cycle energy savings secured through behavior-based residential water conservation in the cities of Modesto and Riverside in California. The UC Davis Center for Water-Energy Efficiency (CWEE) worked with WaterSmart Software, Inc. to (1) research and develop conservation messages targeted at decreasing residential hot water use and energy related to water use (both methods of water-energy reductions will be referred to as “hot water conservation”), (2) design and deploy the WaterSmart technology in a randomized control trial (RCT) in Modesto and Riverside, and (3) measure and monitor the impact of the technology on reducing residential water use and water-related energy consumption. We then designed and deployed pre-, mid-term, and post-treatment surveys to collect data on consumer response to water conservation messaging. These surveys provided a deeper understanding of the consumer response to the WaterSmart program. Last, we applied our methodology for monitoring and measuring the infrastructure-related energy savings of water conservation as it applies to water delivery.

The WaterSmart technology is comprised of customized Home Water Reports (HWR), delivered by mail or email, and an interactive Customer Portal where residents can learn more about their water use and ways to save. A key aspect of the technology is driving behavior change by comparing a household’s water use to that of similar households. This experiment was designed to identify two separate effects of WaterSmart messaging on residential water conservation in the two cities:

- The effect of the WaterSmart Home Water Reports messaging on household water consumption
- The effect of hot-water specific messaging on gas and electricity consumption

Additionally, CWEE worked with WaterSmart to adapt and develop the calculations and original messaging specifically targeted towards hot water conservation (Appendices G and H). We incorporated this messaging into the experiment design to evaluate the effects of “hot water” WaterSmart messaging on household water-related energy consumption. This project aimed to verify and replicate a similar study conducted in Burbank, California between 2015 and 2016, in which WaterSmart reduced household water use by about 3.3% (Jessoe et al., 2017). Understanding whether other communities show the same response to WaterSmart is key for policymakers and utilities. Furthermore, the results of the WaterSmart program in Burbank suggested a positive *behavioral spillover* effect whereby HWRs led to not only water savings, but also electricity savings that were not a function of hot water savings. Of the total reduction in summertime electricity use attributed to the WaterSmart treatment (about 2.2%), only 26% could be explained by water conservation (Jessoe et al. 2017), evidence of spillover effects. The concept of behavioral spillover refers to changes in one behavior affecting changes in another behavior. A similar concept is *response class*, which refers to a group of behaviors that are functionally related to the same stimuli, e.g., when one is reinforced the others also become more likely to occur in the future. Spillover and response classes are relevant to home water and energy efficiency because an intervention that targets one or more efficiency measures may lead to changes in other, non-targeted behaviors.

Home water- and energy-saving measures are often discussed in terms of two general response classes: curtailment and efficiency. Curtailment measures are no-cost activities or habits (e.g., turning the water off while brushing teeth), whereas efficiency measures are investments in equipment or upgrades associated with some cost (e.g., purchasing a high-efficiency washing machine). However, more nuanced classifications for home energy-saving measures also exist (Boudet, Flora, & Armel, 2016), for example adding a third class of maintenance or management behaviors (Karlin et al., 2014) that are low-cost and low frequency (e.g. checking for leaks). No complex classifications currently exist for home water-saving measures or for both energy- and water-saving measures. Such work is needed to understand how spillover occurs between home water- and energy-saving measures.

In this project, we sought to further examine the phenomenon of behavioral spillover from water to electricity conservation by analyzing electricity consumption data and conducting survey research in conjunction with the Modesto and Riverside WaterSmart programs. Through our survey research, we aimed to identify response classes of related water- and energy-saving measures and explore how treatment households responded to Home Water Reports in terms of specific water- and energy-related behavior change.

SETTING

We selected Modesto and Riverside because both cities were interested in trying out WaterSmart to help achieve their state-imposed water conservation mandates during the recent California drought, and because both cities have a high disadvantaged community population. In this context, behavioral conservation mechanisms can be an attractive and cost-effective way to reduce citywide water use without imposing a financial burden on households. Of the total number of eligible households, SWES funding covered the costs of deployment of the WaterSmart technology to nearly all households in Modesto and about one quarter of households in Riverside. Table 1 summarizes households that received the WaterSmart treatments.

Table 1: WaterSmart Deployment Sites

	Population	DAC (by area)	Households eligible for WS	Households receiving WS
Modesto	288,963	63%	35,000	30,132
Riverside	426,055	57.7%	56,000	14,359

Note: Only single-family households are eligible for WaterSmart and they must have at least one year of observable water use at the same location in the year immediately preceding the treatment period.

DATA

The City of Modesto provided monthly water consumption data for each treatment and control household in our sample from January 1st, 2014 through December 31st, 2017. Riverside Public Utility (RPU) provided monthly household water and electricity consumption data from January 1st, 2015 through December 31st, 2017. Southern California Gas Company (SoCalGas) and Pacific Gas and Electric (PG&E) will provide monthly natural gas consumption for Riverside and Modesto, respectively, from approximately January 1st, 2015 through December 31st, 2017.

Table 2 shows the number of households originally assigned to a treatment group (i.e. those included in the randomized control trial (RCT)) and the number of households that were included in final sample used to estimate the treatment effects. In Riverside, all households that were selected for the RCT were included in the final analysis. In Modesto, 46 households moved during the study timeframe. Riverside provided water data for approximately 9,000 more households than they provided electricity data for, so our sample for the energy savings analysis is somewhat smaller than that of the water savings analysis.

Table 2: Data used in RCT and Analysis

Utility	Households included in RCT	Households included in Analysis
Riverside Public Utility (water)	53,110	53,110
Riverside Public Utility (electricity)	44,333	44,327
City of Modesto (water)	46,500	46,454

RESEARCH METHODS

To evaluate the effectiveness of WaterSmart Home Water Reports to generate water and energy savings required measuring the project savings of both resources at two separate scales: the residential scale (water and water-related energy savings in the home) and at the infrastructure scale (upstream energy savings achieved through reduced water delivery to customers). We measured and calculated residential water, electricity, and natural gas[1] consumption and associated savings related to the WaterSmart intervention by using utility customer-level data and performing a randomized control trial experimental design. We then estimated upstream embedded energy savings associated with water reductions using CWEE's methodology for calculating water infrastructure energy intensity, customized for the Riverside and Modesto water systems. We explain the methodology for calculating

[1] Pending receiving natural gas data for both cities.

the project residential and infrastructure water-energy savings below, as well as the methods for survey design.

WATERSMART EXPERIMENTAL DESIGN

We applied a randomized control trial (RCT) methodology to test for the effectiveness of WaterSmart to consistently deliver water and energy resource savings over the one-year project study. This approach involved randomly dividing the target population into treatment and control groups. We designed, deployed, and analyzed two treatment effects. We randomly assigned each household in our sample to one of three groups:

- Treatment #1: Standard Home Water Report (referred to as WaterSmart or WS) – deployment of the WaterSmart technology without additional new hot water messaging
- Treatment #2: Hot water Home Water Report (referred to as Hot WaterSmart or HWS) – enhancing the standard WaterSmart report with additional, targeted hot water messaging
- Treatment #3: Control group – no treatment

By randomly assigning all households in the study to either the control group or one of the two treatment groups, we were able to identify the impact of traditional Home Water Reports on residential water and energy use as well as the marginal value of additional hot water messaging on household resource conservation. Households assigned to the WaterSmart or Hot WaterSmart treatments received a HWR approximately every two months for 12 months for a total of six reports. Each report included information about the household's previous water consumption and suggestions for how to conserve water. Households in the Hot WaterSmart group received the same HWRs with additional messages targeted toward saving hot water. See Appendices A and D for samples of the WS and HWS Home Water Reports for both cities for each of the six report cycles. Additionally, Appendices G and H provide details of how the hot water messages were developed, calculated, and prioritized, along with a sample of the "library" of hot water messages developed. The control group did not receive any Home Water Reports.

To calculate the impact of WaterSmart, we carried out a retrospective analysis of water and energy use by residential customers in the two study areas before and after the technology deployment. Using a difference-in-difference approach with a log-linear regression in the statistical program Stata, we compared average daily water use during the treatment period to baseline water usage for each treatment group to the control group. Each model specification included average daily rainfall, average daily heating and cooling degrees days in each household's billing period, year-month fixed effects to control for aggregate shocks, and household fixed effects to control for unobservable household characteristics.

To ensure that our estimated treatment effects can be reliably interpreted, households must be randomly assigned to the different treatment groups - otherwise we might be conflating systematic differences across groups with the treatment effects. Using the statistical program Stata, we randomly assigned all households in our samples a number between 0 and 1 and then assigned each household to one of the three groups (Control, WaterSmart, or Hot WaterSmart). To validate that assignment to treatment was random, we compared average household water usage for each group during the year prior to the experiment to make sure there were no significant differences. We would typically also compare electricity and natural gas consumption across treatment groups, but in this case we did not have these data available before initiating the experiment.[2]

Table 3: Pre-treatment mean household water and gas use by treatment group in Modesto

	Control	**WaterSmart**		**Hot WaterSmart**		**All**
	Mean	Mean	Difference	Mean	Difference	Mean
			Water (gallons per day)			
Overall	342.81	343.42	0.61	345.02	2.21	343.2
	(233.76)	(225.83)	(0.27)	(231.69)	(0.84)	(228.65)
August – October	457.11	455.89	-1.21	458.4	1.3	456.32
	(403.64)	(336.56)	(0.35)	(347.30)	(0.30)	(361.59)
November – January	258.31	259.52	1.2	260.26	1.95	259.09
	(209.40)	(206.55)	(0.60)	(211.25)	(0.82)	(207.55)
February – April	221.62	221.86	0.24	223.66	2.04	221.77
	(180.57)	(181.02)	(0.13)	(188.46)	(0.98)	(180.86)
May – July	434.4	436.27	1.87	437.18	2.78	435.61
	(327.17)	(322.83)	(0.59)	(329.22)	(0.75)	(324.36)
Number of households	16,368	30,132		15,066		46,500
			Natural Gas - TBD			

Note: Means are reported by treatment group, with standard deviations in parentheses below. "Difference" displays the difference in means between each treatment group and control, with t-stats reported in parentheses below. Hot WaterSmart is a subset of the general WaterSmart group. Uses household level data from August 2015- July 2016.

Table 3 and Table 4 show the differences in water and electricity consumption in the year before the treatment period for Modesto and Riverside, respectively. In these tables, Hot WaterSmart is a subset of the WaterSmart treatment, meaning that the WaterSmart column represents average water use for both treatment groups. Importantly, these tables indicate that treated groups did not use significantly more or less water than the control group during the baseline period, and therefore we trust that

[2] We expect to receive natural gas data from PG&E and SoCalGas shortly and will update the tables accordingly. The Modesto Irrigation District (MID) was unwilling to share customer electricity data with third parties and so we are unable to include customer electricity data for Modesto in this study.

assignment was random. In the absence of WaterSmart, Modesto households used 342 gallons per day of water on average with huge seasonal differences, ranging from 221 gallons per day in the winter to 456 gallons per day in the summer (Table 3). Riverside households used 484 gallons of water per day on average, ranging from 395 gallons in the winter to 581 gallons in the summer (Table 4).

Table 4: Pre-treatment mean household water and electricity use by treatment group in Riverside

	Control	**WaterSmart**		**Hot WaterSmart**		**All**
	Mean	Mean	Difference	Mean	Difference	Mean
		Water (gallons per day)				
Overall	484.69	482.42	-2.27	481.08	-3.61	484.08
	(478.13)	(456.99)	(0.49)	450.49	(0.59)	(472.51)
August – October	553.71	551.52	-2.18	550.41	-3.3	553.12
	(559.63)	(543.55)	(0.40)	531.16	(0.46)	(555.32)
November – January	408.82	406.02	-2.8	403.27	-5.56	408.07
	(426.09)	(399.8)	(0.68)	389.39	(1.03)	(419.14)
February – April	395.1	390.6	-4.5	389.13	-5.97	393.88
	(617.18)	(386.03)	(0.82)	376.14	(0.79)	(564.11)
May – July	581.69	580.48	-1.21	577.83	-3.87	581.37
	(590.14)	(579.71)	(0.21)	561.44	(0.51)	(587.34)
Number of households	38,751	14,359		7,172		53,110
		Electricity (kWh per day)				
Overall	26.52	26.49	-0.03	26.88	0.35	26.51
	(29.59)	(28.98)	(-0.09)	(32.83)	(0.83)	(29.43)
August – October	34.54	34.11	-0.43	34.59	0.05	34.42
	(42.31)	(35.00)	(-0.98)	(38.02)	(0.09)	(40.47)
November – January	22.72	22.62	-0.1	22.82	0.1	22.69
	(21.87)	(21.07)	(-0.43)	(22.82)	(0.33)	(21.66)
February – April	19.55	19.48	-0.07	19.76	0.22	19.53
	(69.32)	(30.84)	(-0.11)	(39.72)	(0.23)	(61.33)
May – July	26.06	26.57	0.51	27.25	1.18	26.2
	(38.59)	(50.69)	(1.12)	(62.19)	(1.94)	(42.21)
Number of Households	32,340	11,993		5,979		44,333
		Natural Gas - TBD				

Note: Means are reported by treatment group, with standard deviations in parentheses below. "Difference" displays the difference in means between each treatment group and control, with t-stats reported in parentheses below. Hot WaterSmart is a subset of the general WaterSmart group. Uses household level data from August 2015- July 2016.

ENERGY INTENSITY DESIGN

This portion of the project aimed to calculate the energy intensity of the Modesto and Riverside water infrastructure systems to determine how much system energy is saved as a result of residential water conservation. To this end, CWEE developed a custom method to calculate water infrastructure energy intensity using water system flow and electricity data for all assets in the water system network (e.g. distribution pumps, well pumps, water treatment plants, etc.).

As water flows through a system, it experiences energy consuming processes including water treatment and pumping. While the energy used is not necessarily stored in the water, it is considered to be “embedded” or “spent” on the water. Energy intensity (EI) is the amount of energy embedded in a volume of water delivered. The standard unit is kilowatt-hours per million gallons (kWh/MG).

Given available infrastructure data, we took a different approach to calculating the energy intensity of water in each city. Modesto has a simpler water system with a single pressure zone, so energy intensity could be calculated as total energy used divided by total water delivered. Riverside, on the other hand, has multiple pressure zones which required the development of a custom network model.

Modesto Energy Intensity Development

The City of Modesto provided data on 119 wells, 29 booster pumps, and 12 storage tanks. Modesto operates its system in one continuous pressure zone, meaning that all water delivered in the system has equal energy intensity. For this reason, we were able to calculate the energy intensity of the system as total energy used divided by total water delivered. However, due to the limited availability of electricity data, we needed to estimated total energy use from other data sources.

The City of Modesto provided the following data to CWEE:

- Monthly well flow data for 119 wells for 2010, 2011, 2014, 2015, and 2016
- Monthly tank and booster flow data for 9 tanks and 29 booster pumps for 2014 to 2016
- Pump efficiency reports for 99 well pumps, taken at various dates between 2010 and 2016
- Pump efficiency reports for 31 booster pumps, all taken in 2016
- Monthly pump runtime, in hours, for 98 well pumps and 31 booster pumps for 2010 to 2016
- Monthly system flow totals, including imported deliveries from the Modesto Irrigation District and other neighboring city water supplies, from 2000 to 2017

Since pump energy usage data was unavailable, electricity consumption for well pumps was instead estimated using the data available and the efficiency-lift method. The Efficiency Lift Method estimates energy required for groundwater extraction using a relationship between pump energy consumption and the specifics of the pumping system, including the total dynamic head and pump efficiency (Equation 1).

Equation 1: Efficiency-Lift

$$Energy\ Use\ (kWh) = \frac{Water\ Use\ (ac\text{-}ft) \times Total\ Dynamic\ Head\ (ft) \times 1.024\left(\frac{kWh}{(ac\text{-}ft)ft}\right)}{Pump\ Efficiency\ (\%)}$$

Where:

Water use = volume of groundwater extracted

Energy use = electricity consumption for a specific well pump

Pump efficiency = operating efficiency of the pump

1.024 = a constant representing the electric energy required (kWh) by a pump to lift 1 acre-foot of water a distance of one foot when operating at 100% efficiency

Total Dynamic Head = total equivalent height that the pump moves the water, taking into account the vertical distance that the groundwater is pumped, friction losses in the pipe, and any additional pressure required for distribution purposes

By combining the monthly flow data for each well with the total dynamic head and pump efficiency values from each pump efficiency report, we estimated energy usage for each well pump in the distribution system. However, we took two more important steps to improve the accuracy of this measurement. First, twenty of the wells in the Modesto service area did not have any associated pump efficiency report data. Because the depth of the well is one of the most important factors in determining its energy consumption, we estimated the depth of each well as an average of the nearest wells with efficiency reports. Second, well depth varies continuously over time. Generally, groundwater depth increases in summer months as extraction rates grow, resulting in a greater vertical distance to extract water and higher energy consumption. In order to capture this variation in groundwater depth, we developed a simple model to estimate groundwater depths over time using publically available data from the California Statewide Groundwater Elevation Monitoring (CASGEM) program.

The California Department of Water Resources (DWR) records monthly groundwater depth measurements for wells throughout the state. We used publicly available data on all thirteen CASGEM wells within twenty miles of downtown Modesto to build a model that estimates the average change in groundwater level in the Modesto service territory for each month between 2010 and 2016 (Figure 1). We then estimated the groundwater depth for every month for each well based on each well's pump efficiency test. By applying the average monthly change of well depth in the Modesto area to the well depths recorded during the pump efficiency tests for each well, we were able to estimate the total dynamic head for each well for all months in the study period.

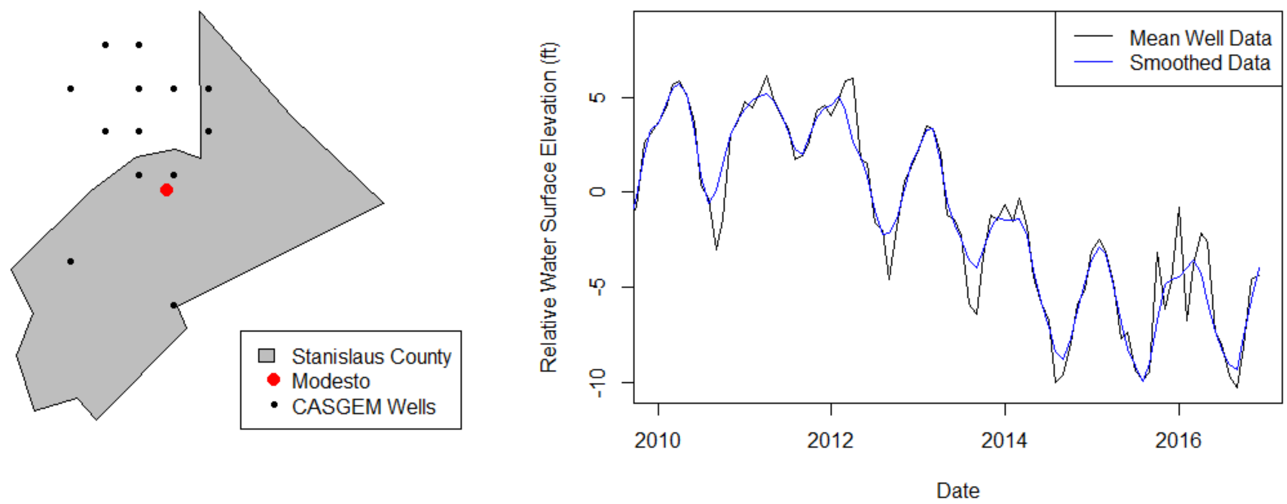


Figure 1: CASGEM well locations and average relative water surface elevation over time

With monthly estimations of total dynamic head, monthly measured flow, and constant pump efficiency, we could then estimate monthly energy use for each well.

Calculating energy use in the booster pumps was much more straightforward. Energy efficiency reports provided by the City of Modesto estimated the energy intensity of each pump. Since booster pumps are not impacted by varying groundwater depths, this single value was sufficient to calculate the energy use for each booster pump based on its corresponding total monthly flow data. Added together, monthly well pump energy use and monthly booster pump energy use give us a monthly total system energy use. By dividing this estimated monthly energy use by the monthly system flow totals provided by Modesto, we calculated an estimated energy intensity for each month from 2014 to 2016 (Figure 2). Much of the variation in energy intensity depended on the proportion of total water deliveries supplied by Modesto directly. Since all imported water is considered to have an energy intensity of zero, months with higher proportions of imported water have lower energy intensities. The aggregate average energy intensity for the study period is 746 kWh/MG.

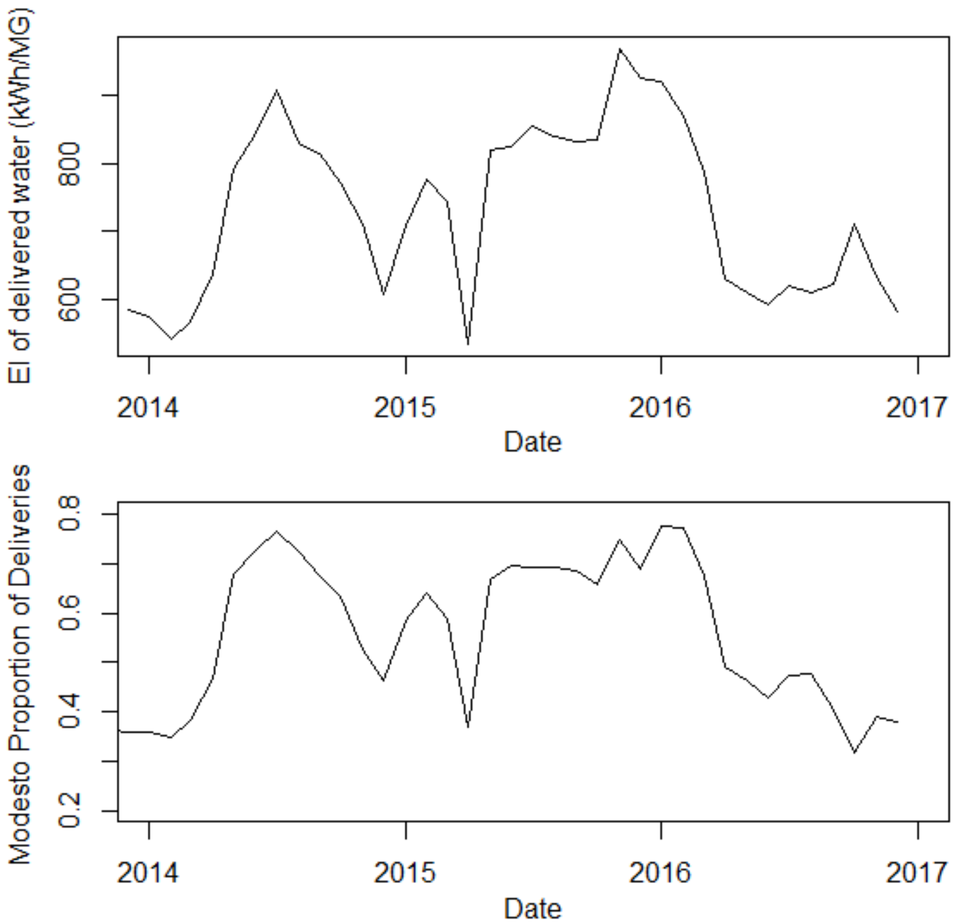


Figure 2: Monthly energy intensity of water delivered in Modesto

Riverside Energy Intensity Development

The Riverside Public Utility water distribution system consists of 42 booster pumps, 10 interconnects, 17 reservoirs, 9 treatment facilities, and 73 wells. These assets serve customers in 41 different pressure zones with widely different pressure needs (Figure 3).

Riverside provided the following data to CWEE:

- Monthly energy billing data for 87 assets for 2014 to mid-2017
- Monthly natural gas usage data for 11 natural gas wells for 2010 to 2011
- Daily flow data for 85 assets from mid-2015 to mid-2017
- Spatial data for 223 different assets, 45,600 lengths of pipe, and 41 pressure zones within the Riverside distribution system
- Supporting descriptive documentation on wells, booster pump stations, treatment plants, and reservoirs

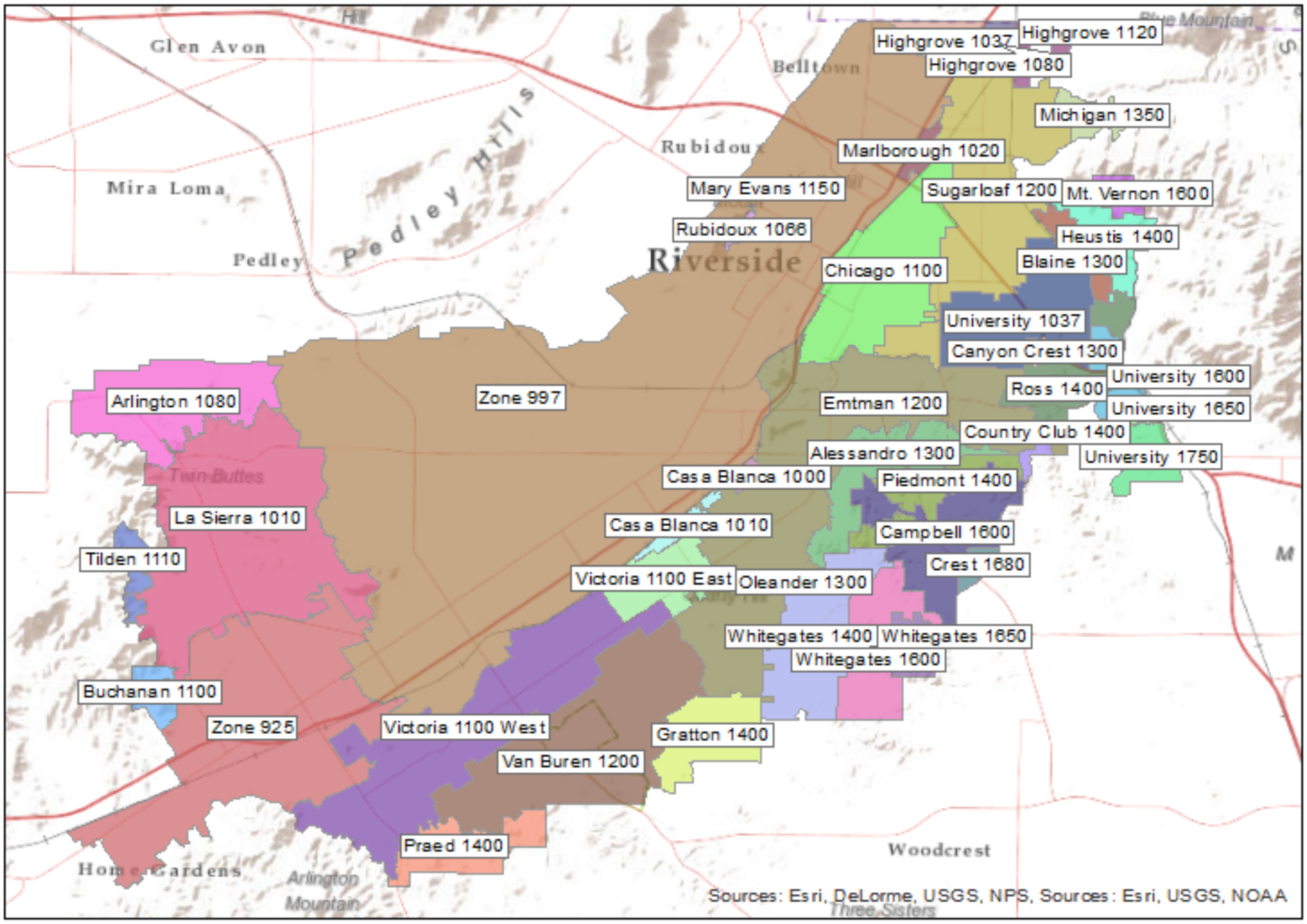


Figure 3: Riverside Public Utility pressure zone map. Numbers in the zone name correspond to pressure needs (driven primarily by elevation).

Given the complexity and spatial heterogeneity of the Riverside distribution system, an asset framework model was necessary to perform the necessary energy intensity calculations. Using spatial data, distribution schematics, and documentation provided by RPU, we built a simplified network model with 138 assets and 198 vectors of flow (Figure 4). As water flows along vectors through the energy-consuming assets, it accumulates energy until it is delivered to a pressure zone.

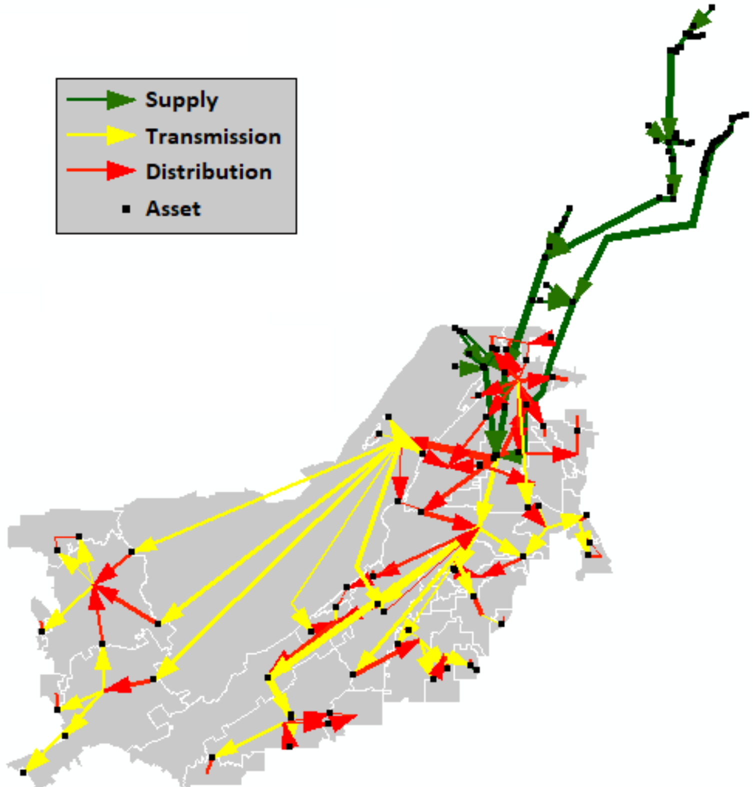


Figure 4: Riverside asset framework network model. Supply vectors deliver source water to the distribution system, transmission vectors transport water between pressure zones, and distribution vectors deliver water to customers in pressure zones.

The asset framework model has two steps. First, the energy intensity (EI) contribution of each energy consuming asset is calculated by dividing the energy consumed at a given time *t* by the volume of water processed within that same time frame, as in Equation 2.

Equation 2. The energy intensity contribution of a source.

$$EI_{j,t} = \frac{E_{j,t}}{V_{j,t}}$$

Where:

$EI_{j,t}$ = flow-weighted EI contribution of process at asset *j* at time *t*
$E_{j,t}$ = energy consumed by process at asset *j* at time *t*
$V_{j,t}$ = volume of water processed at asset *j*

Once the contribution of each process is calculated, the contributions can be linked together through the flow network to establish the EI at each node. We calculated the EI of the flow network using a flow-weighted average (Equation 3).

Equation 3. Flow weighted average.

$$EI_i = \frac{\sum_{j=1}^{n} EI_j Q_j}{\sum_{j=1}^{n} Q_j}$$

Where:

EI_i = flow-weighted EI at current asset *i*
EI_j = EI of flows from upstream asset *j*
Q_j = flow from asset *j*

With the EI calculated at each asset, the energy embedded in the water at any point in the system can be calculated as a flow weighted average of all assets contributing to it. The three types of assets that contribute to EI in the Riverside system are well pumps, treatment plants, and booster pumps. Because energy and flow data were provided directly from RPU, no estimation methods were necessary. However, many assets had incomplete or missing energy or flow data, so in many cases these values had to be projected from the data of similar assets in the system.

The result of applying the EI calculations to the Riverside asset framework model can be seen in Figure 5. We see a strong positive relationship between the pressure requirement of a zone, which is largely determined by its elevation, and the cumulative energy intensity of water delivered to that zone. However, zone elevation does not explain all of the variation in energy intensity – the relative efficiency values of pumps and the number of pumps water must travel through can also have an impact on energy intensity. Travelling a larger distance horizontally also increases energy intensity due to friction losses in pipes. While energy intensity varies widely over space and time, the average energy intensity over the study period in Riverside is 607 kWh/MG.

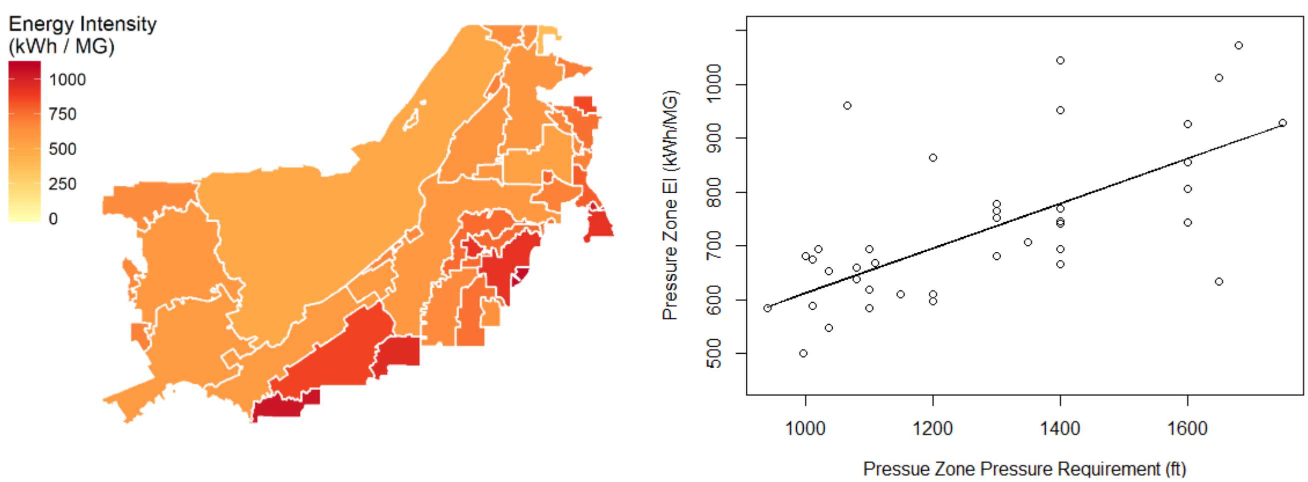


Figure 5 Riverside pressure zone energy intensity

Infrastructure Energy Savings

To calculate water and energy savings within each pressure zone in Riverside, we had to determine which households in the study were located in which pressure zones. We used Bing Maps and Google Maps to geocode and assign each household to its respective pressure zone. We then calculated aggregate energy savings in each pressure zone by estimating the heterogeneous impacts of the WaterSmart experiment on water savings in each zone.

Exploiting differences in the energy intensity of water delivery, we estimated aggregate infrastructure energy savings due to WaterSmart for the entire city of Riverside. We first estimated the spatially heterogeneous water savings by pressure zone using the same log-linear specification as the pooled model described above. We then applied the specific energy intensity factors for each pressure zone to calculate network energy savings. Modesto, on the other hand, only has one pressure zone. Total household savings were added up for the entire service territory and multiplied by the average energy intensity to calculate the estimated energy savings.

SURVEY RESEARCH DESIGN

We administered three surveys in conjunction with the WaterSmart program: (1) Welcome Survey (Appendix I), (2) Post-launch Survey (Appendix J), and (3) Post-treatment Survey (Appendix K). WaterSmart Software, Inc. distributed the Welcome Survey before the first HWR distribution, the Post-launch Survey after the first three HWRs, and the Post-treatment Survey after all six HWRs (treatment period.

Table 6).

The Welcome Survey was intended to collect information to guide Home Water Report content (e.g., presence of irrigation, yard, pool, spa) and to provide a baseline measurement of water-saving actions and investments against which to measure behavioral responses to WaterSmart. The subsequent Post-launch Survey aimed to assess the impact of WaterSmart in terms of customer satisfaction with the utility and uptake of water-saving measures. The final Post-treatment Survey assessed the impact of WaterSmart on self-reported engagement in water- and energy-saving measures, with a focus on exploring behavioral spillover from water- to energy-saving measures.

WaterSmart Software, Inc. administered the Welcome Survey and Post-launch Survey in both Modesto and Riverside. However, we designed and administered the Post-treatment Survey only in Riverside in order to leverage the greater impact the program had on water savings in Riverside compared to Modesto, enabling us to study the impact on water-saving measures and spillover from water- to energy-saving measures.

To further hone in on spillover, and to leverage the Welcome Survey for pre-post comparisons, we adopted a strategic sampling strategy for the Post-treatment Survey. In particular, we recruited all treatment households that participated in the Welcome Survey. We also oversampled treatment households whose consumption data indicated water savings, defined as a 2% reduction in daily average water consumption during treatment (Nov 2016 - Aug 2017) compared to baseline (Nov 2015 - Aug 2016). We excluded households whose consumption data was insufficient to rigorously determine water savings (e.g., when there were estimated rather than actual meter reads or multiple meter reads per month). Finally, we recruited a random sample of treatment households whose consumption data did not indicate savings, and a random sample of control households. This sampling strategy enabled comparisons of households that were responsive to the WaterSmart program to those who were not responsive, and to control households.

All three surveys were distributed via email or mail if the household did not list an email address. For the Post-treatment Survey, recruited households were sent reminders (2-4 for email distribution and 0-1 for mail distribution). No incentives were offered for the Welcome and Post-launch Surveys; Post-treatment Survey participants received a $20 Starbucks e-gift card. Recruitment, survey completion, and response rates are summarized in Table 5.

Table 5: Response rate for surveys

	Modesto			**Riverside**		
Survey	Completed	Recruited	Response Rate	Completed	Recruited	Response Rate
Welcome	1,275	29,798	4%	860	14,493	6%
Post-launch	829	3,272	25%	762	5,684	13%
Post-treatment	N/A			976*	5,703*	17%

*Prior to cleaning for duplicate and incomplete responses, invalid addresses, and bounced emails

There was a single version of the Welcome Survey and Post-launch Survey. There were four versions of the Post-treatment Survey: (1) treatment groups mail recruitment; (2) treatment groups email recruitment; (3) control group mail recruitment; (4) control group email recruitment. The mail recruitment versions asked for respondent mailing address (to verify respondents were HWR recipients), whereas the email recruitment versions did not. The treatment group's surveys included questions about HWRs, whereas the control group's surveys did not. Appendix I is version (1). Data were filtered to include only households where the same email address was given in both surveys to increase likelihood that surveys were completed by the same household member. Only respondents who reported that they recalled receiving reports and viewing them at least once or twice were included in the final sample.

EXPERIMENT TIMELINE treatment period.

Table 6 displays the progression of the WaterSmart experiments in each deployment city. We planned to roll out both experiments on the same timeline, but Riverside was delayed slightly due to the first Home Water Report approval process by the Riverside Public Utility management. We established baseline water consumption for treatment and control groups using the year prior to the treatment period.

Table 6 Timeline of key experiment events

	Modesto		**Riverside**	
	HWR delivery method		HWR delivery method	
	Email	Mail	Email	Mail
First day of baseline water use	Aug 1, 2015	Aug 1, 2015	August 1, 2015	August 1, 2015
Last day of baseline water use	Jul 31, 2016	July 31, 2016	July 31, 2016	July 31, 2016
Welcome Letter and Survey delivered	Aug 25, 2016	Aug 9, 2016	Sep 7, 2016	Aug 30, 2016
Data omitted from analysis	Aug 1 – Sep 11, 2016	Aug 1 – Sep 11, 2016	Aug 1 – Oct 1, 2016	Aug 1 – Oct 1, 2016
First day of treatment period	Sep 12, 2016	Sep 12, 2016	Oct 2, 2016	Oct 2, 2016
1st HWR delivered	Sep 12 – Oct 3, 2016	Sep 26 – Oct 17, 2016	Oct 2 – 23, 2016	Oct 17 – Nov 5, 2016
2nd HWR delivered	Nov 14 – Dec 11, 2016	Nov 26 – Dec 28, 2016	Dec 11, 2016 – Jan 8, 2017	Dec 24, 2016 – Jan 21, 2017
3rd HWR delivered	Jan 17 – Feb 8, 2017	Jan 28 – Feb 22, 2017	Feb 12 – Mar 5, 2017	Feb 25 – Mar 22, 2017
Post-launch Survey delivered	March 2017	March 2017	April 2017	April 2017
4th HWR delivered	Mar 19 – Apr 9, 2017	Apr 1 – 26, 2017	Apr 17 – May 14, 2017	Apr 29 – May 31, 2017
5th HWR delivered	June 6 – 29, 2017	June 24 – July 19, 2017	Jun 15 – Jul 16, 2017	Jul 1 – Aug 2, 2017
Final HWR delivered	July 16, 2016	July 29 – Aug 2, 2017	Sep 17, 2017	Sep 30 – Oct 4 2017
Last day of treatment period	Sep 30 2017	Sep 30 2017	Nov 30, 2017	Nov 30, 2017
Post-treatment Survey delivered	N/A		Nov 4 -Dec 18, 2017	Nov 13-Dec 15, 2017

Note: No post-treatment survey was deployed in Modesto because we did not have electricity data to measure energy savings due to changes in water uses.

RESULTS

Results are presented for (1) behavior-driven water and water-energy savings for the two treatment groups relative to the control group, presented as both individual household average savings and aggregate residential savings for all households (per city); (2) infrastructure water-related energy savings, (3) combined residential and infrastructure energy savings, and (4) detailed survey findings.

HOUSEHOLD WATER AND ENERGY SAVINGS

Table 7 displays the estimated average impact of WaterSmart and Hot WaterSmart on household water and energy consumption. Each column of the table represents one model estimated. The coefficients listed in

Table 7 can be interpreted as the average percentage change in household water use due to being assigned to the WaterSmart or Hot WaterSmart treatments (Columns 1-4). Comparing the treatment period to the baseline period[3], WaterSmart reduced household water use by approximately 1.5% in Modesto (Column 3) and 2.2% in Riverside (Column 1) after controlling for weather and aggregate shocks. Hot water-specific messages had no additional observable impact on water savings in either city (Row 2 of Columns 2 and 4). However, in Riverside, we observed a 0.7% decrease in electricity use for households with the HWS messaging (Column 6) but not for those receiving only the WS treatment (Column 5). This difference suggests that targeted hot-water messaging can provide spillover electricity savings as well as water savings. We do not yet have data to estimate natural gas savings in either city.

[3] We excluded water use between Aug 1 – Sep 11, 2016 for Modesto and Aug 1 - Oct 1, 2016 in Riverside from the analysis because households could not be definitively assigned to pre or post treatment groups during this time period.

Table 7 WaterSmart and Hot WaterSmart effects on household water and energy consumption

	Water				**Electricity**		**Natural Gas**
	Riverside		Modesto		Riverside		
	(1)	(2)	(3)	(4)	(5)	(6)	
WaterSmart (all)	-0.022***	-0.023***	-0.015***	-0.015***	0.000	0.004	
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	data not yet available
Hot WaterSmart		0.001		0.001		-0.007*	
		(0.005)		(0.004)		(0.004)	
Observations	1,400,867		1,572,043		1,360,650		

Note: HH cluster robust standard errors in parentheses. *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. Baseline category is the control group. Each model includes year-month fixed effects, household fixed effects, and the following weather controls: heating degree days, cooling degree days, and rainfall. The treatment period covers Sep 12, 2016 – Sep 30, 2017 in Modesto and Oct 2, 2016 – Nov 30, 2017 in Riverside. Dependent variables for water savings are natural log of gallons per day; for electricity natural log of kWh per day.

AGGREGATE RESIDENTIAL WATER AND ENERGY SAVINGS

We calculated aggregate residential water and energy savings due to WaterSmart using the coefficient estimates from the household-level models in

Table 7. Taking into account the length of the treatment period and baseline water usage in each city, we constructed a rough estimate of overall water and energy savings from WaterSmart and Hot WaterSmart (Table 8). We did not identify any statistically significant differences in water savings between the WS and HWS groups but calculated each group's aggregate savings separately using their respective baseline water usage. Together, both groups saved an estimated 88,385 hundred cubic feet (CCF) of water over the treatment period in Riverside, and 79,477 CCF in Modesto. However, more than twice as many households received treatment in Modesto than in Riverside and thus savings per household were significantly lower in Modesto.

Table 8 Aggregate water and energy savings by treatment group

	WaterSmart		**Hot WaterSmart**	
	Modesto	Riverside	Modesto	Riverside
Treatment period length (days)	383	424	383	424
Water				
Number of treated households	15,066	7,187	15,066	7,172
Mean household water savings rate	1.5%	2.2%	1.5%	2.2%
Mean baseline household water use (gal/day)	341.8	483.8	345.0	481.1
Aggregate water savings rate (CCF/day)	103.3	102.3	104.2	101.5
Total water savings over treatment period (CCF)	39,553	45,358	39,924	43,027
Electricity				
Number of treated households	Data not available	6,014	Data not available	5,979
Mean household electricity savings rate		0		0.7%
Mean baseline household electricity use (kWh/day)		n/a		26.88
Aggregate electricity savings rate (kWh/day)		n/a		1,125
Total electricity savings over treatment period (kWh)		0		477,004
Natural Gas				
Number of treated households	Data not yet available			
Mean household gas savings rate				
Mean baseline household gas use				
Aggregate gas savings rate				
Total gas savings over treatment period (Therms)				

INFRASTRUCTURE ENERGY SAVINGS

Modesto has a single pressure zone and thus water savings induced uniform energy savings throughout the city. Using the estimated energy intensity metric of 745.9 kWh per MG, the total water savings of 59.4 MG resulted in electricity savings of 44,343 kWh over the study period. Riverside, with its 41 distinct water pressure zones, has spatially-variable energy savings as a result of water savings in different locations. Baseline household water usage in each pressure zone ranged from 293 gallons per day to 1,992 gallons per day. This heterogeneity – coupled with the large range in energy intensity factors – makes it important to understand the spatial response to WaterSmart. Table 9 describes average household baseline water usage, average water savings per household, and the number of households in each pressure zone. Of the 39 pressure zones populated by our sample, only nine showed a statistically significant reduction in water use as a result of WaterSmart. The estimated savings from the pressure-zone level regressions is slightly lower – 79,598 CCF compared to 88,385 CCF in the aggregate results – due to the fact that we were unable to accurately assign 200 households to pressure zones and that, when estimated in separate regressions, the sample size for some pressure zones was too small to estimate a treatment effect with any confidence. Thus, to calculate aggregate savings at the pressure zone level, we included only those pressure zones with water use changes that were significantly different from zero (refer to the stars accompanying each pressure zone). We calculated the total change in water use by multiplying the mean change in water use (Col 1) by baseline water usage (Col 3), the number of treated households in that pressure zone (Col 2), and the number of days in the treatment period, 424.

Using the pressure-zone-specific energy intensity metrics explained in the Methods section, and only considering individual pressure zones with statistically significant changes in water use, the total water savings in Riverside resulted in electricity savings of 34,585 kWh. However, if we instead apply the average water savings per household that occurred as a result of WaterSmart to the households in all pressure zones, we estimate a slightly higher energy savings of 39,410 kWh.

Using the more granular pressure-zone level water savings, household energy savings due to Hot WaterSmart were not statistically significantly different from the control group due to the smaller sample sizes. Thus, we estimated only city-wide average residential electricity savings.

Table 9 Aggregate water and energy savings by pressure zone in Riverside

Water Pressure Zone	**Mean household water savings**	**Number of treated households**	**Baseline water use (gal/day)**	**Agg. water savings rate (CCF/day)**	**Total change in water Use (CCF)**	**Total Change in Energy Use (kWh)**
Alessandro 1300*	-4.2%	171	812	-7.80	-3,306	-1,892
Arlington 1080	-4.6%	146	570	-5.11	0	0
Blaine 1300	1.0%	118	425	0.67	0	0
Buchanan 1100	-2.3%	22	577	-0.39	0	0
Campbell 1600	-1.9%	278	858	-6.06	0	0
Canyon Crest 1300	-30.5%	20	1,067	-8.70	0	0
Casa Blanca 1000	0.3%	46	343	0.06	0	0
Casa Blanca 1010**	7.4%	97	383	3.68	1,560	787
Chicago 1100*	-2.6%	584	469	-9.52	-4,037	-1,867
Country Club 1400	5.4%	21	713	1.08	0	0
Crest 1680	-3.7%	58	606	-1.74	0	0
Emtman 1200***	-5.0%	1,183	631	-49.88	-21,148	-9,433
Gratton 1400	4.4%	8	1,992	0.94	0	0
Heustis 1400	-1.4%	162	375	-1.14	0	0
Highgrove 1037	0.1%	74	304	0.03	0	0
Highgrove 1080	1.8%	57	384	0.53	0	0
Highgrove 1120	-3.6%	63	293	-0.89	0	0

Water Pressure Zone	Mean household water savings	Number of treated households	Baseline water use (gal/day)	Agg. water savings rate (CCF/day)	Total change in water Use (CCF)	Total Change in Energy Use (kWh)
La Sierra 1010***	-2.4%	1,211	460	-17.87	-7,577	-3,340
Marlborough 1020	-3.8%	82	311	-1.29	0	0
Mary Evans 1150	-9.0%	4	582	-0.28	0	0
Mt. Vernon 1600*	-38.9%	3	1,295	-2.02	-857	-549
Oleander 1300	15.4%	2	1,487	0.61	0	0
Piedmont 1400	-1.9%	154	707	-2.77	0	0
Praed 1400	-5.6%	82	880	-5.40	0	0
Ross 1400	1.1%	118	444	0.77	0	0
Rubidoux 1066	-8.1%	20	696	-1.51	0	0
Sugarloaf 1200	2.1%	170	564	2.69	0	0
Tilden 1110	3.2%	65	620	1.72	0	0
University 1600**	-10.9%	32	677	-3.16	-1,339	-807
University 1650	1.6%	16	541	0.19	0	0
University 1750	-1.4%	175	421	-1.38	0	0
Van Buren 1200	1.6%	101	1,035	2.24	0	0
Victoria 1100 East	2.2%	70	442	0.91	0	0
Victoria 1100 West	-0.2%	756	515	-1.04	0	0
Whitegates 1400	-4.5%	192	1,370	-15.82	0	0
Whitegates 1600**	-11.6%	45	1,836	-12.81	-5,433	-3,023
Whitegates 1650	-7.2%	16	1,442	-2.22	0	0
Zone 925**	-2.0%	1,585	384	-16.26	-6,893	-3,016
Zone 997***	-2.2%	6,160	398	-72.09	-30,568	-11,447
Overall	-2.2%	14,167	456	0.00	-79,598	-34,585

Note: *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively. Only pressure zones with water use changes that were significantly different from zero were included in the aggregate water savings. Total change in water use is calculated using the mean change in water use (Col 1) multiplied by baseline water usage (Col 3), the number of treated households in that pressure zone (Col 2), and the number of days in the treatment period, 424. One hundred cubic feet (CCF) of water is equivalent to 748 gallons.

PROJECT SAVINGS SUMMARY

Aggregating the savings from direct changes in residential water use and indirect energy savings in the water networks, we estimated the total water savings to be 79,477 CCF and 88,385 CCF and total energy savings to be 44,343 kWh and 39,410 kWh in Modesto and Riverside, respectively. Table 10 summarizes savings in residential water and energy use and the resulting infrastructure energy savings.

Table 10 Total project water and energy savings

	Modesto		Riverside	
	Water (CCF)	Electricity (kWh)	Water (CCF)	Electricity (kWh)
Residential Savings				
WaterSmart	39,553	n/a	45,358	0
Hot WaterSmart	39,924	n/a	43,027	477,004
Infrastructure Savings				
WaterSmart	n/a	22,068	n/a	20,225
Hot WaterSmart	n/a	22,275	n/a	19,185
Total savings	**79,477**	**44,343**	**88,385**	**516,414**

HOUSEHOLD WATER-SAVING MEASURES

In the Post-treatment Survey, treatment households were asked whether they recalled receiving reports, whether they viewed them, and whether they helped them save water and reduce water bills. A little over half recalled receiving them. Of those, 99% viewed them (82.4% viewed "most of them"; 16.1% viewed them "once or twice"), 61% said the reports helped them takes actions to save water, and 47% said they helped them save money on water bills (Figure 6).

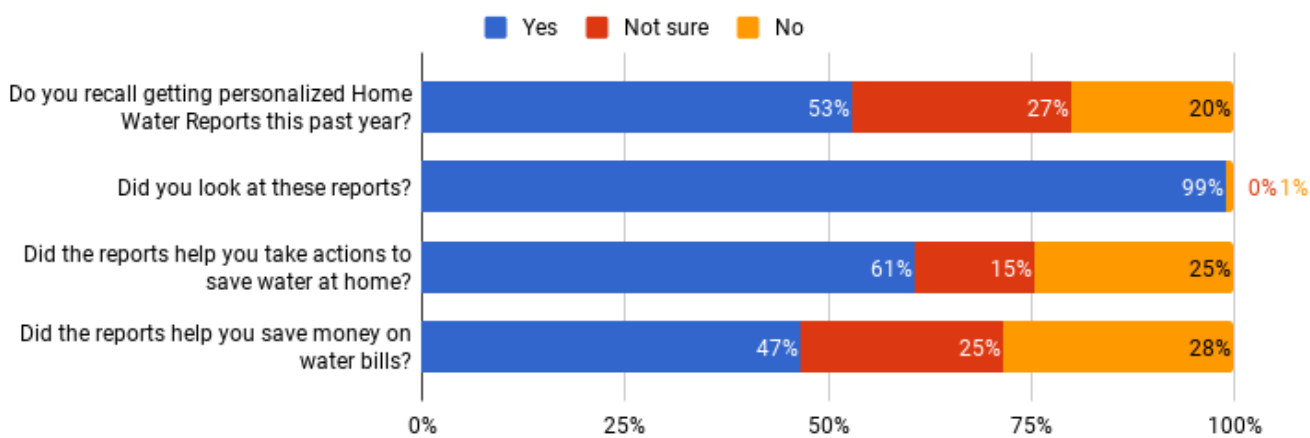


Figure 6 Household awareness and evaluation of HWRs in the Post-treatment Survey

In the Post-launch Survey, treatment households were asked to indicate water-saving measures they had adopted since receiving the first few Home Water Reports. Figure 7 summarizes the proportion of respondents who indicated they adopted each measure assessed. The most common measure reportedly adopted was reducing outdoor landscape irrigation. Taking shorter showers and flushing less frequently were also relatively common. Less commonly adopted measures involved investment in more efficient equipment (fixtures, appliances, irrigation controller) or landscaping (switching to water-efficient plants).

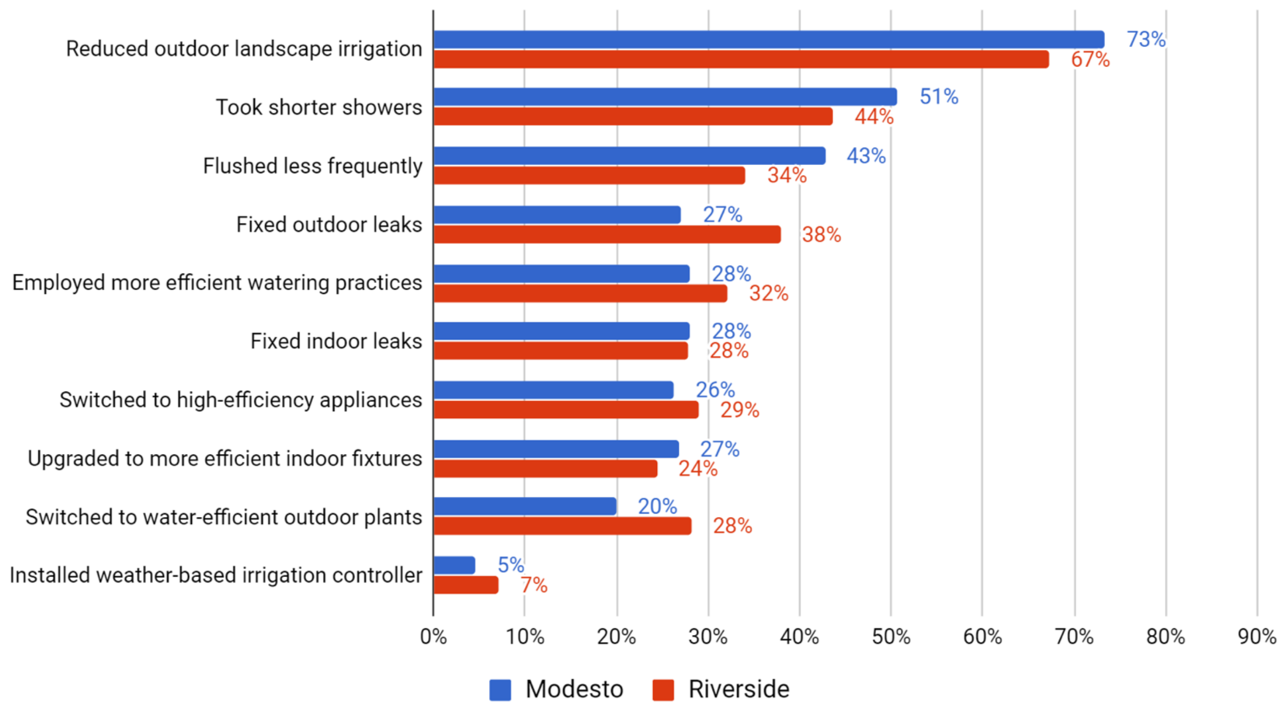


Figure 7 Treatment households' reported increase in water-saving measures in Post-launch Survey

The Welcome Survey asked treatment households whether they engaged in certain water-saving measures. These measures were included in the Riverside Post-treatment Survey to enable pre-post analyses for households that participated in both surveys. Figure 8 shows the proportion of respondents who reported each measure before and after the WaterSmart program. Of the eight water-saving measures assessed in the same way in both surveys, there was a statistically significant difference in one measure. Specifically, HWR recipients were more likely to report "using multiple irrigation/watering start times" in the Post-treatment Survey compared to their baseline responses in the Welcome Survey (McNemar's test for difference in paired proportions, $p = .03$).

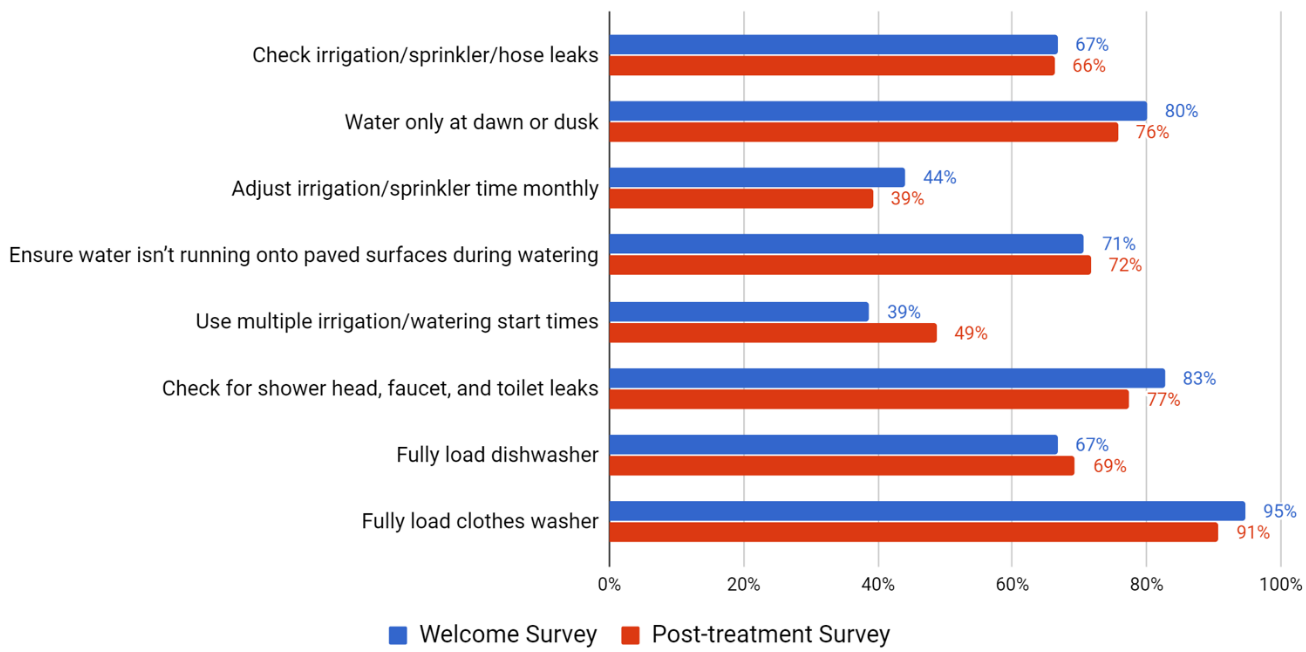


Figure 8: Treatment households' reported water-saving measures before and after the WaterSmart program, for HWR recipients who completed both the Welcome Survey and Post-treatment Survey.

Finally, we assessed differences between control and treatment group's reported water-saving measures in the Post-treatment Survey. We compared responses of control households in the treatment group identified as "water-saving", i.e., those whose water consumption during treatment was 2% lower than baseline, filtering out respondents who did not recall receiving or viewing HWRs in order to focus on households who were responsive to HWRs. Thus, the results should not be interpreted as a randomized controlled experiment of WaterSmart's average effect on all treatment households, but rather as insight into how the reports influenced household behavior.

First, we compared the number of water-saving measures reported by control versus treatment water-saving households using an independent t-test. The test was significant, indicating that treatment households reported more water-saving measures on average (16 measures out of 45), than did control households (14 measures); $t(323) = -2.5$, $p = .01$. Next, we identified specific water-saving measures that the HWRs successfully encouraged by conducting z-tests, comparing the proportion of respondents in control versus treatment water-saving households that reported each water-saving measure. Figure 9 displays water-saving measures reported significantly more often by treatment households than control households.

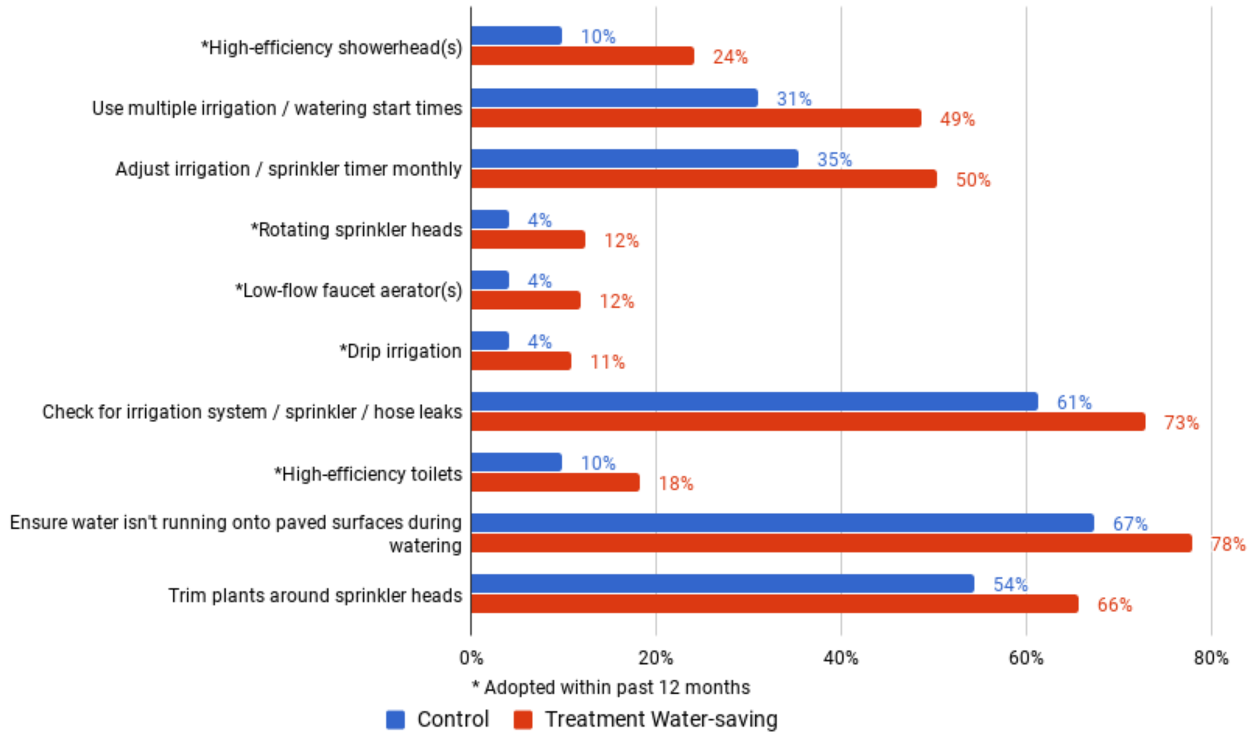


Figure 9: Water-saving measures reported by treatment and control households in Post-treatment Survey

HOUSEHOLD ENERGY-SAVING MEASURES

Since this project sought to understand behavioral spillover from water- to energy-savings, we also compared control to treatment households on reported energy-saving measures in the Post-treatment Survey. Again, we focused on households that demonstrated water savings to hone in on how responsive households may have also modified their energy-related behaviors. First, we compared the number of exclusively energy-saving measures (i.e., excluding measures that save both energy and water) reported by control versus treatment water-saving households using an independent t-test. The test was highly significant, indicating that treatment households reported more energy-saving measures on average (12 measures out of 34), compared to control households (10 measures); $t(323) = -3.9$, $p < .001$.

Next, we identified specific energy-saving measures that were more prevalent among treatment households. Using z-tests, we compared the proportion of respondents in control versus treatment households that reported each energy-saving measure. Energy-saving measures reported significantly more often by treatment households compared to control households are presented in Figure 10.

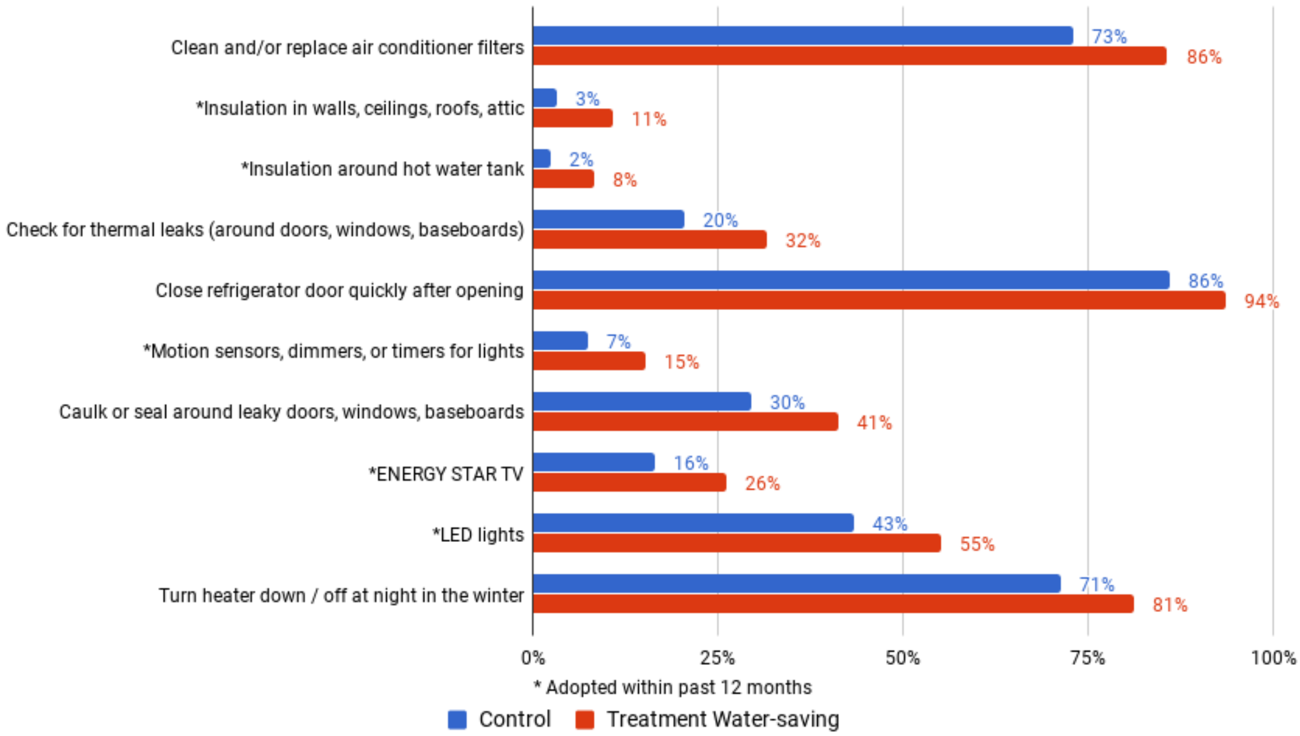


Figure 10 Energy-saving measures reported by treatment and control households in the Post-treatment Survey

SPILLOVER ANALYSIS

The main objective of our survey spillover analysis was to identify classes of related home water- and energy-saving measures. To identify these measure classes, we performed Principal Component Analysis (PCA) on datasets from all three surveys and synthesized the results, relying most heavily on the Post-treatment Survey, which assessed participants' self-reported engagement in 79 different water- and energy-saving measures (See Appendix M for the full results of the Post-treatment Survey PCA). This method grouped together correlated water- and energy-saving measures, i.e., those that were often selected by the same respondents. All respondents from control and treatment groups were included in the analysis. When synthesizing results for measures common to multiple surveys, we retained pairings that were consistent across more than one set of clusters. We arrived at nine classes of home water-and energy-saving measures (Figure 11).

Water Curtailment and Conservation measures are frequent, no cost, low effort behaviors that everyone in the home can engage in to minimize water usage and waste during hygiene, cooking, and cleaning habits and tasks. They include turning off the water during grooming and cooking tasks and using broom or cloth instead of hose when cleaning outdoors.

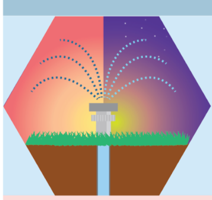
Energy Curtailment and Conservation measures are frequent, no cost, low effort behaviors that everyone in the home can engage in to minimize energy usage related to various household functions (cooking, cleaning, comfort, entertainment). They include turning off lights, TV, and computer when not in use; and thermostat setbacks.

Efficient Envelope measures are infrequent maintenance behaviors or upgrades to the shell of the home and fixtures. They include checking for and fixing indoor thermal and water leaks (including weather-stripping, caulking, and sealing); installing insulation; and cleaning light bulbs, refrigerator coils, and air conditioner filters.

Efficient Appliance measures are investments in or upgrades to efficient devices found throughout the home. They include energy-efficient TV and refrigerator and water-efficient showerhead, toilet, dishwasher, and washing machine.

Edge of Efficiency measures are investments in less standard equipment and innovations in energy and water efficiency. They include tankless water heater, drip irrigation, smart thermostats, LED lights, and motion sensors/dimmers/timers for lights.

Efficient Pool & Spa measures are investments, maintenance practices, and habits related to pool and spa care that save water and/or energy. They include having and using pool/spa covers; checking for pool/spa leaks; and reducing or shortening pool/spa pump cycles.



Efficient Irrigation measures include efficient irrigation equipment (e.g., rotating sprinkler heads), watering practices (e.g.., watering only at dawn/dusk), and maintenance measures (checking for leaks and making sure water doesn't run onto pavement) to conserve water used for irrigation.

Green Gardening measures are water- and energy-saving gardening practices and investments. They include composting, mulching, replacing high water use plants with low water use plants, and watering different plants according to their different needs.

Green Landscape Foundations measures are decisions about fundamental landscape components and systems that save water; these measures can be high cost if hired out, or high effort if DIY. They include graywater and rainwater catchment systems, permeable pavement, and replacing grass with artificial turf.

Figure 11 Water-energy-saving measure classes

To explore how spillover may have occurred in the Riverside WaterSmart program, we mapped the water- and energy-saving measures that survey results suggested were influenced by HWRs on to these response classes. First, we assessed how customer-adopted water-saving measures mapped onto the response classes. In particular, we hypothesized that treatment households adopted water-saving measures within the same response class(es), rather than randomly across different response classes. This would suggest spillover among water-saving measures within a response class, i.e., if one Green Gardening measure was adopted, other Green Gardening measures were likely also adopted.

We then assessed whether the energy-saving measures reported at a higher rate by treatment households belonged to the same measure class(es) as the adopted water-saving measures. For example, if Efficient Envelope water-saving measures were adopted Efficient Envelope energy-saving measures might also be adopted. This would suggest spillover from water- to energy-saving measures.

The water-saving measure that stood out in the Post-launch survey analysis was reducing outdoor landscape irrigation, reported by almost two-thirds of respondents (Figure 7); this measure is part of the Efficient Irrigation class. In the Pre-post analysis of measures assessed in both the Welcome Survey and Post-treatment Survey, using multiple irrigation start times increased most from before to after the WaterSmart program (Figure 8); this measure is also Efficient Irrigation. In the Post-treatment Survey treatment-control comparisons (Figure 9), six of the ten measures reported at a significantly higher rate by treatment households were also in the Efficient Irrigation class. Therefore, it seems Efficient Irrigation was the measure class most strongly impacted by the WaterSmart program. This class does not include any energy-saving measures and therefore does not offer strong hypotheses about how spillover to energy savings might occur.

Looking to the other four water-saving measures highlighted in the Post-treatment Survey treatment-control comparisons, two are Efficient Appliance measures (high-efficiency showerheads and toilets), one is an Efficient Envelope measure (low-flow faucet aerators), and one is an Edge of Efficiency measure (drip irrigation). Turning to the exclusively energy-saving measures, highlighted also in the Post-treatment Survey treatment-control comparisons (Figure 10), we find that these three measure classes are also represented (Table 11), along with two Energy Curtailment and Conservation Measures.

Table 11 Behavioral spillover in WaterSmart program within and between water-energy-saving measure classes

Measure Class	Water-saving Measures	Energy-saving Measures
Efficient Irrigation	Use multiple irrigation times Adjust irrigation timer monthly *Rotating sprinkler heads Check for irrigation/hose leaks Ensure water not running onto pavement Trim plants around sprinklers	N/A
Efficient Envelope	*Low-flow faucet aerator(s)	*Low-flow faucet aerator(s) Clean/replace air conditioner filters *Insulation in walls, ceilings… *Insulation around hot water tank Check for thermal leaks Caulk or seal around leaky doors...
Efficient Appliance	*High-efficiency toilet *High-efficiency showerhead	*ENERGY STAR TV *High-efficiency showerhead
Edge of Efficiency	*Drip irrigation	*LED lights *Sensors/dimmers/timers for lights
Energy Curtailment & Conservation	[NONE]	Close refrigerator door quickly Turn heater down at night in winter
Water Curtailment & Conservation	[NONE]	N/A
Efficient Pool & Spa	[NONE]	[NONE]
Green Gardening	[NONE]	[NONE]
Green Landscape Foundations	[NONE]	N/A

*Within past 12 months. [NONE] means there was no evidence from the survey of uptake of these measures due to WS.

In sum, survey data analysis suggests that a variety of water- and energy-saving measures were adopted in response to WaterSmart in Riverside. For the most part, these measures belong to the same measure classes, suggesting that behavioral spillover occurs within the identified water-energy-saving measure classes. Although we cannot make strong claims about the direction of spillover effects (i.e., which came first: the water- or energy-saving measures), half of the measures that differed between treatment and control households were one-time investments adopted over the course of the 12 month WaterSmart study period.

Further investigation into these measure classes and the particular measures adopted in response to HWRs would yield numerous implications for the design of future WaterSmart programs, including high leverage measures to target and specific ways to frame the messaging. Instead of considering the impact of each individual water-saving measure when considering which measures to promote in HWRs, the total impact of measure classes should be considered since consumers tend to adopt related measures. For example, it might be more fruitful to promote a large measure class that includes many low impact measures over a smaller class of a few high impact measures. HWR content could be organized according to measure classes, for example a report with an Efficient Envelope theme.

CONCLUSIONS

Overall, the WaterSmart program generated approximately 79,477 CCF of residential water savings in Modesto and 88,385 CCF in Riverside during the study period. The Hot WaterSmart program generated an additional 477,004 kWh of direct electricity savings in the residential sector in Riverside. The average infrastructure energy intensity for water delivered in Modesto is 746 kWh/MG, while the average energy intensity in Riverside is 607 kWh/MG. The residential water savings resulted in an additional electricity savings of 44,343 kWh in Modesto's water network and 39,410 kWh in Riverside's water network.

WaterSmart produced greater water savings in Riverside than in Modesto, with overall water use reductions attributed to WaterSmart of 2.2% in Riverside and only 1.5% in Modesto. Reasons for this significant difference are not known. Riverside baseline household water usage was 41% higher than Modesto, which means there may have been a larger margin for households to act upon. However, more research is needed to ascertain exactly what drivers predict how different communities will respond to water conservation programs such as WaterSmart.

Survey research provided many insights into Riverside households' response to the WaterSmart program. We discovered that the program encouraged households to adopt a variety of more efficient irrigation practices and invest in low-flow faucet aerators, high-efficiency showerheads, and high-efficiency toilets. Survey analysis also provided evidence of behavioral spillover from water- to energy-saving measures within the categories of Efficient Envelope, Efficient Appliance, and Edge of Efficiency.

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