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Economic Geography and Productive Efficiency of Solid-Waste Logistics in Japan's Prefectures: Measurements via the Data Envelopment Analysis

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Economic Geography and Productive Efficiency of Solid-Waste Logistics in Japan's Prefectures: Measurements via the Data Envelopment Analysis

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1 Introduction

History shows, inevitable consequence of economic growth is increasing waste. Waste, often dubbed as the "third pollution" calls for excogitation just as air or water pollution does.[1] However, waste processing industry as well as households' decision making process in waste creation seems to suffer the most from market distortions such as hidden subsidy, ad-hoc regulations and inefficiency due to public operation.[2] When the market fails to discipline the industry, benchmarking and measuring efficiency of behaviors by decision makings units in the industry come into play. In cost-wise, waste collection is the major component of municipal solid waste processing activity. For example, 74.7% of the total cost is due to waste collection in Tokyo metropolitan area.[3] This paper thus measures the productive efficiency of solid-waste logistics in Japan, by applying various data envelopment analysis (DEA) models to cross-sectional data at the prefecture level.

Results consistently show that the set of underperforming prefectures is much the same between different model settings, with the most inefficient prefecture being Ehime closely followed by Nagasaki. Our list of underperforming prefectures indicates their geographical characteristics that the number of small inhabited islands is relatively larger than others is a major factor determining their inefficiency. Ehime for example has 33 islands in its jurisdiction with population being 525 and area being $2.71km^2$ per island on average. This production size is too small to achieve the minimum efficient scale in waste collection, as literature supports increasing-return technology at municipal level.[4] At the same time, our results indicate that the production technology is constant-return-to-scale at the prefecture level.

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[1]Small (1971) did first.
[2]See Porter (2002) for further discussion.
[3]Ministry of the Environment of Japan (http://www.env.go.jp/recycle/waste_tech/ippan/h21/data/shori/total/05.xls). National average of all prefectures in Japan is 47.5%. See Bel and Warner (2008) for further evidence outside of Japan.
[4]See Yamamoto (2011).

Results also show that inefficient prefectures have higher spatial correlation with their neighbors, both in terms of efficiency and the volume of illegal dumping of industrial waste.

In this paper, we classify solid waste into four categories. On one hand data provided by Ministry of the Environment of Japan categorizes municipal solid waste (MSW) largely in two kinds, namely household solid waste (HSW) and business solid waste (BSW). On the other hand, there are largely two types of operators, public and private, to collect the waste. Public entities that are in charge of solid waste collection are prefectural governments. Private operators are consigned, contracted, or licensed by a prefectural government. Given that the fundamental decision making unit (DMU) is a prefectural government who has a choice of direct operation and outsourcing private operators, we measure the productive efficiency of solid waste collection at the prefectural level.

It is safe to assume that these public and private operators face different production technologies. For example, while private operators collect both HSW and BSW, public operators tend to concentrate on the collection of HSW. Thus in our analysis we treat the waste differently not only by kind but also by the type of operators who collect them. Our data set contains the number of trucks used as capital input and the number of workers as labor input for each of public and private operators separately, made available by Ministry of the Environment of Japan as well. Thus we have four outputs and four inputs to characterize the production technology of waste collection.

DEA, pioneered by Farrel (1957) is one of the primary methodologies in estimating multi-output-multi-input production technology. It identifies non-parametrically the production possibility frontier then measures the inefficiency of each DMU as the distance to the frontier.[5] A number of research has adopted DEA in measuring efficiency in the various industries, from banking to transportation sectors.[6] However, literature is limited as for the efficiency measurement of the reverse-logistics industry.

Organization of this paper is as follows. Section 2 presents our data. Section 3 provides various DEA productive efficiency measurement results. In section 4 we interpret the obtained results in relation to the reverse logistics industry in Japan. Finally, Section 5 concludes.

2 Data

Our data set is a cross section of fiscal year 2009 made available by Ministry of the Environment of Japan. It contains eight variables for all 47 prefectures in Japan, of which four are outputs and four are inputs as mentioned above.[7] Outputs are the volumes of HSW and BSW collected and inputs are capital and labor measured in terms of the numbers of trucks and workers employed, each by public and private operators separately. Table 1 presents the data, while Figures 1 and 2 provides two partial-factor productivity measures, namely volumes of waste processed per truck and per worker.

//INSERT TABLE 1 ABOUT HERE//

//INSERT FIGURES 1 AND 2 ABOUT HERE//

[5]See, for example, Banker, Charnes, and Cooper (1984) for details.

[6]Oum, Yamaguchi, and Yoshida (2011) provides a comprehensive overview of the efficiency measurement literature in transportation sector.

[7]Fiscal year 2009 starts from April 2009 and ends in 2010 March.

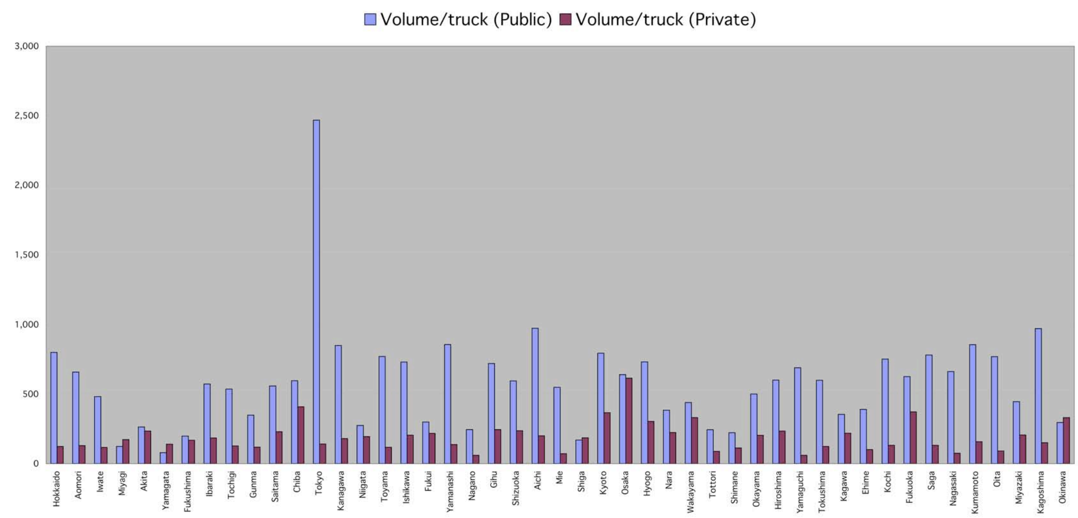

Figure 1: Volume of waste processed per truck as a measure of partial factor productivity.

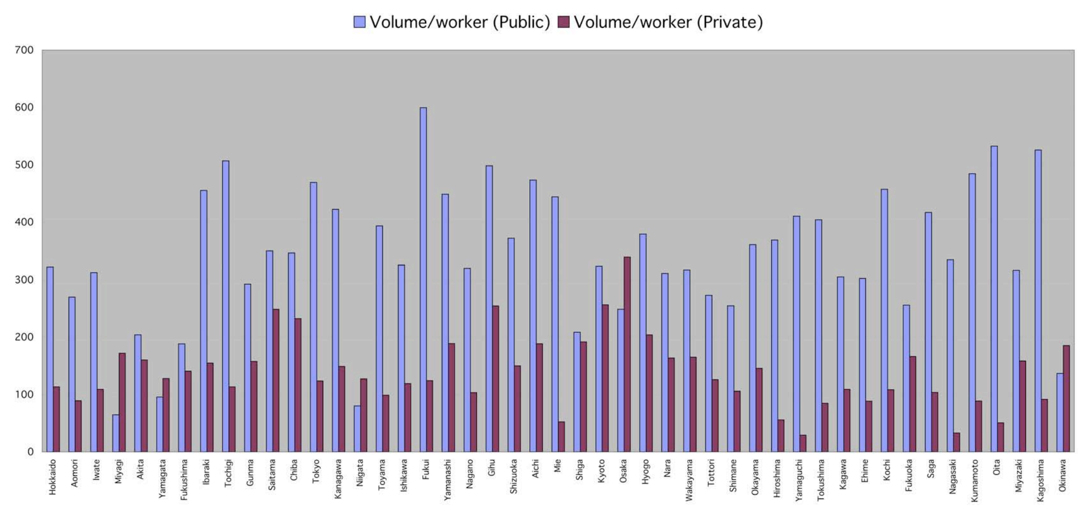

Figure 2: Volume of waste processed per worker as a measure of partial factor productivity.

//INSERT TABLE 2 ABOUT HERE//

It is clear that public and private operations follow quite different production technology with stark contrast in their partial-factor productivity. Average and standard deviation of partial-factor productivity for public and private operation is presented in Table 2, which rejects the null of equal mean for both volume per truck and volume per worker.[8] Our treatment of public and private sectors separately stems from this observation.

Before proceeding to the DEA analysis to identify the production technology, we will conduct a preliminary analysis to grasp the characteristics of our data. Specifically, we look at the returns to scale. Either assuming constant returns to scale (CRS) or variable returns to scale (VRS), DEA assumes that the production possibility set to be convex. This implies that if the actual data are scattered in a way that they exhibit global increasing returns to scale, DEA fails to correctly identify the production technology. To see this point better, we estimate a simple pooled OLS with the following results obtained:

$$\ln Y_{i,j} = \underset{(0.417)}{3.882} + \underset{(0.181)}{1.340} D_{i,j} + \underset{(0.146)}{0.419} \ln K_{i,j} + \underset{(0.128)}{0.711} \ln L_{i,j} + e_{i,j} \tag{1}$$

where subscript i is for the type of operator namely public or private, and j is for prefectures; $Y_{i,j}$ is the volume of both municipal and business wastes collected by type i operator in prefecture j; $D_{i,j}$ is the direct operation dummy which takes the value of unity if i = public and zero otherwise; $K_{i,j}$ is the number of trucks used; $L_{i,j}$ is the number of workers; and $e_{i,j}$ is the error which is assumed to be i.i.d.[9]

Given the coefficients to capital and labor slightly exceeding one in sum with standard deviations being 0.146 and 0.128 respectively, the CRS assumption is a close call. In what follows, we will therefore conduct two separate DEA analysis for both cases, first by assuming that the production possibility set is convex without any normalization of the original data, and second by preparing the original data to account for the potential non-convexity due to the increasing-return production technology.

3 DEA Estimation and Results

3.1 DEA estimation under the assumption of convex production possibility set

We run DEA estimation on the data shown in Table 1 above, both under CRS and VRS assumptions.[10] For the VRS case we measure efficiency in both input- and output-orientation.[11] By DEA, the CRS

[8] For the volume per truck, z score is 7.67 and for the volume per worker it is 11.18.

[9] Adjusted R^2 is 0.904. Numbers in parentheses are standard deviations. All coefficients are statistically significant with p-values being less than 1%.

[10] It may be natural to assume separability between public and private production, however, we do not impose such restriction a-priori into our estimation model.

[11] By construction of DEA, efficiency takes the same value in either orientation under the CRS assumption.

efficiency of prefecture j, denoted by θ_j say, is measured as

$$
\begin{aligned}
\theta_j &= \min \theta \\
s.t. \sum_{\tilde{j} \in J} \lambda_{\tilde{j}} K_{i,\tilde{j}} &\leq \theta K_{i,j} \\
\sum_{\tilde{j} \in J} \lambda_{\tilde{j}} L_{i,\tilde{j}} &\leq \theta L_{i,j} \\
\sum_{\tilde{j} \in J} \lambda_{\tilde{j}} H_{i,\tilde{j}} &\geq M_{i,j} \\
\sum_{\tilde{j} \in J} \lambda_{\tilde{j}} B_{i,\tilde{j}} &\geq B_{i,j} \\
\lambda_{\tilde{j}} &\geq 0 \quad \forall \tilde{j} \in J
\end{aligned}
$$

for $i \in \{public, private\}$ where J is the set of 47 prefectures, and $H_{i,j}$ and $B_{i,j}$ are respectively the volumes of HSW and BSW collected in prefecture j by operator i. To make it an input-oriented VRS efficiency measure, we simply add a constraint $\sum_{\tilde{j} \in J} \lambda_{\tilde{j}} = 1$ to the above linear programming problem. Output-oriented VRS efficiency is obtained by placing θ in above as the coefficients of $H_{i,j}$ and $B_{i,j}$ instead of $K_{i,j}$ and $L_{i,j}$.

Table 3 provides the efficiency scores under these different model settings.

//INSERT TABLE 3 ABOUT HERE//

The least efficient prefecture is Ehime, closely followed by Nagasaki. These two prefectures appear in this order, under all different model settings. Moreover, most of underperforming prefectures appear repeatedly in the group of 10 least efficient DMUs for these different model settings. As shown in Table 4, these are Kagawa, Iwate, Yamaguchi, Okayama, Toyama, and Shizuoka prefectures, in addition to Ehime and Nagasaki.

//INSERT TABLE 4 ABOUT HERE//

The result that scale efficiency is very close, if not equal, to one for most of the DMUs implies that the production technology is well described as CRS.[12] Indeed, correlation between CRS efficiency scores and the input-oriented VRS efficiency scores is 0.884, while that between CRS and output-oriented VRS efficiency scores is 0.900.

3.2 Modified DEA estimation under the increasing-return production technology assumption

Estimation results in (1) above leaves us with no good reason to preclude the increasing-return technology. We thus prepare our data by taking log so as to meet with the assumption of the convex

[12] Average scale efficiency is 0.974 for input-oriented VRS model and 0.976 for the output-oriented VRS model.

production possibility set that is necessary in DEA estimation.[13] We refer to this DEA estimation using these data as modified DEA. Table 5 shows the data prepared in this manner, and Table 6 shows the estimation results.

//INSERT TABLES 5, 6, *AND* 7 *ABOUT HERE//*

Table 7 presents the list of 10 least efficient prefectures in the results from modified DEA, under the assumptions of input-oriented VRS, output-oriented VRS, and CRS respectively. As can be seen in Table 7, the set of 10 most inefficient DMUs are the same under the two VRS assumptions. Moreover, it is again similar to those in the original DEA presented in Table 4, as all of those eight prefectures mentioned in Section 3.1 that appear repeatedly among the group of 10 least efficient DMUs still appear in the list here for VRS assumptions.

Results obtained under the CRS assumption in this modified DEA analysis is quite different from those under VRS assumptions as well as from those in original DEA analysis. For example, Tokyo appears among the 10 least efficient prefectures, while its partial-factor productivity measures are relatively higher than others. This indicates that, due to the data modification that we made by taking log, CRS assumption is no longer appropriate. As shown in Table 6, most of the DMUs with scale efficiency less than one lie on the parts of production possibility frontier where local returns to scale is decreasing. As illustrated in Figure 3, log conversion of slightly increasing-return technology brings upward the output-input ratio of those DMUs with small production scale. By adopting CRS assumption to this converted data scatter, DEA results in poor representation of the production possibility frontier, and hence the overestimation of inefficiency especially for those DMUs with higher production scale, such as Tokyo, is observed.

4 Implications of Efficiency Measurement Results

4.1 Economic geography of the solid-waste logistics in Japan

Let us now derive geographical implications from our analysis above on the reverse logistics industry in Japan. A global spatial relationship can be described by Moran's I. As for efficiency results (under the CRS assumption with original data), Moran's I is 0.09801, which is sufficiently low to conclude that there is not significant spatial autocorrelation of waste-logistics efficiency among prefectures.[14]

Thus we pour our attention to more local geographical characteristics. Especially we focus on the inefficient DMUs to consider the causes of their inefficiency. Probably the first and the foremost of the potential causes of the inefficiency results is the larger number of small, isolated islands in their jurisdiction. In these islands their small population makes it difficult to achieve the minimum efficient scale of waste collection. Average land area of inhabited islands in Ehime prefecture is as small as $2.71km^2$ and average population is merely 525 residents per island, resulting in the lowest efficiency.[15]

[13] As mentioned earlier, public operators collect little BSW, and in some prefectures the volume is zero. We deal with this issue by adding one to all data before computing their natural logs.

[14] We use the spatial weight matrix which is defined by the inverse of the square of distance between prefectures.

[15] Population density is not necessarily smaller on these islands. Ehime Prefecture (2003), *Ehime Prefecture Island Development Plan (Ehime-ken Ritou Shinkou Keikaku) for Fiscal Years 2003 to 2012,* shows that average population density is $224/km^2$ in 2002, which is comparable to the population density of the entire Ehime prefecture ($263/km^2$),

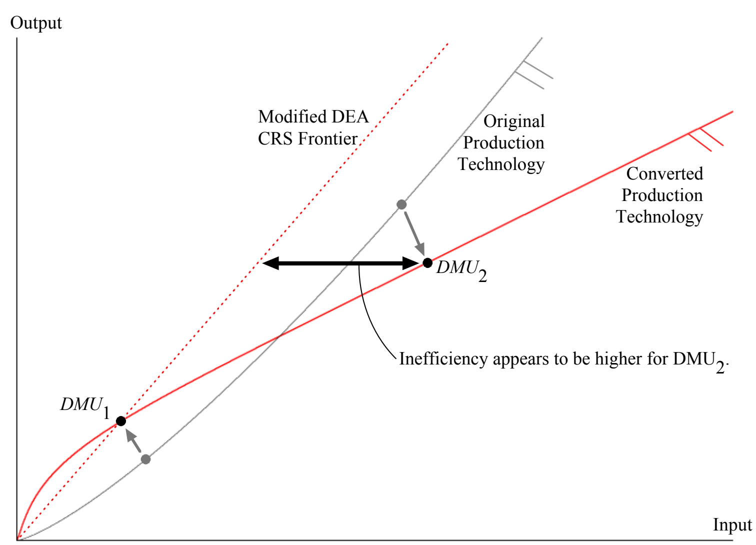

Figure 3: Illustration of higher inefficiency results due to adoption of CRS assumption to modified data.

In addition to Ehime, those prefectures such as Nagasaki, Yamaguchi, Kagawa, and Okayama that are listed among the 10 least efficient DMUs in Tables 4 and 7 have many isolated islands in their administrative districts as shown in Table 8.

//INSERT TABLE 8 ABOUT HERE//

For example, Nagasaki has the largest number of inhabited islands (54 islands), Ehime has the third largest number of isolated islands (33 islands), and Kagawa, Yamaguchi and Okayama also have a large number of inhabited islands with smaller island population. There are several prefectures that achieve higher productive efficiency in waste collection despite the existence of relatively many islands such as Okinawa and Kagoshima. However, the average land area and population per island for, say Kagoshima, are $89.4km^2$ and $6,522$ residents respectively, which is ten times or more greater than Ehime's figure. In this context, we conclude that inefficiency of solid-waste logistics is explained by the number of isolated islands that are smaller than what is necessary to achieve the minimum efficient scale.[16]

Another possible cause for inefficiency is the low pavement ratio of main roads; in fact, among the inefficient DMUs listed in Table 4 and Table 7, Iwate has the worst pavement ratio, and Toyama's pavement ratio is the fourth from the bottom[17]. In addition, the population density of these two prefectures is relatively low, implying the longer trip distance per volume. These together resulted in low efficiency for Iwate and Toyama prefectures.

4.2 Implications for industrial waste management

In the previous section we saw that there is no overall spatial correlation of MSW logistics efficiency between prefectures and that inefficiency of waste logistics is mainly due to their local geographical characteristics. As Ichinose and Yamamoto (2011) show that there is not strong global spatial auto-correlation for the volume of illegal dumping detected in Japan, this finding is applicable not only to authorized waste-logistic firms but also to the illegal dumping of the industrial waste. However, when we look locally at each prefecture, it becomes eminent that inefficient prefectures have higher spatial correlation with their neighbors, both in terms of MSW logistics efficiency and the volume of illegal dumping of industrial waste.

Let us introduce a local spatial correlation indicator, the local Moran's I (I_i), which gives the spatial correlation of an interested variable of DMU i, say x_i, to that of the weighted average of its neighbors, defined as follows.

$$I_i = \frac{(x_i - \overline{x})}{\sum_{j=1}^{N}(x_j - \overline{x})^2/N} \cdot \sum_{j=1}^{N} w_{ij}(x_j - \overline{x}) \tag{2}$$

where N is the number of prefectures and $\overline{x}$ is an average of x_i while w_{ij} is the element of the spatial

or even to that of entire Japan at $342/km^2$ (source: Statistics Bureau, Ministry of Internal Affairs and Communications (2006), *World Statistics (Sekaino Tokei).*)

[16]Naturally, *"what is the minimum efficient scale of solid-waste collection?"* is the next question to be investigated, which is beyond the scope of this paper and left for future research.

[17]see SOP (2012) for more details.

weight matrix that we use to calculate the Moran's I. We use the amount of illegal dumping as the sum of the last five years (from 2006 to 2010) to alleviate the impact of large site of illegal dumping. Figure 4 describes the relationship between local Moran's I of illegal dumping and efficiency (CRS / original data).

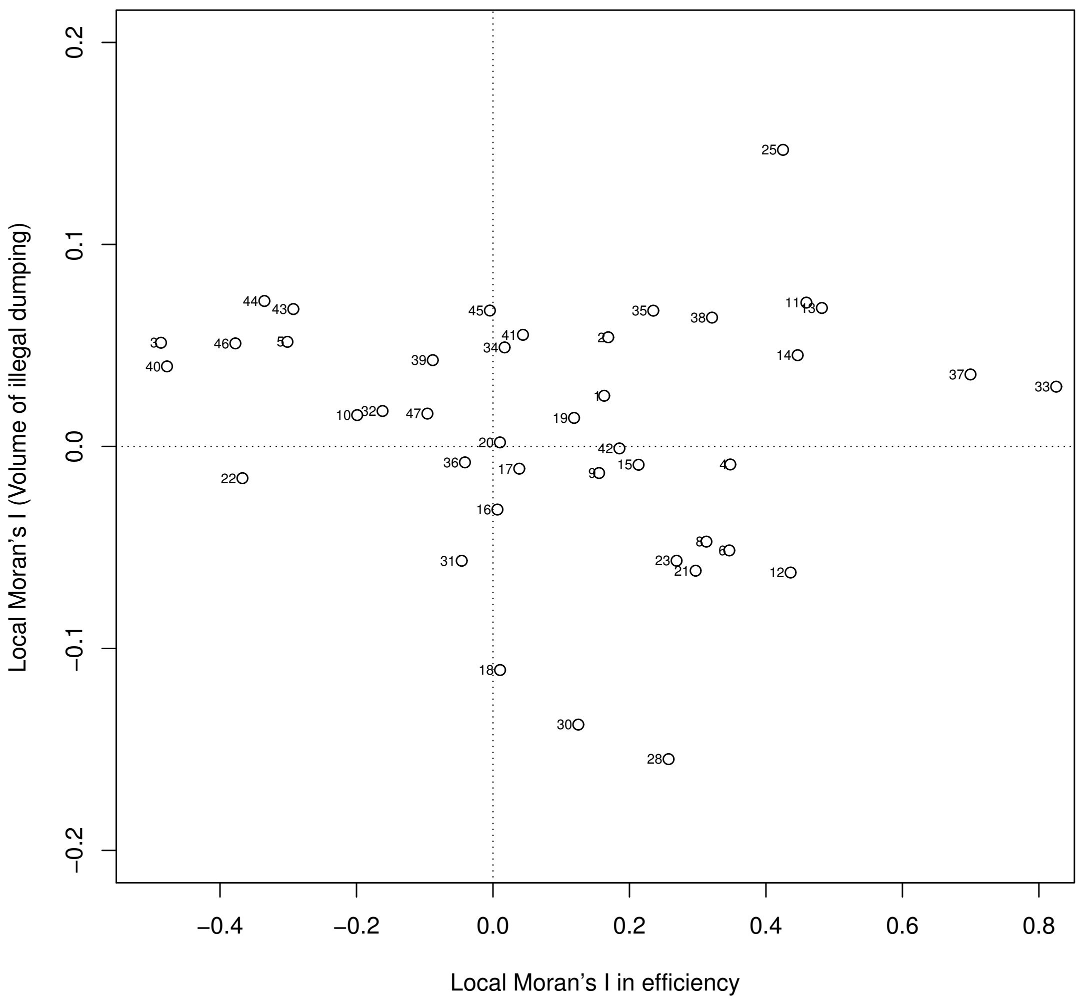

Figure 4: Relationship between efficiency and illegal dumping

Notes: The data for illegal dumping is also available at the website of the Japanese Ministry of Environment. For further information, see `http://wwww.env.go.jp`

We focus on our discussion on the first quadrant of Figure 4. From our definition, the prefectures in the first quadrant are the ones that detects more (less) illegal dumping as the neighbors do more (less) and attains higher (lower) efficiency if neighbors perform higher (lower) efficiency. A closer look of the figure remarkably shows us that seven prefectures out of the ten least efficient prefectures are in the first quadrant[18]. Two (Iwate(#3) and Toyama(#16)) out the three that are not in the first quadrant but in the least ten list of efficiency are those who ranked in the top five in terms of worst pavement ratio.

Since Japanese municipal solid waste is collected mostly with little, if not zero by any chance, user charge by a local government, illegal dumping of municipal solid waste has never been a major policy issue. In turn, a proper disposal of industrial waste - which is usually more toxic - incurs cost to those who emit them. Unlike municipal solid waste, a local government has no responsibility to collect the industrial waste, and the waste generators are solely responsible for its proper disposal. Currently there are not so many illegal-dumping cases particularly among the inefficient prefectures. As Figure 4 indicates, the spatial correlation for illegal dumping are observed among the prefectures that are less efficient in MSW logistics. It warns us that once illegal dumping increases in one of the prefectures, it tends to spread out among the other prefectures which inherently possess inefficient logistics due to the spatial correlation we mentioned. In order to prevent from possible pervasiveness of illegal dumping, the policy that improves the efficiency of the waste logistics at the geographically disadvantaged prefectures is strongly needed.

It is unknown who did illegal dumping in many cases or, even in the case that the authority could specify who did, the firm often bankrupted when it was detected. As a result, the large portion of the tax money are spent in the restoration of illegally dumped sites. Given a proper treatment of industrial waste is cheaper than the restoration, it convinces a tax payer of investing more money in the efficient logistics prior to illegal dumping.[19] In fact, Gifu prefecture who has been struggling with one of the largest illegal dumping at Tsubakihora found in 2004 submitted the budget of about 37.5 million US dollar (or 3 billion JP Yen) for the restoration.

5 Conclusions

This paper measured the productive efficiency of the municipal-solid-waste (MSW) collection in Japan by applying DEA, the data envelopment analysis, to the cross-sectional data in fiscal year 2009 made available by Ministry of the Environment of Japan. Our data includes four outputs and four inputs for all 47 prefectures in Japan. Outputs are the volumes of household solid waste (HSW) and business solid waste (BSW) collected by both private and public operators, while the numbers of trucks and workers used by private and public operators enter as inputs. Either through direct operation or by contracting or licensing private operators, relevant decisions of waste collection are made by prefectural governments in Japan. We thus estimate a multi-input-multi-output production efficiency at the prefectural level via DEA, where several different model settings are employed. Results consistently show that Ehime prefecture followed immediately by Nagasaki is the least efficient, which indicates that geographical characteristics such that the number of inhabited remote islands is relatively larger

[18] Namely, Ehime(#38), Nagasaki(#42), Kagawa(#37), Hokkaido(#1), Yamaguchi(#35), Okayama(#33), and Aomori(#2).

[19] For example, both Aomori and Iwate prefectures charged about 36,000 JP Yen per ton (or 450 US dollars per ton) for restoration fee of the illegal dumping site at the border of these two prefectures while market price of proper treatment is about 8,000 JP Yen per ton (or 100 US dollars per ton). See http://www.pref.aomori.lg.jp/nature/kankyo/2008-0620-kenkyo-top.html for Aomori's case and http://www.pref.iwate.jp/list.rbz?nd=2690&ik=1&pnp=50&pnp=2648&pnp=2690 for Iwate's case (both in Japanese).

than others is a dominant factor determining the inefficiency. The implication that in these small islands minimum efficient scale of production is not achieved is in accord to the literature that waste logistics is increasing-return at the municipal level, while our results indicate that the production of waste collection in Japan is well described as CRS technology at the prefectural level. Results also show that the prefectures that are inefficient in MSW logistics have higher spatial correlation with their neighbors both in terms of waste collection efficiency and the volume of illegal dumping of industrial waste. Since the restoration of illegal dumping sites is highly costly, more investment at inefficient DMUs helps us minimizing the cost of waste management policy.

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Table 1: Original Data.

Prefecture	*HSW volume in tons*		*BSW volume in tons*		*Number of trucks*		*Number of workers*	
	Public	*Private*	*Public*	*Private*	*Public*	*Private*	*Public*	*Private*
Hokkaido	240794	998492	797	460236	302	11788	750	12863
Aomori	39236	300451	983	138783	61	3384	149	4925
Iwate	33667	244422	89	115014	70	3090	108	3298
Miyagi	6787	534362	0	188941	55	4166	105	4206
Akita	6326	262334	0	95465	24	1524	31	2233
Yamagata	1909	241715	0	78084	24	2283	20	2502
Fukushima	7319	476493	28	175261	37	3868	39	4628
Ibaraki	80661	638263	1276	205514	143	4565	180	5446
Tochigi	83112	385972	23	144824	155	4159	164	4686
Gunma	46816	473891	563	130166	136	5096	162	3831
Saitama	288515	1410292	1012	484981	518	8243	827	7624
Chiba	198954	1244341	4393	510992	341	4293	587	7550
Tokyo	2495407	780334	379	1065906	1011	13067	5319	14920
Kanagawa	1501480	512310	5725	605644	1773	6179	3568	7499
Niigata	8552	562333	251	227872	32	4063	110	6210
Toyama	92479	150421	0	92061	120	2048	235	2457
Ishikawa	65075	187626	0	117132	89	1485	200	2557
Fukui	15588	165281	0	57297	52	1020	26	1791
Yamanashi	28277	182077	0	69467	33	1817	63	1331
Nagano	14073	447812	1604	152990	64	9937	49	5809
Gihu	175689	260714	7141	150086	254	1673	367	1614
Shizuoka	245839	618923	133	297629	413	3867	661	6117
Aichi	867996	867723	309	521197	892	6939	1834	7370
Mie	234048	209347	7	143728	426	4929	527	6751
Shiga	12727	286303	0	108781	75	2124	61	2061
Kyoto	281720	197597	2016	259023	357	1247	877	1781
Osaka	977804	805722	5175	1309818	1536	3441	3953	6238
Hyogo	673386	525851	4819	516419	926	3429	1789	5107
Nara	195919	98029	1239	113578	513	943	634	1292
Wakayama	112163	138006	2619	44205	261	550	362	1104
Tottori	4323	121830	317	55985	19	2007	17	1412
Shimane	10580	144918	1642	35168	55	1594	48	1699
Okayama	157920	242736	1568	159002	318	1972	442	2757
Hiroshima	220851	351894	903	285177	369	2713	601	11421
Yamaguchi	212411	151104	603	106106	309	4299	519	8793
Tokushima	162601	36961	638	56228	272	752	404	1100
Kagawa	88756	146652	0	84375	250	1055	291	2120
Ehime	48411	287781	0	70078	124	3522	160	4051
Kochi	88562	102296	174	49530	118	1148	194	1399
Fukuoka	161965	929411	13260	344778	280	3416	685	7659
Saga	43791	139631	0	59091	56	1511	105	1916
Nagasaki	105386	204202	0	103765	159	4061	315	9324
Kumamoto	125012	244914	0	143227	146	2450	258	4376
Oita	117704	149113	0	84184	153	2570	221	4618
Miyazaki	63647	189030	0	121412	143	1507	201	1958
Kagoshima	95171	289858	6	128236	98	2778	181	4566
Okinawa	27088	243758	1889	136570	98	1149	212	2050

Source: Ministry of the Environment of Japan

Table 2: Averages and standard deviations of partial-factor productivity for public and private operators.

	Volume/Truck		*Volume/Worker*	
	Public	*Private*	*Public*	*Private*
Average	625.37	199.73	362.22	141.31
Std. Dev.	365.59	104.72	120.59	61.81

Table 3: DEA results with original data.

Prefecture	*CRS*	*VRS Input-oriented*			*VRS Output-oriented*		
		Technical	*Scale*	*Local Return*	*Technical*	*Scale*	*Local Return*
Hokkaido	0.740	0.954	0.776	DRS	0.973	0.761	DRS
Aomori	0.834	0.843	0.989	IRS	0.836	0.998	IRS
Iwate	0.756	0.768	0.984	DRS	0.780	0.968	DRS
Miyagi	1.000	1.000	1.000	-	1.000	1.000	-
Akita	1.000	1.000	1.000	-	1.000	1.000	-
Yamagata	0.989	1.000	0.989	IRS	1.000	0.989	IRS
Fukushima	1.000	1.000	1.000	-	1.000	1.000	-
Ibaraki	1.000	1.000	1.000	-	1.000	1.000	-
Tochigi	0.961	1.000	0.961	DRS	1.000	0.961	DRS
Gunma	0.882	0.897	0.983	DRS	0.903	0.976	DRS
Saitama	1.000	1.000	1.000	-	1.000	1.000	-
Chiba	1.000	1.000	1.000	-	1.000	1.000	-
Tokyo	1.000	1.000	1.000	-	1.000	1.000	-
Kanagawa	1.000	1.000	1.000	-	1.000	1.000	-
Niigata	1.000	1.000	1.000	-	1.000	1.000	-
Toyama	0.811	0.814	0.996	IRS	0.811	0.999	IRS
Ishikawa	0.834	0.961	0.868	IRS	0.949	0.879	IRS
Fukui	1.000	1.000	1.000	-	1.000	1.000	-
Yamanashi	1.000	1.000	1.000	-	1.000	1.000	-
Nagano	1.000	1.000	1.000	-	1.000	1.000	-
Gihu	1.000	1.000	1.000	-	1.000	1.000	-
Shizuoka	0.834	0.854	0.977	DRS	0.860	0.970	DRS
Aichi	0.995	1.000	0.995	DRS	1.000	0.995	DRS
Mie	0.877	0.893	0.982	DRS	0.900	0.975	DRS
Shiga	1.000	1.000	1.000	-	1.000	1.000	-
Kyoto	1.000	1.000	1.000	-	1.000	1.000	-
Osaka	1.000	1.000	1.000	-	1.000	1.000	-
Hyogo	1.000	1.000	1.000	-	1.000	1.000	-
Nara	0.866	1.000	0.866	IRS	1.000	0.866	IRS
Wakayama	1.000	1.000	1.000	-	1.000	1.000	-
Tottori	1.000	1.000	1.000	-	1.000	1.000	-
Shimane	1.000	1.000	1.000	-	1.000	1.000	-
Okayama	0.805	0.823	0.978	IRS	0.805	1.000	-
Hiroshima	0.923	0.925	0.998	IRS	0.923	1.000	-
Yamaguchi	0.804	0.821	0.980	DRS	0.831	0.968	DRS
Tokushima	0.941	1.000	0.941	IRS	1.000	0.941	IRS
Kagawa	0.732	0.883	0.830	IRS	0.837	0.875	IRS
Ehime	0.634	0.638	0.994	DRS	0.645	0.983	DRS
Kochi	0.937	1.000	0.937	IRS	1.000	0.937	IRS
Fukuoka	1.000	1.000	1.000	-	1.000	1.000	-
Saga	0.842	0.951	0.886	IRS	0.862	0.976	IRS
Nagasaki	0.646	0.648	0.997	IRS	0.667	0.969	DRS
Kumamoto	0.976	0.990	0.986	DRS	0.990	0.986	DRS
Oita	1.000	1.000	1.000	-	1.000	1.000	-
Miyazaki	0.856	0.961	0.891	IRS	0.949	0.902	IRS
Kagoshima	1.000	1.000	1.000	-	1.000	1.000	-
Okinawa	1.000	1.000	1.000	-	1.000	1.000	-

Table 4: List of 10 most underperforming prefectures.

	CRS	*VRS Input-oriented*	*VRS Output-oriented*
Least efficient	**Ehime**	**Ehime**	**Ehime**
2nd least efficient	**Nagasaki**	**Nagasaki**	**Nagasaki**
3rd least efficient	**Kagawa**	**Iwate**	**Iwate**
4th least efficient	Hokkaido	**Toyama**	**Okayama**
5th least efficient	**Iwate**	**Yamaguchi**	**Toyama**
6th least efficient	**Yamaguchi**	**Okayama**	**Yamaguchi**
7th least efficient	**Okayama**	Aomori	Aomori
8th least efficient	**Toyama**	**Shizuoka**	**Kagawa**
9th least efficient	**Shizuoka**	**Kagawa**	**Shizuoka**
10th least efficient	Ishikawa	Mie	Saga

Note: Prefectures in bold face appear in all columns.

Table 5: Data prepared for DEA estimation under the increasing-return production technology assumption.

Prefecture	*HSW volume in tons*		*BSW volume in tons*		*Number of trucks*		*Number of workers*	
	Public	*Private*	*Public*	*Private*	*Public*	*Private*	*Public*	*Private*
Hokkaido	12.39	13.81	6.68	13.04	5.71	9.37	6.62	9.46
Aomori	10.58	12.61	6.89	11.84	4.13	8.13	5.01	8.50
Iwate	10.42	12.41	4.50	11.65	4.26	8.04	4.69	8.10
Miyagi	8.82	13.19	0.00	12.15	4.03	8.33	4.66	8.34
Akita	8.75	12.48	0.00	11.47	3.22	7.33	3.47	7.71
Yamagata	7.55	12.40	0.00	11.27	3.22	7.73	3.04	7.83
Fukushima	8.90	13.07	3.37	12.07	3.64	8.26	3.69	8.44
Ibaraki	11.30	13.37	7.15	12.23	4.97	8.43	5.20	8.60
Tochigi	11.33	12.86	3.18	11.88	5.05	8.33	5.11	8.45
Gunma	10.75	13.07	6.34	11.78	4.92	8.54	5.09	8.25
Saitama	12.57	14.16	6.92	13.09	6.25	9.02	6.72	8.94
Chiba	12.20	14.03	8.39	13.14	5.83	8.36	6.38	8.93
Tokyo	14.73	13.57	5.94	13.88	6.92	9.48	8.58	9.61
Kanagawa	14.22	13.15	8.65	13.31	7.48	8.73	8.18	8.92
Niigata	9.05	13.24	5.53	12.34	3.50	8.31	4.71	8.73
Toyama	11.43	11.92	0.00	11.43	4.80	7.63	5.46	7.81
Ishikawa	11.08	12.14	0.00	11.67	4.50	7.30	5.30	7.85
Fukui	9.65	12.02	0.00	10.96	3.97	6.93	3.30	7.49
Yamanashi	10.25	12.11	0.00	11.15	3.53	7.51	4.16	7.19
Nagano	9.55	13.01	7.38	11.94	4.17	9.20	3.91	8.67
Gihu	12.08	12.47	8.87	11.92	5.54	7.42	5.91	7.39
Shizuoka	12.41	13.34	4.90	12.60	6.03	8.26	6.50	8.72
Aichi	13.67	13.67	5.74	13.16	6.79	8.85	7.51	8.91
Mie	12.36	12.25	2.08	11.88	6.06	8.50	6.27	8.82
Shiga	9.45	12.56	0.00	11.60	4.33	7.66	4.13	7.63
Kyoto	12.55	12.19	7.61	12.46	5.88	7.13	6.78	7.49
Osaka	13.79	13.60	8.55	14.09	7.34	8.14	8.28	8.74
Hyogo	13.42	13.17	8.48	13.15	6.83	8.14	7.49	8.54
Nara	12.19	11.49	7.12	11.64	6.24	6.85	6.45	7.16
Wakayama	11.63	11.84	7.87	10.70	5.57	6.31	5.89	7.01
Tottori	8.37	11.71	5.76	10.93	3.00	7.60	2.89	7.25
Shimane	9.27	11.88	7.40	10.47	4.03	7.37	3.89	7.44
Okayama	11.97	12.40	7.36	11.98	5.77	7.59	6.09	7.92
Hiroshima	12.31	12.77	6.81	12.56	5.91	7.91	6.40	9.34
Yamaguchi	12.27	11.93	6.40	11.57	5.74	8.37	6.25	9.08
Tokushima	12.00	10.52	6.46	10.94	5.61	6.62	6.00	7.00
Kagawa	11.39	11.90	0.00	11.34	5.53	6.96	5.68	7.66
Ehime	10.79	12.57	0.00	11.16	4.83	8.17	5.08	8.31
Kochi	11.39	11.54	5.16	10.81	4.78	7.05	5.27	7.24
Fukuoka	12.00	13.74	9.49	12.75	5.64	8.14	6.53	8.94
Saga	10.69	11.85	0.00	10.99	4.04	7.32	4.66	7.56
Nagasaki	11.57	12.23	0.00	11.55	5.08	8.31	5.76	9.14
Kumamoto	11.74	12.41	0.00	11.87	4.99	7.80	5.56	8.38
Oita	11.68	11.91	0.00	11.34	5.04	7.85	5.40	8.44
Miyazaki	11.06	12.15	0.00	11.71	4.97	7.32	5.31	7.58
Kagoshima	11.46	12.58	1.95	11.76	4.60	7.93	5.20	8.43
Okinawa	10.21	12.40	7.54	11.82	4.60	7.05	5.36	7.63

Table 6: Modified DEA results with the data modified for the increasing-return production technology assumption.

Prefecture	*CRS*	*VRS Input-oriented*			*VRS Output-oriented*		
		Technical	*Scale*	*Local Return*	*Technical*	*Scale*	*Local Return*
Hokkaido	0.900	1.000	0.900	DRS	1.000	0.900	DRS
Aomori	1.000	1.000	1.000	-	1.000	1.000	-
Iwate	0.952	0.969	0.983	DRS	0.984	0.967	DRS
Miyagi	0.953	1.000	0.953	DRS	1.000	0.953	DRS
Akita	1.000	1.000	1.000	-	1.000	1.000	-
Yamagata	1.000	1.000	1.000	-	1.000	1.000	-
Fukushima	0.970	1.000	0.970	DRS	1.000	0.970	DRS
Ibaraki	0.950	1.000	0.950	DRS	1.000	0.950	DRS
Tochigi	0.925	0.999	0.926	DRS	1.000	0.926	DRS
Gunma	0.953	0.990	0.962	DRS	0.994	0.959	DRS
Saitama	0.939	1.000	0.939	DRS	1.000	0.939	DRS
Chiba	0.954	1.000	0.954	DRS	1.000	0.954	DRS
Tokyo	0.936	1.000	0.936	DRS	1.000	0.936	DRS
Kanagawa	0.944	1.000	0.944	DRS	1.000	0.944	DRS
Niigata	1.000	1.000	1.000	-	1.000	1.000	-
Toyama	0.965	0.977	0.988	DRS	0.986	0.979	DRS
Ishikawa	0.999	1.000	1.000	-	1.000	1.000	-
Fukui	1.000	1.000	1.000	-	1.000	1.000	-
Yamanashi	1.000	1.000	1.000	-	1.000	1.000	-
Nagano	0.968	1.000	0.968	DRS	1.000	0.968	DRS
Gihu	1.000	1.000	1.000	-	1.000	1.000	-
Shizuoka	0.924	0.981	0.942	DRS	0.990	0.933	DRS
Aichi	0.929	1.000	0.929	DRS	1.000	0.929	DRS
Mie	0.897	0.976	0.919	DRS	0.988	0.907	DRS
Shiga	0.994	1.000	0.994	DRS	1.000	0.994	DRS
Kyoto	1.000	1.000	1.000	-	1.000	1.000	-
Osaka	0.989	1.000	0.989	DRS	1.000	0.989	DRS
Hyogo	0.943	1.000	0.943	DRS	1.000	0.943	DRS
Nara	1.000	1.000	1.000	-	1.000	1.000	-
Wakayama	1.000	1.000	1.000	-	1.000	1.000	-
Tottori	1.000	1.000	1.000	-	1.000	1.000	-
Shimane	1.000	1.000	1.000	-	1.000	1.000	-
Okayama	0.957	0.966	0.991	DRS	0.981	0.976	DRS
Hiroshima	0.947	0.984	0.962	DRS	0.992	0.955	DRS
Yamaguchi	0.914	0.970	0.942	DRS	0.985	0.928	DRS
Tokushima	1.000	1.000	1.000	-	1.000	1.000	-
Kagawa	0.968	0.968	1.000	-	0.978	0.989	DRS
Ehime	0.907	0.924	0.982	DRS	0.962	0.943	DRS
Kochi	1.000	1.000	1.000	-	1.000	1.000	-
Fukuoka	1.000	1.000	1.000	-	1.000	1.000	-
Saga	0.997	0.997	1.000	-	0.997	1.000	-
Nagasaki	0.907	0.931	0.974	DRS	0.964	0.942	DRS
Kumamoto	0.964	0.995	0.969	DRS	0.997	0.967	DRS
Oita	0.954	1.000	0.954	DRS	1.000	0.954	DRS
Miyazaki	0.978	0.978	0.999	IRS	0.983	0.995	DRS
Kagoshima	0.967	1.000	0.967	DRS	1.000	0.967	DRS
Okinawa	1.000	1.000	1.000	-	1.000	1.000	-

Table 7: List of 10 most underperforming prefectures in modified DEA results.

	VRS Input-oriented	*VRS Output-oriented*	*CRS*
Least efficient	Ehime	Ehime	Mie
2nd least efficient	Nagasaki	Nagasaki	Hokkaido
3rd least efficient	Okayama	Kagawa	Nagasaki
4th least efficient	Kagawa	Okayama	Ehime
5th least efficient	Iwate	Miyazaki	Yamaguchi
6th least efficient	Yamaguchi	Iwate	Shizuoka
7th least efficient	Mie	Yamaguchi	Tochigi
8th least efficient	Toyama	Toyama	Aichi
9th least efficient	Miyazaki	Mie	Tokyo
10th least efficient	Shizuoka	Shizuoka	Saitama

Table 8: Prefectures with ten or more inhabited islands.

Prefecture	*Number of inhabited islands*	*Population/Island*	*Land area/Island* (km^2)
Nagasaki	54	2,882	29.04
Okinawa	40	3,246	25.45
Ehime	33	525	2.71
Kagoshima	28	6,522	89.40
Kagawa	22	366	2.90
Yamaguchi	21	238	3.08
Okayama	15	222	2.08
Hiroshima	14	1,174	6.06
Tokyo	13	2,211	27.74

Source: Yamaguchi(2009) and National Census (2005)