Enforcement and Deterrence with Certain Detection: An Experiment in Water Conservation Policy *

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Abstract

The emergence of new technologies that allow perfect detection of violations at near zero marginal cost can revolutionize the enforcement of environmental regulations. We conducted a field experiment to evaluate enforcement though smart water meters with Fresno, CA that is confronting climate-induced water crises. All Fresno's households were experimentally assigned combinations of enforcement method (automated or visual inspection) and fine levels. Automated enforcement increased punishment of violations by 13,700%, decreased water use by 3%, and reduced outdoor water-use violations by 17%, but fine levels had little effect. It also caused political backlash that raises questions about perfect detection's real-world feasibility.

Keywords — Field Experiment; Automated Enforcement; Remote Sensing; Water Conservation
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1 Introduction

Non-compliance with laws and regulations is an enormous problem for governments around environmental (Alm and Shimshack, 2014), tax collection (Sarin and Summers, 2020), and many other domains. Becker's (1968) canonical model of crime assumes that individuals choose whether to comply to maximize their expected utility based on the probability of getting caught and the expected fine. All too often, the financial and political costs of detection and punishment are treated as a black box with near zero costs. However, detection is often costly because it requires resources (e.g., in-person inspections), regulated entities may hide their violations (e.g., Duflo, Greenstone, Pande, and Ryan, 2013; Gibson, 2019; Reynaert and Sallee, 2021; Vollaard, 2017; Zou, 2021), and can be politically damaging if key constituencies are harmed (Brollo, Kaufmann, and La Ferrara, 2019). These costs ultimately facilitate violations.

However, recent technological advances are rapidly and radically changing enforcement by driving the marginal cost of detection to virtually zero. For example, databases tracking monetary flows and satellites monitoring properties have inhibited tax evasion (Li, X. Wang, and Wu, 2020; Ali, Deininger, and Wild, 2018). In the case of environmental enforcement, remote sensing and real-time monitoring technologies are becoming cheap and ubiquitous, allowing for near-perfect detection of violations. A growing literature emphasizes that lowering reliable monitoring costs is key to significantly improving compliance with environmental and workplace regulations, as well as bill payment (Duflo, Greenstone, Pande, and Ryan, 2018; Greenstone, He, Jia, and Liu, 2020; Banerjee, Duflo, and Glennerster, 2008; Meeks, Omuraliev, Isaev, and Z. Wang, 2020).

This paper studies the adoption of automated enforcement in the context of residential outdoor water use regulations that aim to help cities cope with increasing drought conditions due to climate change (Diffenbaugh, Swain, and Touma, 2020). Utilities typically do not price water at marginal social cost, for political, regulatory, and ethical reasons and instead rely on non-price mechanisms to manage consumption (Brent, Cook, and Olsen, 2015; Brent and Ward, 2019). Residential outdoor watering restrictions are a primary mechanism because lawn irrigation is the single largest end-use of residential water (Hanak and Davis, 2006). Fresno, CA, like almost all other cities with outdoor watering restrictions, employed "water cops" to identify lawn watering at prohibited times. This system was far from effective as violations were rampant and punishments were rare; for example, 68% of households violated the outdoor watering restriction at least once in the summer of 2016, yet only 0.4% of all violations were detected and sanctioned by the water cops (Table 1).[1]

We implemented a randomized field experiment across the nearly 100,000 households in Fresno, exploiting the introduction of automated enforcement of outdoor water use restrictions via smart meters that enabled near-perfect detection of violations. Fresno was one of the first large municipal water utilities with universal smart meter adoption among single-family residential customers, although many other Western cities are following suit. Despite having meters since 2013, five years later Fresno was not using these rich and granular data to detect violations or issue fines, except to occasionally target visual inspections to high water users. We worked with the city to design and implement an evaluation that experimentally varied both the enforcement method — whether households were newly

[1] We define violations as water use above 300 gallons per hour during prohibited hours. This is the threshold the city eventually selected for automated enforcement.

subject to automated enforcement via smart meters or continued the status quo of visual inspection by water cops (i.e., detection rates of 100% versus 0.4%) — and the magnitude of the fines that violating households must pay. For households in the automated group, the experiment also varied the 'excessive water use' threshold that triggers warnings and fines. The experiment took place between July and September 2018, during peak outdoor watering season. More broadly, the experiment provided a perhaps unprecedented opportunity to vary the key parameters – the probability of detection and the penalty - that determine the cost of committing a crime in Becker's model.[2]

There are three primary findings. First, automated enforcement greatly increased compliance with the law. It increased the punishment of violations by 13,700%. The improved enforcement reduced violations by 17% and violating households by 8% per month. Second, automated enforcement decreased summer water consumption by about 3%, totaling 173.7 million gallons per summer in Fresno if scaled citywide. Such water savings would achieve a fifth of the reductions in residential water use that Governor Gavin Newsom requested of California residents on July 8, 2021, in the face of another drought. Further, the automated enforcement treatment reduced water consumption after the pilot, suggesting that the potential water conservation effects are even larger. Third, automated enforcement created political backlash that ultimately led to the program's termination. In particular, it increased the number of households who called utility customer service (almost always with complaints) by 515%.

There are several other findings. Lower fines did not affect the frequency of violations, water consumption or calls to customer service. Moreover, the percentage effect of automated enforcement on water conservation was roughly constant across the distributions of baseline water consumption and income. However, the heavy water users and wealthy complained to the customer service department more frequently. Finally, a decomposition of the effect of automated enforcement suggests that most of the reduction in water consumption comes from the households that never violated the rules, but the detection of violations and resulting fines reduced water consumption of violating households over time.

This research contributes to three main strands of the literature. First, a growing body of work discusses the difficulties in successfully enforcing environmental regulations globally and the resulting flouting of laws and standards (Duflo, Greenstone, Pande, and Ryan, 2013; Duflo, Greenstone, Pande, and Ryan, 2018; Reynaert and Sallee, 2021; Gibson, 2019). A related literature explores the promise of new technologies, like satellite data, for monitoring air pollution (Zou, 2021; Fowlie, Rubin, and Walker, 2019). This paper is the first to experimentally study the environmental benefits and the political costs of remote, continuous, and inexpensive monitoring in a real-world enforcement setting. Second, an extensive literature on crime finds that people respond to expected future punishment (Bar-Ilan and Sacerdote, 2004; Drago, Galbiati, and Vertova, 2009), the perceived auditing probability (Kleven et al., 2011), and past punishment (Kuziemko, 2013; Maurin and Ouss, 2009; Haselhuhn, G.Pope, Schweitzer, and Fishman, 2011). This is also the first randomized field experiment to study the impact of perfect detection of violations on illicit behavior.

Third, we exploit high-frequency data to contribute to a growing literature studying the impact of command-and-

[2]The closest experiments to ours study interventions to reduce absenteeism among health and education service providers in the developing world (Banerjee and Duflo, 2006).

control policies on water conservation. Our findings that a non-price instrument (i.e., the probability of detection) can effectively reduce water use is consistent with recent studies on nudges, peer comparisons, monitoring and enforcement of outdoor water use restrictions, and combinations of policy instruments (Jessoe, Lade, Loge, and Spang, 2021; Pratt, 2019; Wichman, Taylor, and Haefen, 2016; Halich and Stephenson, 2009; Kenney, Klein, and Clark, 2004; Renwick and Green, 2000; Michelsen, McGuckin, and Stumpf, 1999; Hahn, Metcalfe, Novgorodsky, and Price, 2016).[3]

2 Experiment and Data

2.1 Experiment

We partnered with Fresno, California's fifth largest city, which installed smart water meters at all 114,508 single-family households by 2013. These smart meters measure household water consumption and communicate it to the utility every fifteen minutes. Importantly, they do not allow to program water use. Prior to our experiment, the utility was only using smart meters for billing.

Water meters are controversial. Fresno residents fiercely resisted the implementation of smart meters in private homes. In 2006, the San Joaquin Taxpayers Association filed a lawsuit to prevent the installation of residential water meters, which was dismissed. Four years later, Fresno's city charter prohibited the use of smart meters for billing even while allowing for installation. The city finally agreed to metered residential water billing when state and federal authorities threatened to withhold its annual allotment of Central Valley Project water.

Fresno has had summer outdoor watering restrictions since the mid-1990s and restricted residential outdoor water use to three nights per week already prior to 2018. The allowed nights varied with house numbers to balance demand and reduce the load on the stormwater system. Prior to our experiment, the city relied on 'water cops' visually inspecting properties to detect violations of outdoor watering restrictions. In 2016, Fresno had five part-time water cops who issued 3,113 fines.[4]

Fresno also offered "water audits" and "timer tutorials" upon request via the city's web portal, 311, or the utility hotline. During audits, city employees help households evaluate potential leaks and understand how to conserve water. During timer tutorials, city representatives help households reset automated lawn sprinkler timers to comply with the watering schedule. Baseline data suggest that households reduce water use after timer tutorials and audits.

We worked with city officials to implement a randomized field experiment to inform the development of a policy that both achieved conservation and was politically viable. The experiment was conducted between July and September 2018 and was intended to inform the city-wide implementation of automated enforcement and the new fine schedule. We randomly assigned all single-family households in the city to one of twelve groups, varying along two cross-randomized dimensions: 1) enforcement method: automated vs. visual detection of violations, and 2) the

[3]The most comparable study is West, Fairlie, Pratt, and Rose (2021) that intended to study automated enforcement. In that case, the policy was announced but never went into place: without prior announcement, the city identified households that would have been in violation during one earlier week had the policy been in place, and notified them of this hypothetical violation and of the fine schedule. These households, about a third of accounts, reduced water use by 31% after this warning. In contrast, our study evaluates the city-wide, average, treatment effects of an enacted policy, that is the policy-relevant parameter.

[4]Authors' calculations based on most recent violation data available (Browne, Gazze, and Greenstone, 2021).

schedule of fines charged for repeated violations. In terms of enforcement method, we further randomized households in the automated group into one of three 'excessive water use' thresholds: 300, 500, or 700 gallons per hour. In terms of fines, households could either face the baseline fine schedule, or fines at 50% and 25% of the baseline levels.[5] We focus on the effect of automated enforcement across all combinations of thresholds and fines, but the experiment allows for the estimation of households' responses to varying 'excessive water use' thresholds and fines.

The city announced the program as a pilot in June 2018 through a media campaign. Each household received a mailer explaining the upcoming three-month pilot program, during which each home was assigned an enforcement mechanism via a lottery system (Figure A1 presents an example). The mailer announced the recipient's assigned method and fine schedule. After each violation, households received a warning within days specifying the time and hourly water use of the violation, the detection method (including the excessive use threshold that the household faced), and the fine schedule (Figure A2 presents an example). Fines appeared on the following month's water bills. The first notifications were sent on July 18, 2018. Moreover, the city did not sanction violations between August 1 and August 12, 2018, to enable its customer service to catch up with the backlog of customer calls received.

2.2 Data

Fresno had 114,508 single-family residential households. We restricted the experimental sample in three ways. First, we required households to have positive water use below 216,000 gallons during April 2017, to exclude households that had had their water shut off or used more than 300 gallons per hour on average. Second, we required accounts to be matched to a single-family parcel in the assessor files, to obtain median household income at the Census block group from the American Community Survey (years 2010-2014), a variable of interest for heterogeneity analysis.[6] Third, we exclude households who changed street address in May 2018. These restrictions dropped 24,927 households. Due to smart meter malfunctions, we do not have water use data for the experimental period for an additional 676 households, leaving us with a final analysis sample of 88,905 households. We observed households in our experimental sample for an average of 1,965 hours, over 87 of the 92 pilot days, with the occasional smart meter malfunction preventing a balanced panel.

We also collected logs of customer service calls and data on water services provided. The smart meter data runs from January 2017 through February 2019 and phone call data from June 2018 through February 2019.

Table 1 reports on the randomization. We allocated 45% of our sample to the non-automated, baseline fine group which is the control group (Panel A).[7] Each of the other eleven treatment groups includes 5% of sample households. Panel B of Table 1 reports the difference between these groups' and the control group. The treatment groups appear balanced in terms of different measures of baseline water use, violation, and clearance rate. Columns 1 and 2 of Table 1 report the randomization sample and analysis sample group sizes.

[5]For the first, second, and third month with violations, households in the baseline treatment group were charged fines of $0, $50, $100, respectively. Our communications with customers only stated the assigned fine schedule, without reference to the baseline.

[6]The average number of sample households per Census block group is 287.

[7]We based the allocation across automated and non-automated groups on the city's capacity to handle customer calls.

In 2017, the year before the experiment, control households used less than 600 gallons of water a day on average (Column 3). The typical household exceeded the 300 gallon per hour limit (which went into effect in 2018 but is a proxy for outdoor watering in 2017) by about 67 gallons per hour (Column 4) for about 0.141 hours per day or 1 hour per week (Column 5). Thus, there would have been about 12,000 violations per day if the newly designed automated enforcement threshold had been in force in 2017.

Columns (6) and (7) explore the degree of compliance with water restrictions and the frequency of punishment. Because we do not have enforcement data for 2017, the entries rely on data from 2016. Strikingly, 68.3% of households exceeded 300 gallons per hour when outdoor watering was illegal at least once during the summer of 2016. Yet, the water cops only issued violations to 0.4% of households.

To study potential heterogeneous effects of different treatments, we stratified the randomization based on being above or below the median of 1) baseline water use during April 2017 and 2) median income at the Census block group level (Table 1, Columns 8 and 9). We additionally stratified the randomization by city council district. Finally, Column 10 reports opt-out rates by treatment group. Opt-outs would become subject to the 'harshest' automated enforcement group, at baseline fine and 300 gal/hr threshold. In total, 0.5% of households opted out, and these had higher baseline water use and violation rates (Table A1). Treatment groups saw higher dropout rates, underscoring why we present Intention-To-Treat (ITT) treatment effects that include opt-outs in their randomly assigned groups.

3 Empirical Analysis

We assess the impact of the experimental treatments on compliance, water use, and customer service interactions. First, we estimate the average effects of automated enforcement across treatment groups with different fine levels and excessive use thresholds. Second, we explore heterogeneity, including differences in treatment responses across households with different characteristics and responses to different thresholds and fine treatments. Third, we decompose the effects of automated enforcement by households' *ex-post* behavior.

3.1 The Effects of Automated Enforcement

To study the effects of automated enforcement on compliance, water use, and customer service requests, we pool all automated groups to estimate the following regression equation for the months July-September 2018:

$$y_{it} = \beta \text{Automated}_i + \sum_{j \in \{25,50\}} \gamma_j \text{Visual} \times \text{Fines}_{ij} + \varepsilon_{it} \tag{1}$$

where y_{it} is an outcome for household i in month t, Automated_i is an indicator for household i's assignment to an automated enforcement treatment, and $\text{Visual} \times \text{Fines}_i^{25}$ and $\text{Visual} \times \text{Fines}_i^{50}$ are indicators for household i's assignment to visual enforcement treatments with fines at 25% and 50% level relative to the baseline schedule. The automated enforcement indicator restricts the effect of the 9 automated treatments to be equal. Due to random assignment, the OLS estimator $\hat{\beta}$ is the causal effect of automated enforcement. We cluster standard errors at the household level, the level of randomization. For our main results, we also report Westfall-Young stepdown adjusted p-values that correct for multiple hypotheses testing (Jones, Molitor, and Reif, 2019).

Panel A of Table 2 presents estimates from equation (1), reporting the average differences in outcomes between the automated enforcement treatment groups and the control group during the pilot. Panel B probes the robustness of the results controlling for baseline water use data from summer 2017 and Panel C includes household and month fixed effects. Columns 1a-1e show effects on enforcement actions and compliance behavior, Columns 2a-2c detail effects on water use, and Columns 3a-3b document the costs of automated enforcement in terms of customer service workload, which the city also interpreted as a measure of discontent with the policy. The visual inspection treatment effects are reported in Table A2.

The automated enforcement treatment increased compliance with the water conservation policy through its mechanical and reliable detection of violation. The average number of violations per month decreased from roughly 3.7 to 3.1 (Column 1a) and the share of households that violated the standard at least once in a month from approximately 51% to 47% (Column 1b). Thus, there was a 17% reduction in violations and 8% fewer households violated in any given month.[8]

Although violations remained high in the treatment group, the detection and punishment of violations increased dramatically. Households in the automated enforcement groups were more likely to receive warnings and fines, by 1,774% and 13,700% respectively (Table 2, Columns 1c-1d) and paid $7.15 more per month during the pilot (Column 1e), 9% of the average monthly bill in the summer of 2017, which amounted to $79.29. If the pilot were scaled city-wide and the treatment effects remained constant, 15,802 households would be fined per month, and Fresno would collect $2.46 million (=$818,732*3) in fines over the summer.

Further, automated enforcement decreased water consumption. Columns 2a-2c reveal that water consumption declined by roughly 3% and again these estimates are precisely estimated and robust.[9] This decline was largely driven by decreases in heavy consumption hours: automated enforcement reduced the number of hours with use above 500 or 700 gallons by 21% and 25%, respectively (Table A5).[10]

Panel A of Figure 1 reports the results from estimating equation (1) but allows the treatment effect to vary for each month of the sample, including the months before (when we would expect no effect) and after the pilot. The treatment effect increased from a water consumption reduction of 1.5% in July, when the program had been announced but fines had not been issued yet, to 4% in September, when 17.1% of households had received a warning or a fine. When the outcome variable is an indicator for whether a household had at least one violation in a month, the treatment effect increased over the course of the summer from 1.2% in July to 5.9% in September (Panel B). These

[8]Table A3 estimates the difference in the number of months households in the automated and control groups ever exceeded the 300 gal/hr threshold. Households in the automated enforcement group were 3% less likely to ever violate and almost 20% less likely to violate all three months of the pilot.

[9]Table A4 investigates peer effects of automated enforcement, which would bias the estimated impact of automated enforcement downward. We do not find evidence that households living in Census blocks with a higher proportion of households in automated enforcement disproportionately reduced water use.

[10]Fine levels appear to have inconsistent effect in the case of non-automated enforcement. Table A2 reveals that the group assigned to the halved fine schedule decreased water consumption, while the group assigned to the 25% fine schedule increased water consumption by a statistically insignificant amount, potentially due to a slight imbalance in the randomization. These estimates are not statistically significant after correcting for multiple hypotheses testing.

findings are consistent with the possibility that households' knowledge of the new enforcement program increased over time as information about it spread and with the possibility that penalized households decreased their consumption after being sanctioned. Section 3.3 explores the latter possibility further.[11]

Notably, Panel A of Figure 1 shows statistically significant declines in water use in October-November 2018 (-291.3 gal/month per treated household), even after the summer water restrictions were removed. Further, the treatment effect is still evident but smaller in December through February 2019 (when our data ends); individually these effects are not statistically significant at conventional levels, and when the treatment effect is restricted to be equal across these months it is -47.3 gal/month per household with a standard error of 34.5. This finding of a conservation treatment effect that lasts beyond the treatment was also found in recent work about energy consumption in Japan (Ito, Ida, and Tanaka, 2018), and in Brazil (Costa and Gerard, 2021). Overall, Figure 1 suggests that the policy's full conservation effects were larger than what a narrow focus on the three months when it was in force would suggest (as in Table 2 Columns 2a-2c), and could have increased in subsequent years if automated enforcement became Fresno's policy. Indeed, the summer-only estimates indicate that scaling up the policy city-wide would save 173.7 million gallons of water in a summer. However, if non-summer effects are also included and assumed to persist beyond February at the same levels, then a Fresno-wide scaling would save 278.3 million gallons of water annually, 1.6 times more than the summer-only estimates.

Columns 3a-3b of Table 2 report on the effect of automated enforcement on Fresno's interactions with customers, considered a sign of political dissatisfaction. Automated enforcement increased the monthly count of customers who called at least once by 515% (Table 2, Column 3a), and increased the monthly count of customers who requested at-home services at least once by 81% (Table 2, Column 3b). Even conditional on receiving a violation warning, households in the automated enforcement group were 52% (2.8 percentage points) more likely to call customer service than control households (Figure A3).[12] In total, automated enforcement generated 1,224 additional calls to customer service during the three-month experiment. If the city were to scale up automated enforcement citywide, we estimate that it would lead to 3,504 additional calls and 458 additional requests for major services over the summer period. The political costs of these calls were substantial, at least partially because many were paired with calls to City Council members complaining about the new system.

Panel C of Figure 1 is constructed just like Panels A and B, but here the outcome is the probability that a household telephoned Fresno's water customer service line. The customer contact sample runs from June 2018 through February 2019. It is evident that the automatic enforcement treatment caused a sharp decrease in violation rates and a sharp increase in calls during the pilot. It is also apparent that this treatment effect had effectively disappeared by December 2018, with the lag presumably due to households' lag in receiving and responding to bills.

[11] Households do not appear to increasingly move water consumption from banned to permitted hours (Table A6).
[12] The research team hired temporary staff to handle the higher call volume, at a cost of about $10,000.

3.2 Heterogeneous Effects

The previous section quantified the significant benefits and some of the costs of automated enforcement. In this section, we examine whether responses vary across households with differing characteristics and assess the impact of variation in fine levels and 'excessive water use' thresholds in explaining the impacts of automated enforcement.

First, we test whether automated enforcement had heterogeneous treatment effects across the two stratification variables, income and baseline use, as well as across baseline propensity to use excessive water. Specifically, we estimate a version of equation (1) that adds interactions of the automated indicator with indicators for each decile of the characteristic of interest (except the 5th) and includes deciles fixed effects. Thus, the coefficients on these interactions measure whether the treatment effect varies for these deciles relative to the 5th.

The causal effect of automated enforcement on water consumption did not vary proportionally to baseline use (Figure 2, Panel A). In contrast, the effect on the propensity to call customer service sharply increased with baseline use. Panels B and C report on the estimation of the analogous equation for deciles of income and propensity to violate. We conclude that the treatment effect on water use was relatively homogeneous across baseline water use, income, and violation levels, but the heavy water users and wealthy were responsible for a disproportionate share of the increase in calls to the customer service line and presumably of the political resistance to automated enforcement.

Second, we exploit experimental variation in fine and threshold magnitude within the automated enforcement treatment to examine their influence on water use and customer service call propensity. To do this, we estimate the following equation:

$$\begin{aligned} y_{it} = {} & \beta_1 \text{Automated}_i + \beta_2 \text{Automated500}_i + \beta_3 \text{Automated700}_i + \\ & \beta_4 \text{Automated} \times \text{Fines50\%}_i + \beta_5 \text{Automated} \times \text{Fines25\%}_i + \\ & \sum_{j \in \{25,50\}} \gamma_j \text{Visual} \times \text{Fines}_{ij} + \varepsilon_{it} \end{aligned} \tag{2}$$

that characterizes the 9 automated enforcement treatments with 5 indicators. Specifically, the $Automated_i$ indicator captures the effect of the city's default automatic policy which had a 300 gal/hr threshold and the standard fine schedule. The 4 other indicators measure the effects of altering the threshold by raising it to 500 or 700 gal/hr or the fine by reducing it to 50% or 25% of the standard schedule.[13] Intuitively, we expect that higher excessive use thresholds and lower fines lead to less conservation and fewer calls.

Figure 2, Panel D plots estimates of β_2, β_3, β_4, and β_5, thereby displaying the effect of deviations from Fresno's default automated policy that reduced water use by 6.3% and increased the probability of calling the Fresno water

[13] Table A7 reports the coefficients on the fully specified model, that is: $y_{it} = \sum_{z \in \{300,500,700\}} \sum_{j \in \{25,50,100\}} \beta_{zj} \text{Auto}_{zj} + \sum_{j \in \{25,50\}} \gamma_j \text{Visual} \times \text{Fines}_{ij} + \varepsilon_{it}$ (3). The table also reports the p-value on an F-test verifying whether the restricted model in equation (2) is statistically different from the full model in equation (3). In other words, we test $H_0 : \hat{\beta}_{300,100} - \hat{\beta}_{300,50} = \hat{\beta}_{500,100} - \hat{\beta}_{500,50} = \hat{\beta}_{700,100} - \hat{\beta}_{700,50}$ and $\hat{\beta}_{300,100} - \hat{\beta}_{300,25} = \hat{\beta}_{500,100} - \hat{\beta}_{500,25} = \hat{\beta}_{700,100} - \hat{\beta}_{700,25}$ by computing $F = (SS_{red}/SS_{full})$ for household-month level regressions. For a level of significance α, we reject H_0 if F is larger than the upper $1-\alpha$ percentile in the $F(N_{clusters}-1, N_{clusters}-1)$ distribution. SS_{red} and SS_{full} are the residual sums of squares from the parsimonious and the full specification, respectively and $N_{clusters}$ is the number of clusters. For Columns 1c-1d, we use the formula: $F = (SS_{redfull}/s)/(SS_{full}/df_{full})$ where $s = df_{redfull}$, df_{red} and df_{full} are the degrees of freedom from the parsimonious and full model, and we use the $F(s, df_{full})$ distribution. Based on this test and $\alpha = 0.1$, we cannot reject the null hypotheses that the fine-threshold interactions do not matter but for Columns 1c-1e.

department by 2 percentage points. Increases in the threshold for violation monotonically decreased the treatment's effect on water conservation and the probability of calling the Fresno water department. It seems reasonable to conclude that households understood this design feature of the policy. On the other hand, there is little evidence that reductions in the fine schedule affected water conservation or the probability of calling the water department in an economically meaningful way. Our previous work estimates an elasticity of monthly water use in the same city in response to small changes in marginal rates to be 16% (Browne, Gazze, and Greenstone, 2021).

3.3 Decomposition

This section decomposes the experimentally estimated reduction in water consumption due to automated enforcement by reporting treatment effects on water consumption among subgroups of the automated enforcement treatment group, where the subgroups are based on endogenous responses to the policy. Since the subgroups reflect households' responses, the results are associational and this must be considered an accounting exercise, in contrast to the causal estimates in Sections 3.1 and 3.2.

First, we estimate the following equation:

$$y_{it}=\sum_{j=0}^{3}\beta_j \text{Automated}_i * I_i(j \text{ Violations})+\sum_{j\in\{25,50\}}\gamma_j \text{Visual}\times\text{Fines}_{ij}+\varepsilon_{it} \tag{3a}$$

where y_{it} is an outcome for household i in month t, $Automated_i$ is an indicator for household i being randomly assigned to automated enforcement, $I_i(j \text{ Violations})$ are indicators for households who received j enforcement actions. $I_i(j \text{ Violations})$ is a vector of four indicators – zero violations, one violation (i.e., receipt of a warning only), two violations (i.e., warning and one fine), and three violations (i.e., warning and two fines). These independent categories, together, span the automated enforcement treatment group as households are only sanctioned for one violation per month in the three-month pilot. The estimated β_j's associated with these indicators provide estimates of each of these groups' water consumption relative to the control group.

We also estimate equation (3b) that further divides the three subgroups of violators into the periods before and after each violation, i.e.:

$$
\begin{aligned}
y_{it} = & \beta_0 \text{Automated}_i * I_i(\text{Violated0Times}) + \\
& \beta_1^{\text{BeforeWarning}} \text{Automated}_i * I_i(\text{1 Violation}) * I_t(\text{BeforeWarning}) + \\
& \beta_1^{\text{AfterWarning}} \text{Automated}_i * I_i(\text{1 Violation}) * I_t(\text{AfterWarning}) + \\
& \beta_2^{\text{BeforeWarning}} \text{Automated}_i * I_i(\text{2 Violations}) * I_t(\text{BeforeWarning}) + \\
& \beta_2^{\text{BetweenWarning\&Fine}} \text{Automated}_i * I_i(\text{2 Violations}) * I_t(\text{BetweenWarning\&Fine}) + \\
& \beta_2^{\text{AfterFine}} \text{Automated}_i * I_i(\text{2 Violations}) * I_t(\text{AfterFine}) + \\
& \beta_3^{\text{BeforeWarning}} \text{Automated}_i * I_i(\text{3 Violations}) * I_t(\text{BeforeWarning}) + \\
& \beta_3^{\text{BetweenWarning\&Fine}} \text{Automated}_i * I_i(\text{3 Violations}) * I_t(\text{BetweenWarning\&Fine}) + \\
& \beta_3^{\text{AfterFine}} \text{Automated}_i * I_i(\text{3 Violations}) * I_t(\text{AfterFine}) + \\
& \sum_{j \in \{25,50\}} \gamma_j \text{Visual} \times \text{Fines}_{ij} + \varepsilon_{it}
\end{aligned} \tag{3b}
$$

where $I_t(\text{BeforeWarning})$, $I_t(\text{AfterWarning})$, $I_t(\text{BetweenWarning\&Fine})$, $I_t(\text{AfterFine})$ are indicators for months before and after a warning is sent to a household, after the warning but before the first fine (for repeat violators), and after the first fine, respectively.[14] Finally, both equations (3a) and (3b) include indicators for household i's assignment to a visual enforcement treatment with fines at 25% or 50% of the baseline schedule ($\text{Visual} \times \text{Fines}_i^{25}$, $\text{Visual} \times \text{Fines}_i^{50}$).

Panel A of Table 3 reports estimates of equation (3a) in Column 1. Among households in the automated group, only those who never violate (63.8% of them) consume less water than households in the control group, specifically 15.4% less water. By contrast, households in the automated group who violated 1, 2, and 3 times consumed 9.6%, 22.8%, and 48% more water, respectively, than the average household in the control group, and account for 22.1%, 8.6%, and 5.5% of the automated group. Of course, there is a mechanical element to the finding about the three violating groups, because they are violators precisely because of their heavy consumption.

Column 2 of Table 3 reports estimates of equation (3b) and Column 4 details the number of months that the average household in each of the violating groups was in each of the subcategories.[15] None of the violating groups ever consumed less than the control group in a statistically meaningful way. At the same time, each notification of a violation is associated with a within group reduction in water consumption in all three of the violation groups, suggesting that households respond to the warning and to the fines.[16] Finally, we note that because enforcement actions took time, these relative reductions in water use only accrued for relatively short periods (Column 4).

Next, we investigate whether the persistent water use decrease in the automated group can be attributed to technology investments (Allcott and Rogers, 2014). To do so, we divide the automated enforcement group into those

[14] For three-time violators, the second fine is received outside the pilot period.

[15] Rows within a compliance group in Column 4 might not sum to 3 because of missing observations for some household-months.

[16] Figure A4 further probes this finding. It plots the results from an event study style regression that controls for household and week fixed effects, where the events are the warning, a first fine, and a second fine. The figure confirms that each event reduces water consumption and suggests that controlling for pre-trends would lead to even larger treatment effects because of the upward pre-event trends in water consumption in each case.

that did and did not request major services such as timer tutorials and leak audits. Then we estimate the following two equations:

$$y_{it}=\beta_0\text{Automated}_i*I_i(\text{NoServiceRequested})+\beta_1\text{Automated}_i*I_i(\text{ServiceRequested})+\sum_{j\in\{25,50\}}\gamma_j\text{Visual}\times\text{Fines}_{ij}+\varepsilon_{it} \quad (4a)$$

$$\begin{aligned}y_{it}=&\beta_0\text{Automated}_i*I_i(\text{NoServiceRequested})+\\&\beta_1^{\text{BeforeService}}\text{Automated}_i*I_i(\text{ServiceRequested})*I_t(\text{BeforeService})+\\&\beta_1^{\text{AfterService}}\text{Automated}_i*I_i(\text{ServiceRequested})*I_t(\text{AfterService})+\\&\sum_{j\in\{25,50\}}\gamma_j\text{Visual}\times\text{Fines}_{ij}+\varepsilon_{it}\end{aligned} \quad (4b)$$

Panel B of Table 3 reports estimates of equations (4a) and (4b) in Columns 1 and 2. Among households in the automated group, only those who do not request major services use less water than the control group. For the 1% of households in the automated group requesting a service, water use decreases after the request but remains higher than the control group mean. These findings suggest that the automated enforcement group's persistent decrease in water use is not explained by permanent technology investments, at least those that we can measure.

Overall, Table 3's associational evidence suggests that the bulk of the reduction in water consumption comes from the nearly 64% of households that never violated the rules, but the detection of violations and resulting fines reduced water consumption of violating households over time. These findings are consistent with the idea that the threat of penalties and the penalties themselves produced the automated enforcement group's reduction in water consumption.

4 Conclusion

This paper presents results from the first field experiment to study the impact of automating the enforcement of local environmental regulations. To our knowledge, it is also the first experiment to randomize both detection methods and sanctions for violations of such regulations, and the first to do so in a context where compliance is perfectly observed, and on a representative population at the city level.

We study the use of smart meters to enforce outdoor water-use restrictions.[17] We find that automated enforcement increased the punishment of violations by 13,700%, decreased violations by 17%, and reduced water consumption by about 3% during the pilot (with evidence of longer lasting conservation impacts). However, these benefits came with substantial costs to Fresno as the calls (almost all complaints) to the city-owned utility increased by 515%. Although the city had planned to roll out automated enforcement. the political backlash generated by automated enforcement led to a fine moratorium that remains in force three years after the pilot's conclusion with no clear plans to utilize the automated enforcement feature of smart meters.

[17] We note that smart meters were already installed in Fresno, and that their benefits include cost savings for billing, too.

Importantly, our experiment does not speak to the optimality of outdoor watering regulations *per se*. As environmental agencies and private actors increase adoption of remote sensing and continuous monitoring technologies, policymakers must adapt aging regulations to reflect these game-changing new tools and wide availability of high-frequency, real-time data. In doing so, it is clear that the environmental and conservation benefits will have to be weighed against the political costs associated with near perfect detection of violations.

References

Ali, Daniel Ayalew, Klaus Deininger, and Michael Wild (2018). "Using Satellite Imagery to Revolutionize Creation of Tax Maps and Local Revenue Collection". In: *World Bank Policy Research Working Paper Series No. 8437*.

Allcott, Hunt and Todd Rogers (2014). "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation". In: *American Economic Review* 104 (10), pp. 3003–3037.

Alm, James and Jay Shimshack (2014). "Environmental Enforcement and Compliance: Lessons from Pollution, Safety, and Tax Settings. Foundations and Trends". In: *Foundations and Trends(R) in Microeconomics* 10 (4), pp. 209–274.

Banerjee, Abhijit V. and Esther Duflo (2006). "Addressing Absence". In: *Journal of Economic Perspectives* 20 (1), pp. 117–132.

Banerjee, Abhijit V., Esther Duflo, and Rachel Glennerster (2008). "Putting a Band-Aid on a Corpse: Incentives for Nurses in the Indian Public Health Care System". In: *Journal of the European Economic Association* 6 (2-3), pp. 487–500.

Bar-Ilan, Avner and Bruce Sacerdote (2004). "The Response of Criminals and Noncriminals to Fines". In: *Journal of Law & Economics* 47 (1), pp. 1–17.

Bellemare, Marc F. and Casey J. Wichman (2020). "Elasticities and the Inverse Hyperbolic Sine Transformation". In: *Oxford Bulletin of Economics and Statistics* 82 (1), pp. 50–61.

Brent, Daniel, Joseph Cook, and Skylar Olsen (2015). "Social Comparisons, Household Water Use, and Participation in Utility Conservation Programs: Evidence from Three Randomized Trials". In: *Journal of the Association of Environmental and Resource Economists* 2 (4), pp. 597–627.

Brent, Daniel and Michael Ward (2019). "Price Perceptions in Water Demand". In: *Journal of Environmental Economics and Management* 98, p. 102266.

Brollo, Fernanda, Katja M. Kaufmann, and Eliana La Ferrara (2019). "The Political Economy of Program Enforcement: Evidence from Brazil". In: *Journal of the European Economic Association* 18 (2), pp. 750–791.

Browne, Oliver R., Ludovica Gazze, and Michael Greenstone (2021). "Do Conservation Policies Work? Evidence from Residential Water Use". In: *Environmental and Energy Policy and the Economy*. Ed. by M. Kotchen, J.H. Stock, and C. Wolfram. Vol. 2. Chicago: University of Chicago Press, pp. 190–225.

Costa, Francisco and François Gerard (2021). "Hysteresis and the Welfare Effect of Corrective Policies: Theory and Evidence from an Energy-Saving Program". In: *Journal of Political Economy* 129 (6), pp. 1705–1743.

Diffenbaugh, Noah S., Daniel L. Swain, and Danielle Touma (2020). "Anthropogenic warming has increased drought risk in California". In: *Proceedings of the National Academy of Sciences* 112 (13), pp. 3931–3936.

Drago, Francesco, Roberto Galbiati, and Pietro Vertova (2009). "The Deterrent Effects of Prison: Evidence from a Natural Experiment". In: *Journal of Political Economy* 117 (2), pp. 257–280.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan (2013). "Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India". In: *The Quarterly Journal of Economics* 128 (4), pp. 1499–1545.

— (2018). "The Value of Regulatory Discretion: Estimates From Environmental Inspections in India". In: *Econometrica* 86 (6), pp. 2123–2160.

Fowlie, Meredith, Edward A. Rubin, and Reed Walker (2019). "Bringing Satellite-Based Air Quality Estimates Down to Earth". In: *AEA Papers & Proceedings* 109, pp. 283–288.

Gibson, Matthew (2019). "Regulation-Induced Pollution Substitution". In: *The Review of Economics and Statistics* 101 (5), pp. 827–840.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu (2020). "Can Technology Solve the Principal-Agent Problem? Evidence from China's War on Air Pollution". In: *National Bureau of Economic Research Working Paper Series No. 27502*.

Hahn, Robert, Robert D Metcalfe, David Novgorodsky, and Michael K Price (2016). "The Behavioralist as Policy Designer: The Need to Test Multiple Treatments to Meet Multiple Targets". In: *National Bureau of Economic Research Working Paper Series No. 22886*.

Halich, Greg and Kurt Stephenson (2009). "Effectiveness of Residential Water-Use Restrictions Under Varying Levels of Municipal Effort". In: *Land Economics* 85 (4), pp. 614–626.

Hanak, Ellen and Matthew Davis (2006). "Lawns and Water Demand in California". In: *California Economic Policy* 2 (2), pp. 1–22.

Haselhuhn, Michael P., Devin G.Pope, Maurice E. Schweitzer, and Peter Fishman (2011). "The Impact of Personal Experience on Behavior: Evidence from Video-Rental Fines". In: *Management Science* 58 (1), pp. 52–61.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka (Feb. 2018). "Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand". In: *American Economic Journal: Economic Policy* 10 (1), pp. 240–67.

Jessoe, Katrina, Gabriel E. Lade, Frank Loge, and Edward Spang (2021). "Residential Water Conservation During Drought: Experimental Evidence from Three Behavioral Interventions". In: *Journal of Environmental Economics and Management* 110 (102519).

Jones, Damon, David Molitor, and Julian Reif (2019). "What do Workplace Wellness Programs do? Evidence from the Illinois Workplace Wellness Study". In: *The Quarterly Journal of Economics* 134 (4), pp. 1747–1791.

Kenney, Douglas S., Roberta A. Klein, and Martyn P. Clark (2004). "Use and Effectiveness of Municipal Water Restrictions During Drought in Colorado". In: *Journal of the American Water Resources Association* 40 (1), pp. 77–87.

Kleven, Henrik Jacobsen, Martin B Knudsen, Claus Thustrup Kreiner, Søren Pedersen, and Emmanuel Saez (2011). "Unwilling or Unable to Cheat? Evidence From a Tax Audit Experiment in Denmark". In: *Econometrica* 79 (3), pp. 651–692.

Kuziemko, Ilyana (2013). "How Should Inmates Be Released From Prison? An Assessment of Parole Versus Fixed Sentence Regimes". In: *The Quarterly Journal of Economics* 128 (1), pp. 371–424.

Li, Jianju, Xuan Wang, and Yaping Wu (2020). "Can Government Improve Tax Compliance by Adopting Advanced Information Technology? Evidence from the Golden Tax Project III in China". In: *Economic Modelling* 93 (C), pp. 384–397.

Maurin, Eric and Aurelie Ouss (2009). "Sentence Reductions and Recidivism: Lessons from the Bastille Day Quasi Experiment". In: *IZA Discussion Paper Series No. 3990*.

Meeks, Robyn, Arstan Omuraliev, Ruslan Isaev, and Zhenxuan Wang (2020). "Smart Meters and the Benefits from Electricity Quality Improvements". Working Paper.

Michelsen, An M., J. Thomas. McGuckin, and Donna Stumpf (1999). "Nonprice Water Conservation Programs as a Demand Management Tool". In: *Journal of the American Water Resources Association* 35 (3), pp. 593–602.

Pratt, Bryan (2019). "A Fine Is More Than a Price: Evidence from Drought Restrictions". Working Paper.

Renwick, Mary E. and Richard D. Green (2000). "Do Residential Water Demand Side Management Policies Measure Up? An Analysis of Eight California Water Agencies". In: *Journal of Environmental Economics and Management* 40 (1), pp. 37–55.

Reynaert, Mathias and James M. Sallee (2021). "Who Benefits When Firms Game Corrective Policies?" In: *American Economic Journal: Economic Policy* 13 (1), pp. 372–412.

Sarin, Natasha and Lawrence H. Summers (2020). "Understanding the Revenue Potential of Tax Compliance Investment". In: *National Bureau of Economic Research Working Paper Series No. 27571*.

Vollaard, Ben (2017). “Temporal displacement of environmental crime: Evidence from marine oil pollution”. In: *Journal of Environmental Economics and Management* 82, pp. 168–180.

West, Jeremy, Robert W. Fairlie, Bryan Pratt, and Liam Rose (2021). “Automated Enforcement of Irrigation Regulations and Social Pressure for Water Conservation”. In: *Journal of the Association of Environmental and Resource Economists* 8 (6), pp. 1179–1207.

Wichman, Casey J., Laura O. Taylor, and Roger H. von Haefen (2016). “Conservation Policies: Who Responds to Price and Who Responds to Prescription?” In: *Journal of Environmental Economics and Management* 79, pp. 114–134.

Zou, Eric Yongchen (2021). “Unwatched Pollution: The Effect of Intermittent Monitoring on Air Quality”. In: *American Economic Review* 111 (7), pp. 2101–2026.

Tables

Table 1: Summary Statistics and Balance Check

Dependent Variable	Original group size (N)	Group size (N)	Avg. daily water use (gal/day)	Excess water use during banned hrs. (gal/hr)	Number of banned hrs. >300 gal/hr per day	Share HH with any violations, Jul - Sep 2016	Violation clearance rate	Share high users	Share in high income block group	Dropout rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Control Group										
Non-automated Baseline Fine	40,311	40,009	575	67	0.141	0.683	0.004	0.500	0.500	0.003
Panel B: Treatment Groups			***Difference Relative To Non-Automated Baseline Fine***							
Non-automated										
50% Fine Level	4,479	4,445	-7.796	2.105	0.001	0.021***	-0.000	-0.000	0.000	-0.002**
			(6.315)	(6.626)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
25% Fine Level	4,479	4,440	7.333	-6.770	0.005	0.007	-0.001	-0.000	-0.002	0.000
			(6.438)	(6.338)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
Automated: 300 gal/hr										
Baseline Fine	4,479	4,449	-0.113	-0.295	0.002	0.001	0.001	-0.000	-0.001	0.009***
			(6.430)	(6.465)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.002)
50% Fine Level	4,479	4,454	-5.870	-5.125	-0.001	-0.005	0.001	0.001	-0.001	0.006***
			(5.970)	(6.773)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
25% Fine Level	4,479	4,449	-3.080	1.914	-0.000	-0.007	0.000	-0.002	-0.000	0.005***
			(6.270)	(6.836)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
Automated: 500 gal/hr										
Baseline Fine	4,479	4,440	-3.071	-7.448	-0.003	-0.011	-0.001	-0.000	-0.001	0.005***
			(6.164)	(6.134)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
50% Fine Level	4,479	4,444	2.682	-0.502	-0.003	-0.005	0.000	0.000	-0.001	0.004***
			(6.175)	(6.073)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
25% Fine Level	4,479	4,443	11.464*	-0.608	0.010*	0.005	-0.000	0.001	-0.001	0.003**
			(6.812)	(6.521)	(0.005)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
Automated: 700 gal/hr										
Baseline Fine	4,479	4,445	-0.798	-5.841	0.001	0.000	-0.000	-0.001	0.001	0.005***
			(6.295)	(5.759)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
50% Fine Level	4,480	4,438	9.084	-3.451	-0.001	0.001	0.000	0.001	-0.000	0.005***
			(6.524)	(7.333)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
25% Fine Level	4,479	4,449	7.317	-2.004	0.005	-0.002	-0.000	-0.001	0.000	0.003**
			(6.672)	(6.544)	(0.004)	(0.008)	(0.001)	(0.008)	(0.008)	(0.001)
P=value of joint F test	N/A	N/A	0.414	0.967	0.610	0.229	0.677	1	1	<0.001

Notes: This table reports baseline characteristics in the control group (Panel A) and differences between each treatment group and the control group for those characteristics (Panel B). Columns 3 - 5 include data from July - September 2017; Columns 6 - 7 include 2016 data for which we only matched 90% households, evenly distributed across treatment groups; Columns 8 includes data from April 2017; Column 9 includes data from the Census Bureau's 2010-2014 5-year American Community Survey; Column 10 includes data from July - September 2018. Baseline fine amounts are \$0, \$50, \$100, \$200 for the first, second, third and fourth (and thereafter) violations in a year. Violation clearance rate is the ratio of number of warnings and fines received to number of hours in violation during July - September 2016. High users are defined as having water use above the median in April 2017. High-income block groups have median income above the median block group in the city. Standard errors in parentheses are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Effect of Automated Enforcement on Compliance, Water Use, and Customer Contact

	Enforcement & Compliance					*Water Use*			*Customer Contact*	
Dependent Variable	Violations in a month (300+ gal/hr)	Violated at Least Once in a month	Received a Warning	Received a Fine	Fine Levied ($/month)	Monthly Water Use (gal)	Log of Monthly Water Use (gal)	IHS of Monthly Water Use (gal)	Called at Least Once in a month x 100	Requested Major Services at Least Once in a month x 100
	(1a)	(1b)	(1c)	(1d)	(1e)	(2a)	(2b)	(2c)	(3a)	(3b)
Panel A: Base Specification										
Automated Enforcement	-0.637***	-0.041***	0.337***	0.137***	7.15***	-548.4***	-0.029***	-0.038***	1.020***	0.133***
	(0.046)	(0.003)	(0.002)	(0.002)	(0.12)	(82.360)	(0.005)	(0.010)	(0.036)	(0.020)
Implied Elasticity						-0.032	-0.029	-0.017		
Summer Effect if Pilot Applied Citywide	-218,811***	-14,213***	115,924***	46,930***	2,456,628***	-188,389,420***	-173,701,984***	-225,291,397***	350,402***	45,805***
	(15,751)	(1,004)	(856)	(595)	(41,083)	(28,291,922)	(31,486,477)	(56,490,826)	(12,234)	(6,913)
Control Mean	3.735	0.509	0.019	0.001	0.09	17,193.3	9.491	27.85	0.198	0.165
Adjusted p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.007	<0.001	<0.001
N	261,963	261,963	88,905	88,905	261,963	261,963	261,313	261,963	261,963	261,963
Panel B: 2017 Water Use Controls										
Automated Enforcement	-0.671***	-0.044***	0.342***	0.140***	7.21***	-607.7***	-0.032***	-0.044***	1.027***	0.139***
	(0.044)	(0.003)	(0.003)	(0.002)	(0.12)	(54.122)	(0.004)	(0.008)	(0.036)	(0.021)
N	251,904	251,904	84,439	84,439	251,904	251,904	251,533	251,904	251,904	251,904
Panel C: Household and Month FEs										
Automated Enforcement	-0.686***	-0.040***				-618.3***	-0.029***	-0.028***		
	(0.050)	(0.003)				(57.23)	(0.004)	(0.009)		
N	513,121	513,121				513,121	512,127	513,121		

Notes: This table reports household level (Columns 1c-1d) and household-month level (Columns 1a,1b,1e-3b) regression coefficients on the effects of automated enforcement relative to the non-automated baseline fine group on the outcomes described in each column. Included in each regression are indicators for non-automated, alternative fine levels the coefficients for which are reported in Appendix Table A2. Each regression in Panel A includes data for the months of July-September 2018 only. Panel B includes the same data but additionally controls for total water use between July-September 2017. Panel C includes data for the months of July-September 2017 and 2018, and includes fixed effects for household and sample month. The number of observations is not consistent between panels due to imbalanced data coverage during 2017. Column 2b drops observations with zero monthly use. IHS denotes the inverse hyperbolic sine transformation of monthly water use. Major service requests include interior and exterior audits, supply of hardware, and timer tutorials. Watering schedule violations are defined as households exceeding 300 gal/hr during banned hours. The outcome variables in Columns 3a-3b are multiplied by 100 for ease of visualization. Summer effect is calculated by multiplying each coefficient by the number of households in Fresno (114,508) and the number of months in the summer (3). The elasticity in Column 2a is the coefficient on the Automated Enforcement indicator over the control mean; in Column 2b, the elasticity equals the coefficient; in Column 2c, the elasticity is computed according to the formula $\beta(\bar{x})\frac{\sqrt{\bar{y}^2+1}}{\bar{y}}$ (Bellemare and Wichman, 2020). Adjusted p-value reports the multiple inference adjusted p-value of the Automated Enforcement estimate. This correction is done using the Westfall-Young free step-down resampling algorithm over 10,000 iterations (Jones, Molitor, and Reif, 2019). In this case, our null hypothesis is $\beta = \gamma_{25} = \gamma_{50} = 0$. Standard errors are clustered at the household level except for columns 1c-1d which report heteroskedasticity robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

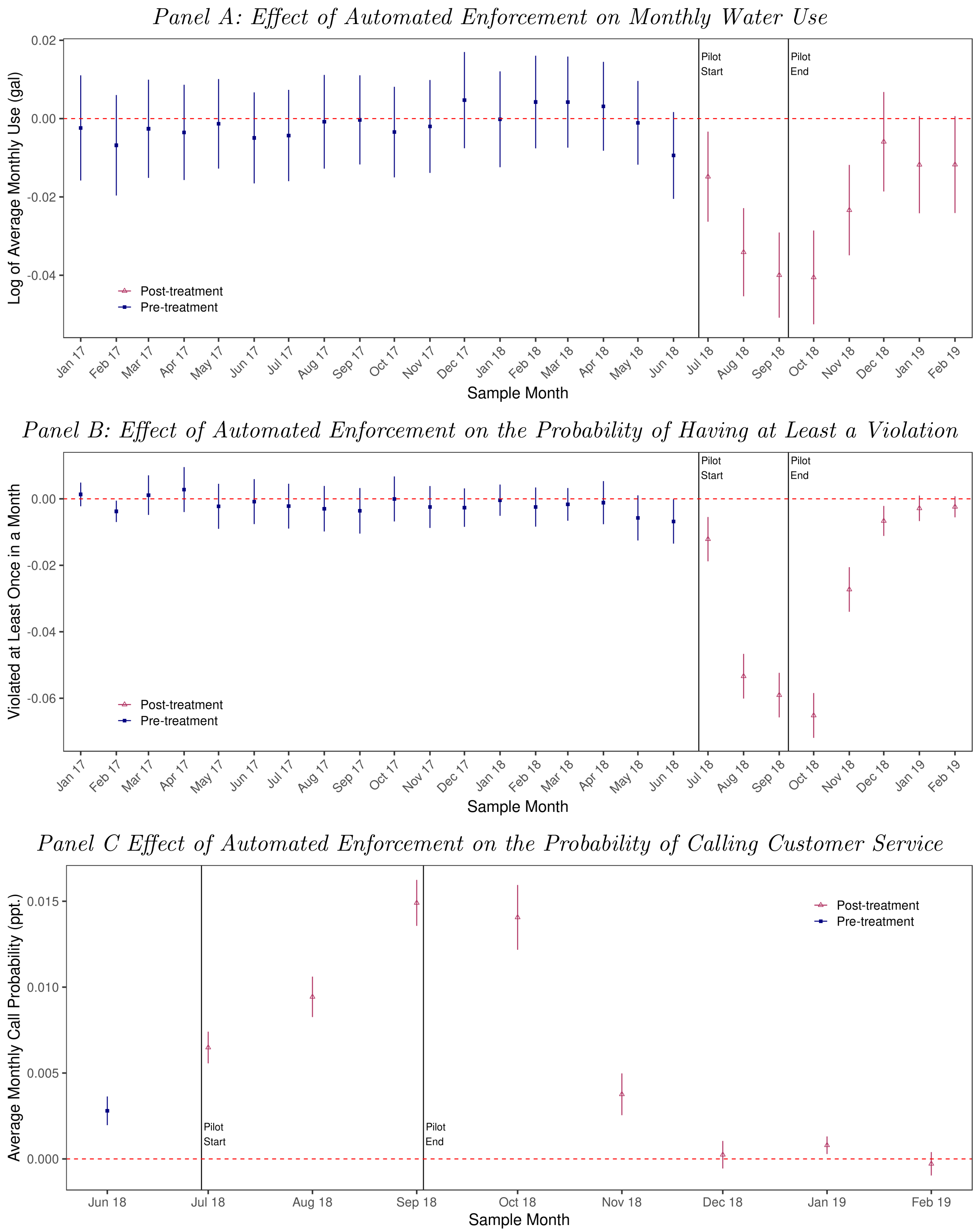
Table 3: Decomposition of Automated Enforcement Effect

	Log of Monthly Water Use (gal) (1)	Log of Monthly Water Use (gal) (2)	Share of Households in Automated Group (3)	Number of Months in Category (4)
Panel A: Enforcement & Compliance				
Automated Enforcement, Zero Violations	-0.154***	-0.154***	0.638	
	(0.006)	(0.006)		
Automated Enforcement, One Violation	0.096***		0.221	
	(0.008)			
Before Warning		0.191***		1.583
		(0.009)		
After Warning		-0.013		1.372
		(0.009)		
Automated Enforcement, Two Violations	0.228***		0.086	
	(0.010)			
Before Warning		0.359***		1.252
		(0.011)		
Between Warning & Fine 1		0.176***		1.372
		(0.011)		
After Fine 1		-0.027		0.369
		(0.019)		
Automated Enforcement, Three Violations	0.480***		0.055	
	(0.012)			
Before Warning		0.626***		1.024
		(0.013)		
Between Warning & Fine 1		0.488***		1.084
		(0.014)		
After Fine 1		0.302***		0.892
		(0.014)		
Panel B: Customer Contact				
Automated Enforcement, No Major Services Requested	-0.032***	-0.032***	0.991	
	(0.005)	(0.005)		
Automated Enforcement, Major Services Requested	0.270***		0.009	
	(0.034)			
Before Service Request		0.351***		2.069
		(0.036)		
After Service Request		0.087***	.	0.916
		(0.049)		
Control Mean	9.491	9.491		
N	261,313	261,313	40,011	

Notes: Panel A reports the log of average monthly water use among households with different ex-post compliance behavior in the automated enforcement group size relative to the non-automated, baseline fine group. Each regression includes data from July-September 2018 only. Column 2 reports coefficients from a regression that interacts ex-post compliance behavior with indicators for the months before and after the enforcement action (warning or fine) was sent to the household. Column 3 reports the share of households in the automated group in each compliance category. That is, those that received no enforcement actions, a warning, a warning and one fine, and a warning and two fines respectively during the experiment period. Column 4 reports the fraction of pilot months households in the automated groups in each compliance category spend before and after receiving each enforcement actions. Rows within a compliance group in Column 4 do not necessarily sum to 3 because of missing observations for some household-months. Panel B produces analogous estimates regarding household major service requests including interior and exterior audits, supply of hardware, and time tutorials. Standard errors in parentheses are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

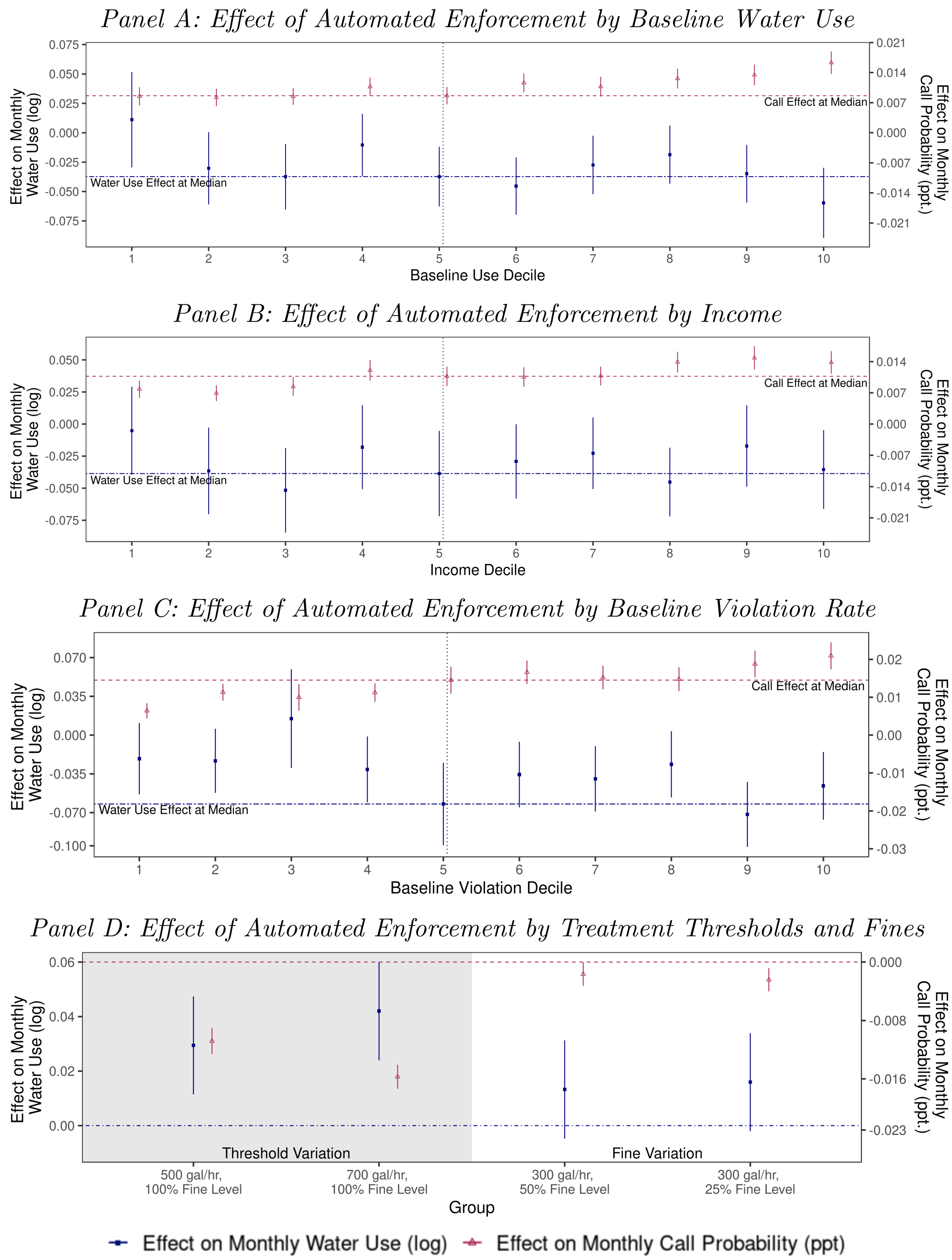
Figures

Figure 1: Effect of Automated Enforcement Over Time



Notes: This figure plots month-by-month coefficient estimates of the effect of automated enforcement on the logarithm of a household's monthly water use (Panel A), the probability of a household violating at least once in a month (Panel B), and the probability of a household calling customer service (Panel C). Panels A and B include data from January 2017 to February 2019. Panel C includes data from June 2018 to February 2019. All panels include sample month fixed effects and indicators for households subject to visual inspection and alternative fine schedules. The vertical bars represent 95% confidence intervals based on standard errors clustered at the household level.

Figure 2: Effect of Automated Enforcement on Cumulative Compliance and Water Use, by Baseline Use, Income, and Treatment



Notes: Panels include data from July 2018 to September 2018. Panel A plots the estimated effect of automated enforcement on the log of monthly water use (blue) and call probability (red) by households' baseline water use deciles. Panel B and C plot the same estimates by households' block group median income decile and baseline violation rate deciles respectively. The regressions in Panels A-C include an indicator for households assigned to automated enforcement, decile indicators and interactions between each decile and the automated group indicator, omitting the fifth decile as the reference category. Panels A-C are the linear combination of the decile's regression output and the coefficient from the automated group indicator. The horizontal line with an alternating pattern is the effect on water use at the median decile. The dashed horizontal line is the effect on call probability at the median decile. Baseline water utilization ranges from 6-146,940 gallons with a median of 7,640 gallons. Household block group median annual income ranges from $11,334-$153,194 with a median of $56,348. Baseline violation rate ranges from 1-867 hours in violation during the baseline period with a median of 9 hours. Panel D plots the estimated effects of assignment to each automated enforcement threshold and fine level relative to the default automated enforcement policy of 300 gal/hr and baseline fine level (i.e. the β_2 and β_3 coefficients from equation (2) in the gray graph area, and β_4 and β_5 coefficients from equation (2) in the white graph area). Each regression includes indicators for visual inspection and alternative fine levels. Baseline water use data is from April 2017, the period used for the stratified randomization. Baseline violation rate deciles are defined using data from July 2017 to September 2017. The vertical bars represent 95% confidence intervals based on household-level clustered standard errors.

Appendix Tables

Table A1: Characteristics of Opt-out Households

Dependent Variable	Total water use (gal/day)	Excess water use during banned hrs. (gal/hr)	Number of banned hrs. >300 gal/hr per day	Share HH with any violations, Jul - Sep 2016	Violation clearance rate	Share high users	Share in high income block group
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Opt-out Households	74***	10	0.0134	0.074***	0.001	-0.004	0.050**
	(20)	(24)	(0.011)	(0.021)	(0.003)	(0.023)	(0.023)
All Other Households	570	66	0.140	0.683	0.004	0.501	0.499
N	84,439	84,439	84,439	80,596	55,055	84,439	84,439

Notes: This table reports household level regression coefficients on the characteristics of households that opted out of the experiment. Columns 1 - 3 include data from July - September 2017; Columns 4 - 5 include 2016 data for which we only matched 90% households; Column 6 includes data from April 2017. Column 7 includes data from the Census Bureau 2010-2014 5-year American Community Survey. Violation clearance rate is the ratio of number of warnings and fines received to number of hours in violation during July-September 2016. High users are defined as having baseline daily water use above the median. High-income block groups have median income above the median block group in the city. Standard errors in parentheses are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Effect of Non-automated Enforcement, Alternative Fine Levels on Compliance, Water Use, and Customer Contact

	Enforcement & Compliance					*Water Use*			*Customer Contact*	
Dependent Variable	Violations in a month (300+ gal/hr)	Violated at Least Once in a month	Received a Warning	Received a Fine	Fine Levied ($/month)	Monthly Water Use (gal)	Log of Monthly Water Use (gal)	IHS of Monthly Water Use (gal)	Called at Least Once in a month x 100	Requested Major Services at Least Once in a month x 100
	(1a)	(1b)	(1c)	(1d)	(1e)	(2a)	(2b)	(2c)	(3a)	(3b)
Panel A: Base Specification										
50% Fine Level	-0.120	-0.005	-0.003	-0.001**	-0.06***	-365.6**	-0.026**	-0.014	-0.068**	-0.081***
	(0.103)	(0.007)	(0.002)	(0.000)	(0.02)	(185.5)	(0.012)	(0.020)	(0.034)	(0.028)
Adjusted p-value	0.880	0.963	0.286	0.151	0.085	0.380	0.311	0.963	0.380	0.085
25% Fine Level	0.109	-0.000	0.001	0.000	-0.06***	184.3	0.007	-0.013	-0.029	-0.074**
	(0.108)	(0.007)	(0.002)	(0.001)	(0.02)	(190.0)	(0.012)	(0.024)	(0.038)	(0.029)
Adjusted p-value	0.921	0.987	0.763	0.931	0.001	0.921	0.963	0.963	0.963	0.144
Control Mean	3.735	0.509	0.019	0.001	0.09	17,193.3	9.491	27.85	0.198	0.165
N	261,963	261,963	88,905	88,905	261,963	261,963	261,313	261,963	261,963	261,963
Panel B: 2017 Water Use Controls										
50% Fine Level	-0.065	-0.002	-0.002	-0.000	-0.03	-192.1	-0.018*	-0.017	-0.068**	-0.079***
	(0.099)	(0.007)	(0.002)	(0.001)	(0.04)	(124.6)	(0.009)	(0.016)	(0.035)	(0.029)
25% Fine Level	0.076	-0.002	0.001	-0.000	-0.10***	67.3	-0.001	-0.006	-0.037	-0.081***
	(0.102)	(0.007)	(0.002)	(0.001)	(0.03)	(122.3)	(0.009)	(0.018)	(0.039)	(0.029)
N	251,904	251,904	84,439	84,439	251,904	251,904	251,533	251,904	251,904	251,904
Panel C: Household and Month FEs										
50% Fine Level	-0.122	-0.002				-140.5	-0.003	0.008		
	(0.104)	(0.006)				(131.1)	(0.009)	(0.021)		
25% Fine Level	-0.013	0.004				34.04	-0.003	-0.013		
	(0.109)	(0.006)				(127.2)	(0.009)	(0.021)		
N	513,121	513,121				513,121	512,127	513,121		

Notes: This table reports household level (Columns 1c-1d) and household-month level (Columns 1a,1b,1e-3b) regression coefficients on the effects of non-automated enforcement with alternative fine levels relative to the non-automated baseline fine group on the outcomes described in each column. Panel A includes data for the months of July-September 2018 only. Panel B includes the same data but additionally controls for total water use between July-September 2017. Panel C includes data for the months of July-September 2017 and 2018 and includes fixed effects for household and sample month. The number of observations is not consistent between panels due to imbalanced data coverage during 2017. Column 2b drops observations with zero monthly use. IHS denotes the inverse hyperbolic sine transformation of monthly water use. Major service requests include interior and exterior audits, supply of hardware, and timer tutorials. Watering schedule violations are defined as households exceeding 300 gal/hr during banned hours. The outcome variables in Columns 3a-3b are multiplied by 100 for ease of visualization. Adjusted p-value reports the multiple inference adjusted p-value of the estimates. This correction is done using the Westfall-Young free step-down resampling algorithm over 10,000 iterations (Jones, Molitor, and Reif, 2019). In this case, our null hypothesis is $\beta = \gamma_{25} = \gamma_{50} = 0$. Standard errors are clustered at the household level except for columns 1c-1d which report heteroskedasticity robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of Automated Enforcement on Number of Months in Violation

	Never Violated (1)	Violated in One Month (2)	Violated in Two Months (3)	Violated in Three Months (4)
Automated Enforcement	0.010***	0.038***	0.018***	-0.066***
	(0.003)	(0.003)	(0.003)	(0.003)
Control Mean	0.329	0.177	0.158	0.335
N	88,905	88,905	88,905	88,905

Notes: This table reports household level regression coefficients on the effects of automated enforcement relative to the non-automated baseline fine group on the outcomes described in each column. Included in each regression are indicators for non-automated, alternative fine levels the coefficients for which are omitted. It includes data for the months of July-September 2018 only. Watering schedule violations are defined as households exceeding 300 gal/hr during banned hours. Standard errors clustered at the household level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A4: Peer Effects of Automated Enforcement

Dependent Variable	Log of Daily Water Use (gal)				
	(1)	(2)	(3)	(4)	(5)
Automated Enforcement	-0.030***	-0.031***	-0.033***	-0.031***	-0.033***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Share Automated		0.028	-0.008		
		(0.037)	(0.027)		
Share 300gal/hr Threshold				0.031	-0.022
				(0.053)	(0.038)
Share 500gal/hr Threshold				0.051	0.007
				(0.054)	(0.038)
Share 700gal/hr Threshold				-0.008	-0.016
				(0.053)	(0.038)
N	7,466,297	7,466,297	7,466,297	7,466,297	7,466,297
Additional Controls			X		X

Notes: This table reports household-day level regression coefficients on the effects of automated enforcement relative to non-automated groups baseline fine group on the log of daily water use. Included in each regression are day fixed effects and indicators for non-automated, automated fine levels the coefficients for which are omitted. Each regression includes data for the months of July-September 2018 only. The table also reports coefficients incorporating the share of the household's neighbors subject to automated enforcement and to one of the three water use thresholds. Neighbors are defined by Census block. Columns 3 and 5 contain household April 2017 water use and Census block group median income fixed effects. Standard errors in parentheses are clustered at the block level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Automation Impact on Number of Hours in Violation (>500 and >700 gal/hr thresholds)

	(1) Violations (500+ gal/hr)	(2) Violations (700+ gal/hr)
Automated Enforcement	-0.289***	-0.131***
	(0.025)	(0.015)
Summer Effect on Automated Enforcement Group	-11,552***	-5,244***
	(999)	(587)
Non-Automated Enforcement		
50% Fine Level	-0.005	0.011
	(0.062)	(0.037)
25% Fine Level	0.032	0.015
	(0.060)	(0.036)
Control Mean	1.350	0.528
N	261,963	261,963

Notes: This table reports household-month level regression coefficients on the effects of automated enforcement on the outcomes described in each column. The sample includes data for the months of July-September 2018 only. The total impact of automated enforcement is calculated multiplying each coefficient by the number of households subject to automated enforcement (40,011). Standard errors clustered at the household level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Automation Impact on Average Hourly Use: Permitted Versus Banned Hours

Dependent Variable	Log of Average Water Use over a Month (gal/hr)		
	Overall	Permitted Hours	Banned Hours
	(1)	(2)	(3)
Automated Enforcement			
July	-0.012**	0.002	-0.027***
	(0.005)	(0.008)	(0.006)
August	-0.032**	0.008	-0.077***
	(0.005)	(0.008)	(0.006)
September	-0.040***	0.006	-0.080***
	(0.005)	(0.008)	(0.006)
Non-Automated			
50% Fine Level	-0.023**	-0.030*	-0.011
	(0.011)	(0.016)	(0.013)
25% Fine Level	0.007	0.012	0.002
	(0.011)	(0.016)	(0.013)
Control Mean	3.009	3.501	2.476
N	261,313	260,408	261,156
Average Number of Hours	667.8	178.4	489.4

Notes: This table reports household-month level regression coefficients on the effects of automated enforcement by month on the outcomes described in each column. Each regression includes month fixed effects. The sample includes data for the months of July-September 2018 only. Standard errors clustered at the household level in parentheses. This table also reports the average number of permitted or banned watering hours per month.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

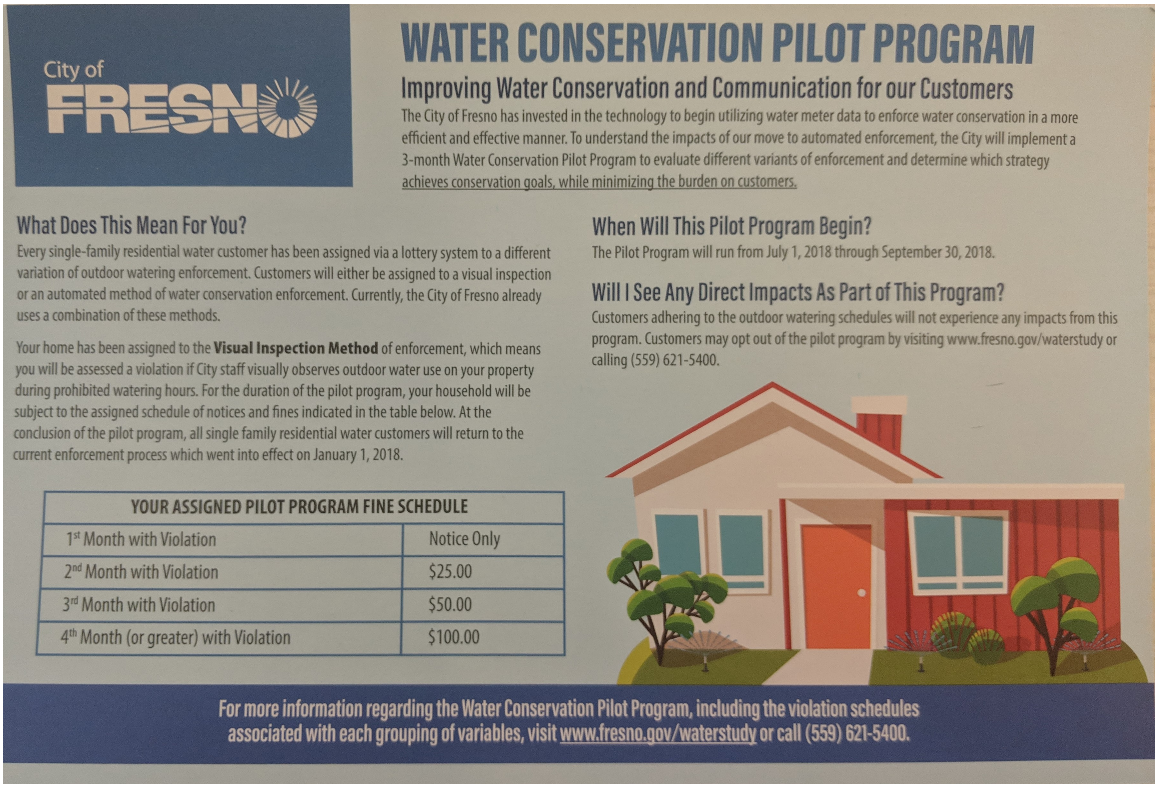
Table A7: Effect of Automated Enforcement on Water Use, Compliance with Watering Schedule, Probability of Customer Contact, Probability of Requesting Major Services: Relative to Baseline Fine & Non-Automated Group, Full Experiment Groups

	Enforcement & Compliance					*Water Use*			*Customer Contact*	
Dependent Variable	Violations in a month (300+ gal/hr)	Violated at Least Once in a month	Received a Warning	Received a Fine	Fine Levied ($/month)	Monthly Water Use (gal)	Log of Monthly Water Use (gal)	IHS of Monthly Water Use (gal)	Called at Least Once in a month x 100	Requested Major Services at Least Once in a month x 100
	(1a)	(1b)	(1c)	(1d)	(1e)	(2a)	(2b)	(2c)	(3a)	(3b)
Automated: 300 gal/hr										
Baseline Fine	-0.937***	-0.081***	0.545***	0.251***	23.75***	-1,012.699***	-0.065***	-0.060***	2.266***	0.308***
	(0.093)	(0.006)	(0.007)	(0.007)	(0.71)	(182.755)	(0.012)	(0.019)	(0.141)	(0.063)
50% Fine Level	-0.893***	-0.074***	0.549***	0.260***	12.43***	-827.376***	-0.049***	-0.056**	1.672***	0.253***
	(0.089)	(0.006)	(0.007)	(0.007)	(0.37)	(175.937)	(0.012)	(0.023)	(0.122)	(0.057)
25% Fine Level	-0.956***	-0.057***	0.571***	0.271***	6.47***	-825.018***	-0.045***	-0.051**	1.773***	0.209***
	(0.085)	(0.006)	(0.007)	(0.007)	(0.19)	(173.592)	(0.012)	(0.022)	(0.127)	(0.056)
Automated: 500 gal/hr										
Baseline Fine	-0.857***	-0.044***	0.305***	0.095***	8.17***	-671.537***	-0.037***	-0.077***	0.883***	0.164***
	(0.089)	(0.006)	(0.007)	(0.004)	(0.44)	(176.558)	(0.012)	(0.025)	(0.095)	(0.055)
50% Fine Level	-0.597***	-0.035***	0.310***	0.116***	5.00***	-503.066***	-0.017	-0.008	0.863***	0.147***
	(0.090)	(0.006)	(0.007)	(0.005)	(0.24)	(176.986)	(0.012)	(0.019)	(0.093)	(0.050)
25% Fine Level	-0.438***	-0.024***	0.313***	0.109***	2.41***	-371.413**	-0.017	-0.016	0.719***	0.071
	(0.095)	(0.006)	(0.007)	(0.005)	(0.12)	(183.957)	(0.012)	(0.020)	(0.086)	(0.044)
Automated: 700 gal/hr										
Baseline Fine	-0.418***	-0.022***	0.148***	0.040***	3.28***	-423.352**	-0.015	-0.017	0.315***	0.033
	(0.095)	(0.007)	(0.006)	(0.003)	(0.28)	(176.774)	(0.012)	(0.022)	(0.064)	(0.041)
50% Fine Level	-0.277***	-0.014**	0.147***	0.046***	2.00***	-180.609	-0.011	-0.040*	0.437***	-0.012
	(0.096)	(0.007)	(0.006)	(0.003)	(0.16)	(185.317)	(0.012)	(0.024)	(0.074)	(0.036)
25% Fine Level	-0.358***	-0.021***	0.148***	0.42***	0.80***	-117.956	-0.007	-0.019	0.246***	0.026
	(0.099)	(0.007)	(0.006)	(0.003)	(0.07)	(187.353)	(0.012)	(0.022)	(0.060)	(0.040)
Non-Automated										
50% Fine Level	-0.120	-0.005	-0.003	-0.001**	-0.06***	-365.633**	-0.026**	-0.014	-0.068**	-0.081***
	(0.103)	(0.007)	(0.002)	(0.000)	(0.02)	(185.496)	(0.012)	(0.020)	(0.034)	(0.028)
25% Fine Level	0.109	-0.000	0.001	0.000	-0.06***	184.273	0.007	-0.013	-0.029	-0.074**
	(0.108)	(0.007)	(0.002)	(0.001)	(0.02)	(190.002)	(0.012)	(0.024)	(0.038)	(0.029)
N	261,963	261,963	88,905	88,905	261,963	261,963	261,313	261,963	261,963	261,963
P-val*	0.497	0.497	0.059	0.006	0.022	0.500	0.500	0.497	0.493	0.499

Notes: This table reports household level (Columns 1c-1d) and household-month level (Columns 1a,1b,1e-3b) regression coefficients on the effects of each treatment group on the outcomes described in each column relative to the non-automated baseline fine group. The sample includes data for the months of July-September 2018. Column 2b drops observations with zero monthly use. IHS denotes the inverse hyperbolic sine transformation of monthly water use. Major service requests include interior and exterior audits, supply of hardware, and timer tutorials. Watering schedule violations are defined as households exceeding 300 gal/hr during banned hours. The outcome variables in Columns 3a-3b are multiplied by 100 for ease of visualization. Standard errors are clustered at the household level except for columns 1c-1d which report heteroskedasticity robust standard errors. This table also reports the P-value from the F-test that this fully specified model is equivalent to a more parsimonious specification that includes indicators of a household's assigned automated enforcement threshold and fine level but not their interaction (our null hypothesis H_0), according to the formula: $F = \frac{SS_{red}}{SS_{full}}$ for household-month level regressions. We reject H_0 if F is larger than the upper $1-\alpha$ percentile in the $F(N_{clusters}-1, N_{clusters}-1)$ distribution, where α is the level of significance, SS_{red} and SS_{full} are the residual sums of squares from the parsimonious and the full specifications respectively, and $N_{clusters}$ is the number of clusters. For household level regressions, we instead use the formula: $F = \frac{(SS_{red}-SS_{full})/s}{SS_{full}/df_{full}}$ where df_{red} is the degrees of freedom from the parsimonious model and df_{full} is the degrees of freedom from the full model, both equal to the number of clusters minus the number of parameters in this case. We define $s = df_{red} - df_{full}$ and reject H_0 if F is larger than the upper $1-\alpha$ percentile in the $F(s, df_{full})$ distribution.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figures

Figure A1: Mailer Announcing the Pilot in June



Notes: This figure displays the front page of the mailer sent at the beginning of June 2018 to all households in our experimental sample to announce the beginning of the pilot program in July.

Figure A2: Excessive Water Use Warning

NOTICE OF EXCESSIVE WATER USE:

Excessive Water Use During Restricted Day/Time

[Street Address], METER # [XXX]

Dear [Ratepayer Name]:

Our records indicate the property at this address has violated the City of Fresno's excessive water use provisions. Based on our records, the property associated with your account used more water than is allowed under the excessive use limit during restricted days or hours as measured by your water meter.

Recorded Violation(s):

Wednesday, 5/16/2018 6:59:00 AM - 490 Gallons used

This is your first month with a violation. This **NOTICE** of a violation has been recorded on your customer account. Subsequent violations are subject to fines in accordance with the fine schedule in place at the time the violation occurred.

The violation identified above is your first violation this month. If you incur additional violations this month, you will not receive another notice. You can look up your violation history at https://appdev.fresno.gov/waterpilot/lookup/. Login: [XXX]. Password: [XXX].

We are currently in a Pilot Program with the fine schedule below:

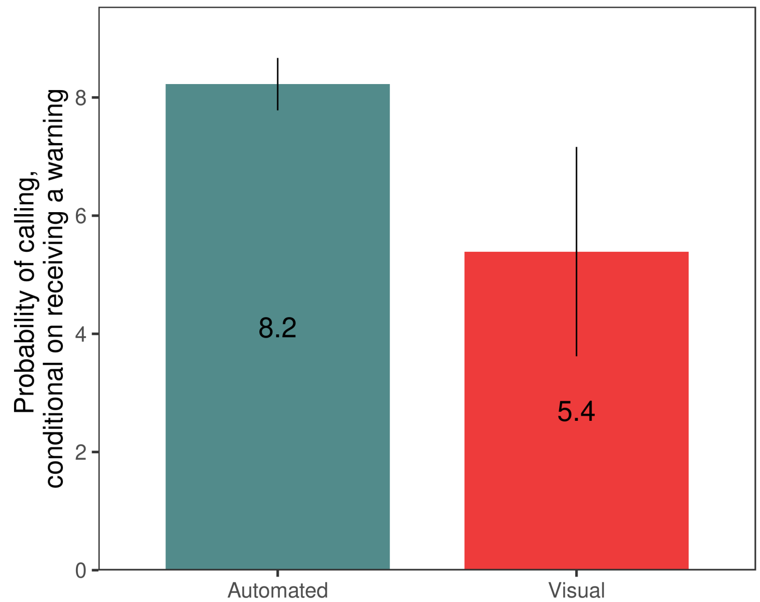
- 1st Month with Violation: Notice Only
- 2nd Month with Violation: [$12.50]
- 3rd Month with Violation: [$25.00]
- 4th Month with Violation: [$50.00]

At the end of the pilot period, the Fine Schedule for this property will return to the standard Fine Schedule that went into effect on January 1, 2018. As a reminder, during the pilot your excessive use threshold during restricted days and hours is [300/500/700] gal/hr.

The City of Fresno offers a variety of free services for water utility customers, including water leak surveys and assistance with setting outdoor irrigation timers. For more information, and/or to arrange an appointment for one of these services, please contact Water Conservation at (559) 621-5400. To further support customers, the City recently launched EyeOnWater, a website and application, which allows customers to monitor their water consumption. Information about EyeOnWater can be found at https://fresno.eyeonwater.com.

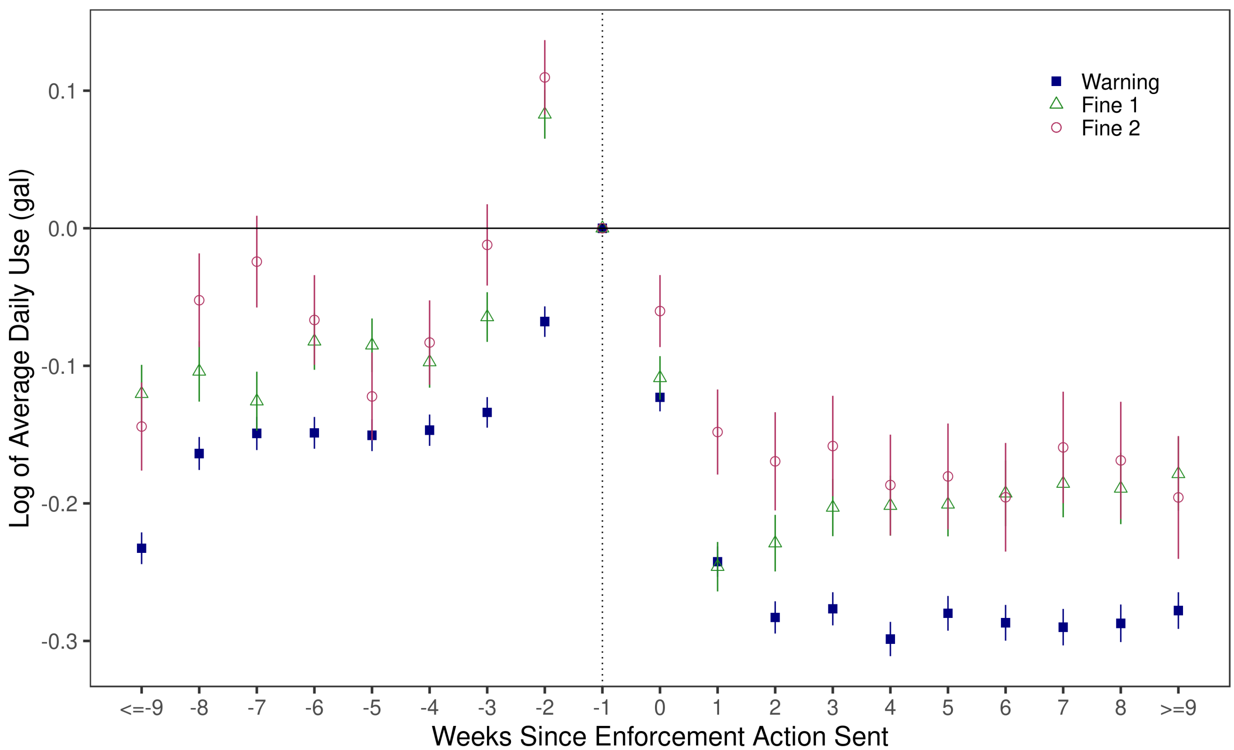
Notes: This figure displays a sample warning of violation sent by the City after a household violated the watering schedule.

Figure A3: Probability of Calling Conditional on Receipt of Warning, by Treatment



Notes: This figure plots the probability that a household in the automated and non-automated group calls utility customer service during July-September 2018, conditional on receiving a warning of violation. The vertical lines represent 95% confidence intervals.

Figure A4: Effect of Fines and Warnings on Water Use



Notes: This figure plots coefficient estimates from a household-week level regression of log of average daily water use on indicators for each week's timing relative to receipt of first, second, and third notices, that is first warning, and first and second fines. Week 0 denotes the calendar week in which the warning/fine was sent, and week -1 is omitted as the reference category. The sample includes data from January 2017 through December 2018. The sample drops notices waived ex-post. The regression includes household and week fixed effects. The vertical bars represent 95% confidence intervals based on standard errors clustered at the household level.