How Managers Can Reduce Household Water Use Through Communication: A Field Experiment

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Abstract

As populations increase and droughts intensify, water providers are using tools such as persuasive messaging to decrease residential water use. However, district-led messaging campaigns are rarely informed by psychological science, evaluated for effectiveness, or strategically disseminated. In collaboration with a water district, we report a field experiment among single-family households using persuasive messaging based on the information-motivation-behavioral skills model (IMB). We randomly assigned 10,000 households to receive different mailings and measured household water use. All messaging reduced water consumption relative to the control. On average, water use dropped 0.68 hundred cubic feet (HCF) (509 gallons) per household in the first month. Had all 10,000 single-family, occupied, non-agricultural residences been mailed the IMB messaging, more than five million gallons would have been saved in the first month. The effects declined but persisted for approximately three months and were three to six times greater in households with high water use (75th to 90th percentiles) relative to average water use. These findings suggest that combining message elements from the IMB model can reduce residential water use and that targeting high-use households is particularly cost-effective.

INTRODUCTION

Water districts need ways to reduce demand during scarcity, particularly when faced with prospects for record droughts (Swain et al., 2014; U.S. National Climate Data Center, accessed June 2019) and unprecedented water shortages across residential and commercial sectors (Bates et al., 2008). Climate change is expected to increase the frequency of droughts in places like California (Diffenbaugh, Swain, & Touma, 2015). While residential water use can be reduced by many means, including new technology, infrastructure changes, economic tools (such as price adjustments), and behavior change for both water providers and water users (Dietz & Stern, 2002; Inman & Jeffrey, 2006; Vedung, 1998), targeting residents' decisionmaking provides an effective, malleable, and politically feasible intervention compared to other methods (Heiman, 2002). As a result, water districts regularly communicate with their customers through websites, emails, and physical mailings by providing exhortations and advice to reduce household water use. Despite the potential for reduced consumption, little research has examined cost-efficient and effective ways to encourage voluntary household water conservation (for discussion, see Hurlimann, Dolnicar, & Meyer, 2009; Landon, Kyle, & Kaiser, 2016; Syme, Nancarrow, & Seligman, 2000).

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We use the information-motivation-behavioral skills model (IMB; Fisher & Fisher, 2000) as a guide for producing and evaluating interventions aimed at water conservation. According to the IMB model, behavior change is more likely when individuals are informed, feel motivated, and know which behaviors to change (Fisher & Fisher, 2000; Fisher, Fisher, & Shuper, 2014). A recent comprehensive review of published household water interventions showed that every messaging campaign included at least one element of information, motivation, and behavioral skills, despite none explicitly using the theoretical framework of the IMB model (Ehret et al., 2020). This indicates the practical value of assessing messaging interventions that are guided by the IMB model.

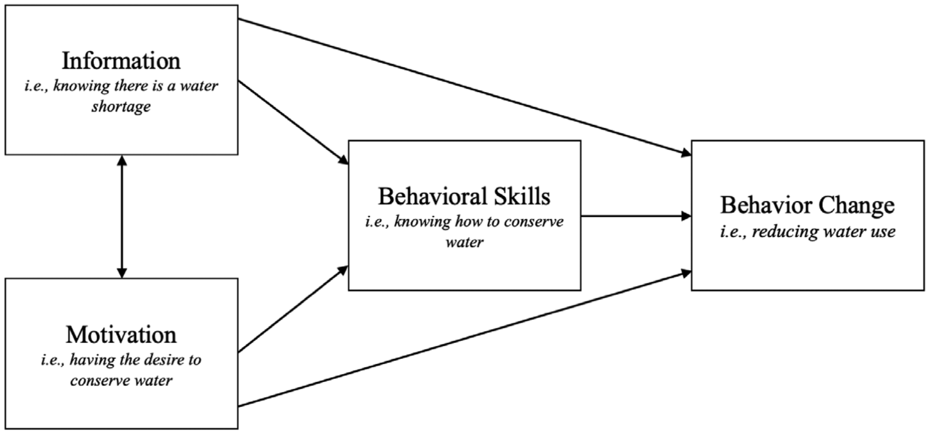
To empirically evaluate whether messaging on motivation and behavioral skills can be effective in reducing household water conservation, we conducted a field experiment in November of 2018 that provided messaging to 7,500 customers of a Central California water district. Treatment groups of 2,500 customers received messages on a postcard and a follow-up postcard with a peel-and-stick element containing: 1) information, motivation, and behavioral skills, 2) information and motivation, or 3) information and behavioral skills. A 2,500 customer group did not receive any mailings from the study. Objective household water use was measured by the local utility on their regular schedule before and after the messaging. We find that each messaging treatment reduced water usage compared to the no-message group and that the effects persisted for more than two months. Households with higher baseline water usage reduced more.

THEORY

Behavioral Interventions as a Policy Choice

Public managers and policymakers often grapple with how policies can be devised to promote desired public behaviors (Olmstead & Stavins, 2009). In designing policies, public managers are influenced by a variety of factors, including political considerations, technical information, and local characteristics (Anderson, Hodges, & Anderson, 2013). For example, while pricing changes and mandatory restrictions work to change behavior, and may be the preferred option for managers, they are politically costly (Hall, 2009; Teodoro, 2010). Managers and policymakers alike are additionally constrained in public resource management by their dependence on customers for policy implementation and service delivery, with customer behavior directly impacting supply, especially when public resources are scarce (Ostrom, 1972). As a result, managers often rely on behavioral interventions to move members of the public toward a preferred behavior.

The success of behavioral interventions ranges from increasing college enrollment among graduating seniors (Oreopoulos & Ford, 2019) and reducing homelessness via short-term rent subsidies (Gubits et al., 2018) to reducing the risk of lead paint exposure among children (Bae, 2012) and the promotion of energy savings through implementation of "smart" thermostat technologies (Harding & Lamarche, 2016). Reviews of hundreds of interventions in the health (Byerly et al., 2018) and pro-environmental behavior domains (Vlaev et al., 2016) point to the importance of such interventions in changing behavior. Despite this evidence of success, behavioral interventions sometimes fail. Policymakers and civil servants aiming for policies that lead to behavior change face constraints including limited budgets, staff time, and an inattentive public. For example, one messaging intervention that disseminated information about the tax benefits for college among high school seniors was intended to boost college enrollment but did not affect enrollment rates (Bergman, Denning, & Manoli, 2019). In another study where high school seniors participated



Notes: Water conservation examples are shown in italics.

Figure 1. The Information-Motivation-Behavioral Skills (IMB) Model.

in mock college application workshops, enrollment rates did increase (Oreopoulos & Ford, 2019). Behavioral interventions would often benefit from further testing and greater integration with other policy tools (for discussion, see Benartzi et al., 2017; Bhargava & Loewenstein, 2015). See a recent review of how policy options are communicated across diverse domains for informed decisionmaking (Brick et al., 2018).

Psychological science can help us to understand why some behavioral interventions succeed where others fail by identifying barriers to change and specific interventions to overcome those barriers (Clayton et al., 2015; Schmuck & Vlek, 2003; Seacat & Northrup, 2010; Steg & Vlek, 2009; Stern, 1992). In particular, the information-motivation-behavioral skills (IMB) model posits that individuals must be informed about a problem, motivated to act, and have the concrete skills to engage in and maintain behavior change (Fisher, Fisher, & Shuper, 2014). Targeting low levels of information, motivation, or behavioral skills can support behavior change (see Figure 1). This framework is broadly consistent with other behavioral theories such as the Reasoned Action Approach (Ajzen, Albarracin, & Hornik, 2007) but differs in the focus on the content of the messaging. The IMB model also outlines a three-step approach to designing interventions that are tailored to a specific population: elicitation, design and implementation, and evaluation. Thus, the IMB model provides a theoretical basis for behavior change and a practical basis for designing interventions.

The IMB model was first applied to HIV/AIDS prevention (Fisher & Fisher, 1992) where interventions provided specific information, motivation, and behavioral skills interventions to at-risk individuals (Fisher & Fisher, 2000). Information (I) in the IMB model refers to whether individuals have accurate knowledge of a problem and its consequences, and so the information component in this context refers specifically to problem awareness. Motivation (M) refers to internal drives or goals that direct and energize an individual to engage in a behavior (Pittman, 1998). Interventions that rely on motivations are often based on social norms, identity, or other tools and techniques that are appropriate to the intervention context (e.g., implementation intentions, commitments, social role models; see Michie et al., 2008; Steg & Vlek, 2009). These interventions may not change trait-level motivation, but rather influence attention and the cognitive accessibility of related concepts. For example, a message that one's neighbors all use irrigation timers may make one's pro-social motivations more accessible, encouraging conformance with the social norms of using irrigation timers provided in the message. Last, behavioral skills (B) reflect an individual's objective and perceived ability to engage in a target behavior. Even when informed and motivated, individuals may not know what to do; messaging can provide those behavioral skills. The IMB model has been applied successfully across multiple health domains (Fisher, Fisher, & Shuper, 2014) and recycling (Seacat & Northrup, 2010).

Applying Psychological Insights to Water Conservation

This paper examines how managers can use persuasive messaging to facilitate voluntary water conservation. Psychological theories like IMB are particularly relevant for water conservation given the prominent role of individual decisions in residential water use (Arbués, Garcıá-Valiñas, & Martıńez-Espiñeira, 2003; Baumann, Boland, & Sims, 1984; Cooley & Phurisamban, 2016); individual users are asked to implement conservation measures ranging from installation of water-saving technology (Bennear, Lee, & Taylor, 2013) to taking shorter showers (Dickerson et al., 1992). Further, messaging interventions may be both the most economical and effective tool at the disposal of public managers. For example, communication to promote energy conservation has achieved comparable or even greater outcomes than price changes (Allcott, 2011; Bertrand et al., 2010). Thus, managers may be able to use communication (Pestoff, Osborne, & Brandsen, 2006) to encourage conservation behaviors (Rich, 1981) and help empower citizens to contribute to a societal good (Bovaird, 2007).

Applying the IMB model to water conservation has two advantages. First, voluntary household water conservation is an individual behavior with similarities to the HIV/AIDS prevention context where the model was developed and shown to be effective. A meta-analysis of sexual risk-reduction interventions including over 174 studies and 116,000 participants found that approaches that included informational, motivational, and behavioral skills components led to greater behavior change (Smoak et al., 2006). Both water conservation and HIV/AIDS prevention require individual behavior change that has both public (increased water conservation and reduced population HIV transmission/infection) and private (lower water bills and better health) benefits. Second, the IMB model (Fisher & Fisher, 2000) provides a theoretical foundation that is congruent with the message content that water districts typically send: 1) general information about a problem (e.g., whether there is a drought), 2) motivating messages, and 3) suggestions for specific behaviors. A recent review of published water conservation studies showed that all messaging interventions designed to reduce water used some components of information, motivation, and behavioral skills even though none of the studies were explicitly informed by the IMB framework (Ehret et al., 2020).

We define water conservation information here as an individual's knowledge of the problem—that water supplies are low. In fact, many conservation campaigns specifically focus on water scarcity (Syme, Nancarrow, & Seligman, 2000) as most water customers do not understand how water is supplied and disposed of (Attari, 2014). However, knowing of a problem is usually not enough to change behavior: the individual also has to see a reason personally to act. This motivation can be a perceived social norm; for example, believing that one's neighbors support water conservation (Richetin et al., 2014). Broadly, motivations help guide and organize behaviors and can be activated with messaging. Consumers also frequently report that they lack the skills to conserve water (Walton & Hume, 2011). For example, they sharply underestimate the water use of household appliances (Attari, 2014), which means that they may not reduce water usage effectively by managing their use of appliances (e.g., by running only full loads of dishes or laundry). Behavioral skills in water conservation include knowing how to reduce water usage indoors and out, and are often presented as water-saving tips.

Importantly, while the IMB model states that "information, motivation, and behavioral skills are fundamental determinants of performance of health behaviors" (Fisher, Fisher, & Harmon, 2003, p. 84), it remains a question as to whether these three are fundamental determinants of water conservation behavior. Moreover, health studies empirically testing the IMB model have produced varied results. Each individual aspect of information, motivation, and behavioral skills messaging appears at times to change behavior even without the presence of the other messages.

Research Questions

We applied messaging guided by the IMB model to water conservation in a large-scale field experiment designed to answer four research questions: Do communications containing information (I), motivation (M), and behavioral skills (B) reduce household water consumption more than no intervention (RQ1)? Are all three components necessary for reducing water use (RQ2)? How much does messaging about motivation and behavioral skills individually contribute to reducing household water use (RQ3)? Does the effectiveness of IMB messaging depend on pre-treatment water use (RQ4)?

Hypotheses

Based on the IMB model as well as a review of household water conservation interventions (Ehret et al., 2020), we predicted that the intervention using all three components would lead to more water conservation than the control group, who did not receive messaging. In addition, we expected all households receiving messaging to reduce their water use compared to the control households. Power analyses suggested that each treatment arm would require approximately 2,500 households (see power analysis section below), making a full factorial design impractical given the number of customers in the district that fit our sampling frame (10,630; see exclusion criteria below) and resources constraints. In addition, elicitation research among the study population suggested that information (problem awareness) about the drought was widespread. Because we observed high levels of knowledge, the control group, which received no messaging, is equivalent to an information-only group. As a result, we chose to test messaging that includes combined elements of information and behavioral skills (IB), information and motivation (IM), and information, motivation, and behavioral skills (IMB), omitting a condition with only information about the water shortage (problem awareness). The resulting design focused on how messaging regarding motivation and behavioral skills contributes to water conservation behavior change. We pre-registered the following hypotheses:

H1: Households receiving IMB messages will use less water than control (no-message/information-only) households (RQ1; IMB < Control).

H2a,b: Households receiving either IM or IB messages will use less water than control (no-message/information-only) households (RQ2; IB < Control; IM < Control).

H3a,b: Households receiving IMB messages will use less water than either IM or IB message households (RQ2, RQ3; IMB < IB; IMB < IM).

The hypotheses are laid out in Table 1. There is no theoretical or empirical evidence to suggest that IM or IB would differ from each other.

Table 1. Hypothesized differences in water use by messaging condition.

	Control (No-message/I)	IMB	IB
IMB	*IMB < Control*		
IB	*IB < Control*	*IMB < IB*	
IM	*IM < Control*	*IMB < IM*	*No prediction*

RESEARCH DESIGN

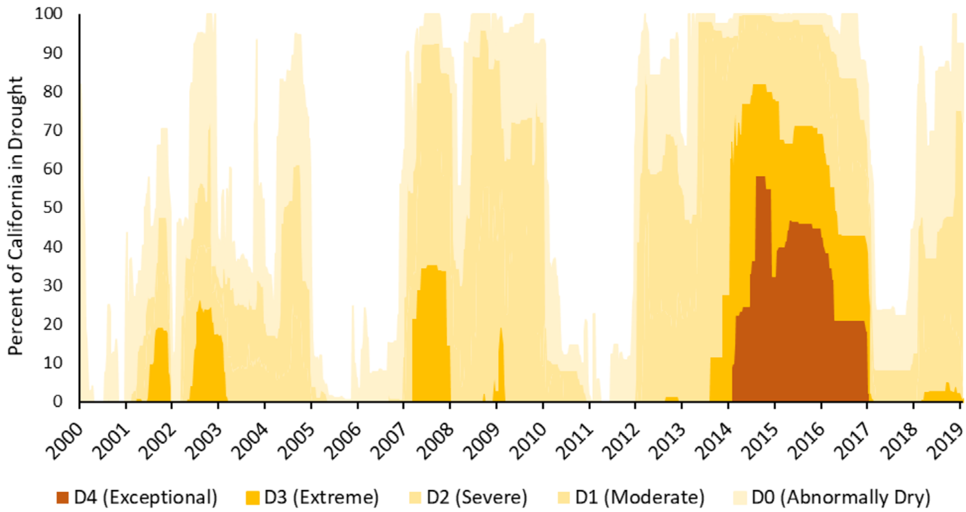
The IMB model is distinct in recommending that interventions be tailored to a specific population in a three-step approach: elicitation, design and implementation, and evaluation. In partnership with a Central Coast California water district, we undertook each of these phases. We conducted focus group sessions and intercept interviews to assess residents' information, motivation, and behavioral skills as well as to inform the design phase. We then designed and implemented a field experiment that mirrored existing water district practices on water conservation messaging. This real-world setting provided strong external validity. Finally, we evaluated the effectiveness of the information, motivation, and behavioral skills messaging using random assignment to treatment, which allows for strong causal inferences.

Pre-Registration

The study design, sample size, analytic constraints, hypotheses, and a full power analysis were pre-registered at the Center for Open Science to enhance transparency and avoid false positives (https://osf.io/d4qyp/?view_only=53760716389b445c89c0abd2a47378a9; also see below). The pre-registration includes heterogeneous treatment effects by baseline water use, square footage, and acreage in order to avoid *ex post* testing of multiple interactions. Based on the availability of pooled time-series cross-sectional data, these panel models account for the fraction of the month in treatment as the main analysis. Pooling and accounting for fraction of the month in treatment are the only two changes to the pre-registered analyses.

Study Setting

In 2007, California entered its latest long-term period of drought conditions (Figure 2), and the government and water managers in California launched a many-pronged campaign to reduce household water consumption. In 2014, Governor Jerry Brown declared a State of Emergency due to drought and issued the *California Water Action Plan* as part of the more comprehensive *Safeguarding California Plan*, calling for significant changes to water use and management across the state (California Natural Resources Agency, 2014). The plan set forth 10 primary actions, with the central goals of reliability, restoration, and resilience. Executive Order B-37-16 sought to promote local urban conservation ordinances and programs in conjunction with the *Water Conservation Act* (SB X7-7, 2009) that required a 20 percent reduction in urban per capita water use by December 2020. The State Water Resources Control Board issued a series of orders to restrict urban water use, including mandatory conservation rules for the 400+ largest water utilities. Mandated fines (up to $500/day) were included for wasteful residential activities such as watering outdoor landscaping with excessive run-off, failing to use a shut-off nozzle on a hose, and washing sidewalks (Weiser, 2014). Many districts further bolstered these restrictions through limitations on outdoor watering.



Notes: As constructed from https://droughtmonitor.unl.edu/Data/DataTables.aspa.

Figure 2. Percent of California in U.S. Drought Monitor Categories 2000 to 2019. [Color figure can be viewed at wileyonlinelibrary.com]

As of 2015, urban water suppliers' average water use was down 33 percent (California Natural Resources Agency, 2017), with particular success in districts with a polycentric water import structure (for example, districts may receive their water from the State Water Project, where water will travel across many districts and institutions before reaching the final user), districts facing more severe drought, and those with lower median incomes (Palazzo et al., 2017). These gains in conservation occurred when California had the lowest measured snowpack since 1950 (California Department of Water Resources, 2018). California saw significant increases in precipitation in the winter of 2017, prompting the Governor to lift the drought declaration and emergency regulations expiring in November 2017. At this time, water districts switched to their regional conservation rules, many lifted all restrictions, and usage varied widely. In 2015, urban water suppliers' average water use was 31 percent below the 2013 established pre-drought baseline (California Natural Resources Agency, 2017). As of July 2019 (for 334 reporting districts), residential per capita use ranged from 690 to 15,225 gallons per month, averaging 3,966 gallons per month (California Water Boards, 2019a). While districts have maintained on average a savings of 6.8 percent below pre-drought water usage (California Water Boards, 2019b), residential use continues to ramp up without many statewide and local restrictions (CBS News, 2018).

The study area was a central California water district with approximately 87,000 customers. Central California remained in drought in 2018 even as the rest of California received more normal amounts of rain and snow before the intervention, and the district was eager to maintain or increase water use reductions. The district actively messages their customers with newsletters, notices within bills, and additional mailers. The district co-designed the messaging with the researchers and managed the printing and mailing of messages.

The 2018 context of this study provides both a difficult and an important case for testing the efficacy of messaging for promoting voluntary reductions in water usage. With the ongoing drought remaining a serious concern for central and southern California, many districts launched messaging campaigns to encourage continued household water conservation. At the same time, those customers had been receiving messaging and making changes to their water use practices for five years. During the intervention, which was carried out in November 2018, the water district received more normal amounts of rainfall, possibly attenuating the treatment effect. We thus evaluate the causal effect of messaging in a least-likely case where conservation gains are difficult to achieve, and any reductions in water use may be lower-bound estimates relative to less difficult contexts.

Heterogeneous Treatment Effects

We pre-registered tests of heterogeneous treatment effects by baseline water use, parcel size, and house square footage. Users with low water use may have had little ability to respond to the treatment due to a floor effect. Moreover, knowing whether there are heterogeneous treatment effects by pre-treatment use could allow the water district to target future messaging. Estimating heterogeneous treatment effects by parcel size and square footage could give some indication of the mechanism by which water use reduction is occurring. If there are heterogeneous treatment effects by parcel size, this is an indication that water use reductions were driven by outdoor water use, whereas heterogeneous treatment effects by the square footage of the household would indicate water use reductions indoors. The duration of the treatment effect is also estimated via heterogeneous treatment effects by *days since treatment*. This estimation is discussed in more detail below. Each of these tests of heterogeneous treatment effects was pre-registered to reduce the risk of false positive effects due to multiple tests for heterogeneous treatment effects.

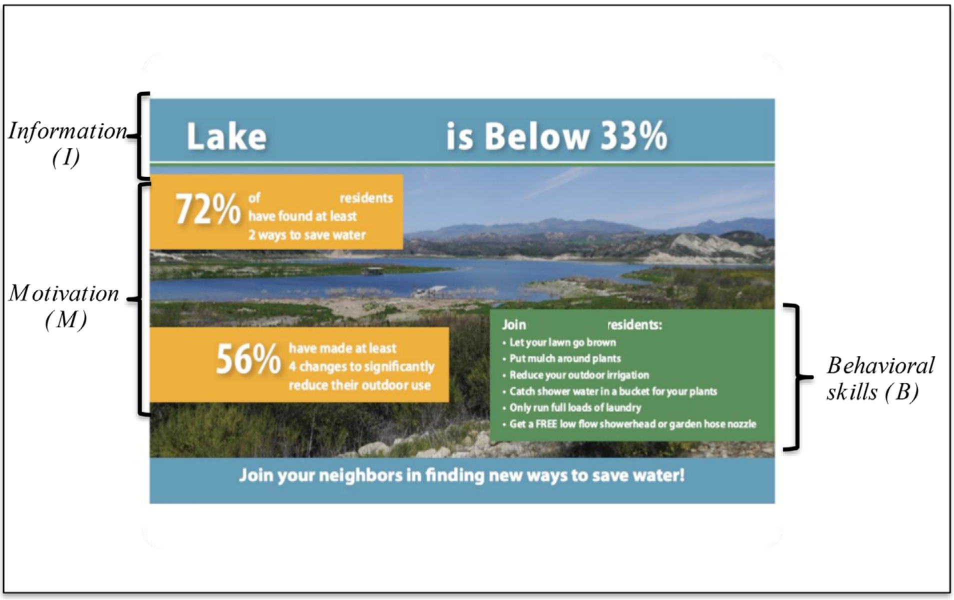
Elicitation Research

In the elicitation phase, we conducted a focus group and intercept interviews (N = 21) to evaluate residents' information about the water shortage, motivation to reduce water use, and behavioral skills. Participants were recruited through flyers, online posts, and in person (in English and Spanish; see Appendix A).[1] Although this is a small sample and therefore has limited generalizability, the elicitation still revealed commonalities that helped tailor messaging to this population. The focus group and interviews both showed that residents had high levels of information about the drought and the need to reduce water use, many had undertaken extensive efforts to reduce water use, and they were resistant to messages asking for more change. Residents suggested that messaging emphasizing social norms and community would be effective. These findings informed our treatment design. The interviews also provided evidence regarding what specific actions residents had already undertaken to conserve water, which were later used as descriptive norms in messaging to support message accuracy. The interviews indicated that residents had each undertaken substantial efforts to reduce water use, but the actions were highly varied, suggesting that targeting key behavioral skills could be effective.

Treatments

The treatments consisted of messaging that combined elements of information (problem awareness), motivation, and behavioral skills, or no message. The control group, which received no messaging, is as close to an "information-only" condition

[1] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.



Notes: This example contains all three IMB elements: information (problem awareness about the drought), motivation (via social norms), and specific behavioral skills. The IMB condition labels were added for this figure. Postcards in the IM and IB conditions were identical except for omitting the B and M boxes, respectively. The names of the lake and the district are redacted in this figure.

Figure 3. Postcard Design for IMB Condition.
[Color figure can be viewed at wileyonlinelibrary.com]

as our research design would allow. In the information and behavioral skills (IB) condition, customers received basic information about the drought and specific behaviors to save water, but no justification for action (i.e., no motivation). In the information and motivation (IM) condition, customers were provided a motivation message about how others in the community are saving water (descriptive norms derived from interview results) and the basic information about the drought, but no behavioral tips. The use of a social comparison message as motivation follows from prior work that suggests this to be one of the most effective means of prompting motivation (e.g., Schultz et al., 2016). These social comparisons (a strong social norm) have been shown to be more effective than general pro-social messaging (a weak social norm; Ferraro & Price, 2013). Customers in the information-motivation-behavioral skills (IMB) condition received all three components. Each treatment household received a postcard with the treatment language, followed eight days later by a MagNot® (a postcard with a magnetic peel-off sticker for displaying inside the house). Treatment was considered complete two days after mailing of the MagNot®. The control group did not receive either mailer. Figure 3 reproduces the IMB treatment postcard. The MagNots® were similar, with key treatment language included on the MagNot®. See Figure A5 for all postcard and MagNot® designs.[2]

[2] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Exclusion Criteria

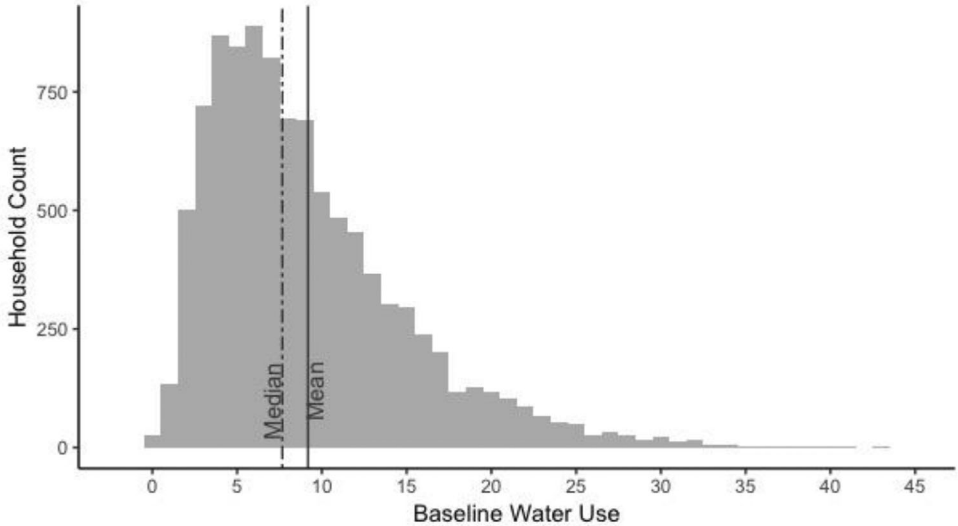
In partnership with the water district, 10,000 occupied, single-family residential households without large landscapes were selected for the experiment. To develop the sampling frame, we pre-registered four exclusion criteria. The first exclusion criterion was commercial or agricultural users, resulting in inclusion only of households the district defined as single-family residences. The second exclusion criterion was monthly water use at or below zero, as these were corrections to prior meter reads and therefore were not accurate for those months. The third exclusion criterion was service and billing addresses that did not match, because they are more likely to be renters who do not pay their own bills and those for whom the residence may be a second home. To exclude unoccupied and quasi-agricultural residences, a fourth inclusion criterion was household water use less than one standard deviation below the mean or more than two standard deviations above the mean of all single-family residences with matched addresses based on the previous three months' water use. Monthly use (the mean of June, July, and August 2018) indicated that this included users who consumed 2–27 HCF (1,500 to 20,200 gallons) per month. Those using less than one standard deviation below the mean (~2 HCF; 1,500 gallons per month) had limited opportunity for further water conservation and may have represented unoccupied or vacation residences. On the upper end, users more than two standard deviations above the mean (~27 HCF; 20,200 gallons per month) were likely to have had unrepresentative outdoor water use (e.g., irrigating a very large lawn) or be quasi-agricultural (e.g., seven users in the district used >90 HCF per month; 67,320 gallons per month). 10,630 users met these sampling criteria. From the sample that met the inclusion criteria, 10,000 households were randomly selected and approximately 2,500 households comprised each of the three treatment groups and the control (no-message/I). Baseline water use in the final sample was skewed right with most users consuming lower quantities and few users consuming very high quantities (see Figure 4).

Households were removed from the study if their addresses were incorrect based on data from the mailing contractor. In addition, a handful of households had one address associated with two or three accounts. In these cases, only one account was maintained for analyses, thus decreasing group sizes by a few households each to a final sample size of 9,987. A pre-registered power analysis revealed that this experiment could detect a 3.8 percent difference in water use (https://osf.io/d4qyp/?view_only=53760716389b445c89c0abd2a47378a9). The power analysis (G*Power) was based on an ANCOVA of four independent groups of 2,500 assuming 80 percent power, an alpha of .05, and one covariate. This analysis was capable of detecting an effect size of $d = .03$ between intervention groups for changes in household water use at a single timepoint. Cohen (1988) suggests $d = .10$ to be a small effect size. For illustration, a one-tailed t-test with two groups of 2,500 (e.g., IMB vs. control), assuming 80 percent power and alpha of .05, would be able to detect an effect size of $d = .07$. Therefore, this design was sufficient to detect relatively small effects.

ANALYSIS

Balance Tests

Pre-registered balance checks were performed based on covariate data available from the partner district: parcel size, dwelling square footage, and days since complete treatment. ANOVAs and chi-squared tests were used to test for balance in Table 2, where significance of any tested covariate indicates imbalance. The tests revealed that randomization did result in balance in the observable covariates.



Notes: Although the sampling frame excluded households with average water usage during July, August, and September of < 2 HCF or > 27 HCF per month, the baseline water usage graphed here includes October instead of July and some households have measured baseline water use outside of those bounds. The mean and median baseline water use are labeled. 1 HCF = 748 gallons.

Figure 4. Three-Month (August, September, October) Baseline Water Use of Our Sample.

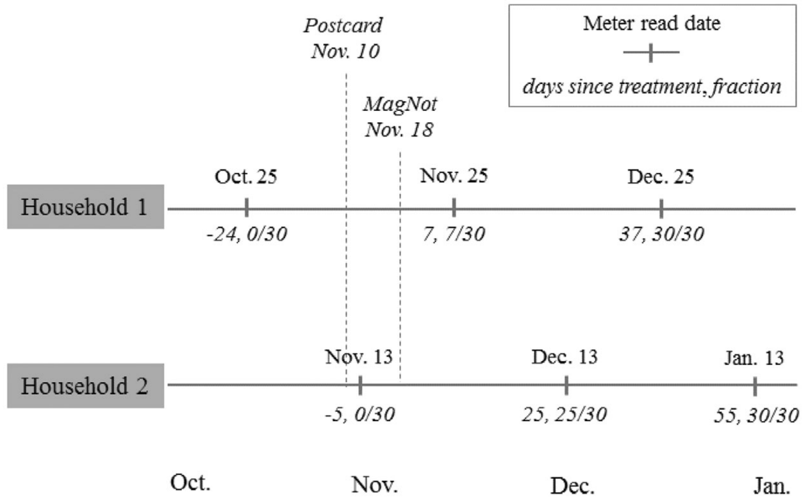
Table 2. Balance test and summary statistics for water usage and covariates.

	Baseline Water Use (3-mo avg; HCF/mo)		Parcel Size (acres)		House Size (thousand ft^2)		Days Since Treatment	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
IMB $n = 2{,}491$	9.18	*6.08*	0.50	*2.37*	1.55	*0.82*	25.1	*7.21*
IM $n = 2{,}499$	9.09	*5.86*	0.59	*3.31*	1.58	*0.81*	25.1	*7.22*
IB $n = 2{,}497$	9.23	*6.15*	0.47	*1.61*	1.59	*0.86*	24.8	*7.10*
Control $n = 2{,}500$	9.23	*6.40*	0.51	*1.76*	1.56	*0.85*	25.0	*7.06*

Notes: Balance tests revealed no differences between groups at $p < .05$.

A multinomial logit with treatment group as the dependent variable and each covariate as a control demonstrates that balance remains conditional on the other covariates; none were statistically significant predictors (at $p < .05$) of treatment even controlling for the other covariates (see Table A1).[3]

[3] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.



Notes: The figure illustrates construction of *days since treatment* and *fraction* variables. *Fraction* is always 0 for control households.

Figure 5. Example Households with Treatment Timing and Meter Read Dates.

Household Water Use and Timing of Measurement

Household water use was the main outcome. Although the treatment was implemented on the same day for each household, the manual meter reads were conducted by the district on different days across households, depending on where the site is located in meter reading routes. The meter read timing for each household was fairly consistent across months (typically within two days), and therefore meter readings could be interpreted as monthly water use. We observed water use three months before, during, and three months after the treatment, amounting to seven total months.

This varied timing of meter reads has two consequences for the analysis: 1) upon meter reading, households were in treatment for differing lengths of time and 2) leveraging this variation allowed us to estimate the duration of the treatment effect. We capture these time dynamics with two variables. First, we incorporate *days since treatment*, which is date of meter read minus date of treatment and can be negative. This variable accounts for any trends in water use, and interacting it with the treatments allows for estimation of the duration of the treatment effect. Second, we measure the *fraction* of the month in treatment to account for the differing times households are in treatment during the meter read period; this is comparable to a dosage or inoculation variable. To understand these timing features, consider two households, both of which received the November 18 MagNot® mailer in Figure 5. Household 1 had a meter reading one week after complete treatment on November 25, leading to a *days since treatment* value of 7 for November and a *fraction* treated of 7/30. In December, the household was fully treated with *fraction* equal to one and a *days since treatment* value of 37. Household 2 had a meter reading on December 13, where *days since treatment* was 25 and *fraction* was 25/30 for December. In the prior month of November, *days since treatment* was −5 and *fraction* of the month in treatment was 0 since the MagNot® had not yet been received. In January, *days since treatment* is 55 and *fraction* is one. Each pre-registered model includes *days since treatment* to account for seasonal changes in water use and an interaction of *treatment* with *days since treatment* to estimate the duration of the treatment effect. A control household whose meter was also read on December 13 would have the same values for *days since treatment*, but its interaction with treatment variables and *days since treatment* would all be zero. The models reported here also include the fraction of the month in treatment to account for the fact that a household in treatment for only seven days (7/30) had limited time to make adjustments compared to one in treatment for 25 days (25/30). While this inserts a complication into the data analysis, the continuous household level variable of *days since treatment* facilitates estimation of the duration of the treatment effect, an object of interest in itself as managers consider the efficacy of their messaging strategies.

Main Specification

The main specification is based on the panel data including cross-sectional and time-series variation. Panel models offer a number of advantages, including accounting for household-level characteristics that may shape water usage using fixed effects, leveraging more data, and, especially in this case, studying the dynamics of change. We applied a within (fixed effects) linear panel model to reveal sample average treatment effects for each treatment condition.

$$\begin{aligned} y_{it} = \alpha_i + \beta_j Treatment_{ijt} + \gamma DaysSinceTreatment_{it} + \delta_j Fraction_{ijt} \\ + \mu_j DaysSinceTreatment_{it} * Treatment_{ijt} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where i indexes households, j indexes treatments, and t indexes months. α_i represents household fixed effects. y_{it} is HCF measured at the meter read each month for each household in HCF per month. $Treatment_{ijt}$ are indicator variables equal to one if a household is in that treatment condition (*IMB, IM, IB*) in that month. $DaysSinceTreatment_{it}$ indicates the number of days before (negative values) or after complete treatment, as illustrated in Figure 5. $Fraction_{ijt}$ represents the fraction of the month a household was in complete treatment at the time of the meter read. All households in the control group have $fraction = 0$ as they are never in treatment, so there are only three estimates of the effect of *fraction*. The interaction of *DaysSinceTreatment* and *Treatment* allows the effect of treatment to change as time passes. The specification in equation (1) was also run with an indicator variable where the treatment conditions were combined (see Table B1).[4] Results were substantively similar. Per the pre-analysis plan, since the balance table revealed no imbalance, covariates were not included.

Heterogeneous Treatment Effects

As pre-registered, heterogeneous treatment effects were estimated for the covariates *BaselineUse* (prior baseline water use: an average of the three pre-treatment months), *SquareFeet* (house square footage), and *Acres* (the total acreage of the property). Fixed effects were not included in this estimation in order to estimate coefficients on the time invariant variables.

$$\begin{aligned} y_{it} = \alpha_i + \beta_j Treatment_{ijt} + \gamma DaysSinceTreatment_{it} + \delta_j Fraction_{ijt} \\ + \mu_j DaysSinceTreatment_{it} * Treatment_{ijt} + \pi_j BaselineUse_i * Treatment_{ijt} \\ + \rho_j SquareFeet_i * Treatment_{ijt} + \tau_j Acres_i * Treatment_{ijt} + \varepsilon_{it}. \end{aligned} \tag{2}$$

[4] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Since baseline water use may be highly correlated with acreage and square footage, the heterogeneous treatment effects were also estimated separately in Table B2.[5]

RESULTS

Treatment Effect (RQ1)

Table 3 shows the fixed-effects panel model results. Model A estimates the primary specification with household fixed effects and Model B includes heterogeneous treatment effects. The main effects of the treatments should be interpreted with caution as they correspond to the effect of treatment when the household has been in treatment for zero days. The significant negative coefficient on *days since treatment* indicates that water use in the control group was falling over the time period, as temperatures cooled and the rainy season began. The significant positive coefficients on the interactions between *days since treatment* and the treatments represent the decay rate of treatment, indicating that the effect of the treatment fell off over time. The significant negative coefficients on the interactions between *fraction* and the treatments indicate that the treatment effect increased as the fraction of the month in treatment increased. Since the interpretation of the substantive size of the treatment effect with these interaction terms is not straightforward in the model output, the model results are displayed visually in Figure 6, which includes estimates of the 90 percent confidence intervals. As shown, all three treatment groups demonstrate statistically significant reductions in water use once in treatment for 15 days compared to control (no-message/I). Predicted water usage at 30 days in treatment (*Fraction* = 1) is 6.24 HCF per month for those in the IMB treatment, 6.24 HCF per month for the IM treatment group, 6.17 HCF per month for the IB treatment group, and 6.92 HCF per month for those in the no-message/I group. We reject the null hypotheses that there is no difference in water use due to messaging (*H1, H2a,b*). We observed an average savings of 0.68 HCF (9.8 percent or 509 gallons) in the first month per household in both the IMB and IM treatment groups and slightly greater savings in the IB treatment group.

Treatment Effects by Message (RQ2; RQ3)

The difference in treatment effects between the three treatment conditions was not distinguishable from zero, and therefore we reject the null that IMB reduces water use more than IM or IB (*H3*). In other words, once motivation or behavioral skills is included in the messaging, the addition of the other component does not improve water conservation. This implies that in our case, motivation and behavioral skills may be substitutable.

Treatment Effect Duration

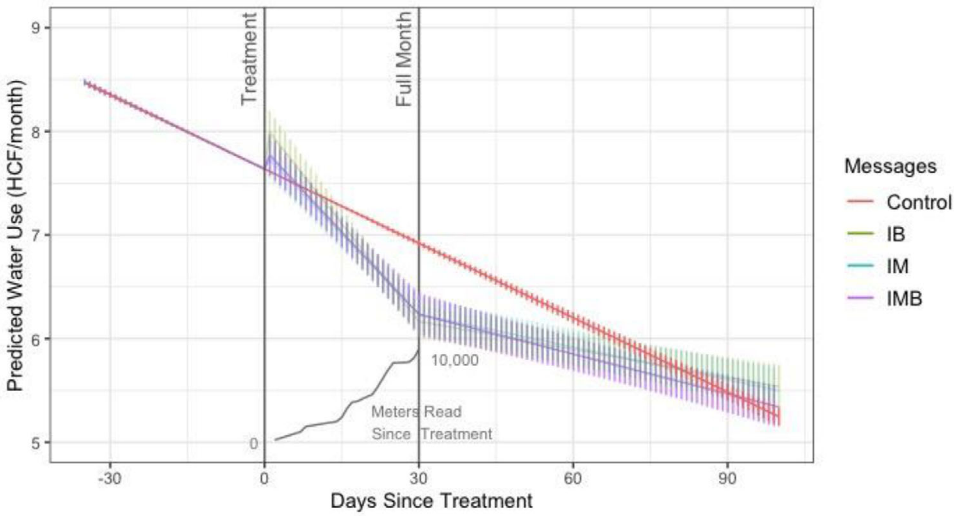
There is indicative evidence based on the decay rate that the IMB condition helped to prolong water use reductions relative to IB (see Figure 6). The interaction terms between the treatment conditions and *days since treatment* in Table 3 represent these different decay rates. The decay rate on the IMB condition is 0.011 HCF/month

[5] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Table 3. Coefficients of water use from the panel models.

	Monthly Water Use (HCF)	
	(1)	(2)
IMB Treatment	0.19	5.28*
	(0.17)	(0.19)
IM Treatment	0.14	5.05*
	(0.17)	(0.19)
IB Treatment	0.42*	5.34*
	(0.17)	(0.20)
Days Since Treatment	−0.024*	−0.024*
	(0.00040)	(0.00040)
IMB x Fraction	−1.20*	−1.07*
	(0.25)	(0.23)
IM x Fraction	−1.23*	−1.14*
	(0.25)	(0.23)
IB x Fraction	−1.62*	−1.46*
	(0.25)	(0.24)
IMB x Days Since	0.011*	0.0090*
	(0.0020)	(0.0020)
IM x Days Since	0.013*	0.012*
	(0.0020)	(0.0020)
IB x Days Since	0.015*	0.012*
	(0.0020)	(0.0020)
IMB x Baseline Use		−0.56*
		(0.010)
IM x Baseline Use		−0.53*
		(0.010)
IB x Baseline Use		−0.54*
		(0.010)
IMB x Parcel Size		−0.015
		(0.023)
IM x Parcel Size		0.0060
		(0.016)
IB x Parcel Size		−0.045
		(0.034)
IMB x Dwelling Size		0.000010
		(0.00010)
IM x Dwelling Size		−0.00010
		(0.00010)
IB x Dwelling Size		0.000040
		(0.00010)
Household Fixed Effects	Yes	Yes
Observations	69,814	69,240
R^2	0.16	0.29
Adjusted R^2	0.02	0.17
F	1,111*	1,268*
	df(10; 59,817)	df(19; 59,316)

Notes: Robust standard errors are in parentheses (*$p < .01$).



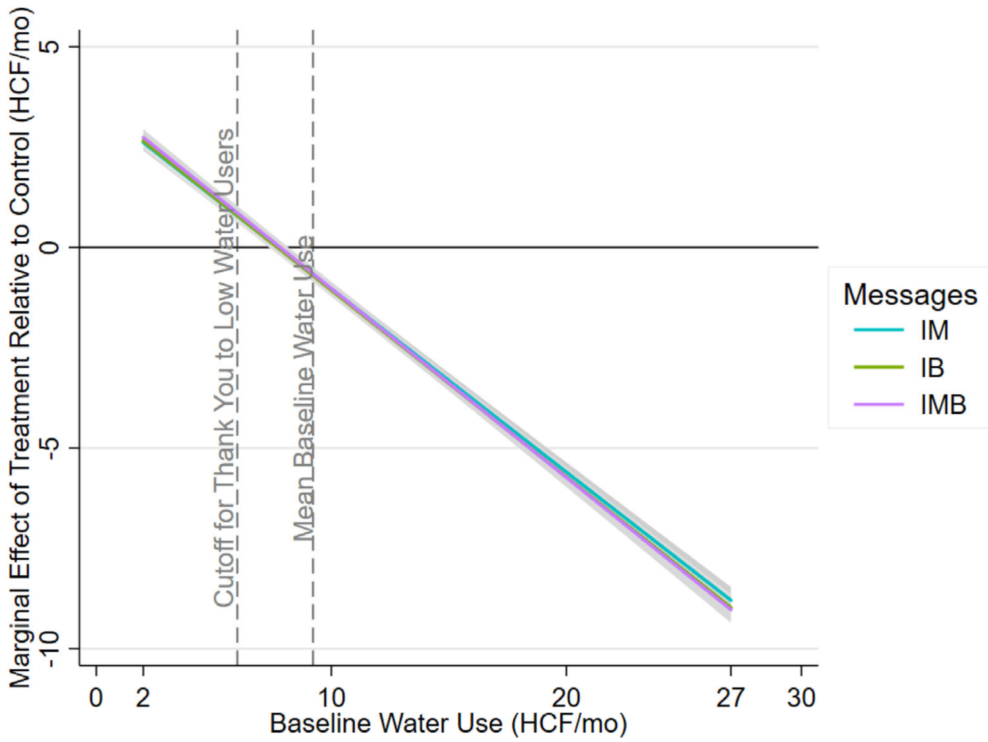
Notes: Figure 6 shows predicted water use for the control and treatment groups from −30 to 90 *days since treatment*. In addition, the figure shows households coming into full treatment, labeled as "meters read since treatment" with all households in complete treatment by 30 days after mailers received. While the measurement period does extend to three months prior to treatment, it is not shown here for compactness.

Figure 6. Predicted Water Use in Treatment and Control Groups with 90 percent Confidence Intervals.
[Color figure can be viewed at wileyonlinelibrary.com]

and the 90 percent confidence interval (0.0078, 0.014) on that decay rate does not overlap the decay rate of the IB condition (0.015 HCF/month). The decay rates of the IMB and IM treatments, as well as the decay rates of the IM and IB treatments, are statistically indistinguishable from each other at $p < .10$. Substantively, we can identify the point estimates that indicate when households in the treatment conditions once again consume the same amount of water as the no-message/I households. The confidence intervals on these estimates are determined by calculating where the 90 percent confidence interval on the no-messaging/I group overlaps the point estimates for the treatment groups. Households in the IMB condition continued to reduce their water use relative to the no-messaging/I households up until 92 days (85 lower bound, 100 upper bound of 90 percent confidence interval) post treatment, whereas the IM condition households intersect with the no-messaging/I households by 82 days (77, 87) and the IB households by 81 days (76, 86). Thus, there is mixed evidence that the IMB messaging effect persists longer than the treatment effect of the IB messages.

Treatment Effects for High- and Low-Use Households (RQ4)

Across all treatment groups, the evidence suggests meaningful differences in treatment effects by baseline water use. Model 2 in Table 3 shows the full model with heterogeneous treatment effects by baseline water use, parcel size, and residence square footage. Figure 7 displays the difference in the predicted water usage between the treatment groups and the control group across baseline water usage and shows larger reductions for high-use households. Accounting for heterogeneous treatment effects, a single-family residence with the mean 9.18 HCF per month baseline



Notes: Figure 7 shows the difference in the predicted water usage between the treatment groups and the control group by baseline water usage. Treatment effects are larger for residents with higher water usage. This was estimated for baseline water usage of 2 to 27 HCF per month for consistency with the sample. Mean water usage and the cutoff for the additional district "thank you" postcards to low water users are marked vertically (see our discussion of treatment effects and robustness checks in the fourth section).

Figure 7. Treatment Effect by Baseline Water Use.
[Color figure can be viewed at wileyonlinelibrary.com]

water use (and at the mean 0.52-acre parcel size, mean home size of 1,568 sq. ft., and 30 days in treatment) had an IMB-condition treatment effect of −0.64 HCF (−479 gallons) per month: a 6.9 percent reduction. As predicted, the messaging had a greater effect on households with higher use. For example, households in the 90th percentile for baseline water use (17 HCF per month) but mean parcel size and home size reduced their water use by 4.3 HCF (3,216 gallons) after being in IMB treatment for one month. There was less evidence of heterogeneous treatment effects by square footage or acreage. When heterogeneous treatment effects were estimated separately (Table B2),[6] the heterogeneous treatment effects by baseline water usage remained and were similar. There were also heterogeneous treatment effects by square footage: larger houses reduced more. This provides evidence that the reduction in water use among high-use households may come from a reduction in indoor rather than outdoor water use, because there is little evidence of heterogeneous treatment effects for parcel size.

[6] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Robustness Checks

SATE Monthly Estimates with Randomization Inference

In randomization inference, we considered the sharp null hypothesis that each treatment group and control would have the same treatment effect. Based on the pre-specified model (see Appendix C), with estimates of the treatment effect separately by month, one-tailed p-values from randomization inference suggest that in Month 1, Month 3, and Month 4 there was no difference by treatment assignment ($p = .45$, .18, .45, respectively; see Appendix C). In Month 2, no differences by treatment assignment were observed ($p = .11$; see Appendix C). These monthly results are presented here for completeness and consistency with the pre-analysis plan and should be interpreted with caution since not all households were in treatment in Month 1 and the fraction of the month in treatment was not included in this specification.

Linearity of Heterogeneous Treatment Effects

A binning estimator (Hainmueller, Mummolo, & Xu, 2019) was used to test whether the interaction term was linear across baseline water use. A Wald test indicated that the heterogeneous treatment effect was not constant across all users ($p < .001$). However, as Figure B1 shows, the nonlinearity does not substantively change the conclusion that households with higher baseline water use were more responsive to treatment.[7]

Additional "Thank You" Mailer

Just prior to sending out our experimental mailers in September 2018, the district also sent 4,000 “thank you” postcards to their low-use customers. Households averaging less than 6 HCF per month over the prior year received a mailer that was unrelated to the study, resembled the postcards used in the treatment, and congratulated customers on being water savers. We were not included in this decision made by the water board. This organizational choice introduced noise into the experiment that may have reduced responsiveness of these customers to the treatment in this study. In addition, the postcards were sent to some members of the control group. Both of these factors are likely to have reduced the size of the treatment effect for low water users. Given that these low-use households had recently been messaged, we conducted a robustness check by reestimating equations (1) and (2) excluding users who received this separate mailing. Consistent with the heterogeneous treatment effects, the larger treatment effects when the low-use households are excluded suggests that those who received the “thank you” mailer responded less to the treatments (see Appendix D).

DISCUSSION

This pre-registered, large-scale field experiment suggests that household water use can be substantially reduced by messaging about problem awareness, motivation, and behavioral skills. The reduction was observed even in an area saturated with

[7] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher’s website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

messaging on bills and other mailers, and even though the treatment may not have reached all members of the household depending on whether and where the MagNot® was placed. In the first 30 days after complete treatment, households in the IMB group used 6.24 HCF, compared to 6.92 HCF in the control group (no-message/I), for a reduction of 0.68 HCF or 509 gallons. Given that households in this district had already reduced use by an average of 30 percent during the preceding drought, additional voluntary reductions were going to be difficult. Thus, this treatment estimate may represent a lower bound when generalized to districts that are not in a long-standing drought and that have not received abundant messaging.

There were no discernable usage differences between the three treatments. Any message improved water conservation over no message. Given that the control can be considered an information-only group, this suggests that adding motivation, behavioral skills, or both achieve similar reductions. For all treatment groups, the effect of messaging persisted for more than two months. On the 60th day of treatment, there was still a 0.35 HCF (261 gallon) per month difference between the IMB group and the control.

As expected, we found meaningful differences in treatment effects between high- and low-use households. When provided the IMB mailer, households in the 90th percentile of water use (high: 17 HCF) saved 3,000 gallons—nearly 25 percent. Even among the 75th percentile (12 HCF), water use was reduced by 1,500 gallons. High users saw the greatest proportional and the greatest absolute reductions after treatment. This finding is consistent with previous intervention studies of high users of energy and water (Allcott, 2011; Tiefenbeck et al., 2018). Notably, the lowest users actually increased their use post-treatment. There are a couple potential explanations. First, since these users were so low in water use to begin with, it is possible that the change reflects some reversion to the mean not related to the messaging. Second, this could be a case of moral licensing (Merritt, Effron, & Monin, 2010). These users had just been told how exceptional they were in the mailers and in the "thank you" postcard, perhaps giving them license to increase their water use.

The findings are qualified by several limitations. First, the treatment conditions were not compared to an information-only manipulation of problem awareness. Rather we assumed that information was high in the control group, because discussions with the water district and examination of their previous mailers revealed that information-only messages were already being communicated to households; this was supported by focus group and intercept feedback collected during the elicitation stage. Second, a mailer may be a weak method to effectively educate households about behavioral skills. Nonetheless, this and similar studies report positive effects (also see recent review of messaging interventions, Ehret et al., 2020). Third, the mailings were limited by an inability to measure whether all members of the household saw the treatment or how often. Presumably some households threw out the postcard and MagNot® immediately, while others mounted the MagNot® prominently and saw it many times. This lack of insight into how the mailers were received makes it hard to know how much exposure is needed in future interventions. In future work, it would be ideal to measure psychological variables such as motivation and perceived norms before and after an intervention, in order to reveal the mediators (mechanisms) of the observed treatment effect.

Additionally, spillover between conditions is a potential concern. Neighbors might have discussed the mailer with each other, and they were likely in different treatment groups. In this case, spillover would have made the control group more similar to a treatment group and the treatment groups more similar to each other, making the observed treatment effects even less likely.

CONCLUSION

This paper responds to the call for "what has been missing [...] A concerted effort by researchers, policymakers, and businesses to do the 'engineering' work of translating behavioral science insights into scaled interventions, moving continuously from the laboratory to the field to practice" (Allcott & Mullainathan, 2010, p. 1205). The results demonstrate that it is possible for local agencies to shape the behavior of residents in pro-social and cost-effective ways at the same time that researchers gain theoretical and practical insights. We derive several recommendations for policy in practice.

First, we recommend that managers consider messaging campaigns when water use reduction is a priority. Had all 10,000 households in our sample been given the IMB treatment, the district would have saved five million gallons in the first month. The mailings cost approximately $1.42 per one-HCF reduction in a water district where the marginal cost of one HCF in the lowest use tier was $5.05. Heterogeneous treatment effects by water use suggested that the cost-effectiveness of the mailers could be even higher if they were targeted toward high-use households. Moreover, the findings of treatment effectiveness in the context of previous steep voluntary reductions indicate that messaging campaigns may be more effective and cheaper where recent water-use reductions have not been undertaken.

Second, we recommend the use of the IMB model to guide the design of messaging for reducing water use, especially given its effectiveness in related domains (Seacat & Northup 2010). Although we observed no difference in the size of the treatment effects in this experiment when only portions of the information, motivation, and behavioral skills elements were included, we still recommend using the full suite of information, motivation, and behavioral skills. The apparent lack of differences may have been due to levels of IMB components in this specific community. These residents had received extensive messaging prior to the intervention and perhaps had unusually high levels of each IMB component, making it less likely that the exclusion of one element would reveal differences. Additionally, there is some evidence that the combined treatment effect decayed more slowly than the IB treatment. Thus, a conservative recommendation for public managers in other domains and other locations is to include all elements. Further research in districts where water-use reduction is less salient would be valuable to evaluate the relative benefit of each IMB element in messaging. In particular, testing for the role of information alone (problem awareness) would require a population that was less informed on drought than the sample households. Additional empirical applications of IMB to water conservation will also help to determine under what conditions each of the components have an effect and the persistence of treatment effects.

Third, we recommend that public managers target high users. Consistent with previous research (e.g., Allcott, 2011; Tiefenbeck et al., 2018), we found heterogeneous treatment effects indicating that high users reduced more. High-use households in the treatment reduced use by 25 percent, while the lowest-use households increased water usage. While some of this may be reversion to the mean, this messaging was at best ineffective and at worst counterproductive in low-use households. Targeting high-use households alone would increase the cost-effectiveness of the interventions, while maintaining much of the substantive effectiveness of the intervention.

Finally, this project demonstrates that partnerships between practitioners and academics to undertake randomized controlled trails can yield benefits to both public managers and to academics. This study, at the top of the "hierarchy of evidence" (Doleac, 2019), shows that targeted, well-designed messages can be cost-effective in reducing water use. These lessons are broadly applicable to public and private utilities, including water and energy providers. Because these findings are embedded in a theoretical and institutional context that allows the lessons to be transferred to other settings, it helps to answer the question of how managers can engage with members of the public when they seek to change behavior across domains and organizations.

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APPENDIX A: RESEARCH DESIGN

Elicitation Procedure

Recruitment

In order to understand the norms and behaviors of the population under study, we conducted elicitation research. First, we placed flyers in coffee shops in the town served by our partner district and posted an invitation to attend the focus groups on nextdoor.com. The flyer language is below (see Figure A1). We recruited in both English and Spanish and convened a small focus group (~5 attendees) in each language. Our intercept interviewees and focus group participants included white, Latinx, and black respondents ranging in age from their 20s to their 70s and included both males and females.

Focus Groups

Three to five members of the research team attended each focus group and took notes on the answers to the topics we raised. The questions used to engage the focus groups are included as Figure A2 below. The researchers then convened to discuss the themes raised in the focus groups. In particular, the focus groups indicated that they were well aware of the drought and of water-saving strategies (which is not surprising given the voluntary nature of the focus groups and the relatively long time commitment). Each focus group was also given a draft copy of the treatment instrument and asked for their feedback.

Intercept Interviews

Shoppers at a plaza were recruited for a survey to establish baseline levels of information, motivation, and behavioral skills. They were asked about their awareness of water issues, their motivation to conserve water, and about behaviors they might have already undertaken or would be willing to undertake. The questions asked are included below (see Figure A3).

Table A1. Multinomial logit for balance.

	IMB (1)	IM (2)	IB (3)
Baseline Use (HCF)	−0.001	−0.006	−0.003
	(0.005)	(0.005)	(0.005)
Parcel Size (Acres)	−0.003	0.013	−0.011
	(0.013)	(0.011)	(0.015)
Dwelling Size (1000 ft^2)	−0.016	0.042	0.036
	(0.037)	(0.037)	(0.037)
Days in Treatment (December)	0.001	0.002	−0.004
	(0.004)	(0.004)	(0.004)
Constant	0.001	−0.078	0.080
	(0.128)	(0.128)	(0.128)
Akaike Inf. Crit.	27,461	27,461	27,461

Note: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

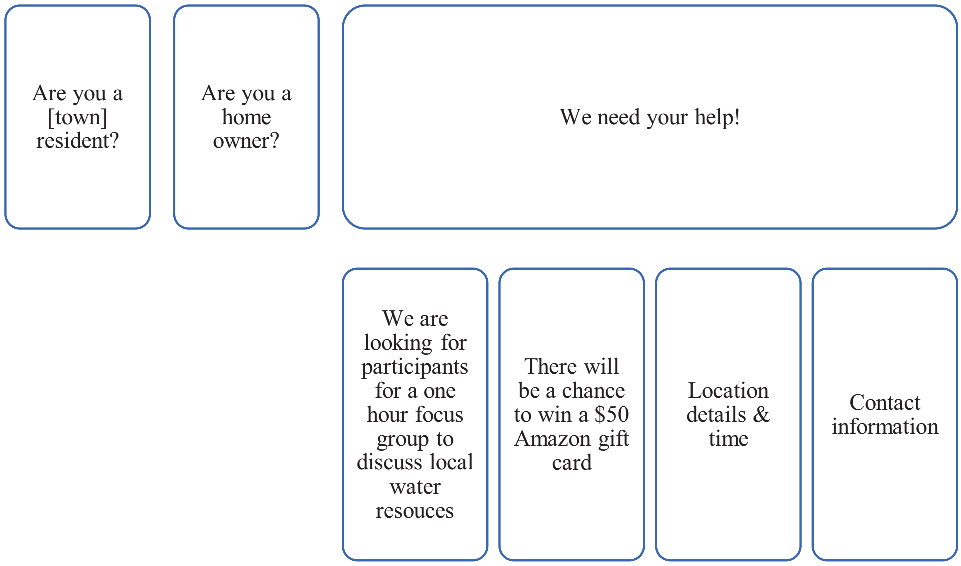


Figure A1. De-identified Recruitment Flyer Language for Focus Group Sessions.

Introduction	We've placed name cards on the table in front of you to help us remember each other's names. Let's find out some more about each other by going around the table. Please tell us your name and what neighborhood you live in.
Questions	What's going on with California and water?
	How does [town] get water?
	Why would anyone save water?

Figure A2. Focus Group Questions.

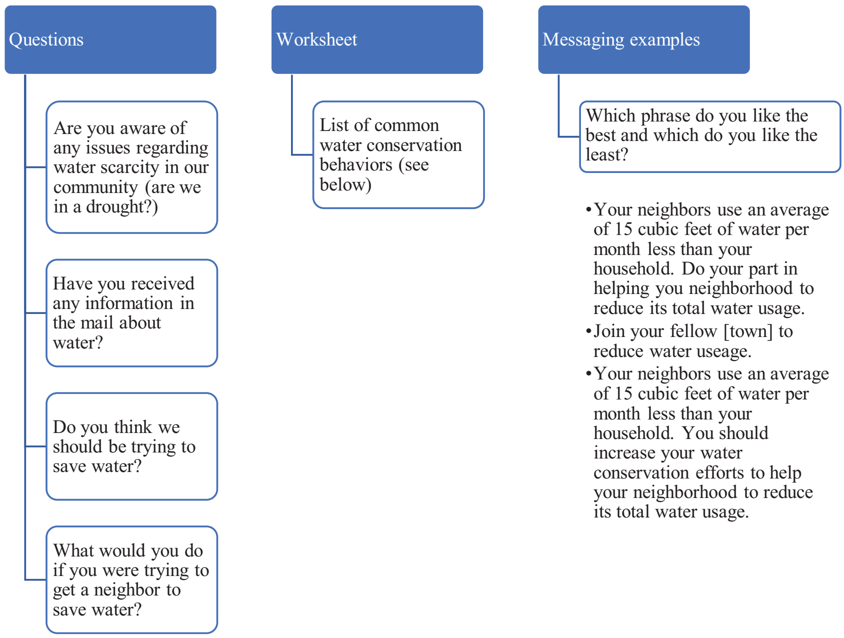


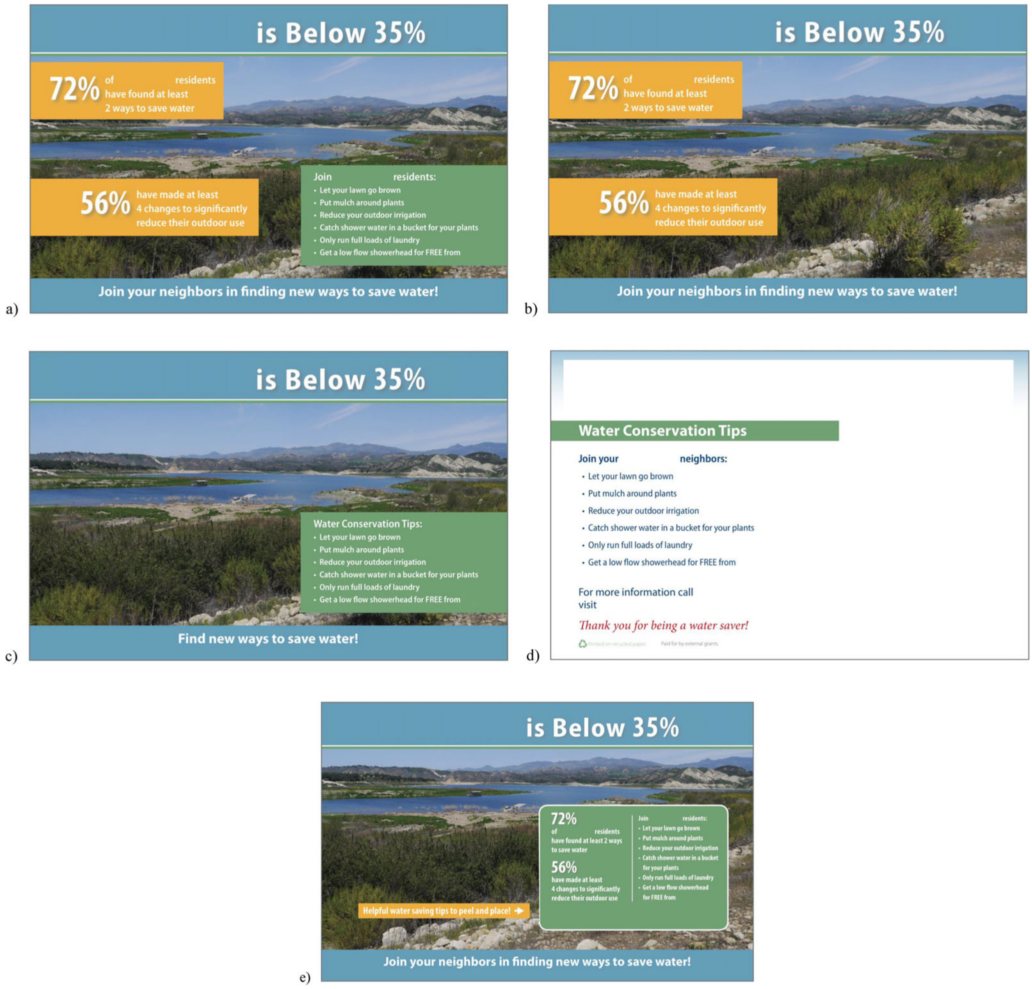
Figure A3. Intercept Interview Questions.

Water Conservation Behaviors

Instructions:
1) Check the items you have done
2) Circle the items you would be willing to do

- ☐ Check faucet, toilet, and pipes for leaks
- ☐ Install water-saving shower heads
- ☐ Install low-flow faucet aerators
- ☐ Install a high efficiency toilet
- ☐ Insulate your water pipes
- ☐ Take shorter showers
- ☐ Turn off the water after you wet your toothbrush
- ☐ Use your dishwasher / clothes washer for only full loads
- ☐ Plant drought resistant lawns, shrubs, gardens
- ☐ Put a layer of mulch around trees and plants
- ☐ Adjust sprinklers and timers to water your lawn efficiently
- ☐ Use a ‘Smart” irrigation controller
- ☐ Turn off the water while brushing your teeth or shaving
- ☐ Water outdoor plants in the morning versus evening
- ☐ Use less electricity

Figure A4. Intercept Interview Behaviors Worksheet.



Notes: a) Information, motivation, and behavioral skills postcard, b) information, motivation, c) information behavioral skills, d) postcard back from IMB treatment, e) IMB MagNot®. All are de-identified for anonymity.

Figure A5. (a-e). Postcards.

APPENDIX B: PANEL MODEL ROBUSTNESS CHECKS

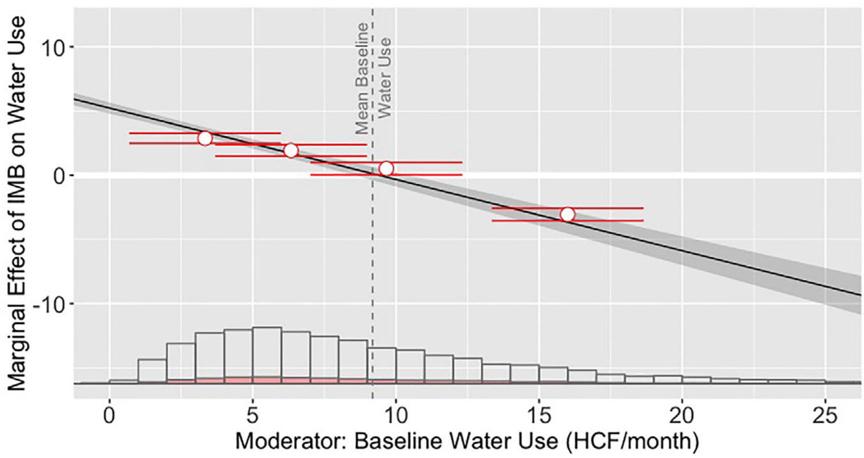


Figure B1. Testing for Non-Linear Heterogeneous Treatment Effects.

Table B1. Coefficients for water use with combined treatments.

	Dependent Variable: HCF (1)	Dependent Variable: HCF (2)
Treatment	0.243**	5.207***
	(0.100)	(0.113)
Days Since Treatment	−0.024***	−0.024***
	(0.0004)	(0.0004)
Fraction	−1.342***	−1.216***
	(0.144)	
	(0.132)	
Treatment x Days Since Treatment	0.013***	0.011***
	(0.001)	(0.001)
Treatment x Baseline Use		−0.542***
		(0.006)
Treatment x Parcel Size		−0.007
		(0.012)
Treatment x Dwelling Size		0.00000
		(0.00004)
Observations	69,814	69,240
R^2	0.157	0.289
Adjusted R^2	0.016	0.170
F Statistic	2,777.793*** (df = 4; 59,823)	3,440.225*** (df = 7; 59,328)

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses; all treatments were combined in order to compare to the control condition of no treatment.

Table B2. Coefficients for disaggregated heterogeneous treatment effects.

	Dependent Variable:			
	HCF			
	(1)	(2)	(3)	(4)
IMB Treatment	5.283***	5.244***	0.196	2.510***
	(0.193)	(0.176)	(0.170)	(0.200)
IM Treatment	5.045***	4.992***	0.111	2.401***
	(0.194)	(0.175)	(0.168)	(0.200)
IB Treatment	5.341***	5.347***	0.392**	2.748***
	(0.197)	(0.179)	(0.175)	(0.204)
Days in Treatment	−0.024***	−0.024***	−0.024***	−0.024***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
IMB x Fraction	−1.072***	−1.077***	−1.211***	−1.108***
	(0.228)	(0.228)	(0.248)	(0.246)
IM x Fraction	−1.135***	−1.149***	−1.232***	−1.160***
	(0.226)	(0.225)	(0.245)	(0.243)
IB x Fraction	−1.460***	−1.494***	−1.594***	−1.561***
	(0.235)	(0.234)	(0.255)	(0.252)
IMB x Days	0.009***	0.009***	0.011***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
IM x Days	0.012***	0.012***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
IB x Days	0.012***	0.013***	0.015***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
IMB x Baseline Use	−0.556***	−0.552***		
	(0.010)	(0.009)		
IM x Baseline Use	−0.531***	−0.535***		
	(0.010)	(0.009)		
IB x Baseline Use	−0.537***	−0.535***		
	(0.010)	(0.009)		
IMB x Parcel Size	−0.015		−0.011	
	(0.023)		(0.025)	
IM x Parcel Size	0.006*		0.041**	
	(0.016)		(0.018)	
IB x Parcel Size	−0.045		0.036	
	(0.034)		(0.037)	
IMB x Dwelling Size	0.00000			−0.002***
	(0.0001)			(0.0001)
IM x Dwelling Size	−0.0001			−0.001***
	(0.0001)			(0.0001)
IB x Dwelling Size	0.00004			−0.001***
	(0.0001)			(0.0001)
Household Fixed Effects	Yes	Yes	Yes	Yes
Observations	69,240	69,814	69,240	69,240
R^2	0.289	0.287	0.159	0.177
Adjusted R^2	0.170	0.168	0.018	0.039
F Statistic	1,268.099***	1,853.510***	860.209***	981.667***
	(df = 19; 59,316)	(df = 13; 59,814)	(df = 13; 59,322)	(df = 13; 59,322)

Notes: *p<0.1; **p<0.05; ***p<0.01, robust standard errors are in parentheses.
Notes: Wald Test p = 0.0000. A binning estimator was used to check the linearity of treatment effects across a range of baseline water use. As shown, there is evidence on non-linearity, especially among lowest and highest users. The size of the treatment effect should be treated with caution here because the implementation of the binning estimator does not accommodate multiple interactions with the treatment variable.

Table B3. Coefficients for water use excluding households < 2 and > 27 HCF.

	Dependent Variable:	
	HCF	
	(1)	(2)
IMB	0.392***	4.792***
	(0.126)	(0.145)
IM	0.285**	4.604***
	(0.125)	(0.146)
IB	0.503***	4.849***
	(0.130)	(0.148)
Days Since Treatment	−0.022***	−0.023***
	(0.0003)	(0.0003)
IMB x Fraction	−1.378***	−1.220***
	(0.185)	(0.169)
IM x Fraction	−1.265***	−1.206***
	(0.183)	(0.167)
IB x Fraction	−1.501***	−1.372***
	(0.190)	(0.174)
IMB x Days Since Treatment	0.011***	0.009***
	(0.002)	(0.001)
IM x Days Since Treatment	0.012***	0.012***
	(0.002)	(0.001)
IB x Days Since Treatment	0.012***	0.010***
	(0.002)	(0.002)
IMB x Baseline Use		−0.438***
		(0.008)
IM x Baseline Use		−0.437***
		(0.008)
IB x Baseline Use		−0.447***
		(0.008)
IMB x Parcel Size		−0.024*
		(0.017)
IM x Parcel Size		−0.005
		(0.012)
IB x Parcel Size		−0.028
		(0.026)
IMB x Dwelling Size		−0.0002***
		(0.0001)
IM x Dwelling Size		−0.0002***
		(0.0001)
IB x Dwelling Size		−0.0001**
		(0.0001)
Observations	69,814	69,240
R^2	0.157	0.289
Adjusted R^2	0.016	0.170
F Statistic	2,777.793***	3,440.225***
	(df = 4; 59,823)	(df = 7; 59,328)

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses; all treatments were combined in order to compare to the control condition of no treatment.

APPENDIX C: PRE-REGISTERED MONTHLY MODELS AND RANDOMIZATION INFERENCE

Randomization Inference Methods

As pre-registered, we applied an ANCOVA design to reveal sample average treatment effects (SATE) at each time point. The ANCOVA was estimated via the least squares regressions in equation (C.1) with imbalanced covariates as necessary. Given the balance displayed in Table 2 (main paper), we did not include any of the covariates.

$$y_i = \alpha_i + \beta_j Treatment_{ij} + \gamma DaysSince_i + \mu_j DaySince_i * Treatment_{ij} + \varepsilon_i \quad \text{(C.1)}$$

Model A estimates the treatment effect controlling for *DaysSince* and the interaction between *DaysSince* and *Treatment*. Model B includes the same specification as Model A, with the addition of the interactions between *Fraction* and *Treatment*. Model C is the pre-registered heterogeneous treatment effect estimation, which is Model A including estimates for *AsoAverage, acres*, and *SquareFeet* and their interactions with the treatments. Model D is the complete specification for heterogeneous treatment effects included in the panel estimate. For Month 1, Month 3, and Month 4, *Fraction* is a constant, thus Model B is not included.

We tested whether the treatment effects for H1, H2a, and H2b were inconsistent with the sharp null hypothesis (no difference by treatment arm) using randomization inference with one-tailed p values. Randomization inference allowed the estimation of p-values that account for the uncertainty of random treatment assignment. We compared our observed average treatment effects to this randomization distribution to compute p-values. To test H3a and H3b, we followed the same procedure testing for differences between IMB with IM and IB, respectively. The results are generally consistent with inference drawn from the panel data. They suggest that the biggest and most statistically significant treatments occur in Month 2 and that the treatment arms are not distinguishable from each other.

The SATE for the complete IMB treatment in Month 1 is 2.67 HCF (randomization inference $p = .05$). This should be interpreted with caution as only 3,396 households (34 percent) were in treatment, leading to low statistical power. Moreover, the average household received the MagNot® mailer only three days before the meter read recorded in Month 1.

A more appropriate test comes in Month 2. The SATE for IMB treatment households in Month 2 is −0.13 (randomization inference $p = .06$). The SATE for households that received IM in Month 2 is −0.12 (randomization inference $p = .02$). The SATE for households that received IB in Month 2 is not distinguishable from zero (randomization inference $p = .16$). The SATE for the IMB treatment condition in Month 2 is not statistically distinguishable from the IM or IB conditions (randomization inference; H3a $p = .399$, H3b $p = .240$) and IM and IB are not distinguishable from each other in Month 2 (randomization inference $p = .19$).

Monthly Model Specifications

Table C1. Coefficients for water use in month 1.

	Dependent Variable: HCF	
	Model A	Model C
Intercept	6.645***	0.833***
	(0.241)	(0.293)
IMB Treatment	0.156	−0.330
	(0.342)	(0.423)
IM Treatment	0.272	0.139
	(0.340)	(0.421)
IB Treatment	0.169	−0.287
	(0.349)	(0.426)
Days in Treatment (month 1)	0.170***	0.025
	(0.053)	(0.035)
IMB x Days in Treatment	−0.021	0.033
	(0.074)	(0.048)
IM x Days in Treatment	−0.032	0.042
	(0.074)	(0.048)
IB x Days in Treatment	0.001	0.079*
	(0.075)	(0.049)
Baseline Use (HCF)		0.776***
		(0.023)
Parcel Size (Acres)		0.091
		(0.127)
Dwelling Size (1000 ft^2)		−0.049
		(0.163)
IMB x Baseline Use		−0.040
		(0.033)
IM x Baseline Use		−0.154***
		(0.032)
IB x Baseline Use		−0.065**
		(0.032)
IMB x Parcel Size		−0.025
		(0.171)
IM x Parcel Size		−0.018
		(0.166)
IB x Parcel Size		0.008
		(0.157)
IMB x Dwelling Size		0.460**
		(0.237)
IM x Dwelling Size		0.658***
		(0.235)
IB x Dwelling Size		0.476**
		(0.232)
R-squared	0.011	0.586
N	3,395	3,395

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table C2. Coefficients for water use in month 2.

	Dependent Variable: HCF			
	Model A	Model B	Model C	Model D
Intercept	9.834***	9.834***	2.433***	2.433***
	(0.379)	(0.379)	(0.361)	(0.361)
IMB	−1.308***	−0.407	−0.936**	−0.992**
	(0.532)	(0.622)	(0.509)	(0.577)
IM	−1.290***	−0.852*	0.042	−0.184
	(0.532)	(0.620)	(0.508)	(0.572)
IB	−0.604	0.315	0.026	0.021
	(0.533)	(0.624)	(0.509)	(0.579)
Days in Treatment	−0.122***	−0.122***	−0.048***	−0.048***
	(0.015)	(0.015)	(0.011)	(0.011)
IMB x Days in Treatment	0.047**	0.173***	0.043***	0.036
	(0.020)	(0.050)	(0.016)	(0.038)
IM x Days in Treatment	0.042**	0.104**	0.010	−0.020
	(0.020)	(0.050)	(0.016)	(0.038)
IB x Days in Treatment	0.017	0.148***	0.015	0.014
	(0.021)	(0.051)	(0.016)	(0.039)
IMB x Fraction		−5.105***		0.291
		(1.832)		(1.421)
IM x Fraction		−2.499*		1.214
		(1.821)		(1.409)
IB x Fraction		−5.265***		0.026
		(1.865)		(1.448)
Baseline Use (HCF)			0.585***	0.585***
			(0.014)	(0.014)
Parcel Size (Acres)			0.015	0.015
			(0.046)	(0.046)
Dwelling Size (1000 ft^2)			0.088	0.088
			(0.103)	(0.103)
IMB x Baseline Use			−0.074***	−0.074***
			(0.020)	(0.020)
IM x Baseline Use			−0.062***	−0.061***
			(0.020)	(0.020)
IB x Baseline Use			−0.068***	−0.068***
			(0.020)	(0.020)
IMB x Parcel Size			0.019	0.020
			(0.057)	(0.057)
IM x Parcel Size			−0.005	−0.005
			(0.052)	(0.052)
IB x Parcel Size			−0.034	−0.034
			(0.068)	(0.068)
IMB x Dwelling Size			0.273**	0.274**
			(0.148)	(0.148)
IM x Dwelling Size			0.054	0.057
			(0.149)	(0.149)
IB x Dwelling Size			0.050	0.050
			(0.145)	(0.145)
R-squared	0.018	0.020	0.421	0.421
N	9,980	9,980	9,898	9,898

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table C3. Coefficients for water use in month 3.

	Dependent Variable: HCF	
	Model A	Model C
Intercept	8.069***	0.541
	(0.674)	(0.619)
IMB Treatment	−1.454*	−0.603
	(0.944)	(0.869)
IM Treatment	−2.002**	−0.027
	(0.946)	(0.866)
IB Treatment	−0.497	0.099
	(0.948)	(0.870)
Days in Treatment	−0.034***	0.028***
	(0.012)	(0.010)
IMB x Days in Treatment	0.023	0.016
	(0.017)	(0.014)
IM x Days in Treatment	0.034*	0.007
	(0.017)	(0.014)
IB x Days in Treatment	0.008*	0.003
	(0.017)	(0.014)
Baseline Use (HCF)		0.463***
		(0.013)
Parcel Size (Acres)		−0.038
		(0.043)
Dwelling Size (1000 ft^2)		−0.137*
		(0.097)
IMB x Baseline Use		−0.061***
		(0.019)
IM x Baseline Use		−0.063***
		(0.019)
IB x Baseline Use		−0.059***
		(0.019)
IMB x Parcel Size		0.022
		(0.054)
IM x Parcel Size		0.050
		(0.049)
IB x Parcel Size		−0.008
		(0.064)
IMB x Dwelling Size		0.050
		(0.139)
IM x Dwelling Size		0.104
		(0.139)
IB x Dwelling Size		0.171
		(0.136)
R-squared	0.002	0.316
N	9,987	9,905

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table C4. Coefficients for water use in month 4.

	Dependent Variable: HCF	
	Model A	Model C
Intercept	4.380***	−1.829**
	(0.961)	(0.925)
IMB Treatment	0.143	0.943
	(1.347)	(1.297)
IM Treatment	−0.064	1.228
	(1.349)	(1.293)
IB Treatment	0.119	0.395
	(1.354)	(1.300)
Days in Treatment (month 4)	0.013	0.054***
	(0.011)	(0.010)
IMB x Days in Treatment	−0.003	−0.008
	(0.015)	(0.014)
IM x Days in Treatment	0.000	−0.015
	(0.015)	(0.014)
IB x Days in Treatment	−0.001	−0.003
	(0.016)	(0.014)
Baseline Use (HCF)		0.322***
		(0.013)
Parcel Size (Acres)		−0.064*
		(0.043)
Dwelling Size (1000 ft^2)		−0.192**
		(0.097)
IMB x Baseline Use		−0.033**
		(0.019)
IM x Baseline Use		−0.013
		(0.019)
IB x Baseline Use		−0.037**
		(0.019)
IMB x Parcel Size		0.015
		(0.054)
IM x Parcel Size		0.053
		(0.049)
IB x Parcel Size		−0.024
		(0.064)
IMB x Dwelling Size		−0.057
		(0.139)
IM x Dwelling Size		0.116
		(0.140)
IB x Dwelling Size		0.174
		(0.136)
R-squared	0.001	0.189
N	9,987	9,905

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

APPENDIX D: "THANK YOU" MAILER EXCLUSIONS

Table D1. Coefficients for water use in month 1 w/o "thank you" households.

	Dependent Variable: HCF	
	Model A month 1	Model C month 1
Intercept	9.198***	1.533***
	(0.333)	(0.523)
IMB Treatment	−0.140	−0.537
	(0.466)	(0.761)
IM Treatment	−0.340	1.315**
	(0.452)	(0.728)
IB Treatment	−0.527	−0.330
	(0.467)	(0.729)
Days in Treatment (month 1)	0.081	0.007
	(0.069)	(0.051)
IMB x Days in Treatment	0.064	0.082
	(0.096)	(0.072)
IM x Days in Treatment	0.031	0.047
	(0.094)	(0.070)
IB x Days in Treatment	0.132*	0.111*
	(0.097)	(0.073)
Baseline Use (HCF)		0.737***
		(0.036)
Parcel Size (Acres)		0.184
		(0.188)
Dwelling Size (1000 ft^2)		−0.115
		(0.000)
IMB x Baseline Use		−0.017
		(0.052)
IM x Baseline Use		−0.206***
		(0.048)
IB x Baseline Use		−0.082**
		(0.048)
IMB x Parcel Size		−0.166
		(0.246)
IM x Parcel Size		−0.106
		(0.251)
IB x Parcel Size		0.046
		(0.268)
IMB x Dwelling Size		0.486*
		(0.366)
IM x Dwelling Size		0.421
		(0.350)
IB x Dwelling Size		0.602**
		(0.345)
R-squared	0.010	0.456
N	2,073	2,073

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table D2. Coefficients for water use in month 2 w/o "thank you" households.

	Dependent Variable: HCF			
	Model A	Model B	Model C	Model D
Intercept	13.101***	13.101***	3.398***	3.398***
	(0.509)	(0.508)	(0.587)	(0.587)
IMB Treatment	−1.974***	−0.653	−1.520**	−1.416*
	(0.717)	(0.845)	(0.852)	(0.960)
IM Treatment	−1.605**	−1.130*	1.466**	1.083
	(0.710)	(0.832)	(0.828)	(0.926)
IB Treatment	−5.051***	−4.688***	−0.996*	−1.141*
	(0.667)	(0.764)	(0.730)	(0.803)
Days in Treatment (month 2)	−0.177***	−0.177***	−0.074***	−0.074***
	(0.020)	(0.020)	(0.017)	(0.017)
IMB x Days in Treatment	0.072***	0.253***	0.074***	0.086*
	(0.028)	(0.067)	(0.024)	(0.056)
IM x Days in Treatment	0.045**	0.108**	0.000	−0.044
	(0.027)	(0.064)	(0.023)	(0.054)
IB x Days in Treatment	0.147***	0.207***	0.047**	0.025
	(0.026)	(0.067)	(0.022)	(0.056)
IMB x Fraction		−7.349***		−0.495
		(2.488)		(2.099)
IM x Fraction		−2.595		1.841
		(2.376)		(1.997)
IB x Fraction		−2.337		0.868
		(2.399)		(2.010)
Baseline Use (HCF)			0.566***	0.566***
			(0.021)	(0.021)
Parcel Size (Acres)			0.194*	0.194*
			(0.130)	(0.130)
Dwelling Size (1000 ft^2)			0.069	0.069
			(0.161)	(0.161)
IMB x Baseline Use			−0.110***	−0.110***
			(0.030)	(0.030)
IM x Baseline Use			−0.095***	−0.094***
			(0.030)	(0.030)
IB x Baseline Use			−0.064***	−0.064**
			(0.027)	(0.027)
IMB x Parcel Size			−0.037	−0.038
			(0.157)	(0.157)
IM x Parcel Size			−0.243**	−0.241**
			(0.135)	(0.135)
IB x Parcel Size			−0.217*	−0.215*
			(0.144)	(0.144)
IMB x Dwelling Size			0.533**	0.531**
			(0.230)	(0.231)
IM x Dwelling Size			−0.256	−0.246
			(0.231)	(0.231)
IB x Dwelling Size			0.157	0.161
			(0.206)	(0.206)
R-squared	0.033	0.034	0.331	0.331
N	6,643	6,643	6,631	6,631

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table D3. Coefficients for water use in month 3 w/o "thank you" households.

	Dependent Variable: HCF	
	Model A	Model C
Intercept	10.321***	1.444
	(0.902)	(0.946)
IMB Treatment	−2.010*	−0.502
	(1.271)	(1.355)
IM Treatment	−2.558**	0.488
	(1.260)	(1.321)
IB Treatment	−6.469***	−1.809*
	(1.198)	(1.204)
Days in Treatment (month 3)	−0.045***	0.028**
	(0.016)	(0.015)
IMB x Days in Treatment	0.031*	0.022
	(0.023)	(0.021)
IM x Days in Treatment	0.039**	0.007
	(0.022)	(0.020)
IB x Days in Treatment	0.098***	0.029*
	(0.022)	(0.020)
Baseline Use (HCF)		0.424***
		(0.019)
Parcel Size (Acres)		−0.184*
		(0.121)
Dwelling Size (1000 ft^2)		−0.189
		(0.150)
IMB x Baseline Use		−0.086***
		(0.028)
IM x Baseline Use		−0.086***
		(0.028)
IB x Baseline Use		−0.050**
		(0.025)
IMB x Parcel Size		0.088
		(0.146)
IM x Parcel Size		0.167*
		(0.126)
IB x Parcel Size		0.144
		(0.134)
IMB x Dwelling Size		0.010
		(0.215)
IM x Dwelling Size		−0.059
		(0.215)
IB x Dwelling Size		0.265*
		(0.192)
R-squared	0.011	0.216
N	6,647	6,635

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table D4. Coefficients for water use in month 4 w/o "thank you" households.

	Dependent Variable: HCF	
	Model A	Model C
Intercept	4.808***	−1.751*
	(1.298)	(1.365)
IMB Treatment	0.227	1.780
	(1.827)	(1.948)
IM Treatment	0.972	2.468*
	(1.810)	(1.900)
IB Treatment	−6.065***	−2.077
	(1.731)	(1.761)
Days in Treatment (month 4)	0.022*	0.065***
	(0.015)	(0.015)
IMB x Days in Treatment	−0.004	−0.013
	(0.021)	(0.021)
IM x Days in Treatment	−0.013	−0.027*
	(0.021)	(0.020)
IB x Days in Treatment	0.063***	0.020
	(0.020)	(0.019)
Baseline Use (HCF)		0.273***
		(0.019)
Parcel Size (Acres)		−0.297**
		(0.119)
Dwelling Size (1000 ft^2)		−0.257**
		(0.148)
IMB x Baseline Use		−0.063**
		(0.028)
IM x Baseline Use		−0.027
		(0.027)
IB x Baseline Use		−0.025
		(0.025)
IMB x Parcel Size		0.128
		(0.144)
IM x Parcel Size		0.264**
		(0.124)
IB x Parcel Size		0.209
		(0.132)
IMB x Dwelling Size		−0.041
		(0.211)
IM x Dwelling Size		0.061
		(0.212)
IB x Dwelling Size		0.246*
		(0.189)
R-squared	0.011	0.114
N	6,647	6,635

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.

Table D5. Coefficients for water use in panel models (w/o "thank you" households).

	Dependent Variable: HCF	
	(1)	(2)
IMB Treatment	0.289	7.930***
	(0.249)	(0.318)
IM Treatment	0.226	7.627***
	(0.237)	(0.307)
IB Treatment	0.937***	6.737***
	(0.236)	(0.269)
Days in Treatment	−0.033***	−0.033***
	(0.001)	(0.001)
IMB x Fraction	−1.754***	−1.626***
	(0.364)	(0.337)
IM x Fraction	−1.709***	−1.646***
	(0.346)	(0.320)
IB x Fraction	−1.966***	−2.024***
	(0.349)	(0.323)
IMB x Days	0.014***	0.010***
	(0.003)	(0.003)
IM x Days	0.018***	0.015***
	(0.003)	(0.003)
IB x Days	0.020***	0.020***
	(0.003)	(0.003)
IMB x Baseline Use		−0.627***
		(0.014)
IM x Baseline Use		−0.582***
		(0.014)
IB x Baseline Use		−0.559***
		(0.012)
IMB x Parcel Size		−0.041
		(0.059)
IM x Parcel Size		−0.026
		(0.024)
IB x Parcel Size		−0.048
		(0.042)
IMB x Dwelling Size		−0.00000
		(0.0001)
IM x Dwelling Size		−0.0003***
		(0.0001)
IB x Dwelling Size		0.0001
		(0.0001)
Household Fixed Effects	Yes	Yes
Observations	46,448	46,364
R^2	0.215	0.328
Adjusted R^2	0.084	0.215
F Statistic	1,089.222***	1,017.809***
	(df = 10; 39,791)	(df = 19; 39,710)

Notes: *p<0.1; **p<0.05; ***p<0.01; robust standard errors are shown in parentheses.