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MICROCHIP BAGS AND WASTE SORTING

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Abstract

We evaluate the effectiveness of placing microchips on the bags for the curbside collection in reducing the unsorted urban solid waste and increasing the fraction recycled. The microchip allows the waste collection company to identify the users that left the bags on the curb and check whether they properly sorted the waste. Our study is carried out in the Italian province of Macerata (Marche, Italy), where the bag microchips were introduced only in some municipalities in 2013. Exploiting monthly information on waste collection and natural experiment methods, we find that, two years after the programme start, the bag microchip increased the fraction recycled by 3-4.5 percentage points and decreased the monthly unsorted waste by 1-2 kilograms per capita.

JEL Class.: C23; D78; Q53.

Keywords: Recycling behavior; unsorted waste; microchip bags; natural experiment; difference-in-differences; synthetic control method.

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Microchip Bags and Waste Sorting†

Matteo Picchio

1 Introduction

In the last decades, the European Union has been attentive to environmental issues with the implementation, application, and enforcement of EU waste legislation. Although municipal waste is a small fraction of the total waste generated in the EU (approximatively 7%–10%), the EU legislator (EU, 2018) has had a clear focus on municipal waste management as a key element for waste prevention.[1] The municipal solid waste is amongst the most complex ones to manage, as it presents tangled challenges, with a variety of administrative, economic, and social problems. An efficient and effective management of this waste stream is therefore commonly accompanied by better performances in overall waste management (Malinauskaite et al., 2017). The European Waste Framework Directive established that by 2020 the fraction recycled of municipal waste shall be increased to a minimum of overall 50% by weight. The Circular Economy Package, among other ambitious targets, set new municipal-waste-recycling targets for the subsequent years. By 2025 at least 55% of municipal waste by weight will have to be recycled, 60% by 2030, and 65% by 2035 (EU, 2018, Art. 1(12)).

To cope with the direction and targets set by the EU and the implied modifications of national legislations, the municipal waste management, often organized at regional or local level, has followed different strategies. However, some converging trends are clearly identifiable, like the introduction of curbside (door-to-door, DtD) collection programmes, which require users to separate their waste at home.[2] The curbside collection is financed

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[1] The European Waste Framework Directive (EU, 2008) and the Circular Economy Package, which includes the revision of legislative proposal on waste with Directive (EU) 2018/851 (EU, 2018), set clear and long-term targets for municipal waste management and recycling.

[2] See Knickmeyer (2020) and Varotto and Spagnolli (2017) for recent literature reviews on the main

by either flat-fees or pay-as-you-throw (PAYT) pricing systems. The latter makes users' cost an increasing function in the unsorted waste produced, generating and incentive to reduce the unsorted waste and increase the fraction recycled. A number of studies estimated the impact of PAYT pricing systems on household recycling behaviour. Empirical findings generally point to a significant positive effect on recyclable waste and a negative impact on the amount of unsorted waste (Allers and Hoeben, 2010; Bucciol et al., 2015; Bueno and Valente, 2019; Carattini et al., 2018; Dijkgraaf and Gradus, 2004, 2009; Ferrara and Missios, 2005; Gellynck and Verhelst, 2007; Kinnaman and Fullerton, 2000; Usui, 2008; Yang and Innes, 2007).[3]

Apart from the costs of being technological equipped to adopt a unit pricing system, the PAYT pricing system could be affected by a further limit: it might generate the incentive to waste tourism or illicit waste dumping or burning (Fullerton and Kinnaman, 1995; Kinnaman and Fullerton, 2000; Kinnaman, 2006). Bucciol et al. (2015) found that in the province of Treviso (Veneto, Italy) PAYT induced illegal dumping, although only limited to those municipalities in which the PAYT system was introduced when the fraction recycled was already high. The assessment of the effectiveness of the PAYT system is further complicated by its frequent coexistence with DtD collection programmes. It is therefore not easy to distinguish the effect of the former from the latter. Bucciol et al. (2015) disentangled the effect of the PAYT system from the one of DtD collection. They found that, whilst the impact of the DtD collection is rather flat but increasing with respect to the initial level of fraction recycled, the effect of the PAYT system negatively depends on it. If a municipality starts from a fraction recycled of 60%, the DtD programme is able to increase it further, while the introduction of the PAYT does not modify it.

The aim of our paper is inspired by the latter result in Bucciol et al. (2015). We assess the effectiveness of a programme started in 2013 in the province of Macerata (Marche, Italy) aimed at further improving the fraction recycled and reducing the unsorted waste. The programme consisted in the insertion of microchips on the bags for the DtD collection. The microchip contains information about the user. Hence, it allows the waste collection company or the local police to identify the users that left the bags on the curb, check whether they properly sorted the waste, and fine the users not complying with the

social factors and psychological intervention strategies influencing household recycling behaviour.

[3]The meta-analysis in Bel and Gradus (2016) clarifies that the effectiveness of the unit pricing system depends crucially on the unit chosen for the computation of the fee: weight-based systems generate the largest effect on waste quantities, whereas volume-based systems (i.e. the bin- and bag-based systems) are not effective.

mandatory rules for recycling. It was introduced in municipalities with DtD collection, a flat-fee pricing system, and an already high level of fraction recycled, on average above 70%. Differently from the province of Treviso in which some municipalities experienced the introduction of a PAYT pricing system (Bucciol et al., 2015), hence an economic incentive, in the province of Macerata the waste management company opted for fines (or the threat of punishment) for those users not complying with the mandatory recycling rules. All in all, this choice is coherent with the results in Bucciol et al. (2015), if they can be generalized to other Italian provinces: given the already large commitment to recycling in the province of Macerata and the risk of encouraging illicit waste dumping and burning, the switch to a PAYT system could have been unfruitful or detrimental.

Our contribution to the literature is twofold. First, we show that also where the fraction recycled is already high, there is still room for improvement using the 'stick', i.e. a simple system to potentially identify users not complying with the recycling rules and fine them. This was implemented without a relevant change in the organization of the waste management and without a big risk of illicit dumping or burning, which could instead characterise the shift to a unit-based pricing system. Second, we do it by using an administrative and detailed dataset on waste collection at municipality level and robust natural experiment econometric methods allowing for time-varying effects of unobservables. The estimated results are therefore interpretable as causal effects of the microchip bag programme under weak assumptions.

The set-up of our paper is as follows. Section 2 describes the waste management in the area under analysis and the main features of the microchip bag programme. Section 3 presents the dataset and the sample used for the empirical analysis. Section 4 explains the econometric models and the strategies for the identification of the causal effect of the programme. Section 5 reports and comments on the main findings. Section 6 concludes.

2 Framework

In the province of Macerata, the waste collection, treatment, and disposal is managed by COSMARI (Consorzio Obbligatorio SMAltimento RIfiuti - Compulsory Waste Disposal Consortium), which is a public company owned by the municipalities of the province of Macerata and covering about 320,000 inhabitants.

As common in Italy until about three decades ago, users (i.e. households, stores, etc.) were still taking mixed waste to big collective bins located in public streets. At the beginning of the 1990s, COSMARI assigned the management of sorted waste to private companies and the usual collective bins for unsorted waste were flanked by bins for separate waste collection. After some years, the fraction recycled was still very low: in 1997 it was about 3% (COSMARI, 2012, p. 29). In 1997, Legislative Decree 22/1997 was passed at national level to comply with the European Union directives and established a completely new regime (Bertossi et al., 2000) in terms of recycling attention and objectives. Moreover, since the beginning of 1997, COSMARI took control of the management of sorted waste and, in a few years, the fraction recycled reached quickly 24% in 2004.

Since the profile of the fraction recycled flattened (in 2006 it was still 26%), in 2007 COSMARI started a curbside collection programme in 7 municipalities and, by 2012, in almost all the municipalities the waste collection based on communal bins on public streets were replaced by the DtD system. With this new system, users have to sort different materials in bags that are freely distributed in the city hall or in other distribution points, like supermarkets. The bag for plastic, aluminium and metal cans, the bag for paper and cardboard, and the bag for unsorted residual waste are collected DtD in specific time slots and days of the week. Organic waste, glass, and diapers and alike are separately sorted in three different (mostly small, 240 lt) communal bins located in public streets. All the municipalities that moved to the waste collection on the curb experienced an immediate increase in the fraction recycled. At provincial level, already in 2012 the fraction recycled scored 59.3%, largely above the 50% target to be reached by 2020 according to EU (2008) and the national average of 40%.[4] The municipalities that shifted to the curbside collection went through a different tariff system for the treatment and disposal of the unsorted waste. For example, while in 2014 the municipalities with the curbside collection were asked to pay €174.40 per tonne of unsorted waste, those without the curbside collection paid €223.00 per tonne. Although this difference in charging municipalities, the way in which municipalities in turn charge their users for waste collection services has not changed and remained characterised by a fixed annual fee per user.

Then, with the aims of increasing the quality and the quantity of the fraction recycled and of laying the foundations for an eventual shift to the pay-as-you-throw system, COSMARI launched in the second half of 2013 the bag microchip programme in 9 municipalities already equipped with the curbside collection.[5] Microchips have been indeed

[4]These figures are gathered from the national waste register of *Istituto Superiore per la Protezione e la Ricerca Ambientale* (ISPRA) and retrieved on 05/11/2020 from https://www.catasto-rifiuti.isprambiente.it.

[5]The capital of the province, Macerata, joined COSMARI in January 2014 and in March 2014 was

incorporated in the bags for the collection of plastic, aluminium and metal cans and in those for the unsorted waste. When the user gathers her/his rolls of bags from a distribution point, each roll of bag is coupled with the corresponding user through the microchip. Hence, the microchips stuck on the bags allow COSMARI or the local police to trace the users that left the bags on the curb and check whether they properly sorted the waste and they did it in the right day.

3 Data

The empirical analysis exploits data from two sources. The main source is the monthly information at municipality level published by COSMARI in its website and containing information on waste collection disaggregated by different types of materials.[6] We collected monthly information from July 2010 until the first semester of 2016, so as to have 6 years of data, 3 years before the introduction of bag microchips and 3 years after it. We stopped the data collection after the first semester of 2016, because from August until October 2016 a series of earthquakes devastated many municipalities of Central Italy, with very important damages also in the province of Macerata. Since the disaster likely affected the waste collection and sorting behaviours and because inland areas were asymmetrically damaged by the earthquakes, by stopping the data collection in July 2016 we avoid the inclusion of spurious components in the effect estimation. We do not use data before July 2010 as the more we go back in time the higher the number of municipalities which had not started yet the curbside collection programme, a fundamental pre-requisite for the subsequent introduction of the bag microchip and therefore for a municipality to be a valid control.

The second data source is yearly information on municipality characteristics gathered from Atlante Statistico dei Comuni 2019 (http://asc.istat.it) published by Istat. More in detail, we collected information from 2010 until 2016 on population, its density, and the number of tourist bed places. These features could indeed be determinants of the fraction recycled and of sorting behaviour.

The province of Macerata was divided in 57 municipalities during the period under

the 10th municipality to experience the bag microchip programme, although only limited to the historical center.

[6]We retrieved the monthly data on waste collection and disposal from https://www.cosmarimc.it/-raccolta-differenziata/?m=raccolta-differenziata on September 2019.

analysis (55 at the time of writing). Before the introduction of the bag microchip, COSMARI run two pilot experiments to assess its effectiveness: in 2011 in the municipality of Petriolo (2,036 inhabitants in that year) and in 2012 in a district of Porto Recanati (whole population of 11,497 persons in 2012). Because of their particular treatments, we decided to exclude these two municipalities from the sample. Moreover, the latter is a highly tourist town, being located on the coast, and displays extremely large increases in the amount of the per capita unsorted waste in summer, much larger than any other municipality in the province. By removing it, we delete au outlying unit. The waste management of Macerata, the capital of the province, and Cingoli was assigned to another company until the end of 2013. Hence, COSMARI does not have their monthly data before January 2014. They both displayed in the first months of 2014 the similar steep increase in the fraction recycled, which is likely due to the change in the company in charge of the waste management and the introduction of the curbside collection. Because of the possible confounding effect due to the change in the waste management company and the contemporaneous shift to the DtD collection, Macerata and Cingoli are removed from our sample. We also removed Civitanova Marche (40,228 inhabitants in 2012) as the bag microchips were introduced in June 2013 only in the city centre (about 18.5% of the total population), leaving peripheral areas with the old system. Furthermore, 8 municipalities did not have the curbside collection programme in the years under analysis. Since the bag microchip can be introduced only if the garbage collection is at the curb and municipalities without the DtD collection typically have very low and quite different profiles of the fraction recycled, we removed them from the sample.[7] In some other municipalities the curbside collection programme started during the period under analysis. They are included in our sample but only from the month after the one in which the curbside collection started. Finally, since the data collected in February 2015 are affected by several inconsistencies, they are not used in the analysis.[8] The final sample is therefore an unbalanced panel with 31 municipalities at the start of the observed time window (second semester of 2010) and 44 municipalities since the second semester of 2014 until July 2016. In total we have 479 semester-municipality observations.

In the econometric analysis, we average the monthly data within semesters. Table 1 reports the name of the treated municipalities and the day in which the treatment started.

[7] The municipalities removed for this reason are Acquacanina, Bolognola, Castel Sant'Angelo, Fiastra, Poggio San Vicino, Sefro, Serravalle, and Ussita.

[8] We contacted the highest management of COSMARI by phone on 20/09/2019 and by e-mail on 20/09/2019 and 14/10/2019 to have clarifications about the data anomaly, but we have received no reply.

In all the treated municipalities the bag microchip was introduced in the second semester of 2013. We will denote this semester as $t = 1$. Table 1 also shows the fraction recycled, the per capita amount of sorted and unsorted waste, the population, the population density, and the number of tourist beds in 2012, which is the year before the programme implementation. In 2012, the treated had a lower fraction recycled (73.4% against 75.4%), about 1 more kilogram (per capita and per month) of both recycled and unsorted waste, and larger population, population densities, and number of tourist bed places.

Table 1: The timing of bag microchip introduction and pre-treatment characteristics of treated and untreated municipalities

Municipality	Date of treatment[(a)]	Fraction recycled in 2012	Monthly unsorted waste per capita in 2012 (Kg/pop*month)	Monthly recycled waste per capita in 2012 (Kg/pop*month)	Population density in 2012 (pop/km^2)	Population in 2012	Number of tourist bed places in 2012
Camerino	25/11/2013	0.675	12.773	26.638	53.103	6,897	1,992
Castelraimondo	30/09/2013	0.743	8.315	24.202	105.686	4,740	566
Loro Piceno	21/10/2013	0.702	9.256	23.089	75.967	2,475	262
Monte San Giusto	28/10/2013	0.746	7.522	22.156	403.743	8,091	109
Recanati	09/12/2013	0.762	8.296	26.683	206.737	21,389	838
San Severino Marche	14/10/2013	0.746	8.906	26.099	66.945	13,004	531
Urbisaglia	21/10/2013	0.764	7.057	23.135	118.329	2,705	114
Treated municipalities	–	0.734	8.874	24.572	147.2	8,472	630
Untreated municipalities	–	0.754	7.602	23.556	109.7	4,572	330

[(a)] These dates were retrieved in September 2019 from the press releases of COSMARI website (www.cosmarimc.it).

Table 2 reports summary statistics of the fraction recycled over semesters, before and after the introduction of the bag microchips and by treatment and control municipalities. Whereas the treated municipalities had a lower fraction recycled before the programme (73.3% against 75.4%), after the introduction of the bag microchips the treated municipalities reached 77.6% of fraction recycled, whereas the untreated municipalities remained stable at about 75%. This is suggestive evidence of a change in the waste sorting behaviour in the treated municipalities. However, our treated and control municipalities are on average somewhat different in terms of pre-treatment waste sorting outcomes and other characteristics, as shown in Table 1. Different units might have diverging trends in waste sorting behaviour simply because in the years under analysis a rising concern for environmental and health issues could have had a stronger impact in terms of waste sorting behaviour in under-performing municipalities, as people living in these municipalities might have been more sensitive to the environmental and health consequences (Bueno and Valente, 2019). Moreover, the adoption itself of the bag microchips could depend on environmental preferences of voters, leading to a policy endogeneity issue (Besley and Case, 2000; Kinnaman and Fullerton, 2000; Carattini et al., 2018). In order to identify the causal effect of the introduction of the bag microchips, we need therefore to disentangle the true effect of the programme from the spurious ones determined by differential time trends between the treated and the control municipalities. This is the aim of the econometric analysis that follows.

Table 2: Descriptive statistics of the fraction recycled and per capita monthly unsorted and recycled waste before and after the bag microchips (averaged within semesters)

	Mean	Std. Dev.	Minimum	Maximum	Observations
a) Fraction recycled					
All semesters, all municipalities	0.753	0.046	0.594	0.876	479
All semesters, treated	0.755	0.039	0.657	0.811	84
All semesters, controls	0.753	0.048	0.594	0.876	395
b) Fraction recycled before and after bag microchip					
Before bag microchip, treated	0.733	0.035	0.657	0.781	42
After bag microchip, treated	0.776	0.031	0.688	0.811	42
Before bag microchip, controls	0.754	0.045	0.636	0.867	178
After bag microchip, controls	0.751	0.050	0.594	0.876	217
c) Monthly unsorted waste per capita (kg/pop)					
All semesters, all municipalities	8.052	2.088	3.361	18.391	479
All semesters, treated	8.277	1.850	5.672	13.489	84
All semesters, controls	8.005	2.135	3.361	18.391	395
d) Monthly unsorted waste per capita (kg/pop) before and after bag microchip					
Before bag microchip, treated	8.961	1.821	6.494	13.489	42
After bag microchip, treated	7.594	1.629	5.672	12.401	42
Before bag microchip, controls	7.564	1.866	3.361	14.256	178
After bag microchip, controls	8.366	2.273	3.541	18.391	217
e) Monthly recycled waste per capita (kg/pop)					
All semesters, all municipalities	24.853	6.452	14.026	94.050	479
All semesters, treated	25.391	2.207	21.409	29.864	84
All semesters, controls	24.738	7.029	14.026	94.050	395
f) Monthly recycled waste per capita (kg/pop) before and after bag microchip					
Before bag microchip, treated	24.627	2.058	21.409	27.758	42
After bag microchip, treated	26.154	2.105	22.463	29.864	42
Before bag microchip, controls	23.415	3.868	14.026	34.664	178
After bag microchip, controls	25.824	8.673	14.766	94.050	217

4 Method

4.1 Empirical framework

Evaluating the impact of placing the microchips on the bags for the curbside on recycling behaviour is challenging because the treated municipalities might not have been randomly chosen. Rather, this selection could have been induced by a series of waste generation determinants, many of whom might be unobserved to the data analyst. For example, treated and untreated municipalities might differ in environmental preferences of voters or/and in previous recycling performances, generating different propensities in the local authorities to find further means to increase recycling. Furthermore, there might be unobserved time-varying confounders, which could pose a further challenge in credibly identifying the causal effect of the programme because, if municipalities reacted differently to common unobserved time-varying shocks, the controls could be bad counterfactuals for the treated.

To address the endogeneity of the bag microchip introduction, we start with the estimation of the treatment effects using standard two-way fixed-effects difference-in-differences (DiD) estimators (Autor, 2003). They require the parallel trend assumption in order to deliver unbiased estimates of the causal effect, i.e. the treated and controls have parallel trends in the absence of the treatment. However, time-varying effects of unobservables may invalidate the identification assumption of DiD, which is based on differencing out time-constant unobserved heterogeneity.

To capture eventual time-varying effects across municipalities, we next estimate the programme effect in a model with interactive fixed-effects (Bai, 2009). Interactive fixed-effects (IFE) models are able to net out time-varying unobserved heterogeneity, without specifying a particular relationship between the regressors and the unobserved terms.

Finally, we use the synthetic control method (SCM) (Abadie and Gardeazabal, 2003; Abadie et al., 2010). Differently from the previous two approaches, the SCM exploits a weighted average of controls for each treated unit. Abadie et al. (2010) proved that it is a generalization of the DiD approach: whereas the DiD model restricts the effect of confounders to be constant in time, the SCM allows the effects of unobserved heterogeneity to vary with time. Indeed, Gobillon and Magnac (2016) showed that the SCM can be described as a model with IFE, but it is without bias induced by time-varying unobserved heterogeneity under stronger assumptions than those required by the standard IFE model:

the SCM requires convexity arguments and constraints on the supports of factor loadings and exogenous variables.

The general equation of interest is:

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \Delta_{it} + v_{it} + u_{it} \tag{1}$$

where:

- y_{it} is the outcome variable for municipality i at time t, with $i = 1, \ldots, N$ and $t = -5, \ldots, 0, 1, \ldots, 6$ ($t = 1$ is the semester in which the treatment started);
- $\mathbf{x}_{it}$ is a vector of covariates (population, population density, and number of tourist bed places) and $\boldsymbol{\beta}$ the conformable vector of parameters;
- Δ_{it} is the treatment effect of bag microchips at time t;
- v_{it} is unobserved heterogeneity;
- u_{it} is an idiosyncratic error term.

Δ_{it} is specified as:

$$\begin{aligned} \Delta_{it} &= \mathbb{1}(t = 1 \wedge d_i = 1)\theta_1 + \mathbb{1}(t = 2 \wedge d_i = 1)\theta_2 + \mathbb{1}(t = 3 \wedge d_i = 1)\theta_3 \\ &+ \mathbb{1}(t = 4 \wedge d_i = 1)\theta_4 + \mathbb{1}(t = 5 \wedge d_i = 1)\theta_5 + \mathbb{1}(t = 6 \wedge d_i = 1)\theta_6 \end{aligned} \tag{2}$$

where $d_i = 1$ if municipality i belongs to the treatment group and $\mathbb{1}(\cdot)$ is the indicator function which returns 1 if the argument is true and 0 otherwise. The six parameters $\theta_1, \ldots, \theta_6$ are the programme effect over time. We will also estimate a constrained model in which $\theta_1 = \ldots = \theta_6$, i.e. the bag microchip effect is imposed to be constant over time.

By assigning a different specification to v_{it}, we will get a different model, returning unbiased estimates under different assumptions. In the classical DiD model, the unobserved heterogeneity is specified as

$$v_{it} = \alpha_i + \xi_t, \tag{3}$$

i.e. as additive fixed-effects at unit and time levels. An easy extension is obtained by adding linear and/or quadratic trends at municipality level, as in Autor (2003) or Wolfers

(2006). In what follows, we will also present the estimation of the DiD model with a linear individual trend:

$$v_{it} = \alpha_i + \xi_t + \phi_i \cdot t. \tag{4}$$

The unobserved heterogeneity in Equation (3) is not able to capture time-varying effects across municipalities, i.e. all the municipalities are required to be affected in the same way by the time effects. The specification in Equation (4) is an attempt to capture unobservables that might change across municipalities and time in diverse patterns. However, this is done using a strong parametric approach. In the IFE models (and SCM), the unobserved heterogeneity is instead flexibly specified, without imposing a particular relationship between the regressors and the unobserved terms or a particular parametric form for the interaction between the individual and the time unobserved components:

$$v_{it} = \alpha_i + \xi_t + \mathbf{f}_t' \boldsymbol{\lambda}_i, \tag{5}$$

where $\mathbf{f}_t$ is a $L \times 1$ vector of time effects (or factors) and $\boldsymbol{\lambda}_i$ is a $L \times 1$ vector of individual effects (or factor loadings). The former is unobserved common shocks, while the latter captures municipality-specific reactions to those common shocks.

4.2 Estimation and identification

Two-way fixed-effects difference-in-differences

The DiD model described in Equations (1)–(3) is the usual two-way fixed-effects model which compares over time a group of treated units and a group of controls not exposed to the treatment after additively controlling for municipality fixed-effects and time fixed-effects. Hence, it can be estimated using Ordinary Least Squares (OLS) after including a full set of municipality and time indicators among the covariates to recover the additive component in Equation 3.

In the standard DiD model, some assumptions must be satisfied in order to deliver unbiased estimates of the programme effects. First, the common trend assumption must be satisfied: treated and controls must experience the same time trends in the absence of the treatment. In our framework, this means that in the DiD model we assume that those municipalities where the bag microchip was introduced would have experienced a trend in the outcome variable parallel to the trend of the control municipalities if the bag microchip had not been introduced. Second, there should not be endogenous selection on transitory shocks, implying that there should not be unobserved time-varying individual-specific heterogeneity affecting the probability of receiving the treatment (Blundell and Costa Dias, 2009). In our framework, this assumption would be violated if COSMARI decided (or the local authorities asked COSMARI) to start (or not) the bag microchip programme on the basis of particular performances of the municipality in terms of garbage collection.

Although it is not possible to formally test these identification assumptions, we can check whether the data supports the parallel trend hypothesis by looking at the trends before the programme. To do it, we modified the model in Equations (1)–(3), by enriching Equation 2 as follows

$$\begin{aligned}
\Delta'_{it} &= \mathbb{1}(t=-5 \wedge d_i=1)\theta_{-5} + \mathbb{1}(t=-4 \wedge d_i=1)\theta_{-4} + \mathbb{1}(t=-3 \wedge d_i=1)\theta_{-3} \\
&+ \mathbb{1}(t=-2 \wedge d_i=1)\theta_{-2} + \mathbb{1}(t=-1 \wedge d_i=1)\theta_{-1} + \mathbb{1}(t=0 \wedge d_i=1)\theta_{0} \\
&+ \mathbb{1}(t=1 \wedge d_i=1)\theta_{1} + \mathbb{1}(t=2 \wedge d_i=1)\theta_{2} + \mathbb{1}(t=3 \wedge d_i=1)\theta_{3} \\
&+ \mathbb{1}(t=4 \wedge d_i=1)\theta_{4} + \mathbb{1}(t=5 \wedge d_i=1)\theta_{5} + \mathbb{1}(t=6 \wedge d_i=1)\theta_{6}, \qquad (6)
\end{aligned}$$

where θ_0 is innocuously normalized to 0. The parameters $\theta_{-5}, \dots, \theta_{-1}$ should all be (jointly) equal to zero if the trends were parallel before the programme start.

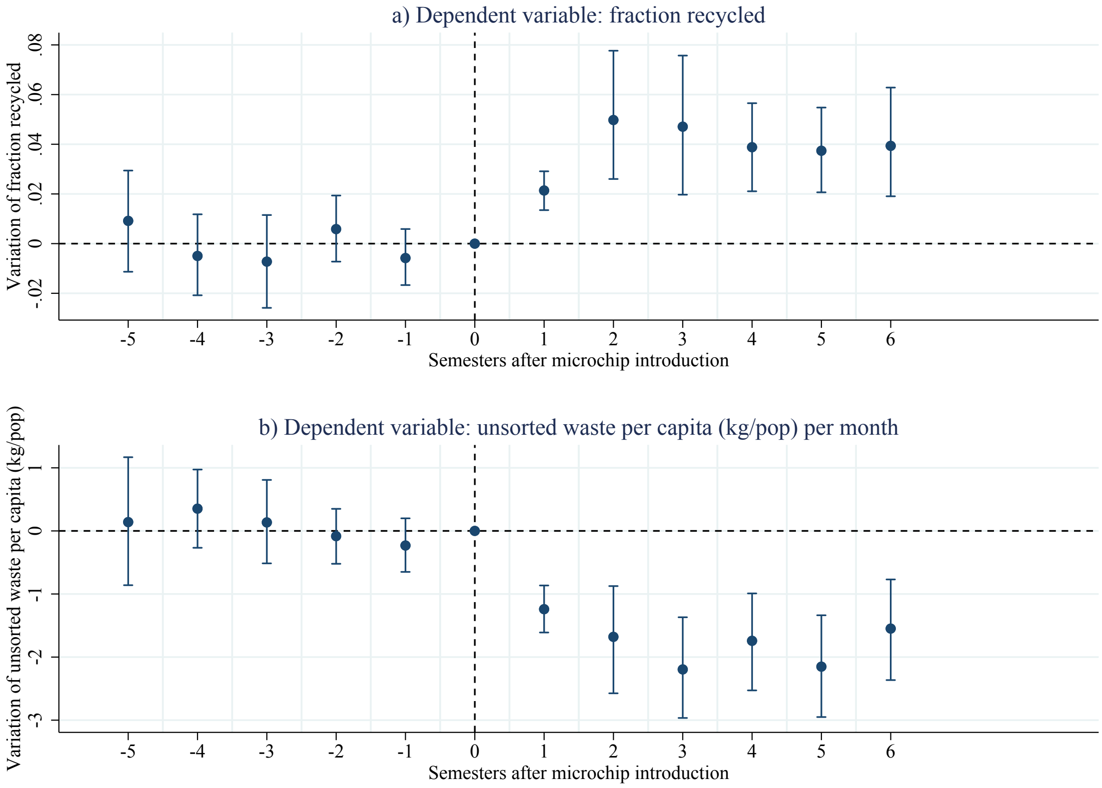
Figure 1 displays the estimation of all the parameters entering into Equation (6). In panel a) the dependent variable is the fraction recycled, whilst in panel b) it is the monthly unsorted waste per capita. Both panels clearly show that before the start of the bag microchip programme, treated and untreated municipalities were sharing the same trends in both outcomes. The tests for the joint significance of the pre-reform parameters, i.e. with $H_0 : \theta_{-5} = \ldots = \theta_{-1} = 0$, cannot confidently reject the null hypothesis.[9]

Interactive fixed-effects difference-in-differences

The two-way fixed-effects model is a model with additive fixed-effects which can control for unobserved confounders that are constant over time. However, it cannot deal with the presence of effects of confounding unobserved characteristics that vary with time or space. It might indeed happen that different municipalities have heterogeneous responses to common shocks and this would generate a violation of the common trend assumption. The IFE model is able to overcome this problem by allowing eventual time-varying effects of unobservables to be correlated to all other covariates. Although IFE models allow

[9]The p-values of the test statistics are reported in the notes of Figure 1.

Figure 1: Parallel trend tests



Notes: The points are estimated effects of the bag microchip at different moments since its introduction. They are obtained by regressing the dependent variable on municipal fixed effects, semester fixed-effects, population, population density, number of tourist bed places, and the interactions between an indicator equal to 1 for the municipalities that introduced the bag microchips and leads and lags of the moment of their introduction. The coefficient of the interaction between the indicator equal to 1 for bag microchip introduction and the lag of order one is innocuously normalized to 0 (and indicated as the semester 0 in the x-axis). The segments are 95% confidence intervals obtained from the wild cluster bootstrap-t procedure proposed by Cameron et al. (2008), with clusters at municipality level (9,999 bootstraps using the Webb's (2014) six-point distribution as weights). A test for the joint equality to 0 of the pre-programme coefficients shows that the trends between the treated and untreated municipalities were parallel before the treatment (p-values equal to 0.370 and 0.396, respectively for panel a) and b), using the aforementioned wild cluster bootstrap-t procedure). The number of municipalities is 44 for a total of 479 observations.

to relax the parallel trend assumption, we still need to assume that there is no interference between units (Rosenbaum, 2007; Abadie et al., 2010). In our framework, this would happen if the bag microchip introduced in one municipality affects the recycling behaviour in untreated municipalities. We anyway test the no interference assumption in the last part of Subsection 5.1.

We estimate the IFE model described in Equations (1), (2), and (5) applying the method in Bai (2009). We used the Stata module *regife* by Gomez (2015). The number L of factors is assumed to be known. Formal criteria for choosing the number of factors (Bai and Ng, 2003; Moon and Weidner, 2015) have been proven not to work well when the cross-section and temporal correlation in the idiosyncratic terms is large (Onatski, 2010). As in Kim and Oka (2014) we will estimate the model with an increasing number of factors until the estimated effects become stable. For both the fraction recycled and the unsorted waste per capita this happens when $L = 4$.

Synthetic control method

In the SCM, the estimation of the programme effects is based on recreating, for each treated municipality, the counterfactual using a convex combination of untreated municipalities. Let us index by i the i-th treated municipality, with $i \in D$, and let us define as C the set of size J containing all the untreated municipalities. The treatment effect for the treated municipality i, for each $i \in D$ and $t > 0$, is approximated by

$$\widehat{\theta}_{it} = y_{it} - \sum_{j \in C} w_{ij} y_{jt}, \tag{7}$$

where the w_{ij}'s are positive weights summing to one which we collect in the $J \times 1$ vector of weights $\mathbf{w}_i$. By averaging across treated municipalities, we get an estimate of θ_t. The role of $\mathbf{w}_i$ is to generate a counterfactual for the treated municipality i through a convex combination of untreated municipalities. $\mathbf{w}_i$ is chosen so that the treated municipality is "well matched" to the untreated municipalities on the basis of a linear combination of pre-treatment outcomes and observed determinants of the dependent variable. Let us define Z_i the $K \times 1$ predictor vector composed by the linear combinations of pre-treatment outcomes and covariates of the treated municipality i, and Z_0 the $K \times J$ matrix in which each column is the counterpart of Z_i for each untreated municipality. The choice of weights in $\mathbf{w}_i$ is such that they minimize some distance $||Z_i - Z_0 \mathbf{w}_i||$. More in detail, given a $K \times K$ symmetric and positive semidefinite matrix $\mathbf{V}_i$, $\mathbf{w}_i$ is chosen so as to minimize $||Z_i - Z_0\mathbf{w}_i||_{\mathbf{V}_i} = \sqrt{(Z_i - Z_0\mathbf{w}_i)'\mathbf{V}_i(Z_i - Z_0\mathbf{w}_i)}$. We pick $\mathbf{V}_i$ as suggested by Abadie et al. (2010): the choice is data driven and such that the prediction error of the pretreatment outcome between the treated and the synthetic control is minimized. We include in Z_i and Z_0 the following predictor variables averaged over the pretreatment period: population, population density, the number of tourist bed places, fraction recycled, and the unsorted waste per capita. The estimation is performed using the Stata package *synth_runner* by Galiani and Quistorff (2017).

As mentioned in Subsection 4.1 and proven by Gobillon and Magnac (2016), the SCM requires convexity arguments and constraints on the supports of factor loadings and exogenous variables. More in detail, the support of exogenous variables and factor loadings of the treated units should be a subset of the support of exogenous variables and factor loadings of the untreated units, with the latter support being convex and bounded. If this is not the case, the synthetic control is not a valid counterfactual: the SCM is based on an extrapolation, as it projects exogenous variables and factor loadings onto a convex set to which they do not belong, generating a bias.

5 Results

5.1 Programme effect

Table 3 displays the estimation results of the microchip bag programme using the different methods exposed in the previous section. In panel (a), the dependent variable is the fraction recycled, whilst in panel (b) it is the monthly unsorted waste per capita. Model (1) reports the results from the usual two-way fixed-effects DiD. Model (2) differs from Model (1) because it also includes linear time trends at municipality level. Model (3) is the IFE DiD approach. Finally, Model (4) reports the findings from the SCM. In the first line of each panel, we report the effect over the whole post-intervention period, assuming therefore that the effect is constant over time. The remaining lines display the effect of the bag microchip introduction over semesters since the start of intervention. Finally, at the bottom of both panels we report the test for the parallel trend assumption for Models (1) and (2), since this is an identification assumption in the classical DiD approach. The parallel trend test assesses the joint equality to 0 of the estimated coefficients of pre-programme indicators. In Figure 1 we have already visualized the parallel trends before the intervention for the two-way fixed-effects DiD. Here, we report the formal test also for the model that further includes linear time trends at municipality level. Since we cannot confidently reject the null hypothesis, these tests support the validity of the parallel trend assumption for both the outcome variables in both specifications.

Table 3: Results for the fraction recycled and monthly unsorted waste per capita (kg/pop)

	(1) DiD		(2) DiD		(3) IFE-DiD		(4) SCM	
	Coeff.	Wild cluster bootstrap p-value[(a)]	Coeff.	Wild cluster bootstrap p-value[(a)]	Coeff.	Clustered p-value[(b)]	Coeff.	Adjusted p-value[(c)]
	a) Dependent variable: Fraction recycled							
Estimate over the 6 semesters after programme implementation								
$\theta_1 = \theta_2 = \cdots = \theta_6$	0.040***	0.002	0.037***	0.003	0.025***	0.000	0.031[(d)]	–
Estimate by semester								
θ_1	0.022***	0.001	0.025***	0.001	0.015***	0.000	0.020***	0.000
θ_2	0.050***	0.002	0.052***	0.001	0.045***	0.001	0.040***	0.000
θ_3	0.048***	0.002	0.050***	0.001	0.044***	0.001	0.039***	0.000
θ_4	0.039***	0.001	0.043***	0.002	0.032**	0.026	0.027***	0.000
θ_5	0.038***	0.002	0.044***	0.003	0.033***	0.008	0.030***	0.000
θ_6	0.040***	0.003	0.045***	0.003	0.031**	0.017	0.030***	0.000
Placebo test parallel trend assumption:[(e)] p-value for $H_0 = \delta_0 = \delta_{-1} = \ldots = \delta_{-4} = \delta_{-5} = 0$	0.370		0.421		–		–	
	b) Dependent variable: Unsorted waste per capita per month (kg/pop)							
Estimate over the 6 semesters after programme implementation								
$\theta_1 = \theta_2 = \cdots = \theta_6$	-1.807***	0.001	-1.326***	0.000	-1.051***	0.000	-1.302[(d)]	–
Estimate by semester								
θ_1	-1.284***	0.001	-0.930***	0.002	-0.814***	0.000	-0.624***	0.000
θ_2	-1.726***	0.002	-1.227***	0.008	-1.579***	0.000	-1.456***	0.000
θ_3	-2.242***	0.001	-1.580***	0.002	-1.281***	0.001	-1.626***	0.000
θ_4	-1.787***	0.001	-0.972**	0.046	-1.251***	0.008	-1.449***	0.000
θ_5	-2.197***	0.002	-1.205**	0.032	-1.008*	0.093	-1.548***	0.000
θ_6	-1.589***	0.002	-0.433	0.472	-1.066**	0.024	-1.109**	0.000
Placebo test parallel trend assumption:[(e)] p-value for $H_0 = \delta_0 = \delta_{-1} = \ldots = \delta_{-4} = \delta_{-5} = 0$	0.396		0.529		–		–	
Municipality fixed-effects	Yes		Yes		Yes		–	
Time fixed-effects	Yes		Yes		Yes		–	
Municipalities × linear time trends	No		Yes		No		No	
Municipalities	44		44		44		38	
Observations	479		479		479		380	

Notes: *** Significant at 1%; ** significant at 5%; * significant at 10%. The regressors for the estimation of the DiD equations in models (1)-(3) are: population, its density, number of tourist bed places, and full set of dummies capturing time fixed effects and municipality fixed effects. The predictor variables in the SCM are: fraction recycled, unsorted waste per capita, population, population density, and number of tourist bed places averaged over the entire pre-intervention period.

[(a)] The wild cluster bootstrap p-values are obtained from the wild cluster bootstrap-t procedure proposed by Cameron et al. (2008), with clusters at municipality level (9,999 bootstraps using the Webb's (2014) six-point distribution as weights).

[(b)] p-values are robust to heteroskedasticity and within-municipality correlation.

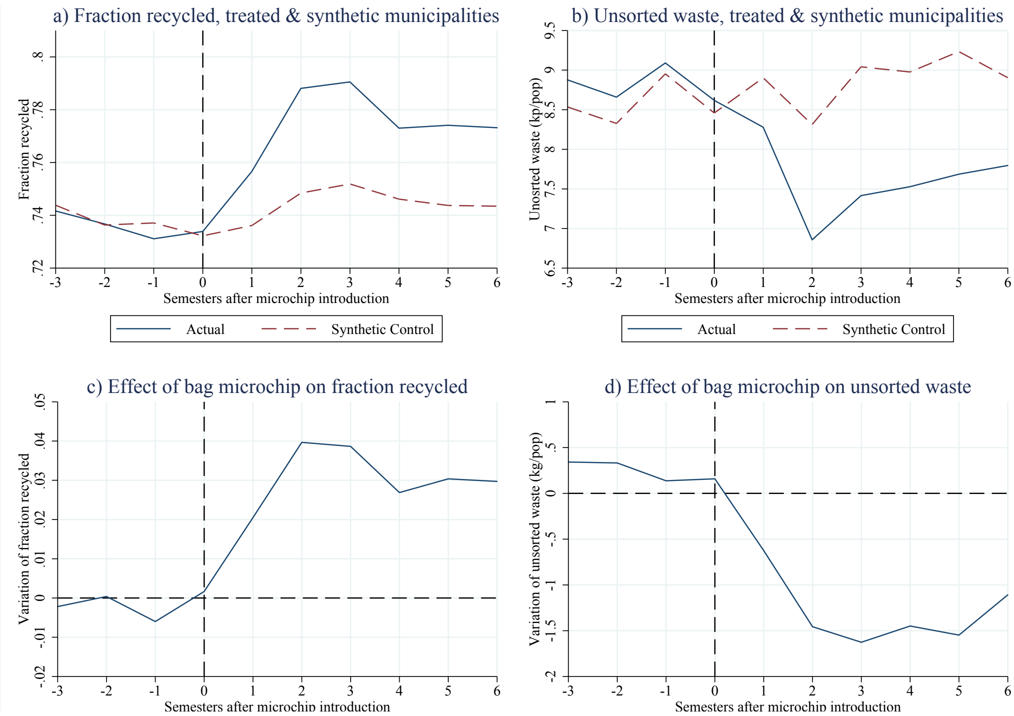
[(c)] The adjusted p-values are based on the estimates of placebo effects by implementing the SCM to each potential control in our sample, similarly to computation of permutation-based p-values (Cavallo et al., 2013). Inference is adjusted by standardising the placebo effects by the corresponding pretreatment match quality as suggested by Galiani and Quistorff (2017).

[(d)] Average of the six estimates per each semester after bag microchip introduction.

[(e)] As in Autor (2003), we include in Equation (2) further indicator variables equal to 1 if the microchip is introduced from 1 to 6 semesters in the future and we test whether the associated coefficients are jointly equal to 0. If the trend between treated and controls is parallel before the bag microchip introduction, the coefficients of these further indicator variables should indeed be jointly equal to zero. The joint tests of significance are obtained from the wild cluster bootstrap-t procedure.

The estimated effects reported in Table 3 are very stable and highly statistically significant across models and estimation strategies. The effect in the first semester is always less strong than later on. This is due to the partial treatment in the initial semester: as Table 1 shows, the programme started in the second half of the semester. The effect is therefore artificially diluted because, for a part of the first semester imputed to the post-intervention period, the treated municipalities had not yet been treated. Later the effect becomes soon more relevant and stable over time. In the last semesters of the observed post-intervention period, the introduction of bag microchips significantly increased the fraction recycled by about 3.0-4.5 percentage points, depending on the estimator used. In terms of unsorted waste, this translated into a reduction of about 1-2 kilograms per capita per month.

Figure 2: Impact of bag microchip introduction using SCM

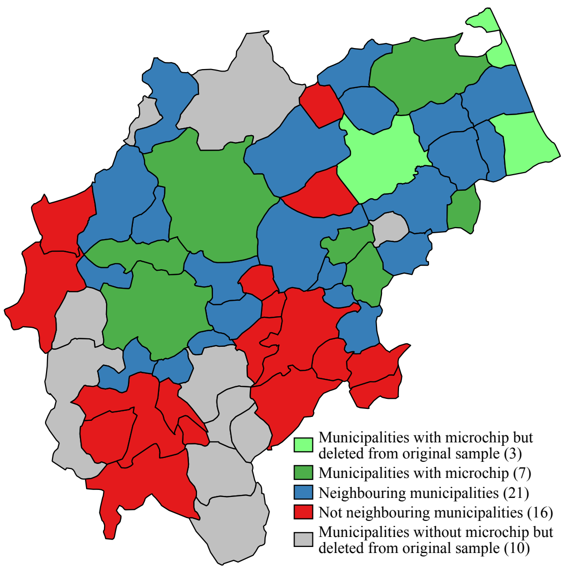


Notes: The predictor variables are fraction recycled, unsorted waste per capita, population, population density, and number of tourist bed places averaged over the entire pre-intervention period.

Figure 2 graphically reports the estimation results from the SCM. It shows in the graphs at the top the evolution over time of the average fraction recycled and unsorted waste for the treated municipalities and the synthetic controls. The graphs at the bottom display the average effect across the treated municipalities. These graphs clearly pinpoint the similar and overlapping profiles of the outcome variables between the treated and the synthetic units before the programme starts. They also evidently visualize the divergent patterns once the bag microchips are introduced.

Finally, an implicit assumption for the identification strategy used in all the proposed estimators is that there should not be interference between units (Rosenbaum, 2007; Abadie et al., 2010): in our framework the introduction of bag microchips in one municipality should not affect the recycling behaviour of users in untreated municipalities, for example in neighbouring municipalities. In untreated municipalities close to the treated ones, citizens could have indeed become aware of the effort of the waste collector to improve the quantity and the quality of the fraction recycled: the launch of the bag microchips was accompanied by communication campaigns that might have crossed the borders of the treated municipalities and impacted on the recycling behaviour of users in neighbouring municipalities. To rule out the possibility that our estimated effects are biased because of interference between units, we re-estimated the classical DiD and IFE-DiD models after removing from the sample the 7 municipalities where the bag microchips were introduced and by redefining as treated units those 21 municipalities that share the borders with the municipalities with the bag microchip programme.[10]

Figure 3: Municipalities used in the test for spatial interference between units



Notes: In the test for spatial interference, the municipalities in blue are treated and those in red are controls.

Figure 3 visually clarifies that in running the test for interference between units we use the municipalities in blue as the new treated units, since they share the borders with

[10]We do not use the SCM in this robustness test as the SCM is well suited for comparative case studies where one unit or a little number of units are treated. Here we have 21 treated municipalities and 16 controls.

Table 4: Test for spatial interference between units

	(1) DiD		(2) DiD		(3) IFE-DiD	
	Coeff.	Wild cluster bootstrap p-value[(a)]	Coeff.	Wild cluster bootstrap p-value[(a)]	Coeff.	Clustered p-value[(b)]
		a) Dependent variable: Fraction recycled				
Estimate over the 6 semesters after programme implementation						
$\theta_1 = \theta_2 = \cdots = \theta_6$	-0.000	0.974	-0.007	0.195	-0.003	0.519
Estimate by semester						
θ_1	0.000	0.972	-0.006	0.359	-0.001	0.878
θ_2	-0.002	0.875	-0.020**	0.020	-0.009	0.460
θ_3	0.006	0.602	-0.015	0.298	-0.001	0.942
θ_4	0.000	0.978	-0.024	0.174	-0.007	0.613
θ_5	-0.009	0.433	-0.035	0.109	-0.009	0.597
θ_6	0.003	0.824	-0.026	0.269	0.002	0.913
		b) Dependent variable: Unsorted waste per capita per month (kg/pop)				
Estimate over the 6 semesters after programme implementation						
$\theta_1 = \theta_2 = \cdots = \theta_6$	0.092	0.801	0.127	0.615	0.129	0.595
Estimate by semester						
θ_1	-0.149	0.642	-0.028	0.937	-0.029	0.919
θ_2	0.676	0.107	0.922**	0.032	0.260	0.440
θ_3	-0.404	0.417	-0.007	0.988	-0.106	0.851
θ_4	0.500	0.256	1.055	0.112	0.336	0.533
θ_5	-0.308	0.619	0.373	0.657	0.124	0.907
θ_6	0.222	0.618	1.012	0.277	0.200	0.727
Municipality fixed-effects	Yes		Yes		Yes	
Time fixed-effects	Yes		Yes		Yes	
Municipalities $\times$ linear time trends	No		Yes		No	
Municipalities	37		37		37	
Observations	395		395		395	

Notes: *** Significant at 1%; ** significant at 5%; * significant at 10%. The regressors are: population, its density, number of tourist bed places, and full set of dummies capturing time fixed effects and municipality fixed effects.

[(a)] The wild cluster bootstrap p-values are obtained from the wild cluster bootstrap-t procedure proposed by Cameron et al. (2008), with clusters at municipality level (9,999 bootstraps using the Webb's (2014) six-point distribution as weights).

[(b)] p-values are robust to heteroskedasticity and within-municipality correlation.

municipalities where the bag microchips were introduced, and the municipalities in red as controls (16 municipalities). Table 4 displays the estimation results. Both in Model (1) and in Model (3) no significant effect is detected and the point estimates are all very close to zero in magnitude. In Model (2), where eventual unobservables that might change across municipalities and time in diverse patterns is captured using a strong parametric approach, a significant effect is detected in the semester after the introduction of the bag microchips. However, since it disappears in the subsequent semesters and it is not present in Model (3), which represents a more flexible way of dealing with time-varying unobservables, we conclude that municipalities in the neighbourhood of those which experienced the introduction of bag microchips had the same recycling behaviours as non-neighbouring municipalities: this is evidence for no spatial interference between units.

5.2 Discussion

After the pilot schemes in 2011 and 2012 run in two municipalities (see Section 3), COSMARI (2013, p. 35) predicted an increase of 6 percentage points in each of the municipalities where the bag microchips would have been introduced. The most robust estimates of ours, i.e. those coming from the IFE-DiD estimator and the SCM, suggest that the effect stabilizes at about $+3$-3.3 percentage points after four semesters. In the most optimistic scenario, i.e. the estimates from the DiD with linear time trend at municipality level, the effect is $+4.5$ percentage points. Hence, the prediction of the waste collector has been too optimistic and the real effect is 25%-50% lower than expected.

Albeit lower than COSMARI expectations, the magnitude of the effect is remarkable, considering that the fraction recycled was already very high in the treated municipalities before the bag microchip programme and that it might be difficult to do better if the performance is already outstanding. As shown at the bottom of Table 1, the fraction recycled by the treated municipalities in 2012 was 73.4%. In the same year, the Italian average was 38.4% and the highest value among European countries, scored by Germany, was 65.2%.[11] Another way of understanding the relevance of the impact is by looking at the effect relatively to the fraction of municipal waste which in 2012 was *not* recycled in the treated municipalities (26.6%): a 3-3.3 (4.5) percentage point decrease is, relatively to 26.6%, a 11.3-12.4% (16.9%) reduction in the fraction that the treated municipalities

[11]These figures come from Eurostat and available from https://ec.europa.eu/eurostat/databrowser/view/t2020_rt120/.

were *not* able to recycle.

If we focus on the impact of the bag microchips on the reduction in the amount of unsorted waste, we can get an idea of the monetary benefits for the treated municipalities. The total population in the 7 treated municipalities in 2014, which is the first year of full treatment, amounted to 59,387 inhabitants. In the same year, the estimated coefficients of the effect on the unsorted waste (average of the coefficients in semesters $t+2$ and $t+3$) implies a monthly reduction per capita that spans from 1.404kg in Model (2) to 1.984kg in Model (1). This implies a yearly reduction in unsorted waste of 16.848-23.808kg per capita. Multiplying these per capita figures by the 2014 population of the treated municipalities yields a reduction of unsorted waste in the treated municipalities of 1,001-1,414 tonnes. Since in 2014 these municipalities were charged by the waste collector €171 per tonne of unsorted waste in January and February and €174.40 per tonne in the remaining months of the year (COSMARI, 2014, p. 32), they saved about €174,000-246,000 thanks to the introduction of the bag microchips. In front of a reduction of unsorted waste, one could expect an increase in the production of sorted waste. However, this is not going to modify the saving estimation for two reasons. First, the treated municipalities did not experience an increase in the production of organic waste, for which they were charged (e.g. €44 per tonne in 2014). In the post-treatment period we did not detect any significant and relevant change in the production of the organic waste.[12] Second, municipalities were not charged for discarding other recyclable wasted.

However, the microchip bags are more costly than the normal ones. According to COSMARI (2013, p. 34), they cost on average €0.093 more than normal bags, with an extra expected expenditure for microchip bags for the 7 treated municipalities of about €307,000. However, this is a predicted cost as reported in the official budget forecasts (COSMARI, 2013). In the subsequent actual balance sheets no similar figures are reported to infer the actual costs supported by each municipality and therefore to understand the actual extra-costs for microchip bags. Assuming the accuracy of the cost predictions and sticking to them, the cost of microchips exceeded the benefits by about 25% in the most optimistic estimate and by about 76% in the least optimistic estimate of the programme effect. The net yearly cost of the programme is €61,000-133,000, which is not sizeable if we smooth it over the population involved: €1.03-2.24 per capita.[13]

[12] We indeed estimated an average insignificant increase in the monthly organic waste of about 0.1kg per person from the classic DiD (both with and without municipal linear trends), 0.2kg per person from SCM, and -0.03kg per person from IFE-DiD. These estimation results are available from the author upon request.

[13] Since the number of domestic and non-domestic users was around 27,000, the net yearly cost for each

Nevertheless, these simple computations of direct monetary costs for the involved municipalities do not take into account other societal and environmental benefits like, just to mention some, the reduction of unsorted waste accumulation in landfills, the reduction in carbon dioxide emissions in case of incineration, and the preservation of natural resources if the market for recycled material are efficient enough.

6 Conclusions

This paper evaluates the effectiveness of a programme that placed microchips on the bags for the waste collection on the curb. It was implemented in the province of Macerata (Marche, Italy) by the waste management company to increase the quality and the quantity of the fraction recycled and as a step ahead towards the eventual introduction of the pay-as-you-throw system.

We found that the programme has been able to further increase the fraction recycled, although already large before the programme start. About 2 years after the programme start, the bag microchip introduction significantly increased the fraction recycled on average by 3-4.5 percentage points, depending on the estimator used. This implies a reduction of the unsorted fraction of 11.3%-16.9%. In terms of mass of monthly unsorted wasted, the introduction of bag microchip generated a significant decrease of about 1-2 kilograms per capita. This is a sizeable impact, given that in the year before the programme, in the treated municipalities the average monthly unsorted waste was 8.9 kilograms per capita.

Our findings are useful for policy-makers and regulators interested in the adoption of programmes to increase the fraction recycled of urban waste. We show indeed that the bag microchip programme has been effective in pushing to a higher level the efficacy of the DtD waste collection. Being based on the risk of punishment, it has proven to be a valid alternative to systems based on economic incentives, which are often coupled with the curbside collection, like unit-based pricing systems. Henceforth, the bag microchip system could be especially useful when leaving the flat-fee system is not socially/politically accepted and/or in case of large risks of incurring in the negative side effects of the unit-based pricing system, as illegal dumping and burning and garbage tourism.

user was about €2.26-4.93.

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