Information, Incentives, and Goal-Setting: A Field Experiment in Water Usage*

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Abstract

We report results from a 12-week field experiment in residential water usage. We examine how personalized feedback from smart meters and weekly goals-based incentives from a digital platform affect water-conserving behavior. Our results reveal large, 8% reductions (ITT) in daily water usage in the first month of the trial. Daily conservation effects wane over time but persist within the 3pm-6pm interval throughout the trial. Treatment households accelerating reductions in seasonal outdoor water usage explain the substantial short-run daily conservation effects. We further establish that weekly water usage goals drive within-week water usage dynamics and explore a "last mile" problem in implementing monetary incentives.

Keywords: D83, C93, L95
JEL codes: D83, C93, L95

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1 Introduction

Nudge-based interventions are now standard tools governments and companies use to promote behavioral change.[1] Whether changing handwashing, retirement savings, healthy eating, or exercise, nudges have proven popular, complementing price-based interventions, which can be sensitive politically. Particularly with sustainable resource consumption, an extensive body of research documents a range of nudge-based impacts on resource usage from repeated monthly or quarterly bill-based interventions involving social comparisons (e.g., Allcott, 2011; Ferraro and Price, 2013; Costa and Kahn, 2013; Byrne et al., 2018; Allcott and Kessler, 2019), information provision, (e.g., Allcott and Rogers, 2014; Wichman, 2017; Andor et al., 2022), and conservation tips.

In this paper, we study an intervention in residential water usage that moves from paper, monthly or quarterly bill-based nudges to digital, daily app-based nudges. Section 2 describes the intervention, which centers on the *WaterSaver* app. The app uses 5-minute smart water meter data to give households daily and hourly feedback on their water usage and nudges them through a given week to look at this information. It also incentivizes water conservation through weekly WaterSaver "challenges" involving water usage targets. In particular, households can earn a reward in a given week if they keep their daily average water usage below the target level provided (and visualized on the app). Through a 12-week field experiment involving ≈ 1000 households and a 2×2 research design, we examine the water-conserving impact of providing weekly monetary ($10) and non-monetary (digital badges) rewards and varying the difficulty of challenges in terms of the amount of conservation required to earn a reward (labelled "hard" versus "easy" targets).

We ran the trial in Australia, a setting with communities approaching "Day Zero" with dwindling water supplies. Creating digital utilities and behavioral programs like the one we study is one of the various policies and technologies the government is experimenting with to facilitate climate change adaptation.

Section 3 reports treatment effects induced by the trial. In the trial's first four weeks, we obtain a 24 L/day Intention-to-Treat (ITT) conservation effect from offering WaterSaver to households. The corresponding Local Average Treatment Effect is 47

[1] Examples of "nudge units" include the Behavioural Insights Team (UK), Social and Behavioural Science Team (USA), Impact and Innovation Unit (Canada), NUDGE (Europe), NudgeRio (Brazil), Indlela (South Africa), Behavioural Economics Team (Australia), or The Nudge Unit (Japan).

L/day. Respectively, these estimated savings are substantial at 8% and 15% of daily average water usage. However, beyond the initial month of the trial, the treatment effects at the daily level wane and become statistically insignificant, similar to previous findings with bill-based interventions (Ferraro and Price, 2013).

Leveraging the smart meter data, we refine our analyses to impacts on daily water usage profiles and break down the impact of incentives and goal difficulty on conservation. We show that the large initial treatment effects stem from water conservation between 12 pm and 9 pm. Moreover, we find little difference in conservation effects between providing monetary and non-monterary rewards but a large difference in easier versus harder goals. In short, when we stretch the households with more challenging conservation goals, they can meet the challenge and conservation effects emerge. While the daily treatment effects do not persist, we do find persistent effects under relatively more challenging goals in the final month of the trial. Quantitatively, we estimate a 5 L/day (ITT) daily water savings between 3-6 pm in the last month of the trial, or a 1.6% conservation effect relative to mean daily water usage.

We investigate underlying behavioural mechanisms in Section 4. Here, we document three key sets of results. First, the large immediate impact of the app comes from households reducing their outdoor water usage, namely from lawn and garden watering, pools, and spas/hot tubs. These behaviors emerge in a trial that starts at the end of summer and goes into autumn. In this context, we interpret the app as shifting seasonal water-conserving behaviors from autumn to summer's end as the weather cools and rain starts. An implication of the trial's large initial treatment effects is that the app can expedite seasonal water usage reductions heading into autumn through short, sharp interventions.[2]

Second, we document large, statistically significant differences in goal attainment between our treatment and control groups. Week-to-week, approximately 60% of the households in our treatment groups (compliers and non-compliers) meet their conservation goals. In contrast, just 35% of households in the control group would have (hypothetically) met their goals given their water usage during the trial weeks. These findings further establish behavioral change from the trial. Moreover, goal achievement among the treatment households remains much larger and statistically

[2]Our trial results also suggest high-frequency feedback and rewards can also potentially delay ramping up of water usage when moving from spring into summer. We do not, however, directly test for this behavioral change.

significant from the control households in the final weeks of the trial, further illustrating the persistence of behavioral impacts.

Lastly, we examine why monetary rewards have little impact on generating water conservation. We study one particular channel – reward redemption rates – which illustrates a "last mile" problem with incentives. We implement monetary incentives through $10 gift cards that households can use at major retail outlets nationwide.[3] Households must click a large "redeem" button on the WaterSaver app, and the reward is automatically emailed and texted to them. Yet just 50 % of all $10 rewards earned are eventually redeemed. These results underscore the importance of automatic reward payment, through bill reductions, in implementing digital behavioral programs.[4]

Section 5 summarizes and concludes the paper.

2 The field experiment

This section describes our field experiment, which we ran in partnership is South East Water (SEW), a 750,000 water utility in Melbourne. The experiment centers on a mobile app that provides households with daily water usage information from their smart water meters. In addition, the app provides incentives to reduce their usage through weekly "challenges". We ran the experiment over 12 weeks (involving 12 consecutive "challenges"), from February 27 to May 22, 2022. Piloting, trial recruitment, and baseline data collection ran from November 1 2021, to February 26, 2022.

2.1 WaterSaver app

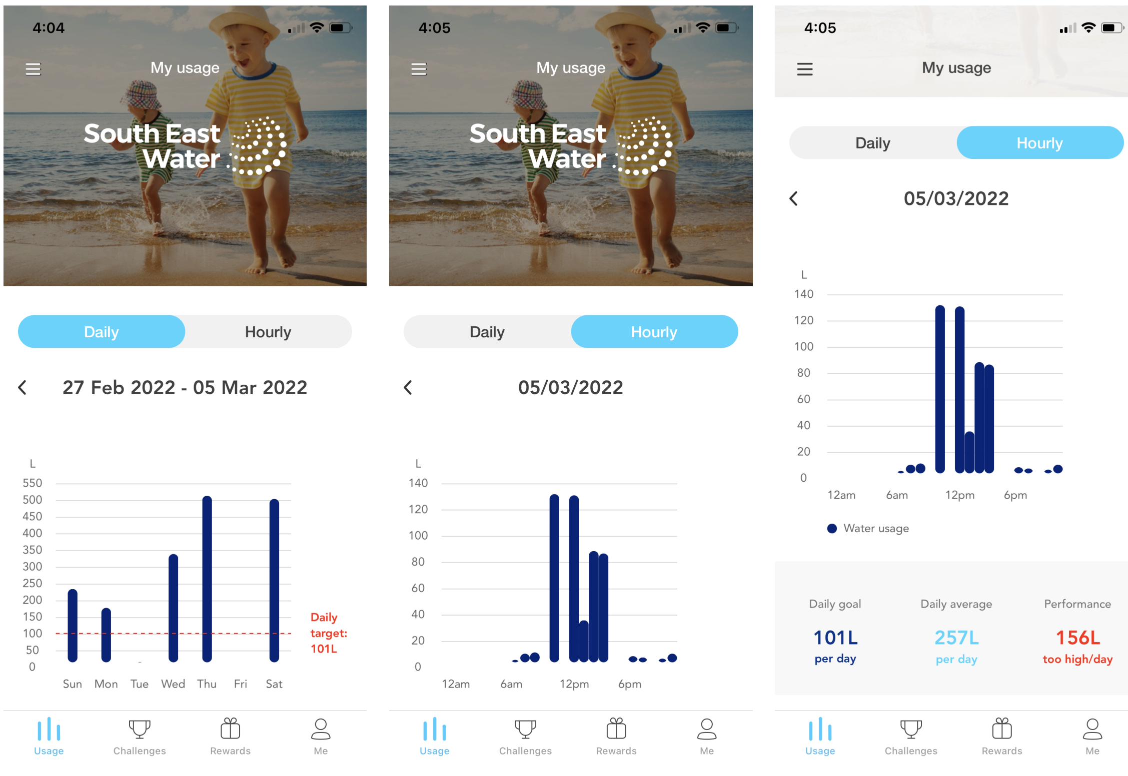
Our trial examines the impact of providing feedback and incentives through the *WaterSaver* app. The app provides feedback by visualizing water consumption data from smart water meters that record household-water usage every 5 minutes. Figure 1 illustrates how the app aggregates and visualizes these data. Panel (a) depicts the app's "Usage" landing screen. By default, this screen plots total daily water usage by day of the current week, starting Sunday and ending Saturday. Panel (b) plots half-

[3] The cards are $10 Woolworths WISH Cards. See https://giftcards.woolworths.com.au/wish/p/wish0001 for details.

[4] Our partner utility does not currently have data warehousing to enable such automatic bill deductions.

Figure 1: WaterSaver App Feedback

(a) Daily Total Water Usage | (b) Half-Hourly Water Usage | (c) How Daily Usage Compares to Target



hourly water usage from the previous day if a user touches the "hourly" tab. These are two key sources of water usage feedback from the app. We emphasize that the information provided in these tabs *do not* include the current day's usage. Presenting real-time information is infeasible with the app and smart meter combination we study.

The app also implements weekly *WaterSaver Challenges* that incentivize water conservation. As mentioned, our field experiment implements 12 consecutive weekly WaterSaver challenges. Table 1 describes the timeline for a given challenge. In short, a challenge starts on Sunday, setting a daily average water usage goal for a household for the upcoming week. The challenge ends the following Saturday, providing the household with a reward if they meet their goal. Panel (a) of Figure 1 highlights an example daily average water usage goal ("target") of 101 L/day. Panel (c) illustrates

Table 1: WaterSaver Challenge Weekly Timeline

	Time	WaterSaver Challenge Activity
Sunday	12:00 am	Challenge begins
	10:00 am	The App nudges the household to inform it about: (1) the outcome of the previous week's WaterSaver challenge; and (2) the upcoming week's challenge, defined by: 1. **Goal**: a households' personalized target daily average water usage level for the week 2. **Incentive**: the household's reward receives if it keeps its daily average water usage below that week's target
Wednesday	7:00 am	SMS text nudges the household to check the WaterSaver app and see how their daily average water usage is tracking against its target
Saturday	11:59 pm	Challenge ends

how scrolling down on the app's screen allows a household to see how their goal and current daily average water usage compare. The example illustrates data for a complete seven-day challenge. The household's 257 L/day consumption level exceeded 101 L/day, meaning it failed to reach its goal.

The app also provided water-saving tips through its Sunday and Wednesday nudges. These tips emphasize common water savings strategies, including taking one-minute shorter showers, ensuring full dishwashers and clothes washers, or using less water for their lawn and garden.

2.2 Design: randomizing goals and incentives

Our field experiment examines how WaterSaver challenge goals ("targets") and incentives ("rewards") affect water consumption. In particular, we implement a 2 × 2 design with the following variations:

- <u>Goals</u>: relative to predicted water usage, to earn a reward, a household must reduce their usage by
  - 3% (easy goal)

– 6% (hard goal)

- Incentives: if a household achieves its goal in a given week, they receive one of two rewards
  - digital badge (non-monetary incentive)
  - $10 gift card (monetary incentive)

Figure 2 depicts the non-monetary and monetary incentives households access by touching the "Rewards" tab at the bottom of the app's screen. Panel (a) shows that the digital badge provides a "Platinum Star" graphic on the app, and panel (b) depicts the $10 gift card. The household must touch a "redeem button" on the app to redeem either reward. Rewards are sent directly to their linked email account as an image (badge) or a digital gift card ($10). The gift cards are redeemable in-store or online at major retail chains across the country, including groceries, department stores, gasoline, and liquor. Households in the monetary reward condition can thus earn up to $120 in gift cards if they meet their WaterSaver goal for 12 consecutive weeks. This total is more than one-third of a typical SEW quarterly water bill. [5]

With goals, the main implementation issue is predicting a household's counterfactual water usage absent the WaterSaver app. One approach to baselining from Burlig et al. (2020) would be to use pre-trial household-level smart meter data to train household-specific machine learning models and forecast each household's water usage over the trial period. Unfortunately, smart meter data was only available for four months before our trial, reflecting that we ran the trial in the early stages of SEW's utility-wide smart meter rollout. Given this data constraint, we take a much simpler 3-step approach to forecasting households' daily average water usage:

1. Using smart meter data, compute household i's average daily water usage from Jan-Feb 2022. Denote this $\bar{y}_i$.

2. Specify a forecast for household i's daily average water usage in month m by:

   Mar: $\hat{y}_{im} = 0.97 \times \bar{y}_i$

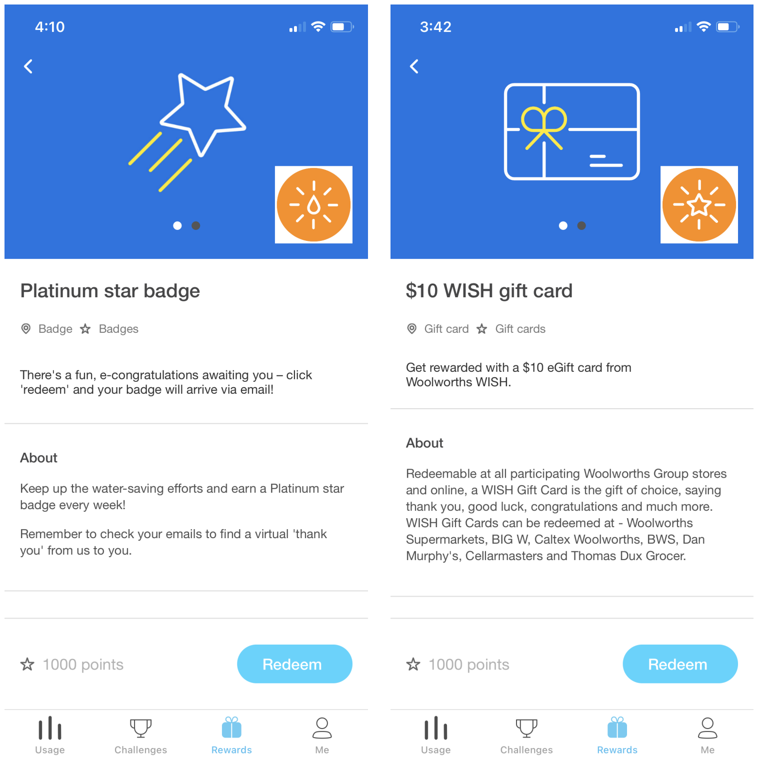
   Apr: $\hat{y}_{im} = 0.88 \times \bar{y}_i$

[5] More ideal would have been to pay the $10 rewards through automatic SEW water bill deductions. Unfortunately, the utility does not currently have integrated smart water meter usage and customer billing data to implement automatic bill deductions.

Figure 2: WaterSaver App Incentives

(a)
Non-Monetary Incentive:
Digital Star Badge

(b)
Monetary Incentive:
Woolworths WISH Card



May: $\hat{y}_{im} = 0.85 \times \bar{y}_i$

where the month-by-month reductions in $\hat{y}_{im}$ relative to $\bar{y}_i$ correspond to trends estimated from historical monthly consumption data from our partner utility from 2010-2021. For instance, relative to January and February, a typical household exhibits 3% reduction in average daily water usage in March each year.

3. Compute the water usage goal for household i in month m as incremental percentage reductions in water usage *beyond* the forecasted seasonal reductions:

Mar: $y^*_{im} = (0.97 - z_1) \times \bar{y}_i$

Apr: $y^*_{im} = (0.88 - z_2) \times \bar{y}_i$

May: $y^*_{im} = (0.85 - z_3) \times \bar{y}_i$

where $\{z_1, z_2, z_3\} = \{0.03, 0.03, 0.06\}$ if i is faces "easy" goals (3% water usage reduction relative to forecasted levels in March and April, 6% in May) and $\{z_1, z_2, z_3\} = \{0.06, 0.06, 0.06\}$ if i faces "hard" goals (6% reduction each month).[6] Week w's WaterSaver challenge goal is set to y^*_{im}, where the start of week w (Sunday) falls in month m.

We calibrate the easy goal based on the state government of Victoria's historical "Target 155" public messaging campaign, which encourages household water usage of 155 L/day per person. Given our partner utility's average water usage of 161 L/day per person, Target 155 involves a 3% water usage reduction, which provides a natural benchmark for our trial.

2.3 Implementation

In total, 7000 unique SEW accounts with smart water metres were emailed between February 2 and 7, 2022 and invited to participate in the trial and complete a baseline survey.[7] 965 (14%) completed the baseline survey and were eligible for the trial.[8]

Next, we constructed our trial groups from the 965 eligible accounts. We randomly chose 135 for our control group. We informed them that we could not provide them with the WaterSaver app due to trial budget constraints. The remaining 815 accounts were randomly allocated to our four main trial groups. The first two columns of Table 2 describe these allocations.[9]

We then emailed households in the experimental groups to download and install the WaterSaver app. After a two-week email campaign to encourage app downloads, we obtained between 101 and 110 downloads across the groups, as illustrated in the third column of Table 2. That is, we had approximately a 50% compliance rate with

[6] We "ramp up" goals in May under both conditions. Doing so allows us to examine whether there are differences in conservation rates in May conditional on facing easier (3% reductions) or harder (6% reductions) goals before May. Intuitively, households previously facing easier goals may face adjustment costs that limit their ability to meet 6% goals in May. In contrast, households with harder goals in March and April may have already adjusted to meet 6% water usage reduction goals in May.

[7] We exclude both hardship accounts and accounts associated with SEW employees.

[8] We obtained this recruitment rate through non-negligible incentives: customers who completed the baseline survey were entered into a draw to win one of 50 $200 Woolworths WISH Cards.

[9] Our pre-trial power calculations based on a within-subject design revealed that we needed approximately 80 participants per experimental condition to detect a 3% water usage reduction (intention-to-treat) with 90% confidence.

Table 2: Experimental Groups, App Downloads, Attrition

Trial Group	Number of Accounts	Downloaded the App	Remaining at End of Trial
1: Easy Goal, Badge	203	110 (54%)	107 (54%)
2: Easy Goal, $10	204	102 (54%)	99 (49%)
3: Hard Goal, Badge	204	107 (54%)	103 (52%)
4: Hard Goal, $10	204	101 (54%)	98 (49%)
5: Control	135		

app downloads. Lastly, there was minimal attrition after the 12-week trial among compliers, as illustrated in the last column of the table. Non-compliers and the control group had similar minimal attrition rates.

2.4 Data

We use four primary data sources to evaluate the behavioural impacts of WaterSaver:

- Water usage: 30-minute level interval data from each (anonymized) household's smart water meter

- Engagement: daily data from Google Analytics on household engagement with the WaterSaver app. These data are the aggregate sum of engagement measures across all households. Unfortunately, individual-level engagement data are not available.

- Surveys: baseline and follow-up survey data on household characteristics and informativeness about water usage. The Appendix lists all baseline and follow-up survey questions and answers.

- Demographics: information on household demographics, where we anonymously match each household to their Australian Bureau of Statistics 'Statistical Area 1' (SA1) census block and assign them their SA1-level demographic data, e.g., annual income, age, education, ethnicity, and so on.[10]

In total, our raw water usage dataset contains 6,499,466 half-hourly observations across the 965 households, spanning 18 January 2022 to 22 May 2022, with the trial

[10] SA1s contain approximately 200 households and are the most narrow census blocks that are publicly available.

starting on 27 February 2022. As mentioned, we use the pre-trial data to construct baseline water usage and forecast individual water usage at the household level.

Table A.1 in the Appendix summarizes how trial participants compare to a representative sample of SEW households. Compared to the representative sample, trial participants: (1) consume more water per year (15% more); (2) are less likely to be a low-income subsidy recipient (33% less likely); (3) are more likely to electronic-billing (28% more likely); and (4) have a higher income (7% higher). Our trial participants tend to be more water-consuming, tech-savvy, and better-off households.

Appendix Table A.2 reports summary statistics across our four experimental conditions and the control group. Overall, the table confirms balance on observables from our random assignment of households to groups.

3 Treatment effects

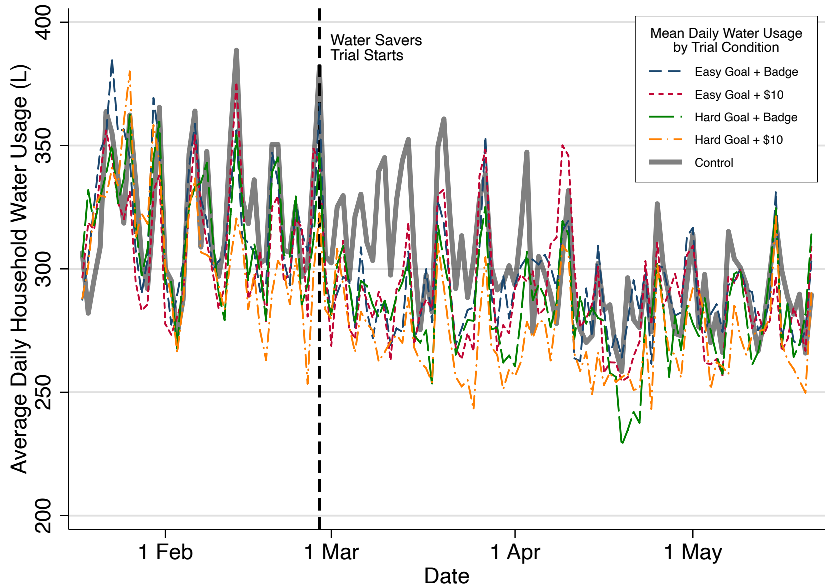
We present the results from the trial in three parts. First, we present visual evidence of trial engagement and its impacts over time. Second, we estimate treatment effects on total daily water usage. Finally, we examine trial impacts on households' hourly consumption profiles.

3.1 Visual evidence

WaterSaver has an immediate and large impact on household water usage. Figure 3 visualizes this result by plotting daily average water usage for each trial group. Before the trial, daily water usage tracks closely between the trial groups and control, further validating our experiment's design and implementation. However, when the trial begins on February 27, there is an immediate drop in daily water usage in the four WaterSaver groups compared to the control. The gap between the control group water usage (in grey) and the WaterSaver groups (in colour) persists for roughly 5 weeks, until April 1. Beyond April 1, Figure 3 shows daily water usage across all five groups converges. This convergence points to WaterSaver having a short-lived impact at the daily level.

Figure 4 provides an initial look into why we see a large initial WaterSaver impact that wanes over time. The figure plots the daily total WaterSaver screen and page views, as well as total user engagements from Google Analytics on a per-household

Figure 3: Daily Mean Water Usage by Trial Condition



basis. The regular spikes in engagement tend to be on Sundays when the app nudges households about the outcome of the previous week's challenge and presents the goals and incentives for the upcoming week's challenge. In the first two trial weeks, households engage with the app between 1 to 4 times per day on average. Six weeks into the trial in April, this engagement rate has converged to 0.5 times per household per day or about 3 times per week.[11]

3.2 Baseline results

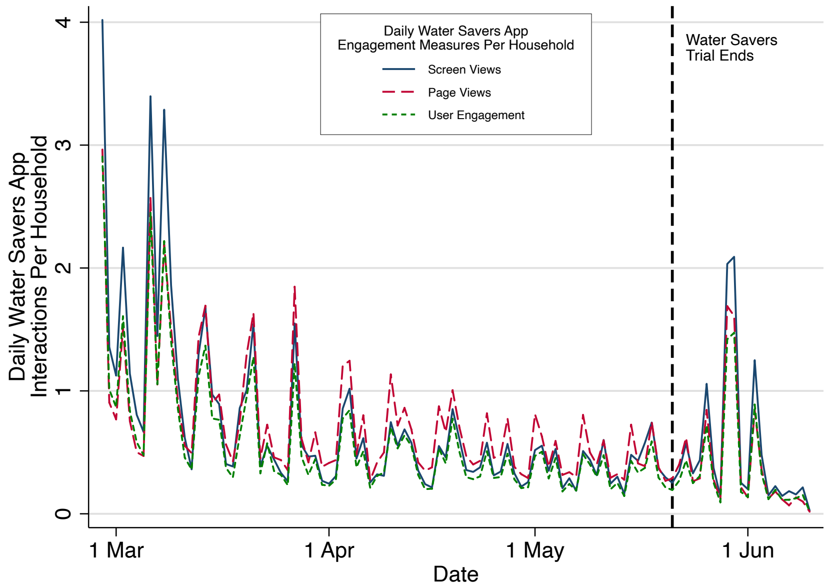
Building from Figure 3, we estimate the impact of WaterSaver on water usage using fixed effects regressions. Equation 5 presents our baseline OLS regression specification, which we work from throughout

$$y_{it} = \beta_0 + \beta_1 1\{WS\}_{it} + \eta_i + \delta_t + \epsilon_{it}, \tag{1}$$

where y_{it} is the water consumption for household i in period t (e.g., t is an individual date or hour), $1\{WS\}_{it}$ is a dummy equaling one if household i has been *offered* the

[11]The spike in engagement after the trial ends reflects our follow-up survey, which reminds households to redeem their rewards before the app shuts down. We return to some of these end-of-trial incentive effects below.

Figure 4: Daily WaterSaver App Engagement from Google Analytics



WaterSaver app on or before period t, η_i and δ_t are household and period fixed effects, and ϵ_{it} is the econometric error. Our coefficient of interest, β_1, measures the impact of *offering* the WaterSaver app to a household on water usage. That is, β_1 captures an Intention-to-Treat (ITT) effect.

We can further estimate the local average treatment effect (LATE) among compliers who *download* the app using the following regression

$$y_{it} = \beta_0 + \beta_1 1\{DownloadWS\}_{it} + \eta_i + \delta_t + \epsilon_{it}, \tag{2}$$

where $1\{DownloadWS\}_{it}$ equals one if household i downloads the WaterSaver app on or before date t. Following Angrist et al. (1996), we can estimate the LATE by estimating equation (2) by 2SLS where we instrument for $1\{DownloadWS\}_{it}$ with $1\{WS\}_{it}$.

Our experiment also allows us to test whether differences in goals and incentives affect water usage. We can identify differential impacts using the following regression

$$\begin{aligned} y_{it} =& \beta_0 + \beta_1 1\{WS\}_{it} + \beta_2 1\{WS\}_{it} \times \{\$10\}_i + \beta_3 1\{WS\}_{it} \times \{Hard\}_{it} \\ &+ \eta_i + \delta_t + \epsilon_{it}, \end{aligned} \tag{3}$$

where $\{\$10\}_i$ is a dummy equaling one if household i has a monetary \$10 gift card incentive for meeting their WaterSaver goal, and $\{Hard\}_i$ equals one if the household faces the "hard" goal of reducing their water usage by 6% relative to predicted levels. In equation (3), β_2 quantifies changes in water usage from having a \$10 gift card incentive relative to a digital badge incentive. The β_3 coefficient quantifies the impact of facing a harder goal relative to the easier 3% water usage reduction goal. We can likewise estimate a LATE from downloading the app based on the specification in (3) by swapping out $1\{WS\}_{it}$ everywhere for $1\{DownloadWS\}_{it}$ and instrument for all the variables with $1\{WS\}_{it}$, $1\{WS\}_{it} \times \{\$10\}_i$, and $1\{WS\}_{it} \times \{Hard\}_i$.

Results

Table 3 reports our ITT and LATE estimates and standard errors clustered at the household level. Both the ITT and LATE estimates of trial impacts in column (1) in the first 4 weeks are substantial. Respectively, the estimates imply 24 L/day and 47 L/day reductions in water usage from being offered and downloading the WaterSaver app. Alternatively, these estimates represent 8% and 15% reductions in daily water usage relative to a mean baseline usage of 305 L/day. The near doubling of the LATE relative to the ITT estimate reflects approximately 50% of households download the app when offered. The estimates in columns (2) and (3) reveal that neither the \$10 gift card nor the hard goal yields statistically significant impacts on daily water usage in the first month of the trial.

A benchmark for these results is the shortly-lived 4.8% reduction in water usage Ferraro and Price (2013) estimate from providing strong social norm comparisons via paper quarterly bills. Comparing our findings and theirs highlights how high-frequency personalized feedback and incentivized goals can enhance short-run water conservation.[12]

Columns (4)-(9) Table 3 confirm the visual evidence from Figure 3: app impacts on water usage drastically wane beyond the first trial month. The \$10 incentive for meeting goals continues to have small, statistically insignificant impacts. In contrast, we find mixed significance in the impact of hard goals with non-negligible coefficient estimates. Given this, we continue to explore differences in goal difficulty on hourly consumption profiles.

[12] A caveat when thinking about scaling utility-wide is uptake into the trial itself, which recall was 14% with additional uptake incentives.

Table 3: Balance Trial Impact Estimates

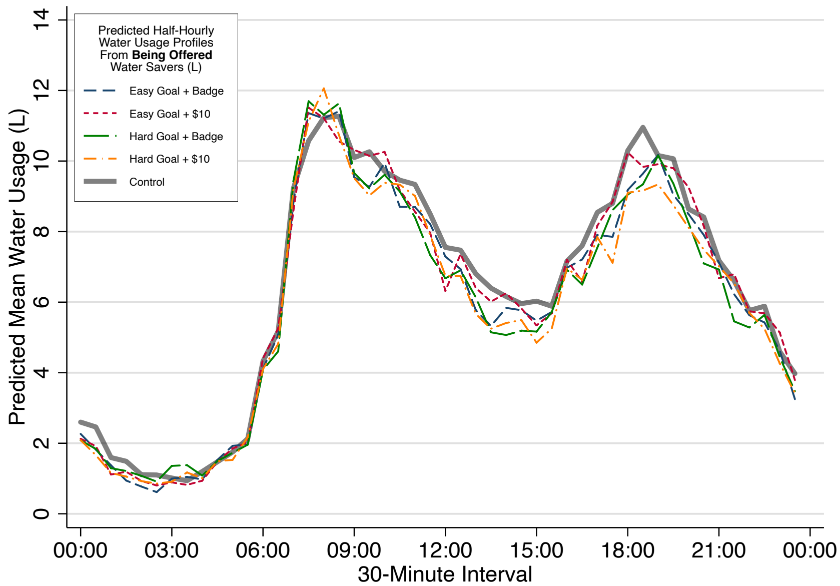
	Trial Weeks 1-4			Trial Weeks 5-8			Trial Weeks 9-12		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel (a): Intention-to-Treat Effects (L/Day)									
Offered WS	-24.09**	-24.72**	-21.56*	-3.26	-4.68	4.27	1.86	0.31	4.04
	(12.16)	(12.41)	(12.45)	(11.92)	(12.33)	(12.44)	(12.54)	(13.07)	(13.03)
Offered WS + \$10		1.24			2.81			3.08	
		(5.69)			(6.75)			(8.14)	
Offered WS + Hard Goal			-5.07			-15.06**			-4.38
			(5.69)			(6.74)			(8.14)
R-Squared	0.481	0.481	0.481	0.457	0.457	0.457	0.453	0.453	0.453
Observations	62753	62753	62753	62276	62276	62276	62559	62559	62559
Panel (b): Local Average Treatment Effects (L/Day)									
Downloaded WS	-46.93**	-46.27**	-41.56*	-6.36	-8.74	8.21	3.63	0.59	7.78
	(23.75)	(23.32)	(24.08)	(23.23)	(23.05)	(23.93)	(24.45)	(24.41)	(25.05)
Downloaded WS + \$10		-1.36			4.95			6.33	
		(11.80)			(13.38)			(16.09)	
Downloaded WS + Hard Goal			-10.89			-29.53**			-8.44
			(11.60)			(13.18)			(15.93)
R-Squared	-0.005	-0.005	-0.005	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Observations	62753	62753	62753	62276	62276	62276	62559	62559	62559

Notes: Dependent variable is daily household water usage, which has a baseline mean of 305 L/day (s.d. = 226 L/day). All regressions include household and date-fixed effects. Standard errors clustered at the household level in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively.

3.3 Daily consumption profile impacts

The smart meter data allows us to examine impacts on hourly consumption profiles. For brevity, we focus on ITT estimates throughout; LATE estimates are roughly double the magnitude of the ITT effects. Figure 5 provides initial visual evidence of daily water usage profile effects. To construct the figure, we estimate (5) for each half-hour interval (so, 48 regressions in total) and interact $1\{WS\}_{it}$ with dummies for the four experimental groups. We plot the mean usage for each interval within our sample period for the control group (in grey). We then add the 48 coefficients from the regressions to the control group's mean usage and plot the adjusted means

Figure 5: Water Usage Profiles Across Trial Conditions and Control



for each of the four experimental conditions.[13]

The midday "belly" in the colored lines in the plot relative to the control group suggests that WaterSaver induces conservation effects primarily during the day and early evening, specifically between 12 noon and 6 pm. In the very early (12 am - 6 am) and late (9 pm - 12 am) hours of the day, we unsurprisingly find no differences in usage between the control and experimental groups. However, we also find surprisingly little evidence of conservation effects between 6 am and 9 am. As mentioned, the app emphasizes shorter showers as an effective strategy, and feedback on shower water usage can drastically reduce water usage (Tiefenbeck et al., 2018). The patterns in Figure 5, however, indicate that salience-enhancing feedback from the app, but not real time, is ineffective in reducing morning shower water usage. When examining mechanisms, we return to this and other behaviors in Section 4 below.

[13]For clarity in visualizing the consumption profiles, we ignore, for the moment, confidence intervals.

Estimating impacts on consumption profiles

Motivated by Figure 5, we estimate treatment effects by the time of day using regressions that predict household i water usage in a half-hour interval t

$$y_{it} = \beta_0 + \sum_{j=1}^{4}\sum_{k=1}^{8} \beta_{jk} 1\{WS\ Group\ j\}_{it} \times 1\{3\ Hr\ Window\ k\} + \eta_i + \delta_t + \epsilon_{it}, \quad (4)$$

where $1\{WS\ Group\ i\}_{it}$ equals one of if household i is assigned to experimental group j and $1\{3\ Hr\ Window\ k\}$ if half-hour period t falls within three-hour time window k. We allow for eight windows in total: 12am–3am, 3am–6am,. . .,9pm–12am. The coefficients in (2) allow us to assess profile effects by experimental condition and part of the day.[14] In light of our findings of waning treatment effect over time, we report profile effects for the first and last four weeks of the trial.

Figure 5 presents the profile effects. Comparing the left and right columns of the figure, we again see consistently large treatment effects from the first four trial weeks and noisier, smaller effects in the last four weeks. Consistent with the visual evidence in Figure 5, these effects primarily exist between the 9am-12pm and 6pm-9pm intervals.

Comparing the top four and bottom four panels ((a)-(d) vs. (e)-(h)) illustrates the impact of setting easy versus hard goals. In short, we consistently obtain larger-magnitude treatment effects under hard goals. As we will see in Section 4 below, this stems from households achieving their goals in these groups at similar rates. In effect, hard goals “stretch” households to achieve higher levels of conservation without discouraging them.

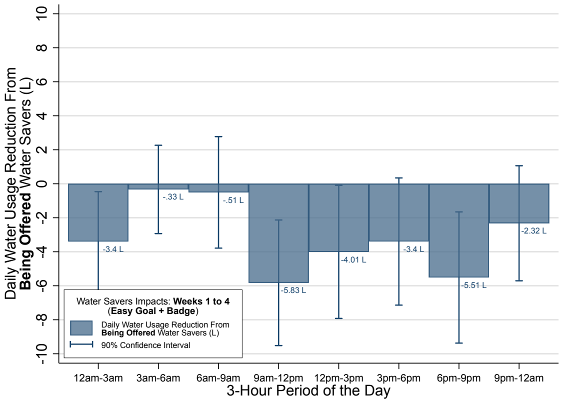
Finally, focusing on the right column of the figure, we obtain a consistent conservation effect in the 3pm-6pm interval in the last four weeks of the trial. Under hard goals, these effects are statistically significant and imply a 4.6 L/day conservation effect.[15] This estimate corresponds to a 1.5% reduction in daily water usage relative to the control group’s mean of 305 L/day. It illustrates how the trial induces persistent behavioral change beyond the first four weeks. However, aggregated daily data mask these effects.

[14] We have estimated treatment effects at hourly and 30-minute levels. They align with the findings based on three-hour time windows and do not offer any additional insight.

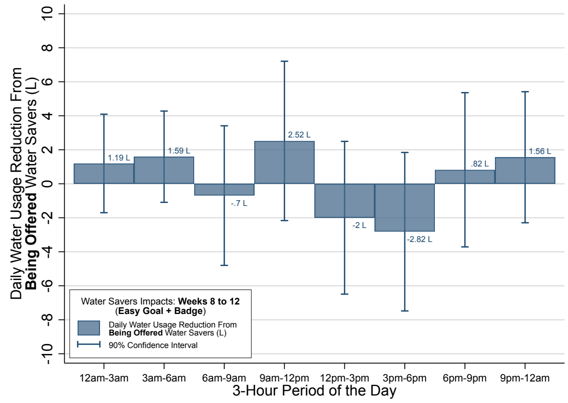
[15] This is the point estimate and significance of the coefficients if we pool the hard goal conditions.

Figure 6: WaterSaver Impacts on Daily Consumption Profiles

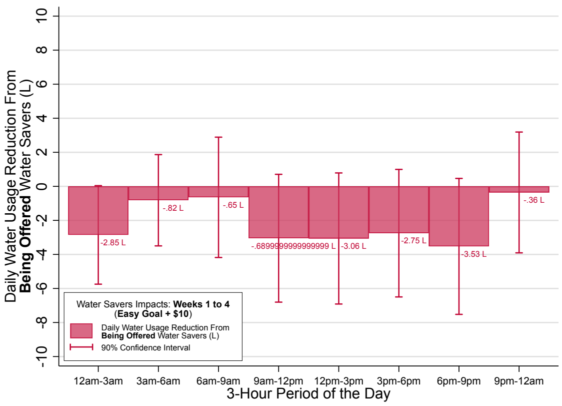
(a) (Badge + Easy Goals) - Weeks 1-4



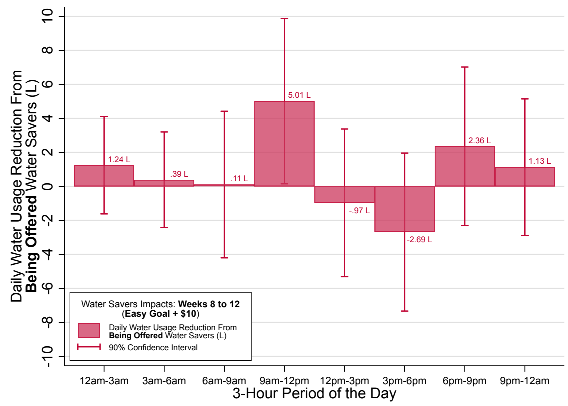
(b) (Badge + Easy Goals) - Weeks 9-12



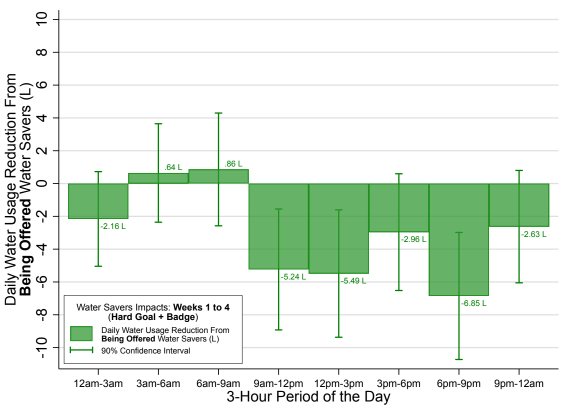
(c) ($10 + Easy Goals) - Weeks 1-4



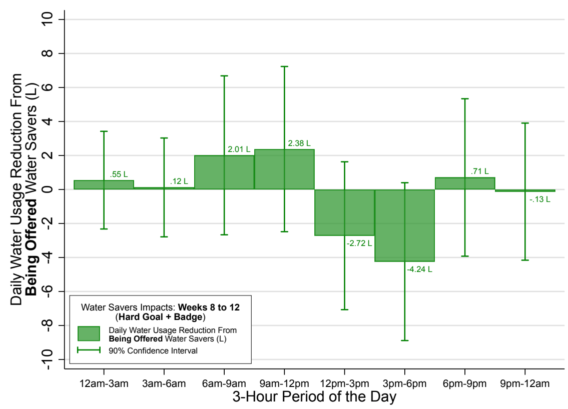
(d) ($10 + Easy Goals) - Weeks 9-12



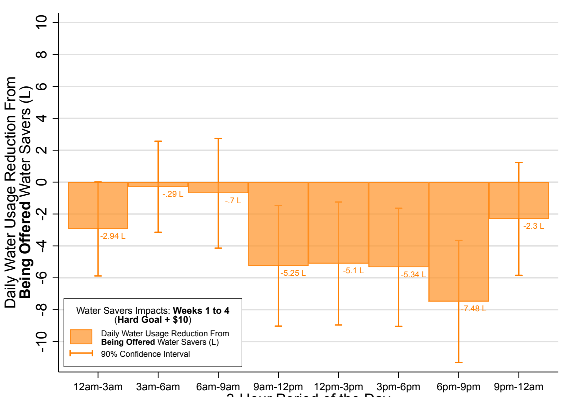
(e) (Badge + Hard Goals) - Weeks 1-4



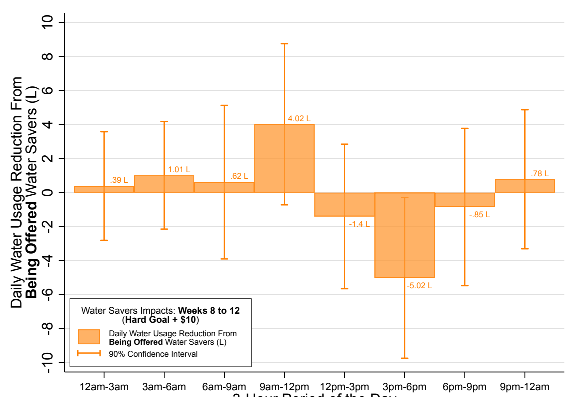
(f) (Badge + Hard Goals) - Weeks 9-12



(g) ($10 + Hard Goals) - Weeks 1-4



(h) ($10 + Hard Goals) - Weeks 9-12



Notes: Regression coefficients from equation (4) and 90% confidence intervals plotted. All regressions include household and date fixed effects. Standard errors clustered at household level are reported in parantheses. Statistical significance at the 1%, 5%, and 10% level is indicated by *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively.

4 Behavioral mechanisms

In this section, we document behaviors undertaken by households to reduce their water usage in response to the trial. We also study how households engage daily with WaterSaver to meet their weekly goals and redeem incentive payments.

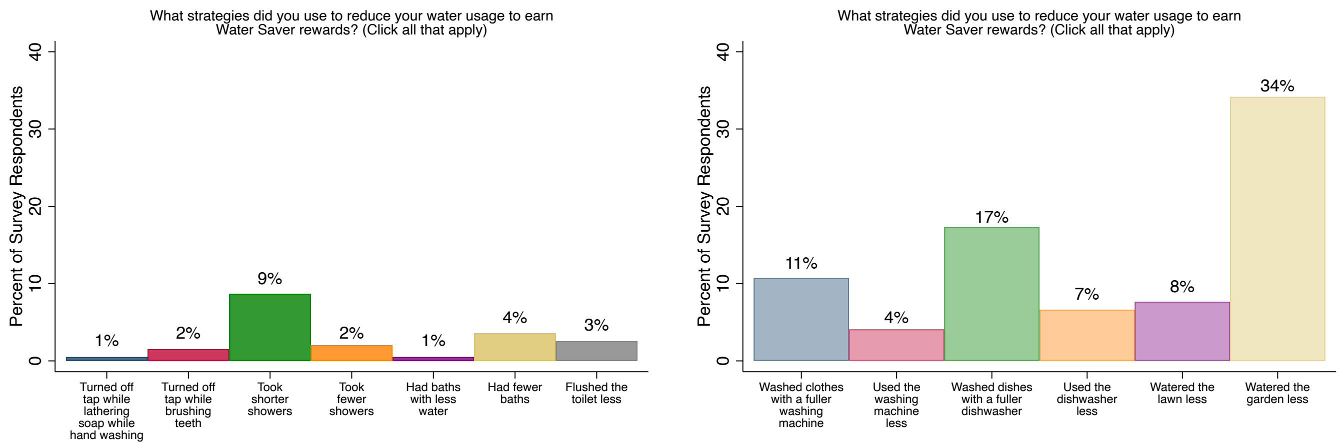
4.1 Survey evidence

The most direct evidence we have on water-conservation behaviors comes from asking customers. In our follow-up survey, we ask *What strategies did you use to reduce water usage to earn WaterSaver rewards?*[16] Households chose from 13 water-saving strategies, where they are allowed to choose multiple strategies. Figure 7 summarizes the survey responses. The substantial share of households reporting reduced garden watering (34%) points to the large, short-run WaterSaver impacts from households cutting back on their outdoor water usage. There is scope to do so in March, when the trial begins, as households move from summer into autumn in Melbourne. The weather becomes wetter, allowing households to reduce external water usage without killing their lawns and plants. Our substantial week 1-4 estimates of WaterSaver's impacts and self-reported water-saving strategies suggest WaterSaver accelerates households' seasonal reduction in water usage between summer and autumn. Waning treatment effects over time reflect the control group stopping to water their gardens in autumn toward winter as the weather gets cooler and wetter.

Other relatively important water-saving strategies - fuller dishwasher (17%), fuller washing machine (11%), shorter showers (9%) – can also contribute to the large, short-run water conservation impacts of WaterSaver. However, unlike outdoor water usage, which is highly seasonal, these behaviours are less likely to exhibit significant seasonal trends. They can also potentially explain the persistent 4.6 L/day water usage reduction between 3-6pm in trial weeks 9-12 under hard goals.

[16] We asked customers this question in our follow-up survey of 407 customers in trial groups 1-4 who downloaded the app and did not drop out of the trial. 202 (49%) of these customers completed the survey. As with the baseline survey, we offered survey response incentives with the follow-up survey. Specifically, we offered customers a chance to win one of 10 $200 Woolworths WISH cards if they completed the follow-up survey. Appendix ?? contains the follow-up survey questions and answers.

Figure 7: Self-Reported Water Usage Strategies to Meet WaterSaver Goals



4.2 Treatment effect mediators

We complement the survey results by documenting how treatment effects vary with baseline water usage behaviors. Our baseline survey (reproduced in Appendix B.1) has all households in our sample report 11 aspects of their appliance stock and home (e.g. if they have a lawn). We modify our baseline regression as follows to examine how WaterSaver treatment effects (ITT) vary with a particular characteristic

$$y_{it} = \beta_0 + \beta_1 1\{WS\}_{it} + \beta_2 1\{WS\}_{it} \times 1\{Char\}_i + \eta_i + \delta_t + \epsilon_{it}, \tag{5}$$

where $1\{Char\}_i$ equals one if a household has a particular water-consuming characteristic. The coefficient of interest, β_2, reveals whether a given characteristic mediates the WaterSaver treatment effect.[17]

Table 4 presents β_2 mediated treatment effect estimates for each characteristic. All estimates are from a sample including our control and households with hard goals, with panels (a) and (b) reporting estimates for trial weeks 1-4 and 9-12, respectively. Panel (a) reveals that households with rainwater tanks, pools, and spas (hot tubs) are the key drivers of short-run feedback effects from the trial.[18] Households with extreme water usage appliances and the ability to use rainwater instead of SEW–supplied water appear best positioned to meet their water usage goals.[19]

[17]Still to develop: mediation analysis in the spirit of the, e.g., Gelbach (2016) decomposition.
[18]We find similar results from households with "Easy" goals.
[19]We did not offer potential survey responses to pool and spa water usage in our follow-up survey,

Table 4: WaterSaver Daily Treatment Effect Mediators – Appliance Stock

	High Flow Shower (1)	Dual Flush Toilet (2)	Top Loading Washer (3)	Balcony Garden (4)	Lawn (5)	Vegetable Garden (6)	Native Plants (7)	Drip Irrig. (8)	Rain Tank (9)	Pool (10)	Spa (11)
Panel (a): Intention-to-Treat Effects (L/Day), Trial Weeks 1-4, Hard Goals Conditions											
WS Base Effect	-11.01*	-1.43	-9.98*	-13.15**	-6.89	-8.09	-11.70*	-10.58*	-5.13	-9.72	-9.00
	(5.88)	(13.35)	(5.92)	(6.12)	(8.33)	(5.68)	(6.04)	(5.95)	(5.58)	(5.91)	(5.54)
WS Interactive Effect	-7.47	-11.42	-8.48	5.14	-8.14	-11.19	-2.14	-13.52	-25.70**	-26.39**	-65.62*
	(12.65)	(13.35)	(10.41)	(8.83)	(8.58)	(9.15)	(10.00)	(11.43)	(10.81)	(11.87)	(34.83)
R-Squared	0.483	0.482	0.482	0.479	0.479	0.479	0.480	0.479	0.480	0.479	0.480
Observations	75160	75324	75406	75078	75160	75078	75160	75078	75242	75078	75078
Panel (b): Intention-to-Treat Effects (L/Day), Trial Weeks 9-12, Hard Goals Conditions											
WS Base Effect	-5.21	15.38	-2.76	-7.09	9.27	-2.83	-5.23	-5.87	-4.05	-6.86	-3.63
	(7.42)	(19.94)	(7.74)	(7.56)	(11.99)	(8.31)	(7.72)	(7.23)	(7.54)	(7.41)	(7.06)
WS Interactive Effect	-15.67	-24.37	-17.88	0.07	-25.69**	-11.29	-6.93	-9.63	-11.23	-2.21	-68.02*
	(15.62)	(20.20)	(12.84)	(14.80)	(12.46)	(11.26)	(13.21)	(20.79)	(13.41)	(17.44)	(38.19)
R-Squared	0.444	0.444	0.444	0.443	0.443	0.443	0.443	0.443	0.444	0.443	0.443
Observations	75396	75578	75646	75314	75397	75314	75397	75314	75480	75314	75314

Notes: Dependent variable is daily household water usage, which has a baseline mean of 305 L/day (s.d. = 226 L/day). All regressions include household and date-fixed effects. Standard errors clustered at the household level in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by *** $p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively.

With cooling weather from summer to autumn, pools are a particularly season-based appliance that can enable early conservation in the trial. As control households stop using pools into autumn, they start looking more like treatment households whose reduction in pool water usage was accelerated in weeks 1-4 of the trial. Consistent with this interpretation, panel (b) shows pools no longer mediate treatment effects by weeks 9-12 of the trial. In contrast, spas (hot tubs) and lawn-based water usage mediate treatment effects in weeks 9-12, both continuing through winter.

4.3 Achieving goals

The survey and experimental evidence on behaviors and trial effects point to WaterSaver inducing genuine behavioral change. Yet, as with all goals-based trials, there is the concern that we pay households who, for idiosyncratic reasons: (1) have high baseline usage before the trial; or (2) have abnormally low usage during the trial (e.g., they go on vacation). In this pessimistic scenario, WaterSaver rewards people based on shocks to individual circumstances, not for behavioral change.

which is why we do not see these self-reported behaviors in Figure 7 above.

Figure 8: WaterSaver Impacts Goals Success Rates

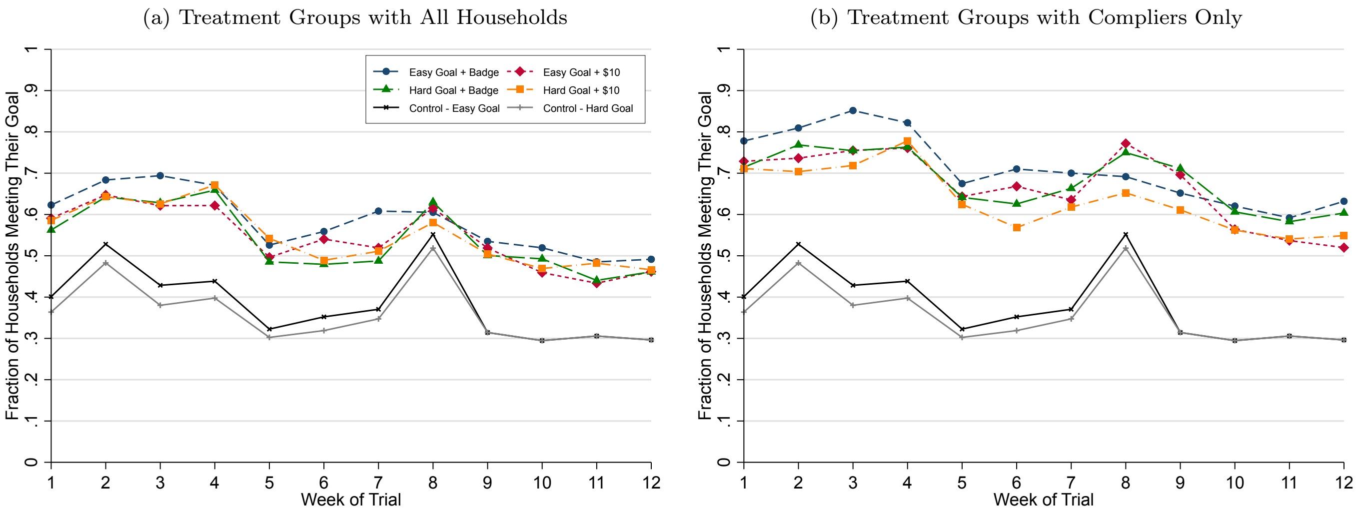


Figure 8 provides evidence that households indeed change their behavior with WaterSaver to achieve goals. Panel (a) plots the share of households achieving their water usage goal each week across the treatment and control groups. For the treatment groups, we compare households' actual water usage to their goal, depending on whether they face easy or hard goals.[20] Panel (a) shows goal success rates initially range between 60 and 70% in trial groups 1-4 at the start of the trial. These rates gradually fall to around 50% by the end of the trial. Auxiliary regressions confirm no statistical differences in weekly goal success rates across treatment groups.

There are, however, large differences in goal success rates between treatment and control. As with non-compliers, we compute goal success rates for our control group by comparing households' actual water usage to what their goals would have been under our easy and hard goals specifications. Throughout the trial, the success rate for control households would have been between 30% and 50%. These rates are well below those of treatment households. We confirm these differences are statistically significant below.

Panel (b) is analogous to Panel (a), except it plots goal success rates for compliers only (e.g., treatment households who selected into downloaded the app). We find even higher success rates, ranging from 70-80% of treatment households achieving goals early in the trial, falling to 50-60% by the end of the trial. These success rates are, however, well-above above those of the control group, again pointing to WaterSaver inducing genuine behavioral change.

[20]Importantly, this includes both compliers who downloaded the app *and* non-compliers who did not. We can compute the hypothetical easy and hard goals for the latter households from their baseline water usage. With these hypothetical goals, we can examine their success rate as if they had downloaded the app.

Dynamics of reaching goals within weeks

The high-frequency consumption and goals data allow us to examine how households' average daily water usage evolves day-to-day, and the influence of WaterSaver goals throughout the week. To identify these dynamics, we estimate the following linear probability model

$$1\{\text{success}\}_{it} = \beta_0 + \sum_{j=1}^{6} \left[\beta_j(1\{\text{dow}_j\} \times 1\{WS\}_{it}) + \delta_j 1\{\text{dow}_j\}\right] + \epsilon_{it}, \tag{6}$$

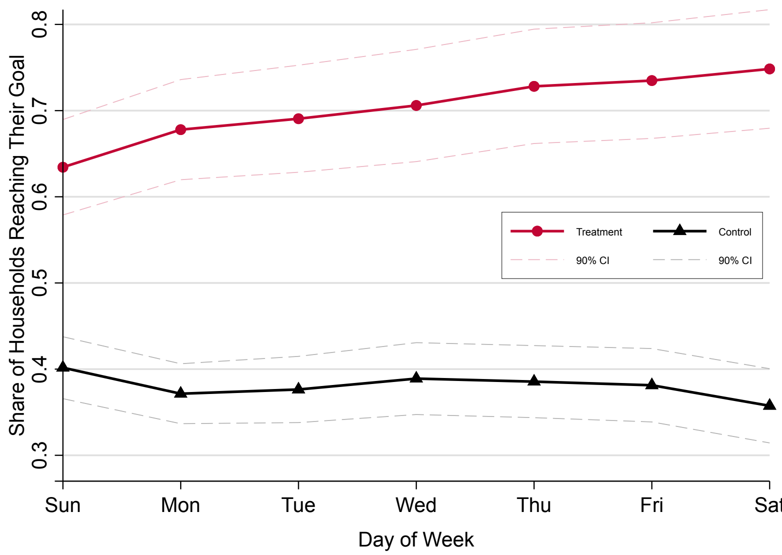
where δ_j quantifies the goal success rate among the control group on day of week j and β_j is the increase in this rate among households with the WaterSavers app. We estimate (6) separately for easy and hard goals. For the former, we include households in treatment conditions 1 (easy goals + badge) and 2 (easy goals + \$10) and control households under easy goals. For hard goals, we instead include households under treatment conditions 3 (hard goals + badge) and 4 (hard goals + \$10) with control households under hard goals. We focus on the LATE of WaterSaver on goals success and not the ITT effect because we are interested in establishing app-induced dynamics in goal attainment. So, we estimate (6) by 2SLS, with $1\{\text{dow}_j\} \times 1\{\textit{Download WS}\}_{it}$ for $j = 1, \ldots, 6$ as the variable of interest, instrumentign with $1\{\text{dow}_j\} \times 1\{WS\}_{it}$ for $j = 1, \ldots, 6$.

Figure 9 presents our dynamic goal attainment results from Sunday to Saturday, per the WaterSaver challenge design.[21] Two key findings stand out. First, the level differences in goal attainment between treatment and control are large and statistically significant, in-line with Figure 8. Second, there is a distinct contrast in the time path of goal attainment rates during WaterSaver challenges. For the control group, the path is flat. This pattern establishes that there are no confounding within-week changes in water consumption that could otherwise be construed as goals-driven dynamics.

In stark contrast, there is a clear upward trend in goal attainment for households with WaterSaver. For example, at the start of a challenge on Sundays, households have already adjusted behavior such that 63% have average daily water usage below their weekly target level. However, this rate gradually rises throughout the week

[21] We focus on goal success rates among hard goals for brevity. Figure 8 above shows little difference between hard and easy goals regarding success rates. Statistically, they are indistinguishable.

Figure 9: Impact of WaterSavers on Goals Achievement by Day of Week



to 76% by the end of the challenge on Saturday, a 13 pp (or 20%) increase in the goal success rate that is statistically significant ($p < 0.05$) compared to Sunday's success rate. This dynamic, particularly when compared to the control group, further illustrates that weekly WaterSaver information and incentives induced households to pursue their goals.

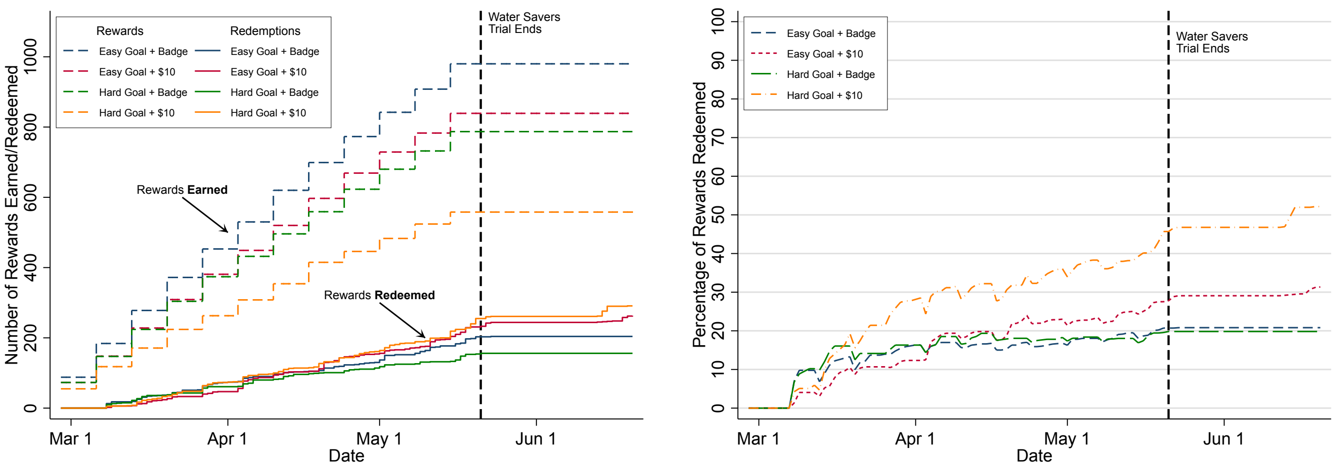
4.4 Redeeming incentives

In this final section, we examine a potential reason the $10 gift card is ineffective in inducing conservation. In developing the trial with our partner utility, the belief was that a $10 per week incentive was economically large and would thus matter.

There are, of course, various potential explanations for why the (near) cash incentive had little impact. Our reward redemption data sheds light on one particular mechanism, reflecting a "last mile" problem with incentives. We illustrate this problem in Figure 10. Panel (a) plots the cumulative number of rewards we should have paid out in each trial group over time (dashed lines) and redeemed rewards (solid line). To take a specific example, households in the Easy Goal + Badge group earned nearly 1000 rewards total, yet only 200 were redeemed.[22]

[22]Recall from Figure 2 above, to redeem a reward, a household must click the "redeem" button under the rewards tab on the WaterSaver app.

Figure 10: WaterSaver Rewards Generated and Redeemed by Trial Group



Panel (b) builds from panel (a) and plots the share of rewards redeemed over the trial. We find households redeem nearly 50% of $10 rewards under the hard goal condition and 30% under easy goals, a statistically significant difference ($p < 0.01$). In stark contrast, households redeem just 20% of the digital badges under either hard or easy goals (a statistically insignificant difference). These lower redemption rates are statistically different from the higher redemption rates with $10 rewards. These results illustrate that money indeed matters. However, the redemption rates under $10 rewards are far from 100%, illustrating how small effort costs in clicking an app's button to claim $10 rewards hinder uptake. Such small costs potentially undermine the effectiveness of monetary rewards in incentivizing households to achieve their goals and reduce water usage.

5 Conclusion

We have reported results from a field experiment in water usage that moves beyond bill-based nudges to smart meter and app-enabled daily nudges and incentives for conservation. Our intervention delivers substantial, 8% (ITT) daily conservation effects in the trial's first month that wane over time. However, higher frequency data reveal conservation effects throughout the trial between 3 and 6 pm.

Our examination of underlying behavioral mechanisms highlights how our intervention shifts seasonal water usage. In particular, it accelerates treatment households' reductions in outdoor water usage when moving from summer into autumn. We also establish our weekly goals-based implementation for incentives anchor and affect within-week consumption dynamics. Lastly, we find significant friction in households' ability to redeem cash-like rewards despite needing only to touch a button to redeem them. We view this finding as underlining automatic reward payment to incentivize behavioral change.

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For Online Publication

A Supplemental figures and tables

Table A.1: Selection - Summary Statistics for Representative and Trial Samples

	Random Sample of Accounts	Accounts with Smart Shower Metres	Diff. (2)-(1)	Accounts in Water Saver Trial	Diff. (4)-(1)	Diff. (4)-(2)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2021-22 Water Usage (KL)						
Annual	151.20	175.58	24.38***	181.49	30.29***	5.91
Quarter 1	32.74	36.33	3.60***	38.20	5.46***	1.87*
Quarter 2	36.54	42.77	6.23***	44.42	7.87***	1.65
Quarter 3	44.84	51.57	6.73***	52.26	7.42***	0.69
Quarter 4	37.08	44.90	7.82***	46.62	9.53***	1.72
Panel B: Account Characteristics						
Percent of accounts classified as ...						
Owner occupier	75.99	73.85	-2.14**	79.93	3.94**	6.08***
Concession	22.08	14.75	-7.33***	18.21	-3.87**	3.64***
Electronic billing	52.25	66.88	14.64***	76.29	24.04***	9.41***
SEW portal users	39.59	47.35	7.75***	55.60	16.01***	8.25***
Panel C: Demographics						
Average weekly income ($)	623.79	669.04	45.25***	666.56	42.77***	-2.48
Average age	53.35	49.98	-3.37***	51.23	-2.12***	1.25**
Percent with higher education	20.02	21.51	1.49***	21.46	1.44**	-0.05
Percent employed	39.01	42.73	3.72***	42.71	3.70***	-0.02
Percent with children	65.24	61.73	-3.52***	62.04	-3.20***	0.31
Average number of rooms in home	2.95	2.86	-0.09***	2.87	-0.08***	0.01
Observations	8613	7063		965		

Notes: Statistical significance of the difference in means at the 1%, 5%, and 10% level is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, respectively. Demographics correspond to those from an account's ABS Statistical Area 1 census block level. All other variables are at the individual account-level.

Table A.2: Balance - Summary Statistics Across Trial Groups

	Control	Group 1 Easy Badge	Diff. (1)-(2)	Group 2 Easy \$10	Diff. (1)-(4)	Group 3 Hard Badge	Diff. (1)-(6)	Group 4 Hard \$10	Diff. (1)-(8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 2021-22 Water Usage (LL)									
Annual	185.58	186.70	-1.12	183.14	2.44	173.90	11.68	176.26	9.32
Quarter 1	38.09	39.96	-1.87	37.86	0.22	36.55	1.53	37.49	0.60
Quarter 2	44.76	46.42	-1.66	44.40	0.37	42.20	2.57	43.55	1.22
Quarter 3	53.34	53.33	0.02	53.53	-0.18	51.13	2.21	49.83	3.51
Quarter 4	49.39	46.99	2.40	47.35	2.03	44.01	5.37	45.39	3.99
Panel B: Account Characteristics									
Percent of accounts classified as ...									
Owner occupier	78.12	79.41	-1.29	78.90	-0.78	77.31	0.81	85.71	-7.59
Concession	21.88	18.91	2.97	17.72	4.15	21.01	0.87	12.18	9.69*
Electronic billing	75.00	73.53	1.47	78.48	-3.48	79.83	-4.83	74.79	0.21
SEW portal users	51.25	55.46	-4.21	58.65	-7.40	58.40	-7.15	52.52	-1.27
BPAY payment	48.75	45.80	2.95	34.60	14.15**	44.12	4.63	46.22	2.53
Credit card payment	34.38	39.50	-5.12	43.88	-9.51	32.77	1.60	38.66	-4.28
Debit card payment	13.12	11.34	1.78	16.88	-3.75	16.81	-3.68	12.61	0.52
Other payment	3.75	3.36	0.39	4.64	-0.89	6.30	-2.55	2.52	1.23
Panel C: Household Characteristics									
Number of family members	2.83	3.00	-0.17	2.87	-0.04	2.88	-0.05	2.90	-0.07
Percent with toddlers	86.57	79.00	7.57	80.20	6.37	86.14	0.43	84.31	2.25
Percent with child 5-12	77.61	71.92	5.69	75.88	1.73	73.50	4.11	76.85	0.76
Percent with teenager 13-18	79.55	78.11	1.44	79.60	-0.06	82.00	-2.45	79.90	-0.36
Panel D: Demographics									
Average weekly income (\$)	654.47	661.75	-7.28	679.17	-24.69	682.67	-28.20	644.77	9.70
Average age	50.54	51.22	-0.68	52.37	-1.84	49.95	0.58	51.64	-1.11
Percent with higher education	19.76	19.84	-0.08	22.61	-2.85	23.32	-3.55*	21.08	-1.32
Percent employed	41.20	42.69	-1.49	43.14	-1.94*	43.90	-2.70**	41.93	-0.73
Percent with children	64.01	62.93	1.08	62.08	1.93	59.67	4.34*	62.48	1.53
Average number of rooms in home	2.91	2.91	-0.00	2.85	0.05	2.79	0.11*	2.90	0.01
Panel E: Applicances									
Percent of accounts with ...									
High flow shower	11.45	8.87	2.58	5.47	5.98	7.43	4.02	11.22	0.23
Dual flush toilet	90.23	89.66	0.57	91.00	-0.77	91.13	-0.91	91.22	-0.99
Top loading washer	33.08	32.51	0.57	32.84	0.25	21.67	11.41*	26.34	6.74
Balcony garden	20.30	10.84	9.46*	15.66	4.64	17.73	2.57	14.22	6.09
Lawn	63.91	68.47	-4.56	67.17	-3.26	61.08	2.83	66.83	-2.92
Vegetable garden	30.83	36.45	-5.63	39.39	-8.57	37.44	-6.61	38.73	-7.90
Drough-resistant plants	22.56	23.65	-1.09	26.13	-3.57	22.17	0.39	23.53	-0.97
Drip irrigation system	11.28	8.87	2.41	14.65	-3.37	13.30	-2.02	13.73	-2.45
Pool	9.77	8.37	1.40	8.59	1.19	9.36	0.41	10.29	-0.52
Spa	6.02	5.42	0.60	4.04	1.97	3.94	2.07	6.37	-0.36
Rainwater tank	21.80	21.18	0.62	23.00	-1.20	26.11	-4.30	29.41	-7.61
Panel F: Baseline behaviours									
Percent of accounts that rarely or never ...									
Turn off water lathering hand soap	60.45	48.77	11.68*	43.28	17.16**	52.71	7.74	53.17	7.28
Turn off water brushing teeth	10.45	17.24	-6.79	6.97	3.48	11.33	-0.88	13.17	-2.72
Wash clothes washer with a full load	1.50	2.46	-0.96	2.50	-1.00	1.97	-0.47	2.94	-1.44
Wash dishwasher with a full load	3.82	1.00	2.82	2.49	1.33	0.49	3.32	4.41	-0.59
Self-reported shower length (minutes)	6.33	6.53	-0.20	6.40	-0.07	6.35	-0.02	6.53	-0.20
Observations	132	203		204		203		205	

Notes: Statistical significance of the difference in means at the 1%, 5%, and 10% level is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, respectively. Demographics correspond to those from an account's ABS Statistical Area 1 census block level. All other variables are at the individual account-level. Household characteristics, appliance, and baseline behaviours are from the baseline survey.

B Survey questions

B.1 Baseline Survey

1. Do you have a mobile device, and if so, which type is it?
   [Android, iPhone, Other, No]
2. How many people currently live in your home?
   [1, 2, 3, 4, 5, 6+]
3. Do you or a member of your household work for South East Water?
   [Yes, No]
4. Do you have any household members who are babies or toddlers under the age of 5?
   [Yes, No]
5. Do you have any household members who are children between the ages of 5 and 12?
   [Yes, No]
6. Do you have any household members who are teenagers between the ages of 13 and 19?
   [Yes, No]
7. Do you have any plans of moving homes in the coming three months?
   [Yes, No]
8. How often do you turn off the tap while lathering soap to wash your hands?
   [Always, Most of the time, Half of the time, Rarely, Never]
9. What is your best guess of how much water is used if the water is left running while washing your hands per wash? (Litres)
   [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
10. How certain are you about your answer? (Where 0 = uncertain and 10 = certain)
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
11. How often do you turn off the tap while brushing your teeth?
    [Always, Most of the time, Half of the time, Rarely, Never]
12. What is your best guess of how much water is used if the water is left running while brushing your teeth per wash?

[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

13. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
14. What best describes the showerhead that you use most of the time?
    [Power or High-Pressure, Traditional, Low-Flow or Restricted Flow, Don't know]
15. What is your best guess of how long a typical shower takes in your home?
    [0, 1, 2, 3, 4, 5, 7, 8, 9, 10]
16. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
17. What is your best guess of how much water is used in just 1-minute of showering?
    [0, 5, 10, 15, 20, 25, 30]
18. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
19. Are any of the toilets in your home dual-flush?
    [All, Some, None, Don't Know]
20. What is your best guess of how much water (in liters) is used from one full flush of a dual-flush toilet?
    [0, 5, 10, 15, 20, 25, 30]
21. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
22. What best describes your clothes washing machine?
    [Front Loading, Top Loading, I don't have a washing machine]
23. How often do you run your clothes washing machine with a full load?
    [Always, Most of the time, Half of the time, Rarely, Never]
24. What is your best guess of how much water is used (in liters) from running a standard front-loading clothes washing machine cycle per wash?
    [0, 25, 50, 75, 100, 125, 150, 175, 200]
25. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
26. How often do you run your dishwasher with a full load?

[Always, Most of the time, Half of the time, Rarely, Never]

27. What is your best guess of how much water is used (in liters) from running a standard dishwasher cycle per wash?

    [0, 20, 40, 60, 80, 100]

28. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

29. Which of the following do you have? [Tick all that apply]

    [Balcony garden,
    Lawn grass,
    Vegetable garden,
    Only native or drought-resistant plants,
    Drip irrigation system,
    Swimming pool,
    Spa pool]

30. What is your best guess of how much water is used from watering a lawn for 5 minutes using a standard garden hose?

    [0, 20, 40, 60, 80, 100]

31. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

32. What is your best guess of how much water your household uses on a typical day in the summer?

    [0, 200, 400, 600, 800, 1000]

33. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

34. What is the best guess of your household's quarterly water bill ($) in the summer?

    [0, 200, 400, 600, 800, 1000]

35. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

B.2 Follow-up survey

1. How often did you or your household members try to reduce your water usage to try to earn WaterSaver rewards?

   [Always, Most of the time, Half of the time, Rarely, Never]

2. How would you rate the WaterSaver app on a scale from 1 to 5

   [1, 2, 3, 4, 5]

3. Which of the following best describes your interest in using the WaterSaver app and reaching water saving goals over the trial period?

   [Very interested the entire time,
   Very interested at first but became less interested over time,
   Moderately interested the entire time,
   Moderately interested at first but became less interested over time,
   Moderately interested at first but became more interested over time,
   Not interested at first but became more interested over time,
   Never interested the entire time]

4. What strategies did you use to reduce your water usage to earn WaterSaver rewards? [Tick all that apply]

   [Turned off tap while lathering soap,
   Turned off tap while brushing teeth,
   Took shorter showers,
   Took fewer showers,
   Had bath with less water,
   Had fewer baths,
   Flushed toilet less,
   Washed clothes with a fuller washing machine,
   Use the washing machine less,
   Washed dishes with a fuller dishwasher,
   Use the dishwasher less,
   Watered the lawn less,
   Watered the garden less]

5. How hard did you find it to earn the WaterSaver rewards each week?

   [Very easy, Easy, Neutral, Hard, Very hard]

6. Which parts of the WaterSaver app did you find most helpful in managing water usage and/or earning WaterSaver rewards? [Tick all that apply]

   [Daily usage graph,
   Hourly usage graph,
   Daily target line,

Tips to reduce usage,
Weekly emails]

7. Did you find the WaterSaver SMS messages helpful in managing water usage?

    [Yes, No]

8. How many WaterSaver SMS reminders would you prefer to receive each week?

    [0, 1, 2, 3, 4, 5, 6, 7]

9. What days of the week would you most prefer to receive WaterSaver SMS reminders? [Tick all that apply]

    [Mon, Tue, Wed, Thu, Fri, Sat, Sun]

10. What time of the day would you most prefer to receive WaterSaver SMS reminders?

    [Morning, Midday, Evening]

11. Do you have any other feedback you would like to provide on the WaterSaver app or the weekly challenges trial?

    [Textbox provided to provide free-form written feedback]

12. How often do you turn off the tap while lathering soap to wash your hands?

    [Always, Most of the time, Half of the time, Rarely, Never]

13. What is your best guess of how much water is used (in liters) if the water is left running while washing your hands per wash?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

14. How certain are you about your answer? (where 0 = uncertain and 10 = certain)

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

15. How often do you turn off the tap while brushing your teeth?

    [Always, Most of the time, Half of the time, Rarely, Never]

16. What is your best guess of how much water is used if the water is left running while brushing your teeth per wash?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

17. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

18. What best describes the showerhead that you use most of the time?

    [Power or High-Pressure, Traditional, Low-Flow or Restricted Flow, Don't know]

19. What is your best guess of how long a typical shower takes in your home?
    [0, 1, 2, 3, 4, 5, 7, 8, 9, 10]
20. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
21. What is your best guess of how much water is used in just 1-minute of showering?
    [0, 5, 10, 15, 20, 25, 30]
22. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
23. Are any of the toilets in your home dual-flush?
    [All, Some, None, Don't Know]
24. What is your best guess of how much water is used from one full flush of a dual-flush toilet?
    [0, 5, 10, 15, 20, 25, 30]
25. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
26. What best describes your clothes washing machine?
    [Front Loading, Top Loading, I don't have a washing machine]
27. How often do you run your clothes washing machine with a full load?
    [Always, Most of the time, Half of the time, Rarely, Never]
28. What is your best guess of how much water is used from running a standard front-loading clothes washing machine cycle per wash?
    [0, 25, 50, 75, 100, 125, 150, 175, 200]
29. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
30. How often do you run your dishwasher with a full load?
    [Always, Most of the time, Half of the time, Rarely, Never]
31. What is your best guess of how much water is used from running a standard dishwasher cycle per wash?
    [0, 20, 40, 60, 80, 100]
32. How certain are you about your answer?
    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

33. What is your best guess of how much water is used from watering a lawn for 5 minutes using a standard garden hose?

    [0, 20, 40, 60, 80, 100]

34. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

35. What is your best guess of how much water your household uses (L) on a typical day in autumn?

    [0, 200, 400, 600, 800, 1000]

36. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

37. What is your best guess of your household's quarterly water bill ($) in autumn?

    [0, 200, 400, 600, 800, 1000]

38. How certain are you about your answer?

    [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]