The Scandinavian
Journal of Economics

Scand. J. of Economics 117(4), 1204–1229, 2015
DOI: 10.1111/sjoe.12122

Do Not Trash the Incentive! Monetary Incentives and Waste Sorting*

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Abstract

In this paper, we examine whether combining non-monetary and monetary incentives increases municipal solid waste sorting. We empirically investigate this issue, exploiting the exogenous variation in waste management policies experienced during the years 1999–2008 by the 95 municipalities in the district of Treviso (Italy). Using a panel regression analysis, we estimate that pay-as-you-throw (PAYT) incentive schemes increase the sorted-to-total waste ratio by 17 percent, and that their effect reinforces that of a door-to-door (DtD) collection system, which is equal to 15.7 percent. Moreover, the panel structure of our dataset allows us to find learning and spatial effects associated with both PAYT and DtD.

Keywords: Environment; pay-as-you-throw (PAYT); waste management

JEL classification: *D*01; *D*78; *Q*53

I. Introduction

Historically, households used to take their mixed waste to communal bins provided along the streets, and they were charged a flat-fee related to parameters such as the house size and/or the number of household members. Local administrators progressively encouraged householders to sort their waste and to put the different materials in dedicated bins, still provided along the street, while keeping the same pricing system. Only more recently,

*We thank the *Agenzia Regionale per la Prevenzione e Protezione Ambientale del Veneto* (ARPAV), *Osservatorio Rifiuti e Compostaggio* (ORC), and the three consortia (Priula, Savno, and TV3) that manage waste in the district of Treviso for kindly providing us with the data and technical information. We further thank Viola Angelini, Paolo Buonanno, Raffaele Miniaci, Giacomo Pasini, Alessandro Martinello, and Sigrid Suetens for useful suggestions.

municipalities decided to collect waste door-to-door (DtD) to promote sorting. The DtD collection is a curbside collection system requiring users to separate their waste at home, usually placing it in dedicated personal bags or bins. In addition to introducing DtD, some local administrators replaced the flat-fee with the so-called pay-as-you-throw (PAYT) pricing system that links the cost for the user to the amount of residual (unsorted) waste produced. Previous research shows that the joint adoption of DtD and PAYT has produced outstanding results with an increase of the sorted waste ratio (SWR; i.e., the ratio of sorted to total waste) between 25 and 35 percent (see Kinnaman, 2006; Allers and Hoeben, 2010). However, to the best of our knowledge, no one has tried to separate the net effects of DtD and PAYT.

The goal of this paper is to study the effectiveness of incentives in municipal solid waste disposal. We disentangle and measure the effect of PAYT from the effect of DtD on the users' production of municipal solid waste. We believe that a measure of the net effect of PAYT is necessary to make a proper assessment of the pricing system, and to provide useful insights for policy makers. In principle, the effect of the monetary incentive represented by PAYT can enhance, leave unchanged, or reduce the effect of the non-monetary incentive represented by DtD. In fact, as suggested by the literature on behavioral economics (e.g., Gneezy and Rustichini, 2000; Benabou and Tirole, 2003; Ariely *et al.*, 2009), the introduction of a pricing system that sets a price for the production of unsorted waste might crowd out users' intrinsic motivation to sort, and therefore might substitute the internalized motivation to sort (Thogersen, 2003).

For our empirical analysis, we collected annual data on waste disposal covering the years 1999–2008 for the 95 municipalities in the district of Treviso, Italy. All municipalities in the district were implementing a waste sorting program, either drop-off or DtD, using flat-fee or PAYT payment methods. This environment is unique for at least three reasons. First, prior to the period we consider, a regional law divided the district into three geographic zones, each managed by a different consortium to which most municipalities belonged. This means that nearly all the municipalities in our sample were not directly responsible for the decisions on waste management; they just followed the policy decided by the consortium. We argue that this exogenous intervention reduces the potential endogeneity problem that is often present in other studies. Second, our sample includes a wide heterogeneity of policies on waste collection (drop-off, DtD) and payment methods (flat-fee, PAYT) that allows us to estimate the effect of these policies separately. Third, the panel structure of our dataset permits us both to control for exogenous features, such as an increasing awareness of waste sorting, and to isolate potential learning effects across years and spatial effects across municipalities. In addition, we merged this dataset with official data on the demographic characteristics of each municipality, as provided by the Italian National Institute of Statistics (Istat) and further elaborated by the statistical unit of the Veneto region. The final dataset allows us to control for the main relevant characteristics of the municipalities and their inhabitants, and to estimate the effect of these variables on the SWR.

Our results show that DtD and PAYT have significant effects of similar size. The adoption of PAYT raises the SWR by 17 percent, and this effect is additive to the effect induced by DtD and equal to 15.7 percent. The positive effect of PAYT on the SWR originates from an increase in the amount of sorted waste and a decrease in the amount of unsorted waste. The two variations compensate each other and, as a result, the amount of total waste remains unchanged.

Our dataset also allows us to investigate the indirect effects of the waste management policies. Local administrators are skeptical about introducing PAYT because this pricing system might induce users to hide part of their waste in order to pay a lower fee (e.g., by way of waste burning, illegal dumping, or waste tourism; see, e.g., Fullerton and Kinnaman, 1995; Levitt and Dubner, 2009).

We find that when PAYT is implemented and most of the adjacent municipalities use drop-off collection and flat-fee billing policies, the SWR increases by a further 13.7 percent. Our analysis then suggests that PAYT induces illegal dumping, although we observe that its effect is only relevant for those municipalities starting from high SWRs prior to its introduction. This result, together with the indirect effects of the policies, suggests that decisions about the policy programs would benefit from coordination between adjacent municipalities.

In Section II, we discuss the theoretical background and present our research hypothesis. In Section III, we discuss our data, and in Section IV, we empirically estimate the effect of the adoption of PAYT on sorting behavior. We conclude in Section V. The Online Appendix provides further details on the model and the data.

II. Theoretical Background and Research Hypothesis

In this section, we present our research hypotheses in connection with the existing body of literature. In Online Appendix A, we provide a basic theoretical formalization of our framework.

Starting from the work by Kinnaman and Fullerton (1999), the household choice of sorting waste has been modeled as a utility maximization problem. The household is assumed to have a limited amount of time to be allocated between work – which allows for consumption – and handling waste produced by the consumed goods. Time devoted to handling waste is subtracted from work, and therefore it represents an opportunity cost for the household. Municipalities can implement two alternative policies, one regarding the collection system (DtD versus drop-off) and one regarding the price system for the disposal of waste (PAYT versus flat-fee).

When a drop-off collection system is implemented, households have to transport (sorted and unsorted) waste to different bins placed in the streets. A DtD collection system makes it more convenient to sort waste compared to a drop-off system. In fact, it allows a household to save time, because the different waste fractions are stored at home in specific bins and collected on different days rather than dropped into the bins located in the streets. DtD represents a non-monetary incentive aimed at promoting household sorting by reducing its cost (see Reschovsky and Stone, 1994; Kinnaman and Fullerton, 1999). In the case of a flat-fee scheme, households pay a fixed price irrespective of the quantity of waste produced and sorted, while in a PAYT scheme they pay a price for each unit of waste left unsorted. A PAYT scheme then represents a monetary incentive aimed at reducing the quantity of unsorted waste.

Based on this framework, we formulate two research hypotheses related to the effect of introducing monetary and non-monetary incentives on waste sorting. Our first hypothesis refers to how the change of collection system from drop-off to DtD affects the sorting behavior of households.

Hypothesis 1. *The adoption of a DtD collection system decreases the quantity of unsorted waste and increases the quantity of sorted waste, increasing the SWR.*

In other words, the introduction of a DtD collection system encourages sorting by making it easier for the household, and reduces the cost of transporting waste from the house to the bins.

The second hypothesis refers to the effect of the adoption of a PAYT payment scheme in the presence of DtD collection.

Hypothesis 2. *The effect on waste sorting of PAYT, net of DtD, is negative.*

Following the results in Thogersen (2003) and Oskamp *et al.* (1991), the effect of PAYT is based on the concept of intrinsic motivation as a lower cost of sorting for a community with environmental concerns. Introducing a monetary incentive to sort (such as PAYT, but not DtD) might have a negative effect on sorting as it can be interpreted as a price not to sort (see the literature on motivational crowding out; e.g., Gneezy and Rustichini, 2000; Benabou and Tirole, 2003). If PAYT has a negative impact on intrinsic motivation, then we expect its effect to diminish the one of DtD inducing households to sort less compared to the case in which a DtD plus flat-fee scheme is provided.

The novelty of our study is to estimate the net effect of PAYT and DtD on waste sorting, disentangling the effect of PAYT in the presence of DtD.

The previous body of literature that investigates the effectiveness of different waste management policies can be divided into two main streams. The first stream uses data from self-reported household surveys to estimate the effectiveness of the PAYT policy (see Fullerton and Kinnaman, 1996; Missios and Ferrara, 2011). The advantage of household-level studies is that they have rich micro datasets; however, these studies are subject to self-selection bias and all the problems common to self-reported data. The second stream is more similar to our approach as it studies community-level data. A leading contribution is Kinnaman and Fullerton (2000), who run a cross-section analysis on some US municipalities. They find that PAYT in combination with DtD has a negative effect on the production of unsorted waste and a positive effect on sorted waste. However, their estimates might suffer from the possibility of endogenous policy choices. When controlling for endogeneity, the joint effect of DtD and PAYT on unsorted waste increases. Moreover, because their dataset comprises only one year, they could not measure effects over time. Dijkgraaf and Gradus (2009) analyze an eight-year panel of 496 Dutch municipalities. They find that adopting PAYT consistently reduces the amount of unsorted waste, and that this effect persists over time. However, their estimates do not control either for the type of collection system adopted or for municipality-specific characteristics. In contrast, Allers and Hoeben (2010) use a 10-year dataset of Dutch municipalities, and do control for municipality-specific characteristics but not for the collection system adopted, making it impossible to disentangle the effects of the pricing system from the effect of the collection system.

Our contribution to this literature is to analyze data from similar municipalities that implemented different policies during the same period. We are able to disentangle the effect of the pricing system from the effect of the collection system, controlling for specific characteristics of each municipality. We are also able to measure the effect of these policies over time and to obtain an estimate of the net effect of monetary incentives, varying both the municipality and the context characteristics.

III. The Data

We collected data on the amount of waste produced annually between 1999 and 2008 in the municipalities of the district of Treviso in north-eastern Italy; further details on this small but highly populated district are given in Online Appendix B.1. Overall, we have 10 annual time-series observations for each of the 95 municipalities in the district. These municipalities implemented a drop-off waste-sorting program in the early 1990s, with dedicated containers placed along the street for the storage of glass,

Table 1. *Variables used in the analysis*

Variable	Description
Outcome variables	
Sorted waste	Annual production of sorted waste (kg per capita)
Unsorted waste	Annual production of unsorted waste (kg per capita)
Total waste	Annual production of total (sorted + unsorted) waste (kg per capita)
Sorted waste ratio	Sorted waste/Total waste (%)
Policy variables	
PAYT	= 1 if a PAYT program is active; = 0 otherwise
Years of PAYT	Number of years a PAYT program is active (apart from the first)
DtD	= 1 if a DtD program is active; = 0 otherwise
Years of DtD	Number of years a DtD program is active (apart from the first)
Spatial variables	
Adjacent to PAYT	= 1 if most adjacent municipalities implement DtD and PAYT; = 0 otherwise
Adjacent to DtD	= 1 if most adjacent municipalities implement DtD and flat-fee; = 0 otherwise
Adjacent to drop-off	= 1 if most adjacent municipalities implement drop-off and flat-fee; = 0 otherwise
Control variables	
Population density	Residents per square km
Under 14	Residents aged 14 or younger (%)
Over 65	Residents aged 65 or older (%)
Non-natives	Non-native residents (%)
Year X	= 1 if the data refer to year X (2000–2008); = 0 otherwise

Notes: The variable "Years of PAYT" is defined as follows: if a PAYT program started in year t^*, the trend variable for PAYT at year t is defined as $\max\{0, PAYT \times (t - t^*)\}$; an equivalent definition applies for DtD.

paper, and cardboard, plastic and cans, food (organic), garden, and residual (unsorted) waste.

The building blocks of our dataset are the following: (1) annual data on household sorted and unsorted waste production at the municipal level, provided by the Regional Agency for Environmental Prevention and Protection of Veneto (ARPAV, 1999, 2009);[1] (2) raw data on the demographic characteristics of each municipality, provided by the Istat, and further elaborated by the statistical unit of the Veneto region. Table 1 describes the main variables used in the analysis.

Importantly, in our dataset we observe different policies along two dimensions: the collection system (drop-off as opposed to DtD) and the

[1] Our data regard the total amount of municipal solid waste from domestic users, and do not include waste from, for example, schools, factories, hospitals, shops. The only exception is street sweeping that is counted together with unsorted waste for practical reasons. As a consequence, we underestimate the household SWR. However, estimates from the consortia suggest that the proportion of waste from street sweeping to the total amount of waste is lower than 2.5 percent of the total waste produced.

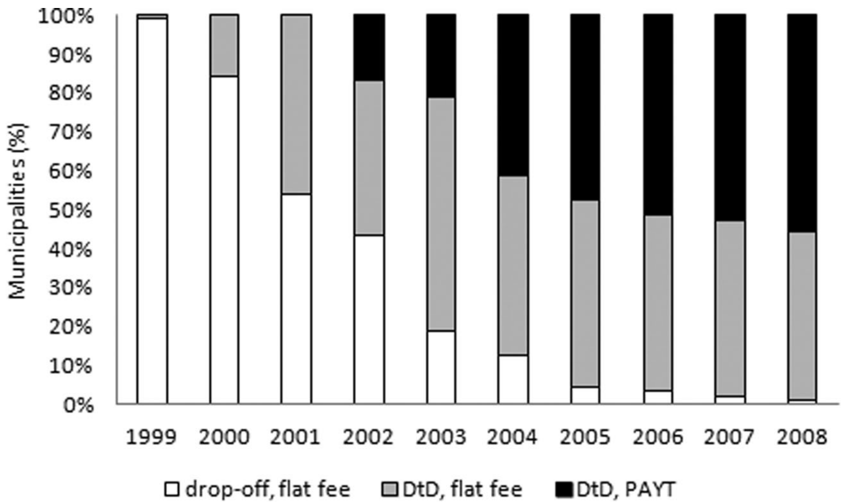

Fig. 1. Dynamics of policy management: municipalities implementing a given policy (percent)

pricing system (flat-fee as opposed to PAYT). The flat-fee is proportional to the floor area of the user's house (number of square meters) and to the number of household members. In contrast, the PAYT fee is made up of a fixed part – which is identical for all users or determined according to specific parameters (e.g., square meters of floor area) – and a variable part depending on the amount of unsorted waste produced.[2] Unsorted waste can be measured in terms of volume or weight; in our sample, the former solution, which happens to involve fewer management costs (Allers and Hoeben, 2010), is adopted.[3] Online Appendix C provides specific details on the collection and pricing systems in the district.

Figure 1 shows how widespread the various collection and pricing systems are in our dataset, separately by year. In 1999, 94 out of 95 municipalities in the district were implementing drop-off and flat-fee programs; the remaining municipality (Vedelago) was implementing DtD and

[2] The fixed part can slightly vary between municipalities, and can incorporate municipal taxes in addition to waste-related costs. The variable part – which represents the monetary incentive and is the focus of the paper – is independently determined by a consortium, and is the same for all the municipalities within the consortium (see Online Appendix B.3 for more details).

[3] In fact, PAYT-based pricing can be linked to either the mass or the frequency of waste. The latter aspect might give rise to something like the infamous "Seattle Stomp", where residents compact their waste to reduce the number of times bins need to be emptied. Although less expensive to implement and manage, volume-based fees seem to be less effective than mass-based fees in reducing the production of unsorted waste (Allers and Hoeben, 2010).

flat-fee programs. In 2000, municipalities gradually started changing policy: as of 2008, 41 out of 95 were implementing DtD and flat-fee programs, 53 were implementing DtD and PAYT programs, and just one municipality (Treviso) was still using drop-off and flat-fee programs. Hence, our dataset includes municipalities with three types of waste management system: (i) drop-off and flat-fee programs (306 observations); (ii) DtD and flat-fee programs (372 observations); (iii) DtD and PAYT programs (272 observations). Municipalities can switch from group (i) to group (ii), and from group (ii) to group (iii), on a yearly basis. If they are willing to switch from group (i) to group (iii), they first make an intermediate step to group (ii). This step takes no less than one year. Note that we observe no municipalities implementing drop-off and PAYT programs. In fact, drop-off and PAYT programs are rarely seen in practice (Reschovsky and Stone, 1994; Kinnaman, 2006) because they make it extremely difficult to detect users' incorrect behavior (i.e., mixing residual with sorted waste).

Our key variable is the municipal solid SWR, which is the target variable commonly considered by policy makers (e.g., Eurostat, 2010).[4] In 2008, the SWR in the district of Treviso was excellent (68.5 percent on average) compared to the national average (30.6 percent), and many of these municipalities are now among the best practitioners of waste management in Italy (Legambiente, 2009) as well as in Europe, exceeding by far the targets of sorting set by the European Commission (Eurostat, 2010). In 1999, before the adoption of DtD and PAYT, the SWR in the district was 35.4 percent. Figure 2 shows the dynamics of the SWR in our sample, computing annual averages for each group of municipalities (excluding years with fewer than 10 observations). We observe an increasing trend in the SWR with all types of waste management systems, even the one with no incentives at all (drop-off and flat-fee programs). However, the SWR is steadily higher in the subsample of municipalities with both incentives (DtD and PAYT programs).

This evidence suggests that the excellent results achieved by the municipalities in recent years are possibly related to the change in waste management systems implemented over the decade we have analyzed. Our empirical exercise in Section IV investigates whether this is indeed the case or whether other observation-specific factors – such as those shown in the descriptive statistics in Table 2 – can explain the increase in the SWR.

[4] Because sorted waste is potentially recyclable, other authors use the term "recycling ratio" instead of sorted waste ratio.

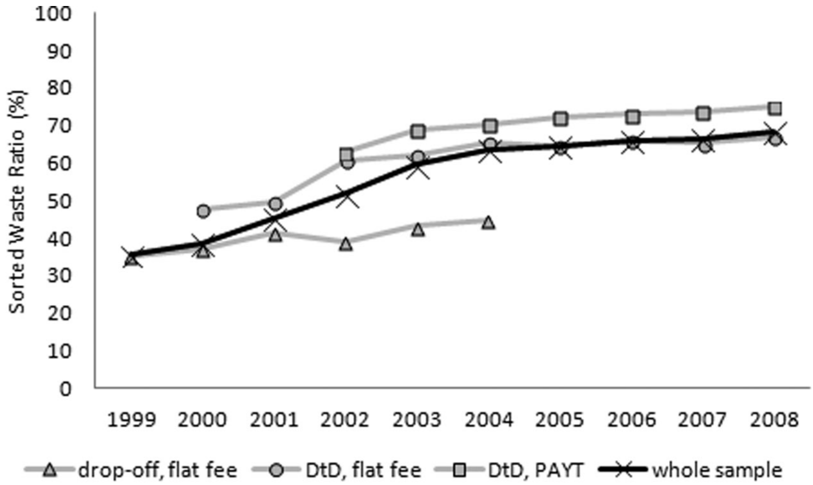

Fig. 2. Dynamics of the sorted waste ratio

Exogeneity of the Policy Assignment

In the late 1980s, a regional law divided the district into three geographic areas and, in each area, encouraged the creation of one independent, non-profit consortium of municipalities to exploit economies of scale. The regional authority asked – but did not force – each municipality to join exclusively the consortium responsible for its area. From the moment a municipality joins the consortium, it delegates all decisions on waste management to the consortium.

The mayors of all adjacent municipalities elect by a majority vote the director and the board of managers of the consortium, who are the only ones responsible for every single decision about the pricing and collection systems of municipal, industrial, and agricultural solid waste.

At the end of 2008, 91 municipalities out of the 95 in the district were members of the consortium operating in their area; these municipalities joined their consortium in different years as they had to wait until the expiration of previous waste management contracts.[5] Four municipalities remained independent, essentially for structural or geographic reasons; further details on the history of these municipalities and consortia are given in Online Appendix B.2. Our analysis, as shown in Section IV, is based

[5] Before the law was introduced, municipalities were in charge of the management of solid waste disposal, and they used to contract the provision of this service through external companies. In many cases, before joining a consortium they had to wait until the expiration of previous waste management contracts; see, for example, http://www.comune.morgano.tv.it/ecologia.asp for the municipality of Morgano.

Table 2. *Descriptive statistics: average values*

Sample	All	DtD and PAYT	DtD and flat-fee	Drop-off and flat-fee
Sorted waste	198.60	243.96	211.50	142.59
Unsorted waste	140.34	90.76	129.78	197.25
Total waste	338.94	334.72	341.28	339.85
Total waste (aggregate tons)	3,341.76	3,454.45	2,788.73	3,913.90
Sorted waste ratio	58.98	72.95	62.20	42.65
PAYT	0.29	1	0	0
Years of PAYT	0.67	2.33	0	0
DtD	0.68	1	1	0
Years of DtD	2.19	3.54	3	0
PAYT × Adjacent to DtD	0.01	0.04	0	0
PAYT × Adjacent to Drop-off	0.01	0.03	0	0
DtD × Adjacent to PAYT	0.34	0.93	0.19	0
DtD × Adjacent to Drop-off	0.04	0.03	0.08	0
Drop-off × Adjacent to PAYT	0.03	0	0	0.10
Drop-off × Adjacent to DtD	0.04	0	0	0.11
Population density	316.11	368.37	281.44	311.82
Under 14	15.29	15.31	15.86	14.59
Over 65	17.38	17.30	17.19	17.70
Non-natives	7.43	8.83	8.65	4.70
Year	2003.50	2005.67	2004.26	2000.66
Observations	950	272	372	306

on 10 annual observations for all 95 municipalities. In a robustness check (available upon request), we repeated the analysis on a smaller sample, including only the municipalities belonging to one consortium, and only in the years following their joining. This restricted dataset includes 91 percent of the observations and confirms our benchmark findings.

While the consortia applied similar policies regarding the management of industrial and agricultural waste, they experimented with alternative policies on municipal solid waste management. We exploit this exogenous variation in the policies to disentangle the effect of the adoption of PAYT net of the effect of adopting a DtD collection. This environment resembles a quasi-natural experiment, because the collection and pricing systems are imposed on the municipality by the consortium and, hence, are not chosen directly by the former (see Online Appendix B.2 for more details).

We performed a battery of non-parametric median tests with the aim of exploring in more depth the exogeneity of the policy assignment in our data (see Online Appendix D.1). In summary, we find no evidence of a systematic difference between municipalities joining and not joining a consortium, between those adopting and not adopting a DtD program, and between those adopting and not adopting a PAYT program. This is consistent with the view that the assignment of a specific waste management system is exogenous.

Empirical Strategy

In our most general analysis, we use a difference-in-difference approach based on the following panel regression model, where i denotes the municipality and t denotes time:

$$\begin{aligned} Y_{it} &= \beta_0 + P_{it}'\beta_1 + S_{it}'\beta_2 + C_{it}'\beta_3 + \mu_i + \varepsilon_{it} \\ &= \beta_0 + \beta_{1,1}(PAYT_{it} \times DtD_{it}) + \beta_{1,2}DtD_{it} + \beta_{1,3}yearsPAYT_{it} \\ &\quad + \beta_{1,4}yearsDtD_{it} + S_{it}'\beta_2 + C_{it}'\beta_3 + \mu_i + \varepsilon_{it}. \end{aligned} \tag{1}$$

Here, β_0, β_1, β_2, and β_3 are coefficients to be estimated, μ_i represents time-invariant municipality effects, and ε_{it} is the error term. Our dependent variable Y_{it} is the logarithm of the SWR (discussed up to the first subsection of Section IV) or the logarithm of per capita (sorted, unsorted, total) waste in kilograms (second subsection of Section IV). The explanatory variables we consider in the analysis can be grouped in the three sets (P_{it}, S_{it}, C_{it}) of policy (P), spatial (S), and control (C) variables listed in Table 1, together with the dependent variables. Our analysis is aimed at evaluating the effects of the policy variables, while taking into account potential spatial and control effects. Specifically we consider the following groups variables.

Policy variables: variables indicating the waste collection (DtD as opposed to drop-off) and billing (PAYT as opposed to flat-fee) policies, as well as the number of years the DtD and PAYT policies are in action. Notice that PAYT is implemented only in the presence of DtD.

Spatial variables: variables informing on the waste collection and billing policies, in connection with the collection and billing policies of the adjacent municipalities. We expect the environment surrounding a municipality to influence our outcome variables, in terms of both waste tourism (i.e., movements of waste from PAYT and DtD municipalities to drop-off ones) and emulation (i.e., the tendency to imitate the virtuous behavior of near municipalities.)

Control variables: variables informing on population density, the proportion of young (under 14) and elder (over 65) individuals, and the proportion of non-native individuals in the municipality. Although they are not the focus of our research, we expect these variables to influence the production of sorted and unsorted waste. In particular, higher population density is found to have a negative effect on total waste while an unclear effect on sorted waste (Dijkgraaf and Gradus, 2009). Younger individuals should be more sensitive to environmental policies (due to recent massive information campaigns), and should therefore sort more (Baldassare and Katz, 1992). Similarly, elder individuals have more free time, and should therefore sort more (Dijkgraaf and Gradus, 2004) and produce less waste due to a frugal lifestyle (Jenkins, 1993; Fullerton and Kinnaman, 1994). In contrast, non-native residents might find it more difficult to sort waste because this requires clear understanding and good comprehension of the language (Dijkgraaf and Gradus, 2004).

Estimation is performed by means of a panel regression model with fixed effects. This model provides consistent estimates even if the specification omits relevant time-invariant variables on the structural characteristics of the municipalities; in general, the coefficients μ_i capture all the time-invariant heterogeneity among municipalities that is not explained with the other variables in the specification, such as municipality surface, intrinsic motivation, or efficiency of the public administration. In addition, this model turns out to describe the data in our sample generally better than pooled regression models (without municipality effects) and random-effects panel models (where municipality effects are absorbed in the error term); the results of these statistical tests are reported in the bottom parts of Tables 3–5.

Panel data like ours can exhibit cross-sectional dependence in the errors. For this reason, we tested all specifications for cross-sectional dependence using the Frees non-parametric Q-test (Frees, 1995). The test, reported at the bottom of Tables 3–5, always found evidence of cross-sectional dependence. In what follows, therefore, we report regression outputs with Driscoll–Kraay standard errors (STATA function `xtscc` v1.3, developed by Hoechle, 2007); for details, see Driscoll and Kraay (1998). This error structure allows for heteroskedasticity, and spatial and serial correlation (in the latter case, we consider a time lag of 2; results do not vary when taking different lags).

IV. Results

Our main results are shown in Table 3. We start the analysis by considering a specification with a dummy variable informing about the presence of a PAYT program, together with control variables on the year and characteristics of the municipality (Column 1). This analysis, which does not separate the effects of DtD and PAYT programs, suggests that PAYT raises the SWR by a large amount (28.9 percent). This figure is in line with previous estimates in the literature (see Allers and Hoeben 2010, for a review), derived from different datasets that do not distinguish between DtD and PAYT programs.

In Column 2, we enrich the specification by including a dummy variable informing about the presence of a DtD program. The combination of the two dummy variables on DtD and PAYT identifies the three groups of municipalities in our sample. In fact, (i) the variables DtD and PAYT

Table 3. *Effects on the (log) SWR*

Method: panel OLS with fixed effects	(1)	(2)	(3)
PAYT	0.289***	0.243***	0.208***
	(0.056)	(0.062)	(0.059)
Years of PAYT			0.024
			(0.014)
DtD		0.163***	0.177***
		(0.044)	(0.043)
Years of DtD			0.002
			(0.011)
Log(population density)	0.974	1.194**	0.993**
	(0.589)	(0.490)	(0.426)
Under 14	0.051***	0.042**	0.038**
	(0.015)	(0.014)	(0.015)
Over 65	0.005	0.015*	0.007
	(0.012)	(0.008)	(0.007)
Non-natives	−0.013	−0.010	−0.009
	(0.009)	(0.011)	(0.011)
Year 2000	0.118***	0.088***	0.089***
	(0.007)	(0.008)	(0.008)
Year 2001	0.257***	0.174***	0.173***
	(0.008)	(0.021)	(0.022)
Year 2002	0.192***	0.126**	0.144**
	(0.058)	(0.046)	(0.060)
Year 2003	0.441***	0.299***	0.302***
	(0.028)	(0.034)	(0.043)
Year 2004	0.438***	0.286***	0.292***
	(0.043)	(0.034)	(0.053)
Year 2005	0.444***	0.276***	0.276***
	(0.051)	(0.038)	(0.062)
Year 2006	0.456***	0.283***	0.275***
	(0.057)	(0.040)	(0.071)
Year 2007	0.455***	0.276***	0.256**
	(0.062)	(0.044)	(0.080)
Year 2008	0.459***	0.274***	0.244**
	(0.068)	(0.048)	(0.090)
Constant	−2.614	−3.880	−2.589
	(3.239)	(2.649)	(2.284)
Observations	950	950	950
No. of municipalities	95	95	95
Fraction of variance due to ind. effects	0.895	0.925	0.901
R^2 within-group	0.658	0.673	0.677
Frees Q-test for cross-sectional independence	7.458***	8.294***	7.080***
F-test for no municipality effects	4.680***	4.340***	4.450***
χ^2 Hausman test for random effects	51.980***	55.330***	83.080***

Notes: The dependent variable is the logarithm of the SWR. Driscoll–Kraay standard errors in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

are both equal to 0 for municipalities implementing drop-off and flat-fee programs, (ii) the variable DtD is equal to 1 and the variable PAYT is equal to 0 for those implementing DtD and flat-fee programs, and, finally, (iii) the variables DtD and PAYT are both equal to 1 for those implementing DtD

Table 4. *Effects conditional on the initial SWR*

	Sorters		
Method: panel OLS with fixed effects	Weak (1)	Strong (2)	All (3)
PAYT	0.101***	0.175**	2.442***
	(0.020)	(0.063)	(0.448)
Years of PAYT	0.010**	0.020	0.024***
	(0.003)	(0.017)	(0.007)
DtD	0.066***	0.286***	−0.183
	(0.015)	(0.053)	(0.641)
Years of DtD	−0.015***	0.059***	−0.001
	(0.004)	(0.014)	(0.008)
Previous (log) sorted waste ratio			0.550***
			(0.095)
PAYT × Previous (log) sorted waste ratio			−0.581***
			(0.113)
DtD × Previous (log) sorted waste ratio			0.106
			(0.171)
Log(population density)	0.514**	0.838**	−0.080
	(0.216)	(0.308)	(0.056)
Under 14	0.020**	0.028	−0.018
	(0.006)	(0.021)	(0.015)
Over 65	0.008	−0.010	0.001
	(0.008)	(0.009)	(0.009)
Non-natives	−0.000	−0.016	0.007
	(0.003)	(0.011)	(0.005)
Year 2000	0.008*	0.086***	
	(0.003)	(0.011)	
Year 2001	0.060***	0.105***	0.025
	(0.007)	(0.028)	(0.025)
Year 2002	0.044*	0.100	0.062
	(0.022)	(0.082)	(0.054)
Year 2003	0.144***	0.166**	−0.010
	(0.016)	(0.054)	(0.035)
Year 2004	0.149***	0.135*	−0.026
	(0.024)	(0.062)	(0.040)
Year 2005	0.156***	0.077	−0.047
	(0.029)	(0.069)	(0.047)
Year 2006	0.173***	0.039	−0.042
	(0.035)	(0.076)	(0.055)
Year 2007	0.175***	−0.019	−0.068
	(0.039)	(0.085)	(0.062)
Year 2008	0.186***	−0.076	−0.065
	(0.044)	(0.095)	(0.072)
Constant	−2.864**	−1.251	2.367***
	(1.232)	(1.598)	(0.574)
Observations	480	470	855
No. of municipalities	48	47	95
Fraction of variance due to ind. effects	0.956	0.904	
R^2 within-group	0.787	0.725	
Frees Q-test for cross-sectional independence	4.362***	4.141***	
F-test for no municipality effects	4.960***	5.190***	
χ^2 Hausman test for random effects	57.710***	63.030***	

Notes: The dependent variable is the logarithm of the SWR. Columns 1 and 2 refer to the groups of weak and strong sorters with a SWR below and above the 1998 median of 40.88 percent, respectively. Driscoll–Kraay standard errors in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 5. *Effects of incentives on the type of waste*

	Dependent variable (in log)			
Method: panel OLS with fixed effects	SWR (1)	Sorted (2)	Unsorted (3)	Total (4)
PAYT	0.170***	0.141***	−0.253***	−0.030**
	(0.040)	(0.030)	(0.057)	(0.013)
Years of PAYT	0.025*	0.020	−0.037***	−0.005
	(0.013)	(0.011)	(0.007)	(0.003)
DtD	0.157***	0.042	−0.334***	−0.116***
	(0.046)	(0.039)	(0.050)	(0.014)
Years of DtD	0.003	−0.023**	−0.030*	−0.027***
	(0.013)	(0.009)	(0.014)	(0.006)
PAYT × Adjacent to DtD	0.018	−0.003	0.007	−0.021
	(0.046)	(0.059)	(0.047)	(0.032)
PAYT × Adjacent to Drop-off	0.137**	0.060	−0.141*	−0.077
	(0.055)	(0.051)	(0.066)	(0.045)
DtD × Adjacent to PAYT	0.053	0.075	−0.008	0.022
	(0.052)	(0.061)	(0.041)	(0.025)
DtD × Adjacent to Drop-off	−0.020	0.007	0.048	0.027
	(0.032)	(0.025)	(0.062)	(0.017)
Drop-off × Adjacent to PAYT	0.070	0.069	−0.015	−0.001
	(0.060)	(0.043)	(0.064)	(0.035)
Drop-off × Adjacent to DtD	−0.104	−0.081	0.111**	0.022
	(0.059)	(0.045)	(0.048)	(0.023)
Log(population density)	0.888*	0.070	−1.500***	−0.818***
	(0.426)	(0.470)	(0.289)	(0.111)
Under 14	0.040**	0.032*	−0.020	−0.007
	(0.017)	(0.015)	(0.023)	(0.008)
Over 65	0.005	−0.000	0.001	−0.006
	(0.007)	(0.018)	(0.007)	(0.013)
Non-natives	−0.009	−0.009	−0.002	0.000
	(0.012)	(0.013)	(0.005)	(0.002)
Year 2000	0.108***	0.152***	0.020	0.044***
	(0.013)	(0.012)	(0.012)	(0.005)
Year 2001	0.176***	0.272***	0.043	0.096***
	(0.023)	(0.020)	(0.028)	(0.010)
Year 2002	0.150**	0.321***	0.068	0.171***
	(0.058)	(0.060)	(0.072)	(0.025)
Year 2003	0.314***	0.525***	0.021	0.211***
	(0.046)	(0.043)	(0.051)	(0.016)
Year 2004	0.299***	0.543***	0.045	0.244***
	(0.061)	(0.049)	(0.074)	(0.021)
Year 2005	0.282***	0.564***	0.083	0.282***
	(0.075)	(0.059)	(0.089)	(0.023)
Year 2006	0.280**	0.628***	0.116	0.348***
	(0.087)	(0.069)	(0.102)	(0.025)
Year 2007	0.262**	0.653***	0.172	0.392***
	(0.097)	(0.076)	(0.114)	(0.028)
Year 2008	0.250**	0.704***	0.228	0.454***
	(0.108)	(0.085)	(0.126)	(0.030)
Constant	−1.988	3.916	13.866***	10.510***
	(2.267)	(2.826)	(1.378)	(0.854)
Observations	950	950	950	950
No. of municipalities	95	95	95	95
Fraction of variance due to ind. effects	0.885	0.601	0.960	0.971
R^2 within-group	0.683	0.683	0.745	0.192
Frees Q-test for cross-sectional independence	7.333***	7.075***	8.424***	6.597***
F-test for no municipality effects	4.310***	9.760***	11.180***	24.340***
χ^2 Hausman test for random effects	82.050***	63.670***	115.930***	124.720***

Notes: Driscoll–Kraay standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

and PAYT programs. The net effect of a DtD program is then measured through the variable DtD using the comparison between groups (i) and (ii), while the net effect of a PAYT program is measured through the variable PAYT using the comparison between groups (ii) and (iii).

Although significantly positive, the effect of PAYT (24.3 percent) is now lower than in Column 1. The reason for this is that we also find a significantly positive effect of DtD (16.3 percent), which is consistent with previous works on the comparison between drop-off and DtD collection (see, for example, the literature review in Kinnaman, 2006). Thus, by not controlling for the collection system, the effectiveness of PAYT is overestimated. Results in Columns 1 and 2 reject our second hypothesis: the PAYT monetary incentive has a significantly positive effect on sorting, which is additional to the one of the DtD non-monetary incentive. We interpret this finding as an indication that the introduction of PAYT does not crowd out intrinsic motivation to sort.

The previous analysis ignores the learning effects of the programs. In fact, users might need time to become acquainted with the incentive scheme of the PAYT pricing system, or with the proper use of the different waste bins provided by a DtD program. The regression analysis in Column 3 is based on the specification in equation (7) apart from the spatial variables that are excluded. The new regression adds to the specification a linear time trend on the use of the two incentive-based waste policies (DtD and PAYT).[6]

The analysis still supports a significantly positive effect for both PAYT (20.8 percent) and DtD (17.7 percent). However, it does not show significant learning effects. Our finding that both PAYT and DtD have a positive and significant effect on the SWR supports the hypothesis that the additional effect of the monetary incentive provided by PAYT is positive (i.e., it increases the one of the non-monetary incentive provided by DtD). The absence of negative net effects due to crowding-out might suggest that the incentive is well designed, and at the municipality level it is aligned to users' intrinsic motivations.[7]

When considering the coefficients of other variables, we find that in all three models the year dummies have a positive and significant effect (especially since 2003), indicating an increase in the concern for waste sorting. This is probably related to the information campaigns (e.g., providing household with calendars for the sorting of the different waste fractions, communicating the results reached over the years, sending a

[6] We measure learning effects with a linear trend for the sake of simplicity; considering a quadratic trend would not change our findings.

[7] While intrinsic motivation is defined at the individual level, when considering municipalities, awareness of waste sorting (or environmental awareness) can be thought as a measure of the average intrinsic motivation of households in a given municipality (Vining *et al.*, 1992).

monthly newsletter, etc.) conducted by the consortia over time. In line with previous finding (e.g., Baldassare and Katz, 1992; Dijkgraaf and Gradus, 2009), we find that higher population density and a larger percentage of children are associated with higher waste sorting. In contrast, we find no significant effects of the proportions of elder individuals and non-native residents.

Effects Conditional on the Initial Level of the Sorted Waste Ratio

Our analysis so far shows that both DtD and PAYT programs considerably increase sorting. However, the discussion in Section II suggests that DtD and PAYT programs might have different implications for the SWR at the municipal level, depending on the level of awareness to waste sorting of the different municipalities. In particular, DtD should be more effective where the awareness to waste sorting is higher, but at the same time, in these contexts, the introduction of a PAYT scheme might weaken the positive effect of DtD on the SWR. Based on the assumption that municipalities with stronger awareness to waste sorting have a higher SWR, everything else being equal, we replicate our previous analysis after splitting the sample into two subsamples of municipalities: weak and strong sorters. We define as weak and strong sorters the municipalities with a SWR below and above the median, respectively, in 1998 (40.88 percent). These two groups might have different degrees of awareness to waste sorting. Our outcome results are shown in Columns 1 and 2 of Table 4.

Consistent with our hypothesis, we find a larger effect of DtD among strong sorters (28.6 percent as opposed to 6.6 percent). The net effect of PAYT is also larger among strong sorters (17.5 percent, as opposed to 10.1 percent for weak sorters). Overall, strong sorters react more to incentives, and especially to DtD; weak sorters in general respond less, but they are relatively more responsive to PAYT. Our conclusions are even strengthened by the learning effects: we see that strong sorters sort more after each additional year of DtD (by 5.9 percent), but not after each year of PAYT; in contrast, weak sorters sort more after each additional year of PAYT (by 1 percent) and less after each year of DtD (by 1.5 percent).[8] This possibly indicates that monetary incentives are relatively more effective when awareness of waste sorting is low.

To provide a more accurate assessment of the effect of DtD and PAYT programs conditional on the initial SWR, in Column 3 of Table 4 we run a Blundell–Bover panel regression on the whole sample, and with the same specification as in Columns 1 and 2, now also including the (log) SWR in

[8] This result is in line with previous findings from the literature (e.g., Reschovsy and Stone, 1994; Jenkins *et al.*, 2003).

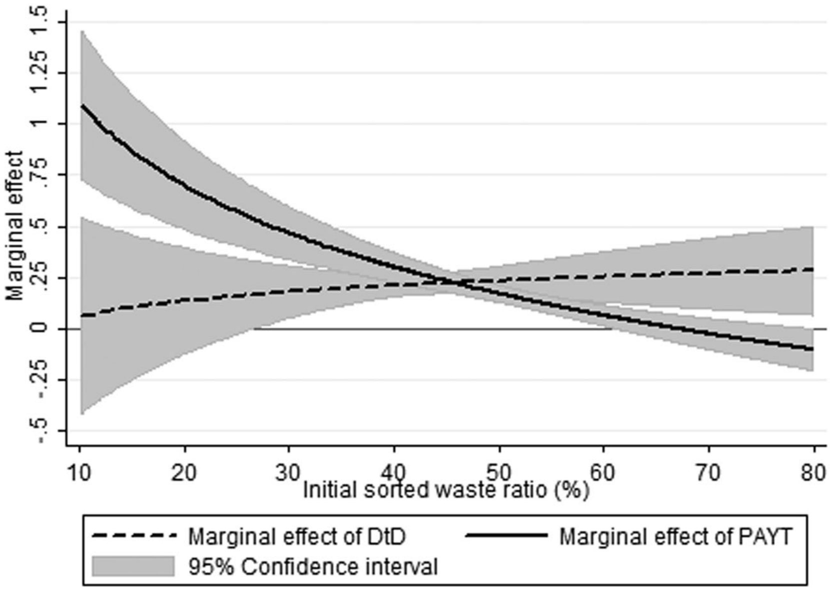

Fig. 3. Effects on the SWR by initial SWR

the previous year and its interaction with the dummy variables for PAYT and DtD. The results remain unchanged but for the fact that the coefficient involving the DtD dummy does not achieve significance taken separately. The interaction between the PAYT dummy and the (log) SWR in the previous year has a negative and significant effect, suggesting that the effect of introducing a PAYT program has, on average, a negative effect when the (log) SWR in the previous year is high. No significant effect is found when interacting the dummy for the DtD program with the (log) SWR in the previous year. The intuition of this result can be better understood by looking at Figure 3, which summarizes the average marginal effect of both programs, separately by the initial SWR levels obtained from this model. The figure shows a clear pattern, with PAYT becoming progressively less effective as the municipality starts from a higher SWR, and DtD becoming progressively more effective as the municipality starts from a higher SWR. For instance, if a municipality starts from a SWR of 20 percent, implementing DtD has no significant net effect, while implementing PAYT has a net effect of increasing the ratio by 70 percent (to 34 percent); in contrast, if a municipality starts from a SWR of 60 percent, implementing DtD has a net effect of increasing the ratio by 30 percent (to 78 percent), while implementing PAYT has no significant net effect. In general, the confidence intervals in Figure 3 suggest that DtD has a significantly positive effect if the initial SWR is above 25 percent, whereas PAYT has a significantly positive effect if the ratio is below 60 percent. Thus, it seems that the monetary incentive of PAYT prevails over the non-monetary incentive of DtD only when the municipality's production of sorted waste is low. Stated differently, this suggests that if municipalities with low initial SWR levels have a low level of awareness of waste sorting, they are less likely to suffer from negative effects due to the introduction of monetary incentives.

Spatial Effects

The analysis has so far ignored spatial effects because the proximity to municipalities having implemented specific programs might influence the effectiveness of the policies adopted. However, the effect of policies implemented by adjacent municipalities cannot be evaluated disregarding the policies actually implemented by the municipality itself. In particular, charging an explicit fee for residual waste production (as in PAYT) might indeed lead households to reduce waste volumes, as well as increasing illegal waste disposal. Forcing people to sort waste (as in DtD) also requires time, and an effort that some might not be willing to bear. In principle, illegal disposal can take several forms. Users might throw unsorted waste in the bins for sorted waste, which would, however, be easily discovered and sanctioned by waste collectors (further details in Online Appendix C.3). Alternatively, users might dump their waste anywhere, for instance on their neighbor's property or in the street. It should be noted, though, that in the district under our investigation (i) each user is responsible for their own bin, which is usually kept indoors, and (ii) there are no communal bins in the streets in which to throw waste. In our environment, if users really want to hide their waste, the only viable options are: to burn it, to dump it in the countryside or in a forest area, or finally to take it to a nearby municipality with drop-off waste collection, where communal bins are easily accessible. To limit this "waste tourism", municipalities with drop-off waste collection put the most sensitive bins under closed-circuit television surveillance, and ask their citizens to report any observed misbehavior regarding waste disposal to environmental guardians or local authorities (see Online Appendix C.3 for more details).

Here, we refer to the general specification of equation (7). In Column 1 of Table 5, we consider the whole sample, and add to the specification of Column 3 in Table 3 dummy variables for spatial effects, constructed as the interaction between dummy variables for the policy implemented in the municipality and in the majority of adjacent municipalities. Overall, nine categories are possible. Stated explicitly, our specification is the following:

$$\begin{aligned}
Y_{it} &= \beta_0 + P_{it}'\beta_1 + S_{it}'\beta_2 + C_{it}'\beta_3 + \mu_i + \varepsilon_{it} \\
&= \beta_0 + \beta_{1,1}(PAYT_{it} \times DtD_{it}) + \beta_{1,2}DtD_{it} + \beta_{1,3}yearsPAYT_{it} \\
&\quad + \beta_{1,4}yearsDtD_{it} + \beta_{2,1}(Dropoff_{it} \times adj.DtD_{it}) \\
&\quad + \beta_{2,2}(Dropoff_{it} \times adj.PAYT_{it}) + \beta_{2,3}(DtD_{it} \times adj.Dropoff_{it}) \\
&\quad + \beta_{2,4}(DtD_{it} \times adj.PAYT_{it}) + \beta_{2,5}(PAYT_{it} \times adj.Dropoff_{it}) \\
&\quad + \beta_{2,6}(PAYT_{it} \times adj.DtD_{it}) + C_{it}'\beta_3 + \mu_i + \varepsilon_{it}. \qquad (2)
\end{aligned}$$

The baseline (omitted) category in our analysis is the one of a drop-off municipality with most adjacent municipalities also implementing drop-off. Given this specification, the coefficient on DtD (PAYT) captures the effect of being in a DtD (PAYT) municipality with most adjacent municipalities implementing DtD (PAYT).

In this new regression, we still find large effects for both PAYT and DtD (17 and 15.7 percent, respectively). The point estimate of the DtD effect is close to our previous results. In contrast, the smaller size of the point estimate of the PAYT effect compared to our previous results might suggest that in the previous regressions the coefficient was incorporating the effect of omitted spatial variables. It should be noted, however, that the coefficient estimates of PAYT and DtD are associated to relatively large 95 percent confidence intervals (between 9 and 25 percent for PAYT, and between 7 and 25 percent for DtD), which include our previous point estimates. Our new findings are consistent with the past findings.

Concerning the spatial effects, we find that the SWR rises by 13.7 percent when the municipality implements PAYT and most of its adjacent municipalities have a drop-off collection system.[9] We interpret this result as evidence of waste tourism: in order to pay lower fees, citizens in PAYT municipalities hide their waste and bring it to near municipalities, where communal bins are still available in the streets.[10] The effect of this waste tourism is quantitatively large, and nearly equal to the net effect of PAYT.

[9] In principle, we could observe waste tourism from the opposite side as well (with a drop-off municipality with adjacent PAYT municipalities). However, our sample includes few observations that meet this condition, and they are mainly concentrated at the beginning of our time period.

[10] This variable is a simplified version of the impact factor used in Dijkgraaf and Gradus (2004), which accounts for the population size and the distance of each municipality with all the others. In our case, all the municipalities share a similar population size and are relatively close to each other. If waste tourism is a relevant issue, the coefficient associated with our variable should be positive, and its size would reveal its impact on the SWR.

Our finding highlights that it is difficult to detect illegal dumping phenomena without considering all potential spatial effects, and might explain why there is no consistent empirical evidence on this issue – some studies find no evidence (e.g., Dijkgraaf and Gradus, 2004), while other studies find moderate or substantial impact (e.g., Fullerton and Kinnaman, 1996; Linderhof *et al.*, 2001). Despite the possibility of relatively simple illegal disposal (due to the proximity of municipalities and the high number of people commuting to work), our results suggest that this option is not fully exploited. This might be so because of a social image concern – citizens are afraid to be caught illegally dumping their waste, thereby signaling misbehavior or poverty (considering that the cost of emptying unsorted waste bins is not high).[11]

All our findings are net of the effects on demographic and time variables. However, it seems relevant to include only the coefficients of the year dummy variables, suggesting – not surprisingly – that the SWR tends to increase anyway over the years, plausibly as a consequence of massive media campaigns in recent years.[12]

Our analysis takes as a dependent variable the logarithm of the SWR, which is a fraction between 0 and 1. The literature proposes alternative models to deal with such variables (e.g., Kieschnick and McCullough, 2003). In a robustness check in Online Appendix D.2, we report results from the main alternative models, where we change the dependent variable (the level of SWR, a logistic transformation, or a log–log transformation) or the model (a fractional response panel probit model such as suggested by Papke and Wooldridge, 2008). Our findings are confirmed, both qualitatively and quantitatively. We still prefer our benchmark analysis for two reasons: (i) it accounts for serial as well as spatial effects, which happen to be relevant in our data according to the Frees test; (ii) it provides more conservative estimates of the spatial effects. Most of the other models considered in Online Appendix D.2 do show effects of being in a PAYT municipality with adjacent drop-off municipalities of the order of 8–10 percent, together with the effects of being in a drop-off municipality with adjacent DtD municipalities negative and between −8 and −9 percent. This further effect is also in line with our interpretation in terms of waste tourism: households in municipalities implementing DtD might prefer to carry their unsorted waste to nearby drop-off municipalities to avoid effort costs. As a result, drop-off municipalities close to DtD municipalities will see their SWR reduced.

[11] Previous research supports this view, showing that increasing the price does not increase the intensity of sorting, possibly because the average cost of disposal is too low to create a response from relatively high-income households (Jenkins *et al.*, 2003).

[12] Environmental economists link the growth in the production of waste as well as the growth in the production of energy to the increase in wealth and welfare (measured by the GDP).

Components of the Sorted Waste Ratio

The SWR might rise due to an increase in sorted waste, a reduction in total waste, or both. From our past regression analyses, we cannot infer anything on this issue. However, knowing how the different components evolve is important because it provides more precise information on how incentives work. We conclude our analysis by looking more closely at the components of the SWR: sorted waste, unsorted waste, and total (sorted plus unsorted) waste. Figure 4 shows the dynamics of the average per capita amounts of waste in our sample, jointly and separately by type of waste management system. Averages are computed by dividing the aggregate amount by the total population size; as in Figure 2, averages are reported only when they are obtained from at least 10 observations. The figure shows that per capita sorted waste increases steadily over the years, roughly at the same pace for all groups (Panel a). In contrast, per capita unsorted waste decreases in all groups apart from the one with drop-off and flat-fee programs, where it tends to increase (Panel b). Combining the two trends, we see that per capita total waste remains stable over time in the groups with DtD and flat-fee programs and with DtD and PAYT programs, whereas it rises in the group with drop-off and flat-fee programs (Panel c). Thus, the figure suggests that DtD and PAYT programs effectively reduce the production of unsorted waste. Again, the statistics shown in this figure might not be able to detect the net effects of DtD and PAYT programs because they do not take into account the characteristics of each municipality. For this reason, we perform a regression analysis controlling for these characteristics below.

Columns 2–4 of Table 5 show the estimates of a model where the dependent variable is now the logarithm of per capita sorted waste (Column 2), per capita unsorted waste (Column 3), and per capita total waste (Column 4) in kilograms. According to our first hypothesis, we should expect DtD and PAYT to reduce the amount of unsorted waste and to increase the amount of sorted waste, if the disposal costs of unsorted waste relative to sorted waste are sufficiently high.

The regression output supports the first hypothesis only partly. Indeed, we find for PAYT a significantly positive effect on per capita sorted waste (which rises by 14.1 percent; see Column 2), a significantly negative effect on per capita unsorted waste (which decreases by 25.3 percent; see Column 3), and an overall small negative effect on per capita total waste (which falls by 3 percent; see Column 4). The same direction of the effect of PAYT is found in Dijkgraaf and Gradus (2004) on a sample of Dutch municipalities. The learning effect is significantly negative for unsorted waste (−3.7 percent for every subsequent year of PAYT adoption). These results support the argument that PAYT does not affect per capita total waste

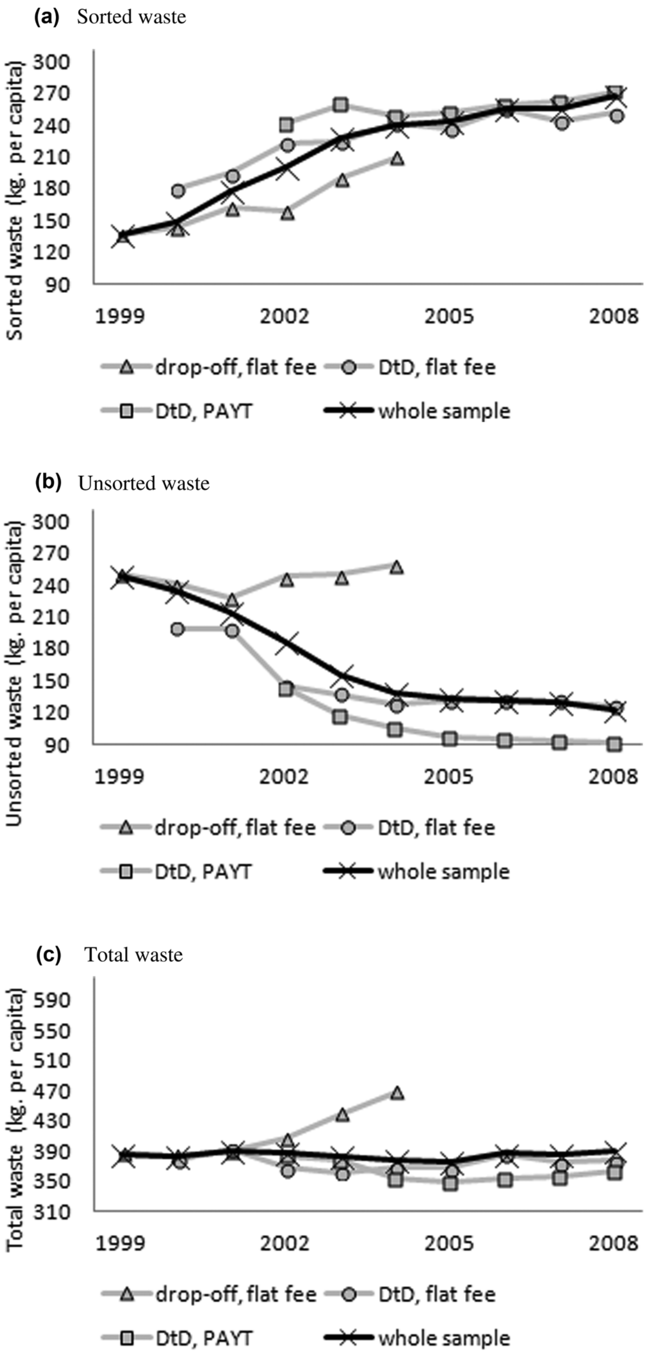

Fig. 4. Dynamics of waste production (kg per capita)

production, but rather induces users to shift from unsortable to sortable products.

In contrast, we find that DtD reduces per capita unsorted waste to a large extent (by 33.4 percent; see Column 3) and also reduces per capita total waste (by 11.6 percent; see Column 4). Surprisingly, it does not significantly increase the production of sorted waste (the coefficient 0.042 in Column 2 is not significant). We also find a learning effect of DtD on total waste (that is reduced by 2.7 percent in every further year). This effect supports our view that DtD is a form of non-monetary incentive aimed at reducing total waste by imposing constraints on the amount of waste production (e.g., providing personal bins of a given size and setting a given frequency for waste collection), while eliminating the time costs of carrying waste to the street. In contrast, DtD does not seem effective in increasing the amount of sorted waste. Hence, even if we observe a similar effect of the two programs on the SWR, PAYT reaches this goal because it leads to more waste sorting, while DtD reaches it because it leads to less waste production.

Estimates of the spatial effects are also consistent with our previous argument on waste tourism in Section 4.2, as we find that the amount of unsorted waste is reduced in PAYT municipalities with mostly drop-off adjacent municipalities (the effect is weakly significant) and increased in drop-off municipalities with mostly DtD adjacent municipalities (the effect is 11.1 percent). Apparently, households in PAYT and DtD municipalities quit the monetary and non-monetary costs of sorting by leaving their unsorted waste in adjacent drop-off municipalities.

V. Conclusions

In this paper, we study the effectiveness of the monetary incentive, as represented by PAYT, on the SWR. We find that PAYT has a significantly positive effect, similar to the one of DtD. In our preferred analysis, the PAYT incentive increases the SWR by 17 percent and we find that it is additive to the effect of the DtD incentive (15.7 percent). In addition, municipalities with a PAYT program increase the amount of per capita sorted waste by 14.1 percent, and reduce the amount of per capita unsorted waste by 25.3 percent. Our results were obtained controlling for specific characteristics of the municipalities, and they are robust to different assumptions of the model. We also find that PAYT programs induce an undesired hiding effect: users dump their waste in adjacent towns where communal bins are available in the streets – at least in municipalities where the SWR is relatively low. This effect is not observable in aggregate without controlling for policies that are applied in a neighborhood. Therefore, a coordination of policies at a macro level seems necessary to avoid this undesired effect.

However, PAYT might entail additional management costs that are likely to be context-specific. Policy makers should then run an accurate cost-benefit analysis in order to choose whether to implement it.

Finally, our results suggest that monetary incentives are an effective tool to foster sorting behavior at the municipal level; potentially, they can be adapted to achieve further goals, primarily the reduction of per capita total waste (European Union, 2008). In fact, we find that the production of total waste tends to increase over time. For example, the application of monetary incentives not only to unsorted waste but also to specific fractions of sorted waste (plastic, paper, etc.) might have beneficial effects on the reduction of the total waste produced.

Supporting Information

The following supporting information can be found in the online version of this article at the publisher's web site.

Online Appendix

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First version submitted March 2013;
final version received March 2014.