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Social norms and tariff salience: An experimental study on household waste management

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A B S T R A C T

We study the introduction of a social information program on waste disposal in a setting characterized by a two-part tariff. Households pay for unsorted waste a fixed amount if their yearly disposal is below a pre-defined cap, and pay per disposal after exceeding the cap. We randomize the receipt of a social information intervention, where customers' disposal is compared to that of similar ones. An additional treatment couples the social comparison with information on the customer's distance from the cap. We find that the report containing the social norm alone leads to a 5% reduction in the volume of unsorted waste. Making the cap salient significantly reduces the effectiveness of the social norm. The two treatments have a similar negative effect on the likelihood of exceeding the disposal cap. The reduction in unsorted waste is partly achieved through an increase in waste sorting, and is not accompanied by higher illegal disposals or lower quality of sorted waste. Our results confirm the effectiveness of descriptive norms in coordinating behavior but indicate that providing information on economic incentives can permanently crowd out their effect.

1. Introduction

The growing popularity of behavioral interventions implies that they are often implemented in settings where traditional policies, such as those relying on economic incentives or sanctions, are in place. In such cases, nudges often add social or other intrinsic motivations to the extrinsic ones provided by economic incentives or sanctions. Other times, these interventions are used to increase the salience and individuals' understanding of the existing taxes and pricing schemes. In spite of the large literature evaluating behavioral policies, our knowledge of their impacts is still limited in several respects. In this study, we focus on three main research gaps. First, the existing evidence on the effectiveness of behavioral interventions, leveraging intrinsic motives in the presence of extrinsic incentives, is mixed. Second, there exists limited evidence on whether information provision on taxes or pricing schemes works by increasing their salience or improving individuals' knowledge. Third, most studies give limited consideration to the negative externalities connected to an intervention. A comprehensive assessment of the impact and cost-effectiveness of policies requires going beyond the behavioral outcome directly targeted by the policy.

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In this paper, we study the impact of leveraging social information on top of existing economic incentives, both in isolation and when the latter are made more transparent and salient. We do so in the context of a social information program on the disposal of unsorted waste. The program's roll-out follows the introduction of a new tariff and collection system by the Italian utility with which we partner.[1] The tariff is based on a hybrid pay-as-you-throw scheme. Users pay a fixed amount if the volume of their yearly disposals of unsorted waste is below a threshold, determined by the utility depending on household size and other characteristics. If they pass the yearly threshold or cap, they pay a fixed amount per disposal above the cap. The collection system allows the utility to track each bag of unsorted waste disposed of by the users. Disposal of sorted waste is instead free and not monitored at the user level.

The social information program consists of a report delivered by mail (or email when available). Users randomly assigned to the Standard experimental treatment receive a report featuring, among other content, social information on how their level of disposal of unsorted waste compares with that of similar neighbors. Users in the Cap treatment see, in addition, information on how their cumulative volume of unsorted waste since the beginning of the year compares with their yearly cap.[2] Users in the control group receive no report.

We evaluate the interventions' impacts on the targeted behavior, as well as on other related outcomes. Using administrative data at the household level, we evaluate the impact of the two treatments on the volume of unsorted waste and the likelihood of exceeding the yearly cap. We exploit post-experimental data to explore the mechanisms behind the treatments' effects, particularly that of providing information on the tariff structure. We monitor outcomes for a year after the experimental period, when all households receive the standard report, to evaluate the persistence of the information on the cap. We hypothesize that any effect of the tariff information based on salience would disappear together with the treatment. Through data available at the unsorted and sorted waste truck route level, we also assess whether the program's introduction affected the quantity of unsorted waste and the quantity and quality of sorted waste.

We show that the standard treatment decreases unsorted waste volume by 6%, while the cap treatment reduces it by 4%. The difference between treatments is statistically significant. The report reduces the risk of exceeding the cap by 13.4%, with no difference by treatment. Using truck-route level data, we provide suggestive evidence that the reduction in the volume of unsorted waste is accompanied by a reduction in its weight. The program, therefore, appears to have led households to lower the frequency of disposals by actually reducing the quantity of waste produced, rather than by filling each bag more (Fullerton and Kinnaman, 1996). Heterogeneous treatment effects by baseline level of waste disposal reveal that the Cap treatment performs worse than the Standard one for the majority of customers. The two treatments perform similarly only among users close to the cap at baseline, who are likely to reap economic benefits from waste reduction.

The decrease in unsorted waste is achieved partly through an increase in sorted waste. Exploiting quasi-random variations in the share of treated households along the routes of trucks collecting sorted waste, exploratory analysis indicates that the amount of sorted waste increases by 7.6% if the intensity of treatment increases by ten percentage points. Finally, we show that these effects are not accompanied by negative consequences of the intervention in terms of lower quality of sorting or more littering.

We provide suggestive evidence that the information on the cap works by improving users' knowledge about the tariff scheme, rather than through a salience channel. In the latter scenario, the cap treatment would affect behavior by providing an arbitrary, salient, reference point for users, which, once removed, would cease to exert influence on disposals (Bordalo et al., 2022; Donk and van Zoest, 2008; Ariely et al., 2003; Kahneman, 1992). We observe persistent differences in disposal volumes between treatment groups in the post-experimental period, when all households receive the standard report. This result differs from Chetty et al. (2009)'s seminal paper on tax salience.

One reason behind the negative effect of adding information on the cap to the social one may lie in the interaction between the intrinsic incentives provided by the social information and the extrinsic ones given by the information on the tariff. In our setting, increasing users' understanding of economic incentives on top of social information does not improve the latter's effectiveness. The growing literature testing the effect of behavioral nudges and economic incentives on pro-social behavior yields mixed results (Drews et al., 2020). Crowding-out effects prevail when economic incentives are weak (Gneezy and Rustichini, 2000b), as they are in our setting where the cost per bag above the cap is low (1.5 Euro). In the electricity conservation domain, there is evidence that combining norm nudges with economic rewards leads to a higher reduction in usage (List et al., 2017); that it has the opposite effect of crowding out the intrinsic motivation to conform to the descriptive norm (Pellerano et al., 2017; Sudarshan, 2017); or that it makes no difference with respect to providing social information alone (Jessoe et al., 2021). Our results are in line with those of Pellerano et al. (2017), who also examine the effect of making a pricing scheme salient on top of a social information program on electricity usage in Ecuador. As in their setting, providing economic information backfires by reducing pro-environmental behavior.

The welfare implications of these results are nuanced. Providing information to consumers can, in principle, enhance welfare by increasing awareness and informing decision-making. However, if economic information undermines consumers' intrinsic motivation to preserve the environment, it may conflict with both policymakers' environmental objectives and consumers' preferences.

We focus on a relatively understudied behavior in the environmental domain: unsorted waste disposal. This domain is policy-relevant, given the severe environmental costs and externalities resulting from the generation, collection, and disposal of unsorted waste. Fostering waste prevention and sorting is important for sustainable waste management. Existing research demonstrates the

[1] Under the previous system, the tariff paid by each user was fixed depending on household size, and individual disposals were not monitored.

[2] The report's contents, detailed in Section 3 below, include standard features of similar types of social information programs, such as tips, environmental appeals, and comparisons of the users' disposals over time. These contents are common to the two versions of the report.

effectiveness of traditional policy tools, such as taxes and regulations, on the reduction of unsorted waste (Poortinga et al., 2013; Bueno and Valente, 2019; Messina and Tomasi, 2020; Colussi et al., 2022; Bucciol et al., 2023). The effectiveness of pricing policies is confirmed by a meta-analysis on unit-based pricing elasticities (Bel and Gradus, 2016). However, concerns about the public acceptability of a high-price policy on waste generation, with consequent risks of leakage to unregulated areas (White et al., 2019; Fullerton and Kinnaman, 1995, 1996; Erhardt, 2019; Bucciol et al., 2023), motivate the use of non-price interventions to reduce unsorted waste.

The literature that analyses the effectiveness of non-price interventions primarily focuses on waste sorting. Generally, these studies offer evidence of the effectiveness of behavioral interventions, and social information programs in particular, on waste sorting, with positive spillover effects in terms of reductions in the quantity of unsorted waste (Bucciol et al., 2015; Varotto and Spagnolli, 2017; Ek and Miliute-Plepiene, 2018; Alacevich et al., 2021).[3] However, economic incentives are found to be more effective than social information in promoting waste separation (Xu et al., 2018).

The few studies that specifically test the effect of social information programs on unsorted waste find them to be effective (Ek and Söderberg, 2024; van der Werff and Lee, 2021), consistent with non-experimental evidence on the importance of behavioral factors in general, and social norms in particular, on household waste management (Hage et al., 2009; Halvorsen, 2012; Raghu and Rodrigues, 2020). In the closest study to ours, Ek and Söderberg (2024) implement a field experiment embedded in a pay-as-you-throw system in two Swedish municipalities. The intervention delivers different versions of a social information message and generates a reduction of 7%–12% in unsorted waste. The presence of a pure pay-as-you-throw system differentiates their setting from ours. In our paper, we exploit the discontinuity in the marginal price of disposals generated by the hybrid pay-as-you-throw scheme. Our paper also looks at the potential impacts on sorted waste and littering, providing a more complete evaluation of the impact of the social information program on the entire set of strategies that households can use to manage their waste.

The remainder of the paper is organized as follows. We describe the context where the field experiment was implemented in Section 2. We present the experimental design in Section 3. Section 4 describes the data we use in the empirical analyses. We show the results in Section 5 and discuss them in Section 6. Section 7 concludes.

2. Context

Collection and disposal management of solid waste in Italy is decentralized at the municipal level. Municipalities contract or are shareholders in disposal management firms under different waste collection and payment systems. The most common methods are flat fees, which are determined according to household characteristics such as house type and size or the number of household members. Over the last decade, an increasing number of municipalities adopted pay-as-you-throw (PAYT), also called Unit Pricing, systems, whereby unsorted waste is charged per unit, and sorted waste can be disposed of for free.[4]

In this paper, we study the effect of a social information program implemented by an Italian multi-utility in a city located in the Northern part of Italy. The hybrid PAYT collection system employed by the utility was first introduced in 2018. Households pay a fixed fee for the disposal of unsorted waste[5] as long as the volume of their yearly disposal is within a certain threshold or cap. As the volume exceeds the cap, households pay an extra fee for each unit exceeding the cap. Each disposal unit corresponds to a volume of 30 liters; payment above the cap is 1.5 € per unit.

The cap is set for each household based on the number of members. The utility defined six basic cap levels for household sizes of 1, 2, 3, 4, 5, and 6 or more members, and the corresponding yearly volumes are 1,080, 1,380, 1,560, 1,740, 1,920, and 2,100 liters.[6] These caps are raised in the presence of babies, elders, or members with health problems. These special categories are connected to the production of sanitary waste. Specifically, when children are born or the customer notifies of specific health problems, the utility increases the cap by about 1,900 liters per year for each child or person with health problems in the household.

Unsorted waste is disposed of in specific locations – collection points – throughout the city. There are about 1,500 unsorted waste collection points for residential disposal in the city area (around 400 Km^2). Users can access the unsorted waste bins at the collection points through a card. This allows the utility to track disposals for each household for correct billing.[7] Collection points also host bins for sorted waste. Users do not need a card to open these bins and can dispose of sorted waste free of charge. Waste is collected by trucks along routes formed by a sequence of collection points for each type of waste (unsorted, paper, cardboard, glass, and plastic). At the end of the truck's route, an operator weights and rates the quality of sorted waste of the truck's content. Collection points of sorted and unsorted waste are routinely cleaned by utility operators. Before cleaning the area, operators rate the tidiness of the collection points using a tablet.

Users can also access waste collection centers (WCC) to dispose of special waste, such as batteries, electronic appliances, and bulky waste. Disposal of special waste at the WCC is rewarded through refunds on the waste bill proportional to its weight and type.[8] Accesses to WCC are recorded at the user level.

Users pay the waste management bills quarterly and can access all the information on their disposals and dues using the utility's web portal and app. The latter two also offer notifications about utility services and tips on correct waste disposal.

[3] Social information programs, like the one that we evaluate, have been applied and tested in various settings, from resource conservation (Allcott, 2011; Allcott and Rogers, 2014; Andor et al., 2020; Ferraro et al., 2011; Bonan et al., 2021b, 2024), contributions to charitable causes (Frey and Meier, 2004; Shang and Croson, 2009; Linek and Traxler, 2021), technology adoption (Bonan et al., 2021a), voting (Gerber and Rogers, 2009), and financial decisions (Beshears et al., 2015; Dur et al., 2021; Andrieş and Walker, 2023).

[4] Over the period 2010–19 the share of municipalities adopting PAYT systems moved from 4 to 8.3% (Colussi et al., 2022).

[5] By unsorted waste we refer to the residual waste that is not recycled.

[6] The average payments are 74€, 117€, 142€, 161€, 192€ and 248€ for households with 1, 2, 3, 4, 5 and above 6 members, respectively.

[7] A door-to-door collection system is also available for a restricted number of citizens living in the city center.

[8] Users weigh their waste by major categories at the collection center and obtain a refund, ranging from 0.01 to 0.3 € per kilogram, in the next bill.

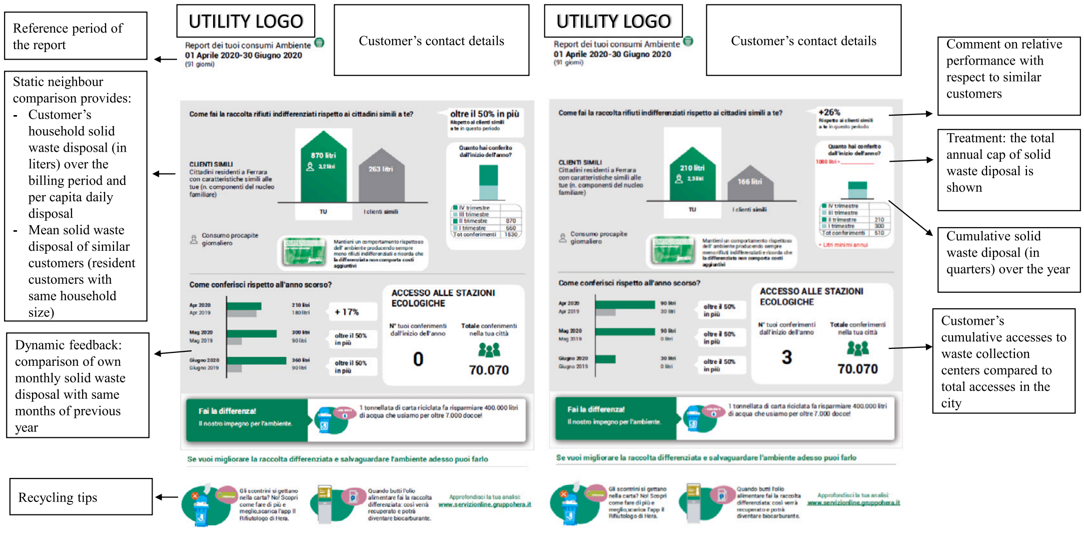

Fig. 1. Waste report.

3. Design

In collaboration with the utility, we designed and evaluated a large-scale social information program targeting unsorted waste, the "home waste report". The program was launched in July 2020, and the reports were delivered by post or email to customers. Only residential utility clients in the municipality were eligible to participate in the program.

Each report, which referred to unsorted waste disposals in specific quarters of the year, was expected to be sent quarterly after the delivery of the waste bill. In practice, implementation issues on the utility's side meant that reports were not sent at regular intervals nor at the end of the quarter they referred to.[9]

The experiment randomly assigns two-thirds of eligible customers to a treatment group receiving one of two versions of the home waste report and one-third to a control group receiving no report. Half of the treated households, or one-third of the overall sample, receive the standard social report (Standard treatment). The other half receives the standard report augmented with information about the disposal cap (Cap treatment).

The standard report is reproduced in Fig. 1 (left panel) and includes the following elements:

- *Static neighbor comparison.* Unsorted waste volume disposed of over the reference quarter, expressed as total liters and liters per capita per day. The user's level of unsorted waste is compared with that of similar customers living in the city over the same period. Similar customers have similar characteristics. In particular, they have the same solid waste disposal cap.
- *Cumulative unsorted waste disposal.* Cumulative unsorted waste disposal since the beginning of the year.
- *Dynamic feedback.* Unsorted waste disposal over the reference period, compared with one's disposal over the same month of the previous year.
- *Access to waste collection centers.* Cumulative number of accesses to WCC since the beginning of the year, alongside the total number of accesses by other citizens over the same period.
- *Make the difference.* This section delivers an environmental message, underlining the importance of recycling in reducing CO2 emissions. This part of the report is not customized.
- *Recycling tips.* Tips on how to improve recycling and its importance. Each report features different tips, but they are not personalized across customers.

Clearly, the report does not include only social information. Some of the additional features, such as tips, are common elements of this type of report (Allcott and Mullainathan, 2010; Bonan et al., 2020); while others, such as dynamic feedback or environmental appeals, are not. While we refer to the treatments in terms of their most prominent features, we evaluate the impact of the report in all its components.

Customers assigned to the cap treatment receive a slightly modified version of the report, where the figure reporting the cumulative solid waste disposal since the start of the year shows how it compares with the user's yearly cap (Fig. 1, right panel). If the volume of waste disposed of by the customer in the quarter exceeds one-fourth of the yearly cap, the figure makes this salient

[9] Appendix Table A.1 reports the date of delivery of each wave of the report and the reports' reference period. In terms of our analysis, this implies that we cannot rigorously test the heterogeneous effect of the report depending on its quarter of reference, which is one of our pre-specified dimensions of heterogeneity.

Table 1
Descriptive statistics and balance.

	(1) Control	(2)	(3) Standard	(4)	(5) Cap	(6)	(7)
	Mean	SD	Mean	SD	Mean	SD	P-value
Disposal cap 2020	1723.751	1699.115	1714.44	1658.309	1727.759	1715.914	0.772
Allowances in 2020	0.046	0.21	0.046	0.209	0.046	0.21	0.935
Monthly disposal in 2019	73.79	75.15	73.15	74.50	73.64	75.23	0.733
Exceeded the cap in 2019	0.097	0.295	0.096	0.294	0.097	0.296	0.937
Above median house size	0.501	0.5	0.502	0.5	0.503	0.5	0.974
Has e-mail	0.384	0.486	0.383	0.486	0.382	0.486	0.966
Access to WCC in 2019	0.439	0.496	0.437	0.496	0.437	0.496	0.93
N. of Accesses to WCC in 2019	1.56	4.22	1.58	4.35	1.58	4.68	0.98
N. of households	15,585		15,663		15,685		

Note: This table reports means and standard deviations of baseline variables by treatment group. The last column reports the *p*-value of a joint significance test of treatment coefficients in a regression with the baseline variables as dependent, with robust standard errors. WCC: waste collection center.

through a message.[10] These pieces of information allow treated customers to keep track of their performance against the yearly cap.

Besides the neighbor comparison, the standard and cap treatments do not disclose new information. The waste bill, delivered quarterly, already informs all customers of their disposals during the period, of the yearly cap, and alerts them if their quarterly disposal exceeds one-fourth of the yearly cap. This information is, however, buried within the several pages of the bill and provided in written form. Through its simplified graphical representation, the home waste report makes these pieces of information more accessible and salient.

The cap treatment responds to a specific need of our partner utility, originating from the limited effectiveness of information delivered through the bill. As mentioned above, the share of households disposing above the cap at baseline is low, specifically below 10%. Nevertheless, these users impose large costs on the utility, not just in terms of waste management. The high bills received by users with disposals above the threshold are associated with complaints and difficulties in repayment. By warning users who are on course for a high bill in a salient and simple way, the cap treatment aims to both reduce the likelihood of users exceeding the threshold and minimize complaints in case they do.

4. Data and samples

The study period for unsorted waste disposal ranges from January 2019 to October 2021, for a total of 34 months. Of these, 18 months are in the pre-experimental and 16 months in the experimental period. We select the study sample from the population of residential customers the program targets. Specifically, from the initial sample of 54,150 resident households eligible for the program, residing in the municipality since (at least) January 2019, which we identified in the PAP, we restrict the study sample to 46,933 households. That is, we exclude from the study customers for whom the information on unsorted waste disposal is completely missing over the period or available only after or before the program's launch.[11] In addition, we deal with outliers in terms of monthly unsorted waste disposal by winsorizing the top 0.1% of disposals. Our final study sample comprises around 75% of all households residing in the city.

All data used in the analysis are provided by our partner utility after being anonymized. At the household level, these data consist primarily of our main outcome variable, which is unsorted waste disposal. We have information on the date and location, in terms of collection point, of each disposal of unsorted waste made by the customer. With this information, we compute the primary outcomes: the volume of solid waste disposed of in the month, expressed in liters, and the probability of exceeding the cap in the year. The administrative data also include contract information: house and household size, the household's yearly cap, and whether the household is entitled to a cap increase due to the presence of infants or members with health problems.

We follow a stratified individual-level randomization procedure to maximize ex-ante balance across the three experimental arms along a battery of observable characteristics. Strata are obtained from the combination of the following variables: the household's disposal cap for unsorted waste in 2020; whether the household is entitled to an increase of the cap due to the presence of infants or members with health problems (at the time of data extraction, i.e. April 2020); house size above the median; whether the household accessed any WCC in 2019; having valid e-mail access, hence possibly receiving the report by email rather than by post. We end up with 96 strata. Within each stratum, we sort customers by baseline unsorted waste disposal volume in the baseline period (April 2019–March 2020) and assign adjacent customers to treatment and control groups.

We conduct balance tests across treatment groups for the variables used to construct the randomization strata, the pre-registered dimensions of heterogeneity, and the outcomes at baseline. Table 1 reports the mean and standard deviation in each treatment arm and a test of the joint significance of the treatments.[12] The results confirm that households' characteristics and outcomes measured

[10] Customers visualize the following message "Be careful. If you keep disposing at this rate, you are likely to exceed your yearly cap".

[11] The resulting sample is an unbalanced panel as we do not observe all households for the same number of months. In a robustness check, we restrict the analysis to a balanced sample of households.

[12] Balance is assessed by looking at the F-statistic of the test for joint significance of the treatment dummies in the following equation: $y_{i0} = \beta_0 + \beta_2 Std\_Report_i + \beta_3 Cap\_Report_i + \varepsilon_{i0}$, where y_{i0} are the variables reported in the table.

at baseline are balanced across treatment groups.

On average, households in our sample had a disposal cap of 1,723 liters in 2020, at the report launch, or about 143 liters per month. This threshold is quite generous, given that the yearly cumulative disposal was 885 liters and the average monthly disposal was 74 liters in 2019. As mentioned already, 9.7% of customers exceeded the cap; and a larger share, about 15% of households, produced yearly cumulative disposal volumes within 30% from the cap in 2019 (Appendix Figure A.1). Among those who exceeded the cap in 2019, the mean volume of disposals above the cap was 800 liters. Almost half of the households accessed a WCC in 2019, with an average frequency of 1.6 accesses over the year.

Besides the household-level information, we have additional information on unsorted and sorted waste at the truck-route level from January 2020 to October 2021. Truck routes are unordered sequences of collection points and are material-specific (unsorted, paper, cardboard, plastic, glass, and cans). For each truck route, we know the collection points covered, the collection date, the type of material, the total weight of material collected, expressed in tonnes, and for sorted material, its quality. The quality assessment of sorted waste follows the company guidelines and classifies recycling waste from low to high quality, using a 3-point scale. We use these data to analyze the effect of the social information program on the quantity and quality of sorted waste at the level of the truck route. We also use this data to analyze if the program affects not only the volume but also the weight of unsorted waste.

Routes change over time: some routes are common and are observed multiple times over the study period; others are observed only once. In our study of the program's effect on weight of sorted and unsorted waste, we restrict the attention to routes observed more than once over the study period, which is 411 for sorted materials and 105 for unsorted ones. The routes differ in the number of collection points that they cover. In the case of sorted waste, it ranges between 1 and 132, with an average of 13 collection points.[13] We make this restriction as it allows us to use a panel model and control for time-invariant route characteristics through route-fixed effects. However, routes could change endogenously in response to changes in the quantity of waste disposed of in the collection points they cover, and such changes could possibly be due to the treatments. We discuss below the implications of this choice for our estimates.

The average monthly weight of the unsorted and sorted waste collected at the end of the route is 4.8 and 1.4 tonnes, respectively. The average recycling quality in our data is good, corresponding to an average rating of 2.2 (on a scale from 1 to 3). Glass and cans are materials displaying the highest score. These figures are consistent with the fact that the city that we study is among the first in Italy in terms of the share of recycling over the total volume of waste (Legambiente, 2020).

Finally, for each collection point (N = 1,572), we have a rating of the cleanliness of the area around it from January 2020 to October 2021. The rating of the collection points is performed by utility workers in charge of cleaning the area around collection points and uses a 4-point scale.[14] The average rating over the study period is 3.2. Checks are performed on average 4 times per week. These ratings are a proxy of littering, specifically of customers abandoning their bags of unsorted waste outside the bins. Such anti-social behavior could be motivated by the desire to avoid swiping their cards and having the bag accounted for in the bill, and thus represents a possible undesired effect of providing information on the tariff.

5. Results

5.1. Impact on unsorted waste

5.1.1. Impact on the volume of disposal

We first analyze if the home waste report affects the volume of unsorted waste, which we denote as the intensive margin of disposal. We estimate the intention to treat effect (ITT) of receiving the report as follows:

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

where y_{it} is customer i's volume (liters) of unsorted waste disposed of in month t.[15] $Treat_i$ is a treatment dummy that takes the value of one for customers receiving the report, irrespective of the type of treatment, and zero otherwise; $Post$ is a dummy variable that becomes one after the delivery of the first report, i.e., July 2020. The regression also includes month-by-year fixed effects, h_t, and household fixed effects, g_i. Standard errors in all specifications are clustered at the household level to allow for within-customer correlation over time in the error term (Bertrand et al., 2004). We control for multiple hypothesis testing for all the hypotheses presented in the PAP.[16] In particular, we calculate and report the false discovery rate (FDR) adjusted p-values (q-values) (Benjamini et al., 2006).

We also assess if providing information on the yearly unsorted waste disposal cap on top of the social information is more or less effective than the standard social comparison alone. To do so, we estimate the following model:

$$y_{it} = \beta_1 Standard_i * Post_t + \beta_2 Cap_i * Post_t + h_t + g_i + \varepsilon_{it} \tag{2}$$

[13] For unsorted waste, we observe an average of 19 collection points. We exclude 9381 and 34 routes from the analysis of sorted and unsorted waste, respectively, as they are observed only once.

[14] Unfortunately, we cannot identify workers doing this job.

[15] Given that, on average, households dispose of waste less than once per week, we organize the data as a monthly panel. In a robustness check, we run the same analysis at the weekly level.

[16] The pre-registered results are the analysis on the individual level unsorted waste volume; on the probability of exceeding the cap; the heterogeneous effects by pre-treatment levels of disposal, passing the cap and the reference quarter of the report.

Table 2
Treatment effects on disposal and the probability of exceeding the cap.

	(1)	(2)	(3)	(4)
	Monthly Disposal		Pr. Exceeding cap	
Treat*Post	−3.724***		−0.012***	
	[0.496]		[0.003]	
	(0.001)		(0.001)	
Standard*Post		−4.442***		−0.013***
		[0.574]		[0.003]
		(0.001)		(0.001)
Cap*Post		−3.008***		−0.012***
		[0.567]		[0.003]
		(0.001)		(0.001)
Observations	1,499,733	1,499,733	140,799	140,799
N. of hh	46,933	46,933	46,933	46,933
Mean Dep	73.72	73.72	0.0893	0.0893
P-val(Std=Cap)		0.0111		0.825
q-val (Std=Cap)		0.003		0.101

Note: This table reports panel estimates of the effect of the report on monthly volume of disposal and on the probability of exceeding the gap in the year. The study period is from January 2019 to October 2021. The model includes individual and period fixed effects. Periods are months in columns 1–2 and years in columns 3–4. Post takes the value of one from July 2020, and zero before in columns 1–2; it takes the value of one for 2020 and 2021 and zero for 2019 in columns 3–4. The mean of the dependent variable at the bottom of columns 1–2 is expressed in liters. Standard errors, in squared brackets, are clustered at the household level. FDR-adjusted p-values (q-values) for pre-specified hypothesis in parentheses. The last two rows of the table report the p-values and q-values for the pre-specified hypothesis of the difference in the effectiveness of the two treatments. *** significance at the 1% level, ** at the 5% level, * at the 10% level.

where $Standard_i$ and Cap_i are dummies taking the value of one if customers are assigned to the standard information treatment and the standard information with cap treatment, respectively, and zero otherwise. The coefficients β_1 and β_2 reveal the effect of receiving the social information with and without cap indication, compared to not receiving the report.

Panel estimates of the effect of the waste report on monthly waste disposal are reported in Table 2. The social information program significantly reduces waste disposal by about 4 liters per month (Column 1). Given an average waste disposal of 73.7 liters per month for control households in the treatment period, this effect corresponds to a reduction of about 5%. Column 2 displays the treatment effects, separated by type of treatment. The norm nudge alone has a larger effect than the social norm augmented with the cap. While the standard report decreases unsorted waste disposal by 6%, the report informing about the cap decreases disposal by 4%. The difference between the two coefficients is statistically significant. These results are robust to MHT correction, as shown in the table through the FDR-adjusted p-values (q-values) reported in parentheses.

We explore the dynamics over time of treatment effects. Fig. 2 plots the effect of receiving the standard and the standard with cap treatments, relative to the control group receiving nothing, over the study period. The figure suggests that the program's impact builds up over time, particularly after the delivery of two reports over a short time span between the end of 2020 and the beginning of 2021. After peaking in the spring of 2021, the impact of the program persists until the end of our observation period in October 2021.[17]

Our results are robust to changes in the specification and sample. First, we replicate the analysis at the weekly rather than at the monthly level. Results, provided in Columns 1 and 2 of Appendix Table A.2, confirm the magnitude of the average treatment effect of Table 2. Second, we run our main specification on the sub-sample of customers for which we have data on disposal over the entire study period, i.e. 34 months. This restriction generates a balanced panel of 25,548 customers observed for the entire period. This is done in Columns 3–4 of Appendix Table A.2. The results are qualitatively confirmed, albeit slightly larger.

5.1.2. Impact on exceeding the cap

We analyze the effect of the intervention on the probability of exceeding the yearly cap, which we denote as the extensive margin of waste disposal. We estimate Eqs. (1) and (2), where y_{it} is a dummy equal to one if household i exceeded the threshold in the year t and 0 otherwise, and $Post$ is a dummy variable equal to 0 in 2019 and 1 in 2020 and 2021. Since exceeding the threshold may only occur once yearly, we organize the data as a yearly panel in this specification. h_t are year fixed-effects and g_i household fixed-effects.

The program reduces the risk of exceeding the cap by 1.2 percentage points (Column 3 of Table 2). Considering that 8.9% of control households exceed the cap in the treatment period, the effect corresponds to a 13.5% decrease. While the standard treatment is more effective than the cap treatment in reducing waste volume (Column 2), it is as effective as the cap treatment in reducing the probability of passing the threshold (Column 4). From these findings, we could infer that the cap intervention is less effective than

[17] We also examine the evolution of the level of disposals by treatment over time (Appendix Figure A.2). The relative decline in the treatment groups appears to be also a decline in absolute levels.

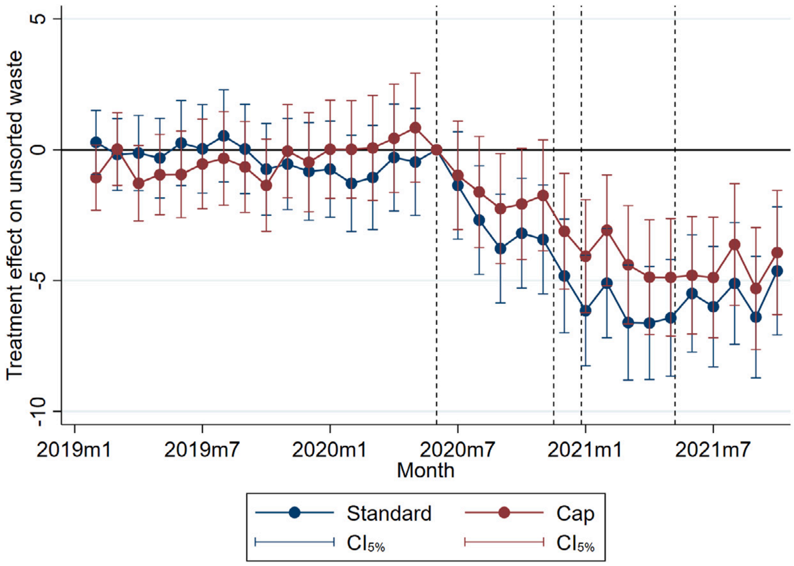

Fig. 2. Treatment effect dynamics.

the social comparison intervention for households (far) below the cap, while they are equally effective among households closer to the cap. To provide further support to this statement, in the next section we will compare the relative performance of the cap and standard treatments for households differing in their position relative to the cap.

Our results are robust to MHT correction and changes in the observation period. Specifically, the yearly-panel specification we adopt does not precisely capture the start and end of the program. First, the program was launched in July 2020, and considering the whole of 2020 as a treated period, as we do in our main specification, leads to underestimating the effect of the treatment. Second, the study period runs until October 2021. This may lead again to an underestimation of the probability of exceeding the cap in 2021, since such likelihood increases over the course of the year.[18] A monthly-level specification allows us to precisely delimit the treatment period and account for the trend in cumulative disposals over the year. Hence, we complement the analysis above with one where the outcome is the probability of exceeding the "theoretical" cap in the month, or monthly allowable volume (which is equal to the cap divided by 12), using specifications similar to (1) and (2). Results are shown in Columns 5–6 of Appendix Table A.2 and confirm the significance and magnitude of the treatment effects. Appendix Figure A.4 shows how the shares of customers exceeding the theoretical monthly cap change over time by treatment.

We now examine whether the report influences the intensive margin beyond the cap, i.e., the volume of unsorted waste exceeding the cap. While changes in behavior below the cap do not produce monetary benefits, customers save €0.05 for each liter-reduction in disposal above the cap. We estimate Eqs. (1) and (2), where y_{it} is the cumulative waste that household i disposes of beyond the cap in the year t. For households not exceeding the cap, the dependent variable is set to zero. Appendix Table A.3 shows the regression results for the whole sample, dominated by a majority (over 90%) of households not exceeding the cap (Columns 1–2); and for the sub-sample of households that exceeded the cap in the year prior to the launch of the program (Columns 3–4). We find no treatment effects on either sample.

5.1.3. Heterogeneous effects

We look at the heterogeneous treatment effects along two pre-specified dimensions: pre-treatment unsorted waste disposal and having passed the cap in the pre-treatment year. We estimate the following equation:

$$y_{it} = \beta_1 Treat_i * Post_t + \beta_2 Treat_i * Post_t * X_i + \beta_3 Post_t * X_i + h_t + g_i + \varepsilon_{it} \tag{3}$$

To capture the first dimension (X_i), we create a dummy variable that is equal to one for households with pre-treatment unsorted waste disposal above the sample median and zero otherwise. Table 3 reports the results. Households with high unsorted waste disposal curb waste by 8.5 liters more than those with low disposal (Column 1). Given an average monthly post-treatment disposal of 73.7, this corresponds to an 11.6% reduction. We detect no significant reduction nor a boomerang effect among households with below-median baseline disposal.

When we distinguish between the two types of treatments, we confirm the stronger reaction of households with high unsorted waste disposal compared to those with low disposal (Column 2). We find a significant positive effect of the cap treatment within the

[18] See Appendix Figure A.3.

Table 3
Heterogeneous treatment effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Monthly Disposal		Pr. Exceeding cap		Monthly Disposal		Pr. Exceeding cap	
X:	High Pre-Treat Disposal				Exceeded cap (2019)			
Treat*Post	0.450		−0.001		−3.118***		−0.007***	
	[0.398]		[0.001]		[0.439]		[0.002]	
	(0,151)		(0.195)		(0.001)		(0.001)	
Treat*Post*X	−8.515***		−0.023***		−6.570**		−0.056***	
	[0.989]		[0.005]		[2.932]		[0.012]	
	(0.001)		(0.001)		(0.026)		(0.001)	
Standard*Post		0.121		−0.002		−3.736***		−0.008***
		[0.448]		[0.002]		[0.502]		[0.002]
		(0.271)		(0.095)		(0.001)		(0.001)
Cap*Post		0.776*		−0.000		−2.502***		−0.006***
		[0.468]		[0.002]		[0.509]		[0.002]
		(0.065)		(0.324)		(0.001)		(0.003)
Standard*Post*X		−9.270***		−0.022***		−7.432**		−0.053***
		[1.141]		[0.006]		[3.451]		[0.014]
		(0.001)		(0.001)		(0.029)		(0.001)
Cap*Post*X		−7.757***		−0.025***		−5.698*		−0.058***
		[1.131]		[0.006]		[3.271]		[0.014]
		(0.001)		(0.001)		(0.061)		(0.001)
Observations	1,499,733	1,499,733	140,799	140,799	1,499,733	1,499,733	140,799	140,799
Number of hh	46,933	46,933	46,933	46,933	46,933	46,933	46,933	46,933
P-val(Std=Cap)|X=0		0.151		0.159		0.0137		0.349
q-val(Std=Cap)|X=0		(0.095)		(0.095)		(0.015)		(0.175)
P-val(Std=Cap)|X=1		0.0339		0.878		0.362		0.793
q-val(Std=Cap)|X=1		(0.03)		(0.293)		(0.175)		(0.271)

Note: This table reports panel estimates of the heterogeneous effect of the report on monthly volume of disposal and on the probability of exceeding the cap in the year. The study period is from January 2019 to October 2021. Households with high pre-treatment disposal are above the median yearly disposal in 2019. The model includes individual and period fixed effects. Periods are months in columns 1-2-5-6 and years in columns 3-4-7-8. Post takes the value of one from July 2020, and zero before in columns 1-2-5-6; and one for 2020 and 2021 and zero for 2019 in columns 3-4-7-8. The mean of the dependent variable at the bottom of columns 1-2-5-6 is expressed in liters. Standard errors, in squared brackets, are clustered at the household level. FDR-adjusted p-values (q-values) for pre-specified hypothesis in parentheses. The last rows report the p-values and q-values for the pre-specified hypothesis of the difference in the effectiveness of the two treatments in the sub-groups. *** significance at the 1% level, ** at the 5% level, * at the 10% level.

households with below-median baseline disposals, possibly suggesting a boomerang effect. The cap treatment performs significantly worse compared to the social treatment within the sub-samples of households with high pre-treatment disposal.

In terms of the extensive margin, the treatment is only effective in reducing the likelihood of surpassing the threshold in households with high pre-treatment disposals (Column 3). The two treatments do not affect the probability of exceeding the cap differently, in particular for households with above-median pre-treatment disposal ($p = 0.878$).

For the second dimension of heterogeneity, we distinguish between households with yearly disposals above or below the cap in 2019. The former group comprises about 9.7% of the total sample. The intervention effectively reduces disposal in both sub-groups, but we detect a stronger reaction among households that exceeded the cap in the pre-treatment year. These households react to the report by curbing disposals by 6.6 liters, or 13%, compared to the control group, twice as much as those who did not exceed the cap in 2019 (Column 5).

While both reports appear similarly effective in curbing disposals for those who exceeded the cap in 2019 (Column 6, $p = 0.362$), the standard report appears more effective than the cap one for those who did not exceed the cap ($p = 0.014$). This is consistent with the overall difference in treatment effects found in Column 2 of Table 2, given that more than 90% of the sample lies in this group. The report significantly reduces the risk of disposing above the cap among both groups of households, with a stronger effect among those who exceeded the cap in 2019 (Column 7). The two versions of the report do not significantly differ in their effects on the likelihood of exceeding the cap across both groups of households (Column 8).

In an exploratory analysis, we further examine the heterogeneity of treatment effects by baseline disposal. We focus on the sub-samples of high depositors, proxied either by being in the top 20% of the disposal distribution at baseline or by having exceeded the cap at baseline. We compute the median baseline disposal within these sub-samples, and test the heterogeneity of treatment effects between users below and above such median values. The rationale for this analysis is that below-median households within these sub-samples of high depositors may be particularly close to the cap, and thus be most responsive to the cap treatment. Appendix Table A.4 shows that the two treatments perform similarly among users close to the cap, who are the below-median depositors in these sub-samples, while the cap treatment performs significantly worse than the standard one among above-median ones.

The boomerang effect that we report in Table 3, along with the last piece of evidence in Table A.4, suggests that very low and very high depositors mainly drive the cap's lower performance compared to the standard treatment. While the two sub-samples react similarly when receiving information on the cap on top of the social comparison, the mechanisms behind these responses are likely to be different. Low depositors may be induced to slack off by the cap information. High depositors, on the contrary, may be discouraged by it.

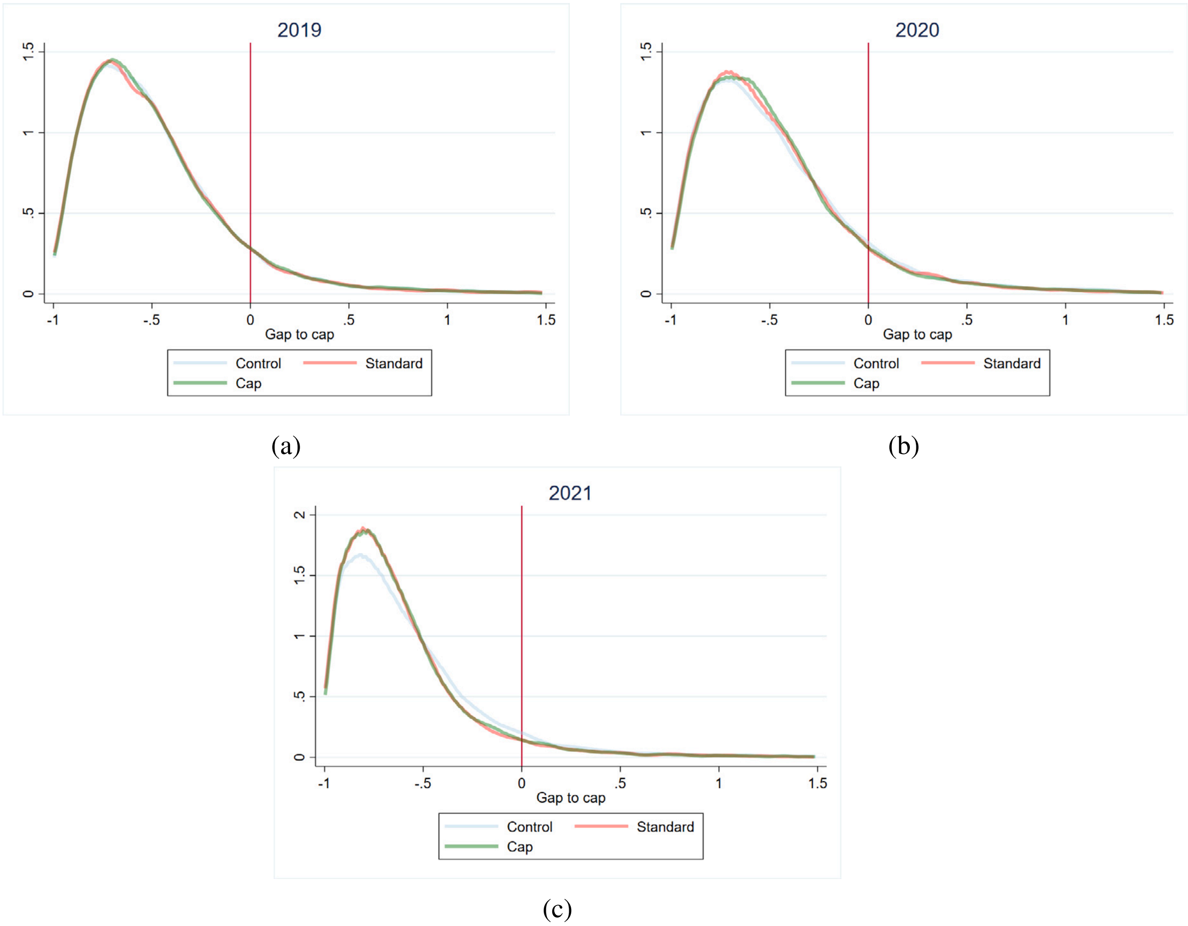

Fig. 3. Gap to the cap, by treatments and years. **Note**: the figures show the density functions of cumulative yearly disposal as a difference from the cap, expressed as a share of the cap in different years.

Results from pre-specified analysis are robust to MHT. Results are also robust to changes in how we compute the dependent variable in the analysis of volumes. In particular, we normalize the dependent variable using the individuals' cap. Such change makes the results on the intensive and extensive margin of disposal more readily comparable. The average and heterogeneous treatment effects are robust to this change (Appendix Table A.5).[19]

To further characterize how treatment effects vary along the distribution of yearly disposals, we plot the distribution of average cumulative disposals in the different treatments for the three years we observe in our data (Fig. 3). We present the yearly cumulative disposal as a percentage deviation from the annual cap. Points to the left of the vertical red lines indicate annual disposal below the cap, while points to the right indicate disposal above the cap. As expected, we do not detect any difference in the distributions of control and treated families before the intervention (Panel a). Differences between the three conditions are more evident in Panels (b) and (c). As already mentioned above, low-disposal households, to the left tail of the distribution, do not react to the intervention. Households with very high disposal, to the far right of the distribution, are similarly unresponsive, consistent with the lack of treatment effects on the volume of disposals exceeding the cap (Appendix Table A.3). We detect the largest changes in the middle of the distribution. Specifically, among treated households, we observe a reduction in the share of households lying below and just above the cap, particularly in 2021, and an increase in the share of households lying around the median of the distribution, relative to the distribution for the control group. This seems to confirm the results presented in Table 3, where stronger treatment effects are found among above-median disposal households.[20] Finally, we detect no evidence of bunching in the disposal distribution below the cap, which would indicate strategic sorting of users to avoid paying per piece for additional disposals. Our data may, however, not be adequate to detect bunching, given the small number of observations around the cap.[21]

[19] In the heterogeneous analysis in Column 3, we distinguish households with high and low pre-treatment disposal using the distribution of pre-treatment levels as a share of individuals' cap.

[20] Appendix Figure A.6 shows the cumulative distribution functions which confirm the same results.

Table 4
Treatment intensity effects on weight and quality of waste.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Unsorted waste log weight		Sorted waste log weight					
			All materials		Paper	Cardboard	Plastic	Glass and Cans
Post*Int treat	−0.160***		0.513***		0.551**	0.552*	0.481***	2.442
	[0.052]		[0.131]		[0.215]	[0.281]	[0.178]	[1.589]
Post*Int treat (std)		−0.184		0.587**				
		[0.261]		[0.241]				
Post*Int treat (cap)		−0.143		0.457*				
		[0.256]		[0.251]				
Avg weight (tonnes)	4.790	4.790	1.417	1.417	1.185	0.935	0.928	5.293
P-val (Int(std)=Int(cap))		0.935		0.758				
Panel B:			Sorted waste quality log score					
Post*Int treat			0.078		0.201**	0.196***	−0.175*	−0.624
			[0.054]		[0.095]	[0.062]	[0.102]	[1.353]
Post*Int treat (std)				0.021				
				[0.144]				
Post*Int treat (cap)				0.121				
				[0.120]				
Avg. Quality score			2.215	2.215	2.020	2.420	2.036	2.688
P-val (Int(std)=Int(cap))				0.679				
Observations	3,081	3,081	3,477	3,477	1,007	1,103	1,038	329
N. Of routes	105	105	411	411	129	67	131	84

Note: This table reports panel estimates of the effect of the intensity of treated households along the route on weight of unsorted and sorted waste (Panel A) and quality of sorted waste (Panel B), overall and by different materials. "Int treat", "Int treat (std)" and "Int treat (cap)" are the average (across collection points) volume of unsorted waste disposed of by households in the (pooled) treatment, standard and cap treatments as a share of the total volume disposed of by all households in the study sample in each collection point. The unit of analysis is a route-day. Post takes the value of one from July 2020, and zero before. The period considered is from January 2020 to October 2021. In Panel A, the dependent variable is the natural logarithm of the weight of unsorted and sorted waste collected along a route in a day. In Panel B, the dependent variable is the natural logarithm of the average quality score of the sorted waste along the route in a day. The model includes routes and month-fixed effects. Models in columns 1–2 also include material fixed effects. The mean of the dependent variable is expressed in liters at the bottom of Panel A and in a score ranging from 1 to 3 at the bottom of Panel B. Standard errors, in squared brackets, are clustered at the route level. P-values for the hypothesis indicated are reported at the bottom of each panel. *** significance at the 1% level, ** at the 5% level, * at the 10% level.

The pre-analysis plan for this study includes a third dimension of heterogeneity: the quarter of reference of the report. As mentioned in Section 3, implementation issues affecting the delivery timing of the reports prevent us from credibly evaluating this aspect. We nonetheless run the pre-registered specification, interacting the treatment with the quarter of reference of the report. The effect of the standard treatment on the volume of disposals is significantly stronger than that of the cap treatment in all but the first quarter of the second year (Appendix Table A.6) (p=0.171).

5.2. Behavioral responses

We have established that the report is effective in reducing unsorted waste volume and helping households keep their annual waste below the contractual cap. We now analyze other dimensions affected by the program that have important environmental implications.[22]

5.2.1. Impact on the weight and quality of sorted and unsorted waste

From an environmental perspective, the reduction in the volume of waste disposal induced by the program is an important outcome only if it is associated with a reduction in the quantity of waste. The effectiveness of the program on both the volume and the weight of waste is achieved only under the assumption that households do not change their bag-filling behavior. If each 30-liter bag of unsorted waste is filled with the same quantity of waste before and after the program, the reduction in the volume of waste implies a reduction in the quantity of waste. However, this may not be the case. On one hand, the treatment, by encouraging a reduction in the number of disposals, may lead users to fill each bag with more waste. In this case, the reduction in nominal volume would not correspond to a reduction in the quantity of waste produced. On the other hand, if the treatment caused a reduction in the quantity of unsorted waste produced, households would take longer to fill out each bag. The longer time needed to accumulate the same volume of unsorted waste may result in increased inconvenience of in-home storage, due, for instance, to stronger smells. As a result, households may dispose of bags containing less waste, and thus reduce the frequency of disposals by less than would be possible given the reduction in the quantity of waste produced. In the first scenario, the amount of waste per disposal

[21] Studies finding evidence of bunching in public economics typically employ several million observations from administrative tax records (Saez, 2010; Mortenson and Whitten, 2020).

[22] The analysis that follows is not pre-specified.

would increase, and our treatment effects based on volume would overestimate the actual reduction in the quantity of waste. In the second scenario, the opposite would be the case. Distinguishing between these two scenarios is important from an environmental perspective, as waste weight and composition are more relevant than nominal volume.

Another important outcome of the program that is worth evaluating is its effect on the quantity of sorted waste. Reducing the volume and weight of unsorted waste may require behavioral changes, from avoiding the purchase of products with a lot of packaging, re-using products instead of disposing of them, and, most importantly, increasing sorting. The report can increase households' efforts in sorting waste directly and indirectly. First, households can reduce the disposal of unsorted waste, which is targeted by the report, by increasing sorted waste. This is an indirect effect of the report. Second, the report also directly affects sorted waste, because the report's tips section provides suggestions on how to improve sorting and directly stresses its importance.

Finally, from an environmental perspective, it is crucial to analyze whether a reduction in unsorted waste and an increase in sorted waste comes at the expense of a lower quality of sorting.

To analyze the effect of the program on these additional outcomes we turn to truck-route-level analysis.[23] Recall that routes are a sequence of collection points followed by trucks that collect specific materials (unsorted, paper, cardboard, glass and plastic). At the end of the truck's route, an operator weights and, in the case of sorted waste, rates the quality of the truck's content. We estimate the following equation:

$$y_{rsd} = \beta IntTreat_r * Post_t + h_s + g_r + n_t + \varepsilon_{rsd} \tag{4}$$

where y_{rsd} is the natural logarithm of the total weight of waste of type s collected along route r in date d.[24] Types of waste are: unsorted and sorted. The latter comprises paper, cardboard, plastic, glass and cans. $Post$ is a dummy variable that becomes one after the delivery of the first report, i.e., July 2020; h_s is the material fixed-effect; g_r is the route fixed-effect, and n_t is the month-by-year fixed-effect.

$IntTreat_r$ is a continuous variable that measures the intensity of exposure of the route r to the treatment, based on where households are expected to dispose of their waste. We compute $IntTreat_r$ as follows. First, for each collection point c along the route r, we calculate the volume of unsorted waste disposed of in the collection point c from the treated households (N) in the pre-treatment period ($\sum_{i=1}^{N} volume_i^c$), as a share of the volume of unsorted waste disposed of in the collection point by all households ($N + J$) in the pre-treatment period ($\sum_{i=1}^{N} volume_i^c + \sum_{j=1}^{J} volume_j^c$). This measure gives us the intensity of treatment exposure at the collection point c:

$$IntTreat_c = \frac{\sum_{i=1}^{N} volume_i^c}{\sum_{i=1}^{N} volume_i^c + \sum_{j=1}^{J} volume_i^c} \tag{5}$$

Given that the truck route follows a fixed sequence of collection points, we take the average of the collection points (K)' treatment intensity exposure over each truck route to have a measure of the treatment intensity at the route level.[25] This is our unit of analysis for sorted waste:

$$IntTreat_r = \frac{1}{n} \sum_{c=1}^{K} IntTreat_c \tag{6}$$

Table 4 shows regression results for the unsorted waste weight (Panel A, Columns 1–2). We find that as the share of treated users increases along a given route, the weight of unsorted waste collected by trucks significantly decreases, regardless of the type of treatment. This exploratory analysis provides evidence that the program contributed to reducing the weight, not just the volume, of unsorted waste.[26]

Table 4 also reports results for the impact of the intervention on the quantity of recycled waste. We find that the intensity of the intervention affects the weight of sorted waste (Panel A, Column 3). In particular, a 10-percentage points increase in treatment intensity, from an average of 0.5 to 0.6, is associated with a 5.1% increase in the weight of sorted waste along the route.

The effect is not different by treatment (Column 4). The reduction in the disposal of unsorted waste thus appears to go hand in hand with an increase in the weight of sorted waste. We replicate this analysis separately for each type of sorted material: paper, cardboard, plastic, glass and cans (Columns 5 to 8). The point estimates are positive for all materials but statistically significant only for paper, cardboard, and plastic. The differential effect of the program on the specific materials can be due to a combination of factors. First, the tips in the report might have targeted specific materials. Second, the margins of improvements vary by type of

[23] Individual-level data do not allow us to investigate treatment effects on waste weight and quality because these outcomes are only observed at the route level.

[24] We employ the logarithm of the weight as it better performs than the level measure, in particular in the sorted waste analyses. This may be due to the dispersion of the dependent variable.

[25] As an example, in the sample of routes used to analyze the effect of the program on sorted waste, the share of waste disposed of by treated households in collection points along the route is 0.5 on average and ranges from 0 to 0.92. The average intensity of the two types of treatments along the routes calculated in the pre-treatment period is 0.28 and 0.25 for the standard and the cap report, respectively. The intensity varies by route. There are routes where none of the households were treated and routes where the majority of them received the report. As described in Section 4, routes differ in the number of collection points they cover. As the number of collection points increases, the intensity converges to 0.66, which is the percentage of treated households in the program (Appendix Figure A.5). On the contrary, routes with a small number of collection points display a higher dispersion.

[26] The differences in the empirical approaches do not allow us to quantitatively compare the decrease in unsorted waste volume estimated in Table 2 and the decrease in weight in Table 4.

materials. For example, while the percentage of glass sent for recycling is already quite high in Italy (78% in 2019), plastic has a recycling rate of only 45% (Pettinao et al., 2019).

To evaluate the program's impact on the quality of sorted waste, we estimate Eq. (4), where y_{irt} is now the natural logarithm of the average quality of sorted waste of truck i, running route r and month t. The quality is measured using a 3-point scale. Results are reported in Panel B of Table 4. We find no evidence of a lower quality of the sorted waste when we analyze all materials jointly (Column 3). When analyzing each material separately, we find that collection quality improves for paper and cardboard, while it decreases for plastic as treatment intensity increases. The negative effect of plastic may be explained by the higher complexity of recycling this material: not all types of plastic can be recycled, and users attempting to recycle more plastic may sort by mistake non-recyclable plastics.

Appendix Figure A.7 shows the dynamics of treatment effects for the quantity of unsorted and sorted waste and the quality of sorted waste. The figure provides support to the identifying common trend assumption.

In a robustness check, we repeat the analysis of the weight of unsorted and sorted waste and the quality of sorted waste, restricting the sample to the routes that are observed at least once both in the pre and post-treatment periods. This is done for the pooled model with all materials in Appendix Table A.7 (Columns 4 and 7). Results are consistent with the ones presented above. We also change the operationalization of the independent variable using the average share of treated households along the route instead of the average share of volume disposed of by treated households. Results are consistent (Appendix Table A.7, Columns 2, 5, and 8). Finally, we estimate the outcomes in levels. Results are similar, although less precisely estimated (Appendix Table A.7, Columns 3, 6, and 9).

To conclude this section, we must consider how the empirical strategy that we use may affect our estimates. In particular, our choice to include in the analysis only routes observed multiple times may lead us to underestimate the treatment effects. This would be the case if the treatment caused a change in routes due to its impact on the quantity of waste. For example, the increase in the quantity of sorted waste caused by the treatment may have resulted in shorter routes, as trucks filled out after fewer collection points. These routes, most affected by the treatment, would be excluded from the analysis given our inclusion criteria. We have suggestive evidence that this indeed may have occurred in the sample of sorted waste: the average number of collection points covered by a route is 46 at baseline and 44 in the experimental period, a statistically significant difference ($p = 0.019$). We should, therefore, consider our estimates of the impact of the program on sorted waste as a lower bound of the treatment effects on waste sorting.

5.2.2. Impact on access to waste collection centers

The hybrid PAYT system may induce customers to reduce unsorted waste by exploiting the opportunity to access WCC. In WCC, people can dispose of bulky items that do not fit in unsorted waste collection points. In addition, WCC can be used to dispose of items that are more correctly disposed of in dedicated bins, such as electronics.

We explore the treatment effects on the probability of accessing and the number of accesses to WCC in Appendix Table A.8, using a household-month specification like in 1 and 2. The treatment has a positive but insignificant impact on the likelihood of visiting these centers in the month (Column 1). However, households in the cap treatment are weakly significantly more likely to visit WCC than the control group (Column 2). No impact is detected on the number of monthly visits (Columns 3–4).

5.2.3. Impact on littering and illicit disposal

Finally, in Appendix Table A.9, we analyze the effect of the intervention on illicit disposals proxied by littering around the collection points. We estimate the following equation:

$$y_{ct} = \beta_1 Post_t + \beta_2 IntTreat_c * Post_t + g_c + n_t + \varepsilon_{ct} \tag{7}$$

where y_{ct} measures the average cleanliness of the collection point c in week t, and is computed as the natural logarithm of the 4-point scale rating of the collection point c.[27] $Post$ is a dummy variable that becomes one after the delivery of the first report; g_c is the collection point fixed effect, and n_t is a week of the year fixed effect. $IntTreat_c$ is a continuous variable that measures the intensity of treatment in the specific collection point c, as described in Eq. (5). The value ranges from 0 to 0.99, and the average is 0.6.

We do not detect any increase in littering that would have resulted in a lower quality score of the collection points. Neither the treatment overall (Column 1), nor the two versions of the report analyzed separately (Column 2), have any impact on the cleanliness of the collection points. We cannot exclude that the program increased leakage to unregulated areas, as we have no data on them.

[27] Given the irregular frequency of the evaluation of the collection points, with some collection points being evaluated more than once a day, while others only once a week, we organize the data as a weekly panel.

6. Mechanisms

One of our main findings is the different effectiveness of the cap compared to the standard treatment on unsorted waste disposal. This differential effect can be explained by two possible reasons. First, users may be misinformed or have misbeliefs about their cap and their expected distance from it. Second, users may know this information, but be inattentive to it. Hence, the cap treatment, in principle, could work through the provision of information and correction of misbeliefs; or could serve as a reminder, offering the cap as a salient alternative reference point to the one provided by the social information. A better understanding of which mechanism is in place would help us derive possible welfare implications of the intervention. If the cap information increases awareness, then the resulting decisions should reflect the users' preferences to a greater extent, and thus improve welfare. If, instead, the cap treatment affects decisions through the provision of a salient, potentially arbitrary reference point, then it may, in principle, shift consumers' decisions away from their preferences under full information, with potentially negative consequences on their welfare.

By embodying information on the tariff structure, the cap treatment allows consumers to better understand the economic costs of higher disposal volumes. If users care about economic savings, this information may motivate them to keep their disposals below the threshold. The literature on the effectiveness of PAYT schemes confirms that economic incentives matter for curbing waste production (Bueno and Valente, 2019; Colussi et al., 2022). In our setting, the relevance of this information varies depending on the volume of disposal relative to the cap. For example, users without any previous experience of exceeding the cap may value this information more than users who have passed the cap before. The former may have little awareness of the level of the cap and hence be highly responsive to this information. Second, users far below the cap, who face a zero marginal cost of disposal, should perceive lower incentive to further curb their disposals compared to users closer to the cap on both sides. The relevance of the economic incentives is, therefore, larger for users close to the cap. Finally, users far above the cap may not be able or willing to respond to the economic incentives built into the tariff.

The social norm represents a reference point for individuals, but so does the cap. The cap treatment adds an alternative reference point to the social norm, which users may measure their behavior against and strive to conform to. The volume of disposal relative to the cap is again crucial in affecting the relevance of this reference point. For users with disposal volumes below the cap, which constitute the majority of households, the salience of the reference point provided by the cap should induce an increase in disposal: seeing that the level of disposal, which the utility has deemed adequate for the household, is large relative to the household's current level of disposal may induce a reduced effort in curbing unsorted waste. The opposite should hold for users with disposal volumes above or just below the cap.

A comparison of the relative performance of the cap and standard treatments, however, does not allow us to be conclusive on which mechanism is at work. Based on the considerations above, the two mechanisms produce similar predictions on which treatment should be more effective in curbing unsorted waste on different types of users. Both the information and salience mechanisms predict that the cap treatment outperforms the standard one among users close to the cap on both sides, and possibly for users far above the cap; and underperforms relative to the standard one for users disposing below the cap and below what is provided by the social norm, as in this case two pieces of information, rather than one, encourage an increase in disposal.

Empirically, we find some support for the theoretical predictions above. The cap treatment is associated with a boomerang effect among low-disposal users, while the standard one is not. Other findings are instead at odds. The cap treatment is never more effective than the standard one, even among users who should be more responsive to the tariff information, such as those near the cap or far above it; or those with above-median baseline disposal volumes. The analyses presented so far do not yet allow us to distinguish which mechanism may be more relevant in our setting.

To distinguish between information provision and reference point salience, we therefore rely on additional data, and perform new exploratory analyses. Specifically, we extend our data and analysis to the post-treatment period, from November 2021 to December 2022. From November 2021, customers in both the cap treatment and the control group started receiving the standard report. By examining the behavior of users who first received the cap treatment and then received the standard treatment in the post-treatment period, we can analyze the persistence of the message conveyed by the cap treatment after its removal. Since salience effects are typically short-lived, while information should remain, if salience were the main channel we would expect the differential effect of the cap treatment to disappear after its removal. The literature on reference points confirms that, when such reference points are arbitrary, they have only short-lived effects on behavior (Ariely et al., 2003; Kahneman, 1992). On the other hand, any understanding of the tariff and cap gained in one year may still be relevant the following year since the cap is fixed for each household as long as its composition or health status does not change.[28]

For this analysis, we focus on customers belonging to the standard and cap treatments and split the study window into three non-overlapping sub-periods: pre-treatment (before July 2020); treatment (July 2020–October 2021); post-treatment (October 2021–December 2022) periods. We run a model similar to Eq. (2). Results are reported in Appendix Table A.10. We confirm that customers in the cap treatment dispose of higher volumes of unsorted waste than those in the standard one over the experimental period. This effect persists in the post-experimental period when the cap information is no longer available in the report. The point estimate is even larger in the post-experimental than in the experimental period, although the difference between the coefficients for the two periods is not statistically significant. This result suggests that the effect of the cap treatment is more likely to work through learning about the tariff scheme, rather than through increased salience of the reference point.

[28] This strategy is similar to the one used by Chetty et al. (2009) for a similar purpose.

Having established that increased awareness of the tariff scheme is likely to be behind the effect of the cap treatment, we now provide some explanations of our empirical findings that are at odds with the theoretical predictions above. Our results indicate that the information on the economic incentives of waste reduction never makes the cap treatment more effective than the standard one, even among users for whom such incentives should be more relevant. The standard treatment outperforms the cap one for most users. We consider different explanations for this finding.

First, it is possible that the incentives provided by the tariff scheme that we study are simply not strong enough to elicit effort on the part of users to curb disposals. The fact that households do not sort just below the cap indicates the limited influence of economic considerations on disposal volumes. A hybrid PAYT scheme, such as the one we focus on, creates a discontinuity in the marginal price of disposals. The marginal price is zero below the threshold and positive above it. If economic incentives were strong and households could perfectly control their disposals, we should observe bunching just below the notch created by the tariff scheme. The lack of bunching at the cap may be due to the features of the specific tariff that we study. The cap may be too generous and the marginal price above the cap may be too low to compensate households for the effort required to limit their disposals.[29] In any case, this mechanism does not explain why the cap treatment performs worse than the standard one, as at most it would predict a similar effectiveness of the two treatments.

Second, the cap treatment may not strengthen the effect of the social information because the cumulative effect of multiple nudges is lower than the sum of the effects of each nudge in isolation. Bonan et al. (2020) report that additional nudges produce small marginal gains when they reinforce existing ones; and Bonan et al. (2024) provide evidence of the reduced effectiveness of multiple nudges due to the high load that they impose on individuals' cognitive ability and attention. Similar to the previous explanation, this one would also predict that adding the information on the cap to the social information would not improve the latter's effectiveness, not that it would reduce it.

Finally, the cap treatment may reduce the effectiveness of the social information because of crowding out. Specifically, the cap treatment, by making salient the extrinsic incentives tied to waste reduction, may crowd out users' intrinsic motivation to preserve the environment and to conform to pro-environmental norms of behavior (Rode et al., 2015; Bowles and Polania-Reyes, 2012; Bénabou and Tirole, 2006; Pellerano et al., 2017; Sudarshan, 2017). If simply mentioning the extrinsic incentives crowds out any intrinsic motivation to reduce waste production, then the crowding-out mechanism should affect all users, regardless of their baseline level of disposal or experience with exceeding the cap. When economic incentives are strong enough, their influence on behavior may offset that of crowding out. This explanation would account both for the lower effectiveness of the cap treatment relative to the standard one for most users, and for their similar effectiveness only among users facing the stronger economic incentives to remain below the cap. Crowding-out could also explain the persistent difference between the standard and cap treatments, as existing evidence demonstrates how intrinsic motivation, once crowded out, cannot be brought back through the removal of the extrinsic incentives (Gneezy and Rustichini, 2000a).

7. Conclusions

Our results show that a treatment based on a social norm alone is significantly more effective than one highlighting the tariff cap in curbing the volume of unsorted waste disposals. The two treatments are equally effective in reducing the likelihood of exceeding the cap, and neither leads to any reduction in disposal volume beyond the cap. Both treatments are more effective for households with high disposals at baseline. Although we are limited in our ability to examine the dynamic effects of the treatments, we can note that the standard treatment is never less effective than the cap one.

The results confirm the effectiveness of social information in shifting behavior toward the descriptive norm displayed in the report, even among users who, thanks to their low disposal volumes, do not benefit in economic terms from doing so. Moreover, the report has persistent effects even in a context where the opportunities for technological investments are limited, as is the case for waste. Households appear to achieve a reduction in disposal through behavioral changes, such as increasing the quantity of sorted waste. Households increase their effort in sorting and acquiring new habits over time, contributing to the persistent effectiveness of the intervention. The changes we detect are not accompanied by negative externalities in terms of reduced quality of sorting or littering.

The welfare implications of our findings are nuanced. Providing consumers with information that increases their awareness of the consequences of their decisions improves the quality of their choices and their welfare as a result. However, if economic information crowds out individuals' intrinsic motivation to preserve the environment, then such information may backfire. This effect may occur particularly if consumers intrinsically care about environmental conservation. This is especially true if the economic incentives faced by consumers are not strong enough to offset the crowding-out effects (Gneezy and Rustichini, 2000b).

Our study has limitations. First, we conduct our RCT in a setting with very high levels of sorting, indicating high environmental concerns among citizens. It is unclear how our results would generalize in a less virtuous setting. Second, the tariff that we study is characterized by very generous caps and low price-rate for disposals above the cap. It would be interesting to investigate the robustness of our results to changes in the tariff. Finally, our analysis of the interaction between the cap and the norm nudges, particularly its dynamics, is limited by implementation constraints. This remains an interesting direction for further research.

[29] We acknowledge that we may have too few observations around the cap to be able to detect bunching. Also, we cannot rule out that households, even treated ones, may be unable to sort below the cap by perfectly controlling their level of disposal. The absence of strategic bunching, which should occur when consumers face block rate schemes, is also common for other resources like electricity, natural gas, water, and whenever consumers cannot predict consumption with precision (Alberini et al., 2022).

CRediT authorship contribution statement

J. Bonan: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **C. Cattaneo:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **G. d'Adda:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **A. Galliera:** Writing – review & editing, Validation, Data curation, Conceptualization. **M. Tavoni:** Writing – review & editing, Validation, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Additional figures and tables

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