# Online Apendix for "The Decoupling of Affluence and Waste Discharge under Spatial Correlation: Do Richer Communities Discharge More Waste?"

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## A Classification of waste in Japan

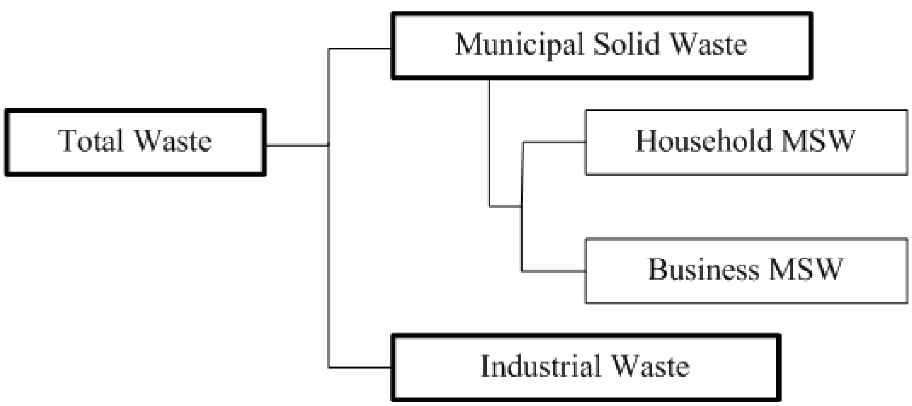


Figure 1: Classification of waste in Japan

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# 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:

$$\begin{aligned}
\texttt{hprice}_i &= \textstyle\sum_{j\in M^i}\left(\frac{\texttt{wasteh}_{j,2004}}{\sum_{j\in M^i}\texttt{wasteh}_{j,2004}}\texttt{hprice}_{j,2004}\right)\\
\texttt{bprice}_i &= \textstyle\sum_{j\in M^i}\left(\frac{\texttt{wasteb}_{j,2004}}{\sum_{j\in M^i}\texttt{wasteb}_{j,2004}}\texttt{bprice}_{j,2004}\right)\\
\texttt{sorting}_i &= \textstyle\sum_{j\in M^i}\left(\frac{\texttt{waste}_{j,2004}}{\sum_{j\in M^i}\texttt{waste}_{j,2004}}\texttt{sorting}_{j,2004}\right)
\end{aligned}$$

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 $i$th municipality is contiguous with the $j$th 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 2), 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 |

Then, our actual spatial matrix, $W$, is

$$W = \begin{bmatrix} D_1 & 0 & 0 & \cdots & 0 \\ 0 & D_2 & 0 & \cdots & 0 \\ 0 & 0 & D_3 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & D_K \end{bmatrix} \tag{1}$$

where

$$D_k = \begin{bmatrix} 0 & 1 & 1 & \cdots & 1 \\ 1 & 0 & 1 & \cdots & 1 \\ 1 & 1 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix}. \tag{2}$$

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 (2) 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

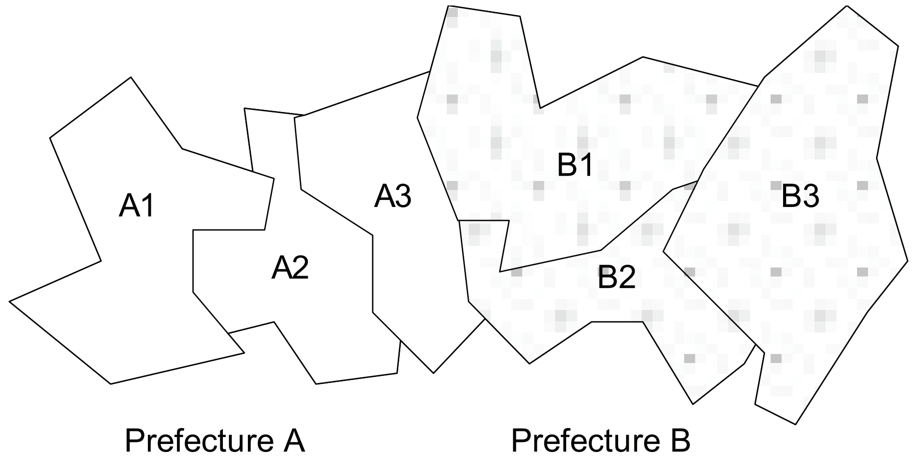


Figure 2: Example of the relationship between municipalities and prefectures

spatial Durbin model, which is defined as below.

$$Y = \beta_0 + \rho WY + X\beta_1 + X^2\beta_2 + Z\gamma + WZ\beta_3 + \mu \tag{3}$$

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

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 D1 and D2. The qualitative features of the results are nearly the same as the SAR and SEM results presented in Section 4.

Our main purpose is to see if there is any evidence for absolute decoupling for household waste generation. Table D3 summarizes the turning points computed based on the MCMC estimation of (4). Again, the results are nearly identical to the turning points presented in the main text.

Table D.1: Spatial Durbin Estimation ( `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.)** |
| $[\ln(\texttt{perinc})]^2$ | -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$^{\dagger}$ | (0.02382) | 0.05303* | (0.02395) | 0.04212$^{\dagger}$ | (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$^{\dagger}$ | (0.05363) | -0.16644 | (0.12810) | -0.09634$^{\dagger}$ | (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$^{\dagger}$ | (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) |
| $\rho$ | 0.59149** | (0.03843) | - | - | 0.58758** | (0.03924) | - | - |
| $\lambda$ | - | - | 0.62507** | (0.038786) | - | - | 0.65226** | (0.03986) |

** 1% * 5% $^{\dagger}$10%

| **Business MSW** | **MLE** | | | | **Bayesian** | | | |
|---|---|---|---|---|---|---|---|---|
| | SAR | | SEM | | SAR | | SEM | |
| **Variable** | **Coef.** | **(Std. Err.)** | **Coef.** | **(Std. Err.)** | **Coef.** | **(Std. Err.)** | **Coef.** | **(Std. Err.)** |
| $[\ln(\texttt{perinc})]^2$ | -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$^{\dagger}$ | (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$^{\dagger}$ | (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) |
| $\rho$ | 0.34856** | (0.06594) | - | - | 0.34493** | (0.06757) | - | - |
| $\lambda$ | - | - | 0.37165** | (0.06451) | - | - | 0.41867** | (0.06639) |

** 1% * 5% $^{\dagger}$10%

| | | | | |
|---|---|---|---|---|
| N | 1,798 | 1,798 | 1,798 | 1,798 |

Table D.2: Spatial Durbin Estimation ( `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$^\dagger$ | (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) |
| | | | | | | | | |
| $\rho$ | 0.63979** | (0.03224) | - | - | 0.63729** | (0.03611) | - | - |
| $\lambda$ | - | - | 0.75401** | (0.03050) - | - | - | 0.75913** | (0.03269) |

** 1% * 5% $^\dagger$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$^\dagger$ | (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) |
| | | | | | | | | |
| $\rho$ | 0.42336** | (0.04107) | - | - | 0.42282** | (0.04644) | - | - |
| $\lambda$ | - | - | 0.5102** | (0.04232) - | - | - | 0.51949** | (0.04518) |

** 1% * 5% $^\dagger$10%

| | | | | |
|---|---|---|---|---|
| N | 1,798 | 1,798 | 1,798 | 1,798 |

Table D.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).

# 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

$$y_i = \sum_{r=1}^{k} \beta_r z_{ir} + \epsilon. \tag{5}$$

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 $\alpha$, $\beta_r$, and $\theta_r$ are the parameters and that $\iota_n$ is an $n \times 1$ vector of 1s. The SARD model version of (5) is

$$y_i = \sum_{r=1}^{k} [S_r(W)_{i1} z_{1r} + S_r(W)_{i2} z_{2r} + \cdots + S_r(W)_{n1} z_{nr}] + (I_n - \rho W)_i^{-1} \iota_n \alpha + (I_n - \rho W)_i^{-1} \epsilon \tag{6}$$

where

$$S_r(W) = (I_n - \rho W)^{-1}(I_n \beta_r + W \theta_r) \tag{7}$$

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 $\beta_r$ and

$$\frac{\partial y_i}{\partial z_{ir}} = S_r(W)_{ij}. \tag{8}$$

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 (6) 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

$$\overline{M}_{direct} = \frac{\mathrm{Tr}(S_r(W))}{n} \tag{9}$$

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

$$\overline{M}_{total} = \frac{\iota_n'(S_r(W))\iota_n}{n} \tag{10}$$

$$\overline{M}_{indirect} = \overline{M}_{total} - \overline{M}_{direct} \tag{11}$$

$\overline{M}_{total}$ 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 E1 summarizes the spatial effect of the policy variables. The definitions of the three effects are based on LeSage and Pace (2009), as explained above.

Table E.1: 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.

Looking carefully Table E1, 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.

## References

LeSage, J. P. and R. K. Pace (2009) *Introduction to Spatial Econometrics*, CRC Press.