From pay-per-bag to pay-per-kg:

The case of Flanders revisited

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Abstract

Weight-based pricing systems for municipal solid waste collection and processing are increasingly popular in many European countries and regions. However the impact on waste generation of such pricing schedules remains debated and depends strongly on the practical details of the system used. This paper assesses the impact of a voluntary transition by Flemish municipalities from the default price-per-bag pricing systems to a more sophisticated weight-based pricing schedule. By (1) exploiting alternative statistical techniques, (2) using more recent data and (3) focusing on the introduction effect of the new pricing schedule, we are able to complement and refine prior research on this topic. Our results indicate that introducing weight-based pricing has initially a significant and substantial downward impact on the amount of residual municipal solid waste per capita. This result is robust under different methodologies that control for selection bias. There are however indications that this initial effect does not persist in the years after introduction.

Keywords:

municipal solid waste; weight-based pricing, selection bias,

difference-in-differences, matching estimator, panel data

Introduction

In search of financial retribution systems that reflect the polluter-pays principle, more and more local authorities rely on weight-based waste pricing schedules for their household waste collection and processing services. Although generally designed to stimulate MSW reduction and recycling efforts, the debate on the impact of weight-based pricing schedules on waste generation is still ongoing (see for instance Linderhof et al. 2001, Dijkgraaf & Gradus 2004 and De Jaeger 2010). Inspired by the need for more empirical evidence, this paper analyzes the impact of the voluntary transition of certain Flemish municipalities from the standard price-per-bag pricing systems to more sophisticated weight-based pricing schedules. Under this more sophisticated weight-based pricing schedule, households are charged for each kilogram of waste they put on the curbside. Each household receives a standardized waste bin, marked with an identification chip. Upon collection, the difference in weight before and after emptying the bin is recorded and this weight measure is used later to bill households for the actual amount of waste they disposed of.

There is a substantial literature in environmental and resource economics that tries to estimate the price sensitivity of consumers for waste collection services for different types of waste, see Dijkgraaf and Gradus (2004) for an overview. This literature uses either detailed household surveys or aggregate municipal data to estimate long and short run price elasticities of demand for waste collection. Beyond doubt this price sensitivity information is important for the design and fine-tuning of price based MSW collection systems but it does not provide an answer to the question how effective the introduction of a weight-based system is in reducing overall MSW volume and/or weight. This is the question that policy makers typically are interested in and this paper wants to answer.

We have at our disposal a panel data set of about 300 Flemish municipalities and 6 years. During that period municipalities gradually introduced weight-based pricing and by the last year in the sample about 72 municipalities (23.4%) had adopted the system. The gradual implementation of the system constitutes a natural experiment and allows us therefore in principle to estimate the impact of introducing a weight-based collection service. But as Flemish municipalities can decide on a voluntary basis whether to adopt a more sophisticated weight-based pricing system or to stick to the default price-per-bag system, adoption of weight-based pricing might not be random. This implies that assessing the impact of weight-based pricing via a regression of MSW on a dummy variable indicating whether weight-based pricing is used or not (and a set typical explanatory variables), might result in biased estimates of the true effect of the pricing systems. Underlying this selection bias is the fact that the decision to participate in the new system is likely to be affected by factors that also have an impact on MSW generation. In others words, one cannot consider the decision variable as exogenous in this setting (see for instance Heckman et al. (1998a) or Wooldridge (2002) for more details on selection bias). If for instance municipalities with a long history of MSW reduction efforts are more/less likely to switch to the weight-based pricing system, the impact of the new system on MSW reduction will probably be over/underestimated.

Dijkgraaf and Gradus (2004) in their assessment of the impact of introducing a unit-based pricing scheme for different types of waste streams in the Netherlands are aware of this problem and tried to correct for what they call "environmental activism" by including a dummy variable that takes value one for municipalities that adopted some unit-based pricing scheme and value zero for municipalities that never adopted such a system. The effect is strongly significant and leads them to conclude that the true impact of adopting a unit-based pricing system is much lower than in their original estimates without controlling for selection bias. But currently, a wide variety of statistical methods exists to address the problem of selection bias (for an introduction see Blundell & Costa Dias 2000).

Using one of these methods, De Jaeger (2010) found no proof for a significant and robust impact of weight-based pricing on MSW generation in Flanders.[2] In this paper, we will consider a much more wider set of techniques to check the robustness of earlier results.

There are several reasons why revisiting the case of Flanders could lead to new insights for both waste management professionals as scholars. First, the paper of De Jaeger (2010) is mainly a methodological contribution, using the case of weight-based pricing in Flanders as an application of the extended difference-in-differences approach. As alternative methods to address endogeneity issues could generate new insights, our paper will add the results of a matching estimator and panel data estimations. Second, the most recent observations included in the analysis of De Jaeger (2010) date back to 2007, while participation in the weight-based pricing schedule experienced an important boost between 2007 and 2010. Third and finally, due to the limited amount of new participants in a given year, De Jaeger (2010) was unable to present a robust analysis of the introduction effect (i.e. the first year impact for new participants) of the weight-based pricing schedule. Extending the dataset with more recent observations however, allows us

[2]Note that the results presented in table 3 in De Jaeger (2010) contain an error, although the corrections do not materially change the conclusions of the paper, the corrected table will be send to the interested reader upon simple request.

to report a more detailed analysis of this introduction effect. Note that due to the long time frame analyzed in De Jaeger (2010) bulky household refuse was considered part of the MSW fraction, distinguishing between bulky household refuse and residual household waste quantities was not possible in the old dataset. The current paper however, builds on more recent and detailed data in which bulky household waste is no longer included in the MSW fraction.

The structure of this paper is as follows. The next 2 sections describe the data and methodology. Results and conclusions are presented in the final 2 sections.

Data

In Flanders weight-based pricing systems for curbside waste collection are mainly used for residual MSW collection (i.e. MSW that is not collected for recycling or composting) and, to a lesser extent, for green waste collection. In this paper we focus on the impact of weight-based pricing on the first fraction, residual MSW (for more details on this pricing schedule see also De Jaeger and Rogge 2013). Hence other separately collected waste fractions, like green waste, but also packaging waste, are not taken into consideration in our analysis.[3] Data on residual MSW quantities for each municipality were provided to us by OVAM (Public Waste Agency of Flanders).

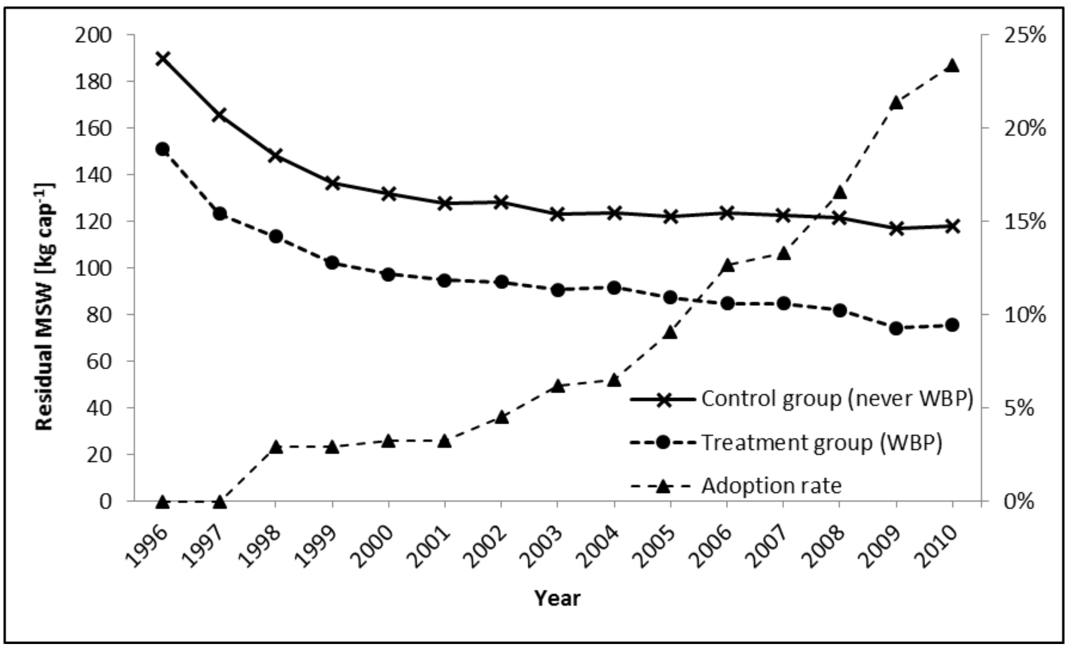
In 1998, 9 pioneering municipalities introduced weight-based pricing for residual MSW collection in Flanders. Since then, this number gradually increased to 72 (out of 308, i.e. 23.4%) in 2010 (reliable data on the incidence of weight-based pricing is currently only available up to 2010). Note that once having adopted the new pricing schedule, very few of the participating municipalities returned to the classical price-per-bag system. As the impact of weight-based pricing on residual MSW generation during the first years was already analyzed in De Jaeger (2010), this paper will focus on the period 2005-2010. Table 1 reveals that during this period the number of participants more than quadrupled.

[3] Note that the Flemish waste agency requires all municipalities to organize separate collection for recyclable waste flows, like packaging waste (cans, plastic bottles, etc.), paper, glass bulky household waste, etc. As this obligation holds for all municipalities, it cannot be the reason for possible differences in residual MSW per capita generation between municipalities.

Table 1: incidence of weight-based pricing in Flanders in number of municipalities for the first three columns and percentages for the last column

Year	New adopters	Drop out	Total # of Participants	Participants share
2005	8	0	28	9.1
2006	11	0	39	12.7
2007	3	1	41	13.3
2008	11	1	51	16.6
2009	16	1	66	21.4
2010	6	0	72	23.4

Combining the data on the adoption of weight-based pricing and residual MSW generation already points to possible problems that might arise if selection bias is not addressed adequately. Figure 1 depicts average residual MSW generation for both the *treatment group* of municipalities using weight-based pricing in 2010 (i.e. the 72 participating municipalities mentioned in the last row of Table 1) and a *control group* consisting of the municipalities which never used weight-based pricing during the observed period. Figure 1 shows that average residual MSW generation is consistently lower in the treatment group compared to the control group. In line with the findings reported in De Jaeger (2010), participating municipalities are on average characterized by lower amounts of residual MSW compared to the control group even before the weight-based pricing was introduced for the first time (i.e. 1998). This observation can be considered as an indication that the adoption decision is not exogenous. In other words, the participation municipalities are not just a random sample of all Flemish municipalities. They seem to share particular characteristics (observable and non-observable) that influence the adoption decision.



Legend: WBP stands for weight-based pricing

Figure 1: Comparison of residual MSW generation between participants and non-participants

Focusing on the introduction effect however, reveals a different picture. If we depict for instance the average amount of residual MSW per capita for municipalities introducing weight-based pricing for the first time in 2006 together with the average amount of residual MSW per capita for the control group, i.e. the municipalities which never used weight-based pricing between 2005 and 2010 (see Figure 2), we observe a substantial downward jump for the newly adopting municipalities. Note that this trend is not present in the control group. The figure again reveals that in the years prior to the introduction of the new pricing system, participating municipalities had on average already a lower amount of residual MSW compared to the control group. Although not depicted in this paper, a similar pattern can be found for municipalities introducing weight-based pricing for the first time in 2008 and 2009, with respective reductions of 27% and 30% in residual MSW generation. Note that for municipalities introducing weight-based pricing for the first time in the other observation years (i.e. 2005, 2007 and 2010) the pattern is less pronounced. This could be caused by relatively low amount of new participants in those years (see also Table 1).

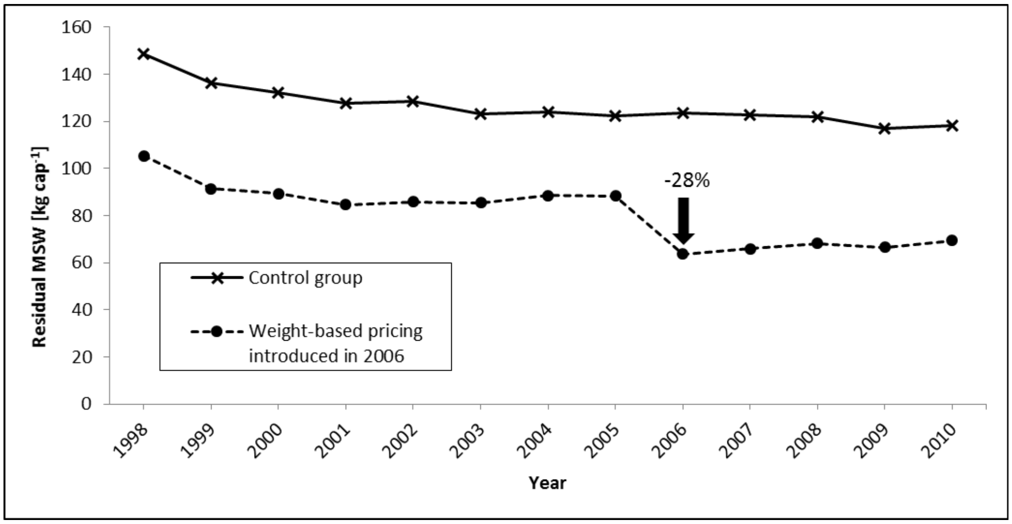


Figure 2: Comparison of residual MSW generation between new participants and non-participants

Although the above figures already reveal some information on the potential impact of (the introduction of) weight-based pricing on residual MSW generation, the potential problems arising from selection bias must be addressed in a more consistent way before conclusions can be drawn.

Methods

There exist many statistical methods to analyze the effectiveness of policy measures while taking into account selection bias. In this paper we will use a selection of models: (1) standard linear regression models, (2) panel data models, (3) a matching estimator, and (4) the difference-in-differences approach. As this paper is intended to illustrate the value of our specific dataset for an international professional audience, we will only briefly describe the three methods and refer the interested reader to other sources for a more detailed and technical description of the above methods. The definition of the variables used to estimate the models can be found in the Table 2.

Table 2: Variable definitions

Weight-based pricing: a dummy variable indicating if the municipality uses/introduced weight based pricing. Source: collected via a database of Openbare Vlaamse Afvalstoffenmaatschappij, municipal websites, provincial archives and telephone interviews with the municipalities.
Residual municipal solid waste: all waste (in kg per capita) generated in a residential environment due to regular activities by private households excluding bulky household refuse and any selectively collected flow such as packaging waste, paper and cardboard, small hazardous waste, etc. Note that waste generated by companies, schools, hospitals, prisons etc. is collected by private waste collection and processing firms and is not included in the definition of residual municipal solid waste. Source: Database of Openbare Vlaamse Afvalstoffenmaatschappij (Public Waste Agency of Flanders).
Young: Percentage of people younger than 5 years of age.

Source: Statistics Belgium (http://statbel.fgov.be/en).
Old: Percentage of people older than 65 years of age. Source: Statistics Belgium (http://statbel.fgov.be/en).
Underprivileged index: percentage of children born in an underprivileged household in the last 4 years. Source: Studiedienst van de Vlaamse Regering (http://www4dar.vlaanderen.be/sites/svr [in Dutch]).
Average income: average income before taxes. This statistic is based on the declaration of incomes subject to taxation for private persons. Source: Studiedienst van de Vlaamse Regering (http://www4dar.vlaanderen.be/sites/svr [in Dutch]).
Population density: average population per square km. Source: Statistics Belgium (http://statbel.fgov.be/en).
Classification of municipalities: the typology of the 308 Flemish municipalities is derived from the well-known Belfius classification (see source below). The latter classification is the result of a factor and cluster analysis based on a set of municipal socio-economic variables. The Belfius classification consist of 16 clusters which we grouped in 4 main categories and 1 benchmark category: • Touristic: municipalities attracting a lot of tourists. This group contains only coastal municipalities. Note that cities attracting a lot of tourists are included in the 'City' group. • City: Large, medium sized an regional cities. • Rural: municipalities with a low level of urbanization • Urbanized: urban or semi-urban municipalities with low average income levels, modest economic activity and, in contrast to the category 'City', a limited level of centrality. • Benchmark category : residential municipalities (urban fringe and rural) and municipalities with economic activity. Source: Belfius socio-economic typology (https://www.belfius.be/publicsocial/NL/Expertise/Studies/LokaleFinancien/GemeentenProvincies/Typology/index.aspx [in Dutch]).
Municipal debt per capita: Total debt (in €) listed in the balance sheets, divided by the total population. Source: Studiedienst van de Vlaamse Regering (http://www4dar.vlaanderen.be/sites/svr [in Dutch]).
Vote share of the municipal council: the share of votes (in %) for the political parties represented in the municipal council. For the treatment years 2005 and 2006 we use the results of the 2000 municipal election and for treatment years 2007-2010 the results of the 2006 municipal election. Source: own calculations based on the official election results (http://www.vlaanderenkiest.be/ [in

Dutch]).
Municipal joint venture: dummy variable taking value 1 if other municipalities in the same municipal waste joint-venture have implemented weight-based pricing. Source: own calculations.

Linear regression model: ordinary least squares (OLS)

We start by estimating simple linear regression models with MSW as dependent variable and a number of covariates as depend variables. The dependent variable y_{it} is the amount of MSW per capita collected by municipality *i* in year *t*. Whether a municipality applies weight-based pricing (WBP in the sequel) in year *t* or not is indicated by the dummy variable w_{it}. It takes value zero as long as the municipality does not apply WBP. From the year it introduces WBP, the variable takes value one for the rest of the time horizon. Covariates that describe municipalities' characteristics are denoted by vector $\mathbf{x}_{it}$ and include average income, population density, two variables that account for the specific consumption patterns of age groups (i.e. the percentage of residents younger than 5 years and older than 65 year), an underprivileged index (i.e. the percentage of children born in an underprivileged household in the last 4 years) and a set of dummy variables classifying municipalities into five categories according to objective geographic, demographic and economic criteria (touristic, city, urbanized, rural, and "other"). Error terms are denoted by e_{it} and are assumed to be independent and identically distributed (IID):

$$y_{it} = \beta_t^0 + \mathbf{x}_{it}'\boldsymbol{\beta}_t + \delta_t w_{it} + e_{it} \quad (1)$$

Starting from this model it can be shown that the estimated coefficient δ_t measures the difference in group average MSW between the municipalities that apply WBP and the ones that do not. For a given year, summing over all municipalities that apply WBP and dividing by the number of these municipalities, it follows:

$$\overline{y}_t^{\text{WBP}} = \beta_t^0 + \overline{\mathbf{x}}_t'^{\text{WBP}}\boldsymbol{\beta}_t + \delta_t \quad (2)$$

Likewise, for a the group of municipalities that do not apply WBP it can be shown that:

$$\overline{y}_t^{\text{no WBP}} = \beta_t^0 + \overline{\mathbf{x}}_t'^{\text{no WBP}}\boldsymbol{\beta}_t \quad (3)$$

Taking the difference, and assuming that the effect of other covariates is the same for both groups of municipalities, it follows:

$$\overline{y}_t^{\text{WBP}} - \overline{y}_t^{\text{no WBP}} = \delta_t + \left[\overline{\mathbf{x}}_t'^{\text{WBP}} - \overline{\mathbf{x}}_t'^{\text{no WBP}}\right]\boldsymbol{\beta} = \delta_t \quad (4)$$

Note that in our estimation the intercept and slopes can vary trough time as we estimate equation (1) for each year separately.

So far we have been comparing municipalities that apply WBP to municipalities that do not. We call this the "general participation effect" model in the sequel. But, another interesting comparison is between municipalities that newly introduced WBP and municipalities that did not introduce it in a given year. Formally, this is a slight variation on model (1):.

$$y_{it} = \beta_t^0 + \mathbf{x}_{it}'\boldsymbol{\beta}_t + \delta_t \Delta w_{it} + e_{it} \tag{5}$$

where $\Delta w_{it} = w_{it} - w_{it-1}$ stands for the first difference of the indicator variable w_{it}. It only takes value one in the year that a particular municipality introduced WBP and zero in all other years. The interpretation of the regression coefficient is again the difference in group average but in this case between newly adopters of WBP and those who did not introduce it in a given year. We will call this model the "introduction effect" model in the sequel. Comparison of the result of both the general participation and introduction effect models will allows us to infer something about the persistence of the effect of WBP on MSW generation. If the introduction effect is stronger than the general participation effect, this is an indication that the effect of WBP on MSW erodes over time.

Panel data models

The models above where estimated year by year. One can exploit the data better by taking into account the panel data structure, i.e. the fact that we have repeated observations on the same municipalities. The literature on panel data models is very large, see for instance Verbeek (2008) or Baltagi (2008) for an introduction. We will confine ourselves to the basic panel data models.

We start by considering *fixed effects* models which can be written as follows:

$$y_{it} = \alpha_i + \lambda_t + \mathbf{x}_{it}'\boldsymbol{\beta} + \delta w_{it} + e_{it} \tag{6}$$

$$\Delta y_{it} = \lambda_t + \Delta\mathbf{x}_{it}'\boldsymbol{\beta} + \delta\Delta w_{it} + \Delta e_{it} \tag{7}$$

The distinguishing feature of fixed effects models is given by the α_i's and λ_t's which are municipality and time specific constants respectively. Hence the intercept is allowed to differ between municipalities and can therefore control for specific characteristics of municipalities even if we have no observable data on that. The difference between both specifications above is that model (6) considers the levels of the variables and captures the general participation effect. Model (7) on the other hand uses first differences of the variables (causing the fixed municipality effects to disappear) and refers to the introduction effect. The interpretation of the slope coefficient δ is similar as in the linear regression model above: it measures the difference in average MSW per capita between group of municipalities that *apply* or that *introduce* WBP compared to the group that does not. Compared to the yearly OLS models higher, the estimated slope coefficient is assumed to be constant through time in the panel data specification.

The big advantage of the panel data method over the OLS model is that the estimated parameters are more robust for misspecification and omitted variable bias. If there would be unobserved characteristics of municipalities that correlate with the introduction decisions, they are likely to be captured by the municipality-specific intercepts so that they do not distort the estimated coefficients of participation or introduction, see Verbeek (2008).

Apart from the fixed effect panel model, we also consider a random effects version. In this model there is a common intercept but the error terms are assumed to consist of a municipality specific component in order to capture unobserved municipality characteristics. We report the results for completeness but for our analysis the fixed effect model is the more natural choice.

Matching estimator (MATCH)

The matching estimator addresses the problem arising from selection bias by composing a new control group before comparing the average value of the outcome variable (in our case the amount of residual MSW) between the treatment group and the control group. In our case we use a so-called nearest-neighbor matching estimator which selects for each participating municipality the "closest" non-participating counterpart in terms of a set of covariates. Regarding these covariates we start from the same set of exogenous variables used for estimating the other models. As we expect that both financial and political motives could influence participation in the weight-based pricing schedule, we include municipal debt per capita and the vote share of the municipal council as additional variables in the matching procedure. As most Flemish municipalities cooperate with neighboring municipalities to provide waste related services via so-called municipal joint-ventures, we also include a dummy variable indicating if other municipalities in the same municipal waste joint-venture have implemented weight-based pricing as a third matching variable. The underlying assumption is that, conditional on the set of covariates, participation is independent of the outcome, implying that the outcome in the absence of participation is the same in both groups. For more details on the matching technique see for instance Heckman et al. (1998b) or Abadie et al. (2004).

Difference-in-Difference estimators (DD and DDD)

The last method that we consider in this paper to overcome potential problems with selection bias, is the difference-in-difference (DD) estimator. It compares the evolution of the outcome variable between participating and non-participating municipalities, see for instance Blundell and Costa Dias (2000), De Jaeger and Eyckmans (2008) or De Jaeger (2010). The intention behind the DD estimator is to compare the progress (i.e. the difference in the outcome variable after and before adoption) of participating municipalities with the progress of non-participating municipalities. The difference in progress between both groups is then considered as the treatment effect. Note that this implies that in absence of participation, both groups are assumed to have the same progress in the outcome variable (common trend assumption). This assumption implicitly defines the counterfactual baseline against which the participation effect is judged. Whether that baseline assumption holds, is very hard to test. “Higher order” DD estimators exist (see Moffit (1991) or De Jaeger (2010)) which allow for more general identification assumptions. For instance the second order DD estimator (which will be indicated by DDD in the sequel) compares the *changes* of the progress between both groups, any difference between those changes are then attributed to participation. In this case the underlying assumption is that in absence of treatment, the change in progress should be identical between both groups. In our paper we will report the results of both the standard DD estimator as well as results from a second order DD (or DDD). Note that in our case the DD (DDD) estimator can be estimated by regressing the (change of the) progress of MSW per capita generation on a dummy variable indicating if the municipality has adopted weight-based pricing (and the same set of exogenous covariates used before).

Results

We first present the detailed results for 2010, next we report the treatment effect estimates for the other years (i.e. 2005-2009) and finally the output for panel data estimations is discussed. Note that for the general effect, a municipality is considered a participant of the weight-based pricing system in a given year if the municipality uses the pricing system in that particular year. This implies that only participation determines the composition of this group and that therefore the number of years that a municipality uses weight-based pricing is irrelevant. For the introduction effect on the other hand, we consider a municipality as a participant in a given year if the municipality used weight-based pricing for the first time in that year. However, the estimated introduction effect should be interpreted cautiously, as the number of municipalities introducing weigh-based pricing is for some years limited (see also Table 1). The control group consists in both cases of the municipalities which never used weight-based pricing during the observed period (or a selection of this group when the matching procedure is used).

The regression and matching output for 2010 is shown in Table 3. The results for the *general participation effect* are depicted in the first 4 columns of the table. The figures for both OLS as the matching procedure show a statistically significant negative relation between weight-based pricing and residual MSW generation. For instance the coefficient of -10.658 for the matching estimator indicates that on average municipalities using weight-based pricing in 2010 generate about 11 kg less residual MSW per capita compared to municipalities that never adopted weight-based pricing. Note that the magnitude of the effect is lower using the matching estimator compared to the OLS estimates. This is an indication of selection bias in the OLS results. The DD and DDD approaches on the other hand, reveal a different picture. Both coefficients for weight-based pricing are not significantly different from zero. In other words, according to the DD and DDD estimates there is no general participation effect for using weight-based pricing in 2010. Of the coefficients for the other covariates, only the percentage of residents younger than 5 years of age (variable labelled “Young”), the percentage of people older than 65 years of age (variable labelled “Old), the population density and the dummy variable for coastal municipalities (variable labelled “Touristic”) are significantly different from 0 in the OLS estimates. According to this result, the particular consumption behavior for both age groups results in higher waste quantities. Note that only the impact of the variable young is confirmed by the DD and DDD estimates. The population density is significantly positive, but only at the 10% level. In addition this effect is not supported by the estimation output of the DD and DDD. Finally the significant positive coefficient for the coastal municipalities points to the importance of waste generation by tourists. Note that the underprivileged index is significantly negative at the 10% level for the DDD estimates.

Estimates for the *introduction effect* in 2010 are presented in the last 4 columns of table 3. Only for the OLS and DD estimates the introduction effects is found to be significantly negative. The lack of a robust negative impact could be caused by the limited number of municipalities (only 6) introducing weight-based pricing for the first time in 2010. The coefficients and inferences for the socio-economic covariates are qualitatively very similar between the estimates for the general participation effect and the introduction effect, with the exception of the underprivileged index which is no longer significantly different from zero in the DDD model.

Results for the other treatment years 2005-2009 are summarized in Table 4. Note that, due to space limitations, this table does not report the estimated coefficients for all independent variables, but only depicts the estimates for the treatment effects. The full regression output is available for to the interested reader upon simple request.

Table 3: OLS, matching and difference-in-differences estimates for the general participation effect and the introduction effect in 2010

	General participation effect (2010)				Introduction effect (2010)			
	OLS	MATCH	DD	DDD	OLS	MATCH	DD	DDD
Weight-based pricing	-34.044***	-10.658***	-0.250	2.281	-30.262**	6.977	-18.075***	-6.920
	(3.708)	(4.156)	(1.183)	(2.318)	(12.067)	(10.534)	(4.061)	(7.241)
Young	6.699***	–	7.408**	10.278**	8.546***	–	10.328**	16.569***
	(2.582)	–	(3.276)	(4.617)	(3.015)	–	(4.068)	(5.295)
Old	4.991***	–	-0.118	4.059	6.421***	–	-2.417	4.981
	(0.940)	–	(2.395)	(4.552)	(1.164)	–	(2.915)	(5.158)
Underprivileged index	0.654	–	-0.503	-1.046*	0.452	–	-0.265	-0.994
	(0.494)	–	(0.340)	(0.590)	(0.600)	–	(0.401)	(0.648)
Average income	-1.118	–	-1.421	0.993	-0.402	–	-2.476	-1.159
	(1.164)	–	(2.121)	(2.525)	(1.461)	–	(2.492)	(2.841)
Population density	0.007*	–	-0.009	0.205	0.005	–	-0.089	0.133
	(0.004)	–	(0.102)	(0.233)	(0.004)	–	(0.113)	(0.240)
Touristic	112.842***	–	–	–	104.891***	–	–	–
	(13.178)	–	–	–	(14.768)	–	–	–
City	-0.250	–	–	–	-1.201	–	–	–
	(5.730)	–	–	–	(6.795)	–	–	–
Urbanized	-5.275	–	–	–	-9.173	–	–	–
	(5.213)	–	–	–	(6.202)	–	–	–
Rural	-7.277	–	–	–	-8.879	–	–	–
	(4.498)	–	–	–	(5.537)	–	–	–
Constant	2.693	–	1.706	7.867***	-41.684	–	2.469**	7.942***
	(34.590)	–	(1.041)	(1.307)	(44.126)	–	(1.198)	(1.329)
Observations	303	303	302	302	237	303	236	236
R-square	0.581	–	0.026	0.042	0.517	–	0.106	0.069
F-value	40.56***	–	1.30	2.18**	24.19***	–	4.53***	2.83**

OLS = Ordinary Least Square model, MATCH = Matching estimator, DD = Difference-in-Difference estimator, DDD = Difference-in-Difference-in-Difference estimator
Standard errors between brackets and asterisks indicate statistical significance: p<0.10*; p<0.01**; p<0.001***.

Table 4: OLS, matching and difference-in-differences estimates for the general participation effect and the introduction effect for 2005-2009

YEAR	**OLS**	**MATCH**	**DD**	**DDD**
		General participation effect		
2005	-28.649***	-23.071***	-12.607***	-18.975***
	(6.702)	(6.204)	(2.720)	(5.075)
2006	-32.900***	-15.346***	-7.084***	0.851
	(5.741)	(4.712)	(1.379)	(2.731)
2007	-30.888***	-11.800***	2.825**	10.176***
	(5.693)	(4.416)	(1.376)	(2.065)
2008	-33.034***	-9.879**	-3.452**	-6.295***
	(4.729)	(4.032)	(1.728)	(2.031)
2009	-35.759***	-15.098***	-2.101	0.749
	(3.906)	(4.338)	(1.800)	(2.343)
		Introduction effect		
2005	-52.489***	-45.841***	-44.596***	-62.556***
	(12.708)	(6.922)	(4.223)	(8.636)
2006	-47.546***	-9.705**	-26.347***	-28.240***
	(10.323)	(4.671)	(2.066)	(3.003)
2007	-32.588	-19.480	-10.124**	5.932
	(20.040)	(22.946)	(4.742)	(6.850)
2008	-43.713***	-19.447***	-23.222***	-25.983***
	(9.604)	(5.883)	(3.378)	(3.965)
2009	-51.364***	-27.633***	-21.683***	-20.809***
	(7.340)	(7.827)	(3.157)	(4.137)

OLS = Ordinary Least Square model, MATCH = Matching estimator, DD = Difference-in-Difference estimator, DDD = Difference-in-Difference-in-Difference estimator
standard errors between brackets and asterisks indicate statistical significance: p<0.10*; p<0.01**; p<0.001***

The *general participation effect* for treatment years 2005-2009 is depicted in the first panel of Table 4. We observe for all years lower estimated effects (in absolute values) for the MATCH model compared to the OLS model. The DD and DDD approaches on the other hand reveal a different picture. In this case we only find a significant negative relation between participation and residual MSW generation for 2005 and 2008. For 2007 we even find a significant positive coefficient. Summarizing, we do not find a significant impact of weight-based-pricing for all years and methods. Simple OLS regression results suggest a significant downward effect of weight-based pricing on residual municipal waste generation. However, after correcting for possible selection bias problems, the effect does not appear to be robust across methods and years.

When looking at the figures for the *introduction effect* on the other hand (second panel of Table 4), we do find much more of a statistically significant and robust negative relation between adoption of weight-based pricing and residual MSW generation for the participation years with 8 or more municipalities introducing weight-based pricing (i.e. 2005, 2006, 2008 and 2009). Immediately after introduction we observe a drop in residual solid waste ranging between minus 10 and minus 63 kg per capita. All methods indicate that municipalities produce significantly less residual MSW in the year the new pricing schedule is introduced. Only for 2007 and 2010 with 3 and 6 municipalities introducing weight-based pricing respectively, the results are less robust across methods.

Table 5: Panel data estimations

	Random effects (on levels)	**Fixed effects (on levels)**	**Fixed effects (on differences)**
Weight-based pricing	-20.187***	-19.080***	-24.95***
	(1.514)	(1.545)	(1.501)
Young	3.126**	3.788***	2.883*
	(1.281)	(1.478)	(1.561)
Old	0.842	-3.418***	-1.602
	(0.621)	(0.872)	(1.395)
Underprivileged index	-1.168***	-1.394***	-0.463**
	(0.208)	(0.225)	(0.219)
Average income	-2.026***	-3.309**	0.276
	(0.385)	(1.400)	(1.091)
Population density	0.012***	-0.198***	-0.039
	(0.004)	(0.038)	(0.078)
Touristic	209.039***	–	–
	(11.851)	–	–
City	14.741**	–	–
	(5.812)	–	–
Urbanized	1.567	–	–
	(5.438)	–	–
Rural	-8.650**	–	–
	(4.419)	–	–
Constant	(110.359)***	312.380***	-1.950**
	11.971	(35.844)	(0.883)
Time fixed effects	NO	YES	YES

Observations	1834	1834	1832
Wald chi²	730.34***	–	–
F-value	–	32.08***	34.69***

Standard errors between brackets and asterisks indicate statistical significance: p<0.10*; p<0.01**; p<0.001***

Finally we turn to the panel data estimations (see Table 5). The first column depicts the output of a basic random effects model. The second column presents the result of fixed effects model on levels (see model 6 in the Methods section). Recall that this model captures the general participation effect. Finally the last column in Table 5 shows the output for a fixed effects model on the first differences (see model 7 in the Methods section). The latter model refers to the introduction effect. The coefficients for weight-based pricing are significantly negative across the three models, indicating that there is a negative relation between using or introducing weight-based pricing and residual MSW generation. Note that the coefficient for the percentage of residents younger than 5 years of age is again significantly positive in the three models. For the underprivileged index we find a consistent and significant negative coefficient. The impact of average income and population density on the other hand, is not stable across the different models, as the sign of the coefficients change when going from the random effects model to the fixed effects model on levels. Similarly the percentage of residents older than 65 years of age is only significantly different from zero in the fixed effects model on levels. Finally the coefficients for the dummy variables classifying municipalities into categories indicate that residual MSW generation is higher for touristic municipalities and cities and lower for rural municipalities compared to the benchmark category (i.e. residential municipalities and municipalities with considerable economic activity).

Concluding remarks

Given the above observations, we find a strong indication that introducing weight-based pricing has a significant initial impact on the amount of residual MSW. We find however no convincing evidence that this effect persists in the years after initial adoption. In other words, switching from the default pay-per-bag pricing schedule to a weight-based pricing system has a significant initial impact on MSW volumes per capita, but long term effects are less clear. In addition, the absence of a robust general effect, could even indicate that the introduction effect is partly offset once the system is in use for a number of years. However before such a conclusion could be drawn, a more thorough analysis of higher year effects is required. However, such an analysis is possible only if larger time series become available. In addition, due to data limitations information on local residual MSW collection fees was not incorporated in this analysis. Including a price index for residual MSW collection services will also raise new methodological issues that require more sophisticated estimation procedures, as pricing decisions probably depend endogenously on characteristics of municipalities. In interesting route for further research therefore involves the construction an incorporation of a price index in a more complex panel data model.

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