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Widening the Scope: The Direct and Spillover Effects of Nudging Water Efficiency in the Presence of Other Behavioral Interventions

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WP 23-46
December 2023

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Acknowledgments

We are thankful to Fabrizio Mauri, Marcello Folesani, and Monica Crippa for the fruitful collaboration. We thank Sara Constantino, Lukas Fesenfeld, Elke Weber, seminar participants at Bank of Italy, GATE-Lab, and ETH for helpful discussion and Conference participants at ESA 2022. Milica Vranic and Matteo Muntoni provided excellent research assistance. We acknowledge financial support from the H2020-MSCA-RISE project GEMCLIME-2020 GA No. 681228; the Energy Demand Changes Induced by Technological and Social innovations (EDITS) project, which is part of the initiative coordinated by the Research Institute of Innovative Technology for the Earth (RITE) and International Institute for Applied Systems Analysis (IIASA) (and funded by Ministry of Economy, Trade, and Industry (METI), Japan); NEWTRENDS (New TrendsS in Energy Demand Modelling) project, funded by the European Commission Grant agreement ID: 893311. Heracom provided financial support and was involved in the experimental design and study data collection. This RCT was registered in the American Economic Association Registry for randomized control trials under trial number AEARCTR-0006546. Declarations of interest: none.

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Abstract

Policymakers and firms use behavioral interventions to promote sustainable development in various domains. Correctly evaluating the impacts of a nudge on behavior and satisfaction requires looking beyond the targeted domain and assessing its interactions with similar interventions. Existing evidence on these aspects is limited, leading to potential misestimation of the cost-effectiveness of this type of intervention and poor guidance on how to design them best. Through a large-scale randomized controlled trial implemented with a multi-resource utility company, we test the impact of a social information campaign to nudge water conservation over two years. We find that the water nudge significantly decreases water and electricity usage but not gas. The effect is driven by customers who do not receive nudges targeting the other resources. Customers receiving the water report are also significantly less likely to deactivate their gas and electricity contracts, regardless of whether they receive other reports. Our results suggest that multiple nudges strain users' limited attention and ability to enact conservation efforts. Users' constraints in attending to multiple stimuli pose important challenges for designing policy interventions to foster sustainable practices.

Widening the scope: The direct and spillover effects of nudging water efficiency in the presence of other behavioral interventions*

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Keywords: *Social information, spillover effects, resource conservation*
JEL Classification: *Q5, Q25, D9*

1 Introduction

Promoting sustainable development practices requires fostering behavioral change in various domains, which have different impacts and costs. Behavioral interventions, such as nudges, have been used at large by governments and businesses to promote proenvironmental behavior among citizens and customers. However, their impact is typically evaluated in a narrow sense. First, most research focuses on the outcome directly targeted by the intervention, ignoring potential spillover effects to other related behaviors. Second, impact evaluations focus on consumption, but from both the policy and business perspectives, customer satisfaction and retention are equally, if not more, important outcomes. The impact of nudges may be reduced if they induce avoidance behavior, which is also a sign of their negative welfare effects. Finally, little evidence exists on the effectiveness of these interventions when similar ones simultaneously target their recipients. For a correct evaluation and effective design of sustainable nudges, it therefore matters whether the behavioral change induced in one domain has positive or negative spillovers in other domains; these interventions alienate customers, possibly diverting them towards companies that are less focused on promoting sustainable conservation practices; and the combined effect of nudges is smaller or larger than the impact of each one in isolation. These considerations are timely and relevant, given policymakers and firms' expanding use of behavioral nudges and the resulting increase in the likelihood that consumers are exposed to multiple, possibly overlapping interventions.

We address these questions in the context of a social information program for water conservation. We leverage the relationship with a large multi-utility company providing water, electricity, and gas to its customers. Through a large-scale randomized controlled trial (RCT), water customers receive a report with information about their water usage, social comparison with neighbors' usage, and tips for conservation. We evaluate the direct impact of the report on water consumption and the indirect impacts on electricity and gas. We also study the program's impact on customer engagement and retention to measure the implications for not just resource usage but also customer satisfaction, which is related to individual welfare effects. We exploit the variation in sending similar reports that target other resources, electricity and/or gas. We stratify assignment to the water report based on the other reports received by customers and assess whether receiving multiple reports influences the effectiveness of the water report. Finally, we discuss the potential mechanisms behind our results.

In our prespecified analysis, we find that the water report significantly decreases water usage by 1.4

percent and electricity usage by 0.5 percent, but has no significant impact on gas over two years. The magnitude of the spillover effect on electricity is comparable to the direct one of similar programs in Europe (Bonan et al., 2020). The water report also leads to higher customer retention. Treated gas and electricity customers are 2.8 and 3 percent less likely to deactivate their contracts than control ones.[1] The results on consumption are robust to multiple hypotheses correction and changes in the sample to account for attrition due to contract deactivation.

The impact of the behavioral program is driven by customers for whom the water report is the only one received: within this group, the program reduces water and electricity usage by 2.4 and 1.3%, respectively. The program's impact on customers already receiving other reports at baseline is nonsignificant. The positive impact of nudging on customer retention is independent of how many reports they receive. We argue that the lack of the effect of the water report when it is added to other reports is partly due to users' limited ability to attend to multiple stimuli. In particular, the water report reduces the attention that users pay to each single report, limiting the conservation gains that they can achieve in each domain. One way to reduce the cost of attending to multiple reports and thus increase their effectiveness is to send the reports jointly. Among customers receiving multiple reports, we find that conservation is larger if reports are sent simultaneously.

Our results on contract cancellation and engagement indicate that the additional report does not generate negative customer reactions even though it is ineffective at fostering own and cross-resource conservation.

The interpretation of the heterogeneous effect of the water report by receipt of other reports crucially depends on whether household characteristics simultaneously affect the likelihood of receiving multiple reports and the reaction to the treatment. Our analysis controls for time-invariant household traits that may affect selection into multiple reports through household fixed effects. To further address concerns of time-varying confounders, we exploit information on the contracts offered by the utility to identify samples for whom concerns about self-selection into multiple reports are less relevant. The heterogeneous effects by multiple reports are robust to using these restricted samples. We therefore exclude that the heterogeneous effects are entirely driven by self-selection.

As for the mechanisms, we provide suggestive evidence of behavioral spillovers dominating technological ones. Although technological spillovers result from mechanical synergies between the use of different resources, behavioral spillovers arise from a desire to consistently conserve resources driven by environmental concerns. According to our results, such behavioral spillovers may be prevented by the cognitive and attention constraints triggered by the receipt of multiple reports.

Our study adds to a growing literature that evaluates the effectiveness of social information pro-

[1] Although the gas and electricity retail markets are liberalized, and customers can freely choose their providers, the water market is regulated, and customers cannot change providers.

grams and feedback on resource conservation (Allcott et al., 2011; Allcott and Rogers, 2014; Ayres et al., 2013; Tiefenbeck et al., 2016, 2019; Fang et al., 2023).[2] Several experimental studies have specifically looked at the direct impact of social information about water usage on water consumption, mainly in the U.S. context (Ferraro and Price, 2013; Ferraro et al., 2011; Ferraro and Miranda, 2013; Bernedo et al., 2014; Brent et al., 2015; Hodges et al., 2020). The evidence documents short-term water conservation effects up to 5 percent. The effect can persist over longer time horizons, although it is 50 percent smaller after only one year (Ferraro et al., 2011; Bernedo et al., 2014).[3] These effects are attributable to short-lived behavioral adjustments and more persistent changes in habits and physical capital. More recently, Jessoe et al. (2021) used high-frequency water consumption data to evaluate a home water program in California during a drought period. They found a 4-5 percent reduction in water usage, but the effect dissipated five months later.

Our paper contributes to this literature in different ways. First, relatively few papers rigorously address the spillover effects of the social information report on the consumption of other resources. Jessoe et al. (2020) examine cross-sectoral spillover using one-year posttreatment data on water and electricity usage for the United States. They find that home water reports induce a 1-2 percent reduction in summertime electricity use, which disappears 4-5 months posttreatment. Carlsson et al. (2020) find that a social information campaign on water use had a positive and sizeable spillover effect on electricity usage for households experiencing positive direct effects. Goetz et al. (2022) evaluate the effects of a hot-water-saving intervention and find persistent direct and spillover effects on dishwasher use and toilet flushing, but no effect for electricity.[4] Our paper evaluates spillover effects on a broader set of behavioral outcomes, namely electricity and gas, and over a more extended period, two years after treatment, allowing us to disentangle considerations of persistence of the effects from seasonality in resource usage.

Second, we evaluate the impact of the water report on customers' retention and engagement. These aspects are crucial for businesses in this sector and policymakers interested in the welfare im-

[2] See Gillingham et al. (2018); Abrahamse (2019); Gerarden et al. (2017) for a broader discussion of the energy efficiency gap and the assessment of energy efficiency policies. An extensive literature also evaluates social information programs in several other domains, from contributions to charitable causes (Frey and Meier, 2004; Shang and Croson, 2009), to technology adoption (Bonan et al., 2021a; Gillingham and Bollinger, 2021), voting (Gerber and Rogers, 2009), waste disposal (Bonan et al., 2023) and financial decisions (Beshears et al., 2015). More broadly, a review of information-based interventions on residential customers' resource consumption can be found in Nemati and Penn (2020) and Delmas et al. (2013).

[3] In developing contexts, Miranda et al. (2020) find 3-5 percent effects in Costa Rica, while Jaime Torres and Carlsson (2018) find 6.8 percent water reduction on customers targeted by home water report and 5.5 percent decrease on untargeted customers living close-by (cross-individual spillover) in Colombia.

[4] Other papers look at behavioral spillovers in waste disposal and recycling (Ek and Miliute-Plepiene, 2018; Alacevich et al., 2021; Sherif, 2021). Beyond this small number of studies, literature exists on behavioral spillovers in the environmental domain, with mixed evidence. Such variability in results can be partially explained by the significant differences in the methods used to quantify impacts (Galizzi and Whitmarsh, 2019) and to measure behavioral outcomes–ranging from behavioral intentions to policy support, self-reported behaviors, and actual behaviors–(Maki et al., 2019).

pacts of these programs. After the liberalization of energy markets, many studies have analyzed household contract switching choices (or lack thereof) and underlined the role of both price and nonprice attributes (Hortaçsu et al., 2017; Shin and Managi, 2017; Fontana et al., 2019; Schleich et al., 2019). Brent et al. (2015) examine whether a social comparison intervention affects other utility conservation programs, such as free home water audits and rebates for efficient toilets or irrigation controllers. They find that receiving the home water report increases program participation. Far smaller effects are found by Allcott and Rogers (2014). However, the role of customized proenvironmental information campaigns on customer retention appears unexplored, despite its importance for business and society. In our setting, reducing churn was a key objective of our partner utility, which faced yearly contract deactivation rates of 10.5 and 11.5 percent in the liberalized gas and electricity markets, respectively.[5] Our results related to the lower deactivation of gas and electricity contracts following the water report provide the first experimental evidence of the role of green nudges in boosting overall customers' experience and loyalty.

Third, we assess the effect of receiving multiple nudges. Relatively few studies have tackled this issue and combined different nudges within the same intervention.[6] Yet, this question is relevant for policymakers and businesses, as they target a variety of information campaigns to the same behavioral outcomes, often through multiple channels (Montaguti et al., 2016). Whether the cumulative effect of multiple nudges is larger or smaller than the sum of each one in isolation is an open empirical question. The marginal effect of additional energy conservation nudges may be decreasing if the first one has already induced a reduction in consumption. An established finding in this literature is that the impact of nudges decreases as the margins for reduction shrink, even backfiring for low users (Byrne et al., 2018; Bhanot, 2017; Bonan et al., 2020). Similarly, willingness to pay to receive social information nudges, similar to the one we study, is lower among low users (Allcott and Kessler, 2019). Alternatively, recipients may be less attentive to additional nudges if cognitive constraints limit the amount of information that they can absorb (Gigerenzer and Gaissmaier, 2011); or if they try to avoid the social pressure of receiving many nudges, as demonstrated by the literature on information and ask avoidance (Andreoni et al., 2017; Exley and Petrie, 2018; Adena and Huck, 2020; Serra-Garcia and Szech, 2022; Golman et al., 2022). This might lead to a backlash against the company and a societal loss arising from additional resource usage. Conversely, multiple nudges may increase individuals' awareness of existing synergies between behaviors, heighten the salience of environmental conservation motives (Bonan et al., 2021b), and reassure about a firm's commitment to sustainable development rather than mere greenwashing. Previous works have looked at the interaction of different nudges in influencing one or more outcomes within the

[5] At the national level, yearly contract switching in the electricity sector is 15.7 percent (ARERA, 2022).

[6] Several papers have focused on the interaction between nudges and economic incentives in different contexts and reached mixed results (Pellerano et al., 2017; Sudarshan, 2017; List et al., 2017; Holladay et al., 2019; Giaccherini et al., 2020; Bonan et al., 2023).

same behavioral sphere, e.g., water or electricity usage (Hahn et al., 2016; Brandon et al., 2019; Bonan et al., 2020, 2021b; Fang et al., 2023). The impact of nudge interactions appears heterogeneous and increases in the ability to target relevant and consistent sources of bias effectively. We contribute to this nascent literature by providing evidence on the heterogeneous impact of a report depending on the receipt of other similar reports. Unlike previous work, we look at the impact of the same nudge targeted to different behavioral spheres, i.e., water, gas, and electricity usage. We provide evidence that multiple nudges deplete consumers' limited attention towards the different resources.

Finally, we try to distinguish technological and behavioral mechanisms. The psychological literature discusses the behavioral sources of spillover effects in the environmental domain and how interventions can be designed to maximize them (Truelove et al., 2014; Dolan and Galizzi, 2015; Nilsson et al., 2017). Behavioral spillovers can be negative–whereby adopting an action reduces the probability of another proenvironmental action being taken–or positive. Negative spillovers can be due to moral licensing, limited cognitive abilities, and willpower. Positive spillovers may result from a desire for consistency across domains and to fulfill broad environmental objectives. Policies priming such higher-order goals and avoiding demanding initial requests are more likely to harness positive rather than negative spillovers. Beyond these psychological mechanisms, spillovers in resource usage may occur because of technological synergies between different behaviors. Our findings that the spillover effects on electricity are stronger when the report mentions broad environmental goals and is delivered jointly with the other reports suggest the relevance of positive behavioral spillovers. This result is consistent with the evidence in Jessoe et al. (2020), where technological spillovers complement behavioral ones.

The remainder of the paper is organized as follows. Section 2 describes the setting of the study. Section 3 provides details of the design and data of the RCT. Section 4 presents the empirical strategy and results in detail. Section 5 discusses the mechanisms behind our findings, and Section 6 concludes.

2 Setting

We collaborate with Gruppo Hera (henceforth, Hera), which serves 4.3 million Italian customers in 330 municipalities, mainly located in the center-north of Italy, specifically in the regions of Emilia-Romagna, Veneto, Friuli-Venezia Giulia, Marche, Tuscany, and Abruzzo. Our study focuses on customers of water services located in Emilia-Romagna.[7]

[7] Specifically in the provinces of Bologna, Forli-Cesena, Ferrara, Modena, Ravenna, and Rimini. In 2019, Hera scored third in the domestic retail market for electricity and gas, with market shares of 3.3 and 11.3%, respectively. These shares did not vary significantly over the following years.

The water market in Italy is regulated at the national level by ARERA (Autorita' di Regolazione per Energia Reti e Ambiente). Tariffs are established by utilities at the municipal level to cover operating costs, investments, and financial and tax charges but must be approved by ARERA. The gas and electricity markets were liberalized in 2007. The liberalization process has been slow, with over 42 percent of domestic customers still buying their energy at the conditions set by the public authority for energy as of 2021 (ARERA, 2022). The complete transition to the free market has been postponed several times and is next scheduled for 2024. Until then, customers can choose between contracts in the regulated market, with tariffs approved by the authority as in the water market, and contracts in the free market. Utilities compete in the free market through diversified price offers. In the context of our study, an important implication of the distinction between regulated and liberalized markets is that customers in the water market (regulated) cannot change providers, but customers in the gas and electricity markets (liberalized) can. Despite the slow transition to a wholly liberalized market, contract switching has become increasingly common in Italy. For instance, in 2021, 15.7 percent of residential electricity customers changed providers at least once over the year (ARERA, 2022).

Since October 2016, Hera has delivered to its customers in the free market an "Opower-style" home energy report with information on electricity and gas use. Initially, residential customers choosing Hera's main offer on the free market could opt to receive the report. Since the beginning of 2019, Hera revised the content and layout of the report and included this new version by default in almost all of its gas and electricity offers on the free market.[8] The promotional material for these offers did not display prominent information about the presence of the report.[9] Qualitative interviews with Hera employees also confirm that the report was not a relevant factor in customers' choice of offer, nor a driver of switching from other utilities to Hera.

Overall, it appears that the desire to receive the energy report was not a source of selection into the category of multiple report recipients. Among gas and electricity customers with contracts on the free market in our sample, the likelihood of receiving energy reports at baseline is primarily determined by when they signed the contracts. Therefore, any selection in receiving multiple reports is related to the choice of a free market rather than a regulated contract and the timing of this choice, and not to the choice of contract within the free market or utility offering the energy report. We will exploit these sources of variation in the likelihood of receiving multiple reports in our analysis.

[8] Two offers could not be bundled with the report. One offered a fixed monthly bill for energy throughout the year, based on the household's consumption in the previous year, and thus was not compatible with the report. The other was an offer that could not by law be associated with any additional service. These offers were selected by a very limited number of customers in our sample.

[9] Examples of offer pages can be found at `https://web.archive.org/web/20200930155014/https://heracomm.gruppohera.it/casa/offerte-luce-gas/welcome-hera`.

3 Experimental design

A new water consumption report was designed and launched in October 2019, targeting all water customers with a valid email address. Eligible customers are randomly assigned to a treatment group that receives the report and a control group that does not.

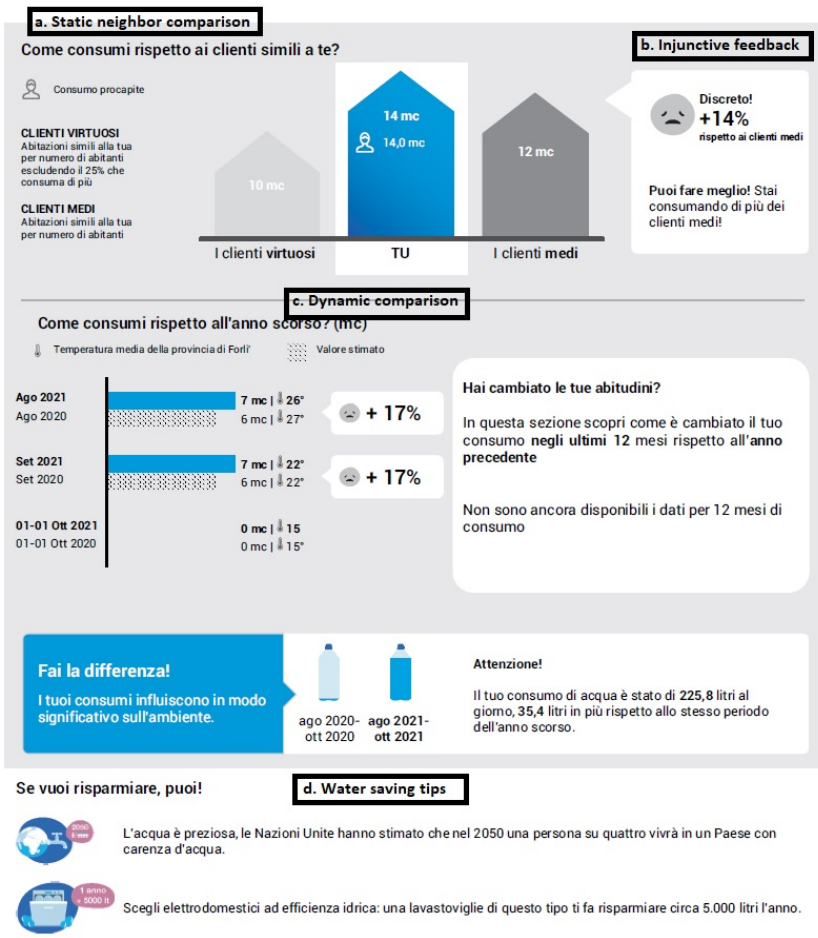


Figure 1: Water consumption report

The water report mirrors in structure, layout, and content the electricity and gas reports sent by Hera to its customers since the beginning of 2019. It includes the following elements (Figure 1):

- *a. Static neighbor comparison*: comparison of the recipient's own average water consumption in the reporting period (about two months) with that of similar customers and of the 25 percent most efficient similar customers. Similar customers are defined as having the same household size as the report recipient. The comparison also includes information on the percentage difference in consumption with respect to the average customer. Following the terminology used by Bicchieri (2005), this comparison provides a descriptive norm of behavior with respect to the two reference groups of similar and efficient customers.

- *b. Injunctive feedback*: based on their water consumption relative to the two reference groups, customers receive an emoticon and a written feedback: a smiling face accompanied by the word "great" if their consumption is below that of the most efficient similar customers; a neutral face with the word "good" if their consumption is lower than the average one of similar customers but higher than that of the most efficient ones; and a frowning face paired with the word "decent" if their consumption is higher than the average of similar others. This feedback provides an injunctive norm (Bicchieri, 2005) of water conservation and is aimed at preventing boomerang effects, resulting from the descriptive norm, among customers with below-average consumption (Schultz et al., 2007).

- *c. Dynamic comparison* compares the recipient's consumption over the reporting period and since the start of the year with own corresponding consumption in the previous year. The descriptive information is also accompanied by an injunctive feedback, which is negative if the customer's consumption increased relative to the previous year and positive otherwise.

- *d. Water saving tips*: tips on how to save water, divided into three categories: behavior change, such as turning off the shower while lathering; small investments, such as replacing the faucet head with an efficient one; or large investments, such as buying a water-efficient washing machine. Tips are season specific.

The report is sent to customers by email bimonthly soon after the delivery of the water bill. Therefore, customers receive the report at different times, according to their billing cycle. The report's reference period is the same as that reported in the bill.

4 Sample and Data

Customers eligible for the study have a single water contract in their main residence address, so customers with multiple contracts and multiple houses are excluded. We exclude customers with household sizes greater than 20, possibly indicating condominiums, and with baseline water consumption above 10 times the sample median consumption. Eligibility also requires that customers have nonmissing water usage in the 12 months preceding the start of the treatment (Oct. 18-Oct. 19). The resulting study sample contains 108,980 customers.

The analysis of spillover effects on gas and electricity usage relies on the subsample of water customers with gas and electricity contracts already active before the experiment's launch.[10] This leads to 91,690 and 75,193 customers holding an active gas and electricity contract at the program's start, respectively. Of them, 70,339 have both gas and electricity contracts with the utility,

[10] We do not apply the same eligibility criteria (at least one year of pre-treatment observations) to gas and electricity contracts, as we do with water contracts.

and 96,544 have at least one other contract besides water. Out of the 108,980 water customers, 18 percent receive electricity and gas reports at the start of the intervention, 6 percent receive electricity reports only, 10 percent receive gas reports only, and 66 percent receive none.

The rollout of the study occurred in two waves. A first wave of 70,161 customers (64 percent of the sample) was assigned to treatment and control groups from October 2019. The second wave, with 38,819 customers (36 percent of the sample), was launched in December 2019. Within each wave, we follow a stratified individual-level randomization procedure to maximize ex-ante balance across treatment and control groups along a battery of relevant observable characteristics (Bruhn and McKenzie, 2009). Strata are obtained from the combination of the following variables: having an electricity and/or gas contract; receiving the report about electricity and/or gas consumption; having an electricity and/or gas contract in the free versus regulated market; and having performed water self-reading in the previous 12 months. This latter measure is a proxy of baseline engagement with the utility and attention paid to water usage, as explained in greater detail later. In sum, while we cannot randomize the receipt of other reports, we ensure through stratified randomization that the treatment and control groups are balanced along this dimension, which is a prespecified source of heterogeneity in the impact of the water report.

After excluding strata with less than 10 observations, we obtain 32 strata. Within each stratum, we sorted customers by water consumption in 2018 and assigned adjacent customers to the treatment and control groups. In the first wave, we assigned every other customer to the control group (50 percent treatment and 50 percent control). In the second wave, every eleventh customer was assigned to the control group (91 percent treatment and 9 percent control).[11]

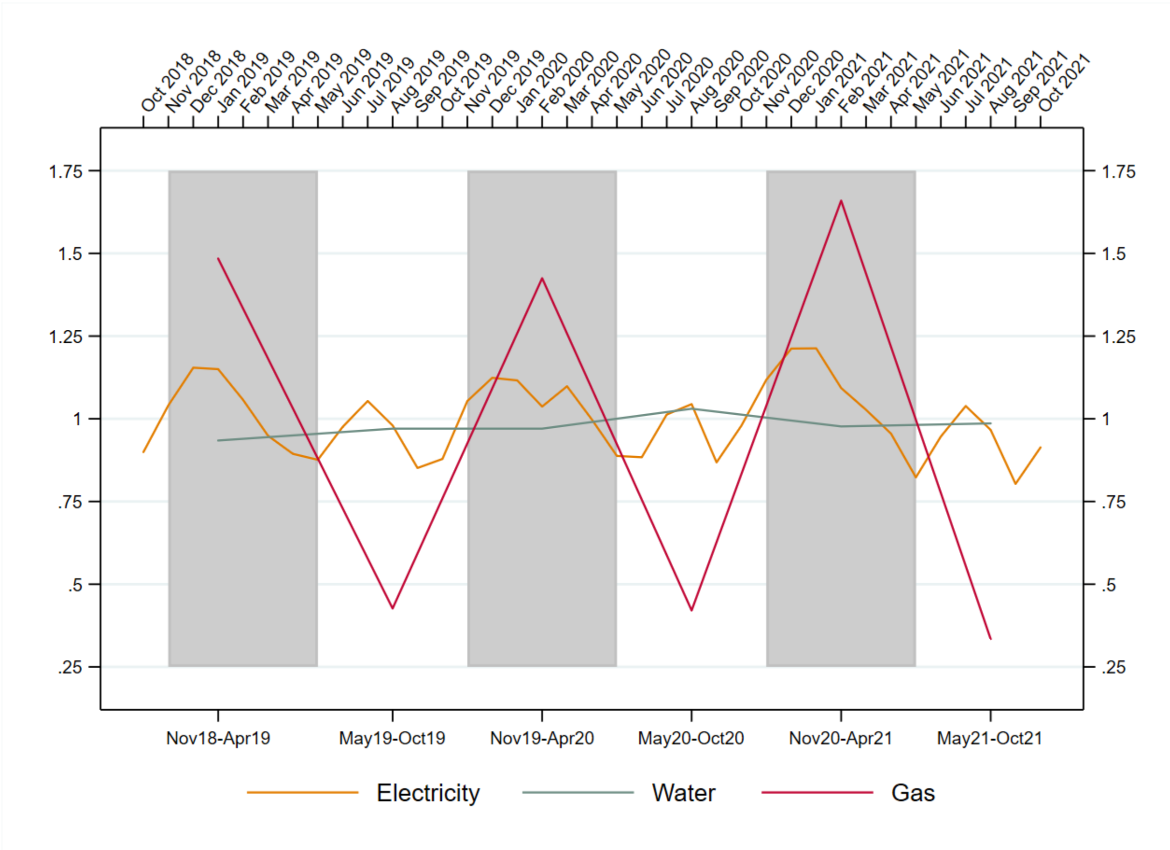
The analysis relies on two sources of data. The main one is administrative data provided by our partner utility after being anonymized. Data on water and gas consumption are based on meter readings performed periodically, at least once per year, by the distributor for all customers and on self-readings provided voluntarily by customers.[12] Given the relatively low and irregular frequency of water and gas readings, we base our analysis on six-month periods, one for the winter (November-April) and one for the summer (May-October). On average, we employ three readings to construct the average usage value in a semester, one of which is always entirely included in the semester.[13] Conversely, data on electricity usage rely on actual consumption, measured through smart meters every month. Usage data for the three resources are expressed as daily level in each

[11] The utility had targets in terms of the number of customers to be reached by the water report by the end of 2019, which explains the limited size of the control group in the second wave.

[12] Readings and self-readings are also the basis of water and gas bills. Without actual consumption information, bills are based on estimated consumption. Estimates are built from past usage, household location, and characteristics, such as household size and, for gas, whether it is used for space heating, water heating, or cooking.

[13] This represents a departure from the preanalysis plan (PAP), where the time granularity for all resources was expected to be the month. We needed to reduce the frequency in light of the lower frequency of actual water and gas usage measurements.

month normalized with respect to the control group's mean consumption in the intervention period.[14]



Note: The figure shows normalized usage of water, gas and electricity over the study period for customers with active gas and electricity contracts at the time of the treatment. Water and gas consumption are given at the semester level, and electricity consumption is at the monthly level. Shaded regions denote winter periods.

Figure 2: Resource usage over the study period

Figure 2 shows normalized electricity, water, and gas consumption in our sample period, October 2018 to October 2021. The lower frequency of water and gas consumption data relative to electricity is apparent, as is the strong seasonality characterizing gas usage. In 94 percent of households, gas is used for space and water heating and cooking. Consumption peaks in winter, given that space heating accounts for the majority of the resource use.[15] Electricity usage is also seasonal, with a first peak during the winter months and a second in the summer, likely due to air conditioning. Water consumption is stable across the different seasons.

Table 1 reports descriptive statistics and experimental sample balance for pretreatment resource usage and selected customer characteristics, namely, the presence of other resources' contracts,

[14] The mean in the control group is a weighted average of the two waves.

[15] The remaining share only uses gas for cooking and water heating and is balanced across treatment and control customers.

Table 1: Summary statistics and balance

	(1)	(2)	(3)	(4)	(5)
	N	Control mean	Control SE	ITT	p-value
Eligible customers with water contract					
N. of occupants in the house	108,980	2.273	0.006	-0.003	0.694
Active gas contract	108,980	0.920	0.001	0.002	0.399
Active elect contract	108,980	0.774	0.002	-0.000	0.914
Gas contract in the free market	108,980	0.887	0.002	-0.000	0.867
Electricity contract in the free market	108,980	0.766	0.002	-0.000	0.751
No report	108,980	0.559	0.003	-0.000	0.969
Mean daily water usage	108,980	0.305	0.002	0.001	0.780
Engagement index	108,980	0.006	0.004	0.006	0.285
Customers with gas contract					
Gas report	91,690	0.397	0.003	-0.000	0.908
Mean daily gas usage	91,690	2.616	0.011	0.021	0.146
Customers with electricity contract					
Electricity report	75,193	0.401	0.003	0.000	0.918
Mean daily electricity usage	75,193	6.113	0.023	0.026	0.421

Note: This table reports customer-level summary statistics (number of observations, mean, and standard error in the control group) and assesses balance across treatment and control groups using a regression. The dependent variable is listed in the first column and is regressed on a treatment dummy and a binary variable for the wave of the program. All variables are expressed at the baseline or in the pretreatment period.

whether they are in the free (vs. regulated) market, the receipt of other reports at the time of the program launch, and the engagement index. In terms of pretreatment daily levels, customers in our sample consume, on average, 0.3 cubic meters of water, 2.6 cubic meters of gas, and 6 KWh of electricity. These values appear relatively similar to the Italian average: 0.5 cubic meters of water, 3.6 cubic meters of gas, and 5.8 KWh of electricity (ARERA (2022), Eurostat 2019). However, they are way lower than what observed in other studies on US-based samples. For instance, Jessoe et al. (2020) report daily household consumption of 1.5 cubic meters of water and 24.5 KWh in California.

Water, gas, and electricity consumption in the pretreatment period are positively and significantly correlated, as shown in Appendix Table A.1. Water usage displays the strongest synergy with electricity.[16] The synergy between electricity and water is likely to be driven by the use of washing machines and dishwashers, owned by 97.3 percent and 50.2 percent of Italian families, respectively.

[16] The Pearson correlation coefficient (rho) is 0.368 for electricity and 0.297 for gas.

Technological synergies between water and gas are instead primarily due to water heating, as only 16 percent of Italian households use electricity to heat water (ISTAT, 2022).

We complement consumption data with data on contract activation, contract deactivation, number of occupants in the house, and municipality. We also have information at the customer and monthly level on the number of accesses to the web portal, accesses to the app, contacts with customer service, and water meter self-reading, which we consider as proxies of the customer's engagement with the utility. We construct an engagement index that aggregates the four variables.[17] We also have data on all reports received by customers, particularly on their date of receipt and contents.

We conduct balance tests across treatment groups for each variable available at the time of treatment assignment. We do this by regressing each baseline variable on a treatment dummy and a binary variable for the wave of the program. The latter is important for two reasons. First, although in the first wave treatment and control groups are equally sized, in the second wave, the control group only accounts for 9 percent of the sample, as described above. Second, customers in the two waves are significantly different along some dimensions. The experimental design guarantees that treatment and control customers are similar within each wave; hence, the inclusion of the wave control guarantees fair sample comparisons. As expected, we do not detect any significant difference in observable characteristics across the two samples.

5 Results

5.1 Resource consumption

5.1.1 Direct and spillover effects

First, we evaluate the direct impact of receiving the water report on water consumption and the indirect effect on gas and electricity usage. We estimate the intention to treat effects (ITT) by separately estimating the following model:

$$y_{it} = a_1 Post_t + \beta_2 Treat_i * Post_t + h_t + g_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is the normalized average daily consumption of the specific resource over the period t (semesters for water and gas and months for electricity). $Treat$ is a treatment indicator. The variable $Post$ is set to 1 from November 2019 for the whole sample, regardless of being enrolled

[17] We employ PCA to aggregate the four variables in a single index. This variable is used as a general customer engagement metric and, in its baseline values, as a prespecified dimension of heterogeneity.

in the first or second wave.[18] This allows us to compare customers across the same homogeneous semesters for water and gas. The regression also includes period fixed effects, h_t, and household fixed effects, g_i. Standard errors are clustered at the household level, i.e., at the randomization level, to allow for within-customer correlation over time in the error term (Bertrand et al., 2004). This specification, as the rest of the analysis, is preregistered.In what follows, we point out whenever we depart from the preregistered specifications.[19]

Results are shown in Table 2. The program significantly decreases water usage by 1.4 percent and electricity by 0.5 percent over the two post-treatment years. We detect no statistically significant treatment effect on gas consumption. This result is consistent with the stronger correlation we observe in our setting between water and electricity use, relative to that between water and gas use. For both water and electricity, treatment effects are stronger in the program's second year, significantly so for water. Ex-post power calculations suggest that the minimum detectable effects on gas usage are 0.56 percent, which aligns with the magnitude of the spillover effect on electricity (0.5 percent). This suggests that the spillover effect on gas, if existent, is likely to be smaller than that on electricity.[20]

The magnitude of the direct effect on water is smaller than that found by other studies over a similar time horizon (Ferraro et al., 2011; Bernedo et al., 2014), which may be due to the different context that we study. For example, most of these studies examine isolated interventions, that is, interventions not implemented on top of other existing nudges. In our case, some customers already receive the gas and electricity reports. In the following section, we examine heterogeneity by receipt of other reports.

The indirect effect on electricity is large, comparable to the direct effect of similar social information programs in Italy (Bonan et al., 2020). Jessoe et al. (2020) report a short-lived effect of the water report on electricity use of 1–2 percent, which, however, vanishes after the first four treatment months. By contrast, the spillover effect on electricity that we detect seems to increase over time and persists for at least two years (Column 6). This suggests that spillover effects are persistent and similar to the direct effects of home reports on electricity and water usage in Allcott and Rogers (2014) and Bernedo et al. (2014).

[18] The actual date of the launch of the water program is October 21 2019, and most of the program's customers are enrolled in the first wave. This conservative definition of the intervention period may bias our treatment effect estimates downward.

[19] In the PAP, we committed to estimate, besides 1, a model where the three resources are pooled, including resource fixed effects. Given the difference in the frequency of outcomes measurement, this strategy does not appear viable.

[20] One could note that the upper limit of the confidence interval for the spillover effect on gas is -0.4%.

Table 2: Impact on resources usage

	(1)	(2)	(3)	(4)	(5)	(6)
			Normalized daily usage			
	Water		Gas		Electricity	
Post	0.083***		-1.195***		0.053***	
	(0.006)		(0.004)		(0.003)	
Treat*Post	-0.014**		-0.001		-0.005**	
	(0.006)		(0.002)		(0.002)	
	[0.066]		[0.617]		[0.08]	
Post Y1		0.118***		-1.112***		0.090***
		(0.006)		(0.004)		(0.002)
Treat*Post Y1		-0.006		-0.003		-0.004*
		(0.007)		(0.002)		(0.002)
Post Y2		0.088***		-1.197***		0.054***
		(0.007)		(0.004)		(0.003)
Treat*Post Y2		-0.022***		0.002		-0.007**
		(0.007)		(0.003)		(0.003)
Observations	651,941	651,941	529,364	529,364	2,364,935	2,364,935
No. of households	108,980	108,980	91,690	91,690	75,193	75,193
P-(Y1=Y2)		0.0219		0.0898		0.167

Note: This table reports panel estimates of the effect of the water report on normalized daily usage of water, gas and electricity. Estimates are for the entire period (Oct. 2018-Oct. 2021) in columns 1, 3, and 5, and distinguish impacts in the first (Y1) and second (Y2) posttreatment years. *P*-values for the difference are reported at the bottom. The model includes individual and period fixed effects. Periods are semesters for water and gas, months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level. FDR sharpened *q*-values for prespecified hypothesis are in squared brackets.

5.2 Customers' engagement

We assess how the program impacts customers' engagement with the utility. A first proxy of engagement is the deactivation of electricity and gas contracts. We create a variable taking the value of 1 if the customer deactivates the contract in the posttreatment period and 0 otherwise. In a cross-section, we include a set of controls, strata fixed effects, and the wave of the program. Table 3 reports the results. Levels of contract deactivation are 21 and 23 percent for gas and electricity over the two posttreatment years, respectively, showing how dynamic these markets are and, consequently, how important it is for companies to reduce churn. The program reduces these figures by about 0.6 (Column 1) and 0.7 (Column 3) percentage points, corresponding to relative changes of 2.8 and 3 percent. [21] We also detect an overall positive impact of the program on the engagement index (column 5).

Table 3: Impact on contract deactivation and customer engagement

	(1)	(2)	(3)	(4)	(5)	(6)
		Contract deactivation			Engagement index	
	Gas	Gas	Electricity	Electricity		
Treat	-0.006**	-0.005	-0.007**	-0.006		
	(0.003)	(0.004)	(0.003)	(0.005)		
	[0.08]		[0.08]			
Treat*No report		-0.002		-0.001		
		(0.006)		(0.006)		
		[0.617]		[0.617]		
Post					3.664***	3.979***
					(0.073)	(0.090)
Treat*Post					0.156***	0.082
					(0.057)	(0.096)
					[0.039]	
Post*No report						-0.564***
						(0.095)
Treat*Post*No report						0.227*
						(0.121)
						[0.087]
Observations	91,685	91,685	75,191	75,191	4,032,260	4,032,260
N. of households	91,685	91,685	75,191	75,191	108,980	108,980
Mean dep var	0.213	0.213	0.229	0.229	0.0688	0.0688

Note: This table reports OLS estimates of gas (columns 1 and 2) and electricity (columns 3 and 4) contract deactivation (churn) in the posttreatment period. All models include average pretreatment resource usage, average pretreatment number of water self-reading, no other reports, n. of occupants, contract length less than 3 years, strata fixed effects, and a dummy for the main wave of program delivery. Main and heterogeneous effects on the engagement index (columns 5 and 6) are estimated using a monthly panel with individual and time fixed effects. The engagement index is calculated using PCA of the following variables: accesses to the online portal, accesses to the app, contacts to the customer service, water self-readings. The mean dependent variable is calculated for the control group. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level. FDR sharpened q-values for prespecified hypothesis are in squared brackets.

Overall, these results suggest that customers value the water report. If we consider customer loyalty and engagement as indicators of users' utility from the program, these results suggest positive welfare effects of the water nudge. The benefits of the report accrue to not only the customers who

[21] Unsurprisingly, water contract cancellation in the control group is low (0.2 percent) and unaffected by the treatment. As explained above, water provision is regulated, and customers cannot choose their provider. The low numbers of water contract deactivations are compatible with customers moving to municipalities served by other utilities or dying.

value it and pay lower bills but also to the utility in the form of higher customer retention. The industry knows that winning a new customer costs several times more than retaining an existing one and engages in expensive retention campaigns. Yet, it is unclear which campaigns best mitigate churn (Ascarza et al., 2016; Ascarza, 2018).

5.3 Heterogeneity

5.3.1 Multiple nudges

We analyze how the report's impact on usage and contract cancellation varies depending on whether the customer already receives other reports, a prespecified dimension of heterogeneity. We address this question by estimating the heterogeneous effects of the water report on customers already receiving other reports (electricity, gas, or both) at baseline. For resource consumption, we separately estimate the direct impact on water usage and the indirect ones on gas and electricity usage, y_{it}, in the following model:

$$\begin{aligned} y_{it} &= \beta_1 Post_t + \beta_2 Prog_i * Post_t + \beta_3 Post_t * NoReport_i + \\ &+ \ \beta_4 Prog_i * Post_t * NoReport_i + h_t + g_i + \varepsilon_{it}, \end{aligned} \tag{2}$$

where $NoReport_i$ is a dummy on whether customer i does not receive any other report at the baseline. The results are shown in Table 4. For water and electricity consumption, the program is significantly more effective among customers for whom the water report is the only one received. The program reduces water and electricity usage in this group by 2.4 and 1.3 percent, respectively. This direct impact on water aligns with the effect of similar water programs implemented in isolation (Ferraro et al., 2011; Bernedo et al., 2014). In these studies, the effect, computed after two years since the beginning of the program, is around 2.6 percent reduction in water use. Conversely, the program does not affect water and electricity use for those already receiving other reports.[22]

Low power issues prevent us from exploring the differential impact of the water report by different types (gas vs. electricity) or number (one vs. two) of reports received at baseline.[23]

We find that the effect of the water report on contract cancellation is not different for customers receiving other reports at baseline and customers for whom the water report was the only one received (Table 3, columns 2 and 4). We also detect a stronger positive impact of the program on overall engagement with the utility, captured by the engagement index, for those receiving the

[22] The coefficients attached to Treat*Post represent the ITT for the group already receiving some reports and are never significant.

[23] Conditional on receiving at least one report, customers receiving gas only, electricity only, or both reports are 6,209, 10,852, and 19,912, respectively.

Table 4: Impact on resources usage by number of reports

	(1)	(2)	(3)
	Normalized daily usage		
	Water	Gas	Electricity
Post	0.072***	-1.194***	0.046***
	(0.008)	(0.004)	(0.003)
Treat*Post	-0.000	-0.000	0.003
	(0.010)	(0.004)	(0.003)
Post*No report	0.020**	-0.003	0.015***
	(0.010)	(0.004)	(0.004)
Treat*Post*No report	-0.024*	0.000	-0.017***
	(0.013)	(0.005)	(0.005)
	[0.087]	[0.617]	[0.009]
Observations	651,941	529,364	2,364,935
No. of households	108,980	91,690	75,193

Note: This table reports panel estimates of the effect of the water report on normalized daily usage of water, gas, and electricity. The model includes individual and period fixed effects. Periods are semesters for water and gas, months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level. FDR sharpened q-values for prespecified hypothesis are in squared brackets.

reports for the first time (column 6). The additional report has no effect on engagement among customers already receiving other reports. These results indicate that benefiting from the water report through water usage reduction is not a necessary condition for customers to value the report. The heterogeneity in the impacts of the water report by receipt of other reports at baseline may be interpreted causally, as the marginal effect of an additional report depending on the number of reports already received. However, given that we do not randomize the number of reports each user receives, it may also be due to differences between customers receiving other reports at baseline and those who do not, which are related to their behavioral responses to the report. Our empirical specification, including individual fixed effects, partially addresses this selection issue, as it controls for the effect of time-invariant individual characteristics that differ between multiple and single- report recipients. However, the presence of omitted time-varying factors that affect both the number of reports received and the household's responsiveness to the water report would make the causal interpretation of the interaction effect between treatment and receipt of multiple reports problematic.

In Appendix B, we show that single and multiple report recipients do differ along several dimensions that may be related to their reaction to the water report (Appendix Table B.1). We then exploit our knowledge of the context, namely, when Hera bundled by default the energy reports to all free-market contracts, to identify a subsample of users for whom the timing of other reports' receipt is plausibly exogenous.[24] We show that our results are robust when conducted on this sub-sample (Appendix Table B.2). These analyses, together with those examining the mechanisms behind the spillover effects of the water report reported in Section 6, lend credibility to a causal interpretation of these heterogeneity results and exclude that these results are entirely driven by self-selection.

The results on the engagement index (Column 6 of Table 3) suggest that users may not attend to additional reports as they did to the first. To shed light on mechanisms driving the lower effectiveness of the multiple reports, we exploit data on users' access to the utility web portal and the app following the receipt of a report. Recall that customers receive the reports by email and that the report typically invites users to visit their personal pages on the utility's website or the app for further information. If they do so, their access is recorded.[25]

We posit that cognitive and attention constraints limit engagement with the different reports, thus reducing their effectiveness. To test this hypothesis, we analyze whether users' reaction to receiving an electricity and/or gas report changes once they start receiving the water report. If the water report reduces users' ability or willingness to attend to other reports, we expect fewer accesses to the web portal and app following an electricity and/or gas report among treated customers in the posttreatment period. For this analysis, we focus on the sample of gas or electricity contract holders who had started receiving any reports before the treatment.[26] We use accesses to the utility's web portal and app in a month, on both the extensive and intensive margins, as our dependent variables. We test how receipt of an electricity or gas report affects these proxies of engagement, and whether such engagement changes among users receiving the water report in the posttreatment period. This analysis therefore exploits within-individual variation in the timing of report receipt and random treatment assignment to the water report as sources of identification. The receipt of a report (gas or electricity) is usually associated with an increase in engagement in the month. However, users assigned to receiving the water report reduce their engagement with the other reports in the posttreatment period (Appendix Table A.2). These results are consistent with the notion that, upon receiving an additional nudge, users reduce their engagement with the nudges that they were already receiving.

[24] Details on the sample definition are provided in Appendix B.

[25] We do not observe whether users open or click on the report but have a proxy for the latter.

[26] Recall that this is one of the dimensions over which we stratified treatment assignment.

5.3.2 Baseline resource usage and engagement

We evaluate the heterogeneity in program impacts by other prespecified dimensions. We consider baseline resource usage (Table 5, columns 1-3) and baseline customer engagement (columns 4-6) and split customers into below and above the median pretreatment value.

First, the direct impact of the treatment on water usage does not vary depending on baseline water usage (Column 1). For gas and electricity, we find that receiving the water report affects customers differently based on their baseline resource usage level. In particular, low gas and electricity users reduce significantly more than high users in response to the treatment (Columns 2 and 3). We detect increased gas and electricity consumption among high users in the treatment group. We also look at heterogeneity in the indirect effect of the water report by baseline water usage, the dimension along which the water report's contents, in terms of the descriptive and injunctive norm, is likely to differ. The results are qualitatively similar (Appendix Table A.3).

The patterns of the indirect effects are not in line with the established result in the literature for direct effects. Social information programs are more effective on high baseline users, both because they have larger margins of reduction and because of boomerang effects among low users (Bonan et al., 2020; Byrne et al., 2018; Bhanot, 2017; Schultz et al., 2007). With the available data, we can only speculate on the possible reasons for these effects. They are consistent with psychological theories of identity. If we believe that low-resource users tend to have a stronger proenvironmental identity, we should expect higher conservation of gas and electricity from them because it is among individuals with a high environmental identity that cross-behavioral spillovers are more likely to occur.

We look at the heterogeneous treatment effects by baseline level of resource usage on contract deactivation in Appendix Table A.4.[27] The treatment does not have a differential effect for customers with high baseline usage (considering both water and other resources) on the probability of cancelling the contract. This means that those who are likely to receive negative feedback in the report are not more likely to drop out.

Second, we examine heterogeneity by baseline customer engagement, proxied by the engagement index. Columns 4-6 of Table 5 report the estimates. We do not find significant differences in the treatment effects between high- and low-engagement samples. This result is reassuring for utilities, in that it suggests that customers with low levels of engagement at baseline also attend to social information nudges.

[27] We acknowledge that this analysis did not feature in the PAP.

Table 5: Heterogeneity by baseline resource usage and baseline engagement

	(1) Water	(2) Gas	(3) Electricity	(4) Water	(5) Gas	(6) Electricity
	X = high resource usage			X = high engagement index		
Post	0.155***	-1.143***	0.080***	0.101***	-1.203***	0.043***
	(0.005)	(0.004)	(0.003)	(0.007)	(0.004)	(0.003)
Treat*Post	-0.006	-0.004	-0.010***	-0.015*	-0.004	-0.005
	(0.004)	(0.003)	(0.002)	(0.008)	(0.004)	(0.003)
Post*X	-0.151***	-0.107***	-0.057***	-0.034***	0.015***	0.017***
	(0.010)	(0.004)	(0.004)	(0.010)	(0.004)	(0.004)
Treat*Post*X	-0.004	0.011**	0.013***	-0.003	0.009*	0.000
	(0.013)	(0.005)	(0.005)	(0.012)	(0.005)	(0.005)
	[0.617]	[0.066]	[0.039]	[0.617]	[0.101]	[0.617]
Observations	651,941	529,364	2,364,935	651,941	529,364	2,364,935
No. of households	108,980	91,690	75,193	108,980	91,690	75,193

Note: This table reports panel estimates of the effect of the water report on normalized daily usage of water, gas and electricity. High-usage customers are those with above median baseline usage of each resource. High-engagement index indicates customers with above the median index. Regressions include individual and period fixed effects. Periods are semesters for water and gas, and months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level. FDR sharpened q-values for pre-specified hypothesis are in squared brackets.

5.4 Robustness

Our results are robust to a series of checks. First, we estimate Equation 1 after excluding outliers in terms of baseline water usage (Appendix Table A.5, Columns 1-3) or households with more than five members (Appendix Table A.5, Columns 4-6). The results are unchanged and confirm the direct effect of the report on water use and the spillover effect on electricity use.

Second, as we previously observed that the treatment induced selective attrition among gas and electricity customers, we run the analysis on the sample of customers who do not change gas and/or electricity providers over the program period (Appendix Table A.5, Columns 7-9). The results are robust to these exclusions. Not only the direction of the effect, but also the point estimates are largely unaffected by these changes, .[28]

Third, recall that out of 108,980 customers with a water contract enrolled in the intervention, 91,690 have a gas contract, 75,193 have an electricity contract, and 70,339 have both. We want to ensure that the different composition of the samples between single water contracts and multiple contracts does not drive the main result on water usage. Therefore, we check the direct effect of the intervention on water usage for the subsamples of customers with multiple contracts. This is

[28] We repeat the exercise for the three resources, after excluding customers who canceled the gas or electricity contract. The results are qualitatively similar and are available upon request.

done in Appendix Table A.6. The results hold.

Fourth, we control for multiple hypothesis testing for all the hypotheses outlined in the PAP. In particular, we calculate and report in square brackets the FDR-adjusted q-values (Benjamini et al., 2006).[29] The results discussed in the paper appear robust to the multiple hypotheses correction, as all q-values attached to statistically significant coefficients ($p < 0.1$) remain below the threshold of 0.1.[30]

6 Discussion

The previous analyses provided evidence of direct and spillover effect of the water report on water and electricity consumption for all customers and of no average effect on gas. Direct and spillover effects of the report are concentrated among users who, at baseline, are not targeted by any other report. The reduced effectiveness of the water report, when received in addition to other reports, appears to be due to users' decreased engagement with each report as the number of reports they receive increases. In this section, we examine whether the spillover effects are due to technological synergies between water and other resources or behavioral mechanisms, such as a desire for consistency across domains. Understanding the mechanism behind spillover effects may shed light on why the larger effectiveness of the intervention is concentrated among single-report recipients. Results will contribute to the design of more effective multiple nudges.

The fact that we find robust indirect effects mainly on electricity would suggest an important role for technological synergies. Water displays a stronger correlation with electricity compared to gas. However, technological spillovers do not rule out the possibility of behavioral spillovers. For example, if we speculate that low users have a stronger proenvironmental identity, this would explain the larger electricity and gas conservation for this group of users. For these people in particular, the water report may increase the moral cost of consuming not only water but also gas and electricity, even if the report does not directly target the latter. This evidence, therefore, should suggest that not only technological but also broader behavioral changes occur in our sample of analysis.

We conduct additional tests to understand further the mechanisms that drive our results.[31] We conduct these exercises mainly focusing on electricity, as it is the only resource measured at a high enough temporal granularity.

Timing of report receipts. An exercise that can detect the presence of behavioral spillovers ex-

[29] We simultaneously include 19 hypotheses in the correction. This represents a departure from the approach described in the PAP. There, we corrected separately for hypotheses related to the main and heterogeneous treatment effects. We believe that the current version is more conservative and therefore preferable.

[30] The only exception is the test of heterogeneity by baseline engagement for gas usage, in Column 5 of Table 5.

[31] The analysis included in this section does not feature in the PAP, so it has to be considered exploratory.

ploits the variation in the temporal distance between the receipt of the water and the electricity reports. Among the customers enrolled in the social information programs for water and electricity, some receive the two reports on the same date, and others receive them on different dates. We posit that receiving both reports on the same date facilitates behavioral spillovers; this will likely make the synergies between resources more salient, thus favoring behavioral consistency. By contrast, if technological synergies are the only mechanism behind the indirect effects of the water report, the timing of receipt should not be associated with any heterogeneity.

To test this hypothesis, we estimate the impact of receiving both reports on the same day or not, for the subsample of treated customers who receive both water and electricity reports (N=10,204 customers). By computing the day difference between the two reports, we identify 16.1 percent of customers who consistently receive both reports simultaneously for the whole study period. We estimate a model similar to 1, where the variable $Treat$ is replaced by an indicator of whether the treated customers receive the reports simultaneously ($SameDay$). The results are presented in Appendix Table A.7 and indicate that electricity conservation is larger among customers receiving both reports simultaneously (Column 2) than for those receiving them separately. Although the effect on water is also negative, it is imprecisely estimated. The lack of a direct effect on water may be due to the lower frequency of observations, which prevents us from capturing short-term effects and reduces power. Nonetheless, sending multiple reports simultaneously results in a reduction in electricity use relative to receiving them separately among the less responsive group of multiple report recipients. This suggests that leveraging behavioral spillovers is one way for companies to increase the effectiveness of their communication strategies involving multiple nudges. This result is also consistent with the idea that the costs of attending to multiple reports matter for their effectiveness. These costs are lower when reports are received simultaneously, primarily because customers need to open a single email instead of two.

Tips content. Next, we exploit the information contained in the report, in particular the variation over time in the content of the two tips presented in a dedicated section of each report (see Figure 1 for details). Twenty different tips were presented bimonthly over the period between October 2019 and October 2021 to customers in the treatment group. These tips may convey broad environmental messages (*"Only 0.75% of the water on Earth is available for human consumption. That is very little, so don't waste it!"*). They may suggest behavior change (*"Water your balcony herbs with water from washing vegetables. It's a small gesture that helps you and the environment."*). They may mention technology, suggesting either investment in technological improvements or more efficient usage of available technologies (*"Choose water-efficient appliances: a dishwasher of this type may save you about 5,000 liters a year."*).[32] We argue that priming a broad environmental message or behavioral changes encourages positive behavioral synergies. Conversely, tips that

[32] See Table C.1 for details on the content of the tips and their classification in the three categories.

suggest technological improvements that impact multiple resources should reduce consumption through technological synergies rather than behavioral change. Therefore, we classify reports based on whether they contain environmental, behavioral, or technological tips. In particular, we denote a report as environmental if both tips in the section are of the environmental type. Consistently, behavioral and technological reports contain only behavioral and technological tips, respectively. We then focus on the month before and after the receipt of each report and test whether electricity usage varies depending on the type of tips featured in the report.[33] To analyze the short-term reaction to the type of tips on energy conservation, we add a triple interaction to our main specification using monthly electricity data. Further details on the analysis are provided in Appendix C, and the results are shown in Appendix Table A.8. We find that the water report is significantly more effective in curbing electricity usage when it contains environmental and, to a lower extent, behavioral tips. Interestingly, tips mentioning technological synergies with electricity do not significantly affect the report's spillover effects on electricity usage. This further indicates that technological synergies are not the sole driver of our effects.

Dynamics and seasonality. A third exercise that can help us clarify the mechanisms combines treatment dynamics and seasonality. In Table 2, we showed that the direct effect of the water report on water usage builds up over time: it is about -0.6 percent in the first year and becomes significantly larger in the second year (-2.2 percent). Similarly, the spillover effect on electricity grows from -0.4 percent in the first year to -0.7 percent in the second; however, the difference is not statistically significant. This seems to suggest that the direct and spillover effects develop separately, ruling out the technological synergy as the sole explanation.

We then look at the differential treatment effects in different seasons, namely winter vs. summer. We broaden the definition of summer and winter to six months each (May to October and November to April, respectively), which overlap with the periods used in the analyses on water and gas usage. The results are reported in Appendix Table A.9). The impacts on water and gas consumption do not differ significantly across seasons, but they differ for electricity. The direct effect on water and the spillover effect on electricity occur at different times of the year. This result is not consistent with technological synergies being the only mechanism behind the spillover effects of the water report on electricity usage. The stronger effect on electricity in winter is instead consistent with the notion that nudges are effective in inducing low-cost behavioral change, as reducing electricity consumption in winter is likely to be associated with smaller losses of comfort than in summer (Mertens et al., 2022).[34]

Overall, the evidence presented here suggests that the spillover effects we observe are not exclusively due to technological synergies between water and electricity but that behavioral mechanisms,

[33] The low frequency of gas data does not allow us to conduct a similar analysis for spillovers on gas consumption.

[34] Recall that the vast majority of customers use gas, not electricity, to heat the house in winter.

such as a desire for behavioral consistency across domains, or heightened proenvironmental identity, are relevant in our setting.

7 Conclusion

We study the direct and indirect effects of a water conservation nudge in the presence of other similar nudges targeted at other resources. We find significant direct effects of a water nudge on water consumption and indirect effects on electricity, but not gas. These effects are concentrated among customers who do not receive reports for other resources. Report recipients are less likely to deactivate their electricity and gas contracts, regardless of whether they receive other reports, suggesting a positive report valuation among customers. Although we find no indication of alienation of customers who receive multiple nudges on related behaviors, our results suggest that recipients of multiple nudges reduce the attention paid to each one. This leads to lower conservation gains within each domain. These negative effects on attention can prevent behavioral synergies. The lower attention and engagement resulting from multiple report is consistent with our interpretation that spillover effects are also due to behavioral synergies and explain the lack of indirect effects among multiple report recipients.

These results have important policy and business implications for energy and water companies' design of conservation nudges. Policymakers and businesses should carefully design the first nudge targeted to a given population. Initial interventions are those likely to have the greatest direct and indirect impacts. They should also be aware of the potential diminishing effects of additional nudges. Policymakers should reduce the cognitive efforts of attending to multiple stimuli, administering them together, and possibly leveraging general proenvironmental motives to encourage behavioral spillovers across domains. Additional research is needed to understand how to design, combine, and implement nudges for different resources to maximize companies' goals while also ensuring societal well-being.

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Appendix

A Additional tables and figures

Table A.1: Correlation in pretreatment resources usage

Pre-treatment period (Oct. 2018 - Oct. 2019)			
	Water	Gas	Electricity
Water	1		
Gas	0.297	1	
Electricity	0.368	0.463	1

Note: The table shows Pearson's correlation coefficients between pretreatment levels of water, gas, and electricity usage. The sample size is 70,339, and it is based on customers who had an active electricity and gas contract at the baseline. Significance levels are < 0.001 for all parameters.

Table A.2: Impact of water report on reaction to other report receipt to web portal and app access

	(1) Portal access	(2) No.portal accesses	(3) App access	(4) No. App accesses
Any report in the month	0.006***	0.024***	0.007***	0.082***
	(0.002)	(0.004)	(0.002)	(0.009)
Any report in the month*Treat	0.007***	0.018***	0.017***	0.059***
	(0.002)	(0.006)	(0.002)	(0.013)
Post	0.021***	0.032***	0.162***	0.640***
	(0.002)	(0.006)	(0.003)	(0.016)
Any report in the month*Post	0.006***	0.013**	0.020***	0.106***
	(0.002)	(0.005)	(0.002)	(0.011)
Treat*Post	0.006***	0.008	0.013***	0.059***
	(0.002)	(0.006)	(0.003)	(0.015)
Any report in the month*Post*Treat	-0.006***	-0.013*	-0.019***	-0.081***
	(0.002)	(0.007)	(0.003)	(0.015)
Observations	1,355,495	1,355,495	1,355,495	1,355,495
No. of households	36,635	36,635	36,635	36,635

Note: This table reports panel estimates of how the effect of receiving any report (gas or electricity) in a month changes after the treatment implementation, for the treatment and control group. The sample includes gas or electricity contract holders who had started receiving a report (any) before the treatment. All specifications include month and individual fixed effects. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table A.3: Heterogeneity by baseline water usage

	(1)	(2)	(3)
	Normalized daily usage		
	Water	Gas	Electricity
Post	0.155***	-1.190***	0.061***
	(0.005)	(0.004)	(0.003)
Treat*Post	-0.006	-0.005	-0.010***
	(0.004)	(0.003)	(0.003)
Post*High usage	-0.151***	-0.012***	-0.018***
	(0.010)	(0.004)	(0.004)
Treat*Post*High usage	-0.004	0.010**	0.012**
	(0.013)	(0.005)	(0.005)
Observations	651,941	529,364	2,364,935
No. of households	108,980	91,690	75,193

Note: The table reports panel estimates of the effect of the water report on normalized daily usage of water, gas, and electricity. High-usage customers are those with above median baseline water usage. The model includes individual and period fixed effects. Periods are semesters for gas and water, and months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table A.4: Impact on contract deactivation and customer engagement

	(1)	(2)	(3)	(4)
	Contract deactivation			
	Gas		Electricity	
Treat	-0.012**	-0.007*	-0.009	-0.005
	(0.005)	(0.004)	(0.006)	(0.005)
Baseline resource usage	-0.004***	-0.003***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)
Treat*Baseline resource usage	0.002*		0.000	
	(0.001)		(0.001)	
Baseline water usage	-0.012***	-0.014*	-0.015***	-0.011
	(0.004)	(0.008)	(0.006)	(0.010)
Treat*Baseline water usage		0.004		-0.007
		(0.009)		(0.011)
Observations	91,685	91,685	75,191	75,191
Mean dep. var.	0.213	0.213	0.229	0.229

Note: This table reports OLS estimates of gas and electricity contract deactivation (churn) in the posttreatment period, by baseline usage levels of the specific resource (odd columns) and of water (even columns). All models include average pretreatment specific resource and water usage, average pretreatment number of water self-reading, no other reports, number of occupants, contract length less than 3 years, strata fixed effects, and a dummy for the main wave of program delivery. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level. FDR sharpened q-values for prespecified hypothesis are in squared brackets.

Table A.5: Robustness results: excluding outliers by baseline resource usage and household size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Excluding outliers by baseline resource usage			*Excluding outliers by baseline household size*			*Excluding switchers*		
	Normalized daily usage								
	Water	Gas	Electricity	Water	Gas	Electricity	Water	Gas	Electricity
Post	0.071***	-1.132***	0.044***	0.082***	-1.189***	0.053***	0.084***	-1.212***	0.074***
	-0.002	-0.003	-0.002	-0.006	-0.004	-0.003	(0.006)	(0.004)	(0.003)
Treat*Post	-0.007***	-0.002	-0.004**	-0.013**	0.000	-0.005**	-0.014**	-0.002	-0.007***
	-0.002	-0.002	-0.002	-0.006	-0.002	-0.002	(0.006)	(0.003)	(0.003)
Observations	645,421	524,070	2,341,264	643,684	523,293	2,337,711	650,805	435,657	1,908,058
No. of customers	108,846	91,685	75,116	107,600	90,635	74,298	108,789	74,109	59,576

Note: This table reports panel estimates of the effect of the water report on normalized daily usage of water, gas and electricity. Regressions in Columns 1-3 exclude the top 1% of users in terms of baseline usage. Regressions in Columns 4-6 exclude users with household size larger than 5. Regressions in Columns 7-9 exclude attriters, i.e. customers who cancelled the specific contract in the posttreatment period. Each model includes individual and period fixed effects. Periods are semesters for gas and water, and months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table A.6: The impact of the water report on water usage, conditional on other contracts

	(1)	(2)	(3)
	Normalized water daily usage		
	Gas contract	Electricity contract	Gas and electr. contract
Post	0.073***	0.071***	0.064****
	(0.006)	(0.006)	(0.007)
Treat*Post	-0.012*	-0.012*	-0.014**
	(0.007)	(0.006)	(0.007)
Observations	548,516	449,770	420,786
No. of households	91,690	75,193	70,339

Note: This table reports panel estimates of the effect of the water report on normalized daily usage of water, conditional on the subsample of customers with gas, electricity, or both contracts. Periods are semesters. Post takes a value of 1 from November 2019, and 0 before. All specifications include period and individual fixed effects. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table A.7: Impact of simultaneous reception of water and electricity reports on resource usage

	(1)	(2)
	Normalized daily usage	
	Water	Electricity
Post	0.055***	0.044***
	(0.012)	(0.005)
Post*SameDay	-0.010	-0.019**
	(0.015)	(0.008)
Observations	61,076	347,672
No. Households	10,204	10,204

Note: This table reports panel estimates of the effect of the simultaneous reception of water and electricity reports on normalized daily usage of water and electricity. The model is based on a subsample of treated customers with an active electricity contract at the time of the treatment who received reports on their usage of both water and electricity during the intervention period. SameDay takes a value of 1 for customers who consistently receive both reports on the same day, and 0 otherwise. Regressions include individual and period fixed effects. Periods are semesters for water and months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table A.8: Spillover effects by type of water tip

	(1)	(2)	(3)
	Normalized daily electricity usage		
Tip type:	Behavioral	Environmental	Technological
Post	-0.001*	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)
Treat*Post	0.000	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)
Tip	0.005*	-0.010	0.001
	(0.003)	(0.008)	(0.004)
Treat*Tip	0.002	0.020**	0.005
	(0.003)	(0.010)	(0.004)
Post*Tip	0.002	0.003	-0.002
	(0.002)	(0.005)	(0.003)
Treat*Post*Tip	-0.005*	-0.012*	0.003
	(0.003)	(0.006)	(0.003)
Observations	1,068,042	1,068,042	1,068,042
No. of customers	65,545	65,545	65,545

Note: The table reports panel estimates of the effect of the water tip reception on normalized daily usage of electricity depending on the type of tip received. The model uses sampling weights. Post takes a value of 1 in a month following the reception of a tip, and 0 in a month before. Treat takes a value of 1 if a customer receives any tip at any point in time, and 0 otherwise. Tip is an indicator of the type of the tip received: it takes a value of 1 if a customer receives two tips that are of corresponding type. All specifications include month and individual fixed effects. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table A.9: Heterogeneity by seasons

	(1)	(2)	(3)
	Normalized daily usage		
	Water	Gas	Electricity
Post	0.051***	0.183***	0.051***
	(0.006)	(0.004)	(0.003)
Treat*Post	-0.013	-0.003	-0.002
	(0.008)	(0.002)	(0.002)
Winter	-0.021***	1.362***	0.036***
	(0.005)	(0.006)	(0.002)
Treat*Winter	-0.015**	0.024***	0.017***
	(0.008)	(0.007)	(0.003)
Treat*Post*Winter	-0.003	0.004	-0.008***
	(0.009)	(0.004)	(0.003)
Observations	651,941	529,364	2,364,935
No. of households	108,980	91,690	75,193

Note: This table reports panel estimates of the effect of the water report on normalized daily usage of water, gas, and electricity. Winter is equal to one from October to March. Each regression includes individual and period fixed effects. Periods are semesters for water and gas and months for electricity. Post takes a value of 1 from November 2019, and 0 before. All specifications include month and individual fixed effects. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

B Selection into multiple reports

In our setting, a selection issue may arise if customers receiving multiple reports purposely chose Hera among the ones on the market when it first launched the energy report for electricity or gas. Or, among Hera customers, some may have chosen to leave the regulated market to take up offers in the free market. Among these offers, they may have chosen those that gave access to the report. This selection into the utility, the free market, or the free-market contracts bundled with the reports may make multiple report recipients systematically more or less responsive than those not enrolled in the electricity or gas report program at baseline.

The qualitative evidence that we presented in Section 2 suggests that it is unlikely that households chose Hera as a provider, the free market, or a specific free-market contract purposely to receive the electricity or gas report. However, selection may still matter if customers' preferences and choices over what contract to sign make them ultimately more likely to receive other reports at baseline. Indeed, customers receiving no other reports differ from those receiving more than one report by several traits. This is shown in Appendix Table B.1. Unsurprisingly, as the gas and electricity reports are bundled with contracts in the free market, multiple report recipients are significantly more likely to have gas and electricity contracts with Hera in the free market. They are also more engaged, which is consistent with the switch to a free-market contract resulting from an active search for the best conditions. These customers live in smaller households, with lower consumption of all three resources. Although these differences are not a source of concern if time invariant, we may worry that they correlate with unobserved time-varying differences in responsiveness to the reports.

We exploit data and contextual features to address potential selection concerns. We aim to identify a sample of users for whom the receipt of multiple reports is unlikely to result from active self-selection into the free market, contract, or energy report. Specifically, we restrict our sample to customers with electricity and gas contracts in the free market–those with similar levels of engagement toward the utility and preferences for the free versus the regulated market. Moreover, we use detailed information on the first report receipt date to focus on customers who started receiving electricity or gas reports after January 2019. Recall that energy reports were sent by default from January 2019 to all free-market customers. Customers in this subsample, therefore, equally self-selected into the free-market and offers that, since January 2019, were bundled with the report.[35] Variation in report receipt at baseline within this sample then depends exclusively on whether the first report, if any, was received between January and October 2019. Our data reveals a large variation in the lag between contract signing and receipt of the first report: such lag for recent contracts is three months on average, with a standard deviation of 220 days. This implies that customers receiving the first report right after January 2019 may still have actively opted in to receive it. These customers may have deliberately chosen a contract bundled with the energy report at the end of 2018, and started receiving the first report only in 2019 because of the aforementioned lag. In a more conservative specification, we restrict the sample to customers who received the first report from April 2019.

Appendix Table B.2 shows the effect of the water report on the normalized daily usage of water, gas, and electricity depending on the receipt of other reports at baseline. When analyzing water

[35] This means that we exclude customers who actively self-selected into specific offers bundled with the report before January 2019.

usage, we exclude customers who received the first report (any) before January 2019 (Column 1) or April 2019 (Column 2). We focus on customers with all three contracts (with electricity and gas in the free market), which allows us to keep the sample and overall loyalty to the utility constant across outcomes. When looking at gas and electricity usage, we exclude from the sample customers receiving, respectively, the gas and electricity report before January 2019 (Columns 3 and 5) and April 2019 (Columns 4 and 6). As in our main analysis, the water report leads to reduced water and electricity usage only among users who had not received other reports since January 2019 (Columns 1 and 5) or April of the same year (Columns 2 and 6). We find that the water report also reduces gas usage among customers not receiving other reports (Column 3 and 4). Also different from our main results is that the water report causes an increase in gas and electricity use among recipients of an energy report before October 2019.
These results alleviate concerns that selection into receipt of the energy report drives the heterogeneous effects of the water report. In general, the larger point estimates for single-report recipients indicate stronger reactions to the report among customers who are likely to be more loyal to and engaged with the utility. These results also suggest that additional reports may have diminishing marginal impacts. This may be because users' limited attention and effort are split across different domains. The increase in gas and electricity consumption among multiple report recipients in the posttreatment period suggests that their attention may have been diverted away from gas and electricity upon receipt of the water report. We further explore the mechanisms behind these heterogeneous effects next.

Table B.1: Balance along other report receipt

	(1) No other report	(2) Other report	(3) *p*-value
Active gas contract	0.787	0.947	0.000
Active elect. contract	0.618	0.830	0.000
Gas contract in the free market	0.689	0.926	0.000
Elect. contract in the free market	0.579	0.828	0.000
No. of occupants in the house	2.385	2.323	0.000
Engagement index	-0.076	0.013	0.072
Mean daily water usage	0.323	0.311	0.000
Mean electricity usage	6.384	6.279	0.000
Mean daily gas usage	2.722	2.594	0.000
Obs.	108,980		

Note: This table reports differences in means between customers receiving no other report and customers receiving some other reports at baseline and p-values from a regression where the dependent variable is listed in the first column and regressed on the "No report" dummy and a binary variable for the wave of the program. All variables are expressed at the baseline or in the pretreatment period.

Table B.2: Impact on resources usage by number of reports, addressing selection issues

	(1)	(2)	(3)	(4)	(5)	(6)
	Normalized daily usage					
	Water		Gas		Electricity	
	Excluding report recipients before Jan. 19	Excluding report recipients before Apr. 19	Excluding report recipients before Jan. 19	Excluding report recipients before Apr. 19	Excluding report recipients before Jan. 19	Excluding report recipients before Apr. 19
Post	0.056***	0.056***	-1.159***	-1.159***	0.040***	0.040***
	(0.008)	(0.008)	(0.005)	(0.005)	(0.003)	(0.003)
Treat*Post	0.008	0.009	0.012**	0.013**	0.012**	0.013***
	(0.014)	(0.015)	(0.006)	(0.006)	(0.005)	(0.005)
Post*No report	0.022**	0.022**	0.001	0.001	0.012***	0.012***
	(0.011)	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)
Treat*Post*No report	-0.035**	-0.036**	-0.016**	-0.017**	-0.024***	-0.025***
	(0.017)	(0.018)	(0.007)	(0.007)	(0.006)	(0.006)
Observations	327,814	326,347	315,489	314,075	1,710,407	1,702,199
No. of households	54,810	54,565	54,810	54,565	54,810	54,565

Note: This table reports panel estimates of the heterogeneous effect of the water report on normalized daily usage of water, gas, and electricity along with the absence of other reports at the baseline. The sample includes customers with gas and electricity contracts in the free market. We exclude customers receiving the first report (any), before January 2019 (odd columns) and April 2019 (even columns), in Columns 1-2, 3-4 and 5-6, respectively. The model includes individual and period fixed effects. Periods are semesters for water and gas and months for electricity. Post takes a value of 1 from November 2019, and 0 before. *** significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

C Heterogeneous effects by type of the water tip

We analyze the content of the tip section in the water report to see whether electricity spillover effects are stronger when tips convey a specific type of message, particularly focusing on tips that could encourage technological or behavioral spillovers. In particular, we want to determine whether the magnitude of the spillover varies depending on the receipt of three types of tips in the water report: behavioral, technological, and environmental. This feature allows us to compare the spillover effects for customers before and after receiving a tip, depending on the type of tip they receive and with respect to customers who do not receive the tip.

We approach this analysis in stages, beginning with some data adjustments and focusing on customers with electricity contracts. First, we attribute a date and type of tip received to customers in the control group. Given that the date of the tip reception is available only for the treatment group, we use the nearest neighbor matching algorithm to allocate the date of tip reception from treated customers to their matched controls. We first divide customers into the 28 strata.[36] Then, within each stratum, we perform the matching between the treatment groups according to their average pretreatment levels of water and electricity usage. We find a match for 65,545 customers (98.1 percent of the electricity customers sample). Given the small size of the control group in the second wave of the program (9 percent control group; 91 percent treatment group), some controls are matched with more than one treatment customer. We increase the number of controls accordingly–making the overall distribution of 50.5 percent treated and 49.5 percent controls–and to each individual in the sample, we assign weights that are proportional to the number of repetitions, which we later use in the regressions.

Next, we generate the following binary indicators: a dummy variable *Post* indicating the month following tip reception and three treatment indicators identifying the type of tip received by a consumer. To construct *Post*, we exploit the information on the date of tip reception available in our data. If it falls before the 15th in any given month, we assign *Post* = 1 to the current month, and if the tips are received after the 15th, we treat the current month as the pretreatment month and assign *Post* = 1 to the following month.

Throughout the program, tips are sent to customers in a random combination of pairs, meaning each customer receives two tips per report. We consider a customer treated with a specific tip type only if both of the tips received are of that type. For example, we define *BehavioralTip* = 1 if both tips received within a report contain behavioral features, and we set *BehavioralTip* = 0 if only one or neither is behavioral[37]. The total share of the tips that are of the same type is 27 percent. The percentage of treatment group consumers receiving behavioral, technological, and environmental tips is 58 percent, 46.8 percent, and 13.2 percent, respectively. Table A.8 reports the results.

[36] Strata are based on the wave of program delivery, having an electricity and/or gas contract, having above median average pretreatment electricity usage, and having performed water self-reading in the last 12 months

[37] This variable remains constant over the pre- and postreception period, for expample, if an individual receives both tips that are behavioral in month *t-1*, the value of *BehavioralTip* takes the value of 1 in month *t-1* and *t*.

Table C.1: Tips classification

Tip text	Tip type		
	Tech.	Beh.	Env.
Water is precious. The United Nations has estimated that by 2050, one in four people will live in a country with a water scarcity.			x
Only 0.75% of the water on Earth is available for human consumption. That is very little, so don't waste it!			x
The water from your tap is not infinite. The future of our planet depends on all of us, every drop you save is beneficial to society.			x
By 2022, Group Hera will reduce its drinking water consumption by 10 percent. Help us to preserve our territory together.			x
Do you know how many liters of water you consume in a day, taking into account your meals, clothes, as well as your smartphone that connects you to the world? About 5,000 liters. Consume consciously.		x	
Do you know how much water you use every day? On average, 30 liters to wash dishes, 100 liters for a washing machine, 65 liters for the toilet. Your habits are important!		x	
Water your balcony herbs with water from washing vegetables. It's a small gesture that helps you and the environment.		x	
Do not place trash in the toilet. Every time you flush a cigarette end or a tissue, you waste up to 9 liters of water.		x	
While waiting for the hot water to flow out of the kitchen tap, collect it in a jug, place it in the refrigerator and then bring it to the dinner table. You will save dozens of water bottles.		x	
While you are waiting for the hot water in the shower, collect it in a basin and use it later to rinse the bathroom or clean the floors.		x	
Condensation from air conditioners? It is perfect for refilling your car's windshield wiper tank while also conserving water.		x	
Put some food coloring in your flush tank and if, without flushing, you find the color in the toilet it means you have a leak: fix it. You will save clean water as well as money on your utility bill.		x	
Washing dishes by hand consumes much more water than the dishwasher. You didn't know that, did you?	x	x	
When you load the dishwasher, do not rinse the dishes under running water, but collect some in the sink and rinse there with the sponge. You will save hundreds of liters a year.	x	x	
Check your home for water leaks on a regular basis by reading the meter. Every drop wasted harms both the planet and your wallet.	x	x	
Did you know that during a shower you consume 15 to 20 liters of water per minute? Listen to your favorite song but...just one!!!	x	x	
Turn off the tap while brushing your teeth. Water is not infinite.	x	x	
Choose water-efficient appliances: a dishwasher of this type may save you about 5,000 liters a year.	x		
A dripping faucet can make you waste between 30 to 200 liters of water a day. Fix it, there is no time to waste!	x		
Install water aerators on all taps in the house. This little change saves 30% of the water consumed annually.	x		