

## **We want to sort! – assessing households' preferences for sorting waste**

### **Abstract**

There are two major ways in which solid waste can be sorted and recycled – at the household level, when households are required to sort waste into a given number of categories, or in specialized sorting facilities. Traditionally, it has been thought that sorting at the household level is an inconvenience, as it uses space and requires time and effort. Our study provides empirical evidence to the contrary, indicating that home sorting is a net source of utility for some people. Through a carefully-designed choice experiment we collected stated choices from members of a Polish municipality with respect to the way their waste is sorted and how often it is collected. In the hypothetical scenario employed, respondents were informed that waste will be sorted anyway – if not at the household level then at a specialized sorting facility. Interestingly, analysis shows that a large group of people are willing to sort waste at the household level even if unsorted waste would be collected at no extra cost. For a minority, increased home sorting of waste would, however, impose a loss of utility. Overall, our results indicate that most respondents preferred to sort waste themselves if given the choice. We provide a few possible explanations of this perhaps surprising result, including the desire to promote a green external image, and a concern about the effectiveness of separation activities performed by others.

Keywords:

Recycling, choice modelling, G-MNL model, solid waste management

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## **1. Introduction**

Much work has been undertaken within economics to understand the determinants of household recycling behaviour (Hong *et al.* 1993; Jenkins *et al.* 2003; Calcott & Walls 2005). A positive Willingness to Pay for recycling can reflect the value people place on reducing the externalities associated with alternative methods of waste disposal such as land fill and incineration, and a desire to turn “waste” into useful secondary materials. However, recycling is costly to households in time and effort (Huhtala 2010); whilst practical experience in recycling schemes world-wide has shown that a wide range of factors can impact on participation rates (Noehammer & Byer 1997). In this paper, we show that some households derive utility from the act of recycling itself, independently of impacts of their behaviour on the waste stream (and therefore, independently of the actual community recycling rate: Kipperberg and Larson, 2012). Faced with a choice of more home sorting of waste or a central sorting of household waste, individuals are willing to pay for waste collection options which require more time and effort on their part. This result emerges from both a simple multinomial logit (MNL) modelling of the choice data, and a more sophisticated generalized multinomial logit (G-MNL) model with covariates in both scale and the random parameters. Using a latent class (LC) model, we observe that this preference for more home sorting of recyclables is restricted to one of two latent classes within the sample – albeit one accounting for around 2/3rds of respondents. Membership of these latent classes depends on education levels and current recycling activities. Possible reasons for a preference for more home sorting are suggested, including a belief in the superior effectiveness of home sorting, and the desire for a better internal or external self-image.

## **2. Why do households recycle?**

Our purpose in this paper is to investigate preferences for household waste disposal options, focusing in particular on whether people prefer to sort their own recyclable wastes at home, rather

than having third parties do this for them. A simple economic calculation would suggest that, unless the act of sorting waste into paper, cans, bottles, compostables etc. generates utility, then less home sorting would always be preferred to more, since sorting requires costly time and effort. One of the findings of this paper is that there exists a significant group of Polish households for whom this simple calculation would appear to imply a positive net benefit from more home sorting. To place this result in its proper context, and to understand how this contributes to our understanding of what drives household behaviour with regard to recycling and waste management, it is first necessary to consider what the existing literature indicates as the main determinants of recycling and waste management at the household level.

Most of the empirical literature on recycling at the household level<sup>1</sup> has focused on factors that determine the direct cost to households of engaging in recycling effort – such as the availability of curbside pick-up recycling rather than “bring” systems where consumers must transport recyclables to central collection points; and on the opportunity cost of *not* recycling as reflected by the price paid for waste collection. This latter factor has received increasing attention as more municipalities and countries have introduced variable fees for solid waste collection (“pay as you throw”) over time (Reichenbach 2008). Recent US evidence shows a clear, significant effect from increasing the marginal cost of garbage disposal through a (higher) variable collection fee on the volume of waste that households generate (Huang *et al.* 2011). One of the earliest economic studies of recycling efforts is that of Hong *et al.* (1993). Their sample is of 2298 households in Portland, Oregon, who could choose to participate in curbside collection schemes of household-sorted recyclables. The authors found that recycling effort was increasing in the waste collection fee and in levels of educational achievement, but decreasing in the cost of household time (valued mostly using the

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<sup>1</sup> Note that there is also an emerging literature which models recycling behaviour at the level of municipalities (organisations of local government responsible for household waste collection), looking for example at their willingness to set up curbside collection schemes (De Jaeger & Eyckmans 2008). Another literature looks at variations in recycling rates across countries (e.g. Mazzanti & Zoboli 2008).

female wage rate) and was lower for home renters than home owners. We include waste collection fees as one attribute in the choice experiment described in Section 4; education levels also emerge as an important factor in explaining choices in our case study.

Another influence on recycling behaviour is the “inconvenience factor”, which can be thought of as a measure of the time, space and effort needed to be allocated by a household to achieve a given level of recycling activity (such as all glass and paper removed from their waste and collected for re-use).

Jenkins *et al.* (2003) study 1,049 households in 20 US metropolitan statistical areas, looking at the influence of the availability of a curbside collection scheme for recyclables as one measure of this inconvenience factor. They find that for all materials (glass, newspaper, plastic bottles, aluminium, yard waste and newspapers), presence of curbside recycling schemes increases recycling effort, but that in no case is the unit price of waste collection a significant determinant of recycling effort.

Kipperberg (2007) repeats the Jenkins *et al* analysis using Norwegian data, estimating separate ordered logit models for 5 different categories of waste. Finally, with regard to an “inconvenience factor”, Kuo and Perrings (2010) show for 18 cities in Taiwan and Japan that actual recycling rates depend on the frequency of collection of both recyclables and rubbish intended for landfilling. We include frequency of collection as a design attribute in our choice experiment.

A summary of the above is that the nature of the recycling schemes provided, the costs of waste collection to households, and household characteristics such as education levels can all help determine household recycling activities. The design characteristics of the recycling system employed in an area, and how this relates to the wider waste handling system (including its financial cost to households) has also shown to determine variation in stated preferences across households, along with their attitudes to waste management. (Kipperberg and Larson, 2012). Another feature that has been shown to matter is income. Huhtala (2010) reports results from a contingent valuation study in Finland, which collected 1131 responses to a questionnaire on WTP for alternative future

waste management options for Helsinki. She found WTP for recycling to be decreasing in household income, which she attributes to the higher opportunity costs of time for high-income households, given that time must be spent in sorting waste for recycling (so that the time cost per hour of recycling for rich households exceeds that of poor households, since richer households are foregoing more earning opportunity in this one hour of extra time spent recycling).

Most of the studies noted above use the availability of curbside collection and waste pricing, along with household characteristics to explain household choice over recycling effort. However, a desire to promote an external image or internal feel-good factor may also be important, since it would be associated with higher utility from the very act of recycling itself. This turns out to be of high potential importance in interpreting the results from our choice experiment. Waste management strategies which rely on appealing to households' social responsibility to increase recycling efforts appeal to the desire of individuals to promote their self- or externally-perceived reputation or green image (Bruvoll & Nyborg 2002). Increasing awareness of the social benefits of recycling can be expected, in this model, to increase household recycling actions, since this increases people's self-image value, although at an increasing marginal private cost of participation. Bruvoll and Nyborg (2002), in a survey of 1162 Norwegian citizens, find that the most frequently cited motivation for home sorting of recyclables was "I should do what I want others to do", with "I want to think of myself as a responsible person" as the second most highly reported reason. However, the authors also found that Norwegian households "...prefer to leave the recycling to others" (p.4) – that is, prefer separation of recyclables by others rather than by themselves. As will be seen, this is the opposite of what our results indicate for a substantial fraction of households in our sample.

Finally, another strand of the literature which is relevant to interpreting the results of our choice experiment is the extent to which indicators of social capital<sup>2</sup> and community norms influence recycling behaviour. Kurz *et al.* (2007) show that a proxy for “sense of community” is closely related to engagement with recycling in Northern Ireland; whilst Videras *et al.* (2012) find that, for a sample of over 2000 US households, intensity and strength of social ties, and pro-environment community norms, are linked to recycling behaviour: “...individuals who have strong connections with neighbours and who think most neighbours do things to help the environment are more likely to recycle” (p.42). Knussen *et al.* (2004), in a study of stated intentions to participate in “bring” recycling schemes in Glasgow, Scotland, found that 29% of the variation in intentions was explained by measures of attitudes, opportunities and what they refer to as subjective norms, in this case the degree to which respondents felt that their families and friends thought that recycling was a good thing. Communities with high levels of social capital can thus be expected, *ceteris paribus*, to engage in more recycling activities.

Summing up the literature discussed above, participation in household recycling schemes can depend on the price of not recycling, the availability and private cost of recycling, aspects of social capital, and desires for a better self-image. We now describe the design of a choice experiment where we investigate choices over household-based recycling in Poland, focusing on the question as to whether people prefer to engage in private recycling effort rather than “leaving the recycling to others”, to borrow a phrase from Bruvoll and Nyborg (2002).

### **3. Case study**

The site of our survey was the municipality of Podkowa Leśna, which is considered to offer amongst the highest quality housing in Warsaw, the capital and the largest city of Poland, especially with

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<sup>2</sup> Social capital can be thought of as social networks that facilitate mutually-beneficial collective action, degrees of trust and the quality of institutions (Saginga *et al.*, 2007, Paudel and Schafer, 2009).

respect to environmental amenities (such as gardens, parks, forests). Our study was designed to provide support for the municipal authorities who are currently considering the reform of the system of waste management, while at the same time ensuring compliance with EU Landfill Directive (1999/31) over reductions in landfilling;<sup>3</sup> and the EU Waste Framework Directive (2008/98) on reaching minimum target levels of recycling.<sup>4</sup>

At the time of our study (summer 2011), the municipality of Podkowa Leśna was inhabited by 3739 people in 1605 households. There were 12 private companies licensed to collect and transport waste, about half of them active. It was at each household's discretion whether to sign an agreement with one of the companies to collect their waste. Some of these companies collect household waste sorted (into 2 to 5 types) while others collect un-sorted waste and sort it centrally (sorting municipal waste has been required by law since the beginning of 2010, however, it is not specified in law exactly how this sorting should take place). Companies also differ in how many times different types of waste are collected per month, ranging from once a week to once a month. This range of current alternatives for waste collection was used to help design the hypothetical options which respondents chose from in our choice experiment.

#### **4. Experimental design and data collection**

The survey started by presenting the reason for this study, namely the provision of guidance for authorities in reforming waste management in the municipality. We collected general information about respondents' connections to Podkowa Leśna (duration of residence, perception of the community and its cleanliness, participation in local organizations etc.). Next we asked about

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<sup>3</sup> This sets targets for reductions in the percentage of biodegradable municipal solid waste disposed of to landfill by 2010, 2013 and 2020 (Polish Government 2010)

<sup>4</sup> Article 11(2) of the Waste Framework Directive requires Member States to take the necessary measures to achieve a target of 50% by weight by 2020 of the preparing for re-use and the recycling of waste materials such as paper, metal, plastic and glass from households.

respondents' current waste collection contract details and their recycling habits. After that, the contingent scenario of our study was introduced, and the attributes and their levels explained. The next part of the survey contained the choice experiment, and the survey ended with questions regarding the socio-demographic characteristics of respondents.

In selecting the most preferred hypothetical future alternative contract for waste, respondents considered the following attributes:

- number of categories waste needs to be sorted into (1, 2, 5);
- number of times a month waste is collected (1, 2, 4);
- cost to the household per month (the bill they will face).

The number of home sorting categories ranged from 1 (no sorting required), through 2 (recyclables, non-recyclables) to 5 (paper, glass, metals, plastic, other). The respondents were informed, however, that in every case the collected waste would undergo a screening process, and due to regulatory requirements, even if it was collected unsorted it would still be sorted in a central professional sorting facility. The survey also reminded people that sorting into more categories required more space in the household and more time and effort. A lower frequency of collecting waste requires that waste is stored on respondent's property longer. The last attribute was monetary, namely the total cost of collecting waste from the household each month. All levels of the attributes used in our study (including cost) were derived from observing the range of current practices of waste-collecting companies operating in Podkowa Leśna.

The experimental design consisted of 6 choice-tasks each with 3 alternatives per respondent; there were 4 questionnaire versions (blocks). The design for the choice experiment was optimized the design for D-efficiency of a multinomial logit model using Bayesian priors (Ferrini & Scarpa 2007) and all prior estimates were assumed to be normally distributed, with their means derived from the MNL model estimated on the dataset from the pilot survey, and standard deviations equal to 0.25 of each parameter mean. An example choice card (translated) is presented in Figure 1.

The main survey was preceded by a pilot study which allowed a test of the survey wording, the collection of respondents' comments and to obtain priors of the parameter estimates. The main study was administered by mail. The questionnaire was mailed to every one of the 1605 households in Podkowa Leśna along with a return envelope with a stamp. We received 311 responses resulting in a response rate of nearly 20%. This response rate may be considered exceptionally high for mail surveys in Poland when compared to other surveys (e.g. Markowska & Żylicz 1999), possibly because the inhabitants of the Podkowa Leśna municipality are better-than-average educated and the survey dealt with local issues. The main socio-demographic characteristics of the sample, the population of Podkowa Leśna and the population of Poland are presented in Table 1.

The comparison of socio demographic characteristics from our sample with the overall population of Podkowa Leśna reveals some differences – our respondents were older and better educated. These differences can be explained with the way our survey was administered; since each household received one survey it can be expected that the older (or adult) household members, responsible for financial decisions of a household, were more likely to fill it in. As a result, our sample characteristics with respect to age and education reflect household heads to more extent than average household members. Sample characteristics with respect to sex and income per household member are very close to characteristics of the population of Podkowa Leśna.

Comparing the characteristics of inhabitants of Podkowa Leśna with general population of Poland shows significant differences in terms of income and education. We note that the site of our study was wealthier (and possibly more socially integrated) than average, what might provide a background for better interpretation of the results. Comparing preferences for recycling across communities differing in wealth, although interesting, was not an aim of this study. The influence of wealth on pro-environmental behaviour is not straightforward, as on the one hand richer respondents may have a higher value of time leading to a higher cost of in-home sorting (Huhtala 2010) but on the other hand, they are often better educated. Higher education levels have been

shown to motivate pro-environmental behaviour (Videras et al, 2012). Finally, since the residents of this municipality may have stronger sense of community, their behaviour may be to a larger extent motivated by social interactions and self-image than in other communities (Videras *et al.* 2012).

## 5. Methods – discrete choice modelling

In a random utility framework, used to analyse respondents' preferences based on their stated choices, respondent  $i$ 's utility associated with choosing alternative  $j$  is:

$$U_i(\text{Alternative} = j) = U_{ij} = \beta'x_{ij} + \varepsilon_{ij}. \quad (1)$$

By introducing the error term it is assumed that utility levels are random variables, as it is otherwise impossible to explain why apparently equal individuals (equal in all attributes which can be observed) may choose different options.

Random utility theory is transformed into different classes of choice models by making different assumptions about the random term. In order for this component to represent the necessary amount of randomness into respondents' choices its variance needs to be sufficiently large or, since the utility function has no unique scale, assumptions with respect to the random term variance may be expressed by scaling the utility function in the following way:

$$U_{ij} = \sigma\beta'x_{ij} + \varepsilon_{ij}. \quad (2)$$

For this model to be identifiable, however, scale needs to be related to the inverse of the error term, as  $\sigma \propto 1/\varepsilon$ .

When random component of the utility function is assumed to be distributed independently and identically (iid) across individuals and alternatives – Extreme Value Type 1 distribution – a Multinomial Logit Model (MNL) is derived, with the following closed-form expression of the probability of choosing alternative  $j$  from a set of  $J$  available alternatives:

$$P(j|J) = \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_{ij})}{\sum_{k=1}^J \exp(\boldsymbol{\beta}'\mathbf{x}_{ik})} \quad (3)$$

The MNL model implausibly assumes not only that the random term is independent and identical for all choices and respondents but also that all respondents have the same preferences (and so the same coefficients in their utility functions,  $\boldsymbol{\beta}$ ). One method for relaxing these assumptions, by allowing for some level of (unobserved) preference heterogeneity and possibly correlations between the alternatives and choice situations, is the Random Parameters Model (RPL). In RPL the utility function becomes:

$$U_{ij} = \sigma\boldsymbol{\beta}'_i\mathbf{x}_{ij} + \sigma\boldsymbol{\Omega}_{ij}\mathbf{Y}_{ij} + \varepsilon_{ij} \quad (4)$$

Note that parameters of utility functions are now respondent-specific. It is assumed that they follow distributions specified by a modeller:  $\boldsymbol{\beta}_i \sim f(\mathbf{b} + \Delta\mathbf{z}_i, \boldsymbol{\Sigma} + \Gamma\mathbf{z}_i)$ , with means  $\mathbf{b}$  and variance-covariance matrix  $\boldsymbol{\Sigma}$ . In addition, it is possible to make means and variances of the distributions a function of observable respondent or choice-specific characteristics  $\mathbf{z}$ .

Even though the RPL model allows for a lot of flexibility in modelling respondents' preference heterogeneity, if no correlations between random variables are allowed, all respondents are assumed to have the same scale coefficient used for normalizing their utility function, i.e. their

choices demonstrate the same extent of randomness (Train & Weeks 2005). A method which allows control for both preference and scale heterogeneity of respondents at the same time is the Generalized Multinomial Logit Model (G-MNL) (Fiebig *et al.* 2010). In this model, the utility function takes the form:

$$U_{ijt} = [\sigma_i \mathbf{b} + \gamma \mathbf{z}_i + (1-\gamma) \sigma_i \mathbf{z}_i]' \mathbf{x}_{ijt} + \omega_{ijt}. \quad (5)$$

Similarly to the RPL model, the coefficients in the utility function are individual-specific. Unlike in the RPL, however, the scale coefficient is now also individual-specific (it is normalized to the mean level in the sample, see the discussion below). In addition, the new coefficient  $\gamma \in [0,1]^5$  controls how the variance of residual taste heterogeneity varies with scale. If  $\gamma=0$  the individual coefficients become  $\beta_i = \sigma_i \mathbf{b} + \mathbf{z}_i$ , while if  $\gamma=1$  they are  $\beta_i = \sigma_i (\mathbf{b} + \mathbf{z}_i)$ . These are the two extreme cases of scaling (or not scaling) residual taste heterogeneity in the G-MNL model (type I and type II respectively), however, all intermittent solutions are possible.

In estimation, the individual scale is usually assumed to be log-normally distributed

$\sigma_i = \exp(\bar{\sigma} + \tau \varepsilon_{0i})$ ,  $\varepsilon_{0i} \sim N(0,1)$ . In order to allow for normalization it is assumed that

$E\sigma_i = \exp(\bar{\sigma} + \tau^2/2)$ , i.e.  $\bar{\sigma} = -\tau^2/2$ . This way the scale is no longer fixed; instead it is assumed to

follow a lognormal distribution, with the new parameter  $\tau$  reflecting the level of scale heterogeneity in the sample.

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<sup>5</sup> To assure  $\gamma \in [0,1]$  it is usually modelled as  $\gamma = \frac{\exp(\gamma^*)}{1 + \exp(\gamma^*)}$ , and it is  $\gamma^*$  that is estimated.

In this paper we apply the G-MNL model to analyse respondents' choices with respect to waste sorting options. However, we also provide contribution to the above model, by allowing for the individual scale parameter to be a function of observable individual-specific characteristics  $\mathbf{k}$  :

$$\sigma_i = \exp(\bar{\sigma} + \tau\varepsilon_{0i} + \boldsymbol{\theta}'\mathbf{k}_{it}). \quad (6)$$

This way we are able to observe which groups of respondents make more deterministic, and which groups more random choices.

## 6. Results

As a starting point for further analysis, we present the results of a simple Multinomial Logit Model (MNL). This is followed by the Generalized Multinomial Logit Model (G-MNL) with respondents' observable characteristics as covariates in their utility function parameters. Next, we report the results of a Latent Class Model, which we use to reveal that there are latent groups of respondents who have very different preferences towards recycling, and we show that these latent types of respondents do not necessarily currently engage in a type of sorting that they prefer, as indicated by the results of the MNL model with group-specific parameters. Possible explanations of this phenomenon are discussed. Finally, we report the results of a binary logit model which is used to identify socio-demographic characteristics of respondents who currently sort some or all of their waste.

Each of the following models was estimated in NLOGIT 5.0. We used NLOGIT default convergence criteria and BFGH as the optimization algorithm. The results of a random parameters logit model were used as the starting values for the G-MNL model. In simulating the log-likelihood we used 2000 random draws. Where applicable, we accounted for the fact that each respondent faced 26 choice tasks by allowing for individual-specific coefficients and scale.

### 6.1. Multinomial Logit Model

In the MNL model, we assumed that each respondent's utility associated with choosing alternative  $j$  was a linear function of its characteristics, namely *sort*, *time*, and *fee*:

- *sort2*, *sort5* – the number of categories waste needs to be sorted to (2 or 5 levels, dummy-coded, no sorting used as a reference level);
- *time2*, *time4* – the number of times waste gets collected per month (2 or 4, dummy-coded, 1 used as a reference level);
- *fee* – the monthly cost of collecting waste per household (in PLN/100).

As a result the underlying utility function was of the following form:

$$U_{ij} = \beta_{sort2} \cdot sort2_j + \beta_{sort5} \cdot sort5_j + \beta_{time2} \cdot time2_j + \beta_{time4} \cdot time4_j + \beta_{fee} \cdot fee_j + \varepsilon_{ij} \quad (7)$$

The results of a MNL model are reported in Table 2. All explanatory variables turn out to be significant determinants of choice. Although the coefficient values cannot be directly interpreted, their signs and relative values reflect how different factors influence respondents' choices (their utility, and hence the probability of choosing a certain alternative). Perhaps surprisingly, the results of this basic model show that, *ceteris paribus*, respondents prefer to sort their waste themselves, and prefer to sort into 5 categories over 2, and 2 over no sorting. People prefer to have waste collected 4 times a month over 2 times a month, and 2 times a month over once a month. As expected, the utility function coefficient associated with the price of collecting waste is negative.

The MNL formulation is usually a starting point for most choice experiment models, however, it has some important limitations arising mainly from rigid assumptions about the distribution of the error term and preference homogeneity, as discussed in section 5. We demonstrate below how these

limitations can be overcome by relaxing some of the model's rigid assumptions using the G-MNL model.

## 6.2. Generalized Multinomial Logit Model

In the G-MNL model each respondent's utility was assumed to be a linear function of the same alternative-specific attribute levels, however unlike in the MNL model, we now allowed each of the utility function coefficients to follow a normal distribution, to account for unobserved preference heterogeneity.<sup>6</sup> Therefore, for each utility function coefficient associated with each of the attribute levels we now provide an estimate of the mean and standard deviation of its distribution.

In addition, in order to observe individual heterogeneity of respondents' preferences, we introduced individual-specific covariates to means of these distributions. These covariates were selected from individual-specific variables representing current recycling patterns, as they were likely to reflect heterogeneity of respondents' preferences. In the final version of the model only those covariates were retained which were statistically significant for the mean of at least one random variable. These statistically significant covariates used in the final version of the model were:

- *sqsorta* – a dummy taking a value of 1 for respondents who currently sort all their waste<sup>7</sup>;
- *sqsortp* – a dummy taking a value of 1 for respondents who currently sort part of their waste<sup>8</sup>;
- *inc* – respondent's household income (in PLN/1000)<sup>9</sup>;
- *price* – current monthly cost of collecting household waste (in PLN/100);<sup>10</sup>

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<sup>6</sup> We chose normal distribution for all our random parameters because it offers a large degree of flexibility for respondents' preference heterogeneity and because a model with all random parameters distributed normally provided a better fit than using e.g. lognormal or triangular distributions.

<sup>7</sup> 51.28% of respondents stated that they currently sort all their waste

<sup>8</sup> 28.74% of respondents stated that they currently sort part of their waste

<sup>9</sup> Respondents' mean household income was 9174 PLN

<sup>10</sup> Mean monthly cost of collecting waste was 57.02 PLN per household

- *compost* – having a compost bin on respondent’s property.<sup>11</sup>

In mathematical notation, we now allowed the  $\beta$  s to be random variables following normal distributions, with additional covariates in each variable mean:

$$\begin{cases} \beta_{sort2} \square N(\mu_{sort2} + \beta_{sqsorta\_sort2} \cdot sorta + \beta_{sqsortp\_sort2} \cdot sortp, \sigma_{sort2}) \\ \beta_{sort5} \square N(\mu_{sort5} + \beta_{sqsorta\_sort5} \cdot sorta + \beta_{sqsortp\_sort5} \cdot sortp, \sigma_{sort5}) \\ \beta_{time2} \square N(\mu_{time2} + \beta_{inc\_time2} \cdot inc + \beta_{price\_time2} \cdot price + \beta_{compost\_time2} \cdot compost, \sigma_{time2}) \\ \beta_{time4} \square N(\mu_{time4} + \beta_{inc\_time4} \cdot inc + \beta_{price\_time4} \cdot price + \beta_{compost\_time4} \cdot compost, \sigma_{time4}) \\ \beta_{fee} \square N(\mu_{fee}, \sigma_{fee}) \end{cases} \quad .(8)$$

In addition, we allowed for unobserved scale heterogeneity – scale was also modelled as a random variable, as explained in Section 5. Finally, to gain a better insight into respondents’ choices, we made each respondent’s scale coefficient a function of their socio-demographic characteristics to represent a possible influence of individual characters on the degree of randomness in respondents’ choices. In the end only education level was significant (*edu* was a dummy variable for having a university-level degree and it entered as a covariate of scale).<sup>12</sup> As a result the individual scale coefficient was modelled as:

$$\sigma_i = \exp(\bar{\sigma} + \tau \varepsilon_{0i} + \beta_{edu} \cdot edu_i). \quad (9)$$

The results of the G-MNL model are presented in Table 3. We start by noting that the new model, allowing for unobserved and observed preference and scale heterogeneity, provides a substantially better fit in terms of pseudo-R<sup>2</sup> and normalized AIC than the more-restrictive MNL model. The results reveal that there was substantial preference heterogeneity among our respondents with respect to

<sup>11</sup> 63.68% of respondents stated that they currently have a compost bin on their property

<sup>12</sup> 68.93% of respondents declared that they have a university-level degree

choice attributes, as illustrated by relatively high values and high statistical significance of coefficients associated with their standard deviations (column 4 of Table 3).

Turning to the analysis of means, we start by noting that value of their coefficients should be interpreted together with the coefficients for their covariates. The resulting picture indicates that the respondents who do not currently sort all or part of their waste ( $sorta = 0$  and  $sortp = 0$ ) have substantially lower coefficients for sorting waste into 2 or 5 categories than respondents who currently do sort their waste. In fact, the coefficient for sorting waste into 5 categories is negative, indicating that for this group of respondents having to sort into that many categories would be worse than no sorting (this result is not statistically significant, however). In contrast, respondents who currently sort waste seem to prefer sorting into 2 categories over no sorting, and sorting into 5 categories over sorting into 2. Interestingly, even though there seem to be no differences in their preferences towards sorting into 2 categories, those respondents who currently sort all their waste are much more in favour of sorting into 5 categories than respondents who declare that they currently sort only part of their waste, as indicated by value of covariates  $sorta$  and  $sortp$  for variables  $sort2$  and  $sort5$ .

One possible explanation of this result is that respondents who already sort have invested in recycling bins or cabinets and have a system of household waste management already in place which reflects their preferences and the range of waste collection contracts on offer. Changing to a new system would involve fixed costs that households would rather avoid. Alternatively, the fact that respondents are heterogeneous in terms of their sorting preferences can be viewed as leading directly to their current sorting behaviour (i.e. those who prefer to sort more already do so).

Preferences towards the frequency of waste collection were less differentiated. In general, respondents preferred to have waste collected more often. We observed that respondents whose

household income was higher, who currently paid higher prices for waste collection and who currently had a compost bin on their property had stronger preferences for more frequent waste collection. This last result may seem surprising, since having a compost bin implies an alternative “destination” for part of the waste stream. However, it is possible that this dummy variable is picking up the effects of living in a house with a garden, rather than an apartment block, and/or the constraints of space available to store wastes prior to collection. Lastly, we note that the monetary coefficient – the monthly fee associated with a particular waste collection alternative - was negative. This variable also proved to be highly differentiated within our sample, indicating a high level of heterogeneity with respect to the marginal utility of income.

By utilizing the G-MNL model we were able to allow the scale coefficient to be non-constant, i.e. allowing for a different level of randomness in respondents’ choices. This proved to introduce a significant improvement in our model, as illustrated by a high value and high statistical significance of the coefficient  $\tau$ , representing the level of differentiation between respondents’ scale coefficients. Finally, we note that allowing for observable utility function scale differences, associated with respondents’ education level, was also a significant component of the model. We found that respondents having a university-level degree had on average lower scale coefficients, hence resulting in higher variance of their responses. The rest of respondents were more deterministic in their choices, possibly following simpler decision rules, resulting in lower scale coefficients.

### **6.3. Latent Class Model**

In order to further investigate the different preferences towards personal sorting of household waste we estimated a third model – the Latent Class (LC) model. The model is essentially similar to random parameters model (see section 5 for details) except that the distribution of preference parameters is discrete. Behaviourally, it allows to identify latent classes of respondents with distinct preferences. The class membership of respondents is probabilistic (and hence the classes are latent); explanatory

variables of class membership and preference parameters of respondents in each class are estimated jointly. In our case we used a three-class specification. The results of the LC model are presented in Table 4.

The results show that the observed choices are best explained if there are three classes which substantially differ in the utility function parameters.<sup>13</sup> While the members of class 1 (18.10%) have negative coefficients associated with sorting into 2 and 5 categories, indicating that they 'dislike' in-home sorting, members of class 2 (24.40%) and 3 (54.50%) seem to prefer to do the sorting themselves. The relative values of the *sort* coefficients for class 2 respondents are substantially higher than those of class 3 – class 2, and the value of *sort5* in relation to *sort2* is much higher. This means that respondents of class 2 have not only stronger preferences for sorting in general, but also prefer sorting into 5 categories much more than into 2.

The coefficients associated with the frequency of waste collection are positive for all groups. Interestingly, however, respondents who have the strongest preferences for in-home sorting (and sorting into more categories – class 2) are also the ones who are the most interested in more frequent waste collection.

Each respondent's class membership is stochastic. However, current practices in an in-house sorting (all or part) of one's waste were found to significantly explain class membership.<sup>14</sup> We found that respondents who already sort all or part of their waste were statistically less likely to belong to latent class 1 and thus have negative preferences for sorting. At the same time, sorting into 2 or 5 categories had a positive, although not statistically significant impact on whether a respondent was

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<sup>13</sup> A 3-class specification provided an improvement in fit vs. a 2-class model (AIC = 1.383 vs. 1.420). We were unable to successfully estimate a 4-class model for comparison due to convergence problems resulting from very high standard errors of a few insignificant parameters in some classes.

<sup>14</sup> The other respondent-specific explanatory variables such as *inc*, *price*, *compost* and *edu* did not significantly improve the results.

more likely to belong to class 2 (the group which preferred the most sorting) rather than class 3 (which had positive, although less pronounced preferences for in-home sorting).

The results of the LC model thus show that there is a significant variation in preferences across different types of households, although we note that class membership depends on more factors than whether a respondent currently sorts his or her waste. In what follows, we estimate separate models for respondents according to their current behaviour as an alternative approach to the latent class results above, in order to investigate the possible differences between respondents' current and declared behaviour.

#### **6.4. Preferences of observed classes of respondents**

In addition to the revealed choices we can separate the respondents into those who (1) don't currently sort, (2) sort into 2 categories or (3) sort into 5 categories to see if their preferences differ. Table 5 presents the results of the MNL model in which all attributes were interacted with three binary variables representing three types of households given above. This way we are able to simultaneously estimate the coefficients of utility functions of these three distinct groups. The results presented in Table 5 are different from those in Table 4 in that in the former case the class of each respondent is unambiguously determined by his current sorting behaviour while in latter case class membership was random and current sorting behaviour only influences the probability of class membership. Therefore, in the LC model based on their choices, some respondents could be more likely to be classified to the one of the pro-sorting classes, even though they did not currently sort. By comparing the log-likelihood and the other indicators of model fit (AIC, Pseudo-R<sup>2</sup>) between different models (all of which were estimated on the same sample) we can see than even though having group-specific parameters for different revealed types of respondents significantly improves the model fit (-1092.74 for the simple MNL model presented in Table 2 vs. -1058.78 for the MNL model with group-specific parameters presented in Table 5), the results are worse than in the case when

classes are allowed to be random and only probabilistically influenced by current sorting behaviour (-927.08 for the LC model, Table 4).<sup>15</sup>

Comparing the preferences of different types of respondents reveals that utility function coefficients associated with sorting into 2 or 5 categories for the respondents who do not currently sort are not statistically different from zero. In contrast, the respondents who currently sort part or all of their waste 'like' sorting and prefer to sort into 5 than into 2 categories. Interestingly, this holds also for group 2 – respondents who currently sort into 2 categories. In addition, as in the case of the LC model, more frequent waste collection is preferred, and the preferences for a more frequent collection are stronger for those who currently sort into more categories. The price coefficient is again negative and highly significant for every group.

There are several possible reasons why respondents' current behaviour may not match their declared preferences, as indicated by a better fit of the LC model vs. MNL with group-specific coefficients, and by respondents who currently sort their waste into 2 categories actually preferring to sort into 5. Some of these reasons include transaction costs or the nature of the contingent scenario in which it was explained that if the new policy was adopted every household in the municipality would have to comply (i.e. 'I will sort more if everyone will do the same' attitude).

### **6.5. Determinants of current sorting behaviour**

Lastly, in order to investigate what socio-demographic characteristics can be used to predict recycling behaviour of the respondents we present the results of the binary logit model for sorting participation. In the two versions of the model, presented in Table 6, the dependent variables are associated with respondent's (1) sorting part or all of their waste (i.e. sorting into 2 or 5 categories

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<sup>15</sup> The LC model results are still worse, however, than the G-MNL results (LL=-838.96) which allows for unobserved preference and scale heterogeneity. We note, however, that even though the MNL with group-specific and the LC model present worse fit than the G-MNL, they allow for easier interpretation of results and provide additional insight into distinct types of respondents' preferences with respect to personal sorting.

vs. no sorting) and (2) sorting all of their waste (i.e. sorting into 5 categories vs. sorting into 2 categories or no sorting). We found that respondents who did not sort at all, or sorted into 5 rather than into 2 categories were somewhat poorer (*inc*). At the same time, respondent's higher education was correlated with more sorting. Respondents who did more in-home sorting usually lived in smaller households (*hh*), however, they had more children (*hhc*) than respondents who did not sort. Interestingly, older people were less likely to recycle (*age*), however, this effect was somewhat compensated by the fact that those who lived in Podkowa Leśna longer (*lived*) engaged in some form of sorting more often. We observed that respondents who sorted also more frequently declared that they are happy with living in Podkowa Leśna (*happy*), disagreed with the statement that the municipality is rather clean (*clean*) and have had participated in voluntary cleaning actions (*clean\_act*). Finally, having a compost bin on their property increased the probability of observing some sorting behaviour, although not necessarily sorting all one's waste.

## **7. Conclusions**

Unlike Bruvoll and Nyborg (2002), we find that some households have a positive preference for personal recycling efforts (more home sorting of wastes), even when the alternative involves the same level of recycling actions by a third party, and thus the same end result in terms of the fraction of household waste which is recycled. Bruvoll and Nyborg (2002) found that a sample of Norwegian households "...prefer to leave the recycling to others" (p.4). This is not what a significant sub-set of our sample prefers. Membership of this "home sorting" class is linked to existing sorting behaviour. Households in this latent class would prefer systems which require higher levels of home sorting, and indeed would be willing to pay more for such systems than for contracts which require lower levels of home sorting. However, there is also a substantial group of households who derive negative utility from more home sorting. These individuals would need to be compensated via lower waste contract fees to enter into contracts which required higher levels of home sorting. This suggests that waste

collection firms should offer differentiated contracts to households, since some will be willing to pay higher prices to avoid having to home sort, whilst others will be willing to pay to carry out this sorting.

We start the discussion of possible reasons for these findings by providing the results from questions relating to respondents' stated reasons for their current home sorting behaviour. Figure 2 illustrates the shares of different reasons indicated as a main factor in choosing a particular waste management option for one's household. The majority of respondents (70%) indicated economic reasons as the main determinant, with 28% stating that care for the environment was the main reasons, and only 2% the inconvenience of the selected method. This high importance of economic factors is echoed by the negative and strongly significant parameter estimate on monthly collection fees in the choice experiment. In Figure 3 we provide the same information for respondents who currently do not sort their waste. Here, respondents indicated the reasons as (i) not being convinced about the usefulness of home sorting (38%), (ii) that it is too time-consuming (23%), (iii) that it takes up too much space (20%) or that (iv) that it is too expensive (19%). Overall, these results confirm the dichotomy of respondents' preferences with respect to sorting – for one group it seems to be not very burdensome whilst being of some benefit to the environment, whilst for others costs outweigh possible benefits. Results from Table 6 show that education, age and having children play a role in determining existing recycling behaviour of individual households.

So why might a substantial group of households prefer more home sorting to less? Three possible explanations are suggested. First, individuals may derive utility from home sorting, possibly due to a desire to promote an environmental self-image, such as Bruvold and Nyborg (2002) discuss. Thus, a stronger desire for a positive self-image leads to a preference for more home sorting of wastes. This is also potentially driven by a desire for a green external image, since recycling behaviour may be observable by neighbours, family and friends (Kurz *et al.* 2007). Second, individuals may believe that

home sorting of wastes is more effective than collective sorting. If people believe that more “waste” should be transformed into useful secondary materials, then a belief in the superior effectiveness of home sorting over collective sorting would also motivate a preference for home sorting, even when it is privately costly in terms of time and effort. This would also explain why, for those respondents who prefer self-sorting, sorting into more categories is preferred to sorting into fewer, since they perceive that this increases the waste reduction and the useability of secondary materials. From qualitative analysis of respondents’ preferences (focus groups and individual verbal protocols conducted as pre-testing of the survey), we discovered that many respondents indeed felt that they would sort better if they were to do this personally. Respondents mentioned separating aluminium foil cover from plastic containers of yoghurt packages, or not mixing paper with food waste which makes paper unusable; and that they do not trust the waste collecting companies to sort well. For instance, some respondents felt that their work is wasted, because collecting companies pick up their different bags with the same truck. This echoes a conclusion from Bartelings and Sterner (1999) in their study of Swedish households, some of whom felt that it was better for them to take responsibility for recycling than relying on other agencies to do this. Third, individuals may feel that they have a moral duty to self-sort recyclables, and so prefer choice options with more self-sorting. Unfortunately, the data available to us does not allow us to test which of these three options have more explanatory power.

In conclusion, we find that a significant group of citizens prefer to sort their own recyclable materials than rely on curbside collection of un-sorted waste, despite the time and effort costs of home sorting. The policy implication is that agencies which have targets for increased recycling and reducing household waste going to disposal routes such as landfilling and incineration can take advantage of preferences for home sorting by promoting awareness of the benefits of such actions, and providing resources which facilitate home sorting. However, a sub-set of respondents would need to be compensated for such actions, or face a higher opportunity cost of not sorting (for example, through increased waste collection fees), for higher levels of home sorting to be taken up

across the whole population. In future work it would be interesting to test the alternative explanations of a preference for home sorting to see which offers the most explanatory power in different contexts.

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Figure 1. Example of a choice card (translation)

Choice Situation 1.	Alternative 1	Alternative 2	Alternative 3
Method of sorting in household	Into 5 categories	Into 2 categories	None
Frequency of collection	Once every 4 weeks	Once every 2 weeks	Once every week
Monthly cost for your household	75 PLN	50 PLN	100 PLN
Your choice:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 2. Respondents' main reasons for choosing a particular current waste management options

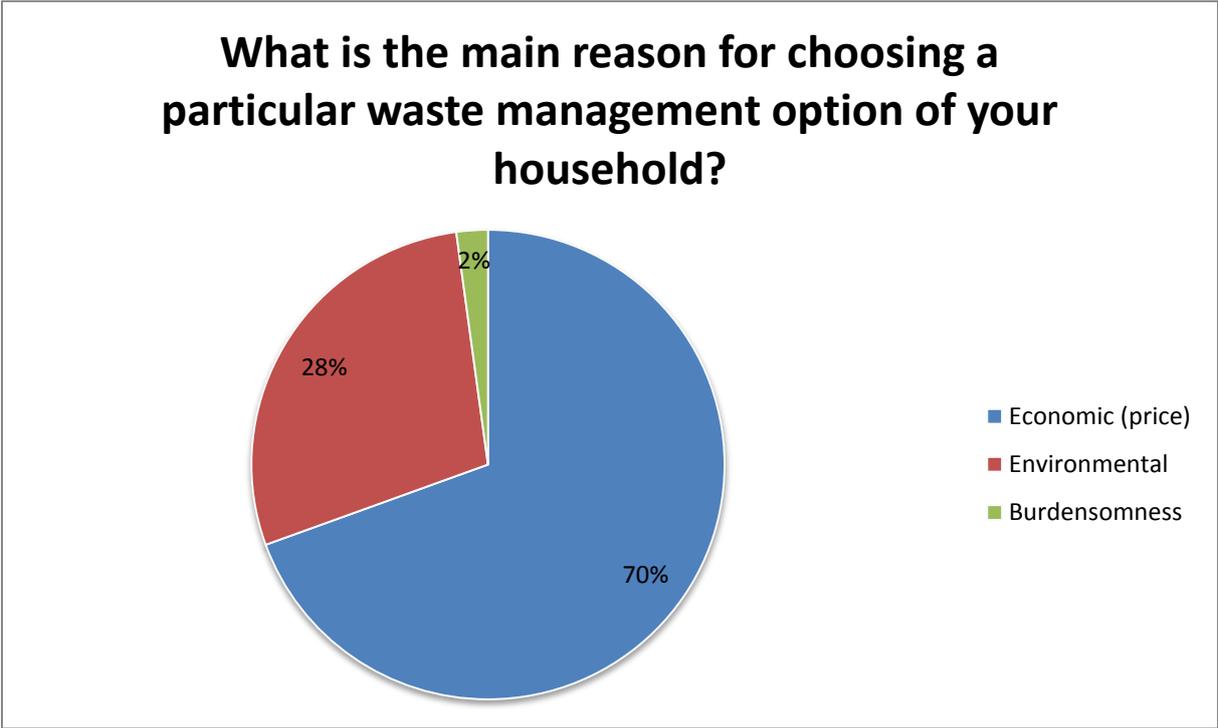


Figure 3. Respondents' main reasons for not currently sorting waste

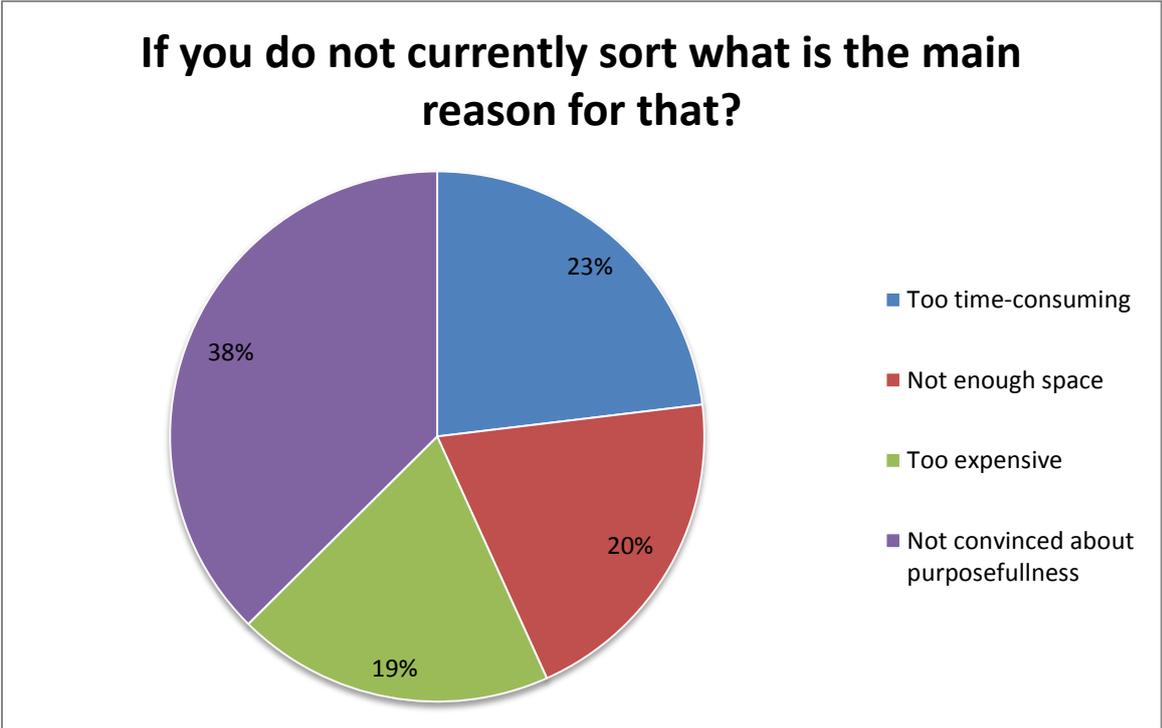


Table 1. Socio-demographic characteristics of the sample, the population of Podkowa Leśna, and the population of Poland

	Sample	Population of Podkowa Leśna <sup>16</sup>	Population of Poland <sup>14</sup>
Female	0.56	0.54	0.52
Age	57.92	47.52	45.43
Income <sup>17</sup>	2810.93	2653.00	1845.17
Education – tertiary	0.67	0.20	0.19
Education – secondary	0.15	0.44	0.34
Education – vocational	0.16	0.12	0.22
Education – primary	0.01	0.25	0.23

<sup>16</sup> Education levels provided for population 15+ years old.

<sup>17</sup> Mean income per household member, in PLN.

Table 2. The results of the MNL model

<b>Variable</b>	<b>Coefficient</b>	<b>Standard error</b>
<i>sort2</i>	0.52070***	0.09981
<i>sort5</i>	1.10643***	0.08155
<i>time2</i>	0.68328***	0.08624
<i>time4</i>	0.91921***	0.10375
<i>fee</i>	-0.03063***	0.00155
	Observations	1371
	Log likelihood	-1092.7431
	AIC(norm.)	1.6010
	Pseudo-R <sup>2</sup>	0.2717

\*\*\*, \*\*, \* Significance at 1%, 5%, 10% level

Table 3. Results of the G-MNL model

Variable / covariate	Coefficient <sup>18</sup>	Standard error	Coefficient <sup>19</sup>	Standard error
<i>sort2</i>	0.93885	0.95106	3.04361***	0.69470
<i>sorta</i>	2.45319**	1.06101	–	–
<i>sortp</i>	2.46687**	1.15400	–	–
<i>sort5</i>	-0.48879	0.97906	5.95109***	0.92825
<i>sorta</i>	7.29191***	1.73473	–	–
<i>sortp</i>	5.41061***	1.64055	–	–
<i>time2</i>	-1.74209	1.31792	1.68742**	0.72536
<i>inc</i>	0.15817**	0.06769	–	–
<i>price</i>	4.39419**	1.85723	–	–
<i>compost</i>	3.20223***	1.02262	–	–
<i>time4</i>	-4.64672***	1.45815	3.03513***	0.59646
<i>inc</i>	0.24446***	0.07491	–	–
<i>price</i>	5.68102***	1.73950	–	–
<i>compost</i>	2.46077***	0.87628	–	–
<i>Fee</i>	-0.14359***	0.02409	0.07639***	0.01339
$\tau$	1.71784***	0.17367	–	–
<i>Edu</i>	-0.91815***	0.29092	–	–
$\gamma$	0.31002***	0.07408	–	–
			Observations	1284
			Log likelihood	-838.9576
			AIC(norm.)	1.3430
			Pseudo-R <sup>2</sup>	0.4053

\*\*\*, \*\*, \* Significance at 1%, 5%, 10% level

<sup>18</sup> For randomly distributed coefficients – means of the distribution

<sup>19</sup> For randomly distributed coefficients – standard deviations of the distribution

Table 4. The results of the LC model

Variable	Latent class 1		Latent class 2		Latent class 3	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
<i>sort2</i>	-1.3317***	0.3685	4.2836***	1.5265	1.1605***	0.1702
<i>sort5</i>	-2.4724***	0.4553	7.6691***	1.7828	1.2413***	0.1578
<i>time2</i>	1.1031***	0.3752	0.6659*	0.3707	0.8385***	0.1682
<i>time4</i>	1.2145***	0.3579	2.7291***	0.6494	1.0790***	0.1705
<i>Fee</i>	-0.0710***	0.0094	-0.0464***	0.0105	-0.0352***	0.0027
Class membership probability variables						
<i>constant</i>	0.1065	0.4019	-1.3592*	0.7156	0.0000	(fixed)
<i>sort2</i>	-1.9306***	0.5511	0.9042	0.7509	0.0000	(fixed)
<i>sort5</i>	-1.3339**	0.6032	0.3064	0.8096	0.0000	(fixed)
class probability	0.1810		0.2740		0.5450	
Observations	1371					
Log likelihood	-927.0775					
AIC(norm.)	1.3830					
Pseudo-R <sup>2</sup>	0.3845					

\*\*\*, \*\*, \* Significance at 1%, 5%, 10% level

Table 5. The results of the MNL model with group-specific parameters

Variable	Group 1 – don't sort		Group 2 – sort part		Group 3 – sort all	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
<i>sort2</i>	0.1518	0.2034	0.5238***	0.1702	0.7796***	0.1643
<i>sort5</i>	0.1139	0.1645	1.1144***	0.1483	1.6045***	0.1309
<i>time2</i>	0.5020***	0.1784	0.6698***	0.1584	0.8094***	0.1308
<i>time4</i>	0.5725***	0.2139	0.8993***	0.1697	1.1473***	0.1761
<i>Fee</i>	-0.0332***	0.0033	-0.0247***	0.0027	-0.0347***	0.0024
Observations	1371					
Log likelihood	-1058.7857					
AIC(norm.)	1.5660					
Pseudo-R <sup>2</sup>	0.2917					

\*\*\*, \*\*, \* Significance at 1%, 5%, 10% level

Table 6. Binary logit model for sorting participation

Variable	Sort – part or all (80.01%)		Sort – all (51.28%)	
	Coefficient	Standard error	Coefficient	Standard error
<i>Constant</i>	0.3928**	0.1924	-0.3802**	0.1687
<i>Inc</i>	0.0006*	0.0003	-0.0007***	0.0003
<i>Edu</i>	0.0998	0.1152	0.6085***	0.0952
<i>Lived</i>	0.0016***	0.0003	0.0005	0.0003
<i>Age</i>	-0.0026***	0.0005	-0.0023***	0.0005
<i>Happy</i>	1.3554***	0.1634	0.6911***	0.1470
<i>Clean</i>	-0.7340***	0.0898	-0.7850***	0.0681
<i>clean_act</i>	0.7903***	0.0904	0.4444***	0.0678
<i>Hh</i>	-0.2168***	0.0391	-0.1807***	0.0299
<i>Hhc</i>	0.2199***	0.0392	0.1841***	0.0300
<i>Compost</i>	0.7560***	0.0857	0.0073	0.0701
Observations	1371			
Log likelihood	-1841.2019			
AIC(norm.)	0.9010			
Pseudo-R <sup>2</sup>	0.1051			

\*\*\*, \*\*, \* Significance at 1%, 5%, 10% level