Efficiency or Technology Adoption: A Case Study in Waste- Treatment Technology

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Abstract

Improvements in the effectiveness and efficiency of supply-side waste management are necessary in many countries. In Japan, municipalities with limited budgets have delayed the introduction of new waste-management technologies. Thus, the central government has used subsidies to encourage municipalities to adopt certain new technologies to improve waste-management efficiency. In this study, we measure the efficiency of waste management and explore how technology is related to technical efficiency. We find that municipalities are likely to adopt less-efficient technologies and that the central government's policies are likely to promote inefficient technology adoption by local governments.

Key Words: Waste-Treatment Technology; Waste Management; Efficiency; Productivity; Technology Adoption

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1. Introduction

Demand for public services that improve waste management has increased in tandem with income growth (Mazzanti and Montini, 2009; Ichinose and Yamamoto, 2011; Shinkuma and Managi, 2011). Although demand-side strategies to reduce waste generation and recycle waste are important policy topics, improving the effectiveness and efficiency of public services regarding waste management (i.e., the supply side of waste management) is also an important policy goal in many countries because government resources are often limited.

Many governments, from local authorities to federal governments, have examined the efficiency of their waste-management services. For example, the United States Governmental Accounting Standards Board has generated a methodology that municipalities use to calculate and disclose waste-management efficiency indicators. In Spain, a document designed to help calculate management indicators was issued to evaluate the effectiveness and efficiency of public services regarding waste management (Benito et al., 2010).

Many studies on demand-side waste-management policy have focused on the effectiveness of unit pricing of waste emissions and recycling (Fullurton and Kinnaman, 1996; Kinnaman, 2003; Kinnaman, 2006). However, only a limited number of studies have focused on supply-side management policy (Ley et al., 2002; Callan and Thomas, 2001). Ley et al. (2002) assess the potential economic effect of a policy designed to restrict the flow of municipal solid waste across U.S. state borders. Alternatively, Callan and Thomas (2001) focus on the cost inefficiency of waste management and explore how the privatization of waste management, economies of scope (a combination of waste disposal and recycling) and economies of scale are related to cost efficiency.

There has been no evaluation of the efficiency of waste-treatment technology in supply-side studies. There are several technologies for incinerating waste, such as the gasification and melting system and the ash-melting system. The central government in Japan encouraged the use of melting systems – a decision that was based on promoting industrial policy rather than environmental policy. The purpose of our study is to measure the efficiency of Japanese waste management and to explore how technology is related to technical efficiency; in particular, we examine whether the technology promoted by the central government has resulted in the improvements in efficiency that were expected.

In Japan, the central government subsidizes municipalities to encourage the adoption of certain new technologies – including gasification and melting systems or ash-melting systems – to improve technical efficiency. Implementing these technologies was expected to reduce waste-management costs. However, in reality, these technologies are likely to be less technically efficient than the central government expected, and their implementation may have resulted in only small increases in efficiency. The government expected the cost savings to come from "learning by doing" (technology diffusion). However, these effects might be too small to offset the high cost of the new technologies. Neither ex-post nor cost-benefit analyses have been performed on the results of these processes; thus, the government does not know the outcome of its policies. In this study, we find that municipalities are likely to adopt less technically efficient technologies; therefore, the central government's technology policy is found to have failed to improve technical efficiency.

Section 2 provides the background of the subject of this study. Section 3 presents the study's methods and data, Section 4 discusses its results, and Section 5 provides concluding thoughts.

2. Background

This study aims to test the hypothesis that the Japanese policy of providing governmental subsidies to encourage municipalities to adopt new waste-management technologies is associated with lower total factor productivity (TFP)[1]. Japan has more incinerators than any other country in the world (e.g., Ministry of Environment, Japan, 2002; Yamamoto, 2004). Decades ago, waste began to be incinerated because this approach was considered to have superior technological efficiency and sanitation benefits. Since then, limitations in landfill capacity have made policymakers look favorably upon new waste-management technologies, such as high-temperature-melting facilities with incinerators or ash-melting systems.

Since the late 1990s, landfill shortages have become a significant problem. For example, the average landfill is ordinarily expected to be filled to capacity within 10 years (Ministry of the Environment, 2002). The use of melting technology reduces the amount of burned ash; thus, less ash is placed in landfills. The scarcity of landfills incentivized and spurred the development of new technologies (e.g., more incineration to reduce the volume of waste) without ex-ante assessments of their economic effects.

The national policy action that was proposed by the Ministry of Health and Welfare, the *Areawide Program of Waste Disposal*, was enacted to promote waste treatment over a wider area, beginning in 1997, to solve the aforementioned problems. In April 1997, the Ministry of Health and Welfare (control of enforcement was transferred to the Ministry of the Environment in 2001) began providing subsidies to local municipalities that utilized certain new and large-scale technologies targeted by the central government: gasification and melting systems and ash-melting systems.

The subsidy policy encourages local governments to adopt new technologies that have been developed since the late 1990s. A surge in interest in waste-treatment technologies coincided with a change in the strategy of private firms that develop these technologies. A steep increase in the demand for new technologies encouraged competition in the waste-treatment technology market.

[1] According to recent studies, the dioxin emissions from waste treatment do not affect human health (Watanabe and Hayashi, 2003). Therefore, this study does not consider this environmental externality.

Companies in struggling industries, such as iron manufacturing and shipbuilding, entered the market as suppliers at this time. In total, 27 major firms were active in this market. The huge market for waste-management services has been encouraged by the subsidy policy of the central government, which issued subsidies totaling approximately $38.4 billion (approximately ¥36.1 trillion) in 2000.

This study models the local government's intention to maximize outputs in the volume of the processing capacities for incinerated waste and recyclables while simultaneously reducing inputs. We hypothesize that municipalities are likely to adopt less technically efficient technologies that, in fact, reduce the efficiency of their waste-management processes; these new technologies include gasification and melting systems and ash-melting systems, among others. Consequently, the central government's technology policy has likely failed to improve technical efficiency. Local governments follow the central government. In addition, local governments have an incentive to minimize short-term costs rather than long-term costs because of a myopic perspective. For example, the local officials who choose waste-treatment technologies often stay in the same position for only a few years before moving to other departments. Thus, their work is evaluated as short-term achievements rather than as contributions to efficient long-term utilization of the local governmental budget. Thus, local officials are often judged on whether they have undertaken something new, such as whether they have instituted use of state-of-the-art new technology in a local waste-management plant (e.g., Yamamoto, 2004). Therefore, we expect newer technology to be associated with lower efficiency because of government officials' failure to think in the long term.

3. Model and Data

3.1 Model of Productivity Changes

This study utilizes data envelopment analysis (DEA), which is a nonparametric approach (Färe et al., 1994; Kumar and Russel, 2002). The method can consider the possibility that producers do not necessarily choose the most efficient allocation and that there may thus be some inefficiency. Typically, waste management is implemented by local authorities who do not choose efficient outcomes. Thus, we employed a DEA method in our study. An alternative approach is the parametric method, which has its own advantages (see the application in Kumar and Managi, 2009).

This study measured the nonparametric frontier production function by applying the Luenberger productivity indicator[2]. DEA was applied to estimate productivity measures using mathematical programming. The advantage of DEA is that multi-input, multi-output production technology may be described without specifying functional forms (see Managi et al. (2004) for an intuitive explanation). We then investigated the factors associated with productivity changes with an econometric analysis. This technique is useful to understand the effectiveness of new technologies. New technologies might require much larger capital or human capital investments than the gains made in terms of waste-treatment and recycling capabilities. In that case, new technology is associated with a lower efficiency or productivity score in the DEA.

Growth in TFP is an essential cause of advancements in economic welfare. We are also interested in the drivers (or decomposed elements) of changes in TFP. The change in TFP is decomposed into two elements: technological change (TC) and efficiency change (EC). TC measures shifts in the production frontier because of innovation, whereas EC measures changes in the position of a production unit relative to the production frontier. A significant increase in EC is expected if

[2] For the Malmquist productivity index (see Färe et al., 1994), either an input- or output-oriented approach must be chosen as its measure. The choice depends on whether one assumes input minimization or output maximization as the behavioral principle of the sample (Managi, 2010). By contrast, the Luenberger productivity indicator does not require a choice between input and output orientations (i.e., maximizing net of outputs minus inputs). Thus, the Luenberger productivity indicator is a generalization of the Malmquist productivity index. In our case, application of the Luenberger productivity indicator implies increasing incineration and recyclables while reducing costs (i.e., reducing the costs of inputs such as capital stock) as discussed below. See Syverson (2011) for a broader review of the productivity literature.

existing resources are not fully utilized in production initially (see Appendix A for a technical explanation of the model).

Few studies have addressed efficiency and productivity issues in the waste-treatment industry. In particular, DEA has not been used as a tool to estimate the efficiency of the waste-treatment sector. Therefore, there are no prior studies examining the effect of waste regulatory reforms on the Luenberger productivity indicator and its decomposed elements. In this article, DEA is applied to measure the efficiency and productivity indicators, and, the effect of regulatory reforms is then examined using the estimation approach for panel data described in the next subsection.

3.2 Determinants of Productivity Changes

This study utilized econometric models to analyze the determinants of productivity changes. An empirical association of technology adoption and consequent changes in productivity may be identified by measuring productivity changes. If there is a difference, we find that the application of the particular technology is associated with changes in productivity or efficiency (i.e., the level of efficiency changed by technology applications). We considered serial correlations because the dependent variable in econometric models is measured using DEA. When the productivities are measured by DEA in the first step and regressed on explanatory variables in the second step, the productivity measures calculated by DEA are likely to be serially correlated (Simar and Wilson, 2007). Guan and Oude Lansink (2006) suggest the use of a dynamic generalized method of moments (GMM) model with a two-year lag to analyze TFP measured by DEA to eliminate the serial correlation problem[3].

Therefore, this study used a dynamic GMM model to analyze productivity changes. We

[3] Alternatively, Simar and Wilson (2007) argue that a bootstrapping method should be used. However, the use of panel data and dynamic specifications make this problem more complex because the bootstrapping method for the DEA is applicable to cross-sectional data.

estimated the following equation:

$$PROCH_{it} = c + \alpha_1 PROCH_{i,t-1} + \alpha_2 PROCH_{i,t-2} + \beta_1 X_{it} + \beta_2 Z_{it} + \varepsilon_{it} \qquad (1)$$

$$\varepsilon_{it} = \eta_i + \nu_{it},$$

where $PROCH_{it}$ is the annual productivity change (such as TFP, TC or EC) measured by the Luenberger productivity indicator for region i at time t. The previous year's productivity change affects the current year's productivity change because further improvement in productivity after high growth in the previous year might be more difficult. To address the dynamics, two lags of the dependent variable are included in (1). X represents socioeconomic characteristics, including variable ratios of privatization, population density, and the financial independence index of the city. Z represents the technology employed by the local authority and is a dummy variable representing the specific technology adopted for region i at time t. The municipality receives a score of one only if a technology is employed in a specific year (see, for example, Appendix B for a map showing the area that applied gasification and direct-melting technology).

The set of technologies is chosen when the technologies are subsidized. Otherwise, common incineration technology is chosen. All of the new technologies are used for the treatment of waste inside the plant. The variable Z is expected to be associated with either higher or lower regional efficiency in waste management based on the adoption of new technologies; ε is an error term and consists of an individual geographical effect η and random disturbance ν.

We expect population density to have a positive effect on productivity. Waste might be collected more effectively in denser areas because of reduced transportation costs. That is, in higher-density areas, local authorities might be able to increase efficiency more easily than in lower-density areas.

Waste-management plants that have undergone privatization are expected to show the effect of the privatization of waste management on total efficiency. In Japan, many local governments dispose of waste themselves. However, some local governments consign all or part of their waste disposal to the private sector. This variable is expected to have a positive correlation with productivity because waste management overseen by private firms is expected to be more efficient. The financial independence index of the municipality is the municipality's revenue collected within the city divided by the overall budget, including the municipality's internal revenue and revenue provided by the central government. If the financial independence index of a municipality is close to one, it does not need to rely on revenue from the central government. The financial independence index is also expected to have a negative correlation with subsidy receipts because better financial performance in the city is most likely caused by better management, which results in not requiring the subsidy. Thus, financially independent cities are generally able to achieve higher productivities.

In this model, the lagged dependent variable is correlated with the error term, $\varepsilon_{it} = \eta_i + \nu_{it}$. Therefore, a first-differencing method is used to remove the individual effect, η. In the first-differenced model, all observations of the dependent variable before $t - 2$ are valid instruments. Arellano and Bond (1991) propose a difference GMM estimator in which all the valid historical instruments are used in equation (1). When instrumental variables that are not correlated with the individual effect η are available, they may be used in the level model.

Arellano and Bover (1995) and Blundell and Bond (1998) propose a system GMM estimator in which the moment conditions in the differenced model and level model are combined. In their studies, the system GMM estimator might dramatically improve the problem of weak instruments. Therefore, the system GMM estimator was used in this study.

3.3 Data

In this study, we use annual panel data from 1,414 city-level data sets in Japan from 1996 through 2002. This period was chosen because it coincides with a wave of new technology implementation and because more recent data are not available. The data used were derived from several Japanese national statistics. The output variables for our efficiency measure are the volume of incinerated waste and the volume of recyclables. These two are distinct outputs. In Japan, all waste is classified into two main categories: non-recyclable waste and recyclables (e.g., glass, aluminum and steel cans, newspaper, etc.). Non-recyclable waste and recyclables are collected separately and brought to the same facility. Non-recyclable waste consists of incinerated waste and non-incinerated waste, both of which are dumped into the landfill directly. However, most non-recyclable waste is incinerated. Data on incinerated waste and non-incinerated waste were not available at the municipality level. Thus, we considered the volume of non-recyclable waste to be the volume of incinerated waste in our study.

The input variables for our efficiency measure are capital stock, the number of vehicles used for the collection of waste, and expenditures on employees. Increasing these inputs raises the outputs in our production function set, and these data are applied as a first-step productivity measure. All other variables explained below are then used in the second-step estimation as determinants of the productivity measure in the first step. These include the ratio of privatization, population density of the city, and the city's score on the financial independence index.

The subsidy is provided by the Ministry of Environment as part of the central government budget, not from the municipal budget. This will indirectly affect the use of the municipal budget. The municipality makes the decision regarding privatization, and the cost of the privatization affects the budget. The values associated with this subsidy and privatization are included in both of the inputs and outputs; therefore, they will not bias productivity measurements.

Data on the volume of incineration, volume of recyclables, capital stock in the waste-treatment sector, number of vehicles used for collection of waste and recyclables, number of and expenditures on employees, ratio of privatization, population density of the city, and financial independence index of the municipality were taken from the *Annual Survey of General Waste Treatment* by the Ministry of the Environment of Japan. The capital stock represents the size of the investment in a municipality's waste-treatment sector, as listed on the balance sheet of the *Annual Survey.* The expenditures on the employees variable represents the total employment expenditure for workers in the sector. All monetary variables were adjusted to year 2000 prices using the producer price index.

To implement the alternative analysis, we used an alternative capital stock variable that is defined as the plant capacity in the region, measured as tons disposed per day, instead of a monetary variable for capital stock. The average plant vintage and a dummy variable representing each technology choice were obtained from the Ministry of the Environment to complete this alternative analysis.

The annual amount of waste treated per person was approximately 410 kg, and this average remained constant over our study period. In addition, population size was relatively constant during our study period. Therefore, we eliminated changes in the demand for waste treatment as a factor; instead, we focused on supply-side causes of changes in productivity. We measured the quantity of recycling in weight instead of monetary units and used a physical definition for productivity, which indicates that productivity only reflects technology, whereas productivity with value added depends on market conditions. In particular, physical output measures are more practical when quality varies little over time.

4. Results

4.1 Measure of Productivity

Table 1 shows the results for average changes in TFP and its decomposition over time. Over our study period, TFP first increased and then decreased, which resulted in a small overall increase in the TFP value of 0.0009. In 1998 and 2000, the EC effect dominated the TC effect, but the TC effect dominated that of the EC for all other years. Both TC and EC influence TFP.

The measured productivities strongly depend on the choice of variables. An alternative measure of capital may also be available, and we choose to apply capital data as the *disposal capacity of treatment furnace* instead of to measure it as the capital stock input (i.e., the conventional meaning of capital). The former approach is better at identifying plant capacity, and the latter more fully describes the actual waste-treatment sector. We measured productivity with the former measure of capital data to better capture the disposal capacity of a treatment furnace. The values of productivity are relatively similar for the two cases. At the city level, the changes in TFP are different over time and by region. We will elucidate the determinants of these changes in this section.

Figure 1 shows a simple plot of the two measures of TFP. We found that these two measures are strongly correlated with one another, although the variations were large. Although we do not report the results because of space considerations, all of the analyses using disposal capacity of the treatment furnace yielded similar results for the sign and statistical significance of the second-step estimation of determinants. In addition, given the same technology usage and inputs requirements, the goal would be to maximize output. However, adopting technology requires more investment and/or means higher costs. The choices of technology or inputs are also of significant concern for municipalities because the *Waste Management and Public Cleansing Act* requires municipalities to use their budgets efficiently (Ministry of Environment, 2000). Therefore, given the same technology choices, a municipality will try to reduce inputs because its goal is to maximize the volume of incinerated waste and recyclables while simultaneously reducing costs. However, we apply input-oriented Malmquist indices (see Färe et al., 1994) as a robustness check for our results. Simple correlation of the Luenberger productivity indicator and the input- (or output-) based

Malmquist index is high at 0.46 (or 0.58). Similar results are obtained for the sign and statistical significance for the second-step estimation.

Before the regression results in the next subsection, we break down our results between incineration, on the one hand, and all other technologies, on the other, to show a simple comparison of the two groups. The last two columns in Table 1 present the results for incineration and for all other technologies. The TFP of subsidized technology is identified if one of the new technologies is used. If no new technology is used, we coded the TFP as TFP of incineration only for this simple comparison (not for the discussion that follows in the next subsection). Next, a plot of cumulative productivity for these two groups is added as Figure 2, which indicates that incineration performs better than the subsidized new technologies.

4.2 Estimation of the Model of Productivity Change

The estimation results of equation (9) and how they affect productivity changes, ECs and TCs are reported in Table 2. Sargan's test for over-identifying restrictions (Sargan, 1958) and the hypothesis of no second-order autocorrelation yielded p-values from 0.26 to 0.33, which implies that the instruments used in the GMM estimation are valid and that there is no serial correlation in the disturbance term. We also examined the stationarity of the residuals using the unit root tests described by Im et al. (2003). In all specifications, the null hypothesis of a unit root in the residuals was rejected at the 1% level.

Our data set included eight technologies; seven of these were new technologies (successive rotation, incineration with prior processing, chemical treatment of incinerated ash, fly ash treatment, gasification and melting, shaft-type gasification and direct melting), and the eighth was a conventional technology (incineration). However, because some of these technologies are correlated with one another in our base model, we analyzed five technologies[4] that are used most frequently: successive rotation, incineration with prior processing, chemical treatment of incinerated ash, fly ash treatment and incineration. Table 2 shows the results of the base model (i.e., model 1, which uses fewer combinations of explanatory variables). For the robustness check, we also estimated alternative specifications when we focused on the other technologies. Some of the new technology variables are not included in Table 2 because of multicollinearity problems with several of the new technologies, which indicate that they are sometimes used simultaneously (i.e., they are not mutually exclusive of one another), and these results are reported in Table 3. Because the sign and significance of socioeconomic characteristics are identical to the results in Table 2, we only reported the results for the effects of each technology on productivity.

First, privatization had statistically significant negative and positive effects on TC and EC, respectively. Privatization had a net negative effect on TFP. These results indicate that inefficient cities catch up to efficiency frontiers via privatization, but the benefits of privatization are offset by the negative effect on technical change.

Population density showed statistically significant results for all three productivity measurements. Negative associations were observed with EC and TFP, whereas there was a positive relationship with TC. Reduced efficiency, which offset technological progress, was observed in higher-density areas. In other words, increasing the area of waste collection (i.e., to include lower-density areas) might encourage efficiency gains. The financial independence index has a positive sign and is statistically significant for all specifications. The financial variable is negatively correlated with each new technology adaptation and ranges from -0.29 to -0.12 of simple correlation.

[4] The dummy variables for waste treatment technologies were created with conventional incineration technology as the base.

Because adoption of new technology is accompanied by a subsidy, less independent municipalities tend to be subsidized.

Regarding the effect of technology, incineration with prior processing had a significantly positive effect, whereas successive rotation, chemical treatment of incinerated ash and ash treatment had significantly negative effects. This result indicates that successive rotation, chemical treatment of incinerated ash and ash treatment decrease productivity. Prior processing played an important positive role because sludge has a high moisture content (approximately 80–85%) that can be reduced through prior processing. Dewatering by high-pressure heating, microbe fermentation, and degradative treatment are utilized in prior processing systems. These systems might help increase productivity.

From these results, we can conclude that new technologies, excluding incineration with prior processing, have lower levels of productivity. Using the estimation results, we found that the minimum negative impact occurs when the following three technologies are alternated: successive rotation, chemical treatment of incinerated ash and fly ash treatment. This approach reduces the productivity change by 0.012. It should be noted that this number is fairly large, particularly because the average productivity change is only 0.00089, as shown in Table 1. However, we calculated the maximum negative impact of new technologies for the case in which local authorities utilize a combination of successive rotation, chemical treatment of incinerated ash and fly ash treatment, and the negative impact of this combination was 0.059, which is 66.29 times higher than the average productivity change. Thus, we can conclude that there is a significant negative impact from the introduction of successive rotation, chemical treatment of incinerated ash and fly ash treatment.

Next, we would like to discuss how disposal capacity, the number of furnaces, and vintage year affect productivity using model 2, which adds several more explanatory variables to model 1. None of these elements is statistically significant; furthermore, although we do not report the results.

we found that the variables do not significantly affect the outcome when alternative robust specifications are utilized, which indicates that increasing plant size, number of plants, and plant age are not significantly related to productivity performance.

Next, we discuss the results of alternative specifications as our robustness check. We focus on the effects of new technology on productivity changes, but we are not able to report the results of the effects of new technology on EC and TC because of space limitations. Table 3 shows the results of the alternative specification. We included the identical socioeconomic characteristics variables as in Table 3 but used different technology dummies. Privatization, population density, and the financial index were statistically significant, as discussed in Table 2. Therefore, in Table 3, we only report technology variables.

In alternative specifications, we assessed gasification and melting, shaft-type gasification and direct melting instead of the chemical treatment of incinerated ash and fly ash treatment. In all specifications, incineration with prior processing had a significantly positive effect, whereas successive rotation had a significantly negative effect. Identical results were obtained in Table 2, and they are robust. All other new technologies – including gasification and melting, shaft-type gasification and direct melting – were negatively correlated with productivity changes. Why are these technologies ineffective for increasing productivity? Gasification and melting and treatment of incinerated ash are effective methods of recycling, but their technical efficiency has been shown to be poor. Because these methods are advanced from an engineering perspective, they are commonly recommended for application to technical problems when funds are available. However, our results show that it is important to consider that these new technologies require more capital and are thus an inferior choice economically. The number of municipalities that used the different technologies and the average input usages for the different technologies are presented in Table 4, which shows that the numbers vary across different technological and input usages.

Finally, to explore how "learning by doing" with new technologies affects productivity, we added an interaction term for the technologies to the base specification that used years after the introduction of technologies. "Learning by doing" might be important, and its effect might be different from that of technology selection. Because the variables used in Table 2 have the same signs and statistical significance, only the main results are reported in Table 5. The interaction term of incineration and year had a significant positive effect. The base technology of incineration improved productivity based on experience with the technology. However, the respective interaction effects of the gasification and melting variable and the direct-melting variable with years of use were negative. Instead of a positive learning effect, we found that productivity declined over time because of additional maintenance costs related to fixing accumulation problems, such as removing melted ash from the furnace. Additionally, traditional incineration plants burn at 900°C, whereas gasification and melting plants require temperatures of approximately 1300°C, and the physical burden to the refractory body results in unexpected financial costs. These new technologies require technical knowledge and experience, and our results show that learning does not solve the accumulating problems of high-cost technologies. Conversely, traditional incineration, which is a known technology that has been applied for many years (even in less-populated regions), requires less technical knowledge, which is why it improved performance.

5. Discussion and Conclusion

Public demand for waste management has increased as income has risen, and improving the effectiveness and efficiency of public services (on the supply side) has become an important political issue in many countries.

In Japan, because municipalities with limited budgets have delayed the introduction of new technologies for waste management, the central government has encouraged municipalities to adopt specific new technologies – such as gasification and melting systems or ash-melting systems – and used subsidies to increase technical efficiency. However, we expected that these technologies are less efficient than the government expected and that the central government's policies, therefore, did not improve efficiency.

Our study sought to measure productivity in Japanese waste management using DEA and then to explore how technology is related to technical efficiency. Our main findings are as follows:

(1) Successive rotation, chemical treatment of incinerated ash and ash treatment decrease productivity, whereas incineration with prior processing increases productivity.

(2) Prior processing plays a positive and important role in waste management because sludge has a high moisture content (approximately 80–85%) that is reduced by prior processing. Currently, dewatering by high-pressure heating, microbe fermentation, and degradative treatment are utilized in prior processing systems; these methods might be effective in increasing productivity.

(3) New technologies, excluding incineration with prior processing, lower productivity.

To prevent policy failures, we suggest that the central government should not seek to specify the technology to be implemented; instead, policies should be implemented that relax the limited budgets of municipalities and encourage flexible decision-making processes.

Appendix A: Productivity indicator.

When municipalities adopt a new waste-management technology, they replace the old technology instead of building a new plant and maintaining existing facilities because it is difficult to obtain public acceptance from citizens of neighboring municipalities. This study applied the Luenberger productivity model, which is formulated as follows (see Managi (2010) for review):

Let $x = \left(x^1,...,x^M\right) \in R_+^M$ and $y = \left(y^1,...,y^N\right) \in R_+^N$ be the vectors of inputs and outputs, respectively. The technology set, which is defined by (A1), consists of all feasible input vectors, x_t, and output vectors, y_t, at time t and satisfies certain axioms, which are sufficient to define meaningful shortage distance functions.

$$T(t) = \left\{(x_t, y_t) : x_t \; can \; produce \; y_t\right\} \tag{A1}$$

The shortage distance function was defined as follows:

$$d_{T(t)}(x_t, y_t) = \max\left\{\delta; ((1-\delta)x_t, (1+\delta)y_t) \in T(t)\right\}, \tag{A2}$$

where δ is the maximum amount by which y_t can be expanded and x_t can be reduced simultaneously given the technology $T(t)$. Following Managi (2010), the direction taken is set to one as a common practice; that is, desirable outputs are proportionately increased, and inputs are proportionately decreased. It should be noted that we include the technology variables in the second step of the determinants of productivity estimates rather than in the first step of the estimation of the productivity indicator.

DEA is used to estimate the proportional distance function under the variable returns to scale by solving the following optimization problem:

$$d_{T(t)}(x_t, y_t) = \max_{\delta,\lambda} \quad \delta$$

s.t. $Y_t\lambda \geq (1+\delta)y_t^i$

$$X_t\lambda \leq (1-\delta)x_t^i$$

$$N1'\lambda = 1$$

$$\lambda \geq 0, \qquad \text{(A3)}$$

where δ is the efficiency index for company i in year t, $N1'$ is an identity matrix, λ is an $N \times 1$ vector of weights, and Y_t and X_t are the vectors of output y_t and input x_t, respectively. When added together, the weights for the variable returns to scale must total one. To estimate productivity changes over time, several shortage distance functions are required. The mixed-period shortage distance function is also measured by DEA. For example, $d_{T(t)}(x_{t+1}, y_{t+1})$ is the value of the shortage distance function for the input-output vector for period $t+1$ and technology in period t.

The Luenberger productivity indicator is defined as (A4) with several shortage distance functions.

$$TFP = \frac{1}{2}\left\{\left[d_{T(t)}(x_t, y_t) - d_{T(t)}(x_{t+1}, y_{t+1})\right] + \left[d_{T(t+1)}(x_t, y_t) - d_{T(t+1)}(x_{t+1}, y_{t+1})\right]\right\}. \qquad \text{(A4)}$$

This indicator is decomposed into two components as follows:

$$TFP = \left\{d_{T(t)}(x_t, y_t) - d_{T(t+1)}(x_{t+1}, y_{t+1})\right\}$$

$$+\frac{1}{2}\left\{\left[d_{T(t+1)}(x_{t+1}, y_{t+1}) - d_{T(t)}(x_{t+1}, y_{t+1})\right] + \left[d_{T(t+1)}(x_t, y_t) - d_{T(t)}(x_t, y_t)\right]\right\} \qquad \text{(A5)}$$

where the first difference represents EC and the second arithmetic mean represents TC.

$$EC = d_{T(t)}(x_t, y_t) - d_{T(t+1)}(x_{t+1}, y_{t+1}) \qquad \text{(A6)}$$

$$TC = \frac{1}{2}\left\{\left[d_{T(t+1)}(x_{t+1}, y_{t+1}) - d_{T(t)}(x_{t+1}, y_{t+1})\right] + \left[d_{T(t+1)}(x_t, y_t) - d_{T(t)}(x_t, y_t)\right]\right\} \qquad \text{(A7)}$$

Appendix B: Map showing areas applying gasification and direct-melting technology in 2007.

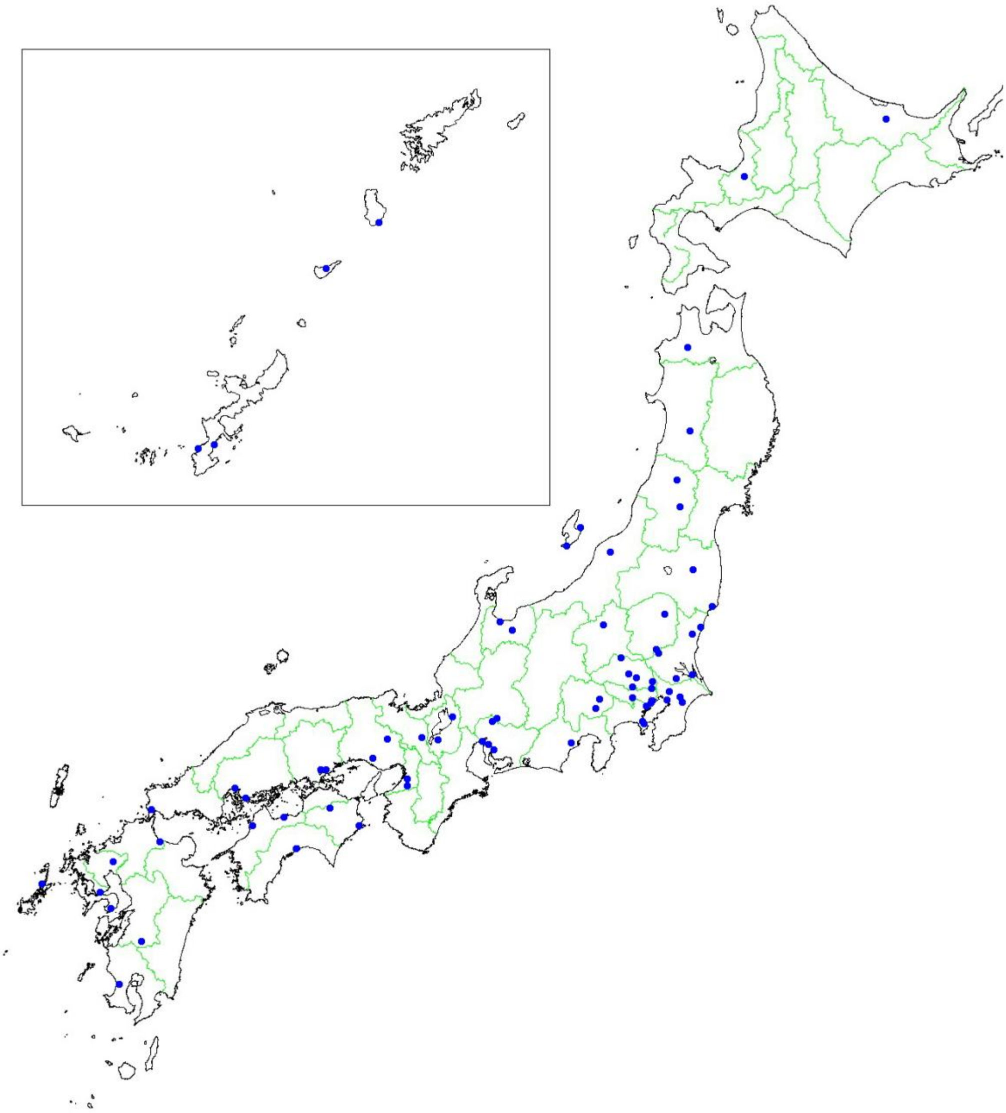

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Figure 1. Simple plot of annual change in TFP and an alternative measure of TFP.

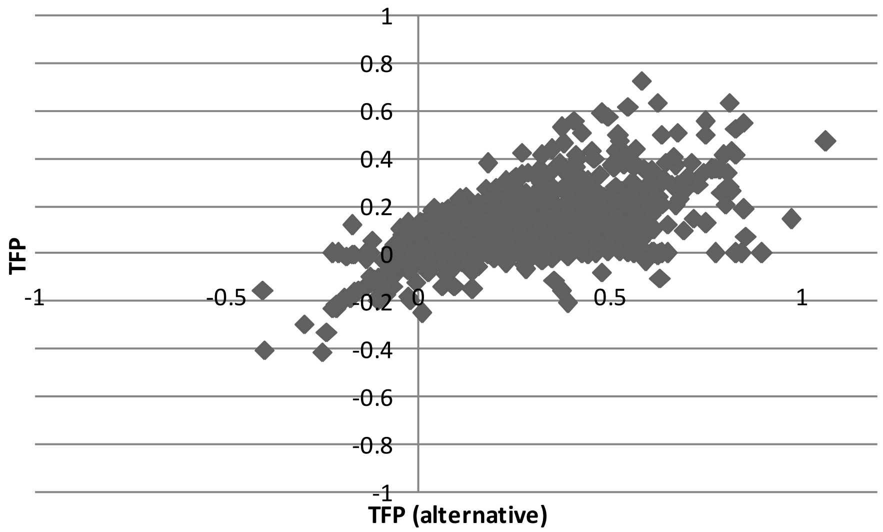

Figure 2. Cumulative total factor productivity.

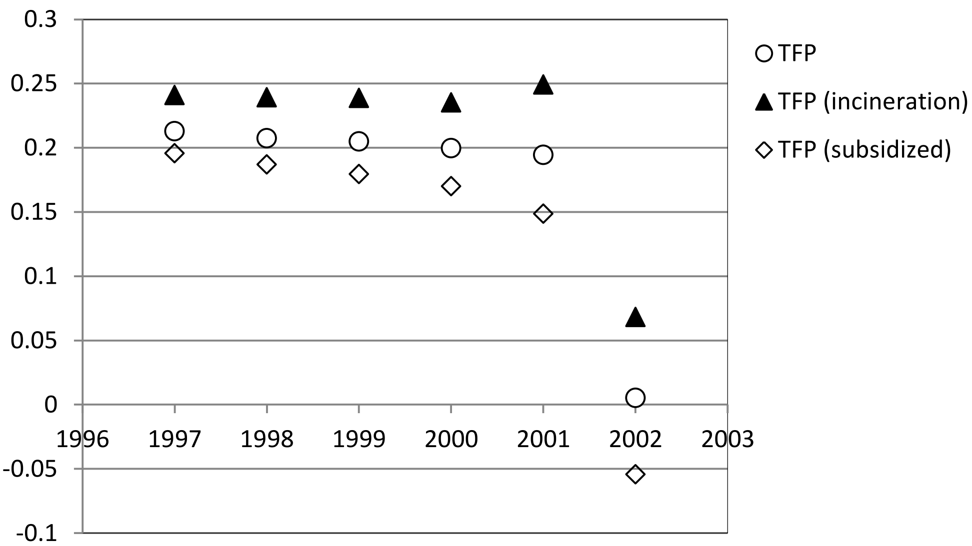

Table 1. Productivity changes.

Year	TFP	EC	TC	TFP (alternative measure)	EC (alternative measure)	TC (alternative measure)	TFP (incineration)	TFP (subsidized)
1997	0.2128	-0.3214	0.5342	0.0894	-0.0804	0.1697	0.2410	0.1956
1998	-0.0053	0.0013	-0.0067	-0.0164	0.0010	-0.0174	-0.0018	-0.0087
1999	-0.0027	-0.0203	0.0176	-0.0121	-0.0187	0.0066	-0.0004	-0.0074
2000	-0.0053	-0.0095	0.0043	-0.0052	-0.0215	0.0163	-0.0036	-0.0095
2001	-0.0051	0.0179	-0.0229	-0.0121	0.0293	-0.0414	0.0140	-0.0213
2002	-0.1892	0.3320	-0.5212	0.0439	0.0903	-0.0465	-0.1809	-0.2030
Average	0.0009	1.67E-07	0.0009	0.0146	-3.90E-17	0.0146	0.0114	-0.0091

Table 2. Results of the effects of social characteristics on productivity changes, efficiency changes and technological changes.

Explanatory Variable	Productivity Changes		Efficiency Changes	Technological Changes
	Model 1	Model 2	-	-
Variables	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Socio-economic variables				
Ratio of privatization	-0.309** (-2.35)	-0.298** (-2.31)	0.265* (12.31)	-0.574*** (-18.21)
Population density	-0.012*** (-2.62)	-0.015*** (-2.81)	-0.03*** (-4.33)	0.018* (1.76)
Financial independence index of local government	0.171*** (18.08)	0.179*** (18.92)	0.166*** (1.80)	0.006 (0.04)
Technology variables				
Successive rotation	-0.012** (-2.27)	-0.031** (-2.51)	-	-
Incineration with prior processing	**0.044***** (9.43)	**0.039***** (9.02)	-	-
Chemical treatment of incinerated ash	-0.018** (-2.52)	-0.010** (-2.38)	-	-
Fly ash treatment	-0.029* (-1.90)	-0.027* (-1.79)	-	-
Disposal capacity	-	8.31E-12 (-0.22)	-	-
Number of furnaces	-	-2.39E-07 (-1.23)	-	-
Vintage year	-	4.93e-11 (0.21)	-	-
Lagged dependent variable (t-1)	-0.042* (-1.93)	-0.073* (-1.90)	-0.065* (-1.89)	-0.028* (-1.98)
Lagged dependent variable (t-2)	-0.190* (-1.89)	-0.186* (-1.79)	-0.347 (-1.36)	-0.091** (-2.33)
Constant	0.33*** (5.11)	0.52*** (5.42)	-0.145* (1.78)	0.475*** (4.18)

Observations	5017	5017	5017	5017
Number of cities	1074	1074	1074	1074
Sargan test	69.12	73.64	54.97	49.28

Note: ***, ** and * indicate significance levels of 1, 5 and 10%, respectively. Values in parentheses are t-values.

Table 3. Effects of new technologies on productivity changes (1): Alternative specifications with added technology variables.

	Model 3	Model 4
Variables	*coefficient*	*coefficient*
Gasification and melting	-0.038** (2.12)	-0.056*** (-3.29)
Shaft-type gasification	-0.045** (-2.48)	-
Successive rotation	-0.012** (-2.23)	-0.010 * (-1.95)
Direct melting	-	-0.075*** (-3.68)
Incineration with prior processing	**0.044*** (9.31)	**0.044*** (9.29)
Fly ash treatment	-0.011* (1.65)	-0.025* (1.65)
Observations	5017	5017
Number of cities	1074	1074
Sargan test	71.26	73.08

Note: ***, ** and * indicate significance levels of 1, 5 and 10%, respectively. Values in parentheses are t-values. Only coefficients of technology variables are reported to save space.

Table 4. Number of municipalities and input usages for different technologies.

Technology	Obs.	Variable	Mean	Std. Dev.	Min	Max
Incineration with prior processing	124	expenditures on employees	762336.8	828722	53481	3267420
		number of vehicles	133.6	127.8	0	722
		capital stock	6554519	7852473	532212	4.32E+07
Chemical treatment of incinerated ash	101	expenditures on employees	762336.8	828722	53481	3267420
		number of vehicles	133.6	127.8	0	722
		capital stock	6554519	7852473	532212	4.32E+07
Fly ash treatment	83	expenditures on employees	762336.8	828722	53481	3267420
		number of vehicles	133.6	127.8	0	722
		capital stock	6554519	7852473	532212	4.32E+07
Gasification and melting	60	expenditures on employees	762336.8	828722	53481	3267420
		number of vehicles	133.6	127.8	0	722
		capital stock	6554519	7852473	532212	4.32E+07
Shaft-type gasification	60	expenditures on employees	681425.7	943078	51517	3754655
		number of vehicles	168.7	176.8	20	757
		capital stock	8105897	9694428	157226	4.32E+07
Successive rotation	35	expenditures on employees	301661.8	418588	0	1377920
		number of vehicles	68.2	78.8	0	313
		capital stock	2551435	3929835	42053	1.72E+07
Direct melting	41	expenditures on employees	684170.0	946779	51517	3754655
		number of vehicles	196.7	202.8	20	757
		capital stock	7873807	8824967	157226	3.50E+07

Note: *Obs*. shows the number of municipalities that used each of the different technologies.

Table 5. Effects of new technologies on productivity changes (2): Alternative specifications with added interaction term of technology variables and year.

	Model 5
Variables	*coefficient*
Incineration×Year	0.0001* (1.64)
Gasification and melting	-0.082** (-2.34)
Direct melting	-0.154*** (-3.50)
Gas fusion×Year	-0.0002** (-2.54)
Direct melting×Year	-0.0001*** (-3.59)
Observations	5017
Number of cities	1074
Sargan test	69.52

Note: ***, ** and * indicate significance levels of 1, 5 and 10%, respectively. Values in parentheses are t-values. Only coefficients of technology variables are reported.