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Consumption feedback and water saving: An experiment in the metropolitan area of Milan

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This paper questions whether informative feedback on consumption can nudge water saving behavioral change. For this purpose, we launched a five-month online information campaign which involved equipping around 1,000 households located in the province of Milan (Italy) with a smart meter. Treated households received monthly reports via email on their per capita daily average water consumption, which included a social comparison component (consumption class size). The difference-in-differences analysis showed that, compared to the control group, treated units reduced their daily per capita water consumption by more than 10% (22 liters or 5.8 gallons). This additional water saving increased with the number of monthly reports, though it did not persist two months after the campaign expired. The impact of the campaign was heterogeneous across consumption classes, while a Regression Discontinuity Design analysis showed that different feedback on consumption class size differentially affected water saving at the margin. Finally, being able to observe the email opening rate, we complemented the ITT analysis by developing a Per Protocol (PP) analysis, where non-adherent units were excluded from the treated group. Both ITT and PP provide consistent conclusions, thus augmenting the level of confidence in the study results.

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1. Introduction

Water scarcity is already affecting a quarter of the world's population (World Economic Forum, 2020), causing economic damage (Franzke, 2021), and negative consequences on human health and well-being (Ebi and Bowen, 2016). Among the different actions aimed at mitigating this issue, the reduction of excessive water consumption, which contributes to local water stress, has become a primary sustainability objective.[1] With respect to this, behavioral nudges have been increasingly acknowledged as powerful and cost-effective actions that can supplement or replace traditional economic levers[2] to correct market failures, engage people in pro-social behavior, and align them with socio-valuable goals (World Bank, 2015; Benartzi et al., 2017). Indeed, academic literature has offered wide and robust evidence on the behavioral sciences' capacity to correct cognitive biases while preserving fundamental individual freedom of choice (Sunstein, 2018; Thaler & Sunstein, 2008).

Behavioral insights are particularly relevant to the water sector, as most people show a biased perception of their water consumption, and systematically underestimate it. Such low awareness can partly be traced back to a lack of clear and frequent information, which, in turn, stems from the widespread technological backwardness in the data collection and communication systems. Data on domestic water consumption can be observed directly via water meters, or indirectly via the water bill. Both ways imply non-negligible searching and evaluating costs. Concerning the former, in many countries (Italy included), homes are equipped with analogue water meters, usually installed outside private homes (or, internally, but not in easily visible places). Moreover, water meters report households' cumulative consumption, limiting users' understanding of their daily consumption.

[1] Among the United Nations' Sustainable Development Goals (SDGs), Goal 12 – 'Responsible Consumption and Production' – calls for effective and timely actions aimed at promoting sustainable behavior.

[2] In this field, traditional economic levers include: increasing water prices, command and control instruments, and market-based incentives aimed at inducing the adoption of water saving technologies (aerated jet breakers, double button discharge, electronic faucets with sensors and photocells) and more efficient domestic appliances (washing machines, dishwashers etc.).

Concerning the latter, water bills usually report the total amount of households' aggregated water consumption over a given period (e.g a quarter), information that is difficult to understand, evaluate and compare. Moreover, since self-reported communications or door-to-door readings occur sporadically, water billing is usually calculated according to estimated rather than real data, further limiting users' awareness of their consumption.[3]

Within this framework, the main goal of this research is to assess the extent to which informative feedback on water consumption can improve households' environmental awareness and nudge water saving behavioral change.

To address our research question, we developed an information campaign involving around 1,000 households in the metropolitan area of Milan, over a five month period, beginning in September 2021 and lasting until January 2022. Based on previous field experiments, treated units received a short report on a monthly basis showing their water consumption, and including a social comparison component (a water consumption diary). Households were ranked according to their water consumption on a 1-1000 scale, and were informed of both their ranking position and the related consumption class size (whether they were 'low users', 'medium users' or 'high users'). Households belonging to the first, second and third consumption tertiles, were ranked 'low', 'medium' and 'high' accordingly.

The campaign was launched in partnership with the CAP holding group, one of Italy's main water companies, which manages the integrated water services in the metropolitan area of Milan and in other provinces of the North Italian Lombardy region. The CAP group was the first Italian company to replace analogue water meters with electronic smart meters, allowing for an automated, remote

[3] Condominiums are often equipped with a single meter and the bills are divided according to the size of the apartments, and not according to the consumption of the individual condominiums, which are not registered.

collection of the water consumption data. These data were elaborated to create the 'water consumption diary'.[4]

Thanks to this natural experiment, we were able to address several research questions. The first concerns the information campaign's effectiveness in nudging a water saving behavior. For this purpose, we compared the treated group with a control group and estimated the average treatment effect through a difference-in-differences (DiD) design. We next investigated whether and how the impact of the information campaign varied over time. For this purpose, we developed a dynamic DiD to determine whether the impact of the treatment varied with the number of informative feedback emails sent to the treated units. Indeed, we were interested in establishing whether sending repeated messages on a monthly basis increased environmental awareness, thus enhancing water savings over time, or rather, whether the opposite occurred, due to a decrease in consumers' attention over time. We also compared the treated group and the control group in the months following the end of the campaign to verify whether the campaign was effective in inducing a permanent change in behavior, or whether its effectiveness was temporary and confined to the campaign period.

Finally, we questioned whether the impact of the information campaign varied across the types of consumers and depended on the type of feedback they received. To address this question, we first developed a heterogeneous analysis to assess whether changes in water consumption were uniform across class sizes. We then applied a regression discontinuity design (RDD) around the class sizes' cut-offs to verify whether sending different feedback to units with comparable consumption levels differentially affected their water saving at the margin.

We contribute to the existing literature on water conservation experiments in several ways. The first way concerns the geographical context. Previous water conservation experiments were mainly developed in the US (Ferraro and Price, 2013; Brent et al., 2015; Hahn et al., 2016; Schultz et al.,2019;

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[4] Initially, a few smart meters were installed across the metropolitan area of Milan on a random basis, and consumers could not apply for a smart meter. In addition, smart meters were installed outside of private apartments, therefore these households cannot yet visualize their real-time water consumption.

Brent et al., 2020), with several applications in various other parts of the world.[5] To the best of our knowledge, ours is the first research applied to the Italian case. Our primary research aim is to verify the external validity of the results of previous social information programs, when applied to a diverse territorial and socio-economic context, characterized by an emerging water scarcity problem. Indeed, this is increasingly becoming a critical issue in Europe, and particularly in Italy, due to the conjunction of the climate crisis-induced increase in the frequency and intensity of extreme weather events, such as droughts (EEA 2019, IPCC 2022), and to the unsustainable behavior of Italian consumers.[6]

Second, compared to the majority of previous experiments, we differentiated our campaign with respect to the type of communicated information. Previous studies mainly communicated the total amount of households' aggregated water consumption over a given period (Ferraro and Price, 2013; Brent at al., 2015; Schultz et al., 2019). Other experiments communicated the daily average of households' aggregated water consumption (Bhanot, 2017; Jessoe et al., 2021), and rarely the litres per capita per day (Goette, et al., 2019). In our experiment, we communicated the *daily* average water consumption (instead of the total water consumption) at a *per capita* level (instead of at households' aggregated levels). The aim of our choice was to provide information in as familiar terms as possible, so that it could be easily quantified and understood by non-skilled users.[7]

[5] Sarac et al. (2003) and Fielding et al. (2013) in Australia; Datta et al. (2015), Miranda et al. (2020), Torres and Carlsson (2018) in Central and South America; Smith and Visser (2013) in South Africa; Sudarshan (2017); Agarwal et al. (2017); Goette, et al. (2019) in Asia; Ansink et al. (2021) and Kažukauskas et al. (2021) in Europe.

[6] The Northern Italian regions declared a State of Emergency in the summer of 2022 due to the worst drought in the last 70 years. Since winter 2021, Italy recorded exceptionally low rainfall and snowfall levels. The May-June-July period was among the hottest ever recorded with many temperature anomalies, including very high peaks and heat waves. As a result, by early summer, the snow on the Alps was completely exhausted in Piedmont and Lombardy, and the Po northern river, the longest river in Italy, recorded critical levels of low water. According to the Permanent Observatory on Water Use in Po River Hydrographic District, on June 2022, 'the exhaustion of the flows along the entire Po (…) remains critical throughout the river shaft, with all measurement sections in a condition of extreme severity with flow rates below historical lows (…) with a deviation from the average of over 90%'. Due to the low flow rates, the estimated salt wedge, both in high and low tide conditions, reached maximum saline intrusion values at around 23 km from the mouth in June 2022. On the demand side, Italy records very high levels of per capita water consumption. With an average per capita consumption of 236 liters per day, Italy is the second European country in terms of withdrawal of drinking water per inhabitant, against the European average of 144 liters per day (ISTAT, 2021).

[7] As mentioned, water bills report the cumulative volume of cubic meters consumed over a quarter by the entire household. Thus, assuming a given water consumption for a hypothetical three person family, the water bill would report an aggregated consumption of 55.8 cubic meters over a quarter, while our information campaign would report an average daily water consumption of 200 liters per person. Both data refer to exactly the same amount of water consumed over a given period, though the latter communication is undoubtedly easier to understand, since the volume, the related unit of

The third way our research contributes to the literature concerns the information notification tool. Previous experiments delivered the information mainly through printed letters, postcards or handouts (Ferraro and Price, 2013; Hahn et al., 2016; Landon et al., 2018; Schultz et al., 2019; Torres and Carlsson, 2018; Carlsson et al., 2021; Fielding et al., 2013; Miranda et al., 2020), printed leaflets in the form of door hangers (Schultz et. al 2007; Goette et al., 2019), or a combination of printed letters, emails and a website (Dolan & Metcalfe 2013; Brent at al. 2015; Bhanot, 2017; Jessoe et al., 2021; Schultz et al. 2016; Daminato et al., 2021). These studies mainly conclude that the experiment effectiveness depends on the type of notification tool used and find that printed copies tend to be more effective than email notifications, which in general are not associated with a significant effect on water conservation. According to various interpretations, the lower success rate associated with online messages could be due to extra effort required to open them. Conversely, in our case, the information was provided exclusively via email. To the best of our knowledge, this represents the first research providing evidence on the effect of an information campaign based solely on email notifications.

Finally, thanks to the email notification tool, we were able to monitor the email click (open) rate, and following previous research on clinical trials (Tripepi et al., 2020; Schulz et al. 2010; Perkin et al. 2016), we combined the traditional intention to treat (ITT) analysis with a Per Protocol 'PP' analysis (also known as 'compliance-only' analysis). While recognizing the ITT superiority and the potential self-selection bias associated with PP analysis, CONSORT (Consolidated Standards of Reporting Trials) guidelines on 'parallel group randomized controlled trials' recommend to combine these two approaches and conclude that when 'ITT and PP provide identical conclusions, the confidence level of the investigator for the study results is augmented' (Schulz et al., 2010).

measurement and the time period can be more easily associated with our daily experience. We thus believe that this choice can therefore induce a greater awareness of the water consumption associated with one's daily habits. Moreover, compared to the water bill, the higher frequency of our information campaign emails can give users more timely feedback on how any changes in their consumption behavior impacts on their water footprints.

Recent literature recognizes that a robust interpretation of the (clinical) trials' results requires both ITT and PP approaches to provide concordant results (Tripepi et al., 2020). Accordingly, in our research, after having verified with a range of tests that the principle of randomization was preserved when excluding the non-adherent units from the treated group, we decided to adopt the ITT as the main method of analysis and to add the PP as a secondary, supportive analysis to further verify the robustness of the ITT estimation results.

To summarize the main results of our analysis, we found that the campaign was effective in promoting an average per capita reduction of 22 liters (5.8 gallons) per day (-10%) in the treated group compared to the control group. The dynamic analysis shows that the effect of the campaign was not constant over time, as estimated additional water saving increased with the number of emails sent. This suggests that repeated emails induce increased awareness. However, we verified that the water conservation effects were not permanent, and expired few months after the end of the experiment. This suggests that, while being effective in correcting our cognitive biases, the information campaign did not represent a sufficient tool to drive structural behavioral change. We also found that the impact of the treatment was heterogeneous across the consumption classes and that different feedback differentially affected consumption choices at the margin. These main results are confirmed when focusing on adherent units only.

The remainder of the paper is organized as follows: Section 2 places our study within the literature on water consumption. Section 3 provides details of the experimental design. Section 4 describes the sample construction and descriptive statistics. Section 5 presents the empirical strategy. Section 6 discusses the results in detail and Section 7 shows the robustness checks. Section 8 concludes.

2. Literature Review

Actions to promote pro-environmental and resource conservation attitudes have been extensively studied in behavioral science literature (see Andor and Fels, 2018 for review). A widely agreed finding is that social information campaigns, on top of being relatively cheap to implement (Wang and Chermak, 2021), can be more effective than traditional instruments in promoting sustainable daily habits and stimulating consumers to adopt pro-environmental behaviors (Ferraro and Miranda, 2013; Ferraro and Price, 2013; Price et al., 2014). This result is confirmed by a variety of field experiments, whose designs differ with respect to a variety of factors. We review those that are most strictly connected to our research.[8]

Geographical context. Existing water conservation experiments were largely and mainly developed in the US (i.e. Ferraro and Price, 2013; Brent et al., 2015; Hahn et al., 2016; Schultz et al.,2019; Brent et al., 2020), with various applications in other parts of the world, such as Australia (Sarac et al., 2003; Fielding et al., 2013), Central and South America (Datta et al., 2015; Miranda et al., 2020; Torres and Carlsson, 2018), South Africa (Smith and Visser, 2013), and Asia (Sudarshan, 2017; Agarwal et al., 2017; Goette, et al. 2019). Very few researchers investigated the impact of a social information program on water consumption in Europe (Ansink et al., 2021 in the UK and Kažukauskas et al., 2021 in Sweden).

Adopted notification tool. Households were reached via postcards or mailers (Fielding et al., 2013; Miranda et al., 2020; Brent et al., 2020), handouts (Seyranian et al., 2015), a combination of letters and emails (Brent at al. 2015; Bhanot, 2017; Jessoe et al., 2021), a combination of letters and a website (Schultz et al.,2016; Daminato et al., 2021), printed leaflets in the form of door hangers (Goette et al., 2019) or more frequently via printed letters (e.g., Ferraro and Price, 2013; Hahn et al., 2016; Landon

[8] These vary, among others, depending on: the inclusion of a social comparison component (Allcott, 2011; Byrne et al., 2018; Bhanot, 2017; Brent et al., 2015, 2020; Jessoe et al., 2021); the type of informative feedbacks sent to the consumers, with a distinction between pure descriptive feedbacks or injunctive normative feedbacks (Bonan et al., 2020; Ferraro and Miranda, 2013); the inclusion of a (environmental, economic, social etc.) motivational leverage (Schultz et al. 2007; Jaeger and Schultz, 2017); the inclusion of monetary or non-monetary rewards with engagement or gamification approaches (e.g. Brent and Ward, 2019; Ferraro and Price, 2013; Olmstead and Stavins, 2009; Torres and Carlsson, 2018; Wichman, 2014; Wichman et al., 2016). Also the frequency of the information campaign differs across studies, and it can be monthly or mixed frequency (Brent at al., 2015; Torres and Carlsson, 2018; Carlsson et al., 2021), bimonthly (Bhanot, 2017; Jessoe et al., 2021) or one-time sending (Ferraro and Price, 2013; Schultz et al., 2016; Landon et al., 2018; Schultz et al., 2019). The duration of the experiments also differs between studies; some studies last one year (Jessoe et al., 2021), others last longer than one year (Brent at al., 2015; Brent and Wichman, 2020; Bhanot, 2021), others last less than one year (Hahn et al., 2021; Bhanot, 2017; Torres and Carlsson, 2018; Carlsson et al., 2021), and others last only a week (Schultz et al., 2016).

et al., 2018; Schultz et al., 2019; Torres and Carlsson, 2018; Carlsson et al., 2021). Few studies provide real-time feedback with pre-installed in-home displays (Kažukauskas et al., 2021), or water meters connected shower heads (Agarwal et al., 2017).[9] Previous studies show that the effectiveness of an information campaign can depend on how it is communicated. Dolan & Metcalfe (2013) report that printed copies of social norms for electricity conservation are more effective than digital copies delivered via email. Brent et al. (2015) use a combination of letters and emails, and find the effect of their campaign to be insignificant for the category receiving the water report via email. Similarly, Schultz et al. (2016) show that web-based delivery is less effective than postal mail. However, none of these studies provide a solid explanation for this result, suggesting that this could depend mainly on the lower success rate associated with online messages, due to the extra effort required in opening them (Schultz et al., 2016). More recently, using a combination of letters and real-time feedback through an online portal, Daminato et al. (2021) show that the use of an online tool drives the main result of their experiment on water consumption.

Type of communicated information. Recently, Wang and Chermak (2021) argued that the size of the water saving can depend on the unit of measurement being used to communicate consumption data, which varies among studies. While some campaigns communicated the *households' aggregated total amount* of water gallons consumed over a given period (Ferraro and Price, 2013; Brent at al., 2015; Schultz et al., 2019) or during the main irrigation season (Landon et al., 2018), others communicated the *daily average* of the households' aggregated total amount of gallons consumed in one or two months (Bhanot, 2017; Jessoe et al., 2021). Few experiments used an app or home-installed meters where households could observe their real-time consumption (Agarwal et al., 2017;

[9] Some studies take advantage of the data collected by using more sophisticated technologies to evaluate the effect of real-time feedback on water consumption. Among these, Agarwal et al. (2017) find that, thanks to real-time consumption feedback for showering, water per shower is reduced on average by 2 liters (9-10%) compared to the control group. Analogously, Kažukauskas et al. (2021), making use of pre-installed in-home displays providing real-time information, study the effect of an instant and continuous comparison of consumption on water and electricity for a sample of 525 households in Sweden. They find that, on average, families belonging to the treated units having additional information on their in-home displays reduce their daily energy consumption by an average of 0.3 Kwh (-6.7%), while the only improvement in water consumption is observed in the short term but disappears in the long term.

Kažukauskas et al., 2021). Apart from the notable exception of Goette et al. (2019), to the best of our knowledge, no paper has so far provided information on water consumption expressed both *per person* and *per day* (daily average per capita water consumption), and none have used liters instead of gallons. The liter is the unit of measurement used in Italy. In other countries with the same unit of measurement, data were expressed in cubic meters (Torres and Carlsson, 2018; Carlsson et al., 2021), which is a less familiar unit of measurement than liters.

3. Information Campaign

Treated units received a monthly report (*the water consumption diary)* on their domestic water use over a five month period, from September 2021 to January 2022. The report was delivered exclusively via email, and included informative feedback and a social comparison component. First, households were informed on their monthly average water consumption, which, differing from previous studies, was communicated on a *per capita* basis using the *liters per day* unit of measurement. Because of this, the provided information was easily understandable and quantifiable. Second, we communicated the average water consumption level for the entire treated group, and provided some further information aimed at facilitating the social comparison in terms of water consumption. In particular, we constructed a ranking on a 1–1000 scale and communicated to each household its ranking position and the related consumption class size: whether households were 'low users', 'medium users' or 'high users' (that is, whether they belonged to the first, second and third consumption tertiles).

Figure. 1 The water consumption diary

Your Monthly Consumption Diary

August 2021

Dear Customer,
here is your water consumption diary.
On August 2021, your households' *daily* water consumption amounted to **259 liters** *per person*.
Over the same month, the average *daily* water consumption in your neighbourhood was **227 liters** *per person*.

Find your ranking position

640°

Based on your water consumption your ranking position is 640 out of 1000

Find which type of consumer you are

MEDIUM USER

Based on your water consumption you belong to the "Medium User" category

Low User **Medium User** **High User**

You are here

4. Experimental Design and Sample Construction

The experiment was developed in the metropolitan area of Milan where the water company CAP Holding Group was replacing old analogue water meters with electronic smart meters. We focused our analysis on a sample of 13,852 single-family homes that, at the time of designing the experiment, were already equipped with smart meters remotely collecting data on the their water consumption. This sample was randomly selected, since families could not apply for smart meters and the water company was not replacing the meters following any pre-determined geographical criteria. Our sample was distributed over 45 municipalities in the metropolitan area of Milan (Italy). Within this sample, we were legally bounded to send informative material to around 1,000 households, which, at the time of signing the contract with CAP, resulted in them giving their consent for profiling activities. Therefore, we opted to assign treated status to the entire subset of households equipped with a smart meter, that had provided privacy consent. The control group was initially composed of the remaining 10,000 households, equipped with a smart meter, that had not provided privacy consent.[10] We are aware that, since people voluntarily decided whether or not to give consent, this assignment criterion could potentially cause a self-selection bias issue, which we tried to mitigate through a matching procedure.

4.1 Propensity score matching

We selected through a propensity score matching (PSM) procedure a control group which, before the treatment, was not statistically different from the treated one along a variety of observable dimensions.[11]

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[10] An alternative would have been to randomly assign these 1,000 households to either the treated group or the control group. However, in light of the risk of a relevant opt-out rate, we preferred to include all of the households that provided privacy consent in the treated group. Interestingly, very few papers (if any) have explicitly discussed how they manage this privacy consent issue.

[11] Rosenbaum and Rubin (1983) propose this method, stating that the propensity score refers to the conditional probability $P(X_i)$ that individual i enters the treatment group given a set of covariates (X_i). The procedure uses a Logit regression

Treated and untreated units were matched on the estimated propensity scores (on the estimated probability of being treated given a set of observable characteristics on treated and control units). We first estimated through a Logit model to what extent the probability of being treated was, explained by the following covariates: number of residents, age and gender of the contract holder, the aggregate households' pre-treatment water consumption levels (*Cday*), and several fixed effects regarding the classification of the consumer type, municipality of residence, and recipient type. From the results, reported in Table 1, we can observe that the size of the estimated coefficients (and related marginal effects) is quite small.

Table 1. Propensity score estimates

Variables	**Estimated coefficients**	**Marginal Effects**
Residents	0.071*	0.005*
	(0.037)	(0.003)
Age	-0.033***	-0.002***
	(0.002)	(0.000)
Gender	0.178**	0.013**
	(0.069)	(0.005)
Cday	0.0003***	0.00002***
	(0.000)	(0.000)
No. Obs.	12,175	12,175
Pseudo-R2	0.047	

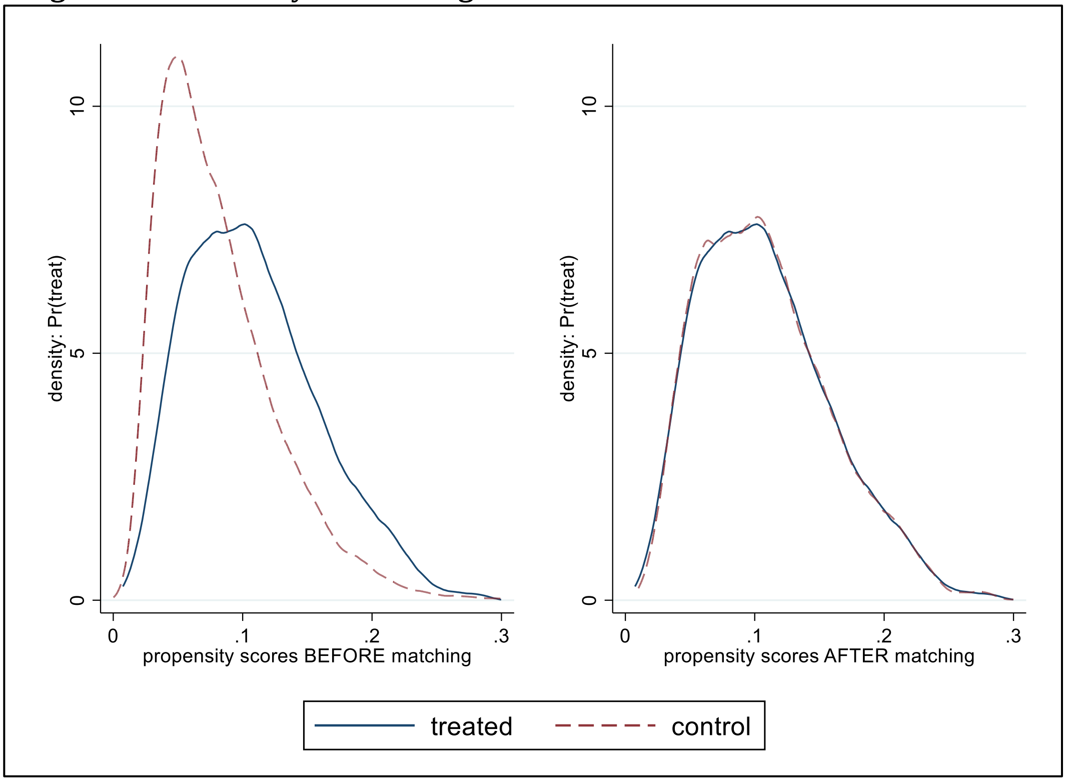
Notes: Logit estimator. Dependent variable: treatment. Standard errors in parentheses. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Based on the estimated propensity scores, we matched each treated unit to a maximum of its three nearest neighbor non-treated units (in terms of estimated propensity score). Non-treated units lying out of the common support of the estimated propensity score were excluded from the analysis. After the PSM procedure, the control group was composed of 3,486 units.

model, Probit and other probability models to estimate the propensity score. The idea is to find a control group that is as similar as possible to the treatment group to reduce selection bias and remove confounding bias of observed variables and other observable factors (Rosenbaum and Rubin, 1983). The PSM made the covariates of the treatment and control groups balanced and comparable to control the effect of the treatment.

A first inspection of the density distribution of the propensity scores in both groups, before and after the matching, visually confirms the common support between treatment and comparison groups, and the soundness of the PSM procedure (see Figure 2).

Figure 2. Probability of receiving the treatment before and after the matching



As well as this, we report the PSM balancing test. This shows that, along several dimensions, the differences between the treated and the untreated units are significant only before the matching procedure. Conversely, the matched treated and untreated units do not show any statistically significant difference, thus allowing us to reject the null hypothesis (Table 2).

Table 2. Balance test

Variables		Mean		t-test	
		Treated	Control	T	p > |t|
Residents	U	2.631	2.470	-5.300	0.000
	M	2.630	2.630	0.100	0.920
Age	U	56.282	64.178	15.250	0.000
	M	56.280	57.950	3.090	0.000
Gender	U	0.637	0.596	-2.550	0.011
	M	0.640	0.620	-0.910	0.362
Cday	U	711.030	612.360	-5.320	0.000
	M	711.030	687.850	-1.050	0.290
ARERA classification	U	0.94	0.93	2.11	0.034
	M	0.94	0.95	-0.72	0.47

Notes: ARERA classification distinguishes residential from non-residential consumers according to the regulator (ARERA) classification.

Table 3 presents the description of the variables and the related summary statistics.

Table 3. Summary statistics and description of the variables

Variable	Mean	S.D.	Min	Max	Description
Residents(a)	2.64	0.95	1	9	Number of residents of each single-family home
Age(b)	57.62	15.14	23	100	Age of the contract holder
Gender	0.63	0.48	0	1	Dummy=1 if the contract owner is male
ARERA classification	0.95	0.22	0	1	Dummy=1 for non-resident domestic use
Cday(c)	583.93	544.20	0.806	9280	Households' aggregated average daily consumption
Cday_pc(c)	231.75	254.57	0.717	8030.95	Households' per capita average daily consumption

Notes: (a) in units; (b) in years; (c) in liters/day.

4.3. Success rate of the information campaign and analysis of the decision to opt-out

We now focus on the treated group and on its rate of compliance. Having sent the consumption diary via email, we could observe how many of the five monthly emails users received were actually opened by the users (click rate). Overall, the 46% of the treated units opened a maximum two out of the five emails sent, while the 54% opened at least three emails (Table 4).

Table 4. Descriptive statistics on the users' opt-out status

Number of opened emails	Number of Users	Percentage	cumulative percentage
None (Zero compliance)	193	19%	19%
One	150	15%	34%
Two	128	12%	46%
Three	149	14%	60%
Four	120	12%	72%
Five (full compliance)	274	28%	100%
Total	1,014	100%	

In the ITT analysis, all the treated subjects are included in the statistical analysis according to the group they were originally assigned to, regardless of their compliance status. By ignoring non-compliance, this approach preserves the balance between the treated and control groups, allowing for an unbiased ATT estimate. However, in case of substantial non-adherence, a shortcoming of this approach is a potential untrue estimation of the magnitude of the treatment effect, since non-complying units – which are *de facto* untreated – are analyzed as if they were treated.

Conversely, the Per Protocol approach restricts the statistical analysis on the complier units, while disregarding non-adherent units. In this latter case, the information on effective compliance on the treatment can be exploited to estimate the treatment's efficacy on those who actually received the assigned treatment. A serious shortcoming of this approach is that, due to a self-selection issue, the balance between the treated and the control groups might not be preserved, leading to a biased ATT estimate. Indeed, the treated units decide whether or not to comply on a voluntary basis, and excluding non-adherent participants from the analysis can lead to a violation of the pre-treatment parallel assumption.

In light of the substantial opt-out rate observed in our experiment, we developed a number of tests to verify the randomized distribution of the opt-out decision. In particular, we analyzed the determinants of the opt-out decision and assessed whether it was a random process or, conversely, whether it depended on users' specific characteristics, on their consumption levels or on the type of informative feedback they received.

To analyze the determinants of the opt-out decision, we estimated a probit model where the probability of opening the email received in the month *t* is explained by a series of observable households' characteristics, time and unit fixed effects, and by the type of feedback received in the previous month *t-1*. Results reported in Table 5 show that none of the estimated coefficients of the explanatory variables are highly statistically significant. In light of this evidence, we can assert that the opt-out decision did not depend significantly on either units' characteristics, or on the type of informative feedback they received.

Table 5. Probit estimates: The determinants of openness

Variables	**Estimated coefficients**
Residents	0.0986*
	(0.054)
Age	0.0049
	(0.004)
Gender	0.1575
	(0.111)
Low class (informative feedback)	0.0506
	(0.093)
Medium class (informative feedback)	-0.0672
	(0.081)
ARERA classification	-0.1516
	(0.254)
Recipient type	-1.0385
	(0.807)
No. Obs.	3944
Wald chi2	330698***

Notes: Standard errors in parentheses. Superscripts ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The dependent variable is coded 1 if the user opens in the month, 0 otherwise.

As Table 6 shows, this conclusion is further supported by the evidence that, even after excluding the non-adherent units, the balance between the treated group and control group is still preserved, as they are not statistically different from 0 with respect to the considered variables. Moreover, the null hypothesis is also rejected when comparing the adherent treated units to the non-adherent treated units.

Table 6. Per protocol sample: Descriptive statistics

	Per-Protocol				Per-Protocol			
	Control N=3,486	**Adherent Treated N= 543**	**T**	**p > |t|**	**Non-adherent Treated N=471**	**Adherent Treated N=543**	**t**	**p > |t|**
Cday	687.85	716.21	1.000	0.320	705.07	716.21	0.290	0.770
Cday_pc	271.39	286.43	1.160	0.250	295.53	286.43	-0.480	0.630
Residents	2.63	2.67	0.780	0.430	2.59	2.67	1.300	0.190
Gender	0.62	0.67	2.030	0.040	0.60	0.67	2.110	0.040
Age	57.95	57.66	-0.430	0.670	54.70	57.66	3.150	0.000
ARERA classification	1.950	1.950	-0.320	0.750	1.940	1.950	0.270	0.790

After having verified that: i) the decision to withdraw from the online campaign did not depend on units' characteristics, nor was it related the type of informative feedback they received; ii) the balance between the treated and control group was confirmed when excluding the non-adherent units, we decided to adopt the ITT as the main method of analysis and to complement it with a PP analysis, which allowed us to assess the impact of the treatment campaign on the users who had been effectively treated. In other words, the treatment group is restricted to the adherent units. We consider a treated unit to be compliant only if they opened at least three of the five emails they received. The complying sub-group (PP group) is composed of 543 out of 1,014 units. This represents a secondary supportive analysis which provides an additional check on the robustness of the ITT results. Indeed, recent literature recognizes that a robust interpretation of trials' results requires both ITT and PP approaches to provide concordant results (Tripepi et al., 2020).

5. Empirical Strategy

The first research question we want to address is whether the information campaign has been effective in reducing water consumption compared to the households that were not involved in the campaign. In other words, we aim to assess the average treatment effect on the treated units (ATT). For this purpose, we estimate the difference-in-differences (DiD) model:

$$y_{it} = \alpha + \beta_1 POST_t + \ \beta_2 TREAT_i \times POST_t + \gamma_i + u_t + \varepsilon_{it} \qquad (1)$$

where y_{it} indicates the average daily per capita water consumption for the user *i* at time *t*; $TREAT_i$ is a dummy variable equal to 1 when the unit *i* belongs to the treated group and 0 otherwise; $POST_t$ is a dummy variable equal to 1 in the post-treatment period and 0 otherwise. While the post-treatment phase covers the entire period of the information campaign (from September 2021 to January 2022), we decided to restrict the pre-treatment period to the months May 2021 to August 2022 when there were no COVID-19 restrictions in place.[12] The interaction term $TREAT_i * POST_t$ identifies the units *i* as belonging to the treated group (T) in the post-treatment period (P). The parameter α is the constant term; β_1 captures the pre-post treatment change in water consumption of the control group; β_2 represents our parameter of interest, as it captures how the treated group has changed at the margin its average water consumption compared to the control group. γ_i and u_t capture the individual and time fixed effects respectively, while ε_{it} is the error term, which is clustered at an individual level. Equation (1) is estimated with OLS using the standard fixed effects estimator.

5.1 Dynamic analysis

A second major interest of our research concerns the dynamic effect of the campaign. We are interested in understanding how the impact of the social information campaign varied over time, whether it increased or decreased with the number of emails sent. The latter case would point to the reinforcing contribution of repeated emails in building environmental awareness, while the former case would point to their limited effectiveness, as water savings would decrease at the margin. Conversely, a constant trend would suggest that sending multiple information campaigns does not affect at the margin water conservation behavior. The dynamic DiD can be specified as:

[12] Our findings are entirely confirmed when including previous months.

$$y_{it} = \alpha + \sum_{j=1}^{J} \beta_j LAG_j + \sum_{k=1}^{K} B_k LEAD_k + \sum_{j=1}^{J} \theta_j (LAG_j * TREAT_i) + \sum_{k=1}^{K} \theta_k (LEAD_k * TREAT_i) + \gamma_i + \varepsilon_{it} \quad (2)$$

Lags and leads are binary variables capturing the months preceding and following the first month of the information campaign. In particular, LAG_j with $j = 1, \dots, 4$ are the months from May 2021 to August 2021, and $LEAD_k$ with $K = 1, \dots, 5$ are the months from September 2021 to January 2022. The inclusion of lags and leads allows us to assess the dynamic trend of the treatment, whether it is increasing or decreasing in time, whether it is stable or volatile, whether it is permanent or temporary. Moreover, this approach allows us to compare water consumption for the treated group and the control group in the months preceding the launch of the social information campaign, and to test the parallel trend assumption which must be satisfied for the DiD to provide unbiased estimates.

We extend this approach by including observations for the three months following the end of the information campaign (from February 2022 until April 2022). This approach allows us to highlight the differences in water consumption among the treated group and the control group after the end of the information campaign, and to assess whether its effect has been temporary and confined to the treatment period, or whether it managed to induce a structural change in the treated group's behavior, promoting a permanent reduction in their water consumption.

5.2 Heterogeneity analysis

Next, we develop a heterogeneous analysis to assess whether the treatment effect varies across types of consumers according to some observable characteristics. First, we grouped both treated and control units into tertiles ('low', 'medium' and 'high' classes) according to their pre-treatment average level of per capita water consumption. Then we re-estimated the ATT and its dynamic effect (equations 1 and 2 respectively) for the three groups separately. We expect the information campaign effectiveness to depend on the pre-treatment water consumption level, as has been found in some studies on water and energy consumption (Ferraro et al., 2011, Ferraro and Price, 2013; Allcott, 2011, Andor et al., 2020). In particular, consistent with a convex water saving costs function, we expect that high consumers will experience the most significative water consumption reduction, since they should have most water saving opportunities at lower marginal costs. Conversely, consumers belonging to the first water consumption tertile should have limited opportunities to further reduce their water consumption. We therefore expect the information campaign to have limited or no effect on their behavior.

Moreover, we inspect the heterogeneous effect by grouping consumers according to their age and family size. We expect the informative campaign to be more effective for younger users and for smaller families. This is because younger users are expected to be more sensitive to environmental issues. We also expect communication and coordination costs to be lower for smaller families than for larger families. If this is true, then the information campaign should spread more effectively in smaller families and we should observe a higher reduction in water consumption.

5.3 Feedback analysis and RDD

We are interested in analyzing whether, within the treated group, consumers behavior varies at the margin depending on the type of feedback received. However, due to the endogenous nature of the informative feedback, a direct comparison across high, medium and low users is likely to lead to a biased estimate of the causal effect of different feedback on water saving behavior. To address this potential endogeneity issue, we develop a regression discontinuity design (RDD) around the consumption classes' cutoffs. We exploit the fact that consumers were classified into three discrete categories with sharp cutoffs. When all the consumers are considered, the average per capita water consumption differs significantly among classes. Nevertheless, the closer we get to the cutoff, the smaller the difference in consumption between the contiguous categories, with the difference in consumption between households just below and above the cutoff being insignificant. In spite of their similarity, consumers around the cutoff are categorized differently and receive different feedback depending on the side of the cutoff they belong to.[13] Therefore, we exploit this quasi-random category assignment among users around the cutoff to estimate the causal effect of different feedback on water saving behavior. The main intuition of the RDD is that, being households just below and above the cutoff similar in their consumption behavior, then any variation in their respective water consumption can be attributed to the different feedback they received.

To implement the regression discontinuity approach, we build a stacked panel dataset in the following way. Within each treatment month *t=1, ...5* (from September 2021 to January 2022), we first define c_t^{min} and c_t^{max} as the minimum and maximum threshold of the medium consumption category. c^{min} defines the cutoff between the low–medium classes, while c^{max} defines the cutoff between the medium–high classes. We then calculate the variables D_{it}^{min} and D_{it}^{max} as the differences between each household's consumption (in per capita daily liters), and the c_t^{min} and c_t^{max} cutoff points. Then, we consider only the treated units whose distance from the cutoff is lower than a given threshold *d*, which satisfy the conditions $D_{it}^{min} \leq d$ and $D_{it}^{max} \leq d$ respectively for the minimum and maximum cutoffs c^{min} and c^{max}. We apply this approach recursively, therefore we construct G=5 groups (corresponding to as many panel datasets), one for each month *t=1, ...,5* of the treatment period. We then stack the *G* panel datasets and run the following regression:

$$y_{igt} = \alpha + \beta_1 RDD_{ig} + \beta_2 POST\_RDD_t + \beta_3\left(RDD_{ig} * POST\_RDD_t\right) + \gamma_{ig} + u_{gt} + \varepsilon_{igt} \quad (3)$$

Notice that the same subject can appear below the cutoff in a certain month and above the cutoff in another month. This implies that the unit of observation is the subject *i* within the group *g*. Therefore,

[13] The difference in consumption between the best and the worst in the low (middle) consumption category is greater than the difference in consumption between the worst in the low (middle) consumption category and the best in the medium (high) consumption category. Nevertheless, in the first case the two subjects fall in the same low (middle) consumption class size and receive the same feedback despite their significant difference in consumption, while in the second case the two subjects are classified in different categories and receive different feedback despite their substantial similarity in consumption.

y_{igt} represents the water consumption of subject i, belonging to group g, in the month t; RDD_{ig} is a dummy which equals 1 if the subject i, belonging to group g, falls above the cutoff, and 0 if the subject i falls below the cutoff; the dummy variable POST_RDD equals 0 in the month when units receive their informative feedback and 1 in the following month. By interacting these two dummy variables we can estimate our parameter of interest β_3 which captures whether, at the margin, the selected treated units change their water consumption behavior differentially, depending on which side of the cutoff they belong to. γ_{ig} are the fixed effects for the subject i within the group g, while u_{gt} are time fixed effects referring to the month t within the group g. We run this regression separately for the two cutoffs c^{min} and c^{max} which allows us to compare the low–medium and the medium–high categories.

6. Results

Column (1) of Table 7 reports the results of the average treatment effect on water use for the entire treated group (ITT), obtained by estimating Equation (1), while column (2) restricts the analysis to the adherent treated units (PP). We find that, on average, the social information campaign had a positive and highly statistically significant effect on water savings. Indeed, the ITT analysis reveals that, after the treatment, treated units reduced their per capita water consumption by 22 liters per day (5.8 gallons/day) with respect to the control group, corresponding to a water saving higher than 10%. The PP analysis shows that the effect is more pronounced when focusing on the adherent households. In this case, per capita water consumption decreases on average by 26 liters (6.9 gallons) per day (-13%).

The combination of the ITT and PP analyses brings interesting insights. Indeed, the campaign had a greater effect on the users who had been effectively treated. This suggests that the average ITT result is partly driven by the adherent units, though, overall, the campaign is effective irrespectively of the non-negligible opt-out rate. Furthermore, our results differ from those of previous studies that did not find a significant effect of information campaigns conducted online, and are consistent with the recent finding of Daminato et al. (2021).

Table 7. Treatment effect on water use

	ITT	PP
	(1)	**(2)**
Post	-66.254***	-65.895***
	(4.887)	(4.972)
Post*Treated	-22.408***	-25.992***
	(8.526)	(9.821)
Constant	262.328***	260.123***
	(2.619)	(2.705)
No. Obs.	38,945	34,786
No. Households	4,500	4,029
R-squared	0.062	0.062

Notes: Month-by-year dummy variables included. Estimates correspond to the period May 2021 and January 2022. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6.1 Dynamic analysis

Figure 3 displays the results of the dynamic ATT obtained by estimating Equation (2).[14] On the left panel of the figure, we plot the results of the ITT analysis. Interestingly, we find evidence that the treatment effect is not constant over time, but increases with the number of reports sent to the treated units. Additional per capita water conservation increases from 11 liters (2.9 gallons) per day after the first round of the experiment to 32 liters (8.5 gallons) per day in the final (fifth) round of the campaign. This finding suggests that sending repeated messages does increase environmental awareness and enhances higher water savings over time, and suggests a rejection of the alternative hypothesis that consumers' attention decreases with the number of messages. Moreover, the figure does not highlight

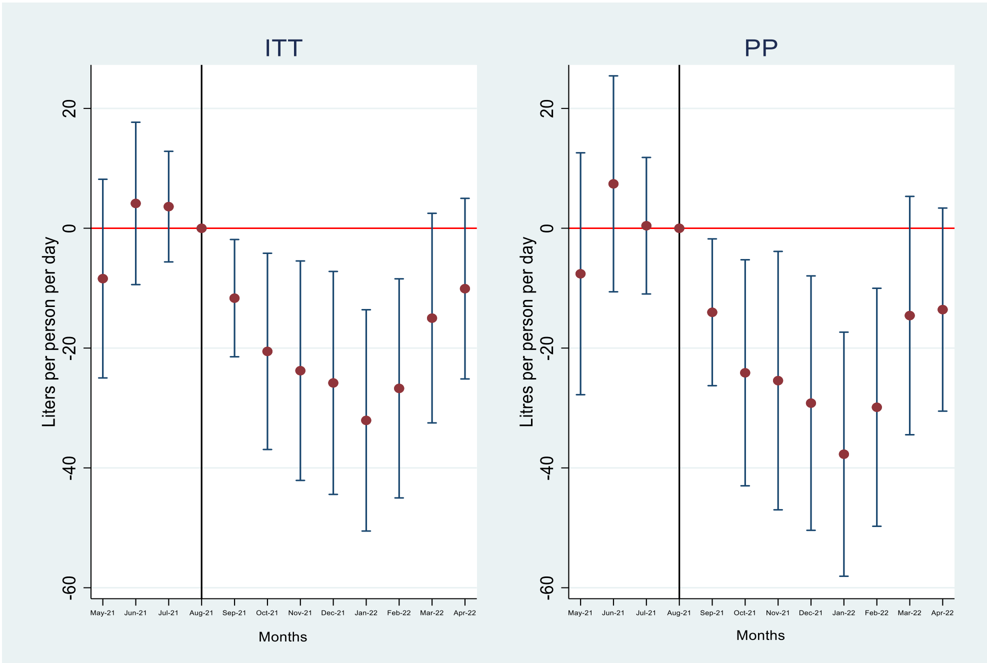
[14] Table A1 in the online ppendix reports the dynamic regression results.

any significant difference in consumers’ water consumption among the treated group and the control group in the pre-treatment period, thus supporting the parallel trend assumption that must be satisfied for the DiD to provide unbiased results.

Also in this case, the PP analysis (panel on the right, Figure 3) confirms that the effect of the campaign is stronger when focusing only on the adherent units which actually opened the emails. Indeed, per capita water savings increases from 14 liters (3.7 gallons) per day after the first round of the campaign up to 38 liters (10 gallons) per day in the final (fifth) round of the campaign.

The long-run analysis reveals that the water conservation induced by the information campaign is not permanent. Indeed, the marginal water savings of the treated group expired few months after the end of the experiment. Both the ITT and the PP analyses highlight that no statistically significant differences between the treated group and the control group persisted two months after the end of the campaign. This suggests that, while being effective in correcting cognitive biases, the information campaign does not represent a sufficient tool to drive structural behavioral change

Figure 3. Treatment effect on water use: Dynamic trend



Note: Point Estimate with 90% confidence interval.

6.3 Heterogeneity analysis

To estimate the heterogeneous effects of the campaign we first categorize both the treated and control units into three classes (‘low’, ‘medium’ and ‘high’) according to their pre-treatment level of water consumption. Table 8 reports the results of the estimation of Equation (1) for each of the three consumption classes, for both the ITT and PP analyses.

Table 8. Treatment effects on water use for users classified according to water use before the information campaign

	ITT			PP		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low Users	Medium Users	High Users	Low Users	Medium Users	High Users
Post	3.709	-2.602	-107.508***	3.841	-2.373	-108.856***
	(2.735)	(3.357)	(11.542)	(2.761)	(3.470)	(11.627)
Post*Treated	-6.333	-4.898	-58.371***	-7.809*	-10.841	-57.670**
	(3.895)	(6.829)	(22.078)	(4.624)	(11.316)	(23.047)
Constant	120.037***	190.084***	425.711***	119.998***	189.963***	420.997***
	(1.356)	(1.614)	(6.504)	(1.494)	(1.752)	(6.745)
No. Obs.	12,794	13,058	13,093	11,421	11,627	11,738
R-squared	0.013	0.038	0.154	0.012	0.037	0.154

Note: Month-by-year dummy variables included. Estimates correspond to the period May 2021 and January 2022. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

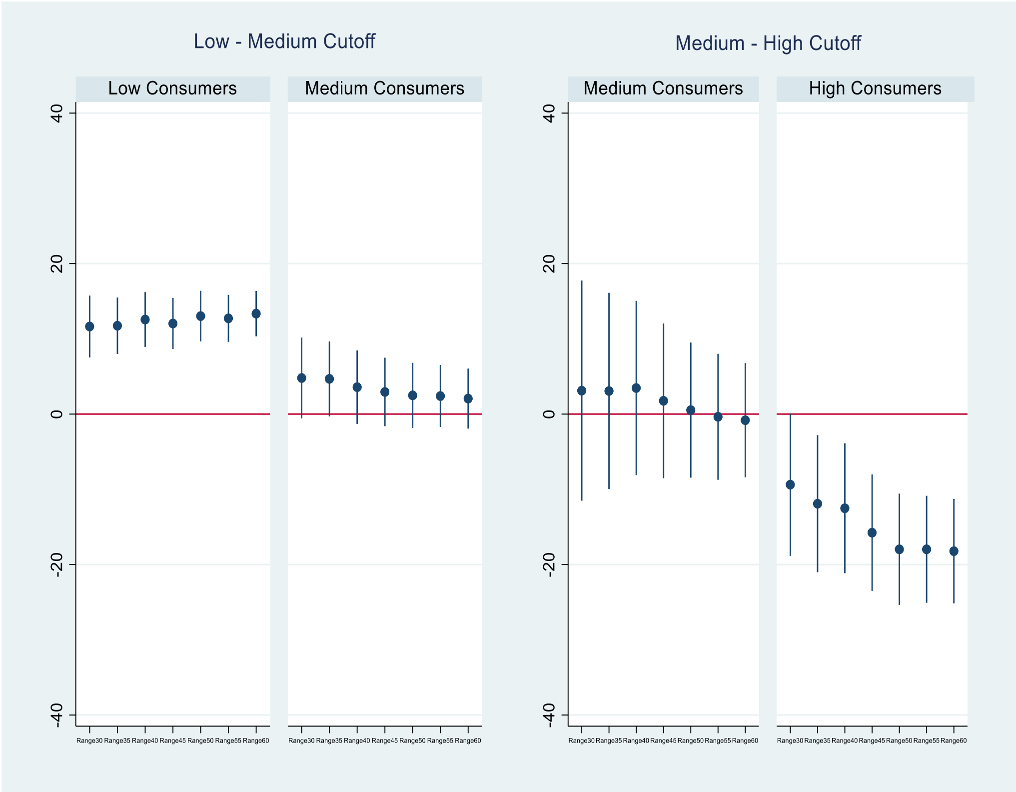
The ITT analysis shows that the impact of the treatment is heterogeneous across the consumption classes: while the reduction of consumption is not statistically significant for the low and medium categories (columns 1 and 2), the high consumption category strongly reduces its water consumption (-58 liters/15.3 gallons per day per capita, -19%), compared to untreated users belonging to the same category (column 3). This result highlights that the average reduction in water consumption of the treated group is highly driven by the high consumer category, which has the greatest opportunity to save water at lower marginal costs. Conversely, low level consumers, who already adopt sustainable habits, have higher marginal water conservation costs and do not find significant opportunities to further reduce their water consumption. The PP heterogeneity analysis confirms the ITT results showing a more pronounced effect. Similar results are valid for the dynamic analysis of heterogeneity reported in Table A2 in the online Appendix.

We further explore the heterogeneous effects across age and family sizes. We re-estimate Equation (1) by differentiating users over and under the age of 50, and households with more or less than two residents. The results, reported in Table A3 and A4 of the online Appendix, show that the campaign has a significant and greater effect on water consumption for users over 50. This result rejects our previous expectation that it would have a greater effect on younger people, with them supposedly being more environmentally conscious. Moreover, we find that the information campaign has a positive and statistically significant effect on the water consumption for both the categories of residents, but this effect is greater in households with two residents. The fact that the information campaign is more effective across smaller families highlights the relevance of communication and coordination costs. For the PP group, the effect of the campaign disappears when we consider households with more than three residents.

6.4 Feedback analysis and RDD

Finally, we find that consumers react differently to different feedback (Figure 4). Indeed, units receiving a 'low user' feedback tend to slightly increase their consumption compared to similar units which receive a 'medium user' feedback. An opposite result is found when we compare medium and high consumers around the cutoff: those receiving a 'high user' feedback significantly reduce their consumption compared to similar users who are in the medium category.

Figure 4. Differential impact of different feedbacks: RDD



7. Robustness Checks

In this section, we investigate how sensitive our main results are to the selection of a larger pre-treatment time span, and to the selection of another date for the delivery of the treatment (placebo test).

7.1. Longer pre-treatment time span

To perform our first robustness check, we estimate the ATT (Equation 1) considering a longer pre-treatment time span, from November 2020 to August 2021. Results are displayed in Table 9, columns 1 and 2, for the ITT and PP approaches. In spite of the longer pre-treatment time span, our main results remain robust. However, the estimated effects of the treatment are smaller (17 and 18 liters/day per capita for the ITT and the PP group compared to the control group, corresponding to a reduction of around 8.8% and 9.4%, respectively).

Table 9. Treatment effects on water use considering a longer pre-treatment period

	ITT	PP
	(1)	(2)
Post	-17.726***	-17.147***
	(3.705)	(3.780)
Post*Treated	-17.448***	-18.429**
	(6.746)	(8.190)
Constant	210.665***	208.885***
	(2.113)	(2.253)
No. Obs.	63,887	57,118
R-squared	0.044	0.043

Note: Month-by-year dummy variables included. Estimates correspond to the period November 2020 and January 2022. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

7.2. Placebo test

As an additional validation of our results, we perform a placebo test by hypothetically assuming another date for the delivery of the treatment for the ITT and PP group. More precisely, we take as the pre-treatment period November 2020 to April 2021, and May 2021 to August 2021 as the treatment months. The results of the placebo test, which are summarized in Table 10, show that there are no statistical differences in water consumption between the two groups (ITT and PP) and the control group, providing further evidence in support of the validity of the pre-treatment parallel trend assumption.

Table 10. Placebo ATT on water consumption

	ITT	PP
	(1)	(2)
Post	46.582***	46.906***
	(5.001)	(5.123)
Post*Treated	8.141	14.181
	(7.243)	(9.261)
Constant	210.624***	208.699***
	(1.938)	(2.073)
No. Obs.	42,787	38,306
R-squared	0.049	0.050

Notes: Month-by-year dummy variables included. Estimates correspond to the period November 2020 and August 2021. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

8. Conclusions

With this research we analyzed the effects of a water informative campaign run from September 2021 to January 2022 on a sample of around 1,000 households, equipped with smart meters and located in the metropolitan area of Milan. The informative campaign was designed to bring some contributions to the existing literature. First, it is the only campaign developed in Italy, a country characterized by an increasing water scarcity issue, due to both the intensifying of climate-related droughts and to the unsustainable behavior of the Italian citizens, who, on average, consume 236 liters (62.3 gallons) of water per day, one of the highest levels in Europe. Second, compared to previous experiments, we communicated the *daily* average water consumption (instead of the total water consumption) at a *per capita* level (instead of the households' aggregated levels), thus providing information in as familiar a format as possible, so that it could be easily quantified and assimilated by non-skilled users. The third contribution of our research related to the information notification tool. Unlike previous studies, we decided to provide the information on water consumption exclusively via email, which allowed us to monitor the email click (open) rate and the related opt-out rate. Thanks to this, we could adopt the ITT analysis as our main analysis and complement it with a Per Protocol 'PP' (or 'compliance-only') analysis. While recognizing the ITT superiority and the potential self-selection bias associated with PP analysis, several researchers on clinical trials now recommend combining these two approaches and conclude that a robust interpretation of a trial's results requires both ITT and PP approaches to provide concordant results (Tripepi et al., 2020).

The main result of our research was that the information campaign was effective in promoting an average reduction in per capita water consumption equal to 22 liters/day (5.8 gallons/day), corresponding to a water saving higher than 10%. Considering the experiment involved around 1,000 households with an average of 2.6 inhabitants, this roughly corresponds to more than 1.6 million liters (424,307 gallons) saved per month and more than 8 million liters (2 million gallons) over the period of the experiment. This result expands on the previous literature which found that website campaigns were not effective in promoting water conservation habits, and reveals that paperless online campaigns can be an effective and cheap instrument in increasing environmental awareness among citizens.

It is important to note that this number refers to the average (ITT) effect of the information campaign regardless of its compliance rate. Moreover, we show that this effect is mainly determined by users who have been effectively treated. Some interesting insights can be derived from the dynamic analysis of the results. Indeed, while we found that the amount of water saving increased with the number of emails (suggesting that repeating emails increased awareness), over the long term the water conservation impact of the campaign was not permanent, and it expired a few months after the end of the experiment. This suggests that information campaigns do not represent a sufficient tool to drive a structural behavioral change and puts into doubt whether the observed water saving was effectively induced by a correction of the users' cognitive biases on their consumption levels, or whether it was induced by the feeling of being observed.

We believe these findings to have some relevant policy implications. Given the current and growing water emergency that is affecting advanced and non-advanced countries, our results show that the implementation of information campaigns, through more advanced electronic tools, would allow the policymakers to achieve the objectives of reducing water consumption in line with the United Nations' SDGs. However, our results also suggest the importance of complementing these information campaigns with other measures aimed at inducing a structural change towards more sustainable behavior.

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Online Appendix

Table A1. Dynamic Effects

	ITT		PP	
	(1)	**(2)**	**(3)**	**(4)**
	May 2021–January 2021	**May 2021–April 2022**	**May 2021–January 2022**	**May 2021–April 2022**
May	-8.292	-8.401	-7.521	-7.597
	(10.081)	(10.079)	(12.273)	(12.270)
June	4.234	4.146	7.500	7.413
	(8.236)	(8.236)	(10.954)	(10.954)
July	3.659	3.615	0.469	0.424
	(5.610)	(5.610)	(6.926)	(6.926)
September	-11.633*	-11.664*	-13.993*	-14.024*
	(5.951)	(5.950)	(7.448)	(7.447)
October	-20.470**	-20.551**	-24.043**	-24.124**
	(9.956)	(9.953)	(11.469)	(11.467)
November	-23.765**	-23.773**	-25.423*	-25.431*
	(11.136)	(11.132)	(13.112)	(13.108)
December	-25.791**	-25.815**	-29.162**	-29.186**
	(11.315)	(11.309)	(12.910)	(12.906)
January	-32.128***	-32.069***	-37.789***	-37.709***
	(11.234)	(11.227)	(12.386)	(12.381)
February		-26.727**		-29.878**
		(11.114)		(12.073)
March		-14.998		-14.571
		(10.631)		(12.090)
April		-10.080		-13.572
		(9.159)		(10.302)
Constant	248.267***	247.821***	246.062***	245.720***
	(3.113)	(3.167)	(2.878)	(2.918)
No. Obs.	38,945	49,511	34,786	44,212
No. Households	4,500	4,500	4,029	4,029
R-squared	0.062	0.061	0.062	0.061

Notes: Month-by-year dummy variables always included. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2. Dynamic Effects considering users classified according to water use before the information campaign

	ITT			PP		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Low Users	Medium Users	High Users	Low Users	Medium Users	High Users
May	0.807	-7.992	-18.293	2.140	-14.511	-9.651
	(3.625)	(6.840)	(28.818)	(4.917)	(9.381)	(34.251)
June	5.250	-3.738	11.061	7.347	-2.122	16.991
	(3.644)	(5.643)	(23.594)	(4.686)	(7.367)	(30.957)
July	3.793	-3.961	11.696	6.126	-1.795	-2.996
	(3.104)	(4.868)	(15.658)	(4.480)	(6.152)	(18.934)
September	-2.142	-4.685	-28.352*	-1.458	-5.356	-33.498*
	(4.759)	(5.662)	(15.632)	(5.459)	(7.846)	(18.930)
October	-5.897	-9.892	-48.293*	-5.676	-16.402	-48.692*
	(5.003)	(10.362)	(25.617)	(6.075)	(16.121)	(26.428)
November	-4.631	-4.529	-65.653**	-4.534	-10.042	-60.526**
	(5.832)	(11.529)	(28.424)	(6.972)	(19.396)	(29.613)
December	-2.027	-9.552	-70.034**	-4.216	-17.725	-65.072**
	(5.368)	(10.450)	(29.360)	(6.350)	(16.986)	(30.110)
January	-4.746	-16.325**	-76.542**	-3.608	-28.718***	-76.688**
	(5.145)	(8.100)	(29.914)	(6.632)	(10.919)	(30.670)
Constant	119.837***	191.904***	429.850***	119.687***	191.897***	422.322***
	(1.629)	(2.184)	(8.785)	(1.657)	(2.102)	(8.089)
No. Obs.	12,794	13,058	13,093	11,421	11,627	11,738
No. Households	1,500	1,500	1,500	1,344	1,338	1,347
R-squared	0.013	0.038	0.155	0.012	0.037	0.154

Notes: Month-by-year dummy variables included. Estimates correspond to the period May 2021 and January 2022. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3. Treatment effects on water use for users under and over the age of 50

	ITT		PP	
	(1)	**(2)**	**(3)**	**(4)**
	Under 50	Over 50	Under 50	Over 50
Post	-32.910***	-37.590***	-32.891***	-38.492***
	(7.825)	(5.069)	(7.944)	(5.069)
Post*Treated	-12.821	-31.455***	-23.282*	-27.734**
	(11.167)	(12.106)	(13.731)	(13.052)
Constant	231.344***	254.357***	230.330***	252.369***
	(3.846)	(2.875)	(4.121)	(2.962)
No. Obs.	13,440	25,505	11,545	23,241
No. Households	1,558	2,942	1,343	2,686
R-squared	0.033	0.084	0.032	0.085

Notes: Month-by-year dummy variables included. Estimates correspond to the period May 2021 and January 2022. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Treatment effects on water use for households with two or fewer residents and with three or more residents

	ITT		PP	
	(1)	(2)	(3)	(4)
	Fewer than two residents	More than three residents	Fewer than two residents	More than three residents
Post	-35.124***	-37.091***	-37.225***	-36.283***
	(9.726)	(3.725)	(9.834)	(3.749)
Post*Treated	-32.877*	-13.817*	-33.152*	-17.484
	(17.479)	(8.225)	(17.695)	(11.054)
Constant	265.718***	234.685***	264.959***	233.183***
	(4.947)	(2.209)	(5.358)	(2.199)
No. Obs.	14,566	24,379	12,784	22,002
No. Households	1,703	2,820	1,498	2,549
R-squared	0.039	0.105	0.036	0.106

Notes: Month-by-year dummy variables included. Estimates correspond to the period May 2021 and January 2022. The dependent variable is the average daily consumption per capita (liters/day). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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