Does Garbage Pricing Increase Immoral Disposal of Household Waste?

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Abstract

Some empirical studies have attempted to clarify the basis of the mechanism of illegal dumping. Previous empirical studies used the proxy variable approach to clarify the degree to which bag pricing affects midnight dumping. However, previous studies on illegal dumping dealt with only a portion of the behavior of avoiding paying a charge for waste collection. There are two methods of fare avoidance: (1) illegal dumping and (2) immoral disposal. In this study, we define "immoral disposal" as the dumping of waste in a manner that is immoral but not illegal. Immoral disposal is less risky than illegal disposal because there is no legal penalty. In order to detect the existence of immoral disposal, we consider the nature of a natural experiment and apply spatial econometrics. We can identify the actual spillover effect of garbage pricing on immoral disposal from the total waste via a spatial econometric approach. A major finding of our study is that immoral disposal exists in two-tier pricing.

JEL classification: C23, H23, K42, Q53

Key words: Pricing bag, MCMC, Extended panel spatial Durbin model, Immoral disposal of household waste

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1 Introduction

Many municipalities have introduced garbage-pricing policies to reduce solid household waste. Concretely, garbage pricing indicates that users pay for municipal waste collection services per unit of waste collected; this is unit-based pricing (UBP) is known to consumers as "pay per bag" or "pay-as-you-throw" (PAYT). Many theoretical and empirical studies have attempted to clarify the basis for the mechanism of illegal dumping. However, previous studies on illegal dumping dealt with only a portion of the behavior of avoiding paying a charge for waste collection. There are two methods of fare avoidance: (1) illegal dumping and (2) immoral disposal. Illegal dumping means the behavior of dumping or burning waste in legally banned places. In this study, we define "immoral disposal" as the behavior of dumping waste in a manner that is immoral but not illegal. This behavior has not been addressed in previous studies. Therefore, we focus on whether garbage pricing empirically increases immoral dumping.

Theoretical and empirical works have attempted to understand the illegal dumping of household waste caused by the economic disincentive of per-bag pricing. Theoretical works include Fullerton and Kinnaman (1995), Palmer and Walls (1997), and Choe and Fraser (1999). Many empirical works have addressed the illegal dumping of household waste. Hong (1999) reported substantial illegal dumping after the adoption of garbage pricing in Korea. Fullerton and Kinnaman (1996) surveyed households using questionnaires, providing four options. They estimated that 28% of the total reduction of garbage at the curb could be attributed to illegal disposal. Kim *et al*.(2008) analyzed data based on the number of complaints from citizens. Controlling for socioeconomic factors, they found that garbage pricing increased complaints from citizens and concluded that it increased illegal dumping. Yamakawa *et al*.(2002) conducted a questionnaire survey of municipal waste management employees in Japan to determine how problematic UBP-caused dumping was. They found that approximately 40% of municipalities that introduced garbage pricing experienced an increase in illegal dumping. On the other hand, Miranda *et al*.(1994), Reschovsky and Stone (1994), Van Houtven and Morris (1999), and Kuo (2010) found no such evidence.

Here, rather than the *illegal* dumping of household waste, we deal with the *immoral* disposal of household waste, which is a part of fare avoidance behavior (avoiding a charge for waste collection). Immoral disposal seems to be done more frequently than illegal dumping, but it has not been addressed in previous studies. For example, people sometimes dispose of their household waste at a convenience store or supermarket near their house in order to avoid paying a charge for its collection. This fare-avoiding behavior is not prohibited by law, but it is considered immoral in Japan. Immoral disposal appears to be widespread in Japan. Signs are posted at many stores in Japan that ask people not to dispose of their household waste there. According to a top economic newspaper in Japan (Nihon Keizai Shimbun, 2005), the headquarters of one convenience store chain in Japan claimed that the amount of waste generated by convenience stores has increased because customers have been dumping their household waste in trash bins in front of stores.

In this study, we aim to clarify the existence of the immoral disposal of household waste induced by the disincentive of per-bag pricing, which has not been dealt with by the previous studies. We focus on immoral disposal because it is an easier method of fare avoidance than illegal disposal because there is no legal penalty. If people are rational, immoral disposal is more common than illegal disposal.

In order to detect the existence of immoral disposal, we consider the nature of a natural experiment and apply spatial econometrics. Concretely, in order to overcome the difficulty in directly obtaining data on immoral disposal, we use real available data such as the amount of garbage collected in a municipality instead of the immoral disposal data or report-based data. The challenge is specifying the amount of immoral disposal given the amount of municipal garbage collected. Here, we briefly explain our estimation strategy using an example of waste at convenience stores. The data on the amount of waste at convenience stores can be obtained because the amount of total waste in each municipality is available as aggregated data, including office waste, such as, the amount of waste at convenience stores, supermarkets, and so forth. If people want to avoid paying per bag, disposing of their household waste at convenience stores is the best strategy because they can safely dispose of their waste without violating the law. In this case, disposing of household waste at a convenience store near their house is natural. If this behavior is not subject to the restriction of municipal borders, the person can randomly pick a trash bin whether the convenience store is inside or outside the municipal border as long as it is relatively close to his/her house. We can separate the amount of immoral disposal from that of total waste by looking at the spillover effect around municipality borders if we apply a spatial econometric approach–that is, an extended-panel spatial Durbin model.

The paper is organized as follows. The next section describes the background of the problem of waste dumping caused by bag pricing. Section 3 explains the spatial Durbin model and the type of data used. Section 4 presents a detailed report of the estimation results. The final section contains concluding remarks.

2 Theoretical Background

Our conceptual framework is based on literature such as Kinnaman and Fullerton (2000) and Allers and Hoeben (2010). First, we set a demand function for waste disposal services. Likewise, in the conceptual setting by Kinnaman and Fullerton (2000), each household consumes a consumption good, c, and generates waste using three disposal methods: regular garbage collection, recyclable collection, and illegal disposal. The household preferences among these disposal methods may depend on a set of demographic characteristics, z.

In our study, we use the term "household waste" in the broader sense. We take the waste generated from households' consumption of goods and services outside their houses into consideration as well. For example, food residuals at restaurants are households' outsourcing of waste that they would otherwise produce if they cooked and ate at home. For another example, when households purchase fish or meat on a plastic tray at a supermarket, while some dispose of the tray at home, others take it back to the supermarket to throw it away. Such waste is treated as "household waste" in our study.

We derive demand functions for waste disposal services through utility maximization subject to the income restrictions. All waste must appear as garbage collection (w_h: household waste and w_o: office waste, recyclables waste (r), and illicit burning and dumping (b).

Thus, each household maximizes utility as follows:

$$\max U(c, w_h, w_o, r, b; z), \tag{1}$$

subject to

$$m = c + p_{wh}w_h + p_{wo}w_o + p_r r + p_b b. \tag{2}$$

where m is household income, consumption good c is the numeraire, p_{wh} indicates the price of unsorted household waste collection, p_{wo} represents the price of unsorted office waste collection, p_r means the price of recyclable collection, and p_b means the price of illegal dumping or burning. If the price of w_h, p_h has been introduced in the municipality, the amount of w_h will decrease. At the same time, there may be the possibility of substitution for office waste (w_o) and illegal dumping (b). In the former case, immoral disposal will be included in the amount of office waste (w_o) because of avoidance of paying per-bag pricing, and in the latter case, the waste will be disposed of via illegal burning and dumping (b).

From the maximization process, we can calculate the demand functions for each method:

$$w_h = w_h(p_{wh}, p_{wo}, p_r, p_b, m; z), \tag{3}$$

$$w_o = w_b(p_{wh}, p_{wo}, p_r, p_b, m; z), \tag{4}$$

$$r = r(p_{wh}, p_{wo}, p_r, p_b, m; z), \tag{5}$$

$$b = b(p_{wh}, p_{wo}, p_r, p_b, m; z). \tag{6}$$

If p_{wh} increases, w_h decreases and substitutes to increase r and b, where (p_b) is not a market price but includes implicitly (a) the time cost of finding the dumping place, (b) the traveling cost, and (c) the fine for littering according to the law of appropriate disposal.

Assuming that the fine for littering according to the law of appropriate disposal is the same for all municipalities is natural because it is the same across the nation. If $p_{wh} > p_b$ in w_h, people may be tempted to dispose illegally and increase the amount of b.

However, there are loopholes in Japan's dumping law. Recall that there are two methods of fare avoidance, illegal dumping, and immoral disposal. Since immoral disposal is not fined, people may dispose of w_o easily–for example, by using a bin at a convenience store–because they can avoid paying both p_{wh} and a portion of

p_b by doing so. If this is true, w_o includes some household trash: w_h may be mixed into w_o in order to avoid paying p_{wh}. Thus, we sum these up as total waste, w_t, which is defined as follows: $w_t = w_h + w_o + r$. This can be expressed as follows:

$$w_h + w_o + r = w_t(p_{wh}, p_{wo}, p_r, p_b, m; z). \tag{7}$$

In the econometric model, no municipality introduced p_r during the data period. Thus, we omit p_r from the equation. In addition, we do not need to consider p_b because the law is uniform across the nation (as mentioned previously). However, some differences among the municipalities exist regarding (i) the time cost of finding the dumping place and (ii) the traveling cost. Empirically, we use a panel model, and assume that these differences are prescribed by the geographical character as a proxy of accessibility to dumping place and traveling cost for bringing the garbage, which is controlled by fixed effects. We have no correct information on p_{wo} for the data restrictions. Instead, we assume that w_o is related to the population density, which is a component of z. The amount of office waste seems to be closely related to population density, as more restaurants and convenience stores are located in densely populated regions. Therefore, population density is thought to be positively correlated with the amount of office waste. In addition, almost all municipalities have introduced p_{wo}, and, therefore, we can regard the effect of p_{wo} as uniform across the nation. From these considerations, we rewrite the equation (7) as follows:

$$w_t = w_t(p_{wh}, m; z). \tag{8}$$

The total waste reduction caused by the introduction of p_{wh} brings (1) the incentive of source reduction by households, which is the behavior of avoiding the use of store packaging, and, unfortunately, (2) the incentive for illegal disposal. However, the amount of illegal disposal is not included in the total waste because of data unavailability [1].

[1]Some readers may wonder why we do not estimate the equations for office waste and household waste separately. In Japan, price data for office waste is quite difficult to obtain because the price of office waste is determined between each office and private collector on a negotiation basis, and so it is unspecified in a municipality. Since it is difficult to specify how much household waste is transferred to office waste, we estimate total waste. However, estimating the two equations separately does not enable us to distinguish the effect of immoral disposal from that source reduction, both of which are thought to be affected by the introduction of per-bag pricing for household waste. The effect of the introduction of per-bag pricing is estimated as a compound reduction effect associated with household waste that is comprised of (1) source reduction, (2) illegal disposal, and (3) immoral disposal. On the other hand, a certain amount of office waste is directly transferred from household waste as immoral disposal. However, the amount of office waste cannot be identified because (1) office waste is assumed to be related to population density and (2) the price of office waste is not introduced. Thus, we have no way to estimate the equations separately.

At the same time, there is an advantage in estimating total waste in one equation. We do not need to consider the amount of office waste in order to specify the existence of immoral disposal; we only need to analyze the spillover effect of neighboring municipalities, as described later.

Typically, if there are convenience stores near a person's residence, he/she would dump garbage at one of them, given the transportation and punishment cost of illegal disposal. Therefore, it is natural to presume that immoral disposal occurs at the trash bins of convenience stores in municipalities that have already introduced garbage pricing, but seldom occurs in those that have not.

There is a reason why we use data on immoral disposal at, e.g., convenience stores: There is a difference in the weight of guilt between dumping illegally on public land and disposing garbage at a trash bin at a convenience store. People who dispose their garbage on public land are subject to serious punishment. If the illegal dumping is detected, people are sentenced to less than 5 years in prison or fined less than 10 million Yen (approximately 100,000 U.S. dollars). By contrast, people disposing garbage at convenience stores might suffer from psychological guilt at most, but disposing garbage at convenience stores is not considered a crime. Therefore, it is quite reasonable to dispose garbage at convenience store garbage bins.

Previous studies are based on human emotion using indirect approaches such as the number of complaints from citizens and questionnaire surveys of municipal waste management employees. In contrast, our estimation strategy is focused on the actual garbage in the trash bins at the convenience stores (immoral disposal); this enables us to estimate the exact increase of immoral disposal caused by garbage pricing, which enables us to estimate the exact increase of immoral disposal caused by garbage pricing.

Next, we explain the introduced estimation strategy. In this paper, we focus on the character of a natural human behavior experiment and apply the spatial econometric method. First, we consider the behavior of immoral disposal by focusing on the people living around municipal borders. For example, If people want to dispose at convenience store trash bins, it is natural to do so near their house. In case the behavior is not subject to the restriction of municipal borders, they can pick a trash bin to dispose at randomly regardless of whether the convenience stores are inside or outside the municipal border as long as the distance to their house is similar. Because there are incentive differences between the people who live in municipalities that have introduced garbage pricing and those who live in municipalities that have not, there may be some differences in the average amount of total waste among them, all else constant. Considering the nature of a natural experiment, we can not only estimate the total waste reduction of the introduced municipality but also the increase in the amount of immoral disposal spilled over from the introduced municipality to the adjacent one. Here, we apply an extended panel spatial Durbin model (explained in the next section) to determine the value of the increase in immoral disposal caused by the introduction of garbage pricing by the bag. In summary, we can identify the actual spillover effect of the garbage pricing on immoral disposal from the total waste.

3 Econometric Model and Data

In this section, we show our estimation strategy for estimating the spatial externalities arising from neighborhood municipal policy characteristics in the form of direct waste dumping in a garbage bin at the store to avoid paying per bag. We estimate the demand function for waste collection services using municipal waste data. Here, we show the estimation model and the dependent and independent variables. Finally, we explain our data.

3.1 Extended Panel Spatial Durbin Model

We extend the panel spatial Durbin model with strictly exogenous variables, which are, for example, time dummy variables. Let y_{it} be the dependent variable of the ith unit and tth time period. In this paper, y_{it} is the log of the amount of waste generation per capita per day (in grams). Let $\mathbf{x}_{it}$ be the $1 \times k_1$ vector of the covariate, which is also spatially correlated. The spatially dependent vector of the covariate is defined by $\mathbf{x}_{it}^s = \sum_{j=1}^{n} w_{ij}\mathbf{x}_{jt}$, where w_{ij} expresses the relationship between the ith and jth unit. This is termed "spatial weight," and it takes the form of a contiguity dummy or the distance between the ith and jth units.

In this paper, we use the contiguity dummy variables, which are characterized by the fact that the ith and jth units are connected by the borders and that $\sum_{i=1}^{n} w_{ij} = 1$. Finally, $\mathbf{v}_{it}$ denotes the strictly exogenous $1 \times k_2$ vector of covariate. Then, the extended panel spatial Durbin model is written as follows:

$$y_{it} = \alpha_i + \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \mathbf{x}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}^s \boldsymbol{\beta}_s + \mathbf{v}_{it}\boldsymbol{\beta}_v + \epsilon_{it}, \quad \epsilon_{it} \sim \mathcal{N}(0, \sigma^2), \tag{9}$$

where $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$, $\mathbf{y} = (\mathbf{y}_1', \mathbf{y}_2', \ldots, \mathbf{y}_T')'$, $\mathbf{X}_t = (\mathbf{x}_{1t}', \mathbf{x}_{2t}', \ldots, \mathbf{x}_{nt}')'$, $\mathbf{V}_t = (\mathbf{v}_{1t}', \mathbf{v}_{2t}', \ldots, \mathbf{v}_{nt}')'$, $\mathbf{X}_t^s = \mathbf{W}\mathbf{X}_t = (\mathbf{x}_{1t}^{s'}, \mathbf{x}_{2t}^{s'}, \ldots, \mathbf{x}_{nt}^{s'})'$, $\mathbf{X} = (\mathbf{X}_1', \mathbf{X}_2', \ldots, \mathbf{X}_T')'$, $\mathbf{X}^s = (\mathbf{X}_1^{s'}, \mathbf{X}_2^{s'}, \ldots, \mathbf{X}_T^{s'})'$, $\mathbf{V} = (\mathbf{V}_1', \mathbf{V}_2', \ldots, \mathbf{V}_T')'$, $\mathbf{Z} = (\mathbf{X}, \mathbf{X}^s, \mathbf{V})$, $\mathbf{W} = \{w_{ij}\}$, $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_n)'$, $\boldsymbol{\theta} = (\boldsymbol{\beta}', \boldsymbol{\beta}_s', \boldsymbol{\beta}_v')'$, where $\mathbf{y}$ is an $nT \times 1$ vector of independent variables, $\mathbf{Z}$ is an $nT \times k$ matrix of covariates, $\boldsymbol{\alpha}$ is an $n \times 1$ vector of parameters and $\boldsymbol{\theta}$ is an $k \times 1$ vector of parameters, respectively and $k = 2k_1 + k_2$.

Then, the model is rewritten in the matrix form as follows:

$$\mathbf{y} = \mathbf{i}_T \otimes \boldsymbol{\alpha} + \rho(\mathbf{I}_T \otimes \mathbf{W})\mathbf{y} + \mathbf{Z}\boldsymbol{\theta} + \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_{nT}), \tag{10}$$

where $\mathbf{i}_a$ is an $a \times 1$ unit vector, $\mathbf{I}_a$ is an $a \times a$ unit matrix, and $\otimes$ denotes the kronecker product.

Then, the likelihood function of the model defined in (10) is expressed as follows:

$$L(\mathbf{y}|\mathbf{Z}, \mathbf{W}, \boldsymbol{\alpha}, \rho, \boldsymbol{\theta}, \sigma^2) \propto \left(\sigma^2\right)^{-\frac{nT}{2}} |\mathbf{I}_n - \rho \mathbf{W}|^T \exp\left\{-\frac{\mathbf{e}'\mathbf{e}}{2\sigma^2}\right\}, \tag{11}$$

where $\mathbf{e} = \mathbf{y} - \mathbf{i}_T \otimes \boldsymbol{\alpha} - \rho(\mathbf{I}_T \otimes \mathbf{W})\mathbf{y} - \mathbf{Z}\boldsymbol{\theta}$.

Because we adopt a Bayesian approach, we complete the model by specifying the prior distribution over the parameters. Therefore, we apply the following hierarchical prior distributions.

$$\pi(\boldsymbol{\alpha}, \rho, \boldsymbol{\theta}, \sigma^2, \mu, \xi^2) = \left\{ \prod_{i=1}^{n} \pi(\alpha_i | \mu, \xi^2) \right\} \pi(\rho)\pi(\boldsymbol{\theta})\pi(\sigma^2)\pi(\mu)\pi(\xi^2), \tag{12}$$

where μ and ξ^2 denote the mean and variance of $\boldsymbol{\alpha}$, respectively.

Given a prior distribution given by (12) and the likelihood function given by (11), the joint posterior distribution can be expressed as

$$\pi(\boldsymbol{\alpha}, \rho, \boldsymbol{\theta}, \sigma^2, \mu, \xi^2 | \mathbf{y}, \mathbf{Z}, \mathbf{W}) \propto \pi(\boldsymbol{\alpha}, \rho, \boldsymbol{\theta}, \sigma^2, \mu, \xi^2) L(\mathbf{y} | \mathbf{Z}, \mathbf{W}, \boldsymbol{\alpha}, \rho, \boldsymbol{\theta}, \sigma^2). \tag{13}$$

Finally, we assume the following proper prior distributions:

$$\alpha_i | \mu, \xi^2 \sim \mathcal{N}(\mu, \xi^2), \quad \rho \sim \mathcal{U}(-1, 1), \quad \boldsymbol{\theta} \sim \mathcal{N}(\boldsymbol{\theta}_0, \boldsymbol{\Sigma}_0),$$
$$\sigma^2 \sim \mathcal{IG}\left(\frac{\nu_0}{2}, \frac{\lambda_0}{2}\right), \quad \mu \sim \mathcal{N}(\mu_0, \tau_0^2), \quad \xi^2 \sim \mathcal{IG}\left(\frac{n_0}{2}, \frac{s_0}{2}\right),$$

where $\mathcal{IG}(a, b)$ is an inverse gamma distribution with scale parameter a and shape parameter b.

Because the joint posterior distribution is given by (13), we can now adopt the Markov chain Monte Carlo method (MCMC). The Markov chain sampling scheme can be constructed from the full conditional distributions of α_i ($i = 1, 2, \ldots, n$), ρ, $\boldsymbol{\theta}$, σ^2, μ, and ξ^2.

From (13), the full conditional distribution of ρ is written as

$$\pi(\rho | \boldsymbol{\alpha}, \boldsymbol{\theta}, \sigma^2, \mathbf{y}, \mathbf{Z}, \mathbf{W}) \propto |\mathbf{I}_n - \rho \mathbf{W}|^T \exp\left\{ -\frac{\mathbf{e}'\mathbf{e}}{2\sigma^2} \right\}, \tag{14}$$

where $\mathbf{e} = \mathbf{y} - \mathbf{i}_T \otimes \boldsymbol{\alpha} - \rho(\mathbf{I}_T \otimes \mathbf{W})\mathbf{y} - \mathbf{Z}\boldsymbol{\theta}$. This distribution cannot be sampled using a standard method such as the Gibbs sampler. Therefore, we adopt the Metropolis-Hastings (MH) algorithm (see, for example, Tierney, 1994).

The following random walk MH step is used: sample ρ^{new} from

$$\rho^{new} = \rho^{old} + c\phi, \quad \phi \sim \mathcal{N}(0, 1),$$

where c is called the tuning parameter and ρ^{old} is the parameter of the previous sampling. Next, we evaluate the acceptance probability

$$\alpha(\rho^{old}, \rho^{new}) = \min\left\{ \frac{\pi(\rho^{new} | \boldsymbol{\alpha}, \boldsymbol{\theta}, \sigma^2, \mathbf{y}, \mathbf{Z}, \mathbf{W})}{\pi(\rho^{old} | \boldsymbol{\alpha}, \boldsymbol{\theta}, \sigma^2, \mathbf{y}, \mathbf{Z}, \mathbf{W})}, 1 \right\},$$

using $\pi(\rho | \boldsymbol{\alpha}, \boldsymbol{\theta}, \sigma^2, \mu, \xi^2 \mathbf{y}, \mathbf{Z}, \mathbf{W})$ in (14) and finally setting $\rho = \rho^{new}$ with probability $\alpha(\rho^{old}, \rho^{new})$; otherwise, $\rho = \rho^{old}$. The proposed value of ρ^{new} is not truncated to the interval $(-1, 1)$ because the constraint is part of the target density. Thus, if the proposed value of ρ^{new} is not within the intervals, the conditional posterior is zero, and the proposed value is rejected with probability 1 (see Chib and Greenberg, 1998).

The full conditional distribution of $\boldsymbol{\theta}$ is

$$\boldsymbol{\theta}|\boldsymbol{\alpha}, \rho, \sigma^2, \mathbf{y}, \mathbf{Z}, \mathbf{W} \sim \mathcal{N}(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\Sigma}}),$$

where $\hat{\boldsymbol{\Sigma}} = (\sigma^{-2}\mathbf{Z}'\mathbf{Z} + \boldsymbol{\Sigma}_0^{-1})^{-1}$, $\hat{\boldsymbol{\theta}} = \hat{\boldsymbol{\Sigma}} \left\{\mathbf{Z}'(\mathbf{y} - \mathbf{i}_T \otimes \boldsymbol{\alpha} - \rho(\mathbf{I}_T \otimes \mathbf{W})\mathbf{y}) + \boldsymbol{\Sigma}_0^{-1}\boldsymbol{\theta}_0\right\}$.

The full conditional distribution of σ^2 is

$$\sigma^2|\boldsymbol{\alpha}, \rho, \boldsymbol{\theta}, \mathbf{y}, \mathbf{Z}, \mathbf{W} \sim \mathcal{IG}\left(\frac{\hat{\nu}}{2}, \frac{\hat{\lambda}}{2}\right),$$

where $\hat{\nu} = nT + \nu_0$, $\hat{\lambda} = \mathbf{e}'\mathbf{e} + \lambda_0$.

The full conditional distribution of α_i is

$$\alpha_i|\boldsymbol{\alpha}_{-i}, \rho, \boldsymbol{\theta}, \sigma^2, \mu, \xi^2, \mathbf{y}, \mathbf{Z}, \mathbf{W} \sim \mathcal{N}(\hat{\alpha}_i, \hat{\xi}^2),$$

where $\boldsymbol{\alpha}_{-i} = (\alpha_1, \alpha_2, \ldots, \alpha_{i-1}, \alpha_{i+1}, \ldots, \alpha_n)'$, $\hat{\alpha}_i = \hat{\xi}^2 \left\{\sigma^{-2} \sum_{t=1}^{T} \left(y_{it} - \rho \sum_{j=1}^{n} w_{ij} y_{jt} - \mathbf{z}_{it}\boldsymbol{\theta}\right) + \xi^{-2}\mu\right\}$, $\hat{\xi} = (\sigma^{-2}T + \xi^{-2})^{-1}$, and $\mathbf{z}_{it} = (\mathbf{x}_{it}, \mathbf{x}_{it}^s, \mathbf{v}_{it})$.

The full conditional distribution of μ is

$$\mu|\xi^2, \boldsymbol{\alpha} \sim \mathcal{N}(\hat{\mu}, \hat{\tau}^2), \tag{15}$$

where $\hat{\tau}^2 = (\xi^{-2}n + \tau_0^{-2})^{-1}$ and $\hat{\mu} = \hat{\tau}^2 \left(\xi^{-2} \sum_{i=1}^{n} \alpha_i + \tau_0^{-2}\mu_0\right)$.

The full conditional distribution of ξ^2 is

$$\xi^2|\mu, \boldsymbol{\alpha} \sim \mathcal{IG}\left(\frac{\hat{n}}{2}, \frac{\hat{s}}{2}\right), \tag{16}$$

where $\hat{n} = n + n_0$ and $\hat{s} = (\boldsymbol{\alpha} - \mu)'(\boldsymbol{\alpha} - \mu) + s_0$.

3.2 Data

3.2.1 Variables

Here, we describe the explanatory variables, such as the dummy variables we include for garbage pricing and other demographic variables. First, we define the dummy variables for garbage pricing. There are three types of garbage pricing policies in Japan: UBP, two-tier pricing, and fixed charge pricing (hereafter, fixed pricing). Fixed pricing is one of the schemes of per-bag pricing that is not related with the amount of waste; the fare is set according to how many people live in a house or by household. Since the marginal cost of discharge is zero, there is no incentive to reduce additional waste. Two-tier pricing is another per-bag pricing scheme. In a municipality that introduces two-tier pricing, people can use a certain number of bags that are distributed by the municipality at no charge. If they use all the distributed bags, they have to buy additional bags to dispose of their waste. In other words, two-tier pricing mixes characteristics of the two schemes: fixed pricing first and unit-based pricing afterward. Thus, the magnitude of waste generation in a municipality depends on how many free bags are distributed per household and how much the extra bags cost. It is important to consider such a program distributes hundreds of free bags to households in practice. For example, Shimotsuma City in Ibaraki Prefecture distributes a token to each household to be exchanged for free bags. At designated stores, citizens can get 100 free bags for households of one or two members, 120 free bags for households of three or four members, and 140 free bags for households of five or more members. If a household uses up its free bags, it must buy extra bags for 50 yen apiece [2]. We describe the three schemes in Figure 5.

As is supported by many studies, the introduction of bag pricing (UBP or two-tier pricing) reduces household waste because it places the burden of waste generation on the citizens and encourages them to refuse too much wrapping in store (e.g., Kinnaman and Fullerton, 2000; Dijkgraaf and Gradus, 2009; Allers and Hoeben, 2010). By contrast, fixed pricing does not change people's actions, because the economic burden is the same for any volume of waste. We transform these categories into dummy variables of whether a municipality introduces a pricing method. Although prior studies in Japan such as Yamaya (2007) and Usui (2008) collected richer bag-price data, we cannot use those data because the studies include only large city data or data for only a single year, respectively. The data of the former paper meets the panel structure condition but not the adjacent condition, whereas the latter paper meets the adjacent condition but not the panel structure condition. Therefore, we avoid using those data. Instead, we use the pricing dummy variables obtained from the Japan Waste Management Association (1998–2002) for our study.

Second, we explain the other demographic variables employed in prior studies on garbage pricing (we take a natural logarithm of all explanatory variables): income per capita, population density, household size, and age structure. $\ln$ *Popd* represents the natural log of population density (persons/km^2). This variable is used as a proxy of scarcity of land space, and it reduces waste generation by composting backyard waste if the population density decreases. In addition, we assume that the population density is related to the amount of office waste, as mentioned in Section 2. $\ln$ *Income* is the natural log of the income per capita but is proxied by taxable gain per capita (Yen). It captures the amount of people's consumption and environmental consciousness to reduce/refuse plastic bags or packaging waste. $\ln$ *Family*, the natural log of the household size, may include a merit scale of consumption because a large household size exhibits increased household consumption but decreased per capita consumption of, for example, shared goods such as newspapers. Further, *Over 65* represents the ratio of people aged over 65 to total municipal population and captures the household character of elderly people.

[2]Details can be found at http://www.city.shimotsuma.lg.jp/page/page000091.html

3.2.2 Data sources

We merge two types of municipal panel data, waste data and demographic data. Here, we show the data source and its size.

First, we explain the municipal waste (i.e., the dependent variable) and UBP data, which includes all municipalities in Japan (approximately 3200 municipalities) obtained from Japan Waste Management Association (1998–2002). We created panel data pertaining to the waste generations for each municipality spanning a 5-year period from the fiscal years 1998 to 2002. Although we use data that is over 10 years old, as municipal mergers occurred only after 2002, the effects of these mergers are not pertinent to these data. Second, other demographic data are obtained from Asahi Shimbun (2003), which provides a collective database containing data for all municipalities. We exclude any missing values, and the final data used in our estimation becomes 2951 (municipalities) $\times$ 5 (years) balanced panel data.

In addition, we create a spatial weight matrix based on a queen contiguity criterion. W is a 2951×2951 matrix. The element (i, j) of W is set equal to 1 if municipalities i and j share border or vertex and 0 otherwise [3].

The descriptive statistics and the definitions of the variables are presented in Table 1. Table 1 also shows the status of the pricing method for the municipalities. A municipality adapts either no bag pricing or only one pricing method out of the following three. The most popular method of pricing waste is UBP by bag: 29% of municipalities had introduced this method in Japan (a pooled sample mean for 5 years). The second most popular method was fixed pricing (16%), and the third was two-tier pricing (3%). 52% of municipalities did not introduce any pricing method. Figure 2, 3, and 4 are geographic distributions of the three types of pricing in 2002.

4 Estimation Result

4.1 Interpretation of Direct and Indirect Effects

We base our interpretation of the total, direct and indirect effects on the discussion of LeSage and Dominguez (2012), and interpret the parameters from the $\boldsymbol{\beta}$ and $\boldsymbol{\beta}_s$ the extended panel spatial Durbin model in Equation (9). In order to interpret the total, direct and indirect effects including the spatial spillover, we use the coefficient estimates of the rth explanatory variables to summarize the average (cross-sample) impact of changing the rth explanatory variable on the dependent variable vector y. To see this, we rewrite the model in (9) as a matrix form into Equation (17).

[3] We do not use a row standardized matrix, in which the elements of each row add up to one, because using a non-standardized matrix to represent the spillover effect per municipality is clearer.

$$\mathbf{y} \;=\; (\mathbf{I}_T - \rho \mathbf{I}_T \otimes \mathbf{W})^{-1}[\mathbf{i}_T \otimes \boldsymbol{\alpha} + \mathbf{Z}\boldsymbol{\theta} + \boldsymbol{\epsilon}] \tag{17}$$

In the tth period,

$$\begin{aligned}(\mathbf{I}_n - \rho\mathbf{W})\mathbf{y}_t &= \boldsymbol{\alpha} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{X}_t^s\boldsymbol{\beta}_s + \boldsymbol{\epsilon}_t, &(18)\\ \mathbf{y}_t &= \sum_{r=1}^{k} S_{rt}(\mathbf{W})\mathbf{X}_{,tr} + v(\mathbf{W})\boldsymbol{\alpha} + V(\mathbf{W})\boldsymbol{\epsilon}_t, &(19)\end{aligned}$$

where $\mathbf{X}_{,tr}$ is the rth row of $\mathbf{X}_t$, $S_{rt}(W) = V(\mathbf{W})(\mathbf{I}_n\beta_r) + \mathbf{W}\beta_{sr}$, $V(\mathbf{W}) = (\mathbf{I}_n - \rho\mathbf{W})^{-1} = \mathbf{I}_n + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \rho^3\mathbf{W}^3 + \ldots$. In this situation, the derivative of y_{it} with respect to x_{jtr} is

$$\frac{\partial y_{it}}{\partial x_{jtr}} = S_{rt}(\mathbf{W})_{ij}, \tag{20}$$

and the derivative of y_{it} with respect to x_{itr} is

$$\frac{\partial y_{it}}{\partial x_{itr}} = S_{rt}(\mathbf{W})_{ii}. \tag{21}$$

Thus, the direct and indirect effects are defined by

$$\begin{aligned}\bar{M}_t(r)_{direct} &= n^{-1}tr(S_{rt}(\mathbf{W})), &(22)\\ \bar{M}_t(r)_{total} &= n^{-1}\mathbf{i}_n' S_{rt}(\mathbf{W})\mathbf{i}_n, &(23)\\ \bar{M}_t(r)_{indirect} &= \bar{M}_t(r)_{total} - \bar{M}_t(r)_{direct}. &(24)\end{aligned}$$

In econometrics, equation (17) is referred to as the data-generating process. If we take a partial derivative of $\mathbf{y}$ in Equation (17) with respect to a change in the rth variable x_{itr}, we can obtain the Equations (22), (23), and (24) [4].

4.2 Estimates of Direct and Indirect Effects

In this subsection, we report the scalar summary measures of direct and indirect effects that arise from changes in the explanatory variables in Table 3. The scalar summary of indirect effect shows a cumulative indirect impacts (spillover) can be found by adding up the increased in the amount of immoral disposal across all other municipalities, excluding the own-municipality change in the amount of total waste directly [5].

The direct effect of UBP (D_{ubp}) did not include zero in the 95% credible intervals, and is negative, as expected[6]. Although Equations (22) and (24) can be used to calculate the direct and indirect effects when

[4]We do not need to explain total effect in the estimation result.

[5]The definition of cumulative effect is shown in LeSage and Pace (2009).

[6]Here, we take a Bayesian estimation approach. Therefore, we do not show the statistical significance level in these estimation results.

the explanatory variables are continuous, our explanatory variables of garbage pricing are dummy variables. Therefore, the equation should be interpreted as the dummy version.

Because all estimations are in natural log form, the coefficients of the dummies are calculated as $e^x - 1$ with x coefficients (Wooldridge, 2008). The magnitude of the direct effect was on average 2.57% ($= e^{-0.026} - 1$) of reducing total waste generation less than that not introducing UBP. The negative indirect effect indicated that UBP reduced the total waste generation of a municipality through the immoral disposal to neighboring municipalities, which represents spillovers cumulated over all municipalities (excluding itself). Therefore, we found evidence of immoral disposal caused by UBP.

On average, the direct effect of municipal waste generation using fixed pricing is 2.12% ($= e^{-0.021} - 1$) less than that not using fixed pricing. Although there is no economic incentive to reduce waste, people might be affected by advertising effects: An announcement introducing garbage pricing might raise people's non-pecuniary motivations, such as environmental awareness. The indirect effect of D_{fix} did not include zero in the 95% credible intervals and was negative. This coefficient shows a 2.37% ($= e^{-0.024} - 1$) reduction if the adjacent municipality introduced fixed pricing. In summary, a part of the reduction in total waste from the introduction of fixed pricing in a municipality induces immoral disposal.

We also find evidence of immoral disposal related to the D_{fem}, which is a dummy variable for the introduction of two-tier pricing. The direct effect did not include zero in the 95% credible intervals and was positive. Because a municipality introducing two-tiers pricing distribute hundreds of free bags to each household, this is considered too many bags, causing an increase in waste generation. Meanwhile, the positive indirect effects indicate spillovers, such that introducing two-tiers pricing in a municipality causes immoral disposal and increases total waste generation in its neighboring municipality. Because the municipality that introduced two-tier pricing provides a certain amount of free bags as mentioned above, people may feel burdened to buy bags, and, hence, dispose immorally. Thus, a two-tier pricing policy promotes individual household transportation of waste to either local convenience stores or those in other municipalities, and thus, it may be inefficient because it reduces the economies of density–one waste collection truck is less resource-intensive than separate trips by a multitude of households.

Next, we explain the estimation results of the demographic variables in Table 2. The posterior mean of the natural log of the average household size in each municipality, $\ln Family$, did not include zero in the 95% credible intervals and is negative as expected. This result indicates collective consumption. For example, there is only one newspaper per household, and, thus, household waste per capita decreases as household size increases. This result is similar to that presented by Callan and Thomas (2006).

The posterior mean of the natural log of population density, $\ln$ *Popd*, is assumed to control the magnitude of immoral disposal caused by population size. However, the posterior mean included zero in the 95% credible intervals.

The posterior mean of the natural log per capita income, $\ln Income$, included zero in the 95% credible intervals. This was thought to be because the variable was affected by many channels, such as consumption amount (positive effect) and environmental consciousness (negative effect). Because of these combined channels, the effect of per capita income is thought to be canceled out and includes zero in the credible intervals.

The posterior mean of the ratio of the population aged over 65, *Over 65*, did not include zero in 95% credible intervals and was negative. The magnitude of this value interpreted that increasing 1 percentage point of the ratio of the population aged over 65 reduced approximately 2.25% of total waste generation. This is because retired people appear to have considerable time and can therefore refuse containers and packaging waste or compost in their backyards.

All posterior means of the year dummies which were set compared to the baseline of *Year 98* did not include zero in the 95% credible intervals and were positive in the total waste. These results suggest a trend of a gradual increase in waste generation.

5 Conclusion

In this paper, we use a balanced panel of 2951 municipalities in Japan on solid waste covering the period of 1998–2002 to empirically examine whether garbage-pricing policy increases immoral disposal. We use a spatial econometric approach, that is, an extended panel spatial Durbin model, to capture the effect of pricing garbage by the bag on an increase in immoral disposal. In particular, we can divide the effect of garbage pricing into two directions: direct and indirect effects. The major finding of our study is that two-tier pricing could perpetuate immoral disposal garbage.

Our results have significant policy implications. First, we can observe the direct reduction of total waste in a municipality introducing UBP or fixed-charge pricing. Second, there is a significant increase in total waste disposal when the neighboring municipality introduces two-tier pricing. People might not choose to buy priced bags and dispose waste appropriately because they may feel burdened buying priced bags, and thus, they may tend to dispose immorally. Therefore, we recommend that municipalities not introduce two-tier pricing because it not only increases their total waste generation but also induces immoral disposal and increases total waste generation in neighboring municipalities.

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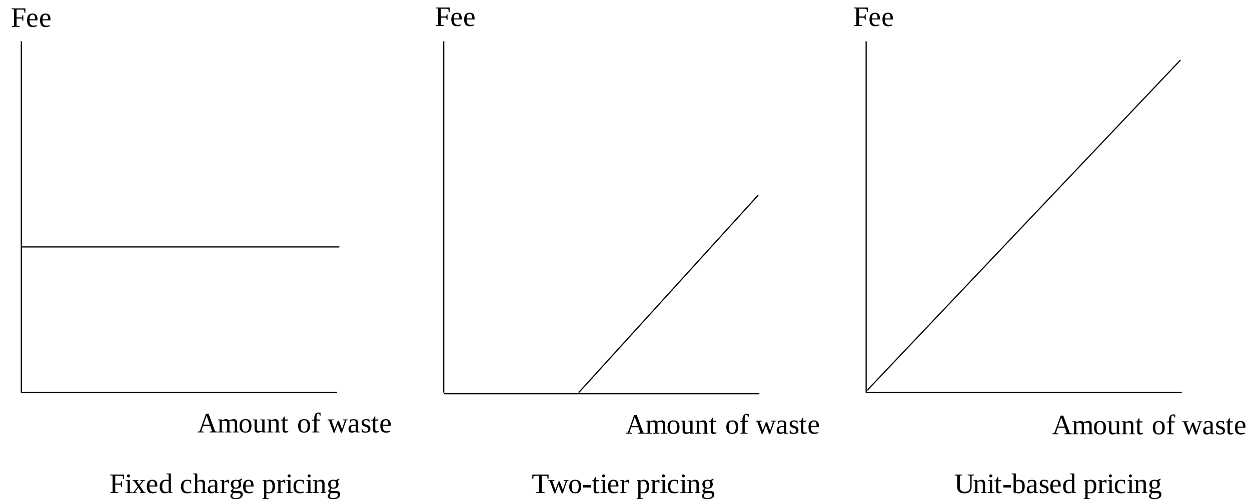

Figure 1: Three types of bag pricing

Table 1: Pooled sample descriptive statistics (2951 municipalities, 5 year period)

Variable	Mean	Std Dev	Min	Max
$\ln w_{total}$	6.620	0.449	2.469	8.773
$\ln Family$	1.110	0.152	0.494	1.551
$\ln Popd$	5.130	1.508	0.258	8.732
$\ln Income$	0.104	0.245	-0.911	2.269
Over 65	0.237	0.069	0.076	0.514
D_{ubp}	0.286	0.452	0	1
D_{fix}	0.163	0.370	0	1
D_{fem}	0.033	0.178	0	1
$W \times D_{ubp}$	0.280	0.309	0	1
$W \times D_{fix}$	0.154	0.226	0	1
$W \times D_{fem}$	0.033	0.104	0	1

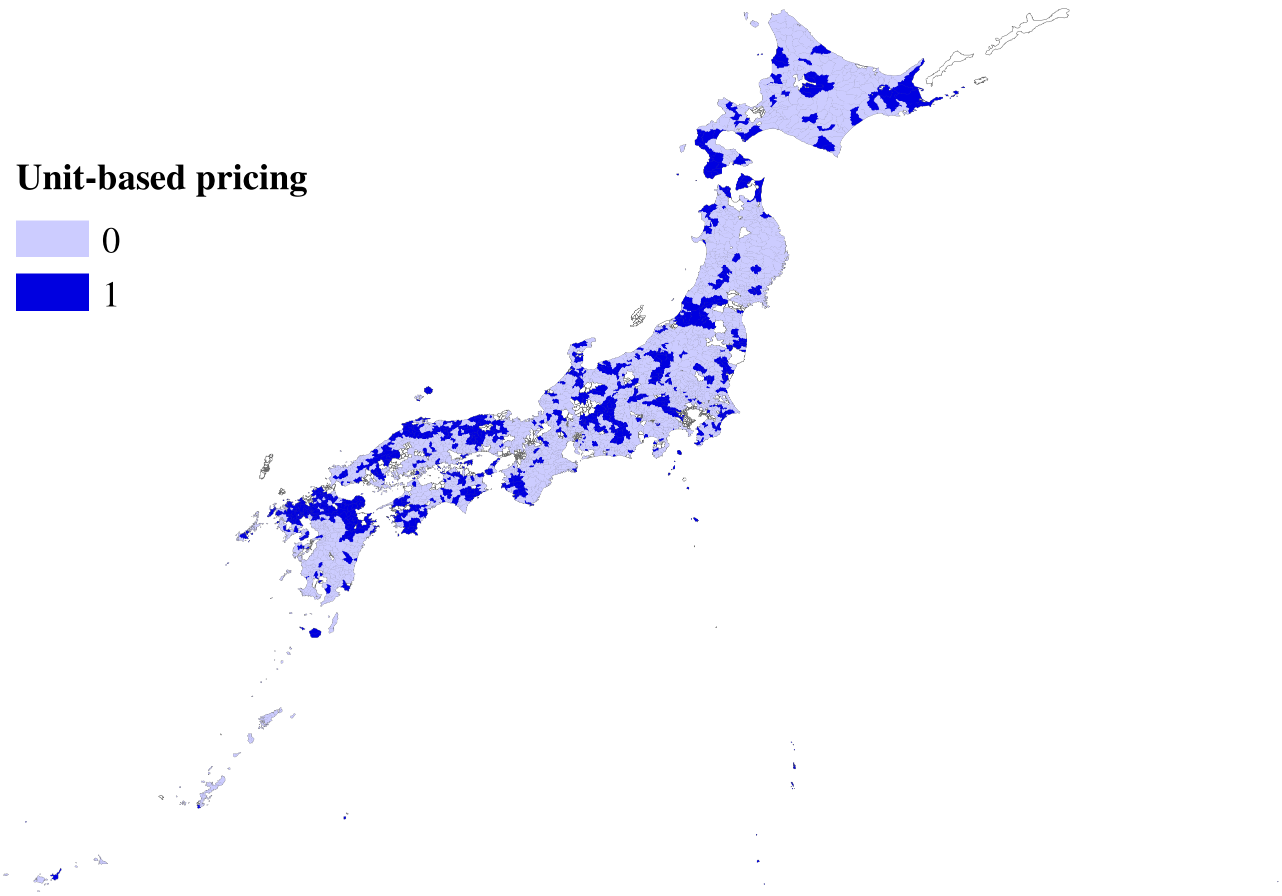

Figure 2: Spatial distribution related to introduction of bag price, in 2002: Unit-based pricing

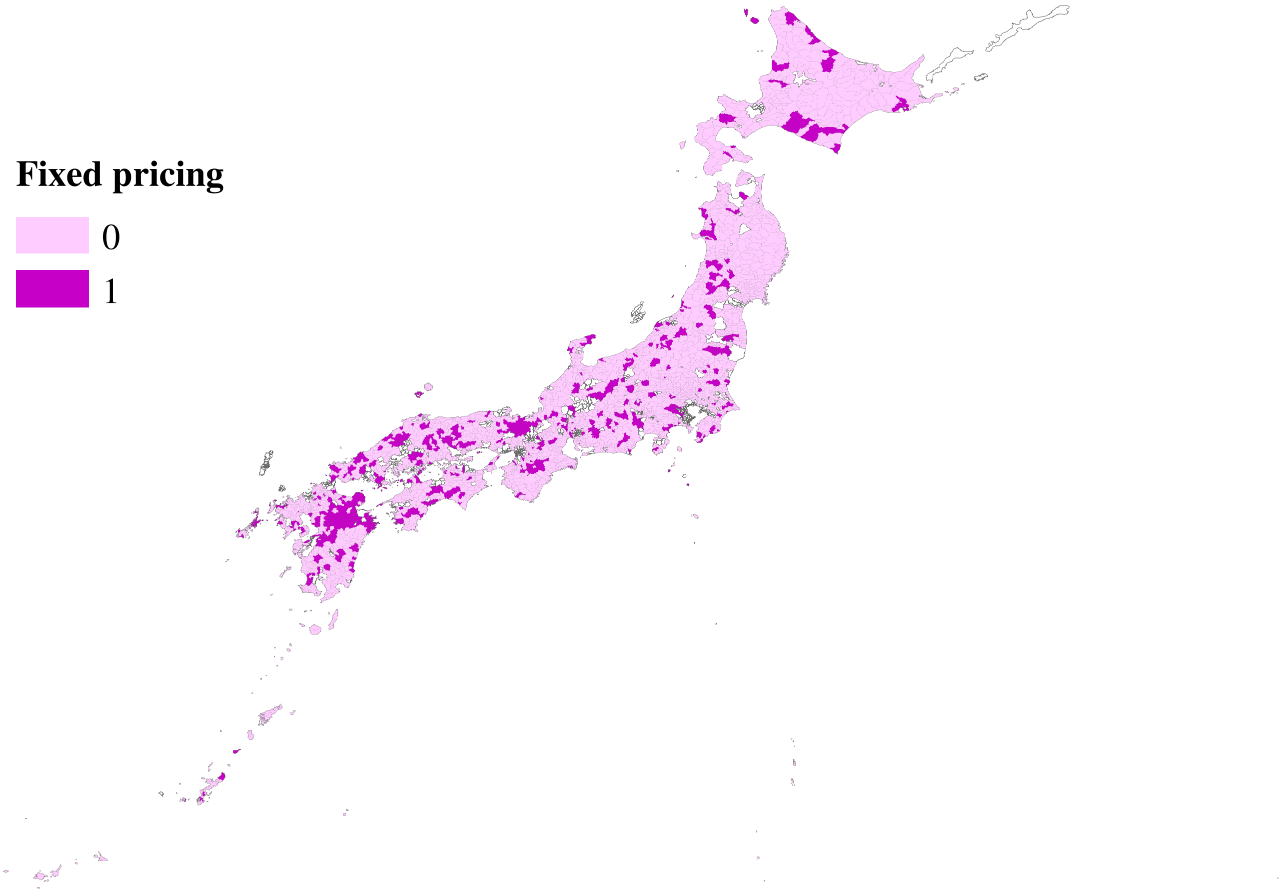

Figure 3: Spatial distribution related to introduction of bag price, in 2002: Fixed pricing

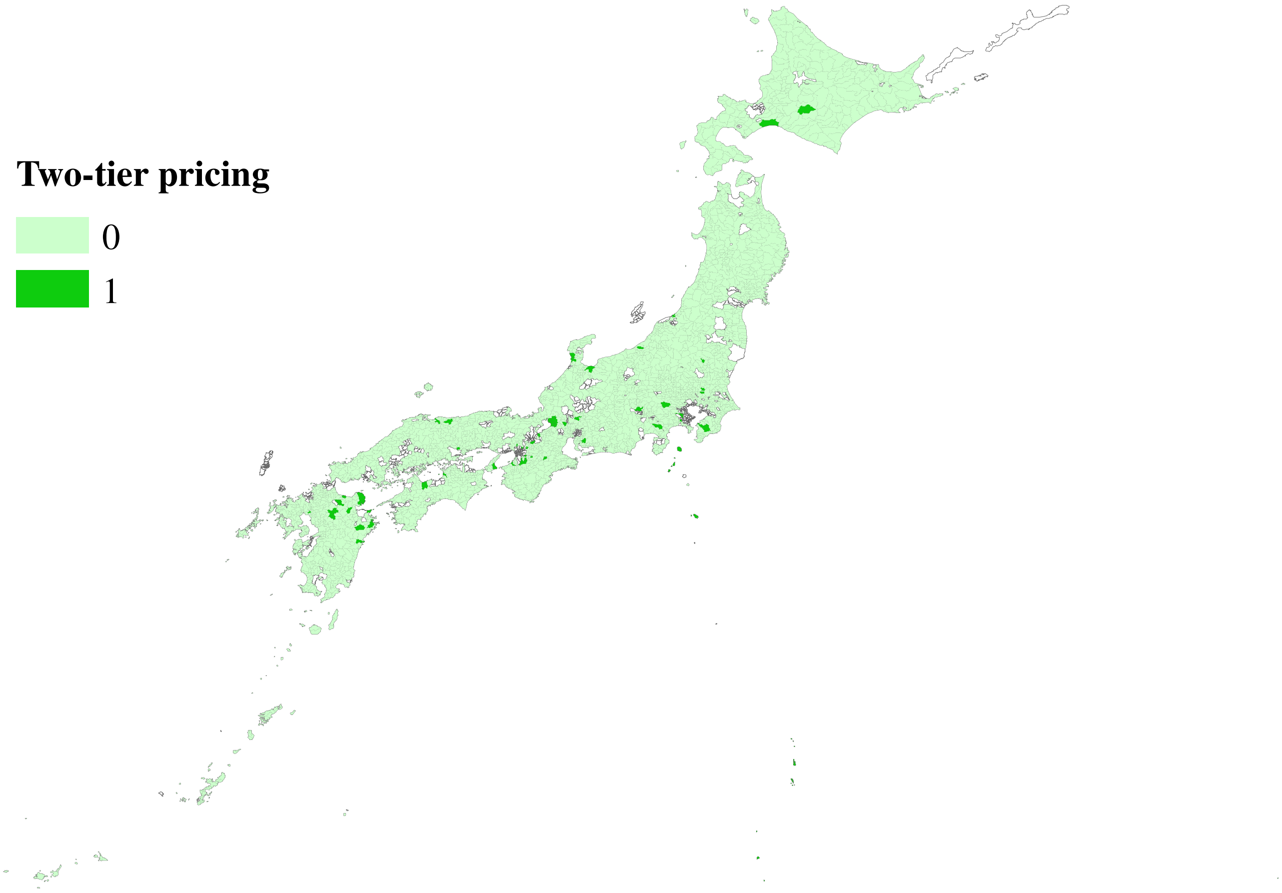

Figure 4: Spatial distribution related to introduction of bag price, in 2002: Two-tier pricing

Table 2: Estimation result

Variable	Coefficient	Std error	2.5%CI	97.5%CI
α	8.067	0.043	7.958	8.133
τ^2	0.123	0.003	0.116	0.130
$\ln Family$	-1.245	0.034	-1.310	-1.182
$\ln Popd$	-0.001	0.005	-0.011	0.008
$\ln Income$	-0.033	0.023	-0.079	0.011
Over 65	-2.249	0.096	-2.443	-2.065
Year 99	0.029	0.004	0.022	0.036
Year 00	0.059	0.004	0.051	0.067
Year 01	0.066	0.004	0.057	0.074
Year 02	0.081	0.005	0.071	0.091
D_{ubp}	-0.025	0.006	-0.037	-0.014
D_{fix}	-0.021	0.007	-0.034	-0.008
D_{fem}	0.019	0.009	0.000	0.037
$W \times D_{ubp}$	-0.039	0.010	-0.059	-0.020
$W \times D_{fix}$	-0.020	0.011	-0.042	0.001
$W \times D_{fem}$	0.033	0.016	0.001	0.064
σ^2	0.018	0.000	0.018	0.019
ρ	0.070	0.004	0.062	0.079

Table 3: Direct and indirect effect

Variable	Coefficient	Std error	2.5%CI	97.5%CI
D_{ubp}				
Direct effect	-0.026	0.006	-0.038	-0.014
Indirect effect	-0.042	0.010	-0.063	-0.023
D_{fix}				
Direct effect	-0.021	0.007	-0.034	-0.009
Indirect effect	-0.023	0.011	-0.045	-0.001
D_{fem}				
Direct effect	0.019	0.009	0.001	0.037
Indirect effect	0.035	0.017	0.003	0.068