Effects of unit-based pricing on household waste collection demand: a meta-regression analysis

Germà Bel[1] and Raymond Gradus[2]

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[1] Department of Applied Economics (Universitat de Barcelona) and GiM-IREA, Facultat d'Economia i Empresa, Barcelona, Spain. E-mail: gbel@ub.edu

[2] (Corresponding author) Department of Accounting, Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam, the Netherlands; email: r.h.j.m.gradus@vu.nl. VU University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands Tel +31 20 5989865

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Abstract

Reducing the quantity of waste is an objective pursued by an increasing number of governments. Pricing waste has been one of the most important tools used for that purpose, and the literature on the demand for household waste disposal shows a wide diversity of price elasticity calculations. We explore this issue by means of a meta-analysis on a database of 25 studies. This allows us analyzing which is the effect on the results of different data, model specification and (statistical) methods. We find no evidence that either treating prices as exogenous or including curbside recycling effects in the model influence price elasticity. There are some indications that price elasticities in the USA are more elastic, and that municipal data provide higher estimates than household data. We find that much of the variation in elasticities is associated with substantial methods; in particular it can be explained by the use of a weight-based system and by the pricing of compostable waste. In contrast, the bag-based system does not present a significant relation with elasticity. Finally, our results do not find evidence of publication bias, while they do indicate some evidence of the existence of a genuine empirical effect.

Keywords: solid waste; unit-based pricing; elasticities; meta-analysis

JEL Codes: H23, Q52, Q53

1. <u>Introduction</u>

The unit-based pricing (UBP) of residential solid waste collection has been implemented in many parts of the world, including municipalities in the United States, the EU, Japan and South Korea. Skumatz (2008) reports that these UBP-programs are available to about 25% of the US population and about 26% of communities in the US – including 30% of the largest cities in the US. Dijkgraaf and Gradus (2014) record that the percentage of Dutch municipalities using this system raised from 15% in 1998 to 36% in 2010, and Riezenkamp (2008) presented similar increases for other countries in Continental Europe. In Japan unit-charging programs for waste were available in 30% of municipalities in 2003 and, interestingly, South Korea initiated a nationwide pay-as-you-throw (PAYT) program back in 1995 (see Sakai et al., 2008).

The increasing shortage of space and growing environmental awareness have forced many local governments to adopt such measures as UBP to reduce the amount of unsorted waste and to promote recycling.[1] But whether UBP yields a large effect on the waste amount remains a somewhat contentious issue. While households may recycle more, compost more, and require less packaging from the stores than without price programs, UBP might also encourage them to burn their garbage or to dump it on the roadside. But this has not happened in the Netherlands, or apparently elsewhere, and as such there is no evidence, according to Allers and Hoeben (2010), of municipalities having become disillusioned with the effects of UBP programs. Yet, in some countries, there is evidence that supports the hypothesis that illegal dumping has become more prevalent. Fullerton and Kinnaman (1996) estimate that for a UBP system in Charlottesville (Virginia, US), illegal dumping constitutes 28% of the total reduction in waste collected at the curb. Likewise, Hong (1999) shows that dumping became substantial after the adoption of a UBP system in Korea. In this regard, social norms and the associated sanctions differ, so the extent of illegal dumping may be related to cultural issues.

The key questions that policymakers seek a response to therefore are: Does UBP reduce quantities of waste and increase recycling, and if so, by how much? In most papers conducted

[1] Other policies, such as a tax on landfill, a landfill ban and an incineration tax, have been important in this respect.

to date this question is answered by estimating price elasticity for unsorted waste (and a cross-price elasticity for recycled waste); however, the estimates reported differ markedly. For example, based on a survey at the municipal level, Allers and Hoeben (2010) found a high price elasticity (-1.77) for biodegradable or compostable waste and the weight-and bin-based systems used by Dutch municipalities. For the subscription system in Portland (Oregon), Hong et al. (1993) reported a non-significant elasticity close to zero.

Despite the fact that the effects of unit-based pricing of waste have been widely debated in public economics, no systematic analysis has been conducted to date to explain why the reported impact of UBP differs so much in the literature. In other fields, meta-regression analyses have been used to explain divergences in results in the empirical literature, thus providing new insights, for example, into the relationship between labor supply and wages (Evers et al., 2006), price and income elasticities of water demand (Dalhuisen et al., 2003), climate change (Alló and Loureiro, 2014), the limits to world population (Van den Bergh and Rietveld, 2004), privatization and costs (Bel et al., 2010) and determinants of inter-municipal cooperation (Bel and Warner, 2014). In addition, these papers also provide a summary of the research results on these issues.

In this paper, we seek to fill the gap in the empirical literature on the effects of UBP by conducting a meta-regression analysis for the unit-based pricing of waste. Specifically, we use a sample of 66 price elasticities obtained from the literature on which to perform our meta-analysis, i.e., we regress the elasticities on the underlying study characteristics. In this way, we are able to analyze whether pricing policies are effective in reducing the amount of waste generated, and also to present a systematic analysis of the impact of various factors on the empirical estimates reported. Our results provide some useful insights for policy makers seeking to use waste management policies to improve environmental conditions.

The rest of this paper is organized as follows. Section 2 presents an overview of the issues raised in the empirical literature regarding unit based pricing and elasticities. Section 3 describes our sample. Section 4 explores the sources of variation in more detail by performing a meta-regression. Section 5 reports the meta-regression robustness test, and section 6 concludes and makes some suggestions for further research.

2. The empirical literature on unit-based pricing elasticities

To the best of our knowledge, the first study to calculate the elasticity of the price of waste upon waste quantities empirically was Wertz (1976). Based on a sample collected in San Francisco, where a fee is charged on the number of containers put out, he estimated a negative elasticity of -0.15. Thereafter, increasingly more data have become available to describe the US experience. Thus, Skumatz and Breckinridge (1990) estimated an elasticity of -0.14 for Seattle (Washington) where a subscription-system is employed. By simply comparing waste before and after the introduction of a bag-based UBP system in Perkasie (Pennsylvania) and Ilion (New York), Morris and Byrd (1990) found elasticities of -0.26 and -0.22, respectively. Likewise, Jenkins (1993) estimated an elasticity of -0.12 using data for nine US communities, while Hong et al. (1993) evaluated the situation in Portland (Oregon) by drawing on a sample of 2,300 households. The first study to be conducted outside the US, as far as we can establish, was Hong (1999), in which the author studied municipal data from Korean cities that opted to implement a bag-based system. Subsequently, studies conducted in other countries in the Pacific and Europe have appeared.

Two streams of research have emerged in the literature. One of these streams reports cross-sectional analyses of municipalities while the second uses household survey data to estimate elasticity. For example, Hong and Adams (1999) stressed that municipality level data tend to be averaged over the population of the municipality and, therefore, they pointed out that the range of values within each variable is limited, 'making it difficult to get statistically significant results'. However, when conducting a household survey, Hong and Adams (1999) found that the price differential did not influence the choice of bin size. As such, they show the price elasticity calculated at mean levels of waste to be low (-0.013) and only significant at the 90 per cent level. Van Houtven and Morris (1999) evaluated a project in Marietta (Georgia) using both municipal and household data. Their estimates of prices elasticities were -0.14 and -0.15 using municipality level data and depending on the estimates used, while they reported a larger elasticity of -0.26 for the bag system when using household data. Linderhof et al. (2001) conducted a study based on more than 127,000 observations obtained in a household survey of all the inhabitants of Oostzaan, the first Dutch municipality to introduce a weight-based pricing system, and found much larger elasticities. Furthermore, they distinguish between compostable and mixed or non-recyclable waste, both of which are collected at the curbside in the Netherlands. In Japan, Yamakawa and Ueta (2002) estimated the difference in the amount of waste collected in municipalities that had introduced a bag program, on the one hand, and those that did not operate a variable charging system, on the other. Similarly, in the Netherlands, Dijkgraaf and Gradus (2004) evaluated an administrative data set for all 458 Dutch municipalities in order to evaluate the country's various systems, while Allers and Hoeben (2010), using a ten-year dataset for all the Dutch municipalities, also estimated the effect of different unit-based pricing systems in the Netherlands. Importantly, the latter authors argue that community-level studies do not usually take unobservable local characteristics with a potential influence on garbage quantities into account. For this reason, they propose a differences-in-differences approach (or fixed effects), which given the size of their panel dataset was feasible.[2]

[2] Linderhof et al. (2001) were also the first to estimate short- as well as long-run price effects. Later, based on a municipal panel sample for Japan, Usui (2008) estimated two waste equations, one including

Typically, an OLS regression model has been adopted to explain residential waste disposal with the marginal price of waste being used as an explanatory variable. However, some articles do tackle the issue of endogeneity. Hong, Adams & Love (1993) estimated the demand for the containers contracted, correcting for the endogeneity of price and participation in recycling activities using the 2SLS estimation method. Further evidence for the case of Portland was reported in Hong and Adams (1999) in which waste was measured directly and the authors also corrected for possible price endogeneity. Drawing on US municipal data, Kinnaman and Fullerton (2000) allow for price endogeneity. Although a priori the bias in the waste fee estimate when treating this policy variable as exogenous might be positive or negative, they show that previous studies with exogenous prices appear to have underestimated the effects of such programs on garbage and recycling totals. Based on municipal data for Massachusetts (US), Callan and Thomas (2006) also simultaneously estimate a waste and recycling equation. Allers and Hoeben (2010) correct for the endogeneity of garbage prices, although they only found evidence of this in the case of compostable waste. Huang et al. (2011), using a municipal sample from New Hampshire (US), also endogenize the introduction of PAYT systems and curbside recycling, but the effect for limiting point elasticity estimates to PAYT-municipalities is larger.[3]

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the number of years that had passed since the introduction of UBP, the other without. On the basis of this, he calculated a short- and long-run point elasticity. Usui and Takeuchi (2014) also calculated long- and short-run price elasticities, but, interestingly, found hardly any differences between the two. As the other studies do not distinguish between short- and long-run elasticities, we are unable to include this variable in our meta-regression. This may be a limitation of our current analysis, because the distinction between short- and long-run elasticities is a potentially important factor.

[3] In the literature the price elasticities of waste are calculated as an arc or a point elasticity estimates. As the arc elasticity of demand is the ratio of the amount of waste before and after introducing UBP to the percentage change in price, it is independent of the actual quantity decrease. Therefore, we do not include this as a moderator variable in our meta-regression. In addition, Huang et al. (2012) shows that point elasticities pooling both PAYT and non-PAYT municipalities are dominated by non-PAYT-

In addition, the effect of a Heckman correction for possible sample selection bias was very small. Based on household data for the Swiss Canton of Vaud, Carattini et al. (2014) estimate a price elasticity of -0.4. Based on a quasi-natural experiment, they deal with the issue of endogeneity and conclude that their estimates are robust.

To ensure comparability of all the studies with respect to waste pricing, we identify three UBP-systems (see also Kinnaman, 2006). The first is the bin- (or subscription-) based system, where residents pay a fee for the size of the container or for each time their container is emptied at the curbside.[4] The second is a related volume-based program, the bag- (or tag-) based system, where residents purchase special bags, tags or labels to put on their own bags. In general, the bag-based system provides a more refined pricing system than the bin-based system, as the volume of the bags is significantly smaller than that of the bin. However, Fullerton and Kinnaman (1996) point out that a disadvantage of the bag-based system is that there is an incentive for households to put as much waste as possible in each bag, which makes them difficult to handle. They estimated a price elasticity of demand for waste (measured in pounds) of -0.076 and showed that the elasticity is much higher (-0.226) when measured by volume. Fullerton and Kinnaman (1996) point out that this can be attributed to the so-called "Seattle stomp", whereby garbage is stomped into a single bag or container to avoid having to pay for multiple containers or bags.

municipalities. As this issue was only raised recently, we have available a too small number observations as to take into account.

[4] In these bin-based systems, households can either pay by unit of volume of the bin or purchase an allowance that entitles them to use the municipality's waste collection services. For most studies it is not possible to distinguish between these two types. For the Netherlands (see Dijkgraaf and Gradus, 2004, 2009 and 2014) where households can only choose between different bin types at specified review times (usually annual), this subscription or volume elasticity is substantially lower than a frequency-based system.

The third system is that of weight-based pricing, where the collection vehicle weighs the bin and matches this information to the owner's identity. As such, owners generating more waste pay a higher collection fee. Linderhof et al. (2001) based their study of curbside collection of compostable and non-recyclable waste on a household panel survey of all inhabitants in a Dutch municipality. They find that the elasticity for compostable waste is four times as high as that for non-recyclable waste, as home composting has become more frequent thanks to the distribution of subsidized composting containers. However, they report that one disadvantage of the weight-based system is its high administrative cost.

Podolsky and Spiegel (1998) claim that price elasticities can be influenced by other policy measures, including the introduction of curbside recycling programs, in a study conducted with a cross-sectional data set for 149 municipalities in five New Jersey counties with curbside recycling collection. As such, they interpret the elasticity as the effect of unit-based pricing and curbside recycling collection. However, Kinnaman and Fullerton (2000) correct for the effect of curbside recycling collection on waste by using the heterogeneity between municipalities. Based on municipal data for Massachusetts (US), Callan and Thomas (2006) simultaneously estimated a waste and recycling equation and estimated a price elasticity of disposal demand of -0.582. The authors estimated a direct effect of -0.195 by holding recycling constant and an indirect effect of -0.387 as a result of increased recycling. Interestingly, Callan and Thomas (2006) show that the direct effect, which can be interpreted as the combination of illegal dumping and source reduction, is not significant, while the indirect recycling effect is significant.

Table 1 lists the 25 studies used in our analysis together with a number of important characteristics of these studies, including sample size, period of analysis, country and the number of observations each study contributes to the sample (total observations = 72).[5] We collected papers from academic journals published in the fields of Environmental Economics, Environmental Studies, Public Policy, and Public Administration, as well as from their online versions. We also collected unpublished papers available in large working paper collections, such as EconLit, GoogleScholar, Ageconsearch, Science Direct, Social Science Research Network, ResearchGate and Repec-Ideas. We also collected papers from data bases specializing in PhD theses and from the grey literature, including OpenSIGLE¸ European Science Research Council (ESRC) and E Thesis Online Services (ETHOS) in Europe, and US GAO and The National Technical Information Service (NTIS) in the U.S. To the best of our knowledge, our data base includes all published and unpublished papers that estimate price effects on demand of unit-based pricing, and comprises 19 works published in journals, two published in books, three working papers, and one unpublished PhD thesis.[6] The database was constructed by the authors. We used as key words for the search "unit-based pricing", "solid waste", and "elasticity". The search was conducted in June 2015.[7]

[5] As we have multivariate studies of factors explaining these elasticities, we exclude Morris and Byrd (1990) from our dataset as it simply compares the waste collection systems in two US municipalities before and after the introduction of a UBP system.

[6] We identified other grey papers that could not be included for a variety of reasons. For instance, the government report undertaken by Efaw & Lanen (1979) could not be included because while the papers in our sample use real prices changes, here the nominal fee is unchanged. Furthermore, their study does not provide enough information about their descriptive statistics. Another grey paper identified – Seguino et al., (1995) – does not use pricing variables, so it could not be considered. Recent M.A. dissertations worth mentioning include Bak (2014), which could not be considered because the measurement unit for quantity (number of bags) is not compatible with those used in the papers in our sample (kilos or tons). Similarly, Dijkgraaf and Gradus (2009, 2014), Wright and Halstead (2011) and Kulas (2015) could not be considered because they use dummy variables for pricing as opposed to price variables.

[7] The methodology is based on the MAER reporting guidelines in Stanley et al. (2013).

(insert Table 1 around here)

In the next section we give further details regarding the meta-sample and an outline of its summary statistics. We then proceed to conduct the meta-regression and tests to differentiate the true empirical effect from publication bias. Note that six estimations in our sample did not display information on weight- and/or bag-based systems.[8] Hence, although we have 72 observations, we include in our meta-regression the 66 observations with information on the collection and payment system in our analysis. Note also that we do not have standard errors (SE) for some of the observations among the 66 we finally used in our meta-regression and, so, we are able to use a total of 61 observations in our test of publication bias.

3. <u>The meta sample</u>

Our meta-sample is derived from the 25 studies identified as containing price elasticity estimates of the unit-based pricing of waste. These studies include a total of 72 estimations of the elasticity of residential waste production with respect to price giving an overall average elasticity of -0.344 (see also Table 2). Of these 72 estimations, we can use the 66 that include all the variables considered in our analysis, with an average elasticity of -0.339. Note that the average elasticity is practically the same in both cases.

There are many reasons why price elasticities of the demand for household waste collection vary in empirical studies. Stanley and Jarrell (1989) classify them into three categories: (1) the uniqueness of the data set employed in each study; (2) biases induced by model specification; and (3) the different (statistical) methods employed. Given that here we

[8] Six observations had to be discarded. Four are from Allers and Hoeben (2010). Note that these observations are from 'Total UBP' (see table 8) and, therefore, represent the mixture of different systems. Callan and Thomas (2006) and Gellynck and Verhelst (2007) take the price effect of all UBP, but they do not specify this system separately and, therefore, we have to discard these as well.

undertake a meta-regression analysis to determine the pattern and diversity of findings in the empirical studies, it is important that we bear these points in mind when constructing our meta-sample.

We define three moderator variables for the data base. First, we construct the variable *Municipality*, which is one if the data collection took place at the municipal level, and zero if the data collection took place at the household level. The descriptive statistics in Table 2 show that only 18% of the observations were made at the household level. In addition, we consider two variables that describe model specifications. Second, we construct the dummy variable *Ex*, which is one if the price variable in the (estimated) waste function is treated as exogenous, and zero otherwise.[9] Some authors did in fact stress the importance of correcting for this endogeneity. Third, we construct the dummy variable *USA*, which is one if the study was conducted in the USA, and zero otherwise. Skumatz (2008) shows that many municipalities in the Northeastern and Western States of the USA employ user-pay principle for waste as 'it is commonly for water, electricity and other services'. As Evers et al. (2006) suggest, one way of tackling this in meta-regression analyses is to use country dummy variables capturing differences in cultural preferences and socio-economic characteristics.[10] [11]

Finally, we describe four variables to capture characteristics related to the waste management system and to pricing methods. The effect of price incentives depends on the way

[9] In the literature different models are used for correcting policy endogeneity of prices including probit, 2SLS or IV/methods.

[10] We also run our regressions using a different cultural/socioeconomic dummy variable (Asian Countries=1). The results suggest that Asian countries tend to have a smaller (in absolute values) elasticity, while everything else remains the same. The results are available upon request.

[11] Other socioeconomic variables cannot be used because most data bases are built on municipalities, where there is large heterogeneity in socioeconomic variables and little information on such variables in municipalities.

they are organized and the way in which curbside recycling is regulated. Some studies suggest that the presence of a curbside recycling program is closely related to user fee programs and, so, include both as explanatory variables to determine the (annual) weight of waste (see, for example, Kinnaman and Fullerton,2000). Therefore, we construct a variable *Curbs*, which is one if both variables are included as explanatory variables in the waste equation, and is zero otherwise.[12] Second, we construct as a dependent variable the dummy variable *Compostable*, which is one if compostable or biodegradable waste is analyzed separately from regular solid waste, and zero if only regular solid waste is analyzed. Third, we construct a variable *Weightbased*, which is one if a weight-based pricing system is analyzed, and zero if not. Finally, we construct a variable *Bagbased*, which is one if a bag-based pricing system is analyzed, and zero if not. Note that the bin-based pricing system serves as a benchmark in this case. Table 2 contains the descriptive statistics of these variables and the dependent variable in our meta-regression, and the variables used in the meta-regression tests.

(insert Table 2 around here)

In the meta-regression tests to differentiate the true empirical effect from publication bias we also use the (reported) standard error, t-statistics and the degrees of freedom associated with the estimated elasticities (see section 5). Note that this information is not (explicitly) available in all the studies. In some, the t-statistics are given, making the derivation of the standard error a straightforward task. In other studies, the model estimations and the standard error of the coefficients of the price variable in the regression equations are given but not the standard error

[12] Note that in some studies information about the curbside collection of recyclables is not available or it is included because it is mandatory, as is the case in the Netherlands for compostable waste. Therefore, we include a variable indicating whether curbside recycling programs are included as an explanatory variable in the waste equation and in case of a (strong) interrelation we would expect a significant relation between elasticity and this variable.

(SE) of the elasticity. In such instances we use the simplification suggested by Evers et al. (2006). For example, Callan and Thomas (2006) report the estimation of the elasticities, the estimation of the waste and recycling functions and the elasticity formulae. Applying the Delta method, a SE can be derived.[13] Similar derivations can be obtained for Strathman et al. (1995), Linderhof at al. (2001) and Carattini et al. (2014). For Pickin (2008), the P-value is given and based on this we were able to derive its SE. Additionally, degrees of freedom are given or can be calculated from the descriptive data in the studies. Finally, we have 61 observations for SE and their t-statistics. Only in the case of nine observations is the t-statistic (in absolute value) less than two.

4. The meta regression

The equation with which we estimate the influence of different study characteristics on elasticity can be stated as follows:

$$\in_i = \alpha_0 + \alpha_1 Municipal_i + \alpha_2 USA_i + \alpha_3 Ex_i + \alpha_4 \, Curbs_i + \alpha_5 Compostable_i + \alpha_6 Weightbased_i + \alpha_7 Bagbased_i + \varepsilon_i \qquad (1)$$

where $\in_i$ is the elasticity reported and the moderator variables are as defined in the previous section (see also Table 2). We tested for the presence of multicollinearity and obtained a mean value of 1.37 for the variance inflation factor (VIF), and values for all variables were below 2. Thus, we do not have problems of multicollinearity.

We estimated different meta-regression models to obtain robust results. First, we estimated an ordinary least squares (OLS) regression. We tested for heteroscedasticity and rejected the

[13] We know from formula (5) in Callan and Thomas (2006) that ∈ = ∅ (β) p/W and so we know from the delta method that $\sigma_\epsilon^2 = \frac{p^2}{W^2} \lfloor \partial\emptyset/\partial\beta \rfloor \Sigma_\beta \lfloor \partial\emptyset/\partial\beta \rfloor'$, where p and W are the price and the amount of waste at the mean level (see equation (3.2) in Evers et al., 2006).

hypothesis of constant variance, as we found that the Breusch-Pagan/Cook- Weisberg test has a value of 9.94 for the chi-square statistic, with a p-value of 0.0016. Therefore, we conducted a robust OLS estimation. Results for both estimations are presented in Table 4.

Next, given that our model contains only categorical independent variables while the dependent variable is continuous, we followed Stanley and Doucouliagos (2013, 2014) and Ringquist's (2013) suggestions that variance weighted least squares (VWLS) is the best approach to estimate a fixed effects regression model for our meta-regression analysis, and we used VWLS to estimate equation (1). [14] Besides issues related to heteroscedasticity in our sample -VWLS does not assume homogeneity of variance-, VWLS is a convenient method to use when all the independent variables are categorical and the dependent variable is continuous (which may yield less powerful results), as they are in our case.

Our sample is formed with observations obtained from little more than 20 studies, each of them containing a different number of estimations, which can lead to a problem of dependence across observations (Nelson and Kennedy, 2009; Ringquist, 2013).[15] To deal with this, when estimating VWLS we included a dummy variable to control for the observations obtained from the study by Allers and Hoeben (2010), which is – by far – the study with the most estimations

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[14] Variance-weighted least squares –WLS- differs from WLS in that (1) VWLS requires that the conditional variance of de dependent variable be calculated before estimating the regression; and (2) the VWLS weights are treated as true variances rather than as proportional variances (Ringquist, 2013, p. 167-168). Note that using VWLS may imply losing observations if categories are insufficiently large to produce estimates of the Standard Deviation (SD), or if the estimated SD is zero.

[15] Other potential sources of dependence across observations are the use of common data sets in different studies, and different studies undertaken by common research teams (see, Nelson and Kennedy, 2009; Ringquist, 2013). We do not believe this to be a serious concern for our analysis. On the one hand, none of the data sets has been used in more than one study; on the other, the different studies attributable to the same researchers were undertaken for different places; moreover, different types of data and different models were used in each of these studies.

– as many as 20 (of which 16 are actually used in our estimations). Furthermore, in order to take full account of within-study autocorrelation, we followed the suggestion in Ringquist (2013, p. 218) and used Generalized Estimating Equations (GEE) to estimate a random effects meta-regression model.[16]

Table 4 shows the results from the estimation of the meta-regression equation (1). [17]

(insert Table 4 around here)

Endogeneity is not a relevant issue in any of the four equations, as shown by the systematic lack of significance of the variable *Ex*. Hence, there is no evidence that the endogeneity issue influences the estimation results of the elasticity. *Municipal* is significant only in the VWLS estimation, with a negative sign, but it is not in the other estimations, which prevents us from

[16] Thus, we control for study to deal with dependence across observations. Note that our robust GEE coefficients and signs are almost identical to those obtained when using a random effects GLS regression. However, the Wald chi-squared statistic with GEE is substantially higher. Another potential way of dealing with intra-study variability is to select the best estimation from among all estimations in a single study, or to calculate a single average effect size from each original study. We disregarded both because that would result in an extremely small sample for our meta-analysis (as Nelson and Kennedy, 2009, warn). Furthermore, this would have meant discarding a large amount of information (Ringqvist, 2013).

[17] Because the price elasticity data used refer to different years and periods, elasticities might have changed over time. We have taken into consideration the time effect in our OLS estimations (in the VWLS and GEE regressions this time effect is part of the fixed effects). We have run new OLS estimations including a variable reflecting the year(s) for which the data was collected. We have used two different specifications. The first one, a dummy variable that is one if the data base refers to 2000 or after, and 0 otherwise. The second one is a continuous variable: year for which the database was built (or average year if different years were included in the data base). The results obtained when considering time effect are almost identical to those obtained in the OLS estimations without it. All signs are identical. Regarding significance of the coefficients, both robust estimations find 10% significance for compostable (instead of 5%). And in the specification of year (or average year) and robust estimation we find USA significant at 10% (similarly to what we find with VWLS and GEE. Table A1 in the appendix shows the results when considering the time effect in OLS estimations.

drawing clear conclusions about the impact of taking data from a municipal or from a household survey. We find *USA* negative and weakly significant in the two most robust estimations, VWLS and GEE equations (at the 10 per cent level). This provides weak evidence that studies conducted in the USA present a higher elasticity (in absolute values).

In the case of the variables capturing choices regarding the waste collection system, our results indicate that *curbside* does not influence the results, as it is not significant in any of the estimations. In contrast, the moderator *Compostable* is associated with higher elasticities (in absolute values). It was found to be highly significant in all estimations, generally at the 5 per cent level. Introducing a separate collection and a fee for compostable waste is, as this outcome shows, therefore highly effective. The *Weightbased* variable is, likewise, very strong, being significant at the 1 per cent level in all cases. When the *Weightbased* dummy is set at 1, price elasticity (in absolute values) is substantially higher at -0.4. In contrast, the variable *Bagbased* is not significant in any of the estimations, suggesting that using bag-based pricing instead of bin-priced systems does not influence elasticity. As suggested by Fullerton and Kinnaman (1996), this may be due to the Seattle Stomp.

Thus, overall, the meta-regression seems to give a slight indication that municipal data provide higher estimates for price elasticities than those associated with household data. Furthermore, there is no evidence that treating prices as exogenous and taking into account curbside recycling effects influences the price elasticity. Our results suggest for some estimates that price elasticities from the USA are likely to be higher (in absolute values). Furthermore, the dependency of the elasticities based on substantial moderators gives robust results. Elasticities based on the *Compostable* variable are significant and considerably higher than those based on non-recyclable waste. In this case it seems that home composting has become especially important. Indeed, Dijkgraaf and Gradus (2004) report that a household’s garden area is a prime determinant of the amount of compostable waste. Elasticities based on weight-based pricing systems are considerably larger than those based on volume-based pricing systems. Finally, using bag-based pricing (compared with the benchmark of bin-based system) does not influence elasticity.

5. Robustness tests

A major concern of any meta-regression model is the identification of any potential publication bias. Studies finding statistically significant relationships between the variables of interest are, it appears, more likely to be published, which might lead to incorrect conclusions regarding the effectiveness of a particular policy. A priori, we do not believe publication bias should be a serious problem in our analysis, mainly because the relationship between price and waste volume is so well established theoretically that very few papers today are likely to find a non-significant relationship. Indeed, the studies analyzed here typically deal with the size of the price effect, rather than with the existence of the effect itself (only in nine cases is the estimated elasticity non-significant). Furthermore, even if our sample is made up mostly of papers published in journals and books, we were also able to include results from three working papers and one unpublished PhD thesis.

Yet, as publication bias could upwardly bias the effectiveness of the policy, we believe it is important to deal with this potential problem. To detect and correct for possible publication bias Stanley and Doucouliagos (2012) propose the funnel asymmetry test (FAT). This test estimates the relationship between a study's reported t-statistics and SE of its coefficients. We estimate the following equation:

$$T_i = \beta_0 + \beta_1 \left(\frac{1}{SE_i}\right) + \varepsilon_i, \tag{2}$$

where T is a study's reported t-statistic and 1/SE is the inverse of the standard error. Evidence for publication bias will be found when $\beta_0 \neq 0$.[18] Additionally, the coefficient β_1 provides an estimate of the true effect of the parameter of interest. Equation (2) is estimated in Table 5. Furthermore, in line with Stanley (2008), to test the true empirical effect, we also conduct a meta-significance test (MST)[19] by estimating the following equation:

$$\log |T_i| = \gamma_0 + \gamma_1 \log(df_i) + \varepsilon_i, \quad (3)$$

where *df* are the degrees of freedom of the estimate reported. Stanley (2008) argues that if $\gamma_1 = 0$ the true effect is disputable. These results can also be consulted in Table 5.

(insert table 5 around here)

Recall that the FAT estimates the relationship between a study's reported effect and its coefficients' standard errors. Evidence of publication bias is found when the intercept is significantly different from zero (Stanley, 2008). Our FAT results (Table 5) do not reject the hypothesis of no publication bias, as the intercept is not statistically different from zero.

We find some evidence of the existence of a 'true' effect or genuine empirical effect (negative relationship between unit base pricing and volume of waste) because the coefficient for *InversSE* is negative and significant at the 5 per cent level. However, we need to remain cautious about the existence of a true effect, as this is not confirmed by the MST test; the coefficient of *Logdf* is not significant.

[18] In some studies, when the SE contains some measurement errors, the square root of the sample size is taken as an alternative variable to test for publication bias. However, here that is not necessary, because the standard errors provide more robust results than those provided by the square root of the sample size (see also Stanley and Doucouliagos, 2012, box 4.10).

[19] The MST is based on the statistical property that the magnitude of the t-statistic will systematically vary with the degrees of freedom if overall there is a genuine empirical effect (Stanley, 2008).

6. **Conclusions**

The advantage of a meta-regression analysis is that it allows us to determine the impact of the phenomenon in question across a wide range of studies. Previous narrative meta-analyses, such as that conducted by Kinnaman (2006), show that the literature consistently estimates the price elasticity of the demand for garbage collection services to be inelastic. Our meta-regression results support this conclusion, but also that ultimately the elasticity depends on how the waste collection process is organized. A system is much more effective and price-elasticity is more elastic if waste collection employs a weight-based pricing system and if compostable waste is priced. In addition, we found for some estimates weak evidence that studies conducted in the USA present a larger elasticity, for one estimate that municipality level data present a larger elasticity, and that a bag-based system does not influence elasticity. Finally, we do not find any strong indication of any relationship between elasticity and treating waste prices as exogenous, nor with taking into account the presence of a curbside collection program. Furthermore, the robustness tests show that there is no evidence of publication bias and present some evidence of true empirical effects.

From a policy perspective, of course, introducing a weight-based system has the largest effect on waste quantities and on enhanced environmental conditions. This result is not surprising since the volume-based systems (i.e., the bin- and bag-based systems) are less refined. Nevertheless, weight-based systems can incur high administrative costs which may offset the (welfare) gain of such systems. However, current systems allow the collection vehicle to weigh the bin before emptying it and to combine this information with the owner's identity (stored in a chip integrated in the collection bin), so the computer can perform all the work. Likewise, more refined bin-based systems are becoming available with small bins for both unsorted and compostable waste, where the household pays for the number of times these bins are left at the curbside. Pricing compostable waste also seems effective for reducing waste, although this seems to be quite closely related to home composting. This means that in municipalities characterized by houses with their own gardens and places to store different bins the introduction of this system is likely to be effective.

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Table 1. Studies with their main characteristics

Table 2. Descriptive statistics of variables used in meta-regression analysis and meta-regression tests

	Average	SD	Max	Min	Nº
Elasticity	-0.339	0.387	0.29	-1.77	66
Municipal	0.818	0.389	1.00	0.00	66
USA	0.318	0.469	1.00	0.00	66
Ex	0.576	0.498	1.00	0.00	66
Curbside	0.288	0.456	1.00	0.00	66
Compostable	0.273	0.449	1.00	0.00	66
Weightbased	0.212	0.412	1.00	0.00	66
Bagbased	0.500	0.504	1.00	0.00	66
Standard error	0.089	0.183	1.235	0.003	61
T-value	-9.131	12.046	6.920	-87.55	61
Degrees of freedom	10052	30034	124060	22	61

Table 3. **Definition of variables**

Elasticity	The elasticity of the price of waste upon household waste quantities
Municipal	Dummy with one if the data collection took place at the municipal level
USA	Dummy with one if the study was conducted in USA
Ex	Dummy with one if price in waste equation is exogenous
Curbside	Dummy with one if curbside recycling collection is a variable in waste equation
Compostable	Dummy with one if pricing is based on compostable
Weightbased	Dummy with one if pricing system is weight-based
Bagbased	Dummy with one if the pricing system is bag-based

Table 4. Meta-regression estimates (OLS, Robust OLS, VWLS-MRA, and GEE)

	OLS	Robust OLS	VWLS	GEE
Municipality	-0.117 (0.116)	-0.117 (0.100)	-0.229*** (0.064)	-0.097 (0.077)
USA	-0.097 (0.105)	-0.097 (0.075)	-0.098* (0.051)	-0.119* (0.070)
Ex	0.058 (0.087)	0.058 (0.079)	-0.047 (0.060)	-0.028 (0.049)
Curbside	-0.018 (0.103)	-0.018 (0.101)	0.070 (0.047)	-0.017 (0.110)
Compostable	-0.230** (0.101)	-0.230** (0.114)	-0.132*** (0.051)	-0.238** (0.102)
Weightbased	-0.440*** (0.134)	-0.440*** (0.129)	-0.409*** (0.083)	-0.396*** (0.075)
Bagbased	0.023 (0.106)	0.023 (0.100)	0.067 (0.053)	0.070 (0.105)
Allers & Hoeben	-	-	0.112 (0.102)	-
Constant	-0.096 (0.168)	-0.096 (0.113)	0.080 (0.052)	-0.069 (0.079)
N	66	66	61	66
F	4.11***	2.70**		
R2	0.331	0.331		
Goodness-of-fit			64.43	
Model chi2			142.66	
Wald(chi)2				103.50
Prob > chi2			0.000***	0.000***

Level of significance: *= 10 per cent; **=5 per cent; ***=1 per cent

Table 5. Meta-regression tests (FAT and MST). Robust SEs

Explanatory variables	FAT test Dep. Variable t-Statistic	MST: Dep. Variable: log (t-Statistic in Absolute Values)
InversSE	-0.1190 (0.0593)**	---
Logdf	---	0. 0661 (0.0834)
Constant	-2.5334 (2.6309)	0. 5255 (0.2656) *
R^2	0.3683	0.0092
F	4.02**	0.63
N	61	61

Notes: Level of significance: *= 10 per cent; **=5 per cent; ***=1 per cent

Appendix:

Table A1: OLS meta-regressions with database year

	OLS	Robust OLS	OLS	Robust OLS
Year (dummy post2000=1; pre2000=0)	-0.047 (0.134)	-0.047 (0.119)	-	-
Average Year data base	-	-	-0.007 (0.009)	-0.007 (0.006)
Municipality	-0.104 (0.123)	-0.104 (0.109)	-0.123 (0.117)	-0.123 (0.104)
USA	-0.104 (0.108)	-0.104 (0.080)	-0.154 (0.126)	-0.154* (0.090)
Ex	0.028 (0.123)	0.028 (0.091)	0.023 (0.097)	0.023 (0.080)
Curbside	-0.023 (0.105)	-0.023 (0.107)	-0.003 (0.107)	-0.003 (0.095)
Compostable	-0.227** (0.102)	-0.227* (0.117)	-0.210** (0.104)	-0.210* (0.122)
Weightbased	-0.438*** (0.135)	-0.438*** (0.131)	-0.439*** (0.134)	-0.439*** (0.132)
Bagbased	0.021 (0.106)	0.021 (0.096)	0.036 (0.107)	0.036 (0.104)
Constant	-0.069 (0.186)	-0.069 (0.110)	14.853 (17.995)	14.853 (12.656)
N	66	66	66	66
F	3.55***	2.31**	3.66***	3.12***
R2	0.333	0.333	0.339	0.339

Level of significance: *= 10 per cent; **=5 per cent; ***=1 per cent