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Do municipal mergers reduce the cost of waste management? Evidence from Japan

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ABSTRACT

This study investigates whether municipal mergers result in lower waste management costs. We develop a novel virtual merging method based on machine learning techniques to compile the data of the control group and estimate the effect of the large-scale consolidation in Japan on the various costs of managing municipal solid waste. We find that these mergers actually led to an increase in the total cost per ton. Estimation results also reveal that the construction cost increased in the post-merger period, which can be explained by the special bonds provided by the national government for new projects in merged municipalities. By contrast, the processing and management cost is little affected by the mergers, except for the absorption-type mergers and municipalities that never joined waste management associations. These results suggest that municipal mergers might not always bring a substantial scale economy in municipal solid waste management. Policymakers should be careful when promoting municipal mergers in the belief that a scale economy will prevail after the reform.

1. Introduction

Municipal solid waste (MSW) management is a major challenge for cities in their quest for sustainability (Saeed et al., 2009; Chifari et al., 2017). Given current trends, waste generation will continue to rise in the future, and waste management in both high- and low-income countries faces various challenges (Chen et al., 2020; Sharholy et al., 2008; Zhang et al., 2010). The World Bank estimates that the world generates two billion tons of MSW annually and expects that volume to grow to 3.4 billion tons by 2050, resulting in huge management costs (Kaza et al., 2018). Reducing these waste management costs is crucial to making cities environmentally and economically sustainable.

In recent decades, many countries have deployed municipal merger reforms in the belief that larger municipal units can exploit economies of scale in the provision of public services and thereby reduce costs (Fox and Gurley, 2006; Blesse and Baskaran, 2016). For example, from 1999 to 2010, the Japanese central government launched the Great Heisei Consolidation by enforcing the Special Municipal Mergers Law to encourage municipalities to merge. As solid waste management in Japan is implemented at the municipality level and municipalities have different waste policies and different cost structures, it is likely that the cost of waste management will be affected by the border reforms that inevitably require a reform of waste policy within the newly created municipality. However, it remains unclear whether such mergers lower costs in practice, as the empirical findings of previous studies are mixed.

Allers and Geertsema (2016) studied the amalgamation of Dutch municipalities and found no significant effect on per capita municipal spending before or after amalgamation. Moisio and Uusitalo (2013) examined the effects of municipal mergers on expenditure in Finland and indicated that mergers did not lower per capita spending but actually increased it compared with the control group. They also found a slight decrease in general administration costs. Moreover, Blesse and Baskaran (2016) studied municipal mergers in a German federal state and found significant reductions only in administrative expenditure after compulsory mergers, but no effect on expenditure after voluntary mergers. They concluded that policymakers should make further use of compulsory mergers to harvest economies of scale. By contrast, Blom-Hansen et al. (2014) found that political system reform in Denmark showed considerable scale effects in the form of lower administrative costs per inhabitant. Reingewertz (2012) studied amalgamation reform in Israel and found a 9% decrease in municipal expenditure, suggesting that municipal amalgamations do bring about economies of scale in the real world.

Given these inconclusive results on whether municipal mergers bring about economies of scale, this study examines whether the cost of waste management falls when municipalities merge. In particular,

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we examine the case study of the Great Heisei Consolidation in Japan by applying difference-in-differences (DID) methods and Mahalanobis distance matching (MDM) to the dataset compiled by our novel virtual merging method. One of the attractive points to studying this case is that the Japanese Ministry of the Environment provides a very detailed database on MSW management from 1999 to date that covers both the pre- and post-merger periods perfectly.

Our study's contributions can be summarized as follows. First, we develop a novel methodology that virtually merges the control group and makes the control group and the treatment group more comparable. The virtual merging method employs machine learning techniques to predict the merging patterns using the municipality characteristics dataset. Second, although many studies have investigated the cost efficiency of municipal mergers in general, this study is one of the first to focus on the resulting effect of municipal mergers on solid waste management costs using MDM and DID methods. Third, we use a 20-year dataset for most Japanese municipalities, which provides more convincing results and deeper discussions. These analyses offer deeper insights into the design of municipal mergers that are effective in reducing waste management costs.

This study's estimation results indicate that the Great Heisei Consolidation in Japan did not bring about significant economies of scale to total waste management costs. On the contrary, we find that the construction cost actually increased in merged municipalities. The plausible channel driving this result is a special bond for construction projects provided by the national government for merged municipalities. However, further analyses are needed to find out if these constructions bring a net social welfare gain to the merged municipalities. Moreover, we find some municipalities merged by absorption, and some municipalities that never joined the waste management association, benefitted from economies of scale, showing a reduction in the processing and management cost. These findings imply that policymakers should be careful when promoting mergers in the belief that economies of scale will accrue after the merger.

The remainder of this paper is organized as follows. Section 2 introduces the background of our study. Section 3 explains the data and methodologies used in our analyses. Section 4 presents our empirical results. Section 5 provides further discussions on the effects. Our conclusions and policy implications are reported in Section 6.

2. Background

2.1. The Great Heisei Consolidation in Japan

The most recent large-scale municipality consolidation, the Great Heisei Consolidation, began in 1999 against the background of the promotion of decentralization, an aging population, fiscal conditions of national and local governments, and expansion of living space.[1] The mergers were expected to strengthen the administrative and financial foundation of municipalities, enable more efficient municipal administration, and meet the needs of residents (Yokomichi, 2017). Municipalities that were going to merge organized consolidation conferences or councils first to discuss the details of the municipal mergers before the final merging decisions. As a result, the number of municipalities in Japan reduced from 3229 in 1999 to 1821 in 2006 when the first stage ended and to 1727 when the second stage finished in 2010, which is approximately 53.5% of the number of municipalities before. Appendix Fig. 8 shows municipality boundaries in Shizuoka prefecture, before and after the Great Heisei Consolidation. The number of municipalities decreased from 74 in 2000 to 35 in 2011.

The Great Heisei Consolidation can be divided into two stages, before and after the merger regulation was amended during the Consolidation. The main difference between the first and second stages of the Consolidation was the stronger fiscal measures in the first stage than in the second. For example, during the first period, the Japanese government encouraged municipalities to merge through a carrot-and-stick approach called the Special Municipal Mergers Law. If municipalities chose not to merge, they would face reductions in certain grants, whereas merged municipalities would maintain their grants for at least 10 years and be permitted to issue special bonds for new public projects, 70% of which would be covered by the central government (Hirota and Yunoue, 2017).

Furthermore, there were two types of mergers in the Great Heisei Consolidation: absorptions, in which a large municipality absorbed a smaller one or several smaller ones, and fusions, in which a new municipality was created by the consolidation of municipalities. The population standard for becoming a city from towns or villages was also eased from 50 thousand to 30 thousand, which also promoted small municipalities merging through fusions. In fact, approximately 85% of the mergers realized during the Great Heisei Consolidation were fusions. We discuss the differences in the effect on waste management costs between these two types of mergers in Section 4. The effect of mergers on cost reduction is expected to be higher in absorption mergers than in fusions because of the smaller size of the municipalities involved.

2.2. The municipal solid waste management in Japan

Local municipalities are responsible for the management of solid waste in Japan and municipalities make their own policies and rules for municipal solid waste management based on the series of laws related to waste management. Therefore, there are various waste separation and collection rules in Japan depending on the municipality one lives in. Furthermore, many municipalities also charge for the disposal of certain kinds of waste which is the so-called pay-as-you-throw policy to reduce the amount of waste generation and ease the financial burden of waste management.

Based on the Basic Law for Establishing a Circular Society in 2000, Japan has been implementing policies for promoting the 3Rs (reduce, reuse, recycle) and investing resources in recycling. The Japanese government has also enacted laws and policies to reduce waste generation and promote recycling, such as the Container and Packaging Recycling Law in 1995, the Home Appliance Recycling Law in 1998, and the End-of-life Vehicle Recycling Law in 2002 (Honma, 2021). Although these policies are expected to reduce the municipal expenditure on waste management by imposing recycling fees on producers and consumers, the total cost of waste management remains substantial. Fig. 1 shows the total MSW management cost in Japan over time. In the 2019 fiscal year, Japan spent 2089 billion yen on processing 42.7 million tons of MSW, including 415 billion yen on construction costs and 1552 billion yen on processing and management costs. Furthermore, the total cost corresponds to approximately 16,400 yen annually per capita which could be a burden for households.[2]

Inter-governmental transfer often plays a substantial role in the construction of waste management facilities. Because the constructions of large-scale facilities are expensive, municipalities usually depend on subsidies and financial support from the central government. In the Special Mergers Law, the support is strengthened in that the merged municipalities would maintain their grants for at least 10 years and be permitted to issue special bonds for new public projects, as we mentioned in the last subsection.

Long before the Great Heisei Consolidation, many neighboring municipalities formed partial affairs associations to collectively address

[1] The administration in Japan is basically divided into three levels: national level, prefectural level, and municipal level. The municipalities are also divided into cities, towns, and villages depending on the population and economic indices.

[2] 1 US Dollar is approximately 110 Japanese Yen as of January 1, 2019.

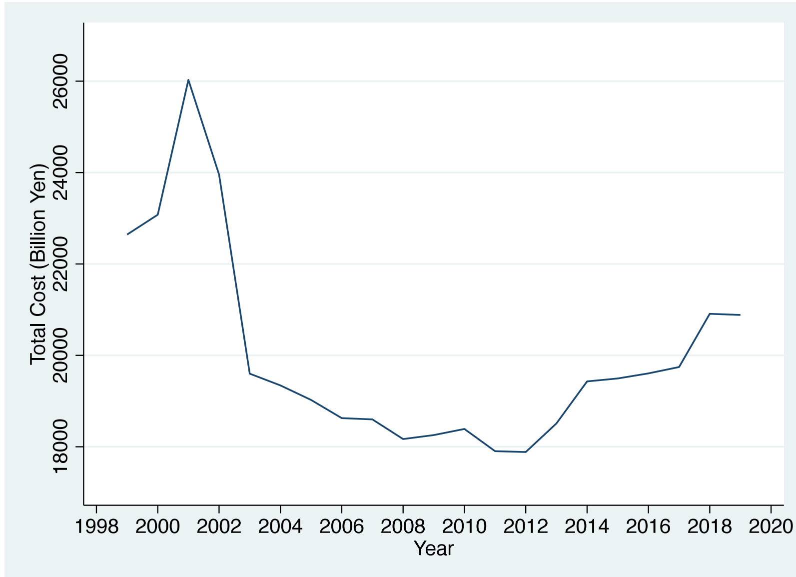

Fig. 1. The total cost of MSW management in Japan.
Source: MOE of Japan, 2021.

the management of MSW. They typically share the facilities for waste management, such as incineration plants, recycling centers, or landfill sites. According to the Ministry of Internal Affairs and Communications of Japan, there were 450 such waste management associations in 2018.

In many cases, as the name suggests, partial affairs associations are helping only a part of waste management in municipalities, as municipal solid waste management in Japan is implemented at the municipality level and their practices are very different from one another. The municipal merger, however, compulsorily requires merging municipalities to integrate such waste management practices as waste separation and collection rules. Therefore, it is expected that the mergers could influence the cost of waste management further. We discuss the effect of partial affairs associations on municipal solid waste management later in Section 5.

Moreover, MSW management services are also provided by third-party companies. Many municipalities contract with private companies to reduce costs (Bel et al., 2014; Silvestre et al., 2020). According to the Ministry of the Environment of Japan, only 20.1% of MSW collection was performed by the municipalities or waste management associations themselves in 2019. As for waste processing, approximately 5.8% of the incineration and 61.4% of the recycling of materials such as paper, glass, and plastics were carried out by other municipalities and private companies in 2019.

3. Data and methodology

3.1. Data

We use a panel dataset of municipalities for 20 years from fiscal year 1999 to 2018 collected from the Annual Survey of Municipal Solid Waste (Ministry of the Environment of Japan, 2020). The survey covers all Japanese municipalities and includes detailed information on MSW management such as the costs in each stage from collection to final disposal, amounts of processed waste, and the population involved. From this dataset, the total cost can be divided into the processing and management cost and the construction cost.

Although the municipalities provided more detailed expenditures such as collection cost and final disposal cost in this survey, we do not have more detailed information about the usage of contributions to the waste management association. This prevents us from analyzing more detailed costs because we do not know the way the contributions are used through the waste management associations. For example, part of the contributions could be used as the final disposal cost; then if we only look at the amount of the final disposal cost provided by the municipalities, there would be a bias as they actually spend more on it by using the contributions. We summarized the cost structure of the waste management dataset in Fig. 2. A similar cost structure applies to the construction cost although it is omitted from the figure.

Regarding municipal mergers, we obtain data on changes to the municipal codes from the portal site of the Official Statistics of Japan (Ministry of Internal Affairs and Communications of Japan, 2020) and manually merge the data into the waste management dataset. We use municipalities that merged in FY 2004 and FY 2005 as the treatment group and those that did not merge between FY 1999 and FY 2018 as the control group.[3] Approximately 85% of the mergers in this period were carried out in FY 2004 and FY 2005 given the strong fiscal measures from the central government during the first stage of the Consolidation as described in the previous section.[4]

Owing to data availability and consistency, we exclude municipalities with missing or corrupted data, municipalities that suffered from the Great East Japan Earthquake, and Tokyo Special Wards. We process the dataset at the post-merger level, which means that the number of municipalities is based on the municipalities after their mergers, and their data before merging take the aggregated value as if they merged during the pre-merger period.

Our main outcome variables are the MSW management costs per ton as that captures the change in efficiency before and after merging without being affected by other factors resulting from the mergers. We use the total cost per ton, the processing and management cost per ton, and the construction cost per ton as outcome variables in our main analysis.

In addition to the waste management and the municipal merger datasets, we also collect a municipality characteristics dataset from the portal site of the Official Statistics of Japan (Ministry of Internal Affairs and Communications of Japan, 2020). This dataset contains the variables we used for matching and virtual merging, including

[3] Municipalities that merged in other fiscal years and those that merged two or more times are dropped from the sample.

[4] We refer to the fiscal year when the municipal code in the Annual Survey of Municipal Solid Waste changes as the year they merged.

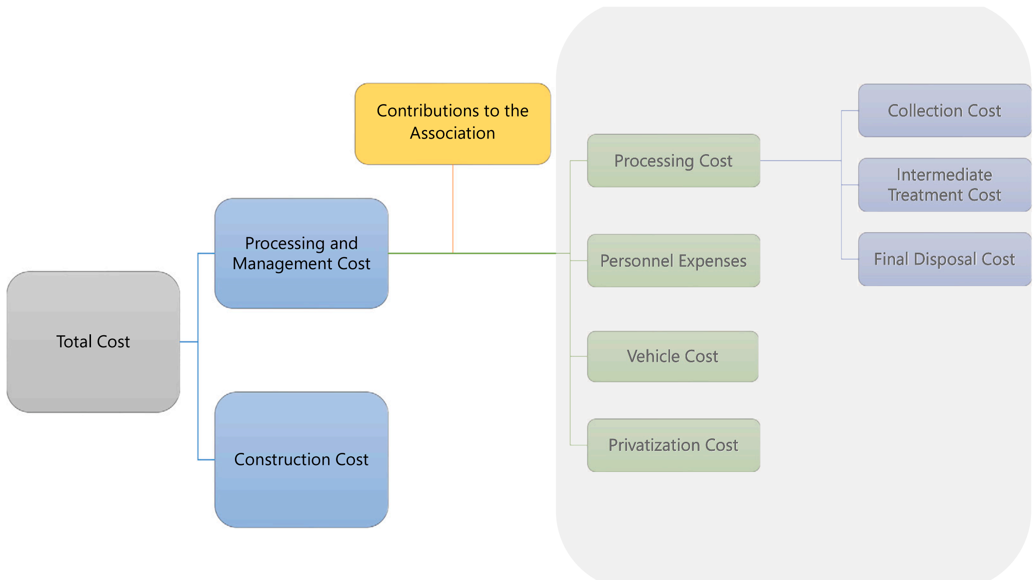

Fig. 2. The cost structure of MSW management in Japan.
Source: MOE of Japan, 2021.

area, population, population over 65 years old, the net balance of settled accounts; financial capability index; taxable income; and sales for the agriculture, manufacturing, and commercial sectors. Owing to data availability, all of these variables are averages during the ten-year period before our research period. The net balance of settled accounts, financial capability index, taxable income, and sales for the agriculture sector are the averages from 1989 to 1998. Population, population over 65 years old, are the averages of 1990 and 1995. Sales for the manufacturing sector is the average of 1997 and 1998. Sales for the commercial sector is the average of 1990 and 1998.

As the compiled datasets differ in the way we process them, we show the descriptive statistics separately later in this chapter.

3.2. The virtual merging method

Researchers studying the effects of municipal mergers necessarily address the issue that the unit of observations change before and after the merger. The typical solution for this is processing the dataset into a post-merger level dataset by aggregating the pre-merger value of the variables for merged or treatment municipalities, which we call the conventional post-merger method in this research. Although the post-merger method is helpful to capture the change in the efficiency of the treatment group from the pre- to post-merger periods, the value of the variables for control municipalities is left untouched, which we think is questionable as the same process is not applied to the control group. To make the treatment and control groups comparable, at least regarding the procedure of data compilation, we propose a virtual merging method.

In the virtual merging method, the municipalities in the control group are virtually merged just as those in the treatment group are, as shown in Fig. 3. The difference is that the mergers in the treatment group are real, whereas the mergers in the control group are hypothetical. Through this virtual merging approach, we can maintain symmetry in the data compilation process between the treatment and control groups, which is more balanced than simply merging the observations in the treatment group only. Nevertheless, both the conventional post-merger level dataset and the virtual merging datasets inevitably create hypothetical outcome variables.

Our virtual merging method takes the following steps:

1. Predict the number of municipalities in each merger via machine learning.
2. Merge the municipalities with the same predicted number randomly at the prefecture level.
3. Build the dataset using the virtually merged municipalities as the control group.

First, to virtually merge the control group data, we summarize the distribution of merging patterns in the treatment group and apply them to the control group. The patterns can be characterized by how many mergers are performed and how many municipalities merged in each merger. However, as the Great Heisei Consolidation reduced the number of municipalities in Japan by almost 50%, the number of merged municipalities is larger than the number of never merged municipalities. Therefore, we are unable to copy the merging patterns of the merged municipalities completely. In addition, as municipalities generally merged within the same prefecture, we only merge municipalities within their own prefecture.

With these concerns in mind, we adopt machine learning techniques to predict the merging patterns using the municipality characteristics. As both the actual and virtual mergers are based on the characteristics at the pre-merger level, we first divided the municipality dataset at the pre-merger level into the treatment and control datasets. We combine the treatment dataset with the municipal merger dataset to obtain the number of municipalities merged in each merger and other variables related to municipal mergers. In this way, we can use the treatment dataset to train the machine learning model and predict the virtual merging patterns using the control dataset. The descriptive statistics of the datasets used for training are shown in Table 1 and the descriptive statistics of the datasets used for prediction are shown in Appendix Table 8.

As for the machine learning model, we adopt the random forest algorithm (Breiman, 2001) using the Python library scikit-learn (Pedregosa et al., 2011). The random forest algorithm produces good out-of-sample fits, particularly with highly nonlinear data, but its black box nature does not offer simple summaries of relationships in the data (Varian, 2014). We also use the GridSearchCV class provided by scikit-learn to find the optimized parameters on the results of a 5-fold cross-validation. The following parameter settings are used: there are 100 trees in the forest, each tree has a maximum depth of 4, a minimum number of 40 samples is required at a leaf node, and a minimum number of 3 samples is required to split an internal node.

After training, we obtained a model with a R^2 of 0.185 and an MSE of 2.312. The partial dependence of some of the variables used in the

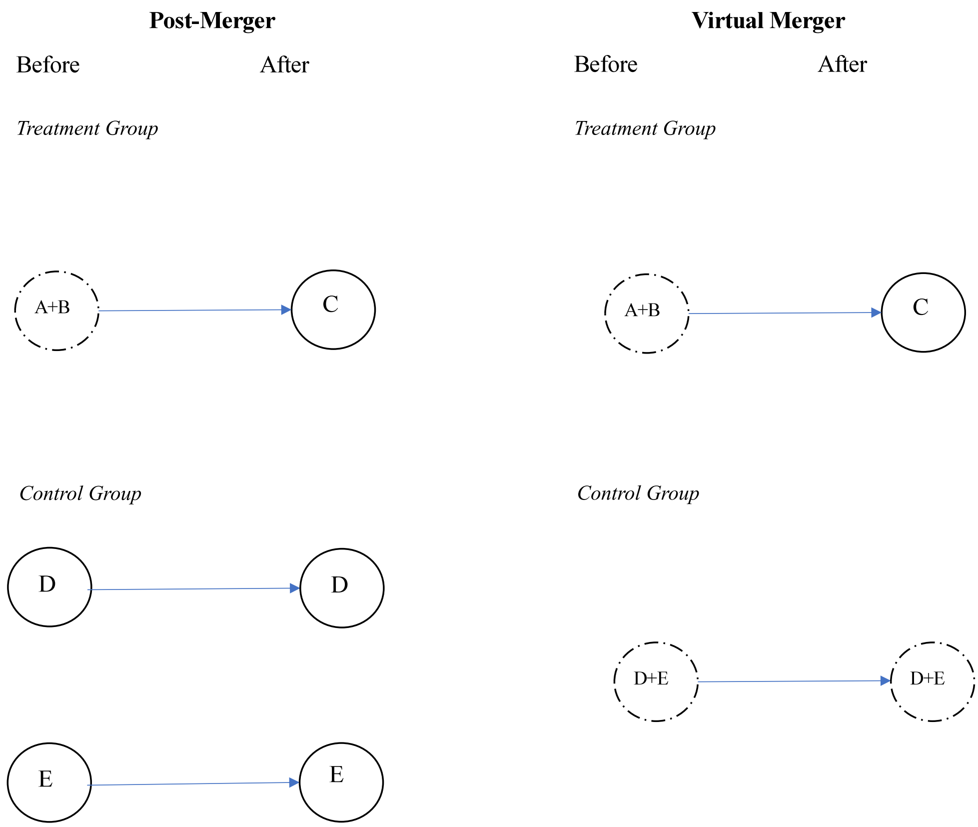

Fig. 3. Difference between the post-merger and virtual merger data.

Table 1
Descriptive statistics of the variables used for training.

Variables	N	Mean	Std. Dev.	Min	Max
Number of municipalities in each merger	1787	4.561	2.562	1	14
Number of municipalities in the same district[a]	1787	5.734	3.764	1	21
Area	1787	10,059	9951	127	80,149
Population	1787	24,813	70,190	196	1.462×10^6
Percentage of over 65 years olds	1787	0.202	0.0528	0.0663	0.443
Net balance of settled accounts	1787	198,605	332,340	-1.997×10^6	4.769×10^6
Financial capacity index	1787	0.357	0.228	0.0420	1.836
Taxable income per capita	1787	1036	340.5	332.4	10,213
Agriculture sales	1787	3132	3591	0	38,607
Manufacturing sales	1787	66,031	273,661	0	8.157×10^6
Commerce sales	1787	80,244	420,296	38	1.087×10^7
City dummy	1787	0.150	0.357	0	1

Note:
[a]Villages and towns in Japan are affiliated to old administrative districts called *Guns*. *Guns* basically do not have actual official functions nowadays but still have influences on many affairs such as postal codes and electoral districts. For cities, this variable takes a minimum value, which is one.

machine learning is shown in Fig. 4. For example, the upper right panel of Fig. 4 shows that the number of municipalities in one merger will be higher if there are more municipalities in the same district.

As the next step, we use the prediction obtained from the machine learning to perform the virtual merging. As the output of the predicted result is continuous, we first round up the predicted results and use those figures as the predicted numbers. Our virtual merging strategy is simply to merge those municipalities in the same prefecture that have the same predicted number. For each prefecture, we virtually merge the municipalities in the control dataset depending on the number of municipalities predicted to merge.

Some municipalities do not find enough partners to merge with. For example, it is possible that only three municipalities are predicted to merge with five municipalities in the same prefecture. In this case, we just merge the three municipalities as we consider that municipalities with the same predicted number should possess similar characteristics. The virtual merging is implemented without replacement.

We use the same seed of 42 to generate random numbers and perform the virtual merging procedure randomly one hundred times and then take the averages of the outcome variables. Fig. 5 describes that the municipalities with the same predicted number in the same prefecture are randomly merged. In this case, the six municipalities with the same predicted number (3) in Prefecture B are randomly merged into two virtual municipalities (G and F).

After all these processes, we obtain the compiled dataset as shown in Table 2. The average processing and management and construction costs per ton are approximately 34,900 yen and 5940 yen in the treatment group and 34,960 yen and 6090 yen in the control group, respectively.

We also report descriptive statistics of the conventional post-merger level dataset in Table 3. The average processing and management

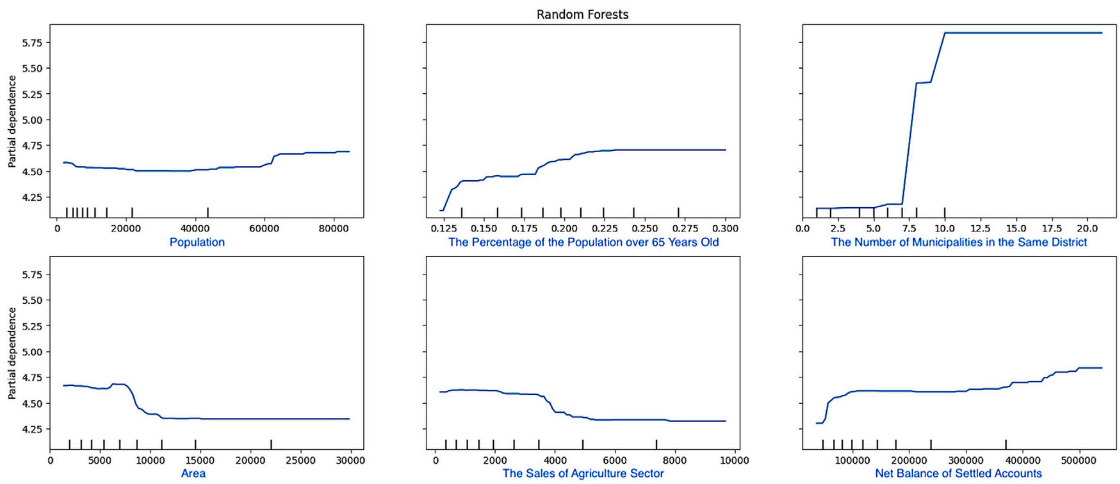

Fig. 4. Partial dependence of some of the variables used in the random forests learning.

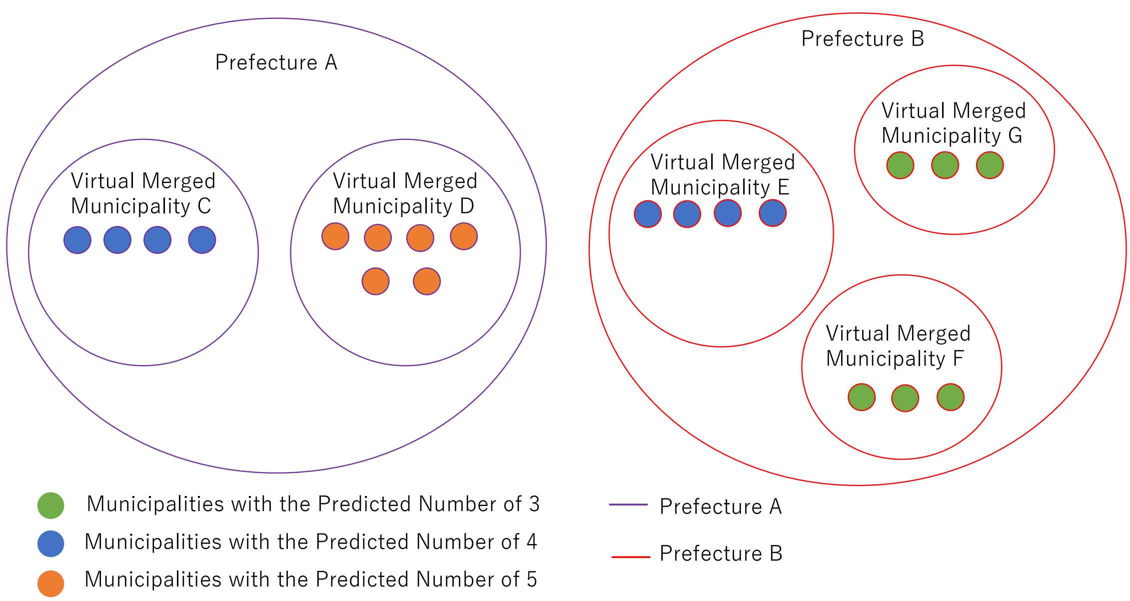

Fig. 5. An example diagram for the merging method of the virtual merging method.

Table 2
Descriptive statistics of the virtual merger dataset.

Variable	Obs.	Mean	Std. Dev.	Min	Max
[All]					
Total cost (*thousand yen/ton*)	15,740	42.29	32.44	0	2328
Processing & management cost (*thousand yen/ton*)	15,740	34.92	15.02	0	580.1
Construction cost (*thousand yen/ton*)	15,740	6	26.95	0	2235
DID indicator (*dummy*)	15,740	0.42	0.49	0	1
[Treatment group]					
Total cost (*thousand yen/ton*)	9240	42.02	27.11	0	580.1
Processing & management cost (*thousand yen/ton*)	9240	34.9	16.99	0	580.1
Construction cost (*thousand yen/ton*)	9240	5.94	19.54	0	503
DID indicator cost (*dummy*)	9240	0.72	0.45	0	1
[Control group]					
Total cost (*thousand yen/ton*)	6500	42.66	38.79	15.65	2328
Processing & management cost (*thousand yen/ton*)	6500	34.96	11.66	13.46	188.4
Construction cost (*thousand yen/ton*)	6500	6.09	34.87	0	2235
DID indicator (*dummy*)	6500	0	0	0	0

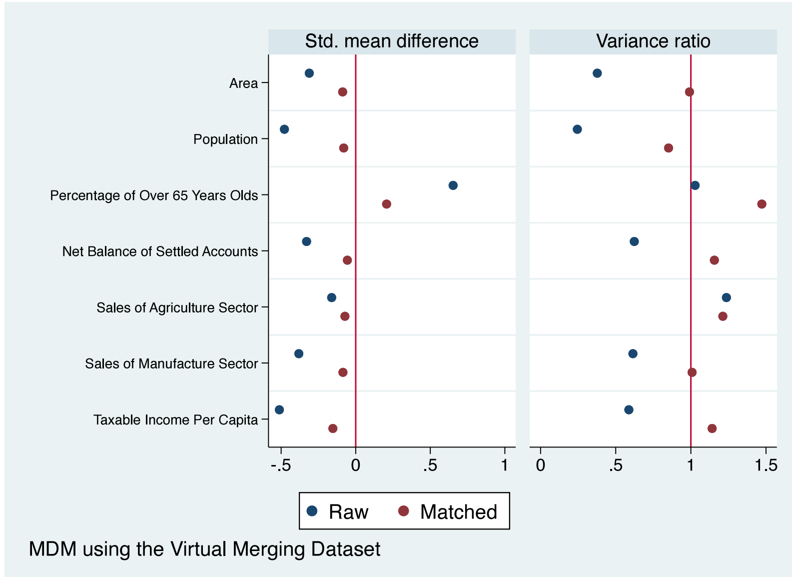

Fig. 6. The graph of balancing statistics of MDM on virtual merging dataset.

Table 3
Descriptive statistics of the post-merger dataset.

Variable	Obs.	Mean	Std. Dev.	Min	Max
[All]					
Total cost (*thousand yen/ton*)	30,480	47.22	71.25	0	6434
Processing&management cost (*thousand yen/ton*)	30,480	38.4	24.01	0	624.3
Construction cost (*thousand yen/ton*)	30,480	7.27	64.34	0	6343
DID indicator (*dummy*)	30,480	0.22	0.41	0	1
[Treatment group]					
Total cost (*thousand yen/ton*)	9240	42.02	27.11	0	580.1
Processing&management cost (*thousand yen/ton*)	9240	34.9	16.99	0	580.1
Construction cost (*thousand yen/ton*)	9240	5.94	19.54	0	503
DID indicator (*dummy*)	9240	0.72	0.45	0	1
[Control group]					
Total cost (*thousand yen/ton*)	21,240	49.47	83.35	0	6434
Processing&management cost (*thousand yen/ton*)	21,240	39.92	26.35	0	624.3
Construction cost (*thousand yen/ton*)	21,240	7.84	75.98	0	6343
DID indicator (*dummy*)	21,240	0	0	0	0

cost per ton is approximately 34,900 yen in the treatment group and 39,920 yen in the control group. The average construction cost per ton is approximately 5940 yen in the treatment group and 7840 yen in the control group. As the treatment groups in both datasets are the same, the only difference is the control group. The virtual merging dataset shows smaller differences in the descriptive statistics between the treatment and control group than the conventional post-merger level dataset does. It is likely that the approach successfully reduced the difference by hypothetically creating merging patterns and averaging out extreme values.

3.3. DID model

We adopt a DID design (Meyer, 1995) to address the endogeneity of merger decisions. As we focus on mergers in 2004 and 2005, we employ the DID design with two different treatment timings. The baseline model can be expressed as follows:

$$y_{it} = \alpha_i + \gamma_t + \beta D_{it} + \epsilon_{it} \tag{1}$$

The outcome variable y includes the total cost per ton and the processing and management cost per ton or the construction cost per ton. D is the DID indicator that captures the treatment effect. The coefficient of D is negative if economies of scale exist. Moreover, year fixed effects γ_t and municipality fixed effects α_i are included in the model to control for the time-invariant characteristics of common time effects and a given municipality, respectively.

One of the most important assumptions of the DID model is the common trend or parallel trend assumption. To examine the validity of the parallel trend assumption, we adjust our main model to implement an event study using the following model:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p=-5}^{-2} \beta_p treat_i * T_p + \sum_{q=0}^{13} \beta_q treat_i * T_q + \epsilon_{it}, \tag{2}$$

where *treat* is a dummy variable that equals 1 when the observation is in the treatment group, T_p is a dummy variable for p years before the merger, and T_q is a dummy variable for q years after the merger. More particularly, T_{-5} indicates the year 1999 for those merged in 2004 and the year 2000 for those merged in 2005. T_{13} indicates the year 2017 for those merged in 2004 and the year 2018 for those merged in 2005. The event study covers all lengths of our research period and the reference group is one year before the merger, which is 2003 or 2004, respectively. Municipality fixed effects α_i and year fixed effects γ_t are included similar to the baseline model.

3.4. Mahalanobis distance matching

Propensity score matching (PSM) is widely used to reduce sample selection bias by matching the observations in treatment and control groups based on their predicted probabilities of being treated (Rosenbaum and Rubin, 1983). However, there are concerns that PSM might not be the most optimized matching method (King and Nielsen, 2019). Keeping this in mind, we adopt the MDM method to reduce the sample selection bias rather than PSM.

As the name suggests, MDM uses the Mahalanobis distance to judge if the observations are “close”. The Mahalanobis distance between two units is smaller when the differences between the values of covariates of the two units are smaller. Therefore, we can use the distance to find the units in the control group that have similar characteristics to the units in the treatment group. This is also the major difference between MDM and PSM, as PSM only uses the one-dimensional propensity score for matching whereas MDM uses multi-dimensional distances for matching.

We choose seven covariates to perform the MDM, referring to previous studies using PSM (Hirota and Yunoue, 2017; Suzuki and Sakuwa, 2016): area, population, the percentage of the population over 65 years old, net balance of settled accounts, taxable income per capita, sales for the agriculture sector, and sales for the manufacturing sector. The choice of variables is slightly different from these previous studies because the research question and methodology of this study are also different from the previous studies. The descriptive statistics of the dataset used for matching are reported in Appendix Tables 9 and 10.

We apply the kernel matching algorithm to find potential control units that could be assigned to the treatment units. In this way, each treated unit is matched with several control units, and the matching weights are determined by kernel functions. We choose the Epanechnikov kernel function (Epanechnikov, 1969) in the kernel matching process, which has a simple quadratic form and is commonly used to produce weights in matching. We use the Stata package kmatch (Jann, 2017) to perform the MDM and generate the matching weights for computing the average treatment effects on the treated. The optimized bandwidth generated by kmatch using the default configuration is 2.37 for the virtual merging dataset and 2.69 for the conventional dataset.

The balancing plots of the MDM using the virtual merging dataset are shown in Fig. 6 and that of the conventional post-merger dataset is shown in Appendix Fig. 9. Comparing the two graphs, it is easy to notice that the virtual merging dataset has a smaller standard mean difference generally even after the matching, suggesting that our virtual merging method has achieved a more balanced dataset. Inspired by Stuart et al. (2014), who applies a weighted strategy to the DID model with propensity score, we use the matching weights generated by the MDM to perform the DID regression and event study.

4. Empirical results

4.1. Virtual merging model

Table 4 reports the estimation results based on our virtual merging dataset. The estimated coefficients imply that the merged municipalities incur a statistically significant increase in the total and construction costs. The increase in the total cost is approximately 5540 yen per ton, whereas the increase in the construction cost is 4990 yen per ton. Compared with the control mean, they are 11% and 64%, respectively. The coefficient of the processing and management cost per ton is small in magnitude and insignificant, suggesting that a merger may not bring economies of scale to the processing and management cost.

The results of the event study model to illustrate the parallel trend are plotted with the responding 95% confidence interval provided in Fig. 7 for the total cost, Appendix Fig. 10 for the processing and management cost and construction cost. First, these figures show a similar trend before mergers, and the confidence interval includes zero in the pre-merger period. These results provide supportive evidence that the parallel trends assumption appears reasonable. Figures also show that the trend changes remarkably after mergers. For the municipalities in the treatment group, we observe a substantial increase right after the merger in every plot, with total costs and construction costs increasing thereafter.

Table 4
Results of the virtual merging dataset.

Variable	(1) Total cost	(2) Processing and management cost	(3) Construction cost
D	5.54***	0.667	4.99**
	(2.05)	(0.67)	(2.18)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Treatment group	441	441	441
Control group	294	294	294
Observations	14,700	14,700	14,700

Notes: Robust standard errors clustered at municipality-level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Results of the conventional dataset.

Variable	(1) Total cost	(2) Processing and management cost	(3) Construction cost
D	4.61***	−0.960	5.76***
	(1.42)	(0.71)	(1.26)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Treatment group	444	444	444
Control group	1043	1043	1043
Observations	29,740	29,740	29,740

Notes: Robust standard errors clustered at municipality-level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Conventional model

Besides the virtual merging method, we also implemented the analysis using the conventional post-merger design for the robustness analysis. We aggregate the pre-merger value of the variables for the merged (or treatment) municipalities and retain the value for the never merged (or control) municipalities. Table 5 reports the results of the estimation of the conventional dataset.

Similar to the virtual merging model, we find that the coefficients of the treatment indicator for the total and construction costs are positive and statistically significant at the 1% level. In this case, the total cost increases by approximately 4610 yen per ton, and the construction cost rises by 5760 yen per ton after the merger. Compared with the control mean, they are 9% and 73.5% increases, respectively. The coefficient of the treatment indicator for the processing and management cost per ton is still insignificant, although it shows a negative sign in this analysis. The results of the conventional analysis are thus consistent with those of our virtual merging model, providing supportive evidence that minimal economies of scale resulted from the Great Heisei Consolidation.

We also carry out event study analyses of the conventional model, as shown in Appendix Figs. 11 to 12. In these figures, we again find similar trends for the treatment and control groups in the pre-merger period for the total and contribution costs. For the municipalities in the treatment group, the total and construction costs increase following the merger. The processing and management cost, however, seems to show a decreasing trend before the municipal mergers, although the trend changes to increasing right after the municipal mergers. This indicates that the parallel trend assumption might not be valid regarding the processing and management cost of the conventional dataset whereas the virtual merging method does not have this problem.

In summary, the results from the virtual matching method and the conventional method above suggest that the Great Heisei Consolidation promotes the total and construction costs while having little effect on the processing and management cost.

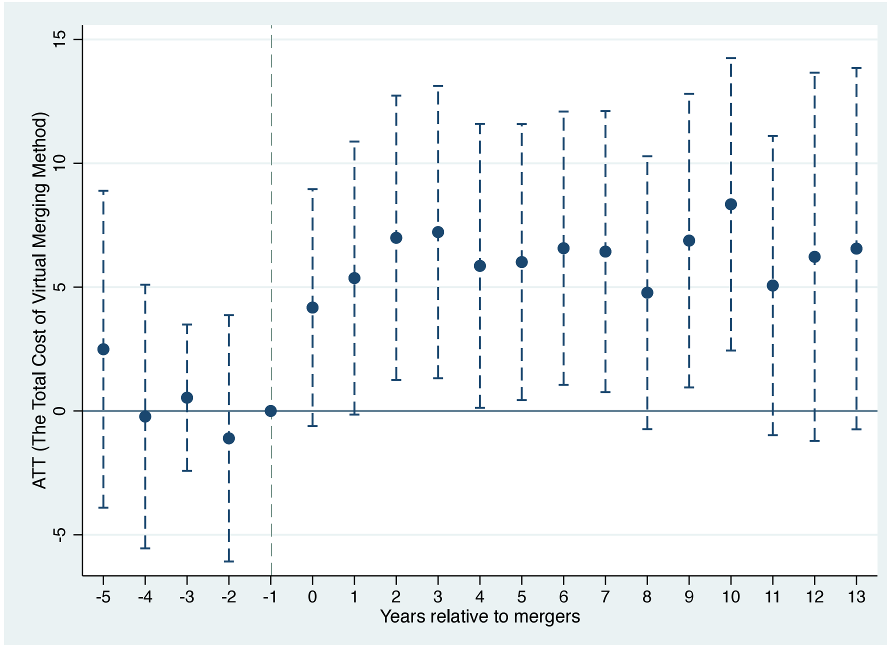

Fig. 7. Event study analysis of the total cost of the virtual merging method.

5. Discussions

5.1. Merger type

This subsection investigates the difference between the two types of mergers in the Great Heisei Consolidation: fusions and absorptions. In the absorptions, a large municipality absorbs a smaller one or several smaller ones, and in the fusions, a new municipality is created by the consolidation of municipalities. In our dataset, approximately 78.5% of municipalities are merged by fusions, and the remainder are merged by absorption. Because smaller municipalities are more likely to suffer from managerial inefficiency, the effect of economies of scale could be more significant. Our virtual merging method, however, is not suitable in this case, because there is no information on the merger type of the virtually merged control group. Therefore, the approach does not have an advantage over the conventional post-merger method. Hence, we divide the treatment group in the conventional post-merger level dataset into municipalities that merged by fusion and those that merged by absorption. We retain the control group and apply the DID model.

The estimated results for fusion-type mergers in Table 6 are similar to the main results, whereas the results for the absorption type are somewhat different. Regarding the absorption-type mergers, the coefficient of the treatment indicator for the processing and management cost is negative and statistically significant at the 1% level. In other words, the processing and management cost is reduced statistically significantly in municipalities that merged by absorption. The coefficient of construction cost remains positive and significant, as in the other models.

There are several reasons why absorption reduces cost more than fusion. First, fusion requires setting up a totally new organization and it leads to an increase in the cost (Allers and Geertsema, 2016). Second, a larger municipality in absorption might already have a sophisticated administration, allowing the smaller partners to improve efficiency through administrative reform (Blesse and Baskaran, 2016). Third, a larger municipality might simply require a smaller municipality to abolish administration offices and reduce operating costs.

5.2. Waste management associations

As noted in Section 2, many municipalities in Japan provide MSW services jointly with neighboring municipalities by forming partial affairs associations for waste management. There can be many kinds of partial affairs associations other than waste management. For example, municipality A can form a waste management association with municipality B, while forming an education association with municipality C. Therefore, it is unlikely that the waste management association has a great impact on the choice of partners for municipal merger. However, there would be differences in the efficiency among the municipalities joining waste management associations and those not. As our virtual merging method does not provide information on waste management associations for the control group, we will use the conventional post-merger dataset in this analysis as well.

We carried out the DID analysis using only the municipalities that never joined associations by selecting the units with zero contributions to the associations during the sample period. The estimation results in Table 7 show that municipalities that never joined waste management associations are substantially affected by municipal mergers. The estimated coefficient regarding the processing and management cost is negative and significant, suggesting that municipal mergers could bring economies of scale to those municipalities. The coefficient regarding the construction costs is positive and statistically significant, and the estimated magnitude is much larger than the baseline results.

As we find that municipal mergers resulted in few economies of scale in the main analyses, it is likely that economies of scale in MSW management had already been achieved for most municipalities—even before the municipal mergers took place. Inefficient municipalities achieved economies of scale by joining waste management associations and/or promoting privatization, whereas some larger municipalities achieved economies of scale alone. Therefore, only small municipalities and municipalities that never joined waste management associations improved cost efficiency through municipal mergers.

5.3. Incinerators

The special bonds for mergers provided by the government, which represented the “carrot” part of the policy, might be driving the increased construction costs for merged municipalities. Municipalities

Table 6
Results by merger type.

Variable	Total cost		Processing and management cost		Construction cost	
	Fusion	Absorption	Fusion	Absorption	Fusion	Absorption
D	6.92*** (2.07)	3.12 (2.46)	−0.299 (0.75)	−2.75*** (0.90)	7.53*** (1.99)	6.19*** (2.37)
Municipal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	28,860	22,860	28,860	22,860	28,860	22,860

Notes: Robust standard errors clustered at municipality-level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Municipalities that never joined waste management associations.

Variable	(1) Total cost	(2) Processing and management cost	(3) Construction cost
D	21.70*** (10.03)	−4.70** (0.71)	26.35*** (9.92)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	4820	4820	4820

Notes: Robust standard errors clustered at municipality-level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that merged during the first stage could issue these special bonds to build waste processing facilities for the newly formed municipality. Appendix Fig. 13 compares the numbers of incinerators built by municipalities merged by the Heisei Consolidation and those that did not merge during the study period. It indicates that the merged municipalities built more incinerators than those that did not merge, providing supportive evidence for the increase in the construction cost. Our results also suggest that the increase in construction cost is substantial for municipalities that never joined waste management associations. Because these municipalities had never built large joint incinerators before, their demand for new incinerators might be high after municipal mergers.

It is not clear, however, whether the increased construction of incinerators is welfare-improving. On the one hand, the new facilities might be equipped with the latest technology that emits fewer pollutants or provides higher power generation. On the other hand, a new incinerator might have a larger capacity and tend to have underutilized furnaces. Higher excess capacity might require recyclables as fuel to increase efficiency, thereby reducing recycling (Yamamoto and Kinnaman, 2022). Without further information, it is difficult to judge whether these benefits are higher than the increased construction cost.

6. Conclusions

Focusing on municipal mergers in the Great Heisei Consolidation in Japan, we examined whether they can bring about economies of scale and reduce the cost of waste management. We developed a new method to process the data and create a virtually merged dataset based on machine learning and random merging techniques. Our Mahalanobis distance matching weighted differences-in-differences analysis based on the new approach and the conventional method gives us robust results on the effect of municipal mergers on waste management costs in Japan.

This study's results generally provide the consistent finding that municipal mergers in Japan in the Great Heisei Consolidation led to an increase in the total and construction costs per ton for merged municipalities. Nevertheless, our further discussion shows the possibility that smaller municipalities could achieve economies of scale to some extent by being absorbed into larger municipalities, and municipalities that never joined waste management associations would also benefit as well. The increased construction cost is likely to reflect the building of new waste management facilities, particularly for the municipalities that had never joined waste associations before.

A full-fledged welfare analysis of having additional incinerators is beyond the scope of this study. Although our findings suggest that municipal mergers lead to higher costs of waste management by increasing the construction of incinerators, it is unclear whether the additional incinerators achieve a positive net benefit for society. A new incinerator might be equipped with the latest technology to reduce air pollution or be able to generate electricity efficiently. These benefits are not considered in our study but might outweigh the increased cost of additional incinerators. We should also consider other side effects of additional incinerators that might affect social welfare as a new incinerator with a larger capacity might be underutilized and therefore inefficient.

Based on these findings, we conclude that municipal mergers do not automatically lead to economies of scale in municipal solid waste management. On the contrary, providing special bonds for mergers can increase the cost through the construction of infrastructure for waste processing. Policymakers should assess municipal merger plans carefully and design merger reforms that can lead to the efficient provision of targeted public services.

CRediT authorship contribution statement

Jinsong Li: Data curation, Methodology, Writing – original draft. **Kenji Takeuchi:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Kenji Takeuchi reports financial support was provided by Japan Society for the Promotion of Science.

Data availability

Data will be made available on request.

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Appendix

See Tables 8–10 and Figs. 8–13.

Table 8
Descriptive statistics of the variables used for predicting.

Variables	N	Mean	Std. Dev.	Min	Max
Number of municipalities in the same *Gun*	1066	4.040	4.421	1	19
Area	1066	14,587	18,129	347	140,810
Population	1066	54,041	184,275	477	3.264×10^6
Percentage of over 65 years olds	1066	0.170	0.0574	0.0502	0.374
Net balance of settled accounts	1066	293,199	493,639	-1.687×10^6	4.952×10^6
Financial capacity index	1066	0.493	0.335	0.0400	2.157
Taxable income per capita	1066	1169	416.9	387.1	8016
Agriculture sales	1066	3676	4418	0	58,028
Manufacturing sales	1066	137,572	424,088	0	6.271×10^6
Commerce sales	1066	266,670	2.707×10^6	23	7.019×10^7
City dummy	1066	14,587	18,129	347	140,810

Table 9
Descriptive statistics of the variables used for matching of virtual merging dataset.

Variables	N	Mean	Std. Dev.	Min	Max
Area	759	35,884	27,724	762	178,887
Population	759	73,104	73,462	949	655,804
Percentage of over 65 years olds	759	0.182	0.0405	0.0770	0.366
Net balance of settled accounts	759	620,433	485,170	51,686	4.016×10^6
Taxable income per capita	759	1101	219.5	387.1	1802
Agriculture sales	759	10,303	7758	40	47,897
Manufacturing sales	759	191,706	252,772	178	2.026×10^6

Table 10
Descriptive statistics of the variables used for the matching of the conventional dataset.

Variables	N	Mean	Std. Dev.	Min	Max
Area	1487	27,193	25,653	347	142,756
Population	1487	52,395	74,548	477	537,044
Percentage of over 65 years olds	1487	0.183	0.0447	0.0502	0.374
Net balance of settled accounts	1487	442,107	544,089	-1.927×10^6	5.005×10^6
Taxable income per capita	1487	1088	246.0	387.1	2240
Agriculture sales	1487	7461	6799	0	38,417
Manufacturing sales	1487	139,020	274,567	0	3.313×10^6

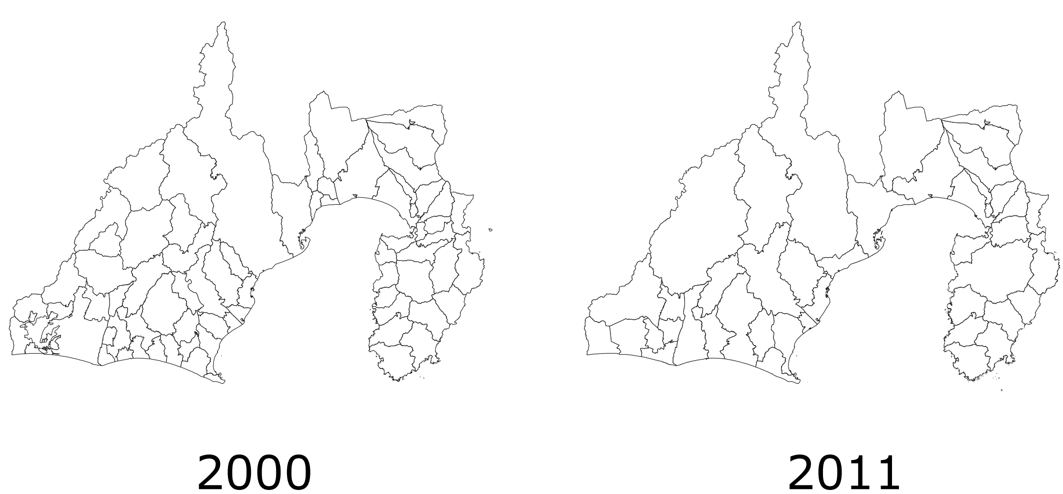

Fig. 8. Shizuoka prefecture before and after the mergers.

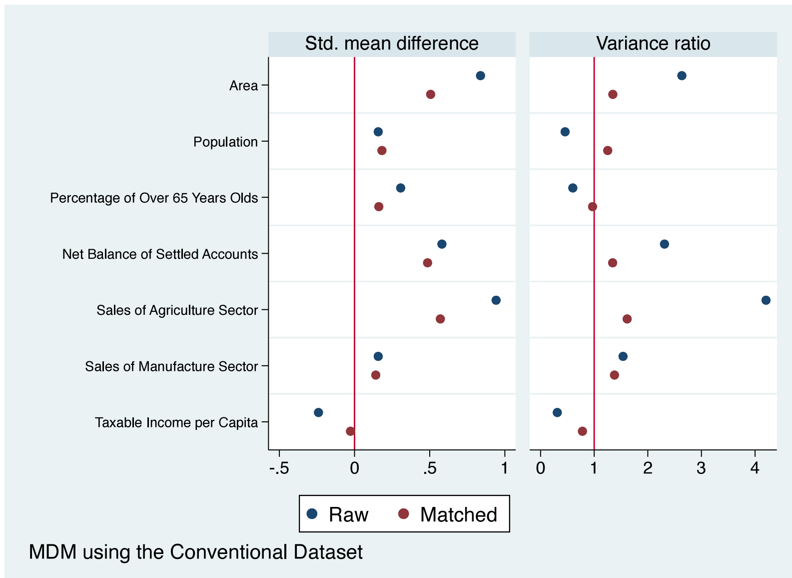

Fig. 9. The graph of balancing statistics of MDM on conventional post-merger dataset.

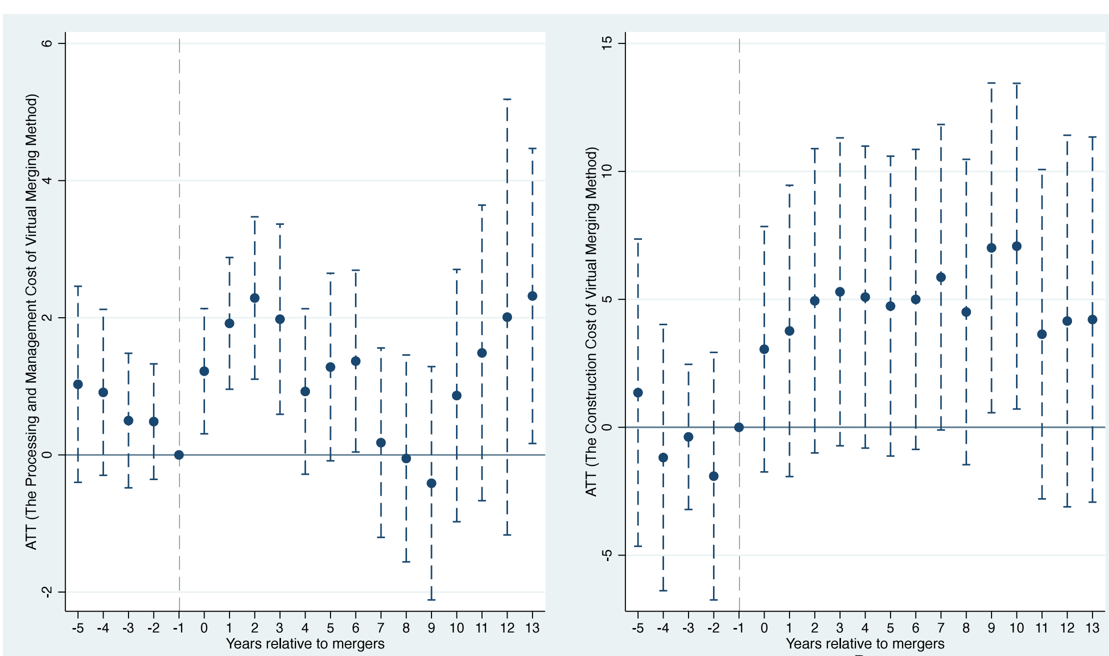

Fig. 10. Event study analysis of the other outcome variables of the virtual merging method.

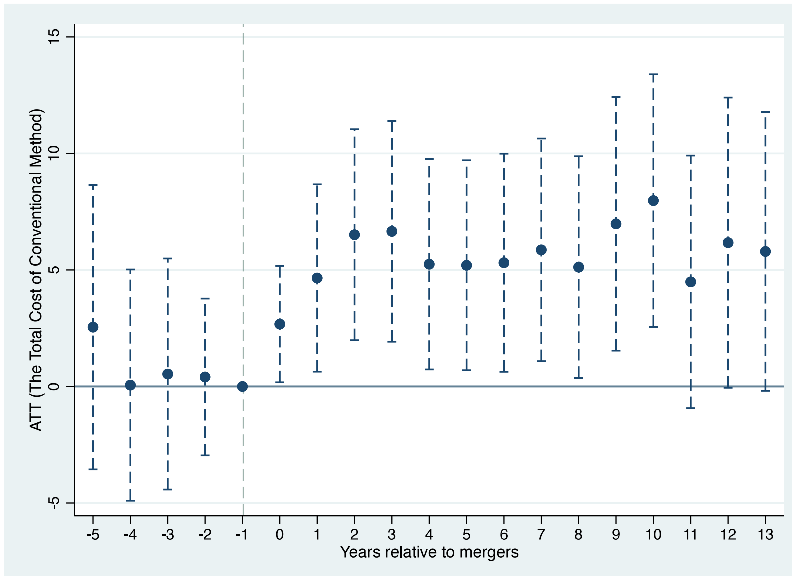

Fig. 11. Event study analysis of the total cost of the conventional method.

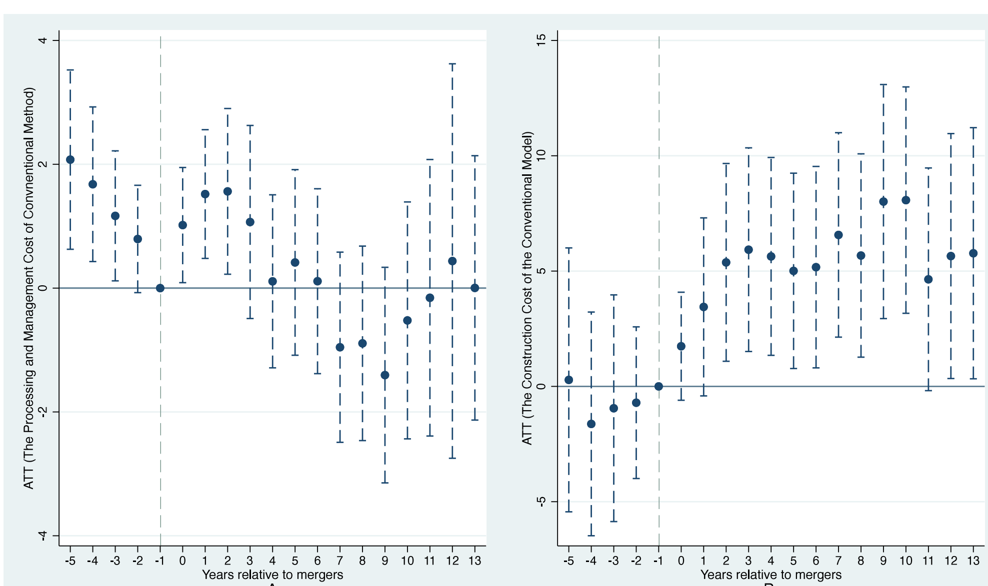

Fig. 12. Event study analysis of the total cost of the conventional method.

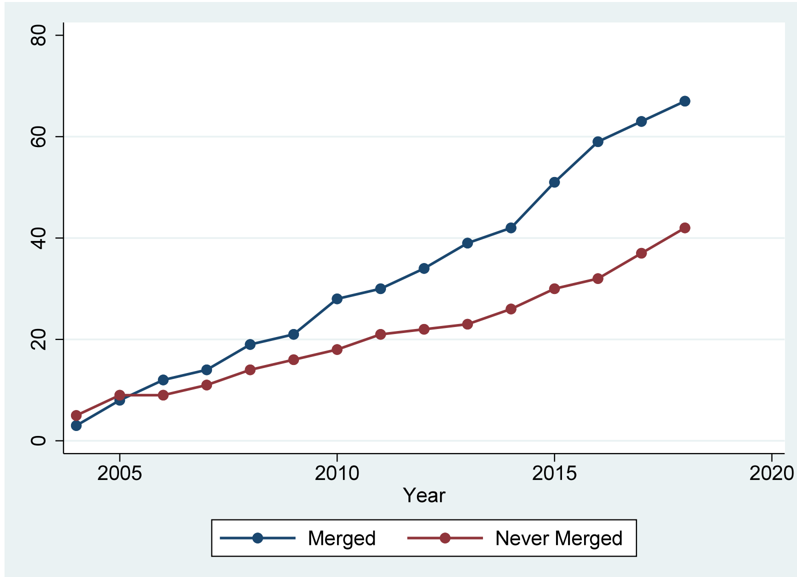

Fig. 13. Numbers of incinerators built by merged and never merged municipalities.

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