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Abstract

We explore Tinbergen's fundamental insight that policymakers need at least as many policy instruments as targets. We extend this idea using a large natural field experiment in water resource management. We use social comparisons and loss-framed messages to help achieve two goals of our partner utility: getting consumers to purchase drought-resistant plants and reducing water use. Our results show that seemingly related behavioral instruments can affect different household decisions. By themselves, social comparisons and loss framing have no significant impact on the number of rebate requests; when combined, however, they lead to a 36% increase in requests. Only loss framing leads to a significant increase in the purchase of drought-resistant plants, and only the social comparison reduces water consumption. These results highlight the importance of testing different combinations of instruments, particularly when policymakers have multiple goals and the relationship between instruments and goals is uncertain.

Keywords: technology adoption, loss aversion, social norms, water conservation
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1 Introduction

Jan Tinbergen, a Nobel laureate in economics, demonstrated that a policy maker needs at least as many policy instruments as she has targets, if her aim is to achieve those targets (Tinbergen 1952).[1] Tinbergen's theoretical formulation presumes that we understand the impact of the policy instruments on targets. In behavioral science, we are only now beginning to understand the relationship between instruments, or treatments, and their subsequent impact on various policy targets.

We utilize a natural field experiment to advance this body of work and elucidate the connection between Tinbergen's instruments and targets. Building on Tinbergen's fundamental insight, we argue that there is a need to *test* multiple policy treatments to meet multiple targets. The need to test multiple treatments follows from Tinbergen's insight about targets and instruments, and the observation that the impact of treatments on targets is often uncertain.

Specifically, we analyze how various policy treatments that are seemingly related affect the take-up of a new technology (a short-run target) and the overall consumption of a commodity (a long-run target) using an experiment in water resource management. We chose water management for our application because water scarcity is becoming a major global public policy challenge with multiple targets (Olmstead 2010; Eliasson 2015). Water suppliers generally face the challenge of meeting growing demand in the face of limited supply. In typical markets, supply-demand imbalances are addressed through price adjustments. However, most water suppliers have limited flexibility to raise prices in times of shortage. In addition, they must meet several other competing objectives, such as ensuring that the water needs of low-income are satisfied and having adequate storage. This balancing act will likely become more challenging in the future given the increasing likelihood of severe droughts in parts of the U.S. (Cook, Ault, and Smerdon 2015). Many water utilities have responded to this challenge by incentivizing residential and commercial customers to conserve water by changing habits and adopting technology —- a strategy typically referred to as demand-side management (DSM). [2]

In recent years, programs that offer customers rebates for adopting water-efficient technologies have become one of the more popular forms of DSM —- particularly in environments where changing prices is infeasible. Unfortunately, the impact of such programs is often limited because of either low participation rates and the tenuous link between adopting the technology and overall water consumption.

In the language of Tinbergen, water policymakers have two broad targets that reflect objectives over different time horizons. In the short-run, policymakers are interested in promoting the adoption of water-efficient technologies as a way to meet a long-run goal of promoting water conservation. Water efficient technologies, by definition, reduce consumption of water per unit of service or output, appropriately measured. However,

1. Tinbergen's targets can be thought of as "objectives" that may reflect aims over different time horizons or across distinct market segments. The policy instruments can be thought of as different incentives or framings of incentives designed to promote a given objective. In keeping with his initial framing, we use the terms targets and instruments.

2. Water utilities use both pricing strategies, such as increasing block pricing, and non-price strategies. Non-price strategies include social norms to reduce water use, public education campaigns, restrictions on particular types of water use (e.g., lawns), rationing, rebate programs for drought-resistant plants, swimming pool filter replacements, low-flow personal appliances, turf removal, drip irrigation systems, and subsidized leak audits and repair.

adoption of these technologies need not result in greater water conservation (i.e., reductions in overall water use). The impact of adopting these technologies on overall water use is an empirical question.

We draw upon insights from the behavioral economics literature to redesign the marketing of DSM programs to help meet these targets. We implemented our natural field experiment in partnership with the San Antonio Water System (SAWS). In the experiment, we sent letters to approximately 23,000 residential homes, reminding them of the existence of a rebate for partially replacing their lawn with drought-resistant plants. Through our partnership, we are able to measure behavior across a variety of margins that influence overall patterns of water use. Specifically, we are able to observe how our policies affect three key variables of interest: (i) the number of requests for rebates of a new technology — in this case, drought-resistant plants; (ii) the actual purchases of one or more drought-resistant plants through the rebate program[3]; and (iii) the monthly water use of households in the experimental sample for a nine month period after the intervention. In what follows, we refer to increasing the actual purchase of drought-resistant plants and reducing overall water consumption as final goals or targets.

Households in a benchmark treatment received a purely informative letter providing details on the program and rebate available for participants (see the Online Appendix for an example of this letter in full). We compare these households to counterparts that received either (i) a loss-framed letter, (ii) a letter with social norm content, or (iii) a letter with both loss-framed content and social norm content (see the Online Appendix for a summary of the content that varied across treatments). Results from the experiment suggest several interesting findings regarding both the adoption decision and subsequent patterns of water use.

In analyzing participation decisions, we break the analysis up into two distinct outcomes: rebate requests, and rebate redemptions for the actual purchase of new drought-resistant plants. We find that neither social norms nor loss framing in isolation were effective strategies for increasing the likelihood a household requests rebates. However, receiving a letter with both social norm information and loss framing increases the number of households requesting rebates by 36% relative to the benchmark treatment. In contrast, only loss framing was an effective strategy in inducing final purchases of the new technology.

Analyzing subsequent unconditional changes in monthly water use, we find that the pure social norm letter was the only treatment to yield significant reductions in water use (approximately 1.4%) over the nine post-treatment months. These results show how seemingly related policy interventions can affect behaviors relevant for outcomes over different time horizons, and that Tinbergen's fundamental insight extends to policies based upon behavioral economics.

Our research builds on several distinct literatures. First and foremost, our study contributes to a growing body of work exploring how principals can draw upon insights from behavioral economics to motivate workers and/or promote behavioral change. For example, there is a growing body of work exploring how one can leverage the power of loss aversion —- stemming from prospect theory (Kahneman and Tversky 1979) — as a way to frame incentives and promote a desired outcome such as worker effort. The central tenant of this work

3. We use variants of the phrases "drought-resistant landscaping," "technology adoption," and "lawn replacement" interchangeably throughout.

is that reference points matter and individuals value losses more than gains. A direct implication of such models is that framing incentives through the lens of what is given up should an agent fail to meet a target should have a greater impact on subsequent patterns of effort than if the incentive is framed through what would be gained should the target be reached. Importantly, behavior consistent with this prediction has been shown in a variety of field experiments (Armantier and Boly 2015; Hong, Hossain, and List 2015; Hossain and Li 2013; Hossain and List 2012; Levitt et al. 2016; de Quidt 2014) exploring the framing of incentives and subsequent worker effort.[4]

Our study advances this literature along two dimensions. To the best of our knowledge, we are the first to compare the effects of framing on outcomes that reflect concerns over different time-horizons. In doing so, we highlight that framings that make salient an intermediate objective such as the redemption of a landscape coupon may have little (or even a perverse) impact on longer run objectives such as changes in monthly water use and vice versa. We believe such concerns are particularly relevant in the context of attempts to motivate effort, and could be relevant for both workers and consumers. For example, workers may be motivated in the short-run by social comparisons or loss-framed incentives, but such contracts could have perverse effects on retention if workers dislike such contracts.[5]

Our findings also contribute to the literature on social norms and the use of normative appeals as a means to promote behavioral change. To date, this literature has largely focused on using such appeals to induce changes along a single margin, such as dollars contributed to a charitable cause (Croson and Shang 2008; Shang and Croson 2009) or the amount of water or energy used by residential households (Allcott 2011; Ferraro and Price 2013; Allcott and Rogers 2014; Brent, Cook, and Olsen 2015).[6] In our study, however, we focus on multiple margins that reflect objectives over different time-horizons —- participation in utility-sponsored programs, the adoption of new technologies, and changes in monthly water use. In this regard, our study is closest in spirit to an emerging literature that explores the use of social norms to induce participation in in-home energy audits as a means to promote the adoption of improved technologies (Allcott and Greenstone 2015; LaRiviere et al. 2016). However, our study differs from this work in that we are the first to explore the use of social norms as a way to motivate consumers to adopt resource-efficient technologies and promote the longer-run objective of conservation.

Our experiment also builds on theoretical work on framing. Recent research clarifies how the same policy

4. Other attempts to leverage insights from behavioral economics as a way to frame incentives and motivate worker effort include Englmaier, Roider, and Sunde (2016), who show that language that makes the marginal incentive underlying a piece-rate scheme salient affects subsequent effort levels; Blanes-i-Vidal and Nossol (2011), who show how the provision of information on relative rank influences subsequent effort levels; and Kessler and Leider (2012), who show how handshake agreements can be used to establish norms and promote greater co-operation in settings with incomplete contracts.

5. Kessler and Leider (2012) provide some evidence from laboratory experiments. In their experiments, subjects were less willing to use "handshake" agreements over time despite the fact that the use of such agreements lead to increased earnings.

6. In the context of environmental and resource economics, this work has focused on providing households with a comparison between their own use and that of their "like" neighbors. Allcott (2011) and Allcott and Rogers (2014) document that households receiving a letter with such normative content (relative to control households receiving no letter) reduce their electricity use immediately by approximately two percent, and among the households receiving repeated letters, this immediate reduction is made (largely) persistent. Related work in residential water conservation using similar randomized interventions finds reductions in residential water use of roughly the same magnitude (Ferraro and Price 2013; Schultz et al. 2016; Brent, Cook, and Olsen 2015), but with greater persistence (Bernedo, Ferraro, and Price 2014).

instrument can be framed differently depending on the information available to the policymaker about preferences of the agents (Roels and Su 2013). Similarly, we contribute to work exploring whether frames influence preferences or beliefs (Ellingsen et al. 2012). Our field research suggests that different types of framing appear to make salient different actions that target a given outcome, such as the decision to adopt a new technology or the decision to conserve water. Specifically, our paper is the first to test the effect of different framings across distinct outcomes of interest and demonstrate that each framing ultimately influences behavior along a distinct margin of choice.

Finally, our research contributes to a growing body of work exploring how best to use insights from behavioral economics to achieve policy goals more effectively.[7] Specifically, our research highlights how subtle changes in the advertisement of a voluntary program can have large impacts on subsequent participation rates and conservation efforts. To our knowledge, we are the first to explore this question in the context of environmental and resource economics and the adoption of water-efficient technologies.[8] More broadly, our findings speak to an important methodological issue in experimental economics — improvement of participation in voluntary programs. Low participation rates and the subsequent consequences have been explored in a number of contexts (e.g., Thaler and Sunstein 2003; Currie 2004; Bertrand et al. 2010; Fowlie, Greenstone, and Wolfram 2015). Results from our experiment suggest that loss framing can increase participation rates in voluntary programs at little or no cost.

The remainder of the paper is organized as follows: Section 2 describes the experimental design and the motivation for design choices. Section 3 clarifies design limitations (institutional and otherwise) and describes testable hypotheses given the design. Section 4 summarizes the data features and summary statistics of the population under study. Section 5 presents the results of our natural field experiment across the extensive and intensive margins. Section 6 briefly concludes.

2 Experimental Design

The treatments we developed were designed to help inform a policymaker's choice of the most effective interventions for promoting technology adoption as a means of managing residential water use. To implement this natural field experiment, we partnered with SAWS, a water utility with an active history of promoting conservation measures.[9] SAWS gave us access to approximately 23,000 households (i.e., the experimental

7. There is similar research in other policy-relevant areas such as food choice (List and Samek 2015), educational attainment (Levitt et al. 2016), and tax compliance (Hallsworth et al. 2014).

8. Previous work in the water area has traditionally looked at DSM programs as a whole. The strategy for estimating the causal impact on water use does not typically use randomized controlled trials (Renwick and Archibald 1998; Renwick and Green 2000). Continuing this line of work, Bennear, Lee, and Taylor (2013) use a matching difference-in-differences estimation strategy. They find that while replacing an old (pre-1991) toilet with a high-efficiency toilet reduces total indoor water use by seven percent (in line with engineering estimates), approximately two-thirds of households that take-up a rebate for such a technology improvement were already planning on replacing their toilet prior to the announcement of the rebate, and most with high-efficiency toilets. More broadly, our work fits into the recent literature on optimal environmental policy and the evaluation of such policy with experimental and quasi-experimental approaches (see, e.g., Kotchen and Grant 2011; Jacobsen and Kotchen 2013; Kahn and Wolak 2013; and Hortaçsu, Madanizadeh, and Puller 2015).

9. See http://www.saws.org/conservation/.

sample) who were the highest residential water users in its area that had not previously redeemed a landscaping rebate. The aim of the experiment was to explore methods to reduce the water use of these customers through changing the "landscape stock," i.e., encouraging households to switch to less water-intensive landscaping arrangements. In particular, SAWS wished to encourage "WaterSaver" landscaping that utilizes drought-resistant plants and shrubs, which can survive with little or no irrigation.[10] This water-efficient technology is focused explicitly on outdoor water use, and is similar to technology that was subsidized during the 2015 Californian water drought.

To inform the design of our experiment, we draw upon the behavioral economics literature. We use two interventions that have been shown to influence outcomes across a variety of markets and settings: social comparisons and a loss framing. We randomized households into four different treatment groups using a two-by-two experimental design summarized in Table 1. Households in each treatment group were sent a personalized letter advertising the "WaterSaver" program. Each treatment cell was represented roughly equally and contains around 5,800 households. The content of the different letter types is described below and examples of the letters are displayed in the Online Appendix.

In the benchmark experimental condition (called the Gain Framing treatment), we sent letters to households that informed them of the rebate offer as well as the limited-time nature of the offer.[11] The most prominently displayed text at the top of the letter states "You can have a FREE $100 landscape coupon."[12] In line with other field experiments that employ framing to alter perception of rewards (e.g., Ganzach and Karsahi 1995; Bertrand et al. 2010; and Hossain and List 2012), we interpret this treatment as a message with "gain" framing. It is consistent with the default message that many firms and water utilities employ when advertising the benefits of participating in a program.

To explore gain-loss asymmetry observed in other contexts, our Loss Framing treatment presents the identical information as the Gain Framing treatment, but alters the top-line text to say "Do not lose your chance to have a FREE $100 landscape coupon." The comparison of post-treatment rebate requests and redemptions across the Gain and Loss Framing treatments serves as our first experimental evaluation.

To complement the previous two treatments, we also investigate the efficacy of social comparisons in motivating take-up of landscape rebates and reduction in water use.[13] In the Social Comparison treatment, we reproduce the content and the emphasized first line of the Gain Framing treatment, but add personalized information on how each household's total water use in 2013 compared to the average home serviced by the water utility. In particular, households receiving a Social Comparisons letter saw bolded text of the form "...you used **XX,XXX gallons more water in 2013** than the average home...."

10. See http://www.saws.org/Conservation/Outdoor/Coupon/.

11. As a point of clarification, all households in our experimental sample are sent one of the four letters. We treat the Gain Framing letter as the benchmark/control group in our field experiment as it represents the kind of letter most similar to past letters sent by the water utility.

12. This prominent text uses the word "coupon" to refer to what we, throughout, call a rebate, in line with the broader literature on such programs.

13. There has been some research on examining the use of social norm information (see Hossain and Li 2013; Roels and Su 2013), but not in the context of product adoption and then subsequent usage of that product.

Such a treatment serves multiple purposes. First, it allows us to investigate whether the same type of social comparisons that have been shown to promote changes in both electricity (see, e.g., Allcott 2011; Allcott and Rogers 2014; and Costa and Kahn 2013) and water use (Ferraro and Price 2013; Brent, Cook, and Olsen 2015) among residential consumers can also affect investments in efficient technology. Second, it allows us to provide an apples-to-apples comparison of the relative effectiveness of two successful behavioral interventions —- loss framing and social comparisons —- as a way to inform policymakers about the most effective strategies for marketing voluntary programs.

The final treatment, called the Combined Framing treatment, combines the Loss and Social Comparison treatments. This treatment is largely exploratory in nature as models predicting an increase in rebate request and take-up due to loss framing have little or no overlap with models predicting increased rebate take-up and decreased water use due to social comparisons. This lack of overlap makes exploring such a treatment particularly interesting from a policy perspective. Specifically, if Loss and Social Comparison treatments influence choice along margins that are largely independent, a single letter containing both types of messaging may simultaneously act on both margins and have a greater impact on behavior than either message in isolation.

Our three outcome variables are: 1) the number of rebates requested; 2) the number of rebates redeemed; and 3) water use over time. We had access to data on pre- and post-randomization water consumption (covering January 2013 — December 2014) for all households in the experimental sample. We also had data identifying households that requested and households that redeemed the landscape rebate, which we use as a proxy for improvements to the efficiency of the "landscape stock". Finally, our data contain information on the number of requested and redeemed rebates per household.

Figure 1 summarizes the timing of our experiment. The treatment conditions represent different types of letters sent to the households on March 24, 2014, all of which advertised a $100 rebate offered to residents of single-family homes towards the purchase of drought-resistant plants. In order to request the $100 rebate, households needed to visit a project-specific webpage in the water utility's domain and complete a brief online application or call a utility's call center before April 30, 2014 (approximately 30 days after receiving the letter in the mail).[14]

3 Hypotheses

We identify three components of our letter that may affect our three outcomes of interest: rebate requests, rebate redemptions, and water use. [15] First, the very act of receiving a letter with informative content may

14. Of the 396 households that requested a rebate during the observation period, one made the request after April 30, 2014 (on May 1, 2014). We include this one household in the total count of experimentally-relevant rebate redemptions, but the results are robust to analyzing the data as if this request never occurred. Results of this robustness check are available upon request. As a limitation, we only observe drought-resistant plant purchase among households redeeming their rebate. In theory it is possible that the different treatment letters also differentially affect technology adoption outside of the rebate program (for example replacing a single square foot of lawn without claiming rebate dollars). In our analysis, we do not address this margin of response.

15. For simplicity, we exclude the intensive margin of rebate requests and redemption in parts of this discussion.

affect each margin, as shown in many standard neoclassical models (Ackerberg 2001). Models of bounded rationality (Shin 1985;DellaVigna 2009; Sexton 2015; Karlan et al. 2016), cue-triggered utility (Laibson 2001), and observation ("Hawthorne") effects (Levitt and List 2007) may work through this channel as well. Yet, unlike the neoclassical model, these behavioral alternatives suggest that receipt of the letter should have a greater impact on rebate requests than on subsequent rates of redemption. Second, the framing of the rebate offer may affect the rebate margin through, for example, loss aversion (Kahneman and Tversky 1979). Finally, the inclusion of a social comparison may effect both the use and rebate margins. Models of household production (Becker 1965), social learning (Conley and Udry 2010; Çelen, Kariv, and Schotter 2010), social norms (Festinger 1954; Cialdini, Reno, and Kallgren 1990; Kessler and Leider 2012; Krupka, Leider, and Jiang 2016), and moral utility (Levitt and List 2007) would all suggest responsiveness to social comparison content in a letter. The models do not, however, say much about the margins on which consumers or workers are most likely to respond.

We highlight two elements of our design that limit the range of hypotheses that we can test, which were based on the preferences of our partner utility. First, because all subjects were sent some letter, we do not have the variation that would allow us to learn about the effects of receiving an informative letter relative to the counterfactual of receiving no letter. One earlier study in the water area by Ferraro and Price (2013) suggested that this treatment effect was not significantly different from zero; however, the baseline treatment in that study was designed to explore whether providing information on strategies to conserve water affected subsequent patterns of monthly use, so it is not clear it generalizes to the interventions studied here. From an academic perspective, we are thus unable to directly identify "Hawthorne" effects, bounded rationality, or any of the other models described above insofar as they pertain to predicting behavior of households receiving informative letters versus no letter. The second limiting element of our design is that letters were only sent to the highest water users. This limits our ability to document heterogeneous treatment effects along the dimension of pre-intervention water use.[16]

Based on the literature, we can offer some conjectures on how different treatments would affect the likely take-up of the WaterSaver landscaping offer. First, given the existing literature on loss versus gain framing, we would expect that framing the letter content from the "loss" domain would induce more individuals to request a WaterSaver landscape rebate than those in the Gain Framing treatment. On the redemption and use dimension, the likely impact is less clear. We are unaware of any prior work comparing gain versus loss framing in energy or water markets.

Unlike the Gain and Loss Framing letters, the Social Comparison letter has a broad empirical basis in which to ground our priors. In particular, the existing field-experimental literature on social comparisons in water use (Ferraro and Price 2013; Brent, Cook, and Olsen 2015) suggests water use should be lower among households receiving a Social Comparison letter versus a Gain Framing letter if the channel is, in fact, the social comparison itself. More specifically, the existing social comparisons literature addressing energy

16. The social comparison literature on public utilities suggests that households using the most water and electricity are less responsive to price changes (Mansur and Olmstead 2012), more responsive to social comparisons in the short-term (Allcott 2011; Ferraro and Price 2013; Brent, Cook, and Olsen 2015), and show greater persistence in the treatment effect over time (Allcott and Rogers 2014; Bernedo, Ferraro, and Price 2014).

and water consumption typically employs a bundled treatment. The treatment is the combined stimulus of receiving a letter that includes tips on how to conserve and a social comparison (although see Allcott and Greenstone 2015 and LaRiviere et al. 2016 for recent notable exceptions).

Crucially, the social comparison content of the letter is not varied independently from the assignment to receive any letter at all. If it is the case that the social comparison, and not the act of receiving a letter, is key, we would expect to see a reduction in water use in the Social Comparison treatment relative to the Gain Framing treatment. Whether we would also see an increase in rebate requests or redemptions in the Social Comparison treatment relative to the Gain Framing treatment is an open question. The only existing study experimentally evaluating the effect of social comparisons on participation in water efficiency programs (Brent, Cook, and Olsen 2015) involves a bundled treatment that limits the ability to relate changes in behavior to receipt of the social comparison in and of itself. Furthermore, current theoretical models do not provide clear guidance on the effect of social comparisons on these two rebate margins.[17] Finally, as mentioned earlier, the Combined Framing treatment is largely exploratory in nature.

4 Data and Summary Statistics

Data for the experimental analysis was provided by SAWS and includes a panel of monthly water use for 23,282 households covering the period from January 2013 to December 2014.[18] In addition, SAWS provided information on participation in the WaterSaver program, including whether a household claimed the previously-mentioned $100 landscape rebate along with the date and number of claims.

Table 2 summarizes key covariates across the four treatment conditions. All of the covariates were measured prior to the beginning of the field experiment except the last one in the table, which is the proportion of households in each treatment for whom we have a complete 24 month time-series. The two summary measures of average water use in the fourth and fifth rows correspond to winter and summer 2013 water use, respectively. The final row of the table reports the results of a randomization test of equality of the multivariate distribution of covariates in the Gain Framing against each treatment (Hansen and Bowers 2008. We cannot reject the null hypothesis of equal pre-treatment covariate distributions.[19]

Nonetheless, comparing, for example, parcel area in the Gain and Loss Framing treatments, one may be

17. For example, a neoclassical model of household production (Becker 1965) would predict that a reduction in water use in response to social comparisons is positively correlated with an increase in rebate request and redemption. Both represent the actions of a household presented with the information that they may not be on their production possibility frontier in terms of transforming water into household services. On the other hand, a particular formulation of a moral cost model might suggest that a social comparison introduces guilt for households consuming “above the norm” that could be resolved either through reducing use, or through requesting (but not necessarily redeeming) the rebate (or some combination of both). These two examples illustrate that the theory on the likely impact of social comparisons on the use of rebates is ambiguous.

18. 391 of the 23,282 households (representing 8,776 monthly water bills) in the experimental sample have less than the complete 24 months of water use data, ranging from 14 months to 23 months. The distribution of these 391 households across treatments is: 101 in the Gain Framing, 104 in the Loss Framing, 87 in the Social Comparison, and 99 in the Combined Framing.

19. We use this test in order to leverage the fact that for covariate balance, the sharp null hypothesis (that is, that covariate distributions are identical across treatment and control) is appropriate. In addition, such a test should have improved power against alternatives with identical means of the covariate distribution, but differing higher moments.

concerned because homes in the Gain Framing treatment are, on average, larger. This difference is due more to outliers in the covariate distribution than an imbalance, per se. Knowledge of these distributional features prior to treatment assignment led us, when determining treatment assignment, to use a block randomization where we block on deciles of age of the home, parcel area, total value of the home, and average water use in winter 2013.[20]

5 Results

5.1 Rebate Requests, Rebate Redemptions, and Indirect Effects on Water Use

Table 3 summarizes the raw rebate request and redemption counts by treatment. In total, 396 households (of 23,282) requested a landscaping rebate. Of these 396 households, 90 were in the Gain Framing treatment, 105 were in the Loss Framing treatment, 77 were in the Social Comparison treatment, and the remaining 124 were in the Combined Framing treatment. Inspecting unadjusted counts, there appears to be evidence that Gain Framing, Loss Framing, and Social Comparisons treatments all performed roughly equally in terms of inducing rebate request, while the Combined Framing seems to stand out as having increased rebate request rate. Only the Loss Framing treatment appears to stand out when measuring rebate redemption rates. None of the treatments appear to have had a substantial impact on the number of rebates requested (redeemed) conditional on requesting (redeeming) any.

This evidence is suggestive, so we examine regression-adjusted estimates of several different quantities of interest. To frame the discussion, we can think of responses occurring along two distinct extensive rebate margins and three distinct intensive rebate margins. The two extensive margins are the unconditional propensity of a household to request, and subsequently redeem, a landscape rebate.[21] The intensive margins relate to the fact that households could request (and, hence, redeem) as many as eight rebates for their home as part of the WaterSaver program. As the intensive margin outcomes are only observed if a household responds along the extensive margin, we should note that the effect of treatment on the number of rebates requested and redeemed cannot be interpreted as causal, per se.[22] Nonetheless, we view such results as descriptive and relevant for policymakers.

20. The results of this block randomization by covariate are presented in the Online Appendix.

21. As our treatment content is delivered through letters and letter opening is fundamentally unobservable, both our summary in Table 3 and the regression-adjusted estimates should be interpreted as estimates of the intention to treat (ITT). Throughout, when we refer to average treatment effects we are thus referring to average ITT effects. Given our focus on policy relevance, we should note that with any intervention delivered through mail, this caveat holds.

22. As our treatments may induce different types of consumers to request a rebate, estimates for intensive margin effects may confound unobserved differences in types across treatments and the subsequent effects of treatment on redemption for a given type of consumer.

Starting from the extensive margins of rebate request and redemption, we estimate models of the form[23]:

$$1\{\text{Request Count}_i > 0\} = \beta_0^{req} + \sum_{f \in \{\text{L, SC, C}\}} \beta_f^{req} T_i^f + X_i' \gamma^{req} + u_i^{req} \tag{1}$$

$$1\{\text{Redeem Count}_i > 0\} = \beta_0^{red} + \sum_{f \in \{\text{L, SC, C}\}} \beta_f^{red} T_i^f + X_i' \gamma^{red} + u_i^{red} \tag{2}$$

$$1\{\text{Redeem Count}_i > 0 | \text{Request Count}_i > 0\} = \tilde{\beta}_0^{red} + \sum_{f \in \{\text{L, SC, C}\}} \tilde{\beta}_f^{red} T_i^f + X_i' \tilde{\gamma}^{red} + \tilde{u}_i^{red} \tag{3}$$

Throughout, Request Count$_i$ and Redeem Count$_i$ are count variables recording the number of rebates that household i requested and redeemed, respectively. Each T_i^f is a dummy variable for being sent a letter with content f, where dummies are used for the loss framing (L), the social comparison (SC), and the combined treatment (C). Finally, X_i is a vector of pre-intervention household covariates found in Table 2. For equation 1 and 2, each β_f is the marginal change in propensity to request (redeem) a landscape rebate due to content f for household i. By estimating these two equations, we recover an estimate of β_0 (the average propensity to request or redeem the rebate among individuals in the Gain Framing treatment) as well as each β_f, the average treatment effect of receiving a letter with content f instead of the Gain Framing letter.

In addition, we explore the number of rebates requested and redeemed by the average complier along each extensive margin by estimating models of form:

$$\text{Request Count}_i | \text{Request Count}_i > 0 = \theta_0^{req} + \sum_{f \in \{\text{L, SC, C}\}} \theta_f^{req} T_i^f + X_i' \delta^{req} + e_i^{req} \tag{4}$$

$$\text{Redeem Count}_i | \text{Redeem Count}_i > 0 = \theta_0^{red} + \sum_{f \in \{\text{L, SC, C}\}} \theta_f^{red} T_i^f + X_i' \delta^{red} + e_i^{red} \tag{5}$$

Table 4 presents empirical estimates where rebate requests are the dependent variable (equations 1 and 4), whereas Table 5 presents the estimates where rebate redemptions are the dependent variable (equations 2, 3, and 5). We discuss each in turn.

The first column of Table 4 reports the results of estimating a "short" version of equation 1 which excludes the vector of household characteristics. The findings from this table confirm the takeaway from Table 3 —- on average, only the Combined Framing letter generated a statistically significant increase in rebate request rates.[24] The Combined Framing letters increased rebate request by .006 percentage points, a 36 percent increase in rebate request rate relative to the Gain Framing letter. Point estimates and confidence intervals after including pre-intervention covariates (column 2) are essentially unchanged. Starting from column 3, we report the results of estimating equation 4, which captures the difference in the number of rebate

23. Results on the probability of rebate request and redemption are qualitatively similar when estimated using logit and probit models via maximum likelihood. The interested reader can find the results of these alternative specifications in the Online Appendix.

24. Note, however, that we do not reject a Wald test of equality of treatment effects across Loss Framing and Combined treatments ($p \approx 0.17$).

requests across the three letter treatments versus the Gain Framing treatment. As a direct analog to Table 3, we first note that in the Gain Framing treatment, the average household requested roughly 1.56 rebates (conditional on requesting any). From these regression estimates, there is no evidence that individuals in the Combined Framing treatment requested rebates more intensely in addition to being more likely to request any. If anything, only individuals in the Social Comparison treatment have a higher request intensity (a roughly 9% higher rate of rebate request), albeit this estimate is only marginally significant.

In Table 5, we keep part of the structure of Table 4 with the "short" regression of redemption rates in column 1 and the "long" regression —- equation 2 —- in column 2. The results across these two columns are essentially unchanged, but they differ from the findings on the request rate in Table 4. In particular, the Combined Framing only generated a marginally significant increase in redemption rates (.002 percentage points). However, the Loss Framing generated a statistically significant increase in redemption rates (.003 percentage points). Due to the overall low redemption rates, both of these extensive margin effects are substantial in terms of percentage change in redemption rate. Continuing to columns 3 and 4, we estimate versions of equation 3 to explore the answer to the (descriptive) question: on average, in which treatment was persistence across the request margin into the redemption margin (that is, the conversion rate) the greatest? We find that rebate requesters in the Loss Framing treatment had a conversion rate nearly double that in the Gain Framing treatment. We find a similar (but smaller) difference in conversion rate with the Social Comparison letter, although this difference is only marginally significant. Finally, we explore the intensive rebate redemption margin in columns 5 and 6 and find no strong evidence that the number of redemptions differs across the treatments on average when conditioning on redeeming at least one rebate.

How do these findings mesh with various theoretical predictions for the take-up of new water-saving technology? Using the point estimates, the Loss Framing letter moves rebate request rates in the direction predicted by a theory of loss aversion. Furthermore, we see that the Combined Framing generates larger increases in rebate request than either the Loss Framing or Social Comparison letters in isolation, but that this only partly translates to actual rebate redemptions. We believe that this finding is novel and suggests that loss framing and social norm appeals may be complements in inducing requests, but substitutes in inducing actual take-up.

Beyond concordance with theory, an important consideration is the economic significance of our treatments. The empirical reality is that, to our knowledge, there are no publicly-available estimates of either the effect of turf replacement on household water use or the returns on each dollar of subsidy for turf replacement. To fill this gap, we provide two crude estimates of the amount of water saved due to turf replacement induced by our Loss Framing treatment relative to the benchmark Gain Framing letter. Neither of these estimates is ideal, but together they represent the types of data inputs used by water utilities when deciding on demand-side management policies. The first calculation builds on information from a water conservation program in southern California administered by Metropolitan Water District of Southern California (MWDSC).[25] The

25. In particular, the program in California involves using subsidies of at least $1 per square foot of conventional lawn replaced with drought-resistant landscaping. This level of the subsidy is the base rate provided by Metropolitan Water District of Southern California (MWDSC). Many of the water agencies within MWDSC's service area also provide top-up incentives per square foot replaced in addition to MWDSC's subsidy.

second calculation utilizes results from Brent (2016) that report the estimated change in water use due to turf replacement based on an econometric model.

To begin, consider the following evapotranspiration model used[26] by MWDSC to project annual water savings (in gallons) per square foot of turf replaced with drought-resistant plants:

$$E[Use_{isa}] = \frac{0.62ET_a[PF_s - 0.4 \cdot 1\{DR_s\}]}{A_i + 0.4 \cdot 1\{DR_s\}}$$

The dependent variable is the expected annual water use (in gallons) of household i on plot s (of size 1 square foot) in geographic area a. ET_a is the reference evapotranspiration constant for an area a representing the amount of water lost (in inches) annually from fixed geographic features (such as local climate). PF_s is a multiplicative constant embodying the water requirements of typical plants in plot s. A_i is a technological parameter reflecting the efficiency of the irrigation at household i. Finally, $1\{DR_s\}$ is an indicator for plot s being comprised of drought-resistant plants. During its planning phase, MWDSC used this model to estimate water use (and, hence, water savings) for households that either did or did not replace their typical plants with drought-resistant plants, fixing parameters as follows:

$$\begin{aligned} ET_a &= 50.2 \text{ inches/year} \\ PF_s &= 0.8 \\ A_i &= 0.4 \end{aligned}$$

Using these parameters, the annual water saving per square foot of turf replaced is approximately 47 gallons.[27]

We use this model to calculate the expected reduction in water use due to the Loss Framing letter as compared to a typical marketing letter (Gain Framing).[28] As noted in Table 3, 17 households redeemed 29 rebates total in the Gain Framing treatment as compared to 35 households that redeemed 58 rebates in the Loss Framing treatment, a difference of 29 rebates. Under the assumption that redeeming a rebate is equivalent to replacing exactly[29] 200 square feet of turf (and using Table 3 counts directly), an additional 5,800 square feet of turf

26. We rephrase the notation of the model used by MWDSC to keep it as similar as possible to our own empirical models and to highlight the underlying assumptions of the model.

27. For comparison, recent turf replacement studies in southern Nevada (Sovocol, Morgan, and Bennett 2006) and Mojave, California (Mojave Water Agency 2014) use annual per-square-foot savings in excess of 50 in forecasting water savings due to the style of turf replacement encouraged in our field experiment. Note that implicit in our calculation is the assumption that households without turf replacement use the theoretical maximum water quantity for outdoor use. Recent survey evidence has suggested that such theoretical maxima may be substantially above actual use for all but the highest users (Water Research Foundation 2016). Given that our study focuses on the highest users in the utility's service area, our assumptions are in line with this survey evidence. In addition, we will assume that water savings accrue once in the year the landscape is changed, as opposed to in perpetuity.

28. We focus on the Loss Framing letter because it is the most successful of the three treatment letters in inducing rebate redemption, but this exercise can be extended to the other treatments. In principle, since this evapotranspiration model excludes any unobserved heterogeneity in either net benefits of the choice of take-up of drought-resistant landscaping or total water use conditional on choices, we could use it calculate water use changes within-household for all our treatments.

29. As mentioned earlier, we do not observe rebate redemptions outside of the rebate program and we do not observe if households that redeem a rebate for drought-resistant plants actually change their landscape. However, each letter mentioned the suggested removal of 200 square feet of turf to plant drough-resistant plants which motivates our choice. We maintain this assumption throughout this Section 5.1.

were replaced due to the Loss Framing[30]

Taken together with the estimated annual water savings per square foot mentioned above, our analysis implies an annual savings of approximately 272,600 gallons of water. Considering that the average annual water consumption in our field experiment is approximately 260,000 gallons in the year prior to treatment, the 29 additional turf replacements offset the annual water use of the average household and then some. At what financial cost[31] do these water savings arise? Given our counterfactual is the receipt of a benchmark letter, the only additional costs with the Loss Framing letter (since changing letter content is zero cost) are the costs of funding the 29 additional rebates. At \$100 per rebate, a total of \$2,900 would be spent to save 272,600 gallons, or roughly \$10.64 per thousand gallons of water saved.[32]

Without institutional detail on how the various evapotranspiration parameters are developed, we worry about estimates from such a model being without strong intuition and insufficiently detailed to evaluate the assumptions. Thus, we consider another estimation approach due to Brent (2016) who estimates a version of a discrete-continuous choice model using data from households in Phoenix, Arizona.

Under this approach, households are first assumed to select a given landscape arrangement and then, conditional on this arrangement, how much water to consume. Importantly, this approach allows Brent (2016) to estimate that households moving from the wet to the dry landscape group (an analogy to our turf replacement) reduce their monthly water consumption by roughly 20%. Given that the average monthly water use of mixed landscape households in Brent (2016) is roughly 16,500 gallons, this amounts to a monthly water savings of 3,300 gallons (or roughly 39,600 gallons annually) per converting household. Assuming that these converting households are comparable to the households in our experiment that adopt drought-resistant turf, the 29 additional turf replacements caused by receipt of the Loss Framing letter would amount to 1,148,400 gallons of water saved annually. Accounting for the additional subsidies paid in the Loss Framing treatment, these estimates imply a cost of approximately \$2.52 for every thousand gallons saved.[33]

5.2 Direct Effect on Water Use

In addition to the impact on take-up of drought-resistant landscaping, we are able analyze the impact of our randomized content treatments on subsequent monthly water use. To do so, we employ a difference-in-differences approach; in particular, we estimate models of the following form:

$$\ln\{\text{Use}_{it}\} = \alpha + \nu_i + \eta_t + \beta_0 \text{Post}_{it} + \sum_{f \in \{\text{L, SC, C}\}} \gamma_f (T_i^f \times \text{Post}_i t) + u_{it} \tag{6}$$

30. 29 additional turf replacements · 200 square feet per replacement = 5,800 square feet of turf replaced.

31. Note that we cannot quantify any welfare costs (either directly due to the content, or indirectly though unobserved behavior change) that the Loss Framing letter imposes on households relative to Gain Framing letter, thus this exercise is in the vein of program administrator cost tests.

32. For comparison, Ferraro and Price (2013), using a set of varied letter contents, report reduction in water use due to social comparisons, and report an estimate of \$0.575 of utility cost per thousand gallons of water saved.

33. We provide a detailed discussion of this calculation in the appendix.

Throughout, our dependent variable is the log of household i's water use in month-year t.[34] Post_{it} is an indicator keeping track of whether the use is prior to or after our treatment letters were sent. As with our previous regressions, T_i^f is an indicator for a household ever receiving a letter with content f. Thus, the interaction of each T_i^f with Post_{it} allows us to estimate a causal parameter — the average treatment effect of receiving a letter with content f when the counterfactual is receiving a Gain Framing letter. In addition, we introduce household fixed effects ν_i to control for time-invariant individual heterogeneity in water use and month-year fixed effects η_t to control for time-varying / seasonal determinants of water use. The results of this estimation are found in Table 6, where, given that randomization occurred at the level of the household, we cluster the standard errors at the household level.

Beginning with column 1, we see a pattern of treatment effects emerge that differs from those realized when exploring the effect of treatment on the rebate redemption decision. Specifically, only the Social Comparison letter generated a statistically significant change in use (a reduction in use of 1.4%). Interestingly, the direction and magnitude of this effect is largely consistent with the existing evidence on the effect of social comparisons on use (Allcott 2011; Ferraro and Price 2013; and Brent, Cook, and Olsen 2015).[35]For perspective, our estimated change in monthly use is equivalent to that which would be expected in the short-run if average prices were to increase by approximately 3.5 to 4.7 percent.[36]

Exploring the remaining results, the lack of statistically significant evidence for a change in use due to the loss framing is consistent with our earlier hypothesis given that the framing only applies to the rebate and the effect on rebate redemption was relatively small. As such, it is unlikely that our ITT estimate of the effect of the loss framed letter on use would be able to identify changes in use that arise solely through its impact on changes in landscape stock. Similarly, we find no statistically significant evidence that including both a loss framing and a social comparison on a letter reduces use beyond any potential use reductions due to the Gain Framed letter. That said, the direction of the estimated effect is in the predicted direction.[37]

We can also move beyond the above static estimates to explore the treatment effects in each month of the observation period. Specifically, we estimate an augmented version of equation (6) by fully interacting each of the three treatment dummies with a dummy for each month-year, and additionally include household fixed effects in the estimating equation. Afterwards, we capture and plot the vector of estimates $\hat{\boldsymbol{\beta}}$ in event time in Figure 2 together with the 95 percent confidence interval around each estimate.[38]

34. As a robustness check for the functional form of the dependent variable, we explored using percentage change in use levels relative to the average use of the Gain treatment post intervention. The results were partly inconsistent with those when estimating in logs; however, when we estimate the percentage change specification excluding the top and bottom 1% of use, the results are qualitatively and quantitatively similar to the log specifications. In addition, our later analysis of treatment effects over time looks nearly identical across the log specification and the percentage change specification dropping outliers. The entirety of this exploration can be found in the Online Appendix.

35. Yet, it is important to note that our counterfactual is quite different from the existing literature. As such, this result may suggest that it is the content of the social comparison that drives the observed change in use.

36. These calculations are based on an average, short-run price elasticity of water that falls in the range of -0.3 to -0.4 (Olmstead, Hanemann, and Stavins 2007; Olmstead and Stavins 2009; Mansur and Olmstead 2012).

37. Note, however, that we do not reject a Wald test of equality of intent-to-treat effects across Social Comparison and Combined Framing treatments ($p \approx 0.71$).

38. We build these confidence intervals off of standard errors that are clustered at the household level.

This exploration is of particular interest given that evidence from electricity markets suggests we should observe rapid decay of treatment effects in the absence of additional treatment letters (Allcott and Rogers 2014; Asensio and Delmas 2016), and more general evidence of decay of non-pecuniary policy instruments in the field (Gneezy and List 2006; DellaVigna et al. 2016). At the same time, past evidence from water markets suggests relative persistence of social comparison treatment effects (Ferraro and Price 2013; Brent, Cook, and Olsen 2015).

The temporal pattern in Figure 2 reveals one insight and raises one concern. The insight is that we see within nine months (if not sooner), the difference in use between households that received a Social Comparison letter and households that received a Gain Framing letter has all but vanished. This finding suggests that while sending letters may generate reductions in water use in the short-term, the long-term impact is significantly less pronounced.[39]

However, a simple ocular check of Figure 2 also uncovers one concern —- the apparent difference in water use of households in the Social Comparison treatment relative to the Gain Framing treatment in the two months prior to treatment.[40] In particular, given that this difference contributes towards average pre-treatment water use differential (see the Social Comparison row in columns 1 and 3 of Table 6), we may worry that the difference-in-differences estimator from our regressions may merely capture a differential pre-trend.

To explore how much this pre-treatment difference contributes to the estimated difference-in-differences treatment effect, we re-estimate the empirical models in Table 6 excluding data from the one pre-treatment month with a statistically significant pre-treatment use difference (month "-1" in the event time of Figure 2). The results, found in Table 7, are largely unchanged in magnitude, although are now only significant at the ten percent level.

6 Conclusion

This paper builds on Tinbergen's fundamental insight regarding policy instruments and targets. Tinbergen argued that that policymakers need at least as many policy instruments as targets to achieve those targets. We extend this idea using a natural field experiment in water management. Our research highlights the need to test several behavioral mechanisms when policymakers have multiple targets over different time horizons, and the relationship between instruments and targets is uncertain.

Our field experiment attempts to understand how to use insights from behavioral economics to encourage technology adoption and reduce water use. We tested four treatments designed to encourage the adoption of a turf-replacement technology and water conservation. Households were sent various treatment letters, including a gain framing, a loss framing, a social comparison, and a combination of a loss framing a social comparison. We find that the combination of a social comparison and loss framing leads to a 36% increase in

39. This result is in line with regression discontinuity results described in Allcott (2011) but at odds with the short and long-term results in Ferraro and Price (2013) and related work.

40. We do not find a similar pattern when producing identical event-study figures for the Loss Framing and Combined Framing treatments. These figures are displayed in the Online Appendix.

rebate requests relative to a benchmark letter, but it is only the loss framing on its own that reliably increases actual rebate redemption. In the nine months after treatment, the only intervention that led to a significant reduction in water use relative to the standard letter was the social comparison treatment, which resulted in a 1.4% drop in consumption.

Taken together, our results suggest that our treatment letters make salient different actions and influence behavior along different dimensions. Importantly, messages that make salient the incentives for participating in the "WaterSaver" program influence short- and intermediate-run objectives (rebate claims and redemptions) but have little impact on long-run patterns of use. Messages that focus on relative consumption patterns, in contrast, have little impact on participation in the "WaterSaver" program but nonetheless lead to significant reductions in monthly water use (the long-run outcome of interest). In this regard, our findings support Tinbergen's conjecture – at least two distinct policy instruments were required to meet the dual targets of technology adoption and reductions in water use over longer time horizons.

Notwithstanding our findings, we believe that the problem Tinbergen originally described may need to be reframed. In his original formulation, Tinbergen presumes that one can specify whether targets are independent (e.g., inflation and unemployment, or technology adoption and water conservation). In fact, we do not always know whether policy targets are ex-ante independent. It may be the case, for example, that technology adoption and conservation are interrelated and thus could be influenced by a single policy instrument.

A more general point is that many economic production processes, and the policies that improve these processes, need to be discovered or better understood. It is our belief that behavioral scientists and natural field experiments have a critical role to play in this discovery process. We believe our paper provides a blueprint that highlights how to use field experiments to test different behavioral interventions, especially when policymakers have multiple objectives for which the underlying production process is unknown.

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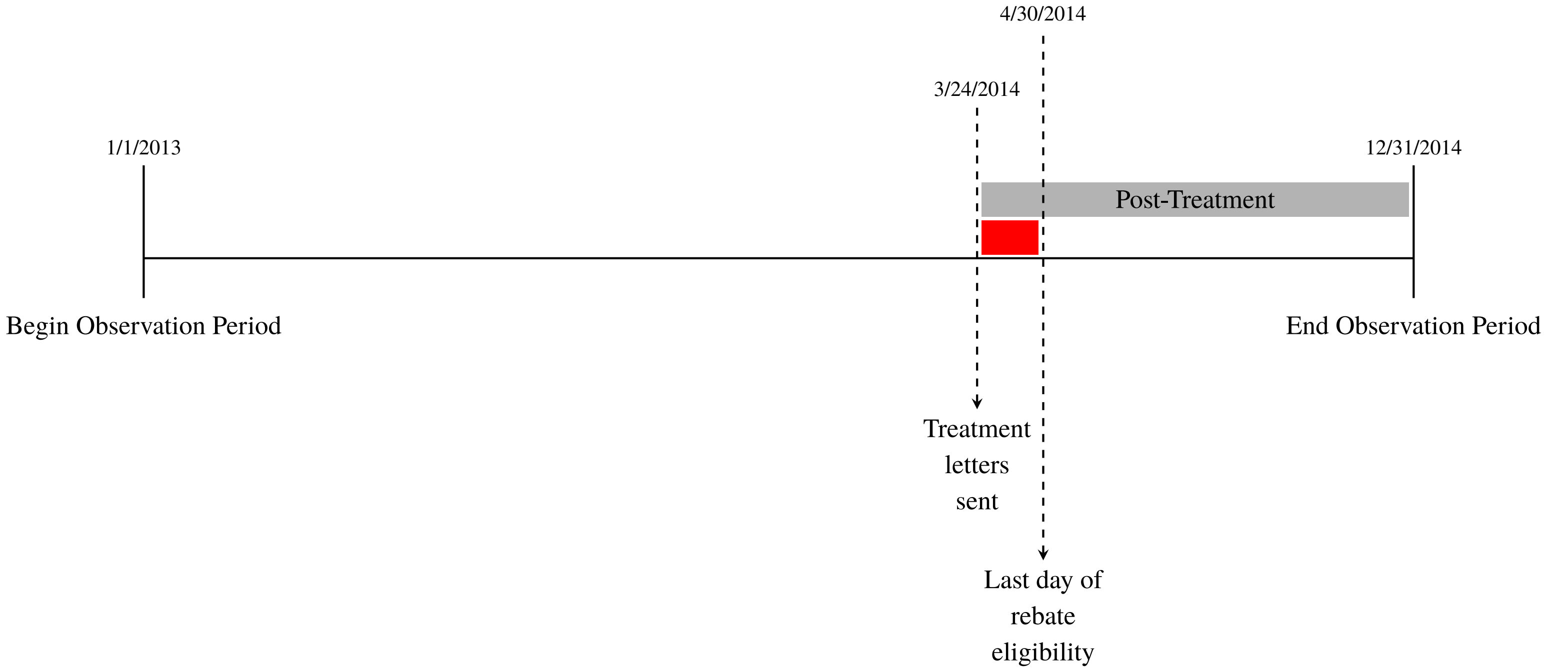
Figure 1: Event Timeline



Note: We begin observing monthly water use for our sample of approximately 23,000 households as of January 1, 2013. On March 24, 2014, we randomized households into the control group and three treatment conditions, and sent out treatment letters. Households had until April 30, 2014 to respond to the rebate (duration denoted in red). We observe post-treatment monthly water use through the final monthly bill of 2014 (duration denoted in gray).

Table 1: Experimental Design and Treatment Assignment in Field Experiment

	Gain Framing	Loss Framing
No Comparison	5,821	5,819
Social Comparison	5,819	5,823

Note: Elements of each cell indicate the number of households assigned to each treatment. Throughout, the Gain Framing treatment is used as the relevant baseline or control group. In addition, we refer to the treatment cell representing the intersection of Loss Framing and Social Comparison as the Combined Framing treatment throughout.

Table 2: Covariate Composition by Treatment

	Gain Framing	Loss Framing	Social Comparison	Combined Framing
Age of Home (In Years)	24.80	24.80	24.88	24.84
	(0.26)	(0.26)	(0.26)	(0.26)
Parcel Area (Square Feet)	40,447.31	31,762.49	39,258.62	37,008.25
	(3,879.44)	(1,885.62)	(4,387.23)	(2,519.45)
Total Value of Home (in USD)	395,203.98	396,462.86	396,399.05	407,939.35
	(4,345.44)	(4,407.54)	(4,356.72)	(5,149.08)
Average Water Use - Winter (Gallons per Month)	16,578.20	16,152.83	16,348.76	16,263.91
	(405.94)	(135.98)	(161.74)	(141.31)
Average Water Use - Summer (Gallons per Month)	26,839.44	27,983.64	27,176.86	27,493.79
	(178.75)	(931.61)	(182.55)	(386.03)
$\mathbb{1}$(Full Time-Series)	0.98	0.98	0.99	0.98
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Sample Size	5,821	5,819	5,819	5,823
Randomization Test (Hansen & Bowers (2008))		$p = 0.361$	$p = 0.833$	$p = 0.259$

Note: Each row represents a covariate that we use in our cross-sectional regression-adjusted estimates to improve precision. Each column represents one of the four treatment groups. All households in the water utility's service area received a letter advertising a $100 landscape rebate good towards the purchase of drought-resistant plants, but the additional content varied by treatment. The Gain Framing treatment describes households who received a letter advertising a $100 landscape rebate framed as a potential gain if claimed (this serves as our benchmark group throughout). The Loss Framing treatment mirrored the Gain Framing treatment, but framed the $100 landscape rebate as a potential lost opportunity if not claimed. The Social Comparison treatment mirrored the Gain Framing treatment with additional information about how household i's use in the previous year compares to an average household served by the water utility. Finally, the Combined Framing treatment combines the relevant features of Loss Framing and Social Comparison treatments in the same letter. All households in the sample used substantially more water than the average household served by the water utility, so the Social Comparison always told households how much *more* water they had used in the previous year relative to the average household. For the case of age of home, parcel area, total value of home, and average winter water use, we calculated the relevant decile for each covariate and use these deciles (instead of the continuous counterparts) as part of the block-randomized treatment assignment. Tabulations of the results of the block randomization are available in the Online Appendix.

Table 3: Rebate Request and Redemption by Treatment (Unadjusted)

	Count of HHs Requesting	Mean Number of Rebates per Request	Count of HHs Redeeming	Mean Number of Rebates per Redemption	Total Sample Size
Gain Framing	90	1.56	17	1.71	5,821
Loss Framing	105	1.60	35	1.66	5,819
Social Comparison	77	1.70	24	1.67	5,819
Combined Framing	124	1.52	29	1.62	5,823
Total	396	1.59	105	1.66	23,282

Note: The table records raw counts of rebates requested and rebates redeemed in each treatment. "Counts of HHs" columns record the extensive margin count of the number of households either requesting any rebates or redeeming any rebates, respectively, by treatment. Since households could request and redeem more than one rebate, we also record the mean number of rebates requested and redeemed by treatment. All households in the water utility's service area received a letter advertising a $100 landscape rebate good towards the purchase of drought-resistant plants, but the additional content varied by treatment. The Gain Framing treatment describes households who received a letter advertising a $100 landscape rebate framed as a potential gain if claimed (this serves as our benchmark group throughout). The Loss Framing treatment mirrored the Gain Framing treatment, but framed the $100 landscape rebate as a potential lost opportunity if not claimed. The Social Comparison treatment mirrored the Gain Framing treatment with additional information about how household i's use in the previous year compares to an average household served by the water utility. Finally, the Combined Framing treatment combines the relevant features of Loss Framing and Social Comparison treatments in the same letter. All households in the sample used substantially more water than the average household served by the water utility, so the Social Comparison always told households how much *more* water they had used in the previous year relative to the average household.

Table 4: Impact of Treatment Letters on Rebate Request

	(1)	(2)	(3)	(4)
Loss Framing	0.003	0.002	0.044	0.038
	(0.002)	(0.002)	(0.071)	(0.072)
Social Comparison	-0.002	-0.002	0.146*	0.139*
	(0.002)	(0.002)	(0.074)	(0.074)
Combined Framing	0.006**	0.006**	-0.031	-0.032
	(0.002)	(0.003)	(0.069)	(0.070)
Gain Framing / Constant	0.015***	0.013***	1.556***	1.512***
	(0.002)	(0.005)	(0.053)	(0.273)
Controls	No	Table 1 Covariates	No	Table 1 Covariates
R^2	0.001	0.001	0.017	0.024
N	23,282	23,125	396	395

Note: The dependent variable in columns 1 and 2 is an indicator for whether household i requested any rebates, while the dependent variable in columns 3 and 4 is the number of rebates requested conditional on requesting any. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined Framing is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The Gain Framing coefficient is the constant in the regression and denotes letters that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. All standard errors are robust to heteroskedasticity. Control variables include the full set of covariates in Table 1. The addition of control for the age of the home reduces the sample size by 157 households, which are those households where the year the home was built is unavailable.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

Table 5: Impact of Treatment Letters on Rebate Redemption

	(1)	(2)	(3)	(4)	(5)	(6)
Loss Framing	0.003**	0.003**	0.144**	0.148**	-0.049	-0.095
	(0.001)	(0.001)	(0.062)	(0.063)	(0.139)	(0.144)
Social Comparison	0.001	0.001	0.123*	0.125*	-0.039	-0.079
	(0.001)	(0.001)	(0.067)	(0.068)	(0.149)	(0.156)
Combined Framing	0.002*	0.002*	0.045	0.049	-0.085	-0.141
	(0.001)	(0.001)	(0.056)	(0.056)	(0.145)	(0.149)
Gain Framing / Constant	0.003***	0.000	0.189***	-0.217**	1.706***	1.549***
	(0.001)	(0.001)	(0.041)	(0.099)	(0.113)	(0.178)
Controls	No	Table 1 Covariates	No	Table 1 Covariates	No	Table 1 Covariates
R^2	0.000	0.001	0.017	0.034	0.003	0.061
N	23,282	23,125	396	395	105	105

Note: The dependent variable in columns 1 and 2 is an indicator for whether household i redeemed any rebates. In columns 3 and 4, the dependent variable is an indicator for whether household i redeemed any rebates conditional on *requesting* any rebates. Finally, in columns 5 and 6, the dependent variable is the number of rebates redeemed conditional on *redeeming* any. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined Framing is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The Gain Framing coefficient is the constant in the regression and denotes letters that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. All standard errors are robust to heteroskedasticity. Control variables include the full set of covariates in Table 1. The addition of control for the age of the home reduces the sample size by 157 households, which are those households where the year the home was built is unavailable.

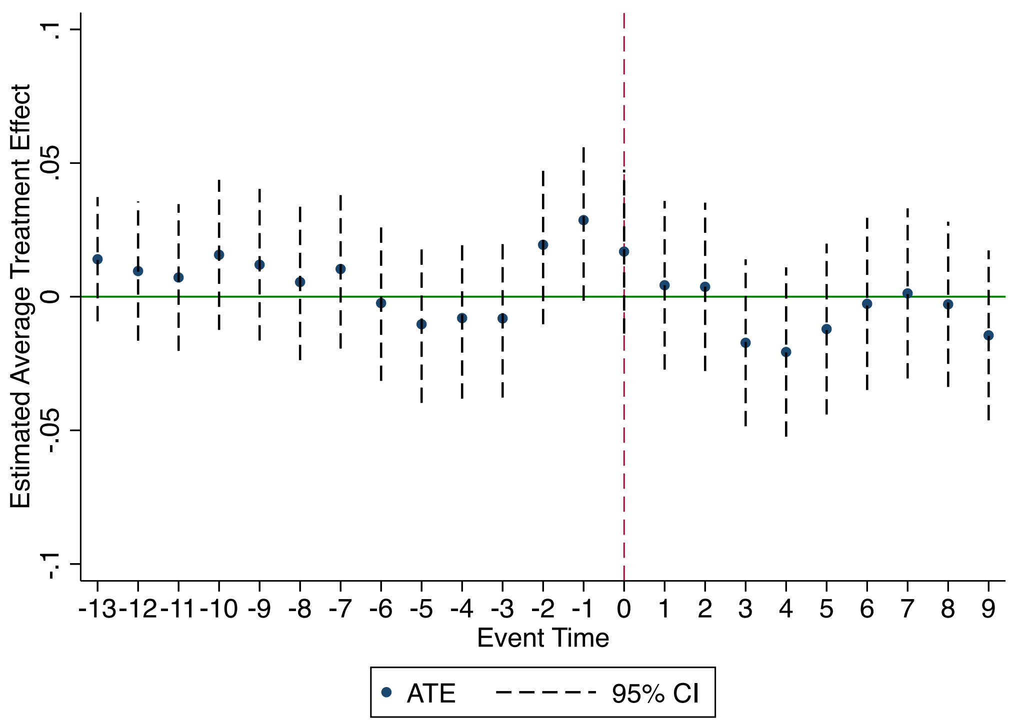
$* p < 0.1$, $** p < 0.05$, $* * * p < 0.001$

Table 6: Impact of Letter Treatments on Log Water Use

	(1)	(2)	(3)	(4)
Loss Framing X Post	0.003	0.002	0.003	0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Social Comparison X Post	-0.014**	-0.014**	-0.014**	-0.014**
	(0.007)	(0.007)	(0.007)	(0.007)
Combined Framing X Post	-0.011	-0.011	-0.011	-0.011
	(0.007)	(0.007)	(0.007)	(0.007)
Post	0.063***	0.061***	-0.335***	-0.338***
	(0.005)	(0.005)	(0.007)	(0.007)
Loss Framing	0.002		0.002	
	(0.007)		(0.007)	
Social Comparison	0.013*		0.014**	
	(0.007)		(0.007)	
Combined Framing	0.009		0.009	
	(0.007)		(0.007)	
Gain Framing	9.643***		9.541***	
	(0.005)		(0.006)	
Household Fixed Effects	No	Yes	No	Yes
Month-Year Fixed Effects	No	No	Yes	Yes
R^2	0.002	0.287	0.156	0.441
N	556,527	556,527	556,527	556,527

Note: The dependent variable is log total water use of household i in billing period t. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The omitted letter-type is one that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. Post is an indicator for months after the treatment letters were sent. All standard errors are clustered at the household level, i.e., the level at which the randomization occurred. A total of 1,633 monthly bills (spanning 919 households) are excluded from this log use specification due to zero recorded monthly use.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

Figure 2: Estimated Average Treatment Effect of Social Comparison Letter on Log Water Use Over Time



Note: The figure depicts the average treatment effect of a Social Comparison letter, plotted in event time. All estimates are regression-adjusted estimates after controlling for household and month-year fixed effects. The dependent variable is log total water use of household i in billing period t. All standard errors are clustered at the household level.

Table 7: Impact of Letter Treatments on Log Water Use — Excluding 2/2014

	(1)	(2)	(3)	(4)
Loss Framing X Post	0.003	0.002	0.003	0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Social Comparison X Post	-0.013*	-0.013*	-0.013*	-0.013*
	(0.007)	(0.007)	(0.007)	(0.007)
Combined Framing X Post	-0.011	-0.011	-0.011	-0.011
	(0.007)	(0.007)	(0.007)	(0.007)
Post	0.031***	0.030***	-0.336***	0.061***
	(0.005)	(0.005)	(0.007)	(0.007)
Loss Framing	0.002		0.002	
	(0.007)		(0.007)	
Social Comparison	0.012*		0.012*	
	(0.007)		(0.007)	
Combined Framing	0.009		0.009	
	(0.007)		(0.007)	
Gain Framing	9.675***		9.542***	
	(0.005)		(0.006)	
Household Fixed Effects	No	Yes	No	Yes
Month-Year Fixed Effects	No	No	Yes	Yes
R^2	0.000	0.287	0.147	0.434
N	533,433	533,433	533,433	533,433

Note: The dependent variable is log total water use of household i in billing period t. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The omitted letter-type is one that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. Post is an indicator for months after the treatment letters were sent. All standard errors are clustered at the household level, i.e., the level at which the randomization occurred. A total of 1,633 monthly bills (spanning 919 households) are excluded from this log use specification due to zero recorded monthly use. In addition, all monthly bills for the month of February 2014 are excluded.
$* p < 0.1$, $** p < 0.05$, $* * * p < 0.001$

Appendix: Cost-Effectiveness Calculation

Brent (2016) estimates a version of a discrete-continuous choice model using data from households in Phoenix, Arizona. Under this approach, households are first assumed to select a given landscape arrangement and then, conditional on this arrangement, how much water to consume. The types of landscape arrangement are discretized into three categories: dry (high water-efficiency), mixed, or wet (low water efficiency) landscape arrangements. The terms "dry", "mixed," and "wet" are not merely colloquial in Brent (2016). They correspond to a time series pattern of a household's landscape, which is scored using a vegetation index to reflect water intensity.

After coding all households into one of the three categories, Brent (2016) estimates conditional water demand functions (crucially, conditioning on landscape type), the propensity to change landscape from wet to dry, and the change in water demand due to changing landscape. This final piece directly informs our interest in the economic significance of our own results on adoption of drought-resistant landscaping. In particular, Brent (2016) finds that households moving from the wet to the dry landscape group (an analogy to our turf replacement) reduce their monthly water consumption by roughly 20%.

In Table 1a of Brent (2016), we see that the average monthly water use of mixed landscape households is roughly 16,500 gallons, meaning that change from wet to dry landscaping amounts to a monthly water savings of 3,300 gallons (or roughly 39,600 gallons annually) per converting household.[41] Assuming that these converting households are comparable to the households in our experiment[42] that adopt drought-resistant turf, the 29 additional turf replacements caused by receipt of the Loss Framing letter (relative to the counterfactual of receiving the Gain Framing letter) would amount to 1,148,400 gallons of water saved annually[43], an estimate about four times higher than our earlier estimate using the evapotranspiration model, which would imply a cost of approximately $2.52 for every thousand gallons saved.

41. Brent (2016) reports average use for this group in Table 1a in terms of centum cubic feet (CCF), which we convert to gallons – 1 CCF to 748 gallons.

42. Mapping changes in landscape type of the kind observed in our field experiment into changes in vegetation index scores (used in Brent (2016)) is not possible as we do not have detailed geographic information on the households in our study. For this reason, our preferred interpretation of this exercise is as qualitative. In addition, we do not know the current landscape stock of the households in our experiment at the time of randomization, meaning we cannot ex-ante evaluate whether the average household in our experiment is more like the wet, dry, or mixed households in Brent (2016). Finally, under the definition of conversion from wet landscape to dry landscape defined in Brent (2016), 3% of households convert, which is approximately twice as large as the adoption rates that we estimate in our setting.

43. 39,600 annual gallons saved per converting household * 29 converting households = 1,148,400 annual gallons saved.

Online Appendix: Figures and Tables

Figure A1: Gain Framing Letter

San Antonio Water System

[redacted]

March 24, 2014

YOU CAN HAVE A FREE $100 LANDSCAPE COUPON

Dear [redacted],

You have been specially selected to receive a **free** $100 WaterSaver Landscape Coupon from San Antonio Water System (SAWS). Please apply for the coupon online by April 30, 2014 to take advantage of this opportunity and learn about ways to save money and water.

This program gives you a $100 discount on drought-tolerant plants that are extremely well suited to your San Antonio property. This allows you to turn part of your traditional lawn into an attractive, drought-tolerant garden that requires less water. This program should also help you to reduce your water bills. No matter what type of property you have, you can benefit from this coupon.

WHAT YOU NEED TO DO:

Website: Go online to www.saws.org/coupon to complete an application. Your coupon will arrive in the mail.
Telephone: Call us at 210-704-SAVE if you have questions.

NEXT STEPS:

After you have removed 200 square feet of grass and capped the irrigation in the new bed, redeem your coupon at any of the participating retailers. You may also request a **free** expert landscape consultation to give you planting tips, to offer suggestions on where to put the new bed, and to check your irrigation system by calling the number listed above. The consultant will also provide you with other tips to save even more money on your water bills.

Thank you for participating in this program and for helping to conserve a valuable resource.

Sincerely,

Vickie Castilleja
Conservation Planner

2800 U.S. Hwy. 281 North • P.O. Box 2449 • San Antonio, TX • 78298-2449 • www.saws.org

Figure A2: Key Content Variation Across Treatments

Gain-Framing Letter

YOU CAN HAVE A FREE $100 LANDSCAPE COUPON
Dear [redacted],
You have been specially selected to receive a **free** $100 WaterSaver Landscape Coupon from San Antonio Water System (SAWS). Please apply for the coupon online by April 30, 2014 to take advantage of this opportunity and learn about ways to save money and water.

Loss-Framing Letter

DO NOT LOSE YOUR CHANCE TO HAVE A FREE $100 LANDSCAPE COUPON
Dear [redacted]
You have been specially selected to receive a **free** $100 WaterSaver Landscape Coupon from San Antonio Water System (SAWS). Please apply for the coupon on-line by April 30, 2014, or you will lose this opportunity and forego a chance to learn about ways to save money and water.

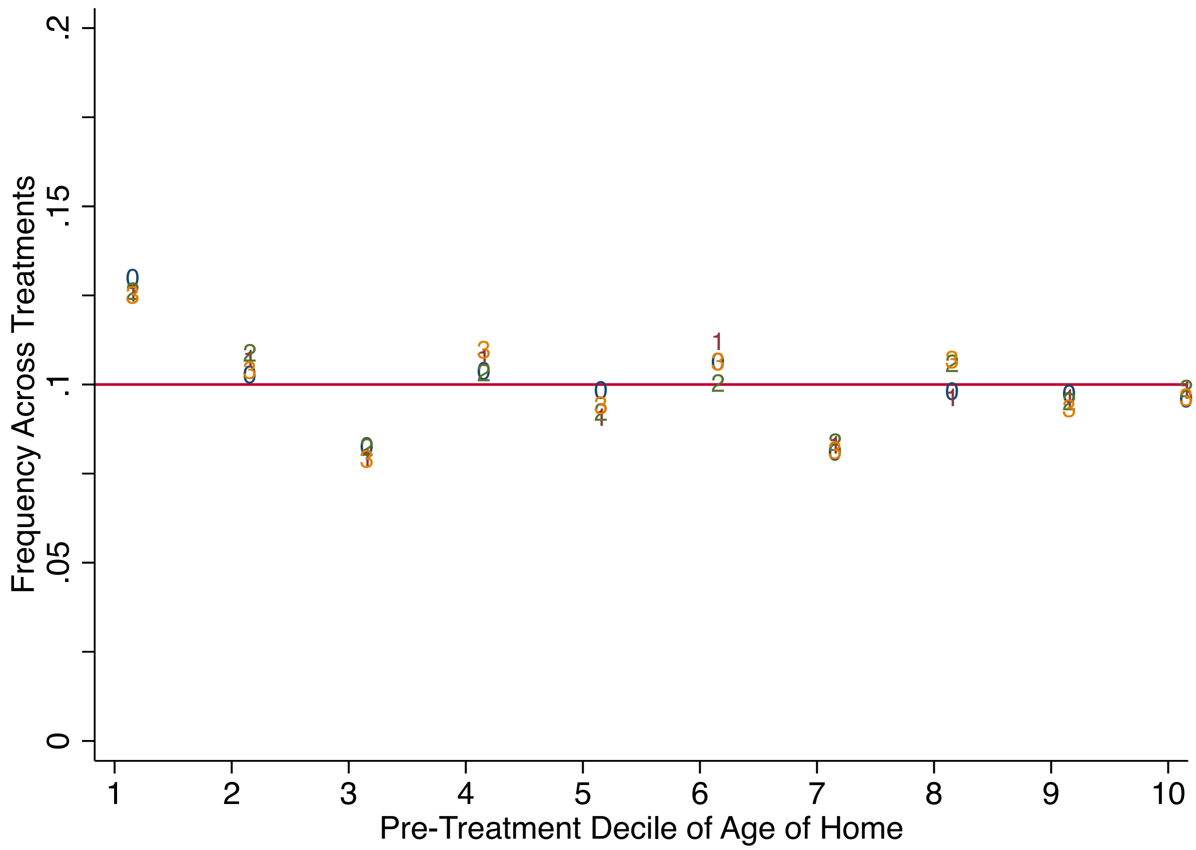
Social Comparison Letter

YOU CAN HAVE A FREE $100 LANDSCAPE COUPON
Dear [redacted] ,
You have been specially selected to receive a **free** $100 WaterSaver Landscape Coupon from San Antonio Water System (SAWS). We have selected you because you used **87593 gallons more water in 2013** than the average home in San Antonio.
Please apply online by April 30, 2014 to take advantage of this opportunity and learn about ways to save money and water.

Combined Framing Letter

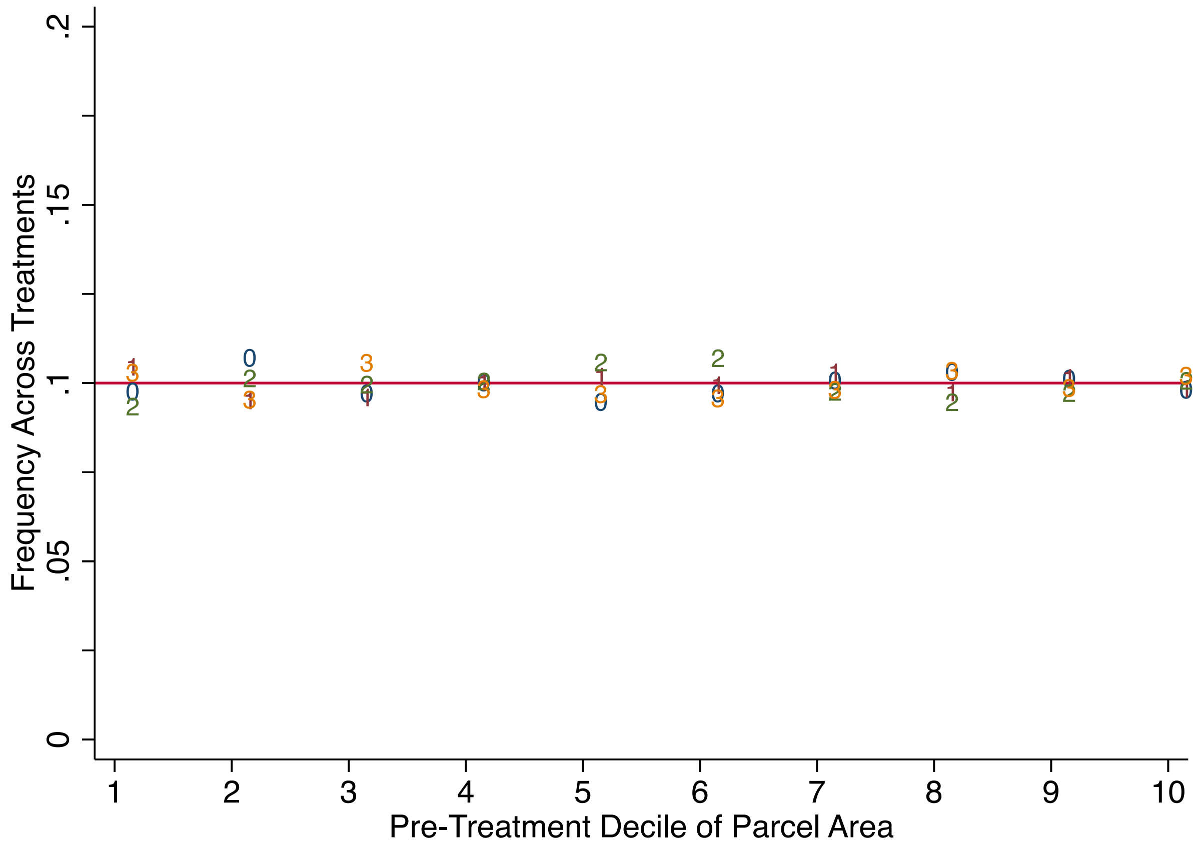
DO NOT LOSE YOUR CHANCE TO HAVE A FREE $100 LANDSCAPE COUPON
Dear [redacted],
You have been specially selected to receive a **free** $100 WaterSaver Landscape Coupon from San Antonio Water System (SAWS). We have selected you because you use **72635 gallons more water per year** than the average home in San Antonio.
Please apply online by April 30, 2014, or you will lose this opportunity and forego a chance to learn about ways to save money and water.

Figure A3: Treatment Assignment (Proportion) by Local Decile of Age of Home



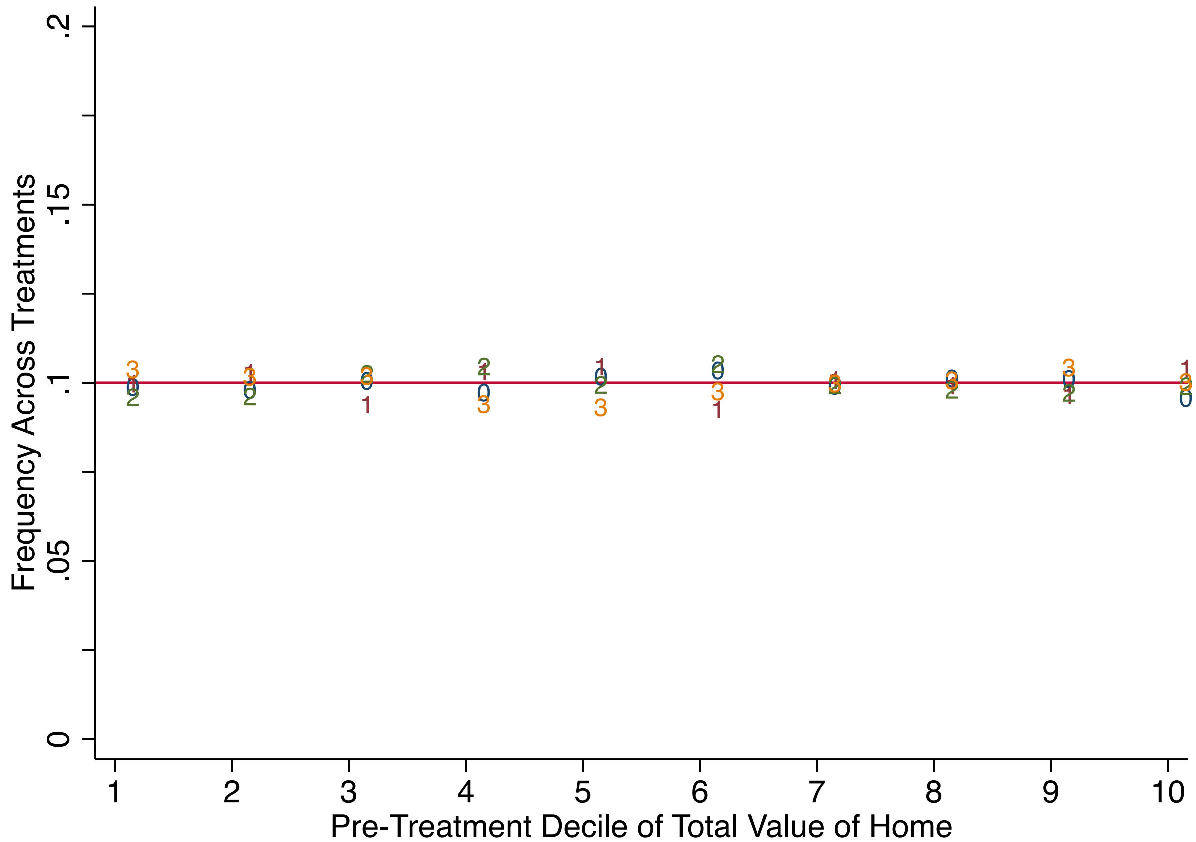
Note: The figure summarizes one measure of balance of treatment assignment along the decile of pre-treatment age of home. Exact balance across all deciles and all 4 treatment conditions would require each decile represent 1/10 (the solid red line) of the assigned households for each treatment. Actual treat assignment proportions can be identified by the treatment number. The Gain Framing treatment is denoted as 0. The Loss Framing treatment is denoted as 1. The Social Comparison treatment is denoted as 2. Finally, the Combined Framing treatment is denoted as 3.

Figure A4: Treatment Assignment (Proportion) by Local Decile of Parcel Area



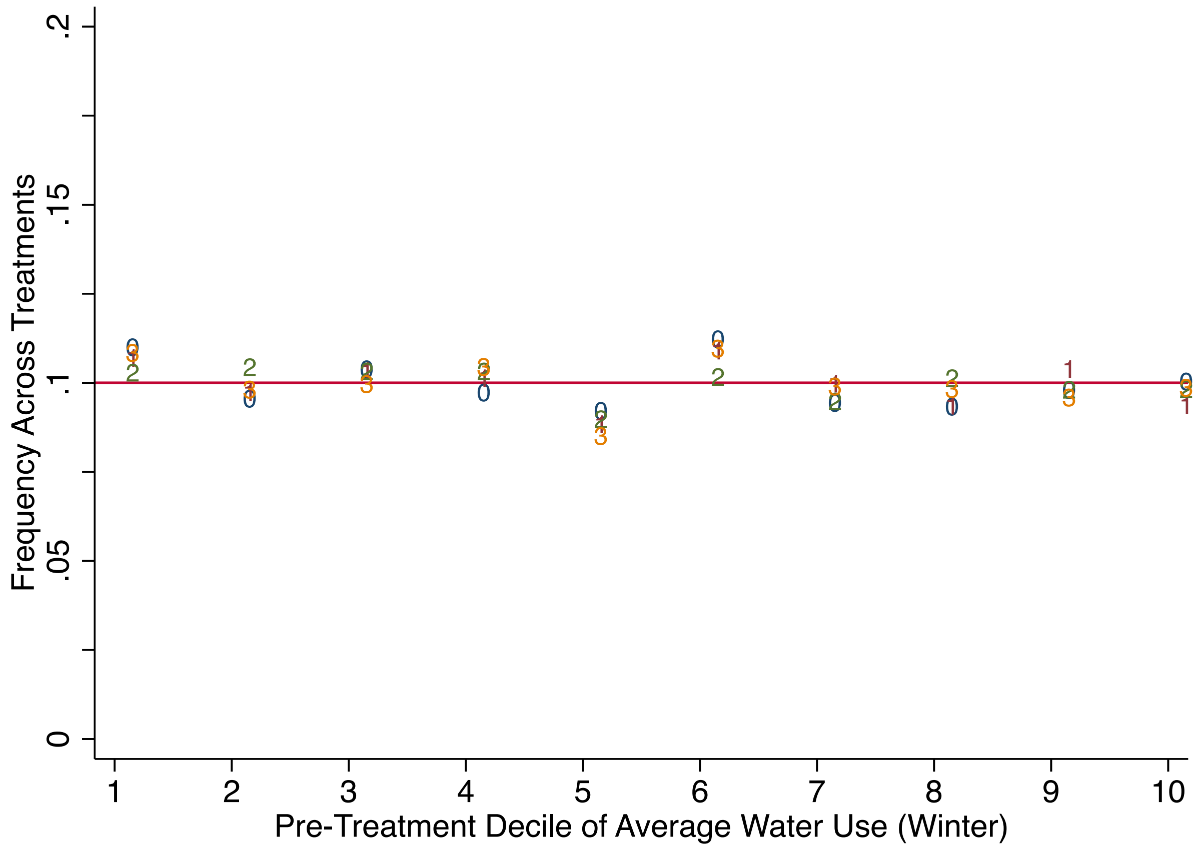
Note: The figure summarizes one measure of balance of treatment assignment along the decile of pre-treatment parcel area of the home (in square feet). Exact balance across all deciles and all 4 treatment conditions would require each decile represent 1/10 (the solid red line) of the assigned households for each treatment. Actual treat assignment proportions can be identified by the treatment number. The Gain Framing treatment is denoted as 0. The Loss Framing treatment is denoted as 1. The Social Comparison treatment is denoted as 2. Finally, the Combined Framing treatment is denoted as 3.

Figure A5: Treatment Assignment (Proportion) by Local Decile of Total Value of Home



Note: The figure summarizes one measure of balance of treatment assignment along the decile of pre-treatment total value of the home (in U.S. dollars). Exact balance across all deciles and all 4 treatment conditions would require each decile represent 1/10 (the solid red line) of the assigned households for each treatment. Actual treat assignment proportions can be identified by the treatment number. The Gain Framing treatment is denoted as 0. The Loss Framing treatment is denoted as 1. The Social Comparison treatment is denoted as 2. Finally, the Combined Framing treatment is denoted as 3.

Figure A6: Treatment Assignment (Proportion) by Local Decile of Winter Water Use



Note: The figure summarizes one measure of balance of treatment assignment along the decile of pre-treatment Winter 2013 average water use (in gallons). Exact balance across all deciles and all 4 treatment conditions would require each decile represent 1/10 (the solid red line) of the assigned households for each treatment. Actual treat assignment proportions can be identified by the treatment number. The Gain Framing treatment is denoted as 0. The Loss Framing treatment is denoted as 1. The Social Comparison treatment is denoted as 2. Finally, the Combined Framing treatment is denoted as 3.

Table A1: Age of Home Decile by Treatment Assigned

	Gain Framing	Loss Framing	Social Comparison	Combined Framing
1th Decile	753	729	731	725
2th Decile	596	622	631	603
3th Decile	480	462	478	459
4th Decile	602	624	599	636
5th Decile	571	527	535	546
6th Decile	617	650	582	617
7th Decile	471	482	486	473
8th Decile	569	559	614	620
9th Decile	565	558	552	541
10th Decile	557	571	573	559
Sample Size	5,781	5,784	5,781	5,779

Note: Each row represents a decile of home age. A total of 157 households are missing data on the year their home was built (used to construct home age). Of these 157, 40 are in the Gain Framing treatment, 35 are in Loss Framing treatment, 38 are in the Social Comparison treatment, and the remaining 44 are in the Combined Framing treatment. Each column represents one of the four treatment groups. All households in the water utility's service area received a letter advertising a $100 landscape rebate good towards the purchase of drought-resistant plants, but the additional content varied by treatment. The Gain Framing treatment describes households who received a letter advertising a $100 landscape rebate framed as a potential gain if claimed (this serves as our benchmark group throughout). The Loss Framing treatment mirrored the Gain Framing treatment, but framed the $100 landscape rebate as a potential lost opportunity if not claimed. The Social Comparison treatment mirrored the Gain Framing treatment with additional information about how household i's use in the previous year compares to an average household served by the water utility. Finally, the Combined Framing treatment combines the relevant features of Loss Framing and Social Comparison treatments in the same letter. All households in the sample used substantially more water than the average household served by the water utility, so the Social Comparison always told households how much *more* water they had used in the previous year relative to the average household.

Table A2: Parcel Area Decile by Treatment Assigned

	Gain Framing	Loss Framing	Social Comparison	Combined Framing
1th Decile	570	610	545	601
2th Decile	625	555	591	557
3th Decile	567	560	581	617
4th Decile	585	585	586	574
5th Decile	553	594	617	566
6th Decile	567	580	624	559
7th Decile	588	601	569	573
8th Decile	602	568	552	604
9th Decile	591	592	567	576
10th Decile	573	574	587	596
Sample Size	5,821	5,819	5,819	5,823

Note: Each row represents a decile of parcel area. Each column represents one of the four treatment groups. All households in the water utility's service area received a letter advertising a $100 landscape rebate good towards the purchase of drought-resistant plants, but the additional content varied by treatment. The Gain Framing treatment describes households who received a letter advertising a $100 landscape rebate framed as a potential gain if claimed (this serves as our benchmark group throughout). The Loss Framing treatment mirrored the Gain Framing treatment, but framed the $100 landscape rebate as a potential lost opportunity if not claimed. The Social Comparison treatment mirrored the Gain Framing treatment with additional information about how household i's use in the previous year compares to an average household served by the water utility. Finally, the Combined Framing treatment combines the relevant features of Loss Framing and Social Comparison treatments in the same letter. All households in the sample used substantially more water than the average household served by the water utility, so the Social Comparison always told households how much *more* water they had used in the previous year relative to the average household.

Table A3: Total Home Value Decile by Treatment Assigned

	Gain Framing	Loss Framing	Social Comparison	Combined Framing
1th Decile	577	582	560	606
2th Decile	572	600	561	594
3th Decile	587	548	598	595
4th Decile	568	602	610	549
5th Decile	594	610	580	544
6th Decile	604	540	614	570
7th Decile	579	588	579	583
8th Decile	591	579	572	588
9th Decile	590	563	567	609
10th Decile	559	607	578	585
Sample Size	5,821	5,819	5,819	5,823

Note: Each row represents a decile of total home value in U.S. dollars. Each column represents one of the four treatment groups. All households in the water utility's service area received a letter advertising a $100 landscape rebate good towards the purchase of drought-resistant plants, but the additional content varied by treatment. The Gain Framing treatment describes households who received a letter advertising a $100 landscape rebate framed as a potential gain if claimed (this serves as our benchmark group throughout). The Loss Framing treatment mirrored the Gain Framing treatment, but framed the $100 landscape rebate as a potential lost opportunity if not claimed. The Social Comparison treatment mirrored the Gain Framing treatment with additional information about how household i's use in the previous year compares to an average household served by the water utility. Finally, the Combined Framing treatment combines the relevant features of Loss Framing and Social Comparison treatments in the same letter. All households in the sample used substantially more water than the average household served by the water utility, so the Social Comparison always told households how much *more* water they had used in the previous year relative to the average household.

Table A4: Winter Average Water Use Decile by Treatment Assigned

	Gain Framing	Loss Framing	Social Comparison	Combined Framing
1th Decile	642	624	600	633
2th Decile	558	568	609	573
3th Decile	606	603	602	582
4th Decile	568	591	602	610
5th Decile	538	516	524	497
6th Decile	655	636	593	640
7th Decile	551	582	553	578
8th Decile	545	546	591	574
9th Decile	572	606	572	560
10th Decile	586	547	573	576
Sample Size	5,821	5,819	5,819	5,823

Note: Each row represents a decile of winter average household water use. Each column represents one of the four treatment groups. All households in the water utility's service area received a letter advertising a $100 landscape rebate good towards the purchase of drought-resistant plants, but the additional content varied by treatment. The Gain Framing treatment describes households who received a letter advertising a $100 landscape rebate framed as a potential gain if claimed (this serves as our benchmark group throughout). The Loss Framing treatment mirrored the Gain Framing treatment, but framed the $100 landscape rebate as a potential lost opportunity if not claimed. The Social Comparison treatment mirrored the Gain Framing treatment with additional information about how household i's use in the previous year compares to an average household served by the water utility. Finally, the Combined Framing combines treatment the relevant features of Loss Framing and Social Comparison treatments in the same letter. All households in the sample used substantially more water than the average household served by the water utility, so the Social Comparison always told households how much *more* water they had used in the previous year relative to the average household.

Table A5: Impact of Treatment Letters on Rebate Request — Logit

	(1)	(2)
Loss Framing	0.157	0.151
	(0.145)	(0.145)
Social Comparison	-0.158	-0.158
	(0.156)	(0.156)
Combined Framing	0.326**	0.330**
	(0.140)	(0.140)
Gain Framing / Constant	-4.154***	-4.300***
	(0.106)	(0.601)
Controls	No	Table 1 Covariates
N	23,282	23,125

Note: The dependent variable is an indicator for whether household i requested any rebates. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined Framing is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The Gain Framing coefficient is the constant in the logit regression and denotes letters that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. All standard errors are robust to heteroskedasticity. Control variables include the full set of variables on which randomization was blocked, in particular: the year the home was built, household parcel size, household total value, average water use in winter 2013, and average water use in summer 2013. In addition, we include an indicator for whether the household had a full 24 months of billing history or not. The addition of control for the age of the home reduces the sample size by 157 households, which are those households where the year the home was built is unavailable.
$* p < 0.1$, $** p < 0.05$, $* * * p < 0.001$

Table A6: Impact of Treatment Letters on Rebate Request — Probit

	(1)	(2)
Loss Framing	0.062	0.060
	(0.057)	(0.058)
Social Comparison	-0.061	-0.060
	(0.061)	(0.061)
Combined Framing	0.130**	0.135**
	(0.056)	(0.056)
Gain Framing / Constant	-2.158***	-2.214***
	(0.042)	(0.220)
Controls	No	Table 1 Covariates
N	23,282	23,125

Note: The dependent variable is an indicator for whether household i requested any rebates.. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined Framing is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The Gain Framing coefficient is the constant in the probit regression and denotes letters that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. All standard errors are robust to heteroskedasticity. Control variables include the full set of variables on which randomization was blocked, in particular: the year the home was built, household parcel size, household total value, average water use in winter 2013, and average water use in summer 2013. In addition, we include an indicator for whether the household had a full 24 months of billing history or not. The addition of control for the age of the home reduces the sample size by 157 households, which are those households where the year the home was built is unavailable.
$* \, p < 0.1$, $** \, p < 0.05$, $*** \, p < 0.001$

Table A7: Impact of Treatment Letters on Rebate Redemption — Logit

	(1)	(2)
Loss Framing	0.726**	0.731**
	(0.296)	(0.297)
Social Comparison	0.346	0.345
	(0.318)	(0.318)
Combined Framing	0.536*	0.538*
	(0.306)	(0.306)
Gain Framing / Constant	-5.833***	-5.202***
	(0.243)	(0.369)
Controls	No	Table 1 Covariates
N	23,282	22,742

Note: The dependent variable is an indicator for whether household i redeemed any rebates. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined Framing is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The Gain Framing coefficient is the constant in the logit regression and denotes letters that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. All standard errors are robust to heteroskedasticity. Control variables include the full set of variables on which randomization was blocked, in particular: the year the home was built, household parcel size, household total value, average water use in winter 2013, and average water use in summer 2013. In addition, we include an indicator for whether the household had a full 24 months of billing history or not. The addition of control for the age of the home reduces the sample size by 157 households, which are those households where the year the home was built is unavailable.
$* \, p < 0.1$, $** \, p < 0.05$, $*** \, p < 0.001$

Table A8: Impact of Treatment Letters on Rebate Redemption — Probit

	(1)	(2)
Loss Framing	0.245**	0.250**
	(0.099)	(0.100)
Social Comparison	0.115	0.118
	(0.105)	(0.106)
Combined Framing	0.179*	0.184*
	(0.102)	(0.102)
Gain Framing / Constant	-2.757***	-2.543***
	(0.079)	(0.120)
Controls	No	Table 1 Covariates
N	23,282	22,742

Note: The dependent variable is an indicator for whether household i redeemed any rebates. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined Framing is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The Gain Framing coefficient is the constant in the probit regression and denotes letters that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. All standard errors are robust to heteroskedasticity. Control variables include the full set of variables on which randomization was blocked, in particular: the year the home was built, household parcel size, household total value, average water use in winter 2013, and average water use in summer 2013. In addition, we include an indicator for whether the household had a full 24 months of billing history or not. The addition of control for the age of the home reduces the sample size by 157 households, which are those households where the year the home was built is unavailable.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

Table A9: Impact of Letter Treatments on Water Use (Percentage Change Specification)

	(1)	(2)	(3)	(4)
Loss Framing X Post	-0.011	-0.013	-0.011	-0.013
	(0.015)	(0.015)	(0.015)	(0.015)
Social Comparison X Post	-0.009	-0.009	-0.009	-0.009
	(0.009)	(0.009)	(0.009)	(0.009)
Combined Framing X Post	-0.012	-0.014	-0.012	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)
Post	0.048***	0.049***	-0.190***	0.209***
	(0.007)	(0.007)	(0.016)	(0.009)
Loss Framing	0.009		0.009	
	(0.015)		(0.015)	
Social Comparison	0.007		0.007	
	(0.009)		(0.009)	
Combined Framing	0.012		0.012	
	(0.010)		(0.010)	
Gain Framing	0.952***		0.853***	
	(0.007)		(0.008)	
Household Fixed Effects	No	Yes	No	Yes
Month-Year Fixed Effects	No	No	Yes	Yes
R^2	0.000	0.104	0.019	0.122
N	558,160	558,160	558,160	558,160

Note: The dependent variable is the level of water use of household i in billing period t, normalized by the post-treatment average use in the Gain Framing treatment. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The omitted letter-type is one that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. Post is an indicator for months after the treatment letters were sent. All standard errors are clustered at the household level, i.e., the level at which the randomization occurred. The increase in sample size in this table relative to Table 6 in the text is due to the inclusion of 1,633 monthly bills (spread across 919 households) with zero water use in a particular month that are included.

$* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

Table A10: Impact of Letter Treatments on Water Use (Percentage Change Specification) — Excluding Zero Use

	(1)	(2)	(3)	(4)
Loss Framing X Post	-0.011	-0.012	-0.011	-0.012
	(0.015)	(0.015)	(0.015)	(0.015)
Social Comparison X Post	-0.009	-0.009	-0.009	-0.009
	(0.009)	(0.009)	(0.009)	(0.009)
Combined Framing X Post	-0.011	-0.013	-0.011	-0.013
	(0.010)	(0.010)	(0.010)	(0.010)
Post	0.052***	0.053***	-0.184***	-0.184***
	(0.007)	(0.007)	(0.016)	(0.016)
Loss Framing	0.009		0.009	
	(0.015)		(0.015)	
Social Comparison	0.006		0.007	
	(0.009)		(0.009)	
Combined Framing	0.012		0.012	
	(0.010)		(0.010)	
Gain Framing	0.953***		0.853***	
	(0.007)		(0.008)	
Household Fixed Effects	No	Yes	No	Yes
Month-Year Fixed Effects	No	No	Yes	Yes
R^2	0.000	0.104	0.019	0.122
N	556,527	556,527	556,527	556,527

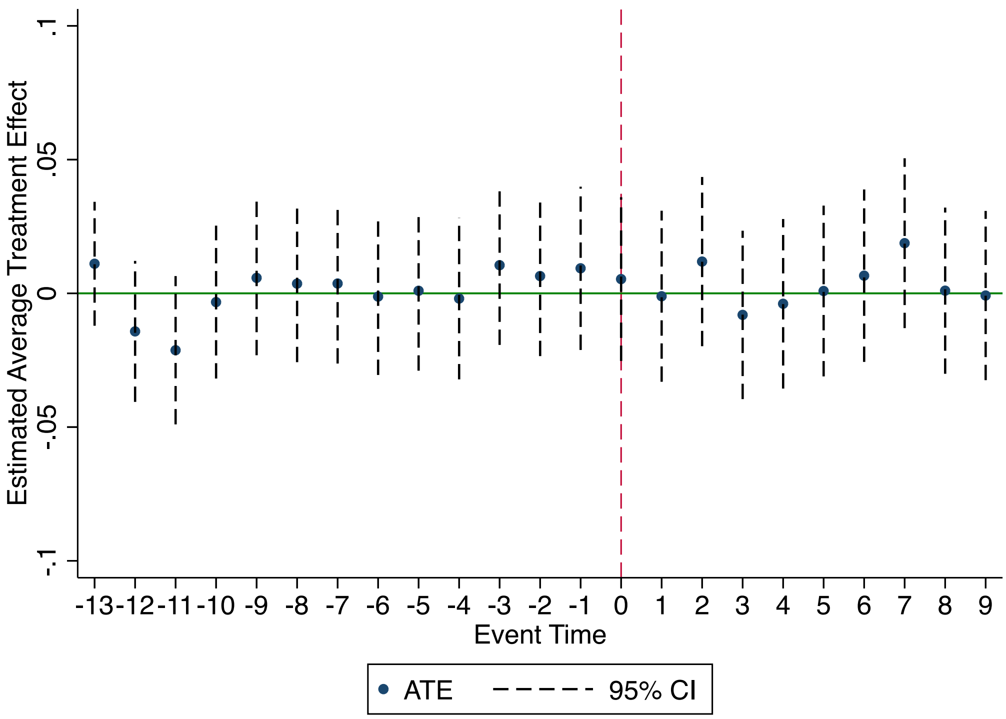
Note: The dependent variable is the level of water use of household i in billing period t, normalized by the post-treatment average use in the Gain Framing treatment. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The omitted letter-type is one that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. Post is an indicator for months after the treatment letters were sent. All standard errors are clustered at the household level, i.e., the level at which the randomization occurred. A total of 1,633 monthly bills (spanning 919 households) with a recorded water use of zero are excluded from this specification.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

Table A11: Impact of Letter Treatments on Water Use (Percentage Change Specification) — Excluding Outliers

	(1)	(2)	(3)	(4)
Loss Framing X Post	0.007	0.006	0.007	0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Social Comparison X Post	-0.013**	-0.012**	-0.014**	-0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
Combined Framing X Post	-0.007	-0.008	-0.007	-0.008
	(0.006)	(0.006)	(0.006)	(0.005)
Post	0.054***	0.054***	-0.183***	-0.187***
	(0.004)	(0.004)	(0.005)	(0.005)
Loss Framing	0.004		0.004	
	(0.006)		(0.006)	
Social Comparison	0.011*		0.011*	
	(0.006)		(0.006)	
Combined Framing	0.008		0.008	
	(0.006)		(0.006)	
Gain Framing	0.909***		0.815***	
	(0.004)		(0.005)	
Household Fixed Effects	No	Yes	No	Yes
Month-Year Fixed Effects	No	No	Yes	Yes
R^2	0.002	0.339	0.131	0.475
N	547,056	547,056	547,056	547,056

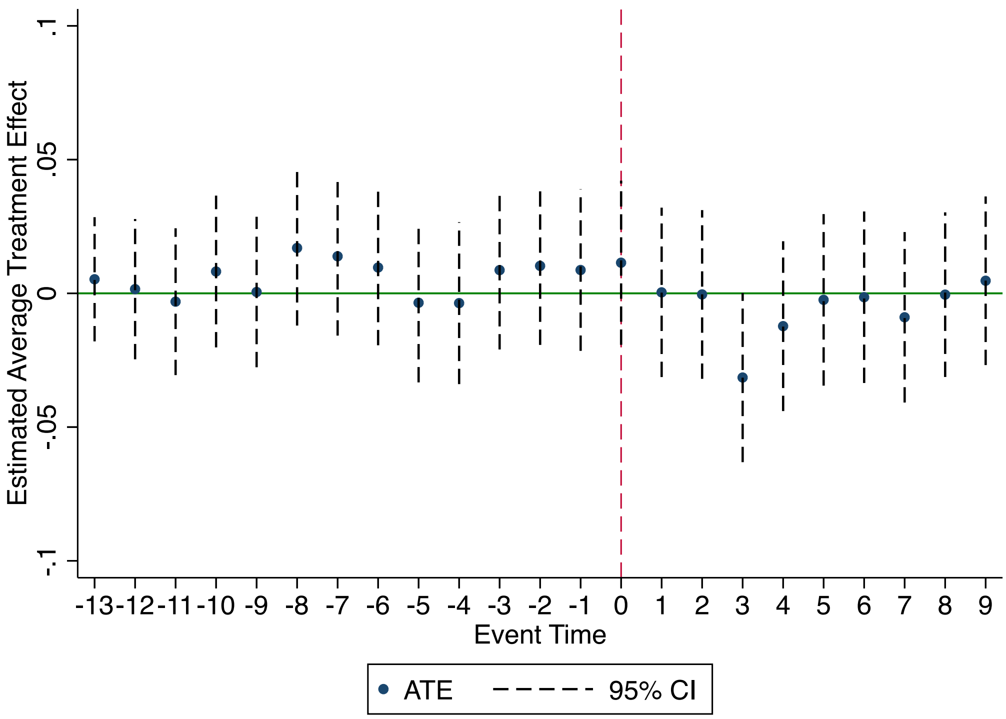
Note: The dependent variable is the level of water use of household i in billing period t, normalized by the post-treatment average use in the Gain Framing treatment. All households in the experimental sample received a letter at the same time, but the content of the letter varied. Loss Framing is an indicator for receiving a letter advertising a $100 landscape rebate, but framed as a potential lost opportunity if not claimed. Social Comparison is an indicator for receiving a letter identical to the control group but with additional information about how household i's use compares to an average household. Combined is an indicator for receiving a letter combining the relevant features of Loss Framing and Social Comparison treatments in the same letter. The omitted letter-type is one that advertised a $100 landscape rebate framed as a potential gain, which we are treating as the benchmark group. Post is an indicator for months after the treatment letters were sent. All standard errors are clustered at the household level, i.e., the level at which the randomization occurred. A total of 11,104 monthly bills (spanning 4,725 households) with a recorded water use in the top or bottom one percent of use (i.e., outliers) are excluded from this specification. $* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

Figure A7: Estimated Average Treatment Effect of Loss Framing Letter on Log Water Use Over Time



Note: The figure depicts the average treatment effect of a Loss Framing letter, plotted in event time. All estimates are regression-adjusted estimates after controlling for household and month-year fixed effects. The dependent variable is log total water use of household i in billing period t. All standard errors are clustered at the household level.

Figure A8: Estimated Average Treatment Effect of Combined Framing Letter on Log Water Use Over Time



Note: The figure depicts the average treatment effect of a Combined Framing letter, plotted in event time. All estimates are regression-adjusted estimates after controlling for household and month-year fixed effects. The dependent variable is log total water use of household i in billing period t. All standard errors are clustered at the household level.