IDEC DP² Series Vol. 3 No. 10

Developmnet Discussion Policy Paper

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December, 2013

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Bayesian Estimation of the Decoupling of Affluence and Waste Discharge under Spatial Correlation: Do Richer Communities Discharge More Waste?

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Abstract

A number of developing countries have come to face the growing problems of municipal solid waste management caused by rapid economic growth. Although there are many studies on the environmental Kuznets curve, very few address the issue of municipal solid waste, and there is still controversy concerning the validity of the waste version of the Kuznets curve hypothesis. In this paper, we provide empirical evidence in support of the waste Kuznets curve hypothesis by applying spatial econometrics methods to municipal-level data from Japan. The study finds valid evidence for the waste Kuznets curve hypothesis using the absolute decoupling method. It is demonstrated that the turning point for household municipal solid waste is approximately 3.7 million yen per person, which is far less than the maximum income in the sample. The success of our study partially stems from our highly disaggregated data and use of a spatial econometrics model that accounts for the mimicking behavior of neighboring municipalities. The former aspect indicates that distinguishing between household and business waste reveals the waste-income relationship, whereas the latter indicates the importance of peer effects when municipal governments formulate waste-reduction policies.

1 Introduction

The compatibility of economic growth with environmental protection has become one of the most important research questions in the field of environmental economics, and a number of researchers have devoted considerable efforts to developing a solution to this problem. One hypothesis that seems to have won a consensus regarding this compatibility is the environmental Kuznets curve hypothesis. The environmental Kuznets curve hypothesis claims that an economy tends to degrade its environmental quality during its initial move toward economic growth but that beyond a certain threshold its environmental quality begins to improve as per

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capita income continues to grow. Many researchers support the environmental Kuznets curve hypothesis based on measures of environmental quality, such as the sulfur dioxide and suspended particulate matter generated per capita. However, there are still several environmental indicators that challenge the validity of the environmental Kuznets curve hypothesis.

One such indicator is municipal solid waste (MSW). When environmental quality is measured in terms of waste generation per capita, the environmental Kuznets curve hypothesis is specifically called the waste Kuznets curve (WKC) hypothesis. Although waste is a serious environmental issue for many countries with high economic activity and is becoming a more acute challenge in many rapidly developing countries, there is a lack of solid empirical evidence that demonstrates that per capita waste generation follows the path predicted by the WKC hypothesis. Using a spatial econometric analysis of highly disaggregated data from Japan, this paper provides empirical evidence that MSW and per capita income follow the relationship predicted by the WKC.

The contribution of our paper is twofold. First, we use highly disaggregated municipality-level data (from 1798 municipalities in Japan) and consider the spatial dependence across municipalities. As mentioned by Mazzanti and Zoboli (2009), one of the obstacles in the examination of the WKC hypothesis is the use of spatially aggregated data, such as country-level data. Often, the definition of waste varies from country to country, thereby inevitably making the results of cross-country analyses biased. Moreover, studies that employ country-level data inadvertently neglect the heterogeneity among municipalities in the same country, such as between Beverly Hills, California, and Kodiak Island, Alaska. Such disparities can be more significant than cross-country differences between, for example, the US and Canada. We therefore focus on spatial disaggregation within one country using municipality-level data instead of country-level data. Furthermore, there is increasing evidence that the waste management of a municipality is highly affected by that of its neighbors. For example, Eyckmans, De Jaeger and Verbeke (2009) and De Jaeger (2011) found waste-price mimicking behavior among municipalities using Flemish municipality-level data. Hage *et al.* (2008) and Ham (2009) also found spatial dependence between municipalities within the context of waste management.[1] To capture such spatial autocorrelations, we introduce a spatial econometric approach to the analysis of WKC. In particular, we estimate the WKC trend using a spatial autoregressive model (SAR) and a spatial error model (SEM). Our method is therefore closely related to that of Maddison (2006), who performed an empirical environmental Kuznets curve analysis using SAM and SEM. The greatest difference from Maddision (2006) is that our results include Bayesian estimation, which is highly popular in the spatial econometric literature. Within the context of WKC analysis, only Mazzanti *et al.* (2012) considered the spatial issue, but they only employed Moran's I statistics and did not estimate the WKC trend using SAR or SEM.

Our second contribution is that in our data we classify MSW into two different types: household solid waste and business solid waste (hereafter, household MSW and business MSW, respectively). The former type is the waste that is generated by households, whereas the latter is the waste that is generated by small businesses, offices, restaurants, and schools. It is generally understood that the amount of household waste is directly related to the income of the residents in the municipality, whereas the same relationship does not seem to hold for business waste. In fact, the amount of business waste is affected not only by the residents of the municipality but also by the behavior of restaurant patrons or commuters to offices or schools from distant municipalities. Thus, businesses and households employ different decision-making processes when discharging waste. Using aggregate data that combine the two different types of

[1] In particular, Ham (2009) applied several different spatial econometric models to the UK's municipality-level data and found evidence of spatial clustering among municipalities with similar recycling rates and evidence of the regional convergence of recycling rates. Hage *et al.* (2008) investigated the determinants of the household plastic packaging collected per resident using Swedish municipal-level data in 2005 and found that the amount of plastic waste collection in a municipality is positively related to that of neighboring municipalities.

MSW into a single index to study the WKC may therefore make it difficult to identify a robust relationship between income levels and the amount of waste generated. To our knowledge, no other study of WKC has introduced the idea of separating MSW into household and business MSW.

We believe the lack of spatial econometric approaches and disaggregation of the waste type in previous literature makes it difficult to examine the WKC hypothesis accurately. Thus, the purpose of the present study is to reexamine the WKC hypothesis by including these two features in the analysis. Although this study uses the data of a developed country, Japan, to examine the WKC hypothesis, it will be highly informative for devising an effective waste management policy for developing countries because the future situations of these countries will likely be similar to the status quo in developed countries. In fact, a number of developing countries are now confronting a growing problem of municipal solid waste disposal. Zhang *et al.* (2010), for example, report that the total amount of MSW generation in China, a leader of the developing countries that has achieved impressive economic growth, increased from 31.3 million tons in 1980 to 212 million tons in 2007. In India, the amount of discharged waste in Delhi is expected to rise from approximately 7 thousand tons per day in 2001 to 17-25 thousand tons per day in 2021 (DUEIIP (2001)). In addition to the problem of increasing waste generation, many developing countries suffer from the lack of a sanitary MSW disposal system or of MSW regulations, which are especially essential for proper waste disposal management.

In developing countries, the issue of waste disposal management is an especially important environmental problem that must be solved immediately. Examining the relationship between economic growth and the amount of discharged waste in those countries is considered appropriate for the development of an effective waste management policy because the policy developed through such procedures is expected to have wide application to future waste generation in developing countries. The present study examines the effects of specific measures of waste management policy, such as the introduction of unit pricing for waste disposal or the number of waste separation categories enacted by the municipality. This study will also be beneficial for the establishment of valid waste management policies in developing countries.

One of the first studies regarding WKC is Cole *et al.* (1997). The researchers used OECD panel data for 1975-1990 and examined the validity of the environmental Kuznets curve hypothesis for several environmental indicators, including municipal solid waste. They found evidence to support the environmental Kuznets curve hypothesis for indicators such as sulfur dioxide and suspended particulate matter but not for municipal waste. In a later study, Fischer-Kowalski and Amann (2001) examined the WKC hypothesis using more recent panel data from OECD countries, but they also failed to find evidence that supported the WKC hypothesis for MSW generation.[2] Mazzanti and Zoboli (2009) examined EU panel data and found overall evidence in favor of the environmental Kuznets curve hypothesis for landfill waste but not for MSW generation.[3] By conducting a country level analysis, Mazzanti and Zoboli (2005) and Mazzanti (2008) examined European countries but did not find evidence in favor of the environmental Kuznets curve hypothesis for MSW generation. In addition to such country level analyses, there were several studies that used province-level data, such as that of Managi and Kaneko (2009), who employed data from 29 Chinese provinces; Mazzanti *et al.* (2012) employed data from 103 Italian provinces. None of these studies, however, found evidence of absolute delinking for MSW generation.[4] Raymond (2004) used international cross-sectional data and found evidence that supported the WKC hypothesis. However, because Raymond used a waste/consumption indicator as his dependent variable, the results cannot be applied

[2]Although Fischer-Kowalski and Amann (2001) could not find evidence of the WKC hypothesis for MSW generation, they found that the hypothesis holds for landfilled waste.

[3]They only found evidence of a relative delinking between income and MSW generation.

[4]Absolute delinking occurs if the turning point is within the range of the observed income levels, whereas relative delinking indicates a positive but decreasing relationship between economic growth and waste discharge.

directly to the case of MSW, which is the focus of our study. Berrens *et al.* (1997) and Wang *et al.* (1998) examined the environmental Kuznets curve hypothesis for hazardous waste using county-level, cross-sectional data in the US, and both found evidence that supported the environmental Kuznets curve hypothesis; however, these studies did not examine any environmental indicators related to MSW generation.

A few limited studies that support the environmental Kuznets curve hypothesis for waste generation are Mazzanti *et al.* (2008) and Mazzanti *et al.* (2009). Although both studies used disaggregated data at the province-level in Italy and found some evidence of WKC, they found that only a few of the richer provinces exhibit delinking between economic growth and the amount of waste discharge. Abrate and Ferraris (2010), using data for selected municipalities in Italy from 2004 to 2006, provide partial evidence of WKC.[5]

There is little evidence that suggests the validity of the WKC hypothesis. All the positive evidence concerns cases of hazardous waste, relies on a waste/consumption indicator, finds that only a few of the richer provinces exhibit delinking between income level and waste generation, and/or examines only selected jurisdictions. In contrast, we present reliable evidence of WKC, especially for household MSW. We do so by disaggregating the data regarding MSW discharge according to the different types of waste generators and by employing a spatial econometric approach.

The remainder of this paper is structured as follows. Section 2 describes the current state of Japan's solid waste management system and presents the data used in the estimation. The econometric models and our definition of spatial dependence are explained in Section 3. Section 4 provides the estimation results and presents related policy implications. Section 5 summarizes the discussion.

[5]Because there are no publicly available data regarding the waste collected in each municipality, these researchers used the data from an extraction survey provided by the company EcoCerved.

2 Practical Background and Data

2.1 The State of Municipal Solid Waste in Japan

In Japan, waste is generally separated into two categories: industrial waste and domestic waste. The *Waste Disposal and Public Cleansing Law* defines certain types of waste generated by industrial activity as industrial waste and the rest as domestic waste. A typical example of industrial waste is waste generated by a factory, whereas a typical example of domestic waste is waste generated by households, small businesses, restaurants, convenience stores, or office buildings. Thus, in Japan, domestic waste corresponds to MSW, as is typically understood in studies of the WKC hypothesis. In what follows, we refer to domestic waste as MSW to remain consistent with the previous literature.

Japanese MSW can be classified into two types: MSW from households and MSW from business activities. As defined in the previous section, the former type of waste is classified as household MSW and the latter as business MSW.[6] The Ministry of the Environment (2008) reported that a total of approximately 49.7 million tons of MSW was disposed of in Japan in 2005, of which, 33.5 million tons (67%) was household MSW, and 16.2 million tons (33%) was business MSW.

Although there are differences in the waste disposal systems used across municipalities, as noted below, the waste generator associated with each type of MSW is in many cases obliged to purchase disposal bags as designated by the municipality and to bring the MSW to the appointed location on the designated day. In Japan, most collected waste is incinerated at an intermediate waste treatment facility before it is landfilled. For example, in 2005, 77.4% of disposed waste was directly incinerated, 5.1% was directly recycled, and 2.9% was directly landfilled. The remaining 14.6% underwent intermediate processing with the aim of recycling

[6] An illustration by a simple figure is available in Appendix A.

the waste or reducing its weight. Overall, 14.7% ended up in landfills, and 14.1% was eventually recycled.[7] The amount of waste that is landfilled greatly depends on the method of intermediate waste disposal employed by each municipality and, thus, is not decided at the household level. Because the volume of landfilled waste reflects a different type of result in our empirical analysis based on the per capita income level of households, we decided not to include this amount in this paper.

In the past, the priority of the MSW management policy in Japan was to provide acceptable levels of sanitary waste disposal. For this purpose, incineration has become widely used as the waste disposal method in Japan. However, because of the increased amount of MSW in recent years, waste reduction is now a major aim of the waste management policy. In fact, the Japanese government promotes what is called the "3Rs" principle and aims to build a sustainable society. "3Rs" is an acronym for "Reduce, Reuse, Recycle", and the order of words indicates the hierarchy of waste management strategies.[8]. In accordance with this principle, several types of waste management legislation, such as the *Basic Act for the Promotion of the Recycling-Oriented Society*, the *Act on Promoting Green Purchasing*, and the *Containers/Packaging Recycling Act*, have been introduced in Japan. Whereas national legislation establishes the national strategy for waste management, the practical operation of MSW disposal services is planned and conducted by each individual municipality. In fact, chapter four of the *Waste Disposal and Public Cleansing Law* stipulates that each municipality is responsible for creating its own plan for disposing the MSW generated in its region. Thus, the waste management policies for MSW differ widely across municipalities.[9] For example,

[7] We excluded the recyclable waste that is collected through "group collection" when we calculated the recycle ratio. This scheme is employed by citizen groups and private recyclers and is independent of municipality-level waste collection systems.

[8] Similar principles have been introduced in several countries and regions. For example, the EU has introduced a five-stage hierarchy of waste management strategy: first comes the prevention of waste, followed by reuse, recycling, other recovery, and disposal.

[9] In contrast, regarding industrial waste, the law stipulates that the waste should be disposed of by the generator itself.

some municipalities collect plastics as combustible waste, whereas other municipalities collect plastics as incombustible refuse. When processing recyclable waste, some municipalities pick up only packaging materials, whereas others collect waste paper or used textiles in addition to packaging materials. Waste collection systems vary across municipalities. For example, some municipalities have set up waste-collection points, whereas others have introduced door-to-door collection schemes that are similar to the curbside collection systems used in Europe and the United States.

Moreover, there are municipalities that simultaneously use both types of collection systems. A number of municipalities have adopted the waste-collection points system for household MSW while introducing a door-to-door collection system for business MSW. Because the *Waste Disposal and Public Cleansing Law* permits municipalities to outsource waste collection to the private sector, the operating body responsible for waste collection is not the same across municipalities. Although there are several municipalities that provide waste collection services themselves, a number of municipalities outsource all or a part of their operations. The same is true of waste disposal operations.

Thus, a municipality can be considered an independent decision-making entity within the context of waste management. Consequently, aggregating the data (at the national level, for example) is problematic because it may obscure the effects of disparate waste management policies that differ across municipalities. We therefore use data at the municipality level in our empirical analysis.

2.2 Data

In the following empirical analysis, we developed a municipality-level, cross-sectional dataset for Japan in 2005. The waste-related data were obtained from the Japanese Ministry of the Environment (2008), whereas other socioeconomic data, such as information regarding income per capita and population density, were obtained from the Ministry of Internal Affairs and Communications (2008).

There are two main reasons we use cross-sectional data rather than panel data. The most important reason is the large number of municipality mergers led by the national government from the late 1990s to the mid-2000s. In fact, the total number of municipalities was reduced by more than half as a result. The mergers caused an attrition problem that seriously weakens the reliability of the related panel data.[10] The other reason we use cross-sectional data is the availability of socioeconomic data. Because crucial socioeconomic data (e.g., information regarding household composition) are only released every five years, we could not develop a panel dataset that included sufficient longitudinal information. For these reasons, we employ the latest available cross-sectional data, those from 2005, in the following analysis.

/////// Insert Table 1 near here. ///////

Table 1 presents descriptive statistics for the variables we use. In Table 1, `waste` is the total MSW generation per capita (unit: grams per day per capita) in a municipality. These data can be disaggregated into two classes: `wasteh` and `wasteb`. The former is the household MSW, and the latter is the business MSW. As described above, because the relationship between income level and the amount of waste discharged will be different for households and businesses, it is important for us to separate waste into household MSW and business MSW when analyzing the WKC hypothesis.

The most important non-waste variable in this study is `income`. This variable is defined as the total taxable gains (unit: million yen) in a municipality. `perinc` (million yen per capita) is simply calculated by dividing `income` by the number of income tax payers. Thus, `perinc` is considered the income per household rather than the income per capita. `perinc2` is the square

[10] See Wooldridge (2002, chapter 17) for details.

of perinc.

In analyzing the effect of waste disposal policies, we define hprice, bprice, and sorting. hprice(bprice) is a dummy variable that equals one if a municipality introduces unit pricing for the disposal of household MSW (business MSW). To avoid the endogeneity problem with regard to waste policy, a one-year lag is adopted for both hprice and bprice[11]. However, this approach cannot be directly employed with the new municipalities that came into being as a result of the mergers in 2005. In these cases, we use the weighted average of the one-year lagged policy variables for each municipality in the pre-merger period.[12] Under the assumption that both household and small-business behavior are rational, we expect less waste generation if unit pricing is introduced. Although studies such as Kinnaman and Fullerton (2000) and Eyckmans *et al.* (2009) considered the effect of charges for waste collection, they examined charges for total MSW rather than distinguishing between household MSW and business MSW.

sorting is the number of categories of waste that the municipality sets and requires the waste discharger to separate. Each municipality can use its own discretion in setting this number. For instance, one municipality might separately collect combustible waste, noncombustible waste, used paper, used plastics, and metals, whereas another municipality might collect most of these waste types (or recyclables) together. Like hprice and bprice, to avoid the endogeneity problem, we calculate the weighted average of the policy variables for those municipalities that constitute a new post-merger municipality.[13] To our knowledge, among the studies of WKC, none have used sorting as an explanatory variable. We hypothesize that sorting has a negative sign because those who employ more time-consuming sorting practices (namely, with greater sorting) will be aware of the reduction in waste generation. Note that MSW policies,

[11]In this manner, we follow Mazzanti *et al.* (2012).
[12]For further details regarding this variable, see Appendix B.
[13]See Appendix B for details.

pricing policies, and sorting practices are quite different across municipalities.

We also use other socioeconomic variables that affect waste generation. `shousehold` is the ratio of single-person households to total households. We expect that there will be less per capita MSW generated if there are more than two people in a household. `elderly` is the ratio of households composed of elderly couples to the total[14], and we expect that an elderly household will generate less per capita MSW than a younger household because the amount of goods consumed by elderly people is less than that consumed by younger people. The effect of household size was also considered in Kinnaman and Fullerton (2000), Mazzanti and Zoboli (2009), and Abrate and Ferraris (2010); Kinnaman and Fullerton (2000), Mazzanti and Zoboli (2009), and Eckmans *et al.* (2009) examined the effect of elderly households.

`commutein` indicates the ratio derived by dividing the number of commuters from areas outside the municipality by the number of people who commute from the municipality to elsewhere. We believe this variable indicates the level of economic activity because economically growing municipalities provide employment opportunities for more people and, thus attract people who live outside the municipality. Although studies such as Eckmans *et al.* (2009), Mazzanti *et al.* (2011) and Mazzanti *et al.* (2012) considered the effect of population inflow as defined by the inflow of tourists, no study has focused on the influence of commuters from areas outside the municipality. We expect `commutein` to be positively related to the amount of waste discharged and the volume of landfill waste. Finally, `popden` denotes the population density (the population per 1,000 m^2). This indicator was used in a number of studies, including Hage *et al.* (2008), Mazzanti and Zoboli (2009), and Abrate and Ferraris (2010). Because population density tends to be high in economically significant municipalities, we expect `popden` to be positively related to the amount of waste discharged.

[14] An elderly couple household is defined as a household that is composed of a husband of age 65 or over and a wife of age 60 or over.

3 Econometric Models

There are two different measures of waste generation in our data set: household MSW and business MSW. We separately test for each of these waste generation measures whether the WKC hypothesis holds.

3.1 The Need for Spatial Consideration

One caveat here regards our choice of econometric methods. Our initial conjecture that the behavior of Japanese municipal governments tends to 'mimic' the waste-collection policy employed by their neighbors requires that we assume spatial correlation in our econometric model.[15] Thus, we test the WKC hypothesis by adopting two different spatial econometric models: a spatial autoregressive model (SAR) and a spatial error model (SEM).[16]

The SAR model assumes that the dependent variable, i.e., the amount of waste, is spatially correlated across municipalities, whereas the SEM model assumes that the errors are spatially correlated. In Japan, each municipality belongs to one of 47 prefectures. In this two-tiered system, municipalities in the same prefecture tend to have the same information and regulations, which are provided by their prefectural government. They also tend to implement similar waste management policies. Thus, municipal governments in Japan tend to mimic each other more with regard to their waste-reduction efforts than in their actual waste reduction. Given that these efforts are latent and act as omitted variables in our analysis, we suspect that the errors rather than the amount of waste are spatially correlated.

To reflect this two-tiered regional government system, we design the spatial weight matrix such that before row standardization, its ij element is one if municipality $j(\neq i)$ is in the same

[15] Our Moran's I test results indicate the existence of spatial interdependency among municipalities for all types of waste generation measures. See Table 2 and Table 3 for details.

[16] To check the robustness of our evidence, we also estimate the spatial Durbin model (SDM). The assumptions and results of the SDM are summarized in Appendix D, and they support the conclusions derived using SAR and SEM.

prefecture as the municipality i and zero otherwise.[17] In what follows, we refer to this matrix as spatial weight matrix I (SWM1). This matrix captures the administrative relationship between municipalities rather than focusing on more orthodox geographic relationships (with the elements of the matrix as the inverse of the distance between the municipalities squared.[18]) We refer to the latter matrix as SWM2, and we use these two matrices alternatively in estimating all the models.

3.2 OLS and the Lagrange Multiplier Tests

We begin by specifying the following quadratic relationship between waste generation and per capita income, which is standard in the environmental Kuznets curve literature:

$$Y = \beta_0 + X\beta_1 + X^2\beta_2 + Z\gamma + \epsilon \tag{1}$$

where Y is the $n \times 1$ vector of waste generation per capita; X is the $n \times 1$ vector of the per capita income of the municipalities; and Z is the $n \times k$ matrix of the exogenous variables, where β_0, β_1, β_2 and γ are the corresponding parameters. In our model, parameters that satisfy $\beta_1 > 0$ and $\beta_2 < 0$ imply evidence for the WKC hypothesis.

The above simple OLS model is considered the model under the null hypothesis such that $\rho = \lambda = 0$. In a more general model,

$$\begin{aligned} y &= \beta_0 + \rho W^L Y + X\beta_1 + X^2\beta_2 + Z\gamma + \mu \\ \mu &= \lambda W^E + \epsilon \end{aligned}$$

where the parameters ρ and λ are spatial autocorrelation coefficients; $W^L(W^E)$ as the spatial weight matrix defined above, and ϵ is the error, which is assumed to be independent and

[17]i.e., it is block diagonal with all diagonal elements being zero. Row standardization then divides all the numbers in the ith row by $N_i - 1$, where N_i is the total number of municipalities in the prefecture to which municipality i belongs. Note that each row sums to unity. See Appendix C for more details.

[18]Each element is $1/d_{ij}^2$ for all $i \neq j$, where d_{ij} is the distance between two municipalities i and j, and the diagonal elements are again zero. Row normalization is employed in this case as well such that each row sums to unity.

identically distributed (iid) with mean 0. We compute the Lagrange multipliers for both lags and errors under the null of $\rho = \lambda = 0$ and the robust Lagrange multipliers for lags and errors under the null of $\rho = 0$ and $\lambda = 0$ without any restrictions on the values of λ and ρ.[19] Comparing these figures indicates whether it is more appropriate to assume SAR or SEM. We will elaborate on these findings in the results section.

3.3 Spatial Autoregressive and Spatial Error Models

Following Anselin (2001) and others, we consider two alternative spatial econometric models: the spatial autoregressive model (SAR) and the spatial error model (SEM). The spatial lag model is

$$Y = \beta_0 + \rho WY + X\beta_1 + X^2\beta_2 + Z\gamma + \epsilon \tag{2}$$

Again, the parameter ρ is a spatial autocorrelation coefficient, and W is the spatial weight matrix defined above. We assume here that ϵ is iid with mean 0.

Another econometric specification is the spatial error model, in which the spatial interdependence occurs through the error terms. Formally, this model is represented as follows:

$$Y = \beta_0 + X\beta_1 + X^2\beta_2 + Z\gamma + \mu \tag{3}$$

$$\mu = \lambda W\mu + \epsilon \tag{4}$$

The behavioral assumption in the SAR model is that municipalities care about the actual amount of waste generated by their neighbors; we consider this assumption to be unlikely. Instead, we expect SEM to be more appropriate than SAR because municipalities in the same prefecture are expected to be consistent with regard to waste reduction efforts that are largely unobservable, such as educational programs and public advertisements encouraging waste reduction.[20] Should the contiguity effect exist, it will appear in the error term as the omitted

[19] See Anselin *et. al.* (1996) for details.

[20] In Japan, there are several types of educational programs related to waste reduction that are provided by

variable, which yields the spatial error model.

3.4 The Estimation Methods

The field of spatial econometrics has rapidly developed since the seminal textbook by Anselin (1988) was written. This development enables us to expand the scope of spatial econometrics. It is inappropriate to estimate (2) using OLS because of the endogeneity problem with regard to the spatial lag term. Given the large sample ($n = 1,798$) in our work, it would be standard to use maximum likelihood estimation. However, the results of the Jaque-Bera test (reported in Tables 2 and 3) cause us to reject the normality of the error distribution. To address this problem, we use the generalized spatial two-stage least squares approach developed by Kelejian and Prucha (1998) for the estimation of SAR and GMM in the manner of Kelejian and Prucha (1999) for SEM.

Another method to address relaxing the assumption of constant variance normal disturbances is to use Bayesian estimation. The introduction of Bayesian estimation has a very significant impact. One of the reasons for this impact is that "Bayesian models allow for the direct estimation of the influence of heteroskedasticity and outliers" (Ross(2013), p. 458). With the help of the development of numerical computation techniques, the Bayesian method has been widely applied in the spatial econometrics literature.

In light of these advances, we have added Bayesian estimation results. For our purposes, being able to check the variance of the linear combination of the estimates without using the linear approximation (delta method) is an additional advantage of using Bayesian models. The difference between the conventional and Bayesian approaches is the use of prior information in Bayesian estimation.[21] Our assumption regarding the prior distribution ($\pi(\cdot)$) is as follows.

municipalities. For example, some municipalities organize seminars for residents or businesses that promote an understanding of how to reduce waste generation or how to sort waste. Furthermore, there are several municipalities that set up tours of waste disposal facilities or recycling facilities so that residents can learn about the municipality's waste management scheme.

[21]There are philosophical discussions between conventional frequentists and Bayesians regarding the use of

$$\pi(\boldsymbol{\beta}) \sim N(c, \sigma^2 T) \tag{5}$$

$$\pi(\sigma^2) \sim NIG(a, b) = \frac{b^a}{\Gamma(a)} (\sigma^2)^{-(a+1)} \exp(-b/\sigma^2) \tag{6}$$

$$\pi(\rho) = U(\lambda_{min}^{-1}, \lambda_{max}^{-1}), \tag{7}$$

where a, b, c, T are parameters. $N(\cdot)$ is the normal distribution, whereas $NIG(\cdot)$ denotes the normal inverse-gamma distribution. We assume non-informative priors for ρ and $U(\cdot)$, namely, that they are uniformly distributed,ion and that $\lambda_{min}(\lambda_{max})$ denotes the minimum (maximum) eigenvalue of the spatial weight matrix. By combining this prior information into (2), (3) and (4), we can derive the posterior distribution of each spatial econometric model. To solve the models, we use Metropolis - Hastings sampling, which is one of the Markov Chain Monte Carlo (MCMC) approaches. We set the number of samplings to 150,000 and discard the first 5,000 as the "burn-in".[22]

4 Results

Through our empirical analysis, we found solid evidence in favor of the WKC hypothesis for household MSW. The estimation results are summarized in Tables 2 and 3. Note that each variable in the estimation (except for the dummy variables) is in the form of a natural logarithm. Each table contains estimates from different econometric models for each of the alternative spatial weight matrices[23]. The dependent variables are indicated in the top-left corner of each table.

/////// Insert Table 2 near here. ///////

prior information. Thus, we estimate in both ways to compare the results. Poirier (1988) provides an excellent survey of Bayesian methods and the frequentist method.

[22]See LeSage and Pace (2009, p.133 - 141) for details of the computational methodology.

[23]Recall that SWM1 captures administrative proximity, with the ij element being non-zero if municipalities i and $j\,(\neq i)$ are in the same prefecture and zero otherwise. In contrast, SWM2 is a more-orthodox spatial weight matrix based on the geographical distance between the municipalities.

/////// Insert Table 3 near here. ///////

4.1 Evidence for Spatial Interdependence

All Moran's I tests and LM tests (LM_{err}, LM_{lag}, RLM_{err} and RLM_{lag}) are statistically significant at the 5% level or better for all models, which indicates the existence of spatial correlation and thus supports our tests of spatial models in investigating the WKC hypothesis. Our initial conjecture was that neighboring municipalities' mimicking behavior is mostly not measurable and, hence, appears in the error term as a missing variable. Indeed, as indicated by Table 2, the values obtained from the robust LM tests reveal that RLM_{err} is always significant and consistently larger than RLM_{lag}.[24]

First, we focus on the results of the household MSW. Through the GS2LS and GMM estimation methods of spatial models, the lag coefficient ρ is insignificant, whereas λ for the spatial error is significant for household MSW under SWM2, the distance-based spatial weight matrix. These results seem to support our view that municipal governments care more about their neighbors' efforts to reduce waste than about their neighbors' actual performance at waste reduction. However, the results for the contiguity-based spatial weight matrix (SWM1) presented in Table 2 and the Bayesian estimation results demonstrate that both ρ and λ are significant, thereby implying that municipalities follow the actual waste generation performance of others on top of the above-mentioned mimicking behavior.[25]

The results for business MSW are not necessarily consistent with the results for household MSW. For business MSW, whereas the spatial lag coefficient ρ is insignificant and RLM_{err} is

[24]Note that we have

$$LM_{err} + RLM_{lag} = LM_{lag} + RLM_{err}$$

Direct comparison of RLM_{err} and RLM_{lag} as a model-specification strategy is outlined in Anselin and Ray (1991), Maddala (1992), Florax and Folmer (1992), Anselin and Florax (1995), and Florax *et al.* (2003).

[25]Results of the spatial Durbin regression including WZ. The spatial correlation of the policy variables fortifies this view, with both ρ and λ being statistically significant. The spatial Durbin regression is conducted via a Bayesian approach for the technical reason that G2SLS uses WZ as an instrument. See Appendix D and Tables A1 and A2 for details.

greater than RLM_{lag} for both spatial weight matrices, it is only with SWM2 that the spatial error coefficient λ is significant. However, the magnitude of λ is still less than that of household MSW. For example, according to the result from SEM with SWM2, it is 0.504 in the case of business MSW. Therefore, our initial conjecture regarding the intangible mimicking behavior of these municipalities is only weakly supported for business MSW.

The validity of SEM implies that the spatial correlation stems not from the strategic behavior of particular municipalities but rather from the unobservable characteristics of each municipality. The SAR model is considered a more appropriate model in most previous studies that used data from European countries, such as Hage *et al.* (2008), Eyckmans *et al.* (2009), and De Jaeger (2011). However, the significance of the SEM in our study reflects the particular attributes of waste management in Japan, which is quite different from its European counterpart. One of the reasons could be that red-tapism, or a focus on justification of the waste management policy rather than the actual outcome, is more pervasive and dominant in local Japanese governments compared with the consequentialism that is prevalent among European countries. To ensure that a waste management policy attains the designated aim, we should not be satisfied with just implementing a proper policy package; rather, we must monitor the consequences on a regular basis. Although it would be interesting to examine these differences between Europe and Japan, this issue is one for future research.

4.2 Evidence for WKC

We summarize the results for the tests of the WKC hypothesis. To confirm the WKC hypothesis, we must obtain a positive sign for the estimated coefficient for per capita income and a negative sign for the estimated coefficient for its squared term. For household MSW, these coefficients satisfy the sign requirements and are statistically significant at the 1% level in all spatial models, thus demonstrating WKC. This result is robust regardless of which of the two alternative spatial weight matrices we employ, SWM1 or SWM2.

However, as indicated in Tables 2 and 3, WKC does not hold as expected for business MSW because a number of people commute to offices or schools from distant municipalities; hence, business MSW is not directly related to the per capita income of the residents of the municipality.[26] These results imply that the dependence of waste generation on income growth depends on the type of MSW. Thus, to demonstrate WKC, we must distinguish household MSW from business MSW. To ignore this factor as previous studies have done makes it difficult to demonstrate WKC.

4.3 Turning Points on WKC: Absolute Decoupling

Next, we investigate the actual income distribution over the observed WKC to determine whether the turning point of the curve falls within the observed income range. Based on the definition provided by OECD (2002), we conclude that absolute decoupling occurs if the turning point is within the range of the observed income levels; otherwise, relative decoupling occurs.

/////// Insert Table 4 near here. ///////

Table 4 presents a summary of the turning points obtained through our analyses.[27] As indicated in the table, absolute decoupling is observed, with the turning point being less than the maximum of the observed income. Furthermore, the quadratic term of per capita income is estimated to be consistently strictly negative for the household MSW. In particular, the results of SEM for household MSW demonstrate that the turning point is at a log per-capita income

[26] Another potential reason WKC is not observed for business MSW is that the amount of business MSW processing is to some extent substitutive to that of household MSW with greater income elasticity. This point should be investigated in future research.

[27] These results are obtained by calculating the stationary point of the estimated equations (2) and (3) with respect to per capita income and applying the delta method for the standard deviations. The delta method computes the standard deviation of the turning points through a linear approximation around the point estimates of the slope and second-order coefficients of income. Therefore, we provide its intervals via results from Bayesian estimation below.

of approximately 1.3, or 3.7 million Japanese yen.[28] Recognizing that the standard errors for SAR in Table 4 seem to be sufficiently small , while the turning points for SEM have much larger standard errors. Because the results with SWM2 are nearly the same for both SAR and SEM, the results demonstrate the robustness of the absolute decoupling, at least for the SAR model.

/////// Insert Table 5 near here. ///////

/////// Insert Figure 1 near here. ///////

For further robustness, we compute the same turning points using the coefficients derived by Bayesian estimation and summarize the results in Table 5. By computing the stationary point ($= \frac{\hat{\beta}_1}{2\hat{\beta}_2}$), each of 150,000 sampling processes, and storing them, we can replicate the probability density function for the turning points. Figure 1 shows the histogram of the turning points for SAR and SEM. The figure indicates that 95% of the sample is within the range of 1.1 to 1.4. Given that the log of the average per capita income is 1.09, with a minimum of 0.746 and a maximum of 1.78, absolute decoupling is observed with 5% significance.

4.4 Implication of Policy Variables

Regarding the policy variables, it is noteworthy that the signs of `hprice` and `sorting` are significantly negative for household MSW. This result implies that charges for garbage collection and increases in the number of waste separation categories significantly decrease the amount of waste. This tendency is also observed in Tables A1 and A2, where we run the spatial Durbin model, which incorporates the neighbors effects on explanatory variables.[29]

In contrast, the sign of unit pricing for business MSW(`bprice`) is significantly positive, and

[28] This value is approximately 37 thousand US $ per household. Recall that `perinc` is taxable gain (not actual figures on a payroll).

[29] As shown Table A3, the indirect effect on household MSW is positive, whereas the direct effect is negative for both policy variables, with the total effect being negative. Please see Appendix E for details.

it is inconsistent with our expectation. Unlike the unit pricing scheme for household MSW, `bprice` has already been introduced in numerous municipalities, and the value of `bprice` does not vary significantly among municipalities. This lack of difference may make estimation of the effect of `bprice` difficult. Because the effect of unit pricing schemes for business MSW is ambiguous, additional strategies (e.g., setting physical targets for business MSW reduction) are necessary to further reduce the amount of business MSW.

4.5 Implication of Socioeconomic Variables

We also find interesting results with respect to the socioeconomic variables examined here. First, the variable `commutein` is positively and significantly related to all the waste-generation measures. As noted above, this variable indicates the level of economic activity. Therefore, it is quite natural that the amount of waste discharged increases as `commutein` increases.

The population-related data also yield several implications. First, the sign of `shousehold` is significantly positive in all the models. This result indicates that an increase in the ratio of single-person households to total households significantly increases the amount of both household MSW and business MSW. Although Kinnaman and Fullerton (2000) considered the effect of household composition on waste discharge by using family size as an explanatory variable, they did not find statistically significant results. As was the case for `elderly`, the results are rather unclear. The results are significantly negative for business MSW; however, the results are positive but not statistically significant for household MSW. Because a household's economic activity is thought to decrease as its members age, business MSW will decrease as the percentage of elderly couple households increases. This result is consistent with that of Kinnaman and Fullerton (2000), whereas Mazzanti and Zoboli (2009) and Eyckmans *et al.* (2009) reached the opposite conclusion. Finally, the variable `popden` is positive and statistically significant in almost all the models. This result implies that the amount of waste discharged significantly increases as population density increases. Mazzanti and Zoboli (2009) and Mazzanti *et al.* (2012) obtained similar findings, whereas Kinnaman and Fullerton (2000), Hage (2008), Abrate and Ferraris (2010) and Eyckmans *et al.* (2009) did not.

5 Conclusions

In this paper, we found strong evidence of WKC when analyzing the MSW discharged by municipalities in Japan. Disaggregating the data for MSW discharge based on the types of waste generators at the municipal level, we extended the literature by demonstrating that the data for household MSW support the WKC hypothesis but that those for business MSW do not. We demonstrated that the relationship between income level and the amount of waste discharged is different for households and businesses. The amount of household MSW is directly affected by the behavior of the residents of the municipality, whereas the amount of business MSW is significantly affected by the behavior of the people who come to the municipality from distant municipalities. Thus, distinguishing between these two types of waste may be the key to confirming the WKC hypothesis for MSW generation.

In recent years, a number of developing countries have faced growing municipal solid waste management problems because of rapid economic growth. To address this problem, authorities are enhancing MSW management policies, including continuous construction of new waste disposal facilities. However, our result demonstrates the possibility that this increasing tendency in the total amount of MSW will come to an end in the not-so-distant future. Thus, policymakers should account for this probability when they develop future waste management strategies.

Our results also suggest the importance of diverse MSW management policies that are tailored to each region's income level. As is well known, there is considerable wealth disparity between urban and rural areas in developing countries. Some parts of urban areas will enter the declining period of waste generation earlier than rural areas. Therefore, it may be appropriate for urban authorities to ease waste regulations in anticipation of the possibility of a decrease in the amount of MSW. In fact, in the decreasing period of waste generation, it may be beneficial to spend resources not on waste reduction policy but rather on the policies aimed at the solution of other serious environmental problems, such as air pollution and water contamination.

A Classification of waste in Japan

/////// Insert Figure A1 near here. ///////

B Derivation of Policy Variables

As mentioned in Section 2.2, we must use additional steps to generate policy variables for all the municipalities because some of the municipalities merged in 2005 and did not exist in the previous year. We define the policy variables for unit pricing and the number of sorting categories as follows:

$$\texttt{hprice}_i = \sum_{j \in M^i} \left(\frac{\texttt{wasteh}_{j,2004}}{\sum_{j \in M^i} \texttt{wasteh}_{j,2004}} \texttt{hprice}_{j,2004} \right)$$

$$\texttt{bprice}_i = \sum_{j \in M^i} \left(\frac{\texttt{wasteb}_{j,2004}}{\sum_{j \in M^i} \texttt{wasteb}_{j,2004}} \texttt{bprice}_{j,2004} \right)$$

$$\texttt{sorting}_i = \sum_{j \in M^i} \left(\frac{\texttt{waste}_{j,2004}}{\sum_{j \in M^i} \texttt{waste}_{j,2004}} \texttt{sorting}_{j,2004} \right)$$

where i and j denote the particular municipality, M^i is a set of municipalities that are merged into municipality i after the merger, and the number 2004 indicates that the data are from 2004. For example, $\texttt{hprice}_{j,2004}$ is a dummy variable that takes a value of one if municipality j introduced unit pricing for household MSW disposal in 2004. According to the above definition, if municipality i did not merge with any other municipalities between 2004 and 2005, then $\texttt{hprice}_i = \texttt{hprice}_{i,2004}$, $\texttt{bprice}_i = \texttt{bprice}_{i,2004}$, and $\texttt{sorting}_i = \texttt{sorting}_{i,2004}$ hold. However, if municipality i did merge with other municipalities, then the policy variables are defined as the weighted average of the one-year lagged policy variables for each municipality in the pre-merger period. The weight is defined as the share of waste discharge.

C Formal Definition of SWM1

We assume that municipalities are considered contiguous if they are in the same prefecture. When the ith municipality is contiguous with the jth municipality, the (i, j) element of the spatial weight matrix takes a value of one in our case. For instance, if there are three municipalities in each of two prefectures A and B (see Figure A2), the spatial weight matrix is as follows:

	A1	A2	A3	B1	B2	B3
A1	0	1	1	0	0	0
A2	1	0	1	0	0	0
A3	1	1	0	0	0	0
B1	0	0	0	0	1	1
B2	0	0	0	1	0	1
B3	0	0	0	1	1	0

/////// Insert Figure A2 near here. ///////

Then, our actual spatial matrix, W, is

$$W = \begin{bmatrix} D_1 & 0 & 0 & \cdots & 0 \\ 0 & D_2 & 0 & \cdots & 0 \\ 0 & 0 & D_3 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & D_K \end{bmatrix} \tag{8}$$

where

$$D_k = \begin{bmatrix} 0 & 1 & 1 & \cdots & 1 \\ 1 & 0 & 1 & \cdots & 1 \\ 1 & 1 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix}. \tag{9}$$

Note that $K(=47)$ is the number of prefectures. As is assumed in the previous literature, the diagonal elements of D_k in the spatial weight matrix are set to zero, and the row elements sum to one when we use (9) in the actual estimation.

D Spatial Durbin Model

It has often been observed that some policy variables are spatially correlated. From its construction, ignoring this type of spatial correlation affects the error term as an omitted-variable problem. To capture this interdependence properly, we estimate a model called the spatial Durbin model, which is defined as below.

$$Y = \beta_0 + \rho WY + X\beta_1 + X^2\beta_2 + Z\gamma + WZ\beta_3 + \mu \tag{10}$$

$$\mu = \lambda W\mu + \epsilon \tag{11}$$

We call this model the spatial autoregressive Durbin model (SARD) when $\lambda = 0$ and the spatial error Durbin model (SEMD) when $\rho = 0$. The estimation results are summarized in Tables A1 and A2. The qualitative features of the results are nearly the same as the SAR and SEM results presented in Section 4.

/////// Insert Table A1 near here. ///////

/////// Insert Table A2 near here. ///////

Our main purpose is to see if there is any evidence for absolute decoupling for household waste generation. Table A3 summarizes the turning points computed based on the MCMC estimation of (11). Again, the results are nearly identical to the turning points presented in the main text.

/////// Insert Table A3 near here. ///////

E Estimation Results for Spatial Effects

One of the notable differences between the conventional OLS and the SARD model is the interpretation of marginal effects by the explanatory variable, such as z_{ir}. Suppose a usual OLS, such as

$$y_i = \sum_{r=1}^{k} \beta_r z_{ir} + \epsilon. \tag{12}$$

Then, a marginal effect on a dependent variable (y_i) by z_{ir} is $\frac{\partial y_i}{\partial z_{ir}} = \beta_r$. Suppose further that α, β_r, and θ_r are the parameters and that ι_n is an $n \times 1$ vector of 1s. The SARD model version of (12) is

$$y_i = \sum_{r=1}^{k} [S_r(W)_{i1} z_{1r} + S_r(W)_{i2} z_{2r} + \cdots + S_r(W)_{n1} z_{nr}] + (I_n - \rho W)_i^{-1} \iota_n \alpha + (I_n - \rho W)_i^{-1} \epsilon \tag{13}$$

where

$$S_r(W) = (I_n - \rho W)^{-1}(I_n \beta_r + W\theta_r) \tag{14}$$

and $S_r(W)_{ij}$ is the i, j th element of $S_r(W)$. It is now clear that the derivative of y_i by z_{ir} is no longer equal to β_r and

$$\frac{\partial y_i}{\partial z_{ir}} = S_r(W)_{ij}. \tag{15}$$

Thus, a change in the independent variable of a region could have an effect on the dependent variable in all other regions. In fact, taking the own derivative of (13) results in $S_r(W)_{ii}$, which is the impact on a dependent variable in region i caused by changing x_{ir}. Note that this impact includes the feedback effect that region i has on region j and that region j also affects region i. The average of this effect among all n regions is called the direct effect ($\overline{M}_{direct}$) (LeSage and Pace (2009, p. 36), which is

$$\overline{M}_{direct} = \frac{\mathrm{Tr}(S_r(W))}{n} \tag{16}$$

Note that $S_r(W)$ contains $(I_n - \rho W)^{-1} = I_n + \rho W + \rho W^2 + \cdots$ and that the diagonal of the higher order of W, which has zeros on its diagonal, is not necessarily zero. LeSage and Pace (2009) also define the total effect as

$$\overline{M}_{total} = \frac{\iota_n'(S_r(W))\iota_n}{n} \tag{17}$$

$$\overline{M}_{indirect} = \overline{M}_{total} - \overline{M}_{direct} \tag{18}$$

$\overline{M}_{total}$ simply measures how a change in region i influences all other regions. It is straightforward to interpret subtracting a region's own effect from $\overline{M}_{total}$; the result is called the indirect effect.

Table A4 summarizes the spatial effect of the policy variables. The definitions of the three effects are based on LeSage and Pace (2009), as explained above.

/////// Insert Table A4 near here. ///////

Looking carefully Table A4, we note that the effect of unit pricing for households and business entities is completely the opposite. For households, the direct effect is positive, which indicates that average households reduce waste if they face the introduction of unit pricing. Business entities, in contrast, have a positive value for the direct effect. The reason for this effect could be that the unit pricing for business waste has been introduced in municipalities that already had greater business MSW generation. This result is another example of how household MSW and business MSW are different in terms of their generation processes.

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Tables

Table 1: Summary statistics

Variable	Mean	(Std. Dev.)	Min.	Max.	N
`waste`	983.73	(367.28)	148.33	6876.98	1,798
`wasteh`	743.95	(277.26)	148.33	6414.28	1,798
`wasteb`	239.78	(199.94)	0	3091.43	1,798
`bprice`	0.72	(0.44)	0	1	1,798
`commutein`	1.11	(2.42)	0.13	63	1,798
`elderly`	0.11	(0.04)	0.02	0.29	1,798
`hprice`	0.43	(0.49)	0	1	1,798
`income`	88,801	(270,743)	320	6,690,409	1,798
`perinc`	3.03	(0.42)	2.11	5.95	1,798
`popden`	0.84	(1.71)	0.001	13.73	1,798
`shousehold`	0.23	(0.07)	0.07	0.69	1,798
`sorting`	10.94	(4.60)	2	26	1,798

Note 1: The first four variables are dependent variables, all of which are on a per-capita basis.
Note 2: See the text for sources and units.

Table 2: Estimation results of wasteh (above) and wasteb (below) with SWM1

Household MSW	OLS		GS2LS		GMM		Bayesian			
			Spatial Lag Model		Spatial Error Model		Spatial Lag Model		Spatial Error Model	
Variable	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(perinc)]^2	-1.17723**	(0.22543)	-1.16418**	(0.23399)	-1.25192**	(0.22965)	-1.11051**	(0.21454)	-1.2555**	(0.23134)
ln(perinc)	3.14051**	(0.51386)	3.06812**	(0.58259)	3.24965**	(0.53073)	2.76203**	(0.48955)	3.2573**	(0.53654)
ln(commutein)	0.07442**	(0.02039)	0.07646†	(0.04505)	0.08124**	(0.01923)	0.08529**	(0.01923)	0.0819**	(0.01915)
ln(elderly)	0.01125	(0.02182)	0.01030	(0.02596)	0.04670*	(0.02367)	0.00612	(0.02067)	0.0488**	(0.01908)
ln(popden)	0.01499**	(0.00519)	0.01544**	(0.00659)	0.02732**	(0.00557)	0.01733**	(0.00504)	0.0278**	(0.00579)
ln(shousehold)	0.12087**	(0.02225)	0.11922**	(0.02801)	0.12865**	(0.02275)	0.11109**	(0.02111)	0.1284**	(0.02273)
ln(sorting)	-0.06137**	(0.01283)	-0.06038**	(0.01393)	-0.07490**	(0.01316)	-0.05661**	(0.01219)	-0.0750**	(0.01332)
hprice	-0.07742**	(0.01250)	-0.07695**	(0.01256)	-0.08311**	(0.01257)	-0.07454**	(0.01200)	-0.0832**	(0.01263)
bprice	-	-	-	-	-	-	-	-	-	-
Intercept	4.92159**	(0.29576)	4.31279*	(1.89707)	5.03220**	(0.30896)	1.66758**	(0.37362)	5.0328**	(0.31273)
ρ	-	-	0.10113**	(0.31128)	-	-	0.53962**	(0.03978)	-	-
λ	-	-	-	-	0.635**	(0.131) -	-	-	0.6481**	(0.03677)
Jarque Bera	14902**									
Moran's I	0.120**									
LM_{err}	742**									
RLM_{err}	409**									
LM_{lag}	336**									
RLM_{lag}	4.08*									

** 1% * 5% † 10%

Business MSW	OLS		GS2LS		GMM		Bayesian			
			Spatial Lag Model		Spatial Error Model		Spatial Lag Model		Spatial Error Model	
Variable			**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(perinc)]^2	-1.9184†	(1.0664)	-1.95832	(1.19993)	-1.52172	(1.11788)	-1.988†	(1.0542)	-1.496	(1.0883)
ln(perinc)	2.9279	(2.4325)	3.00894	(2.70550)	1.89223	(2.57515)	3.079	(2.4056)	1.825	(2.5200)
ln(commutein)	0.5953**	(0.0966)	0.60433**	(0.17137)	0.67324**	(0.09506)	0.611**	(0.0955)	0.679**	(0.0960)
ln(elderly)	-0.3431**	(0.1036)	-0.31900†	(0.16480)	-0.33114**	(0.11366)	-0.296**	(0.1026)	-0.327*	(0.1121)
ln(popden)	0.2382**	(0.0246)	0.23596**	(0.03651)	0.29443**	(0.02685)	0.235**	(0.0245)	0.301**	(0.0269)
ln(shousehold)	0.5061**	(0.1056)	0.52374**	(0.07456)	0.56011**	(0.11074)	0.535**	(0.1034)	0.566**	(0.1086)
ln(sorting)	0.2077**	(0.2077)	0.21221**	(0.01824)	-0.06949**	(0.01566)	0.217**	(0.0597)	0.255**	(0.0646)
hprice	-	-	-	-	-	-	-	-	-	-
bprice	0.5118**	(0.0656)	0.49758**	(0.07774)	0.47624**	(0.06514)	0.488**	(0.0649)	0.475**	(0.0653)
Intercept	3.3158*	(1.4020)	2.42186	(2.19543)	4.03939**	(1.49666)	1.785	(1.4209)	4.097**	(1.4785)
ρ	-	-	0.18326	(0.33617)	-	-	0.313**	(0.0646)	-	-
λ	-	-	-	-	0.467	(0.306)	-	-	0.511**	(0.0518)
Jarque Bera	19559**									
Moran's I	0.0219**									
LM_{err}	130**									
RLM_{err}	139**									
LM_{lag}	28**									
RLM_{lag}	36.8**									

** 1% * 5% † 10%

N	1,798	1,798	1,798	1,798	1,798

Table 3: Estimation results of wasteh (above) and wasteb (below) with SWM2

	OLS		GS2LS		GMM		Bayesian			
Household MSW			Spatial Lag Model		Spatial Error Model		Spatial Lag Model		Spatial Error Model	
Variable	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(perinc)]^2	-1.17723**	(0.22543)	-1.04387**	(0.26485)	-1.00891**	(0.24461)	-0.90902**	(0.20450)	-0.9883**	(0.24617)
ln(perinc)	3.14051**	(0.51386)	2.69397**	(0.70819)	2.63829**	(0.56489)	2.24409**	(0.46775)	2.5888**	(0.57070)
ln(commutein)	0.07442**	(0.02039)	0.07644†	(0.04291)	0.06946**	(0.01915)	0.07781**	(0.01889)	0.0690**	(0.01894)
ln(elderly)	0.01125	(0.02182)	0.00607	(0.02536)	0.03329	(0.02474)	0.00079	(0.02004)	0.0371	(0.02511)
ln(popden)	0.01499**	(0.00519)	0.01661*	(0.00657)	0.03610**	(0.00601)	0.01821**	(0.00461)	0.0385**	(0.00629)
ln(shousehold)	0.12087**	(0.02225)	0.11696**	(0.02705)	0.12441**	(0.02306)	0.11382**	(0.02025)	0.1231**	(0.02311)
ln(sorting)	-0.06137**	(0.01283)	-0.05358**	(0.01477)	-0.05571**	(0.01355)	-0.04512**	(0.01173)	-0.0553**	(0.01359)
hprice	-0.07742**	(0.01250)	-0.06920**	(0.01457)	-0.06757**	(0.01318)	-0.06065**	(0.01169)	-0.0667**	(0.01327)
bprice	-	-	-	-	-	-	-	-	-	-
Intercept	4.92159**	(0.29576)	3.22084†	(1.78180)	5.35472**	(0.33361)	1.49710**	(0.34041)	5.4001**	(0.33967)
ρ	-	-	0.30286	(0.31505)	-	-	0.60949**	(0.03586)	-	-
λ	-	-	-	-	0.628**	(0.211) -	-	-	0.6967**	(0.03509)
Jarque Bera	14902**									
Moran's I	0.120**									
LM_{err}	742**									
RLM_{err}	409**									
LM_{lag}	336**									
RLM_{lag}	4.08*									

** 1% * 5% †10%

	OLS		GS2LS		GMM		Bayesian			
Business MSW			Spatial Lag Model		Spatial Error Model		Spatial Lag Model		Spatial Error Model	
Variable			**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(perinc)]^2	-1.9184†	(1.0664)	-2.15811†	(1.17548)	-2.08774†	(1.17171)	-2.073*	(1.0172)	-2.142†	(1.1561)
ln(perinc)	2.9279	(2.4325)	3.63246	(2.69141)	3.57611	(2.69927)	3.431	(2.3235)	3.752	(2.6745)
ln(commutein)	0.5953**	(0.0966)	0.58119**	(0.15675)	0.62008**	(0.09455)	0.584**	(0.0923)	0.620**	(0.0935)
ln(elderly)	-0.3431**	(0.1036)	-0.22740	(0.19758)	-0.25082*	(0.11749)	-0.231*	(0.0997)	-0.237†	(0.1195)
ln(popden)	0.2382**	(0.0246)	0.21615**	(0.04166)	0.29222**	(0.02840)	0.217**	(0.0229)	0.296**	(0.0290)
ln(shousehold)	0.5061**	(0.1056)	0.54125**	(0.13440)	0.59903**	(0.11156)	0.539**	(0.1009)	0.610**	(0.1163)
ln(sorting)	0.2077**	(0.2077)	0.21861**	(0.07161)	0.25518**	(0.06561)	0.220**	(0.0580)	0.261**	(0.0645)
hprice	-	-	-	-	-	-	-	-	-	-
bprice	0.5118**	(0.0656)	0.44533**	(0.10238)	0.43274**	(0.06547)	0.449**	(0.0628)	0.427**	(0.0668)
Intercept	3.3158*	(1.4020)	0.73325	(3.33579)	3.22628*	(1.58638)	0.949**	(1.3681)	3.159*	(1.5696)
ρ	-	-	0.47770	(0.56593)	-	-	0.455**	(0.0422)	-	-
λ	-	-	-	-	0.504**	(0.164)	-	-	0.544**	(0.0418)
Jarque Bera	19559**									
Moran's I	0.0219**									
LM_{err}	130**									
RLM_{err}	139**									
LM_{lag}	28**									
RLM_{lag}	36.8**									

** 1% * 5% †10%

N	1,798	1,798	1,798	1,798	1,798

Table 4: Turning points based upon GS2LS and GMM (household MSW)

	SWM1		SWM2	
	SAR	SEM	SAR	SEM
Turning Point	1.318	1.298	1.290	1.307
Standard Error	0.015	0.445	0.035	0.668
	From Original Data			
	mean	min.	max.	s.d.
ln(`income`)	1.090	0.746	1.780	0.134

Note: standard errors are computed by the delta method.

Table 5: Turning Points (Household MSW)

	min	2.5%	25%	50%	75%	97.5%	max
				Spatial Weight Matrix 1			
SAR	1.141	1.189	1.221	1.243	1.268	1.336	1.667
SEM	1.159	1.235	1.274	1.299	1.328	1.407	2.126
				Spatial Weight Matrix 2			
SAR	1.117	1.170	1.210	1.233	1.261	1.346	2.125
SEM	-3.161	1.225	1.275	1.308	1.352	1.491	22.227
				From original data			
ln(`income`)	0.7459	0.8716	1.0056	1.0851	1.1799	1.3857	1.7832

Note: The quantile figures above are based on sample generated during MCMC procedure.

A Tables for Appendix

Table A.1: Spatial Durbin Estimation results of `wasteh` (above) and `wasteb` (below) with SWM1

Household MSW	MLE				Bayesian			
	SAR		SEM		SAR		SEM	
Variable	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(perinc)]^2	-0.99704**	(0.21462)	-1.25346**	(0.22911)	-0.99882**	(0.21440)	-1.25002**	(0.22846)
ln(perinc)	2.57410**	(0.49123)	3.27246**	(0.52937)	2.57975**	(0.48848)	3.26013**	(0.52860)
ln(commutein)	0.08860**	(0.01918)	0.07960**	(0.01987)	0.08929**	(0.01911)	0.08033**	(0.02037)
ln(elderly)	0.04078†	(0.02382)	0.05303*	(0.02395)	0.04212†	(0.02390)	0.05384**	(0.02419)
ln(popden)	0.03124**	(0.00565)	0.02895**	(0.00565)	0.03126**	(0.00564)	0.02930**	(0.00571)
ln(shousehold)	0.13174**	(0.02301)	0.12960**	(0.02302)	0.13152**	(0.02338)	0.12982**	(0.02310)
ln(sorting)	-0.07522**	(0.01327)	-0.07647**	(0.01316)	-0.07539**	(0.01362)	-0.07648**	(0.01312)
hprice	-0.08310**	(0.01266)	-0.08262**	(0.01253)	-0.08363**	(0.01293)	-0.08239**	(0.01241)
bprice	-	-	-	-	-	-	-	-
w.ln(commutein)	-0.15629	(0.10196)	-0.05890	(0.26354)	-0.15471	(0.10444)	-0.02460	(0.29625)
w.ln(elderly)	-0.09551†	(0.05363)	-0.16644	(0.12810)	-0.09634†	(0.05372)	-0.15757	(0.14226)
w.ln(popden)	-0.03688**	(0.01060)	-0.02558	(0.02497)	-0.03658**	(0.01054)	-0.02283	(0.02762)
w.ln(shousehold)	-0.06683	(0.07024)	0.03018	(0.17425)	-0.06598**	(0.07162)	0.01362	(0.19363)
w.ln(sorting)	0.05366†	(0.02802)	0.05855	(0.06713)	0.05520*	(0.02845)	0.06090	(0.07314)
w.hprice	0.07222*	(0.02957)	0.04044	(0.07144)	0.07298*	(0.02987)	0.04094	(0.0779)
w.bprice	-	-	-	-	-	-	-	-
Intercept	1.14199**	(0.35559)	4.55076**	(0.43722)	1.16172**	(0.37640)	4.53359**	(0.46548)
ρ	0.59149**	(0.03843)	-	-	0.58758**	(0.03924)	-	-
λ	-	-	0.62507**	(0.038786)	-	-	0.65226**	(0.03986)

** 1% * 5% †10%

Business MSW	MLE				Bayesian			
	SAR		SEM		SAR		SEM	
Variable	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(perinc)]^2	-1.71031	(1.04533)	-1.58119	(1.10202)	-1.69290	(1.03688)	–1.52144	(1.09055)
ln(perinc)	2.99726	(2.38342)	2.41787	(2.53421)	2.95687	(2.35625)	2.24383	(2.51182)
ln(commutein)	0.64468**	(0.09403)	0.64492**	(0.09492)	0.64536**	(0.09362)	0.64849**	(0.09571)
ln(elderly)	-0.24268*	(0.11693)	-0.27769*	(0.11743)	-0.24111*	(0.11799)	-0.28078*	(0.11854)
ln(popden)	0.31353**	(0.02774)	0.31509**	(0.02774)	0.31374**	(0.02802)	0.31542**	(0.02798)
ln(shousehold)	0.55491**	(0.11321)	0.56621**	(0.11274)	0.55042**	(0.11527)	0.56433**	(0.11319)
ln(sorting)	0.24466**	(0.06527)	0.24665**	(0.06486)	0.24294**	(0.06624)	0.24577**	(0.06440)
hprice	-	-	-	-	-	-	-	-
bprice	0.45782**	(0.06502)	0.46575**	(0.06491)	0.46069**	(0.06596)	0.46479**	(0.06519)
w.ln(commutein)	1.30748*	(0.54112)	-1.70002*	(0.84244)	-1.29493*	(0.55501)	-1.76240†	(0.92866)
w.ln(elderly)	-0.15377	(0.28288)	-0.32785	(0.42155)	-0.15386	(0.28361)	-0.33645	(0.46185)
w.ln(popden)	-0.30459**	(0.05219)	-0.31267**	(0.07688)	-0.30439**	(0.05233)	-0.31470**	(0.08415)
w.ln(shousehold)	-0.02740	(0.34473)	0.22560	(0.52282)	-0.03051†	(0.34604)	0.23622	(0.56094)
w.ln(sorting)	-0.38689**	(0.14421)	-0.46348*	(0.21310)	-0.39112**	(0.14480)	-0.48164*	(0.23848)
w.hprice	-	-	-	-	-	-	-	-
w.bprice	0.12247	(0.29013)	0.42023	(0.43611)	0.13368	(0.29068)	0.40332	(0.47670)
Intercept	2.34559	(1.50667)	4.70979**	(1.71361)	2.37540	(1.47392)	4.90584**	(1.76429)
ρ	0.34856**	(0.06594)	-	-	0.34493**	(0.06757)	-	-
λ	-	-	0.37165**	(0.06451)	-	-	0.41867**	(0.06639)

** 1% * 5% †10%

N	1,798		1,798		1,798		1,798	

Table A.2: Spatial Durbin Estimation results of `wasteh` (above) and `wasteb` (below) with SWM2

Household MSW	MLE				Bayesian			
	SAR		SEM		SAR		SEM	
Variable	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(`perinc`)]^2	-0.86209**	(0.20365)	-0.86127**	(0.24175)	-0.85828**	(0.20304)	-0.85477**	(0.24341)
ln(`perinc`)	2.14486**	(0.46474)	2.28737**	(0.55909)	2.13801**	(0.46192)	2.27206**	(0.56382)
ln(`commutein`)	0.08797**	(0.01877)	0.08126**	(0.01901)	0.08797**	(0.01855)	0.08111**	(0.01916)
ln(`elderly`)	0.00121	(0.01970)	0.03763	(0.02453)	0.00097*	(0.01930)	0.03815	(0.02456)
ln(`popden`)	0.02320**	(0.00491)	0.04373**	(0.00607)	0.02306**	(0.00485)	0.04392**	(0.00605)
ln(`shousehold`)	0.10448**	(0.02036)	0.12250**	(0.02263)	0.10467**	(0.01996)	0.12278**	(0.02287)
ln(`sorting`)	-0.04588**	(0.01189)	-0.04929**	(0.01333)	0.04626**	(0.01162)	-0.04895**	(0.01319)
`hprice`	-0.06044**	(0.01142)	-0.07216**	(0.01293)	-0.06071**	(0.01134)	-0.07204**	(0.01286)
`bprice`	-	-	-	-	-	-	-	-
w.ln(`commutein`)	-0.02836**	(0.00826)	-0.03190	(0.00603)	-0.02836**	(0.00821)	-0.03190*	(0.00609)
w.ln(`elderly`)	-0.04447	(0.02895)	0.05116	(0.04303)	-0.04338	(0.02873)	0.05166	(0.04321)
w.ln(`popden`)	-0.01546**	(0.00626)	-0.05137**	(0.01135)	-0.01566*	(0.00632)	-0.05114†	(0.01162)
w.ln(`shousehold`)	0.08701*	(0.03669)	0.01625	(0.05360)	0.08637*	(0.03699)	0.01644	(0.05296)
w.ln(`sorting`)	-0.01552	(0.04664)	0.00938	(0.05945)	-0.01465	(0.04600)	0.01071	(0.05863)
`w.hprice`	-0.02767**	(0.02855)	0.05086	(0.04143)	-0.02722	(0.02877)	0.050465	(0.04095)
`w.bprice`	-	-	-	-	-	-	-	-
`Intercept`	1.35513**	(0.32594)	5.57646**	(0.33141)	1.37490**	(0.33699)	5.58776**	(0.33325)
ρ	0.63979**	(0.03224)	-	-	0.63729**	(0.03611)	-	-
λ	-	-	0.75401**	(0.03050) -	-	-	0.75913**	(0.03269)

** 1% * 5% †10%

Business MSW	MLE				Bayesian			
	SAR		SEM		SAR		SEM	
Variable	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**	**Coef.**	**(Std. Err.)**
[ln(`perinc`)]^2	-1.77520	(1.15979)	-1.80041	(1.25388)	-1.62361	(1.02865)	-1.81911	(1.15855)
ln(`perinc`)	2.71348	(2.31652)	3.11388	(2.67025)	2.68955	(2.33876)	3.20218	(2.65446)
ln(`commutein`)	0.64092**	(0.09401)	0.66823**	(0.09588)	0.64287**	(0.09717)	0.66771**	(0.09730)
ln(`elderly`)	-0.21377*	(0.09884)	-0.23973*	(0.11602)	-0.21342†	(0.10229)	-0.23833*	(0.11613)
ln(`popden`)	0.25118**	(0.02514)	0.32092**	(0.02893)	0.25080**	(0.02482)	0.32167**	(0.02888)
ln(`shousehold`)	0.49980**	(0.10173)	0.52770**	(0.11074)	0.49730**	(0.10347)	0.52793**	(0.11190)
ln(`sorting`)	0.25460**	(0.05883)	0.24990**	(0.06483)	0.25336**	(0.06017)	0.25007**	(0.06673)
`hprice`	-	-	-	-	-	-	-	-
`bprice`	0.42941**	(0.06255)	0.40712**	(0.06477)	0.43092**	(0.06287)	0.40614**	(0.06375)
w.ln(`commutein`)	0.00108	(0.04039)	0.03669	(0.03106)	0.00095	(0.04045)	0.03646	(0.03061)
w.ln(`elderly`)	-0.57965*	(0.09988)	-0.64851	(0.12400)	-0.57451**	(0.10457)	-0.65521**	(0.12331)
w.ln(`popden`)	-0.00327	(0.02757)	0.00611	(0.04064)	-0.00364	(0.02749)	0.00658	(0.03970)
w.ln(`shousehold`)	-0.15997	(0.19498)	0.51202*	(0.22994)	-0.15774	(0.19732)	0.52926*	(0.23283)
w.ln(`sorting`)	-0.99851**	(0.19058)	-0.83959	(0.20182)	-0.99082**	(0.19469)	-0.83927**	(0.19646)
`w.hprice`	-	-	-	-	-	-	-	-
`w.bprice`	-0.12016	(0.11908)	0.21663	(0.13895)	-0.11768	(0.12082)	0.22186	(0.13786)
`Intercept`	1.43598	(1.34965)	3.46565*	(1.56858)	1.44714	(1.36594)	3.43101	(1.55106)
ρ	0.42336**	(0.04107)	-	-	0.42282**	(0.04644)	-	-
λ	-	-	0.5102**	(0.04232) -	-	-	0.51949**	(0.04518)

** 1% * 5% †10%

N	1,798	1,798	1,798	1,798

Table A.3: Result of spatial effect estimates: Spatial Durbin model

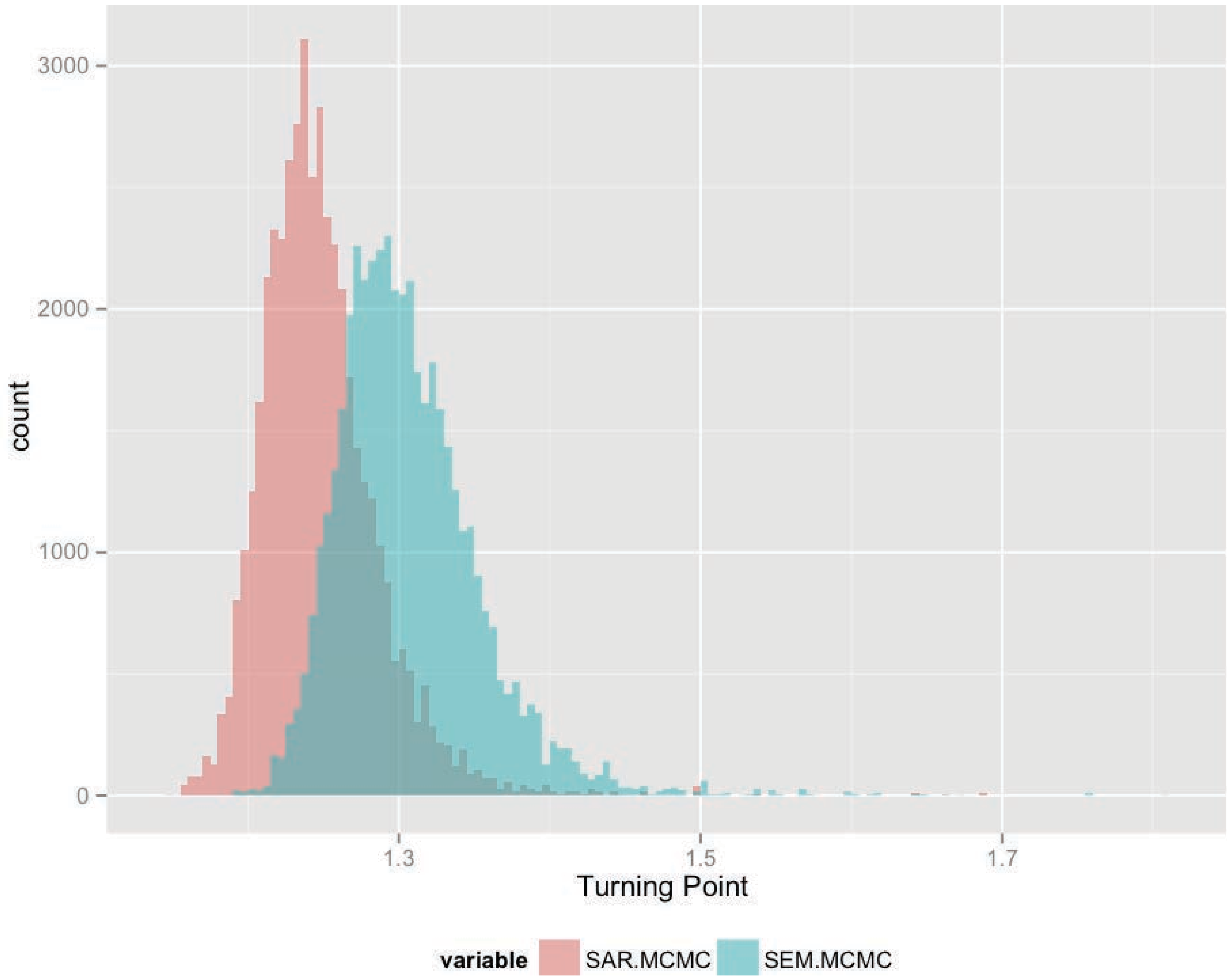
	2.5% lower	50% mean	97.5% upper	2.5% lower	50% mean	97.5% upper
			Spatial Weight Matrix 1			
	household MSW			business MSW		
Direct effect						
`hprice/bprice`	-0.1071	-0.0817	-0.0574	0.347	0.475	0.602
`sorting`	-0.1019	-0.0762	-0.0485	0.125	0.255	0.387
Indirect effect						
`hprice/bprice`	-0.0774	0.06385	0.20852	-0.227	0.6297	1.5108
`sorting`	-0.0736	0.06616	0.20774	-0.975	-0.5436	-0.1223
Total effect						
`hprice/bprice`	-0.1633	-0.0165	0.1282	0.230	1.106	1.972
`sorting`	-0.1488	-0.0106	0.1282	-0.718	-0.295	0.115
			Spatial Weight Matrix 2			
	household MSW			business MSW		
Direct effect						
`hprice/bprice`	-0.0939	-0.0670	-0.0406	0.293	0.420	0.5482
`sorting`	-0.0805	-0.0531	-0.0283	0.135	0.264	0.3964
Indirect effect						
`hprice/bprice`	-0.1639	-0.0256	0.1136	0.159	0.7678	1.3771
`sorting`	-0.2166	-0.0798	0.0557	-0.815	-0.3766	0.0535
Total effect						
`hprice/bprice`	-0.2243	-0.09271	0.04708	0.5543	1.1961	1.784
`sorting`	-0.2707	-0.13113	0.00263	-0.5333	-0.1135	0.294

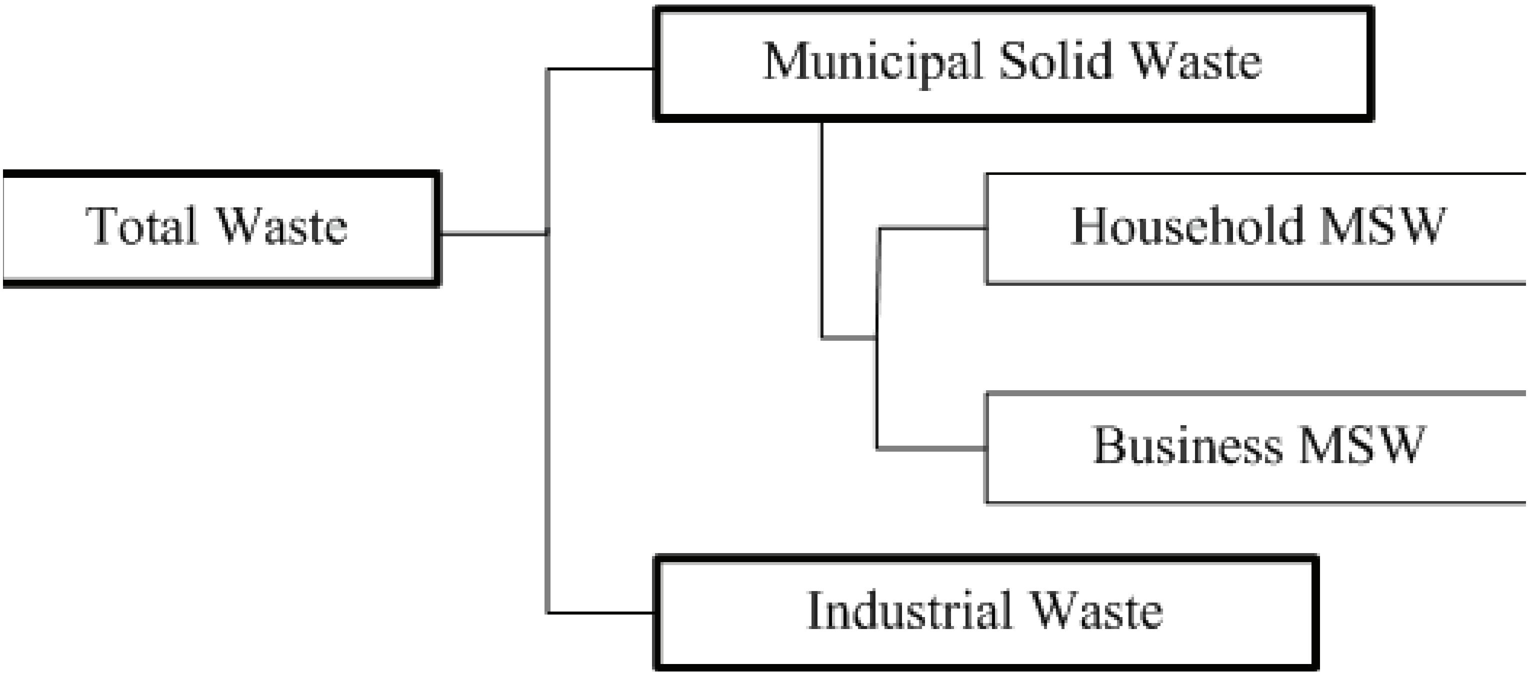
Note: The definition of all three effects (direct, indirect and total) are taken from LeSage and Pace (2009, p34 - 40).

Table A.4: Turning Points (Household MSW)

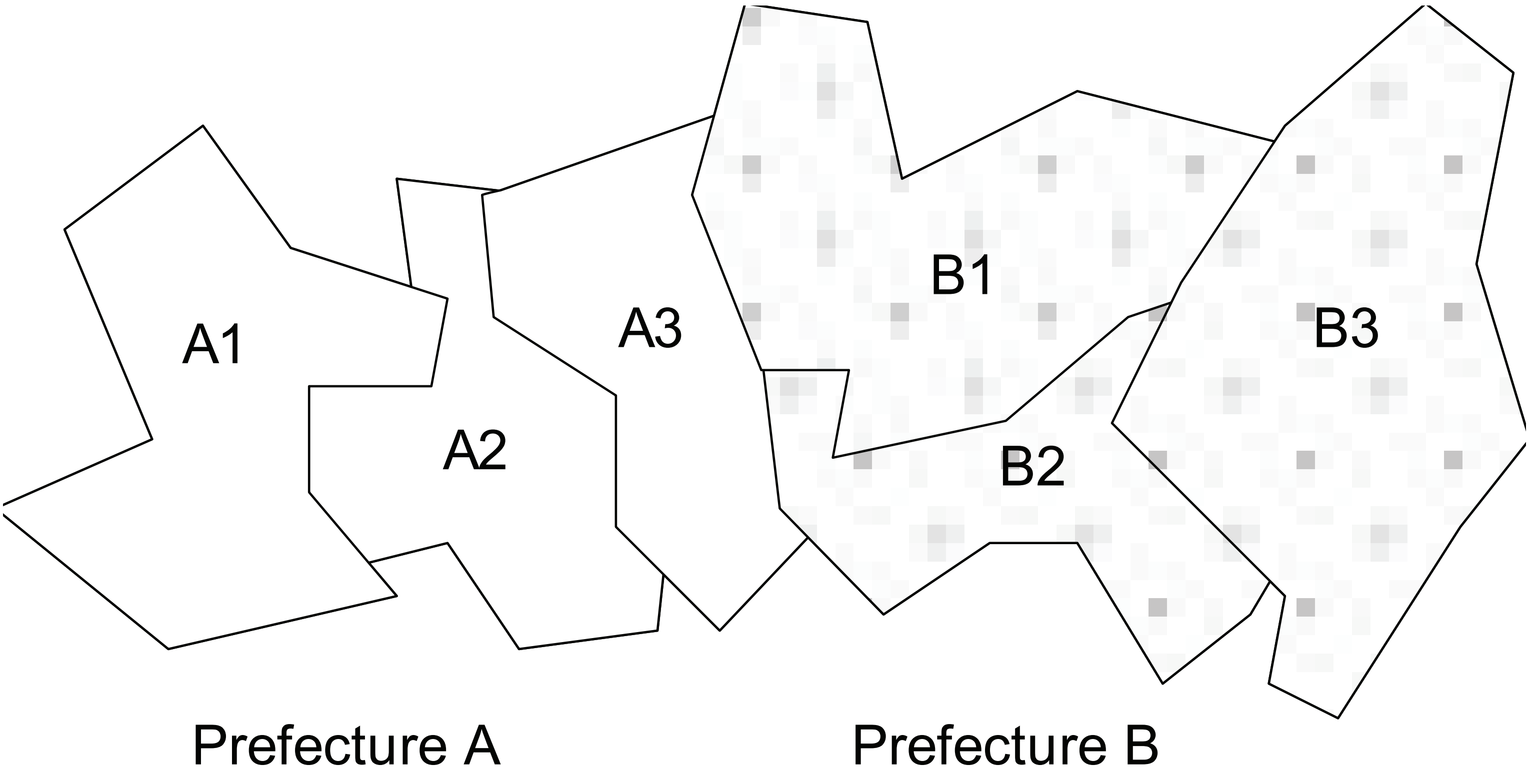
	min	2.5%	25%	50%	75%	97.5%	max
				Spatial Weight Matrix 1			
SAR (Durbin)	1.1633	1.2225	1.2630	1.2913	1.3242	1.4261	1.7774
SEM (Durbin)	1.1494	1.2398	1.2798	1.3041	1.3330	1.4165	1.7079
				Spatial Weight Matrix 2			
SAR (Durbin)	-1.9878	1.1818	1.2199	1.2448	1.2787	1.371	5.8676
SEM (Durbin)	-1.5863	1.2325	1.2889	1.3278	1.3822	1.587	5.9257
				From original data			
ln(`income`)	0.7459	0.8716	1.0056	1.0851	1.1799	1.3857	1.7832

Note: The quantile figures above are based on sample generated during MCMC procedure.


3000
2000
1000
0
count
1.3
1.5
1.7
Turning Point
variable
SAR.MCMC
SEM.MCMC



Total Waste
Municipal Solid Waste
Household MSW
Business MSW
Industrial Waste


A1
A2
A3
B1
B2
B3
Prefecture A
Prefecture B