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# Estimating the Relationship between Unit-based Garbage Pricing and Municipal Solid Waste Generation: A Multivariate Double-Selection Approach

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**Abstract**

Many countries have introduced unit-based pricing (UBP) programs for garbage to encourage households to reduce waste generation and to reallocate waste for recycling. Previous studies have shown that UBP programs reduce waste generation. However, since few studies have addressed how the level of UBP induces households to separate recyclable material from unsorted waste, we investigate this issue using data on Japanese municipal waste management. Japanese municipalities can choose whether to implement UBP and to collect recyclable material. Thus, we can only observe the relationship between the level of UBP and the amount of recycling in those municipalities that implement both options. Ignoring this complicated selectivity may cause selection biases, resulting in a loss of consistency in an estimates. Therefore, to overcome this problem caused by the selectivity, we employ a double sample-selection model. Moreover, a system estimation is implemented to consider the correlations among different types of recyclable material. In addition, similarly to related studies, we consider the endogeneity of the level of UBP. The estimation results indicate that a higher level of UBP for garbage induces more recycling for some recyclable materials, namely PET bottles, plastic containers, and paper containers, but also decreases the amount of garbage collected.

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## 1 Introduction

A unit-based pricing (UBP) program is a local waste management policy that has been introduced in many countries. In general, a UBP program aims to reduce waste management expenditure, as well as encourage households to reduce the amount of waste they generate and separate recyclable material from unsorted waste. [1] Under this garbage pricing policy, inhabitants dispose of their garbage using priced bags or tags designated by the municipal authorities, but usually dispose of recyclables[2] at no charge. Therefore, there is a growing need to analyze whether UBP is effective. In this study, we focus on the garbage reduction effect and the substitution effect between garbage and recyclables caused by UBP.

A number of previous studies have analyzed the effect of UBP on garbage reduction or on promoting recycling. These studies have attempted to address several problems that occur in such estimations. One significant problem is the endogeneity of UBP. It is quite possible that UBP is an endogenous variable, because the level or presence of UBP may be related to an unobserved factor that affects the amounts of garbage or recyclables collected. Ignoring this endogeneity would lead to a loss of consistency. To handle this problem, some researchers adopt a quasi-experimental approach, such as a difference-in-differences (DID) model (Allers and Hoeben (2010)) or a two-stage least squares (2SLS) approach (Hong *et al*.(1993); Kinnaman and Fullerton (2000); Huang *et al*.(2011)). After considering the endogeneity of UBP, these studies confirmed that UBP effectively reduces the amount of garbage generated and promotes recycling.

Next, we focus on the types of recyclables. A handful of studies have analyzed the types of recyclables for which UBP is effective, but most have employed data for aggregated amounts of recyclables. However, it is crucial to check the effect of UBP for each recyclable material, because the effect may vary for different materials. In this respect, the studies of Jenkins *et al*.(2003) and Usui (2008) are notable. Jenkins *et al*.(2003) investigate the recycling behavior of households with respect to certain recyclables. They find that access to curbside recycling has a significant positive effect on the collection of all recyclables. However, the level of UBP is insignificant in their regressions. Therefore, the effect of UBP on recycling activity remains unclear. Employing Japanese municipal data, Usui (2008) shows that the elasticities of UBP for the collected amounts of glass bottles, cans, and polyethylene terephthalate (PET) bottles are significantly positive. He also finds that these elasticities vary with the type of recyclable.

Furthermore, in many countries, municipalities can choose whether to collect recyclables, and may undertake or defer recycling, depending on various factors. Kinnaman (2005) finds that the state's policy affects municipalities' decisions on whether to recycle. Usui (2008) observes that a municipality's decision on whether

[1]For example, the Japanese government recommends that their municipalities introduce UBP programs, because it is one way of establishing robust recycling practices in society (Ministry of the Environment, Japan (2013)).

[2]In this study, we refer to materials that can be recycled and are collected by municipalities as "recyclables."

to collect a type of recyclable depends on certain factors, such as the amount of waste generated and the available landfill capacity. Therefore, municipalities determine whether to collect recyclables based on their own waste management circumstances or on residents' environmental awareness. Some factors are occasionally unobservable, but also affect the amount of recyclables collected. In this situation, if we estimate an equation to determine this amount using only those municipalities that collect recyclables, and run an ordinary least squares (OLS) regression, it is well known among econometricians that the results might include a sample selection bias and, thus, lose consistency.

In summary, previous studies have typically encountered the following problems when estimating the substitution effect of UBP on the collection of recyclables: 1) the endogeneity of UBP; 2) a self-selection bias of UBP; 3) the aggregation of different types of recyclables; and 4) a sample selection bias with regard to the collection of recyclables. Most studies have found partial solutions to these problems. However, to the best of our knowledge, there is no study that simultaneously addresses all of the problems. Therefore, we address the bias problem caused by the double sample selection with regard to collecting recyclables and garbage pricing, as well as the endogeneity of UBP. Furthermore, we employ the multivariate double sample-selection model (MDSSM) to estimate the recyclable and garbage regression equations simultaneously, taking the correlation between the two into account. Our estimation employs waste management data for Japanese municipalities, because municipal data on the amounts of recyclables collected and the levels of UBP are published in Japan. The estimations of the UBP coefficients in each equation enable us to assess the substitution effect caused by UBP between garbage and recyclables, without bias.

This study contributes to the body of literature in three ways. First, by applying the MDSSM to the stated problem, we obtain consistent and efficient estimates. Second, we estimate the cross-price elasticity for each type of recyclable. While many previous studies estimate the own-price elasticity of garbage, only a few have estimated both the own-price elasticity for garbage and the cross-price elasticity for each type of recyclable. Our results show that the cross-price elasticity of PET bottles, plastic containers, and paper containers are significantly positive. Moreover, the magnitudes of the cross-price elasticities of plastic and paper containers are much larger than that of PET bottles.

The remainder of this paper is organized as follows. Section 2 provides the theoretical and institutional background. Section 3 describes the econometric model used in this study, and section 4 presents the data. Then, section 5 discusses the estimation results, including their implications. The final section concludes the paper.

## 2 Analytical strategies

In this section, we explain the current situation confronted by Japanese municipalities with regard to solid waste management. Here, we discuss the institutional background of providing municipal recyclables collection and garbage pricing. After an overview of the institutions involved in Japanese municipal waste management, we present the econometric problem stemming from these institutions.

### 2.1 Institutional background

As shown in Figure 2, Japan faces a shortage of landfill capacity owing to its relatively small geographical size. A country's waste generation and gross domestic product (GDP) are closely related (Daskalopoulos *et al.*(1998)). As a result, disposable goods, plastic bottles, and paper containers have proliferated in Japan since the country's rapid economic growth during the 1970s, with containers and packaging accounting for about 60% of total waste, by volume (Ministry of Economy, Trade, and Industry (2003)). As a result, the Japanese government established the Law for the Promotion of Sorted Collection and Recycling of Containers and Packaging (hereafter, "the Recycling Law" ) in 1995.

Japanese municipalities are not obliged to collect recyclables, because the Recycling Law lets them choose from a number of diverse recyclables collection approaches. Thus, it is natural to assume that a municipality would freely choose from among these waste treatment options, especially when deciding on whether to collect container and packaging recyclables such as glass, PET bottles, plastic containers, and paper containers.

Based on the above argument, we find that municipal disposal management is confronted mainly by the following cost-benefit budget trade-offs: 1) the benefit of saving landfill sites by getting rid of some waste and collecting recyclable waste vs. the costs of collecting recyclables; and 2) the cost of additional fuel owing to the shortfall of feedstock from paper or plastic containers vs. the decrease in the cost of saving landfill sites from reducing the volume of waste being incinerated. These budget trade-offs are closely related to cost minimization.

Japanese municipalities also have a choice in terms of garbage pricing. The introduction of UBP for garbage disposal and the level of UBP are determined by each municipality, depending on its circumstances. This institutional background to Japanese municipal waste management means that we can only observe the amount of recyclable waste collected in those municipalities that provide this collection service. Similarly, we can only observe UBP for those municipalities that use UBP programs.

Here, we estimate whether UBP reduces the amount of garbage collected, as well as whether it affects the substitution of garbage for each type of recyclable item by carefully considering the Japanese institutional background.

## 2.2 Literature review

Here, we summarize the findings of previous studies in the following categories: 1) the correction of the sample selection bias that occurs when estimates are based only on data for municipalities that offer some kind of recyclables collection service; 2) the correction of the self-selection bias that arises from endogenous local policy variables (e.g., introducing UBP in a municipality if it is not randomly introduced); and 3) the system of regression equations considered, because the problem occurs as a result of correlation between the equations.

### 2.2.1 Endogeneity of UBP

If the level of UBP is determined by a municipal waste management policy or by inhabitants' environmental preferences that affect the collected amount of waste, the level should be treated as an endogenous variable. Studies such as Kinnaman and Fullerton (2000), Callan and Thomas (2006), and Huang *et al.*(2011) employ the IV approach to control for the endogeneity caused by introducing UBP. On the other hand, Allers and Hoeben (2010) adopt a quasi-experimental approach, such as the difference-in-differences (DID) model. These studies confirm that UBP is effective for garbage reduction and the substitution of recyclables. Kinnaman and Fullerton (2000), Suwa and Usui (2007), and Allers and Hoeben (2010) use a first-stage regression to simultaneously examine the demand for the waste and recyclables collection service and a municipality's decision to implement recycling.

### 2.2.2 Self-selection of UBP

A self-selection bias in UBP arises if municipalities' decisions on whether to introduce the program depend on their own circumstances and, consequently, are not randomly introduced among municipalities. If there are also unobservable determinants of a policy to introduce UBP, estimates based on an OLS regression that ignore this selectivity will lose consistency. Studies such as Suwa and Usui (2007) and Huang *et al.*(2011) employ Heckman 痴 two-step estimation to control for the selectivity of UBP. On the other hand, as already mentioned, Kinnaman and Fullerton (2000), Suwa and Usui (2007), and Allers and Hoeben (2010) use a first-stage regression to simultaneously examine the demand for the waste and recyclables collection service and a municipality's decision to implement recycling.

### 2.2.3 Sample selection of recyclables collection

It seems natural to assume that a municipality would choose a waste management policy from among the various options, depending on its own circumstances. Therefore, it is important to consider the determinants of municipal decisions with respect to collecting and separating recyclables. Accordingly, a municipal decision on recyclables collection should be considered as an endogenous variable in the econometric procedure. In order to specify the substitution effect of UBP on recyclable items, we have to consider the sample selection bias.[3] According to Usui (2008), a sample selection bias will occur when using data that include regions that do not collect recyclables, and the nonexistence of a collection service will cause a sample to be truncated. However, if we remove the zero values for municipalities that do not collect recyclable items, and run an OLS regression only on the sample of positive observations, a selection bias may arise. This is because the expectation of the error terms is not zero, which violates the assumptions of the OLS method.

The bias arises because it depends on a municipality's decision on whether to collect recyclables. If a municipality wants to reduce the amount of landfill waste, it will introduce recyclables collection. However, this also depends on the costs and benefits of doing so. As mentioned in section 1, the municipality must pay the disposal cost of the landfill site. Therefore, each municipality has an incentive to reduce household waste, but this depends on the scarcity of its landfill sites.

#### 2.2.4 Double sample-selection model

Huang *et al*.(2011) also address the endogeneity of garbage pricing using a dummy for the pricing and the 2SLS. They apply Heckman's two-step estimation to a sample that only includes municipalities with garbage pricing in order to correct for the selection bias. Huang *et al*.(2011) use a subsample in which UBP is implemented to investigate how bag prices affect the amount of garbage collected. In this case, the sample-selection problem also occurs if the decision to introduce UBP is affected by the amount of material collected. Furthermore, when we use the subsample to estimate the substitution effect of the UBP level on the amount of recyclables collected, we face a double-selection structure, namely the introduction of UBP and the recyclables collected. To deal with this complicated selection structure, Tunali (1986) and Mohanty (2012) suggest using a double sample-selection model (DSSM).

#### 2.2.5 System of equations

When the error terms of different equations are correlated, an OLS estimator for each equation is no longer asymptotically efficient. This problem may appear when estimating several waste materials. Callan and Thomas (2006) and Suwa and Usui (2007) address this issue. They consider the correlation of the error terms among the equations for the amounts of garbage and recyclables collected, and estimate the two equations using a three-stage least squares (3SLS) regression and a seemingly unrelated regression (SUR). Then, Callan and Thomas (2001) discuss economies of scope among multiple types of waste. If economies of scope exist, this might appear as a strong correlation between the decisions to collect each type of recyclable material. Therefore, it is important to consider the system of equations and check for the existence of economies of scope.

[3] See Heckman (1979) or Amemiya (1985).

### 2.3 The estimation strategy in this study

Previous studies on the above-mentioned issue and a comparison with this study are presented in Table 1. Moreover, Yen (2005) develops a multivariate sample-selection model (MSSM) that considers the correlation among multiple sample-selection models for cigarette and alcohol consumption, and estimates the two simultaneously. By applying the model of Yen (2005) to waste management data, we propose a multivariate double sample-selection model (MDSSM) that combines the MSSM and DSSM. Using this model, we consider both the doubly selected structure of the sample and the system estimation among different types of collected materials.

# 3 Model

In this section, we first describe the economic model for household behavior with regard to waste disposal. Next, we explain the econometric model to estimate the demand for garbage and recyclable disposal, as derived from the economic model.

## 3.1 Economic model

First, we consider a household's choice with regard to waste disposal. We assume the following utility maximization problem for a municipal representative household:

$$U_i = U(C_i, G_i, R_i, \alpha_i)$$
$$s.t.\ Y_i = C_i + P_{Gi}G_i + P_{Ri}R_i,$$

where $i$ is the index of the municipality, $U_i$ is the utility function , $C_i$ is a composite consumption good, $G_i$ is the amount of disposed garbage, $R_i$ is the amount of recyclables, $\alpha_i$ is a demographic variable, $Y_i$ is income, and $P_{Gi}$ and $P_{Ri}$ denote the UBP for garbage and recyclables, respectively.

Solving the utility maximization problem, we obtain the following household demand functions for garbage and recyclables:

$$G_i = G_i(P_{Gi}, P_{Ri}, Y_i, \alpha_i)$$
$$R_i = R_i(P_{Gi}, P_{Ri}, Y_i, \alpha_i).$$

Since recyclables are collected with no charge in most Japanese municipalities, we do not consider $P_{R_i}$ here. Thus, we can rewrite the demand functions as follows:

$$G_i = G_i(P_{Gi}, Y_i, \alpha_i)$$
$$R_i = R_i(P_{Gi}, Y_i, \alpha_i).$$

These demand functions are estimated using the econometric model described in the next section.

## 3.2 Econometric model

This section describes the econometric model employed to determine the amount of recyclables and garbage collected under a UBP program. As mentioned earlier, each Japanese municipality implements its own waste management policies, such as garbage pricing and how to manage solid waste materials (i.e., the four recyclables and garbage). Here, we denote these municipal decisions using dummy variables. Let $D_{Pi}$ be a dummy that takes 1 if the $i$ th municipality introduces garbage pricing, and 0 otherwise. Then, $D_{Pi}$ is assumed to

$$D_{Pi} = 1 \text{ if } W_i'\alpha + \epsilon_i > 0$$
$$D_{Pi} = 0 \text{ if } W_i'\alpha + \epsilon_i \leq 0,$$

where $W_i$ is vector of explanatory variables, $\alpha$ are the parameter vectors, and $\epsilon_i$ are random error terms.

Next, let $D_{M_{ij}}$ be a dummy that takes 1 if the $i$ th municipality collects the $j$th type of solid waste material $(j = 1, 2, \ldots, m)$, and 0 otherwise. Then,

$$D_{M_{ij}} = 1 \text{ if } Z_{ij}'\beta_j + u_{ij} > 0$$
$$D_{M_{ij}} = 0 \text{ if } Z_{ij}'\beta_j + u_{ij} \leq 0,$$

where $Z_{ij}$ is vector of explanatory variables, $\beta_j$ are parameter vectors, and $u_{ij}$ are random error terms.

If recyclables collection and garbage pricing are implemented in the $i$ th municipality, the amount of recyclables collected is described as follows,

$$\log M_{ij} = X_{ij}'\gamma_j + \gamma_p \log P_i + v_{ij}, \tag{1}$$

where $M_{ij}$ is the amount of the $j$th type of solid waste materials, $(j = 1, 2, \ldots, m)$[4], $P_i$ is the unit-based price, $X_{ij}$ is vector of explanatory variables other than $P_i$, $\gamma$ is a parameter for the explanatory variables, $\gamma_p$ is a parameter for price elasticity, and $v_{ij}$ are random error terms.

In accordance with previous studies, we take the log of $M_{ij}$ and $P_{ij}$ to denote the estimated coefficient as a price elasticity. This enables us to compare our price elasticity with those in previous studies. Note that equation (1) can only be estimated if both the collection of $M_{ij}$ and garbage pricing are introduced. However, it is well known that this causes a sample selection bias. As mentioned earlier, methods to correct this bias include Heckman's two step estimation (Heckman (1979).) and the type II Tobit approach (Amemiya (1985)). However, in our application, the sample is doubly selected, which complicates the structure of the econometric model used in the estimation. To address this problem, a double sample selection model (DSSM) has been developed. Meng and Schmidt (1985) and Tunali (1986) present estimation methods under partial observability of dependent variables. Mohanty (2012) applies the DSSM approach to estimating wage rates observed under both workers' job seeking and employers' job offers.

Furthermore, we need to consider the correlation between error terms for different materials. In general, single equation approaches that ignore this correlation suffer from a loss of statistical efficiency. Yen (2005) developed a multivariate sample selection model (MSSM) to investigate the levels of cigarette and alcohol consumption of US individuals.

[4]In this study, $j = 1$: glass, $j = 2$: PET bottles, $j = 3$: plastic containers, $j = 4$: paper containers, and $j = 5$: garbage.

We develop a model to deal with the data on the collected amount of municipal solid waste by combining the DSSM and MSSM, which we call the multivariate double sample selection model (MDSSM). The MDSSM allows us to consider the correlations among multiple equations, as well as the doubly selected structure of the independent variables.

Depending on whether garbage pricing and recyclables collections are introduced, the regimes of observation for municipal solid waste collection are classified as follows:

$$\log M_{ij} = X_{ij}'\gamma_j + \gamma_{pj} \log P_i + v_{ij} \quad \text{if} \quad D_{p_i} = 1 \text{ and } D_{M_{ij}} = 1, \quad j = 1, 2, \ldots, m \tag{2}$$

$$\text{unobservable} \quad \text{if} \quad D_{p_i} = 1 \text{ and } D_{M_{ij}} = 0, \quad j = 1, 2, \ldots, m \tag{3}$$

$$\text{unobservable} \quad \text{if} \quad D_{p_i} = 0 \text{ and } D_{M_{ij}} = 1, \quad j = 1, 2, \ldots, m \tag{4}$$

$$\text{unobservable} \quad \text{if} \quad D_{pi} = 0 \text{ and } D_{M_{ij}} = 0, \quad j = 1, 2, \ldots, m. \tag{5}$$

There are three error term vectors in the model. These are assumed to follow a multivariate normal distribution. The covariance matrix of all error terms is as follows:

$$\begin{bmatrix} \epsilon_i \\ u_i \\ v_i \end{bmatrix} \sim N(\mathbf{0}, \mathbf{\Sigma}), \quad \mathbf{\Sigma} = \begin{bmatrix} \sigma_\epsilon^2 & \Sigma_{u\epsilon} & \Sigma_{v\epsilon} \\ \Sigma_{\epsilon u} & \Sigma_{uu} & \Sigma_{vu} \\ \Sigma_{\epsilon v} & \Sigma_{uv} & \Sigma_{vv} \end{bmatrix}.$$

Employing a GHK simulator (Geweke, Keane and Runkle (1994), we estimate the parameters $\alpha$, $\beta$, $\gamma$, $\gamma_P$, $\rho^{uu}$, $\rho^{uu}$, $\sigma_{vu}$, $\rho^{vv}$, and $\sigma$ using the simulated maximum likelihood method. The details of the likelihood function are provided in the Appendix.

## 4 Data

The data on the amount of recyclables collected from each municipality in 2010 are provided by Ministry of the Environment, Japan (2012). In this data, the recyclables are classified into 11 categories. Of those, we focus on "Glass," "PET bottles," "Plastic containers," and "Paper containers," because the Recycling Law requires producers of the four materials to implement recycling, as mentioned in the previous section.

The descriptive statistics on the amount collected for each of the four categories per capita per day is presented in Table 2. Recall that the collection of recyclables is implemented at the discretion of the municipalities. Therefore, data on the collected amount in each category are only available for those municipalities that collect those recyclables.

Data on the garbage generation in each municipality for 2010 are also provided by Ministry of the Environment, Japan (2012).[5] In Japan, garbage is essentially divided into burnable waste and non-burnable waste. Waste in the former group is burned in an incinerator, while that in the latter group is buried in a landfill site.

For the level of UBP for garbage in each Japanese municipality, we employ the data of Yamaya (2010a) and Yamaya(2010b), because the pricing data are not published by Ministry of the Environment, Japan. Yamaya (2010a) and Yamaya (2010b) collected data on unit-based prices across all Japanese municipalities, using questionnaires administered through mail and telephone. The data were collected from 1,726 municipalities (including 23 wards in Tokyo) in February for Fiscal year(FY)2010. The data pertaining to the price per garbage bag, or per corresponding tag, are also shown in Table 2. Japanese municipal garbage collection is usually implemented with 40–50 liter garbage bags (approximately 10 gallons). This volume is used as a standard unit to generate the garbage fee. Figure 3 shows the distribution of the pricing levels. Here, the vertical axis represents the number of municipalities and the horizontal axis represents the price (in JPY) per 40–50 liters.[6]

For all municipalities, other socioeconomic data were obtained from the Asahi Newspaper (2012), which is a collective database for all municipalities. These data include the taxable gain per capita, average household size, average age, and population density. This study employs the following socioeconomic variables: "Household income," which is the household taxable gain per capita (JPY); "Household size," which is the average household size; and "Population density," which represents the population density (population/area).

[5]In this study, the amount "Solid waste" is defined as the sum of "Burnable waste," "Non-burnable waste," "Mixed waste," "Recyclable waste," and "Other waste." The amount of garbage collection does not include the following: 1) "Bulky waste;" 2) "Self disposal;" 3) "Recyclables collected by voluntary groups;" 4) the amount carried into municipal facilities; and 5) the aggregated amount of the above-mentioned four recyclables. The average amount of "Garbage" in Table 2 is calculated by subtracting the sum of the four recyclables ("Glass," "PET bottles," "Plastic containers," and "Paper containers,") from "Solid waste."

[6]The average Japanese JPY/USD exchange rate in 2015 was about 120 JPY/USD. When comparing the average fee levied per bag in Japan to those in the United States and Europe, note that the volume of a bag in the latter countries is 32 gallons, whereas an average bag in Japan is about 10 gallons. We measured the price per bag based on the 10 gallon bag. Adjusting for the different bag sizes in the United States and Europe, the average fee per bag in Japan amounted to about 125 cents, with a standard deviation of 67cents.

“Population density” functions as an efficient index to measure the effect of community size on waste emission. “Household size” functions as an appropriate barometer of scale merit in household consumption. Since household members usually share many goods (*e.g.*, a newspaper), a large household may result in decreased per capita consumption. Furthermore, “Over65” represents the ratio of people over the age of 65 years in a municipality.

## 5 Estimation results

The multivariate double sample-selection model (MDSSM) is applied to the data on the collected amount of garbage and the four types of recyclables in Japanese cities.[7]

### 5.1 Testing for the endogeneity of UBP

In most previous studies, UBP is regarded as an endogenous variable. Thus, we test for the endogeneity of UBP. Our results show that UBP is only endogenous in the equation for "Garbage."

In this test, we employ a method suggested by Wooldridge (2002).[8] In the first stage, the level of UBP is estimated using instrumentals such as "Dummy for landfill," "Dummy for incineration," "Dummy for RDF," and "Cost ratio," in addition to other exogenous variables. The levels of materials are estimated by adding the residual of the first-stage estimation to the explanatory variables in the second stage. The estimation results are shown in Table 3. The endogeneity of UBP is tested using the *t*-value of the coefficients of the residuals. If the parameter is significantly different from zero, endogeneity is not rejected. From the table, we find that the level of UBP is endogenous only in the equation for "Garbage." Therefore, in order to address the endogeneity issue and obtain consistent estimates, the level of UBP is replaced by the predicted value calculated in the first stage of the MDSSM estimation.

### 5.2 The MDSSM estimation

The MDSSM is applied for all materials. However, we do not consider a selection between "Glass" and "PET bottles" collection, because the ratio of collection between the two is over 95% among all Japanese municipalities. Therefore, a selection bias caused by municipal collection is less likely to appear. "Garbage" is also collected in all municipalities and, thus, does not face a collection selection problem (but does face a selection problem in terms of garbage pricing). For the MDSSM estimation, we employ the GHK simulator[9] to evaluate the likelihood contribution. The maximum simulated likelihood (MSL), including the GHK simulator, is consistent if the number of random draws $R$ rises faster than $\sqrt{N}$. Therefore, $R$ is set to 50, because $\sqrt{N}$ is $41.545$ in this estimation. Details of the GHK simulator and the MSL can be found in Train (2009). Table 5

[7]Ox version 7.01 (see Doornik (2001)) is employed for all estimations.

[8]See Chapter 6 in Wooldridge (2002).

[9]The GHK simulator requires a random draw from truncated normal distributions in the evaluation process. In this study, we implement 50 random draws. The GHK simulator also needs the Cholesky decomposition of the covariance matrix of error terms. In our data set, the Cholesky decompositions frequently fail owing to a property of the matrix when searching for the maximum of the log likelihood. Therefore, we use the following adjustment algorithm: if the matrix is not positive definite (i.e., the minimum eigenvalue is smaller than zero), the covariance matrix is replaced by the matrix in the previous iteration. In the actual estimation, the adjustment is not required just before the convergence, but is applied frequently in the early iterations.

presents the MDSSM estimation results. The estimation of the demographic variable coefficient indicates some information pertaining to the municipal decisions on recyclables collection and the introduction of UBP. The results also show the factors that determine the amount of garbage and recyclables collected. The estimation results are composed of three parts: “Selection,” “Level,” and “Correlation.”

### 5.3 Testing for correlation among the error terms

Next, we attempt another estimation using the MDSSM. Here, the off-diagonal elements in the covariance matrix of error terms $Sigma$ are set to zero. The test rejects the restriction on the covariance matrix, even at the $1\%$ significance level, which implies that the unrestricted MDSSM is valid.

This estimation with the restriction is equivalent to an independent estimation using a probit model for the implementation of UBP and recyclables collection, and to an OLS for all types of materials. The results are presented in Table 4. The likelihood ratio test is implemented to check the validity of the MDSSM by comparing the likelihood of the restricted MDSSM $(L_r)$ and the unrestricted MDSSM $(L_u)$.

The likelihood ratio test statistic $-2(\log L_r - \log L_u)$ is $711.49$. This statistic follows a $\chi^2$ distribution with 28 degrees of freedom.[10] The result of the test rejects the restricted model.

### 5.4 Selection

The estimations of the coefficients for the introduction of UBP and recyclables collection, shown in Table 5, reflect information pertaining to the municipal decisions. The logs of “Household income” and “Population density” have a negative effect on the municipal decision to introduce UBP. This suggests that a municipality with a smaller income and smaller population density is more likely to implement garbage pricing. The log of “Household income” has a positive effect on the municipal decision to collect “Plastic containers.” This suggests that a municipality with a higher income is more inclined to collect plastic containers.

### 5.5 Level

The results pertaining to the levels of recyclables and garbage collected shown in Table 5 indicate important policy implications. The results show that the coefficient of price [11] is estimated as significantly negative in the “Garbage” equation. This is consistent with economic intuition. According to the result of the endogeneity test, the level of UBP is treated as an endogenous variable only in the garbage regression equation. As pointed out in Kinnaman and Fullerton (2000) and Huang *et al.*(2011), unobservable residential factors, such as environmental

[10] The number of off-diagonal elements are shown as $M(1-M))/2$, where $M$ is the dimension of $\Sigma$. These elements are restricted to zero at $H_0$.

[11] The coefficients for “Price,” “Household income,” “Population density,” and “Household size” indicate the elasticities of the collected amounts because we take the natural logarithms of these levels in our estimation.

awareness, may affect both the UBP level and the amount of garbage collected. In this case, the level of UBP in the garbage regression equation must be an endogenous variable.

In our estimates, the elasticity of the price after considering endogeneity is -0.730, which is much smaller than when we ignore endogeneity (-0.107). As pointed out in Kinnaman and Fullerton (2000), the probability of adopting UBP might be a positive function of the quantity of garbage collected. The difference between the two elasticities implies that such a relationship is likely to exist and, consequently, ignoring it could understate the effect of UBP on the amount of garbage collected. The result of the own-price elasticity in this study is comparable with those of previous studies, such as Kinnaman and Fullerton (2000) and Huang *et al*.(2011), because their elasticities, which ignore endogeneity, are underestimated. On the other hand, the elasticities of the prices for the collected amounts of "PET bottles," "Plastic containers," and "Paper containers" are estimated as significantly positive. These results suggest that UBP facilitates garbage reduction and recycling by encouraging citizens to sort their recyclables from their waste. In contrast, the elasticity of the price of the amount of "Glass" collected is insignificant.

The coefficients of the frequencies for most materials (except "Paper containers") have a positive effect. In other words, the amount collected increases if the frequency of collection increases, because people find it easier to dispose of their waste. The results of the demographic variables have significant implications for the amounts collected. The results show that a larger "Household size" appears to decrease the amounts of "PET bottles," "Paper containers," and "Garbage" collected. This may be a combined effect of collective consumption and work sharing in terms of separating waste in a larger household. For example, household members might share one paper container of food or beverages. Consequently, the amount of paper waste per capita decreases as the size of a household increases. The elasticity of "Household income" is significantly positive for all levels. This variable is affected by many factors: 1) it is a proxy for the opportunity cost of time (negative relation with waste generation); 2) it is a proxy for the amount of consumption (positive relation with waste generation); and 3) it might be a proxy for the level of education.[12] Because the positive effect dominates other negative effects, the coefficients may result in positive signs for all levels.

### 5.6 Correlation matrices

The estimation results for the factors in the error term correlation matrices are shown in the lower part of Table 5. We find that some correlation coefficients in the matrix are statistically significant, although the values are generally small. In the remainder of this section, we explain the non-negligible results for the correlation matrix factors in the error terms in the selection equations, those in the level equations, and those between the selection

[12]The lack of data with respect to education levels in Japanese municipalities means we cannot control for the effect of education level on waste generation.

equation and the level equation.

#### 5.6.1 Matrix for selection

The correlation between the error term for the collection of “Plastic Containers” and that for the collection of “Paper Containers” ($u_3$ and $u_4$) is statistically significant, though it is weak. This implies that implementing municipal recyclables collection may stimulate the collection of other recyclables. One possible interpretation is that recycling facilities (e.g., car and plant waste) are shared, which will reduce recycling costs.

#### 5.6.2 Matrix for selection $\times$ level

The coefficients of the error terms of the selection equation and those of the level equation ($u_3$ and $v_g$) are statistically significant and negative. Thus, the error term of the “Garbage” level equation is negatively correlated with the error terms of the “Plastic containers” selection equations. This may indicate that an unobservable level of environmental awareness of citizens affects both activities. This awareness may work to reduce the amount of garbage and induce a municipality to introduce recycling.

The correlation coefficients between the error terms of “Price” selection and “Glass” level ($\epsilon$ and $v_1$) or “PET bottles” level ($\epsilon$ and $v_2$) are statistically significant and negative. This may imply that some unobservable municipal characteristics encourage UBP introduction, but reduce the amount of recyclable items such as “Glass” and “PET bottles.” These results suggest the necessity of considering the self-selection bias caused by introducing UBP.

Moreover, the correlations between the level and selection error terms for the same recyclable ($u_3$ and $v_3$, and $u_4$ and $v_4$) are insignificant. This implies that sample selection biases do not appear in the estimates of the amounts of recyclables collected.

#### 5.6.3 Matrix for level

The correlations between the error terms of the level equations for “Glass” and “PET bottles” ($v_1$ and $v_2$) and between “PET bottles” and “Plastic containers” ($v_2$ and $v_3$) are positively correlated, though they are weak. This implies that uncontrolled variables (e.g., environmental awareness) have a positive effect on the amounts of different recyclables collected. Furthermore, this suggests that using the system estimation is better than using an OLS to estimate the level equations for recyclables.

# 6 Conclusion

This study attempts to clarify the effects of UBP on the amounts of garbage and recyclables collected, based on Japanese municipal data pertaining to waste management. Thus far, many studies have investigated the effect of garbage pricing on solid waste management. However, most are based on a single-equation approach, which suffers from a loss of efficiency. Moreover, data on the amounts of recyclables collected are selective, because each municipality in Japan decides autonomously on what recyclables to collect. Consequently, the data for each type of recyclable material are only available for those municipalities that collect that type. Similarly, municipalities can decide whether to collect recyclables or introduce garbage pricing, including its level. Ignoring this sample selection structure results in inconsistent estimates. Thus, a careful econometric treatment is essential when analyzing data pertaining to recyclables collection.

Therefore, we apply a multivariate double sample-selection model (MDSSM) in the estimation process to address the double selection caused by municipal decisions on garbage pricing and recyclables collection. In the estimation of the amount of garbage collected, we also consider the endogeneity of the UBP level. The estimation results from the MDSSM indicate that higher UBP for garbage induces larger amounts of PET bottles, plastic containers, and paper containers collected for recycling, and decreases the amount of garbage produced. Thus, higher levels of UBP mean that more of some types of recyclables are collected. Thus, we have clarified the substitution effects of municipal garbage pricing on selected types of recyclables emissions.

Our research conducted a complicated empirical approach that considered the multiple sample selection caused by the endogenous municipal policy decisions on introducing garbage pricing and recyclables collections. However, recent studies such as Allers and Hoeben (2010) employ panel data, and determine the treatment effect of UBP using a quasi-experimental method. In Japan, Ministry of the Environment publishes panel data on waste management for all Japanese municipalities. Therefore, using this panel data is a matter for future research.

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# APPENDIX

## A Error terms

The covariance matrix of all error terms is as follows.

$$\begin{bmatrix} \epsilon_i \\ u_i \\ v_i \end{bmatrix} \sim N\left(\mathbf{0}, \mathbf{\Sigma}\right), \quad \mathbf{\Sigma} = \begin{bmatrix} \sigma_\epsilon^2 & \Sigma_{u\epsilon} & \Sigma_{v\epsilon} \\ \Sigma_{\epsilon u} & \Sigma_{uu} & \Sigma_{vu} \\ \Sigma_{\epsilon v} & \Sigma_{uv} & \Sigma_{vv} \end{bmatrix}.$$

According to the specification in Yen (2005), we define correlation matrices for the convenient estimation of the covariance matrix. Let $S = \mathrm{diag}[\sigma_1, \sigma_2, \ldots, \sigma_m]$ be the diagonal matrix with a standard deviation of $v$ and $\epsilon$. In addition, let $R_{uu}$, $R_{vu}$, and $R_{vv}$ be correlation matrices among elements of $[\epsilon, u]$ and $[\epsilon, u]$, $v$ and $[\epsilon, u]$, and $v$ and $v$, respectively.[13] The standard deviations of $[\epsilon, u]$ are set to unity because each selective mechanism is binary. Then, the correlation matrix $R_{uu}$ is an $(m+1) \times (m+1)$ matrix, and is shown as follows:

$$\boldsymbol{R_{uu}} = \begin{bmatrix} 1 & \rho_{\epsilon 1}^{uu} & \ldots & \rho_{\epsilon m}^{uu} \\ \rho_{1\epsilon}^{uu} & 1 & \ldots & \rho_{1m}^{uu} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m\epsilon}^{uu} & \rho_{m1}^{uu} & \ldots & 1 \end{bmatrix}.$$

Note that $R_{vu} = R'_{uv}$ is an $m \times (m+1)$ matrix because it indicates a correlation between and $[\epsilon, u]$ and $v$. Then, $R_{vu}$ is shown as follows:[14]

$$\boldsymbol{R_{vu}} = \boldsymbol{R'_{uv}} = \begin{bmatrix} \rho_{1\epsilon}^{vu} & \rho_{11}^{vu} & \ldots & \rho_{1m}^{vu} \\ \rho_{2\epsilon}^{vu} & \rho_{21}^{vu} & \ldots & \rho_{2m}^{vu} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m\epsilon}^{vu} & \rho_{m1}^{vu} & \ldots & \rho_{mm}^{vu} \end{bmatrix}.$$

Here, $S$ and $R_{vv}$ are both $m \times m$ matrices, described as

$$\boldsymbol{S} = \begin{bmatrix} \sigma_1 & 0 & \ldots & 0 \\ 0 & \sigma_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \sigma_m \end{bmatrix}, \ \boldsymbol{R_{vv}} = \begin{bmatrix} 1 & \rho_{12}^{vv} & \ldots & \rho_{1m}^{vv} \\ \rho_{21}^{vv} & 1 & \ldots & \rho_{2m}^{vv} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m1}^{vv} & \rho_{m2}^{vv} & \ldots & 1 \end{bmatrix}.$$

Employing these correlation and standard error matrices, each piece of the covariance matrix is described as follows:

$$\Sigma_{11} = R_{uu}, \quad \Sigma_{21} = \Sigma'_{12} = S' R_{vu}, \quad \Sigma_{22} = S' R_{vv} S.$$

[13]Hereafter, the index $i$ is omitted for simplicity.

[14]Note that the element $\rho_{12}^{vu}$ in the correlation matrix is not equal to $\rho_{21}^{vu}$.

Let $\Sigma_{11}$, $\Sigma_{21}$, and $\Sigma_{22}$ be defined as follows.

$$\boldsymbol{\Sigma_{11}} = \begin{bmatrix} \sigma_\epsilon^2 & \Sigma_{u\epsilon} \\ \Sigma_{\epsilon u} & \Sigma_{uu} \end{bmatrix}, \ \boldsymbol{\Sigma'_{21}} = \boldsymbol{\Sigma_{12}} = \begin{bmatrix} \Sigma_{v\epsilon} \\ \Sigma_{vu} \end{bmatrix}, \ \boldsymbol{\Sigma_{22}} = \Sigma_{vv}.$$

Then, $\Sigma$ is rewritten as

$$\boldsymbol{\Sigma} = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}.$$

# B Likelihood function

Depending on the selection pattern for $p_i$ and $M_{ij}$, the likelihood contribution for each municipality $i$ is classified according to the following three regimes (hereafter, $i$ is omitted). Each regime follows the description of Yen (2005).

## B.1 Regime in equation(2): $D_P = 1, \ \ D_{M_j} = 1 \ \ \forall j$

To formulate the likelihood function, we first consider a sample regime in which $P$ and all $M_j$ are positive. Let $f(u, v, \epsilon)$ be the joint probability density function(pdf) , $g(v)$ be the marginal pdf of $v \sim N(0, \Sigma_{22})$, and $h(\epsilon, u|v)$ be the conditional pdf of $\epsilon, u|v \sim N(\mu_{\epsilon,u|v}, \Sigma_{\epsilon,u|v})$, where $\mu_{\epsilon,u|v} = \Sigma_{12}\Sigma_{22}^{-1}v$, and $\Sigma_{\epsilon,u|v} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$.

Then, the likelihood contribution of this regime is

$$\begin{aligned} L_1 &= \prod_{j=1}^{m} M_j^{-1} \int_{-W'\alpha}^{\infty} \int_{-Z'_1\beta_1}^{\infty} \cdots \int_{-Z'_m\beta_m}^{\infty} f(u, v, \epsilon) du_m \ldots du_1 d\epsilon \\ &= \prod_{j=1}^{m} M_j^{-1} g(v) \int_{-W'\alpha}^{\infty} \int_{-Z'_1\beta_1}^{\infty} \cdots \int_{-Z'_m\beta_m}^{\infty} h(\epsilon, u|v) du_m \ldots du_1 d\epsilon \\ &= \prod_{j=1}^{m} M_j^{-1} g(v) \Phi_{m+1}(r + \mu_{\epsilon,u|v}; \Sigma_{\epsilon,u|v}), \end{aligned}$$

where $\prod_{j=1}^{m} M_j^{-1}$ is the Jacobian determinant of the variable transformation from $[v_1, v_2, \ldots, v_m]'$ to $[M_1, M_2, \ldots, M_m]'$, and $r = [r_\epsilon, r_1, r_2, \ldots, r_m]' = [W'_i\alpha, Z'_1\beta_1, Z'_2\beta_2, \ldots, Z'_m\beta_m]'$.

## B.2 Regime in equation(3): $D_P = 1, \ \ D_{M_j} = 1 \ \text{ for } j = 1, \ldots, l, \ D_{M_j} = 0 \ \text{ for } j = l+1, \ldots, m$

Next, we consider a mixed regime, in which the first $l$ materials are collected, while the others are not.[15] Here, let $\tilde{v}$ be an $l$-vector containing the first $l$ elements of $v$. Then, $[\epsilon, u, \tilde{v}]'$ has a $(1 + m + l)$-variate normal

[15]This regime also includes the case: $D_P = 1, \ \ D_{M_j} = 0 \ \ \forall j$.

distribution, with zero mean, and the covariance matrix $\tilde{\Sigma}$. $\tilde{\Sigma}$ is an $(m+l+1)\times(m+l+1)$ sub-matrix of $\Sigma$. This is shown as

$$\tilde{\mathbf{\Sigma}} = \begin{bmatrix} \Sigma_{11} & \tilde{\Sigma}_{12} \\ \tilde{\Sigma}_{21} & \tilde{\Sigma}_{22} \end{bmatrix}.$$

Let $g(\tilde{v})$ be the marginal pdf of $\tilde{v} \sim N(0, \tilde{\Sigma}_{22})$, and let $h(\epsilon, u|\tilde{v})$ be the conditional pdf of $\epsilon, u|\tilde{v} \sim N(\mu_{\epsilon,u|\tilde{v}}, \Sigma_{\epsilon,u|\tilde{v}})$, where $\mu_{\epsilon,u|\tilde{v}} = \tilde{\Sigma}_{12}\tilde{\Sigma}_{22}^{-1}\tilde{v}$, $\Sigma_{\epsilon,u|\tilde{v}} = \Sigma_{11} - \tilde{\Sigma}_{12}\tilde{\Sigma}_{22}^{-1}\tilde{\Sigma}_{21}$.

Then, the likelihood contribution of this regime is described as follows:

$$\begin{aligned} L_2 &= \prod_{j=1}^{l} M_j^{-1} \int_{-W'\alpha}^{\infty}\int_{-Z_1'\beta_1}^{\infty}\cdots\int_{-Z_l'\beta_l}^{\infty}\int_{-\infty}^{-Z_{l+1}'\beta_{l+1}}\cdots\int_{-\infty}^{-Z_m'\beta_m} f(\epsilon, u, \tilde{v})du_m\ldots du_1 d\epsilon \\ &= \prod_{j=1}^{l} M_j^{-1} g(\tilde{v})\int_{-W'\alpha}^{\infty}\int_{-Z_1'\beta_1}^{\infty}\cdots\int_{-Z_l'\beta_l}^{\infty}\int_{-\infty}^{-Z_{l+1}'\beta_{l+1}}\cdots\int_{-\infty}^{-Z_m'\beta_m} h(\epsilon, u|\tilde{v})du_m\ldots du_1 d\epsilon \\ &= \prod_{j=1}^{l} M_j^{-1} g(\tilde{v})\Phi_{m+1}(D(r+\mu_{\epsilon,u|\tilde{v}}); D'\Sigma_{\epsilon,u|\tilde{v}}D), \end{aligned}$$

where $D = \mathrm{diag}(2D_p - 1, 2D_{M_1} - 1, \ldots, 2D_{M_m} - 1)$.

### B.3 Regime in equation(4) and equation(5): $D_P = 0$

Finally, we consider the regime in which a municipality does not implement garbage pricing. In this regime, the likelihood contribution is described as follows:

$$L_3 = \Phi_{m+1}(Dr; D'\Sigma_{11}D).$$

Aggregating the contributions of likelihoods $L_{1i}$, $L_{2i}$, and $L_{3i}$, the following log likelihood function is derived.

$$\log L = \sum_{i=1}^{n} D_{Pi}D_{Mi}\log L_{1i} + D_{Pi}(1-D_{Mi})\log L_{2i} + (1-D_{Pi})\log L_{3i}. \quad (6)$$

Maximizing the equation (6) using a GHK simulator (Geweke *et al*.(1994)) for numerical integration, we obtain the maximum likelihood estimates[16] of the parameters $\alpha, \beta_j, \gamma, \gamma_{Pj}, \rho^{uu}, \rho^{uu}, \sigma_j, \rho^{vv}$, and $\sigma$.

[16] Previous studies that use DSSM, such as Mohanty (2012), use Heckman's two-step estimation instead of a maximum likelihood estimation.

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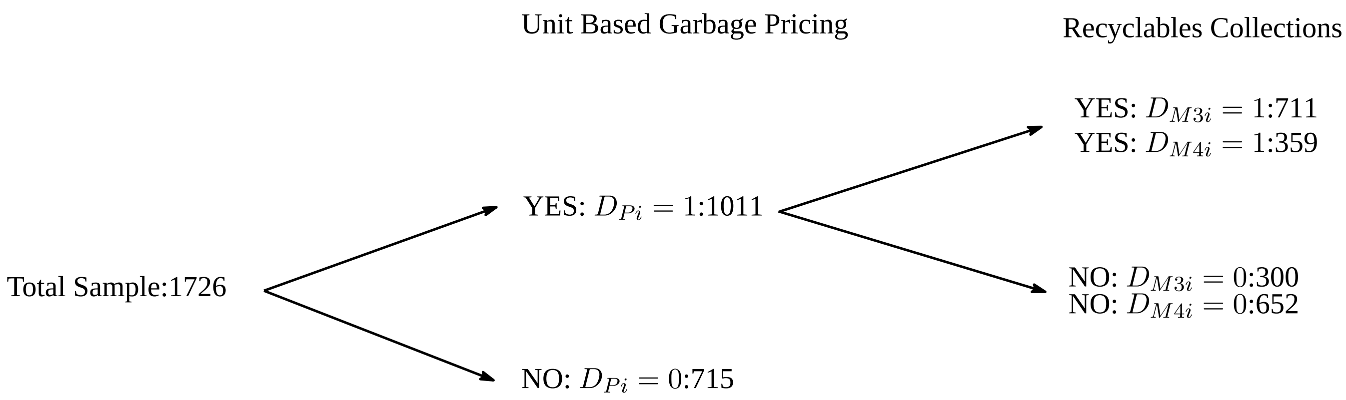
Table 1: Previous Studies: Four Problems

| **Author(s) (Publication Year)** | **Aggregate or Material Specific?** | **Estimate own price Elasticity?** | **Estimate cross price Elasticity?** | **System Estimation?** | **Address Price Endogeneity?** | **Correct Selection Bias?** |
|---|---|---|---|---|---|---|
| Kinnaman and Fullerton (2000) | Aggregate garbage, Aggregate recyclables | YES | YES | NO | YES | NO |
| Jenkins *et al*. (2003) | Material-specific recyclables | YES | YES | NO | NO | NO |
| Callan and Thomas (2006) | Aggregate garbage, Aggregate recyclables | YES | YES | NO | NO | NO |
| Suwa and Usui (2007) | Aggregate garage, Aggregate recyclables | YE S | YES | YES | NO | NO |
| Usui (2008) | Aggregate garbage, Material-specific recyclables | YES | YES | NO | NO | YES |
| Allers and Hoeben (2010) | Aggregate garbage, Material-specific recyclables | YES | YES | NO | YES | NO |
| Huang *et al*. (2011) | Aggregate garbage | YES | NO | NO | YES | YES |
| This paper | Material specific Material-specific recyclables | YES | YES | YES | YES | YES |

Table 2: Data Summary

| Variables | Mean | St.dev | Definition | The number of observations($N$) |
|---|---|---|---|---|
| | | | Implementation rate | |
| Plastic Containers Collection | 0.722 | | Implementation rate for municipal plastic containers collection | 1,726 |
| Paper Containers Collection | 0.336 | | Implementation rate rate municipal paper containers collection | 1,726 |
| Garbage Pricing | 0.586 | | Implementation rate for municipal garbage pricing | 1,726 |
| | | | Dependent variables | |
| Glass | 18.779 | 15.786 | Amount of glass collected per capita per day (g) | 1,011 |
| PET Bottles | 5.722 | 5.530 | Amount of PET bottles collected per capita per day (g) | 1,011 |
| Plastic Containers | 15.166 | 14.593 | Amount of plastic containers collected per capita per day (g) | 711 |
| Paper Containers | 11.132 | 12.881 | Amount of paper containers collected per capita per day (g) | 359 |
| Garbage | 693.40 | 230.80 | Amount of garbage generated per capita per day (g) | 1,011 |
| | | | Explanatory variables | |
| Household Income | 1.178 | 0.314 | Household income(taxable gain) per capita (million JPY) | 1,726 |
| Population Density | 0.859 | 1.742 | Population density of the municipality(Thousand) | 1,726 |
| Household Size | 2.604 | 0.363 | Average size of the household | 1,726 |
| Over65 | 0.274 | 0.0680 | Ratio of people over 65 years of age | 1,726 |
| Dummy for Landfill | 0.795 | | Dummy for municipality-owned landfill site | 1,726 |
| Dummy for Incineration | 0.877 | | Dummy for municipality-owned incinerator for burnable waste | 1,726 |
| Dummy for RDF | 0.0742 | | Dummy for municipality owned refuse derived fuel (RDF) generator | 1,726 |
| Cost ratio | 0.160 | 0.140 | Ratio of municipal waste management cost over total budget | 1,726 |
| Frequency(Glass) | 1.937 | 1.288 | Frequency of municipal glass collection per week | 1,726 |
| Frequency(PET) | 2.104 | 1.412 | Frequency of municipal PET bottles collection per week | 1,726 |
| Frequency(Plastic Containers ) | 1.785 | 1.845 | Frequency of municipal plastic containers collection per week | 1,726 |
| Frequency(Paper Containers) | 1.351 | 1.553 | Frequency of municipal paper containers collection per week | 1,726 |
| Frequency(Garbage) | 2.076 | 0.578 | Frequency of municipal garbage collection per week | 1,726 |
| Price of Bags and Tags(UBP) | 47.053 | 25.803 | Level of the municipal garbage pricing (JPY) | 1,011 |

Figure 1: Date Structure



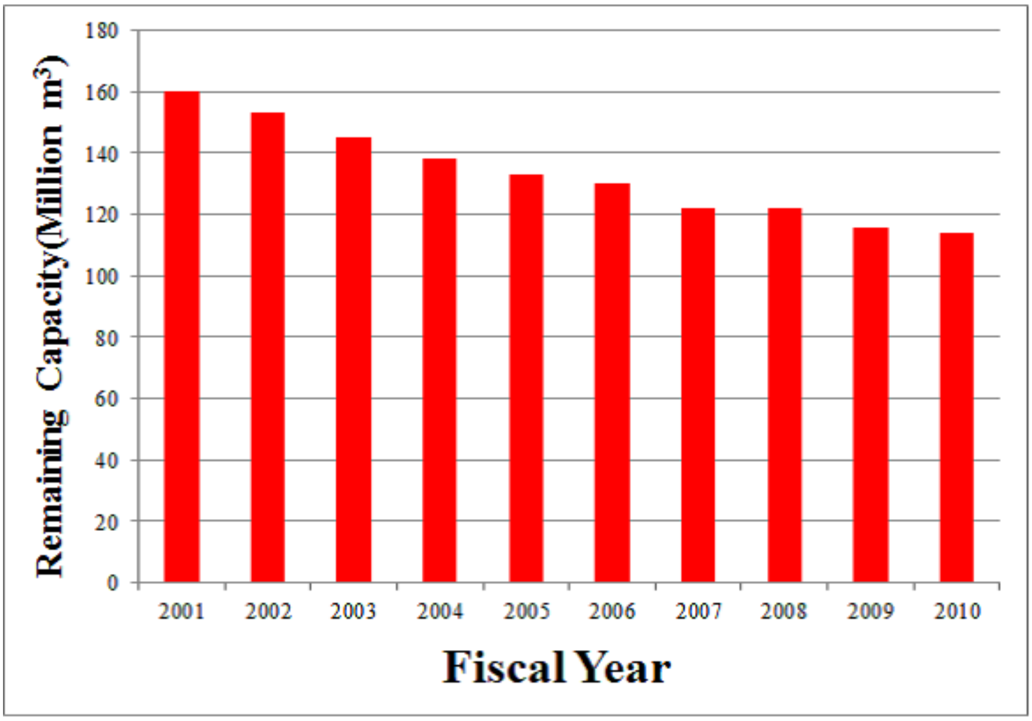



Figure 2: Remaining Landfill

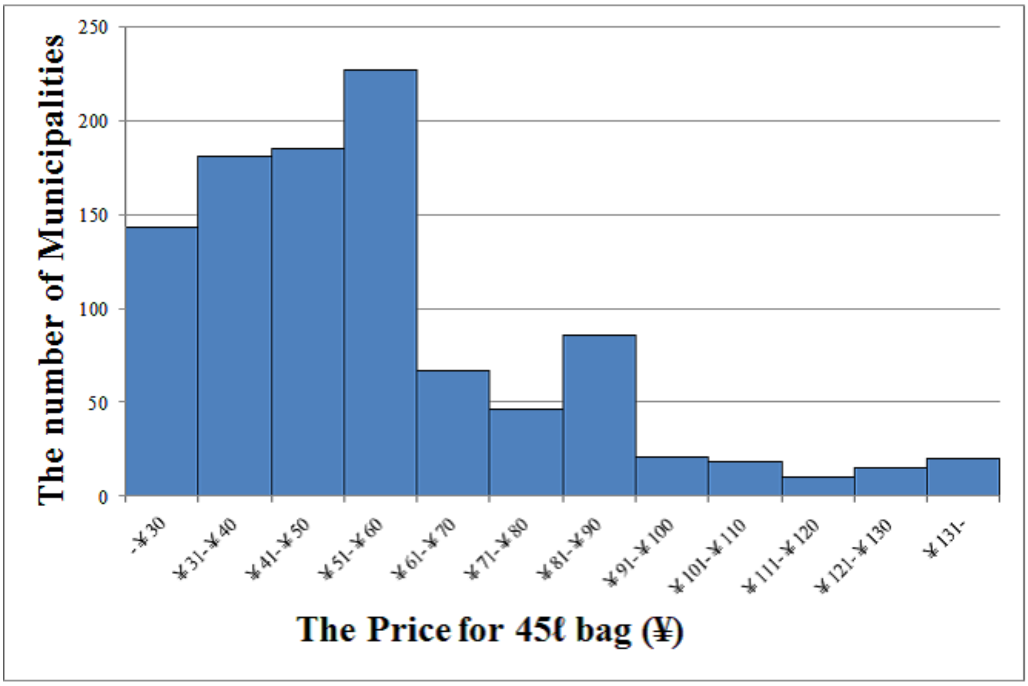



Figure 3: Distribution of the Garbage Price

## Table 3: Estimation Results of Endogeneity Test

| Variables | Glass | PET Bottles | Plastic Containers | Paper Containers | Garbage |
|---|---|---|---|---|---|
| Constant | 2.194 | 1.298 | 0.816 | -0.130 | 9.856 *** |
| | (1.612) | (1.327) | (3.193) | (4.609) | (0.649) |
| $\log$ (Household Income) | 0.391 * | 0.187 | 1.401 *** | 2.161 *** | 0.378 *** |
| | (0.212) | (0.174) | (0.388) | (0.467) | (0.0853) |
| $\log$ (Population Density) | -0.0463 | -0.0398 | -0.237 ** | -0.126 | -0.0553 ** |
| | (0.0539) | (0.0443) | (0.0958) | (0.184) | (0.0215) |
| $\log$ (Household Size) | 0.348 | -0.708 ** | -0.263 | -1.866 * | -1.155 *** |
| | (0.353) | (0.291) | (0.607) | (0.995) | (0.141) |
| Over 65 | 1.056 | -1.255 ** | 2.922 * | 7.586 ** | -2.017 *** |
| | (0.687) | (0.569) | (1.571) | (3.173) | (0.269) |
| Frequency(Glass) | 0.116 *** | | | | |
| | (0.0175) | | | | |
| Frequency(PET Bottles) | | 0.139 *** | | | |
| | | (0.0138) | | | |
| Frequency(Plastic Containers) | | | 0.482 *** | | |
| | | | (0.0303) | | |
| Frequency(Paper Containers) | | | | 0.00908 | |
| | | | | (0.0399) | |
| Frequency(Garbage) | | | | | 0.0482 *** |
| | | | | | (0.0154) |
| Dummy for Plastic Containers Collection | | | | | -0.102 *** |
| | | | | | (0.0201) |
| Dummy for Paper Containers Collection | | | | | 0.0555 *** |
| | | | | | (0.0190) |
| $\log$ (Price) | -0.110 | 0.240 | -0.310 | 0.242 | -0.518 *** |
| | (0.344) | (0.283) | (0.540) | (0.880) | (0.138) |
| Residual of Price Equation | 0.0347 | -0.174 | 0.794 | 0.0744 | 0.408 *** |
| | (0.347) | (0.286) | (0.550) | (0.893) | (0.139) |
| Std.Err | 0.695 | 0.572 | 1.402 | 1.258 | 0.278 |
| $R^2$ | 0.0598 | 0.206 | 0.329 | 0.241 | 0.257 |
| $N$ | 1011 | 1011 | 711 | 359 | 1011 |

Note: The numbers in parentheses are standard errors.
Note: Levels of statistical significance: ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$.

Table 4: Estimation Results of MDSSM with No Correlations

| | Selection equation | | | Level equation | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Garbage Pricing | Plastic Containers | Paper Containers | Glass | PET Bottles | Plastic Containers | Paper Containers | Garbage |
| Constant | -0.117 | -0.356 | -0.908 *** | 2.038 *** | 2.091 *** | -2.759 ** | -0.505 | 9.818 *** |
| | (0.441) | (0.361) | (0.352) | (0.322) | (0.268) | (0.766) | (1.021) | (0.657) |
| $\log$ (Household Income) | -0.948 *** | 1.179 *** | 0.0473 | 0.374 *** | 0.274 *** | 1.078 *** | 2.145 *** | 0.380 *** |
| | (0.168) | (0.173) | (0.169) | (0.121) | (0.100) | (0.316) | (0.419) | (0.086) |
| $\log$ (Population Density) | -0.0777 *** | -0.0353 | -0.143 *** | -0.0414 ** | -0.0647 *** | -0.117 ** | -0.112 * | -0.0556 ** |
| | (0.0283) | (0.0298) | (0.0281) | (0.0208) | (0.0171) | (0.0478) | (0.0605) | (0.0218) |
| $\log$ (Household Size) | 0.0807 | 0.610 ** | 0.490 ** | 0.379 ** | -0.864 *** | 0.399 | -1.795 *** | -1.150 *** |
| | (0.235) | (0.244) | (0.235) | (0.166) | (0.139) | (0.395) | (0.514) | (0.142) |
| Over 65 | 0.379 | 0.276 | -1.028 | 1.100 ** | -1.475 *** | 4.189 *** | 7.808 *** | -2.016 *** |
| | (0.763) | (0.774) | (0.764) | (0.527) | (0.439) | (1.297) | (1.703) | (0.273) |
| Dummy for Landfill | 0.199 ** | 0.193 ** | 0.0433 | | | | | |
| | (0.0800) | (0.0826) | (0.0813) | | | | | |
| Dummy for Incineration | -0.0171 | -0.0260 | 0.0565 | | | | | |
| | (0.102) | (0.105) | (0.103) | | | | | |
| Dummy for RDF | 0.300 ** | -0.296 ** | -0.250 * | | | | | |
| | (0.129) | (0.127) | (0.130) | | | | | |
| Frequency(Glass) | | | | 0.116 *** | | | | |
| | | | | (0.0175) | | | | |
| Frequency(PET Bottles) | | | | | 0.139 *** | | | |
| | | | | | (0.0138) | | | |
| Frequency(Plastic Containers) | | | | | | 0.479 *** | | |
| | | | | | | (0.0301) | | |
| Frequency(Paper Containers) | | | | | | | 0.00939 | |
| | | | | | | | (0.0393) | |
| Frequency(Garbage) | | | | | | | | 0.0548 *** |
| Dummy for Plastic Containers Collection | | | | | | | | -0.105 *** |
| | | | | | | | | (0.0203) |
| Dummy for Paper Containers Collection | | | | | | | | 0.0487 *** |
| | | | | | | | | (0.0192) |
| $\log$ (Price) | | | | -0.0758 * | 0.0688 * | 0.452 *** | 0.315 ** | -0.511 *** |
| | | | | (0.0450) | (0.0371) | (0.107) | (0.135) | (0.140) |
| $\sigma_j$ | | | | 0.692 *** | 0.570 *** | 1.396 *** | 1.244 *** | 0.282 *** |
| | | | | (0.0154) | (0.0127) | (0.0370) | (0.0464) | (0.00626) |
| Log likelihood | -19877.78 | | | | | | | |
| $N$ | 1726 | | | | | | | |

Note: The numbers in parentheses are standard errors.
Note: Levels of statistical significance: ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$.

Table 5: Estimation Results of the Multivariate Double Sample Selection Model(MDSSM)

| | Selection equation | | | Level equation | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Price | Plastic Containers | Paper Containers | Glass | PET Bottles | Plastic Containers | Paper Containers | Garbage |
| Constant | 0.593 * | -0.505 | -0.938 *** | 3.051 *** | 2.247 *** | -2.344 *** | -0.865 | 10.576 *** |
| | (0.314) | (0.351) | (0.353) | (0.312) | (0.268) | (0.775) | (1.123) | (0.726) |
| $\log$ (Household Income) | -0.918 *** | 1.174 *** | 0.0479 | 0.835 *** | 0.395 *** | 1.176 *** | 2.047 *** | 0.278 *** |
| | (0.151) | (0.168) | (0.170) | (0.134) | (0.102) | (0.334) | (0.428) | (0.0959) |
| $\log$ (Population Density) | -0.0824 *** | -0.0479 | -0.137 *** | 0.00293 | -0.0447 *** | -0.102 ** | -0.146 ** | -0.0788 *** |
| | (0.0252) | (0.0297) | (0.0286) | (0.0225) | (0.0173) | (0.0490) | (0.0686) | (0.0247) |
| $\log$ (Household Size) | -0.536 ** | 0.604 ** | 0.479 ** | 0.0274 | -0.918 *** | 0.442 | -1.762 *** | -1.439 *** |
| | (0.212) | (0.239) | (0.236) | (0.186) | (0.140) | (0.397) | (0.531) | (0.164) |
| Over 65 | 0.0179 | 0.398 | -1.058 | 0.582 | -1.488 *** | 3.653 *** | 7.296 *** | -2.268 *** |
| | (0.685) | (0.764) | (0.766) | (0.0130) | (0.443) | (1.298) | (1.721) | (0.314) |
| Dummy for Landfill | -0.00304 | 0.243 *** | 0.0989 | | | | | |
| | (0.0442) | (0.0766) | (0.0887) | | | | | |
| Dummy for Incineration | 0.0468 | 0.00898 | 0.0661 | | | | | |
| | (0.0580) | (0.0895) | (0.102) | | | | | |
| Dummy for RDF | 0.0732 | -0.131 | -0.171 | | | | | |
| | (0.0802) | (0.102) | (0.137) | | | | | |
| Frequency(Glass) | | | | 0.0700 *** | | | | |
| | | | | (0.0130) | | | | |
| Frequency(PET Bottles) | | | | | 0.140 *** | | | |
| | | | | | (0.0128) | | | |
| Frequency(Plastic Containers) | | | | | | 0.471 *** | | |
| | | | | | | (0.0298) | | |
| Frequency(Paper Containers) | | | | | | | 0.00991 | |
| | | | | | | | (0.0407) | |
| Frequency(Garbage) | | | | | | | | 0.0504 *** |
| | | | | | | | | (0.0152) |
| Dummy for Plastic Containers Collection | | | | | | | | 0.359 *** |
| | | | | | | | | (0.0332) |
| Dummy for Paper Containers Collection | | | | | | | | 0.130 |
| | | | | | | | | (0.131) |
| $\log$ (Price) | | | | -0.0381 | 0.0916 ** | 0.378 *** | 0.318 ** | -0.730 *** |
| | | | | (0.0342) | (0.0362) | (0.109) | (0.136) | (0.156) |
| $\sigma_j$ | | | | 0.925 *** | 0.597 *** | 1.419 *** | 1.278 *** | 0.364 *** |
| | | | | (0.0240) | (0.0156) | (0.0416) | (0.0717) | (0.0186) |

Correlation matrix

| Error Terms | $\epsilon$ | $u_3$ | $u_4$ | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_g$ |
|---|---|---|---|---|---|---|---|---|
| $\epsilon$ | 1 | | | | | | | |
| $u_3$ | -0.118 *** | 1 | | | | | | |
| | (0.0368) | | | | | | | |
| $u_4$ | -0.0410 | 0.319 *** | 1 | | | | | |
| | (0.0372) | (0.0392) | | | | | | |
| $v_1$ | -0.979 *** | 0.102 *** | 0.0118 | 1 | | | | |
| | (0.00338) | (0.0347) | (0.0358) | | | | | |
| $v_2$ | -0.456 *** | 0.148 *** | 0.0295 | 0.459 *** | 1 | | | |
| | (0.0455) | (0.0387) | (0.0412) | (0.0345) | | | | |
| $v_3$ | -0.110 | 0.142 | 0.00435 | 0.122 * | 0.247 *** | 1 | | |
| | (0.0781) | (0.116) | (0.0547) | (0.0671) | (0.0486) | | | |
| $v_4$ | 0.119 | 0.0956 | 0.231 | -0.0449 | 0.0925 | 0.0127 | 1 | |
| | (0.106) | (0.0934) | (0.228) | (0.0939) | (0.0677) | (0.0674) | | |
| $v_g$ | 0.125 *** | -0.825 *** | -0.301 | -0.0728 * | -0.0201 | -0.156 ** | 0.000247 | 1 |
| | (0.0439) | (0.0301) | (0.212) | (0.0380) | (0.0345) | (0.0640) | (0.0803) | |
| Log likelihood | -19522.03 | | | | | | | |
| $N$ | 1726 | | | | | | | |

Note: The numbers in parentheses are standard errors.
Note: Levels of statistical significance: ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$.
Note: These results are estimated using the GHK simulator with a 50 times random draw.