Empirical Studies on the Economics of Waste Management

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（廃棄物管理の経済学に関する実証的研究）

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Contents

Chapter 1

Introduction

Waste management has been one of the major challenges to achieving sustainable development for cities and countries all over the world. The World Bank Group estimates the world generates two billion tons of municipal solid waste annually and expects growth to three point four billion tons by 2050 (Kaza et al., 2018). What makes things worse is that huge amounts of plastic waste are emitted into the ocean annually which could affect the whole ecosystem (Ritchie and Roser, 2018). In 2015, the United Nations set up the Sustainable Development Goals (SDGs) putting sustainability in the first place. Only with proper waste management could we achieve a better world.

Waste, as a kind of negative externality, is hard to be reflected in markets and causes market failures. To address this problem, many policies dedicated to waste management are enacted. Most of the existing studies in waste management are focusing on the direct effects of policies on waste management. This thesis, however, looks at the indirect effects of policies related to waste management. Particularly, we investigate the impact of two policies: the import ban on waste plastics and municipal mergers. The former case considers the impact of waste-trade policy on environmental quality, while the latter case considers the impact of general administrative policy on the municipalities' practice of waste management. By enhancing the analytical point of view, we extend the field of study to include more complex and comprehensive situations. The thesis is arranged as follows.

Chapter 2 investigates the effects of the plastic waste ban on local air quality in China. While the import of plastic waste has been greatly reduced since then, we want to figure out if this ban has improved the environment. Using the fixed-effect DID method and the city-level daily pollutants concentration panel data, we find that the ozone concentration decreased in treatment areas after the import ban. Additional analyses also suggest that the effect of the ban is larger in the later period of the year 2018 and in the harbor cities, but weaker among heavily polluted cities.

Chapter 3 investigates whether municipal mergers result in a lower cost of waste management by looking at the Great Heisei Consolidation in Japan. Using both fixed-effect DID design and PSM-DID design based on our new virtual merger methods, we find that the municipal mergers in Japan increased the total waste management costs and construction costs, which can be explained by the special bonds for new projects provided to merged municipalities by the national government, while the processing and management cost seems to be little affected by the mergers. We also carry out analyses on different types of mergers and municipalities with or without waste management association memberships to explore the heterogeneous effects.

Chapter 4 investigates whether the Great Heisei Consolidation results in lower waste generation and promotes recycling of the waste using the DID design based on both OLS and GLM approaches. We find that these mergers actually led to higher annual waste generation per capita in the merged municipalities with an announcement effect. Furthermore, merged municipalities are more likely to change to non-charging policies for the disposal of combustible and incombustible waste, which we think is the main reason for the higher annual waste generation. The number of waste separation categories is higher in the merged municipalities but we think the effect is weak compared to the effect of charging policies. Other results show that municipal mergers do not contribute to the recycling of plastic waste as well.

Chapter 5 is the last chapter and concludes.

Chapter 2

Estimating the Effect of China's Solid Waste Import Ban on the Ozone Pollution

2.1 Introduction

Air pollution is detrimental to human health and causes substantial loss, particularly in a fast-growing economy like China. In 2017, the Global Burden of Disease estimated that approximately 852,000 deaths in China were attributable to PM 2.5 exposures and an additional 178,000 chronic respiratory disease-related deaths to ozone (Health Effects Institute, 2019). Economic losses from air pollution are huge and were estimated to be 12.9% of China's annual gross domestic product in 2019 (World Bank, 2022). Recent studies suggest diverse effects of air pollution, including lower cognitive performance (Zhang et al., 2018), loss of labor productivity (He et al., 2019), and sleeplessness (Heyes and Zhu, 2019).

The Chinese government has initiated several actions to reduce the severity of air pollution. Consequently, the annual average concentrations of PM 2.5, PM 10, and NO_2 in China gradually decreased from 2014 to 2018 (Ministry of Ecology and

Environment of China, 2018). Despite witnessing a steady decline in PM 2.5 exposures, however, China still had the highest population-weighted seasonal concentration of ozone among the world's 11 most populous countries (Health Effects Institute, 2019).

The melting process of material plastic waste recycling, however, could generate volatile organic compounds (VOCs) (Tsai et al., 2009; Yamashita et al., 2009), which react with NOx in the presence of sunlight to form ground-level ozone (Atkinson, 2000). China has been the world's largest importer of plastic waste and processes huge amounts of hard-to-recycle plastics from other countries, accounting for approximately 56% of the global market (Brooks et al., 2018). Nonetheless, in July 2017, the Chinese government introduced a policy that imposed a ban, effective from January 1, 2018, on the import of several types of solid waste, including plastic waste.

In this study, we apply difference-in-differences (DID) methods to investigate the effects of the plastic waste ban on air quality in China by focusing on surface-level ozone. The import ban on plastic waste leads to a reduction in the supply of plastic waste which will slow down the plastic recycling process that releases VOCs, thereby decreasing VOCs emissions. This reduction further reduces the ozone concentration, as VOCs are one of the main precursors of ozone formation. Therefore, we can expect an improvement in air quality in the areas around the plastic recycling facilities.

This study contributes to the literature on the economics of air pollution in developing countries in two ways. First, many studies on the effect of air pollution control focus on policies that directly affect emission sources, such as shutdown and installation of control equipment (Cao et al., 2009)), driving restrictions (Viard and Fu, 2015), and subsidies to winter heating (Almond et al., 2009). However, in the case of plastic recycling, the number of pollution sources is large, and enforcing the regulation is often difficult. Although we do not have the exact number of recycling facilities dealing with plastic waste, Ministry of Commerce of the People's Republic of China (2017) reports that there are about one hundred thousand recycling facilities in China, which could be a piece of evidence. Import ban can be regarded as an indirect policy instrument that reduces the amount of plastic waste used by plastic waste recyclers, particularly some small-scale recyclers who do not have proper treatments for the VOCs exhaust. In this study, we exploit this unique event and investigate the impact of a substantial drop in the availability of the input for a polluting activity. Second, although several studies have evaluated the global impact of the plastic waste ban very well (Brooks et al., 2018; Qu et al., 2019; Huang et al., 2020), they do not focus on the domestic environmental impact. One of the aims of the policy is to alleviate the severity of local pollution; hence, investigating whether and how the ban could improve the local environment is of relevance to policy makers.

The estimation results of our main analysis suggest that the daily ozone concentration was reduced by 2.8% in treatment areas after the import ban. We also extended the research period and change the outcome variables to other pollutants to test the robustness. Additional analyses also suggest that the effect of the ban was larger during the last few months of 2018 and the first few months of 2019. Heavily ozone-polluted cities are little affected by the ban while coastal cities with ports are affected more.

The remainder of this chapter is structured as follows. Section 2 briefly describes the policy background and explains air protection control in China related to ozone concentration. Section 3 describes our empirical strategy, the model, and the dataset. Section 4 presents the empirical results, robustness checks, and heterogeneous effects. Section 5 concludes this chapter.

2.2 Background

2.2.1 The Plastic Recycling and VOCs Emission in China

A large volume of plastics is produced and recycled in China. In 2014, the production of all types of plastics in China amounted to 73.9 million tons, and the corresponding consumption was 93.3 million tons. In the same year, the amount of waste plastic recycled was 28.3 million tons, accounting for approximately 30% of the total consumption (Cao et al., 2019). Plastic recycling includes material recycling, chemical recycling, and energy recovery (Al-Salem et al., 2009; Lazarevic et al., 2010). Chemical recycling and energy recovery, however, are not encouraged in China because of fears about the environmental pollution produced by inappropriate treatment in the recycling processes, as a result of which, there are many material recycling plants in China (Huang et al., 2013).

A typical material plastic recycling process includes three main stages. The first stage is collection, where the plastic waste is collected and transported to the plastic recycling facilities. The second stage is sorting, where plastic waste is sorted from other materials and also sorted into different types. While the third stage, which is reprocessing, could cause air pollution if the melting process is treated inappropriately. During the reprocessing stage, plastic waste is first washed and shredded into pieces. Those plastic pieces will be heated to melt and then extruded into amounts of pellets, which are the final products of the plastic recycling activity. The heating temperatures in the melting process range from 200°C to 300°C, which may produce harmful components, such as VOCs. He et al. (2015) analyzed the emissions of different types of plastic solid waste and found that the melting extrusion of seven different thermoplastics could produce a substantial volume of VOCs. The total VOC concentrations emitted during recycling were highest in Acrylonitrile butadiene styrene (ABS) and lowest in polycarbonates, which also could bring definite cancer risks to the residents nearby.

These pollutants are often emitted into the atmosphere without sufficient treatment in China. Many devices in small workshops recycling imported plastic wastes are not advanced or sophisticated, which could release harmful exhausts into the air (China Economic Daily, 2018). For example, most of the plastic recycling activities in one of the largest plastic recycling centers in China, Xingtan (Guangdong Province), where about 1,000 plastic waste recycling plants are concentrated, are carried out in the open air with no measures to treat the emitted harmful gases. Those exhaust VOCs gases emitted from plastic waste recycling granulation have an effect on the ambient environment in Xingtan (Huang et al., 2013).

Despite the small-scale recyclers, some large recycling companies also contributed to the pollution activities. The Ministry of Ecology and Environment of China initiated a campaign in July 2017 to manage and control the recycling industry. The ministry examined the acts of 1,768 large recycling companies, many of which engaged in plastic waste recycling, and found that 60% of these companies were operating illegally. The illicit acts included using invalid filters, creating fake monitoring data, selling the permit for importing solid waste to other unqualified firms, and building new plants without permission (PRC Central Government, 2017).

Notably, a company needs to obtain a permit from the authorities to import solid waste. The permits can be obtained only by companies with qualified facilities that meet the standards set by the government. Some of these companies, however, sell and transfer their permits or imported plastic waste to other firms and small workshops, as one of the government reports shows (Ministry of Ecology and Environment of China, 2017a). These firms and workshops may not meet the standards or even not have a filter installed. The permits illegally sold by qualified companies help them and workshops with no permits to obtain materials and process them without enough care for the environment.

2.2.2 The Control of the VOCs Emissions

In January and February 2013, severe haze covered many provinces in China. This led to a widespread environmental concern that pushed the Chinese government to tighten the air pollution regulations (Jin et al., 2016). During 2013 and 2014, China rolled out a new, nationwide air pollution program in three waves across cities to provide real-time monitoring of six air pollutants, PM2.5, PM10, O_3, CO, NO_2, and SO_2 (Greenstone et al., 2021). Since then, the Chinese government has implemented various policies to alleviate the severity of air pollution.

By contrast, the concentration of surface ozone has increased, emerging as one of the major air pollutants in 74 large cities (including cities in key regions such as Beijing, Shanghai, Guangzhou, and Shenzhen) based on the newly amended national ambient air quality standard. As Figure 2.1 shows, the share of cities meeting the standard for ozone among these 74 large cities was about 62.2% in 2016, while the share dropped to 35.1% in 2017. The average daily ozone concentration in the 74 large cities also increased from 154$\mu g/m^3$ in 2016 to 167$\mu g/m^3$ (Ministry of Ecology and Environment of China, 2017b). As the acceptable concentration of ozone set by the WHO is about 100 $\mu g/m^3$ (World Health Organization, 2006), the average daily ozone concentration in the 74 large cities is much larger than the WHO standard.

The control measures for ozone were largely untouched in China until the policy called *13th Five-Year Plan for the Prevention and Control of VOCs Pollution* was introduced in 2017 (Health Effects Institute, 2019). Through this policy, the government emphasized the importance of reducing VOCs as the main precursors of ozone. The government also set a target for the local governments of the heavily VOCs polluted areas in 16 provinces to reduce the VOCs emissions by 10% before 2020. This policy is very helpful for us in locating the provinces that also suffered from VOCs pollution when we choose suitable control groups for the DID analysis afterward.

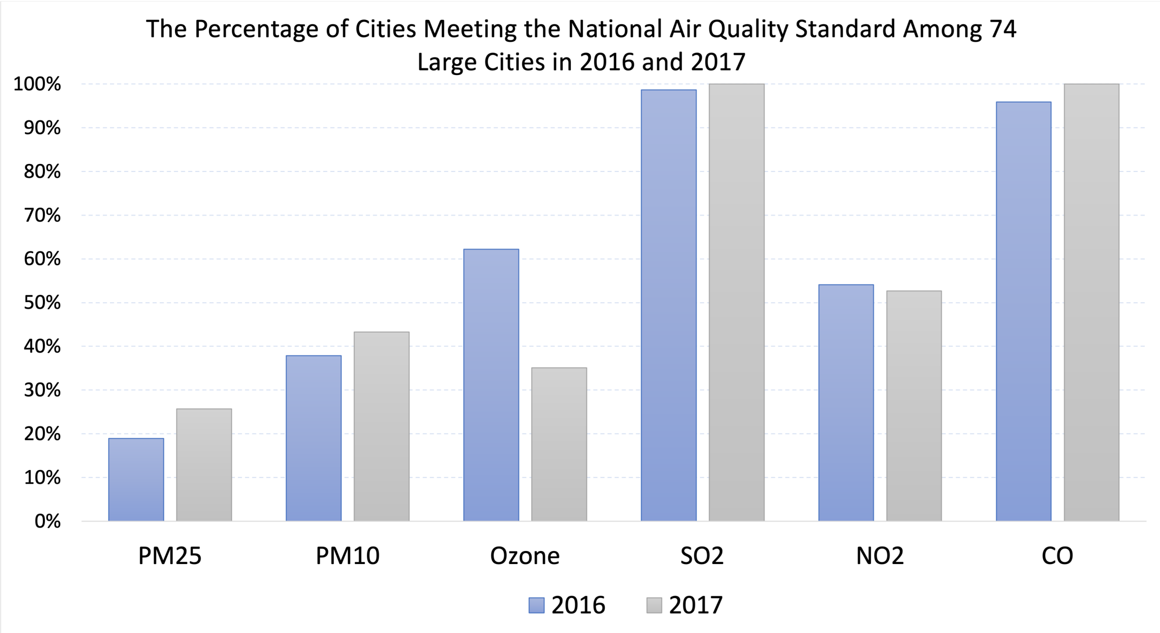

FIGURE 2.1: The Percentage of Cities Meeting the National Air Quality Standard Among 74 Large Cities in 2016 and 2017

Source: Report on the State of the Ecology and Environment in China 2017

2.2.3 The Control of the Import of Plastic Waste

The Chinese government had been controlling the import of waste for a long time and eventually concluded it with a ban. The government has frequently revised the *Law of the People's Republic of China on Prevention and Control of Environmental Pollution by Solid Waste* in recent years. Since its introduction in 1996, the law has been revised four times in 2005, 2013, 2015, and 2016 (Sun, 2019). Furthermore, the government has been strengthening border control. In 2013, the Green Fence campaign was implemented to enhance border controls. Sun (2019) employed difference-in-differences (DID) methods and found that the Green Fence campaign had a significant effect on reducing the waste imported into China. The government then revised the campaign to the so-called Blue-Sky Campaign and implemented stricter regulations every year from 2017 onward.

The ban on the import of plastic waste was announced in July 2017. The Chinese

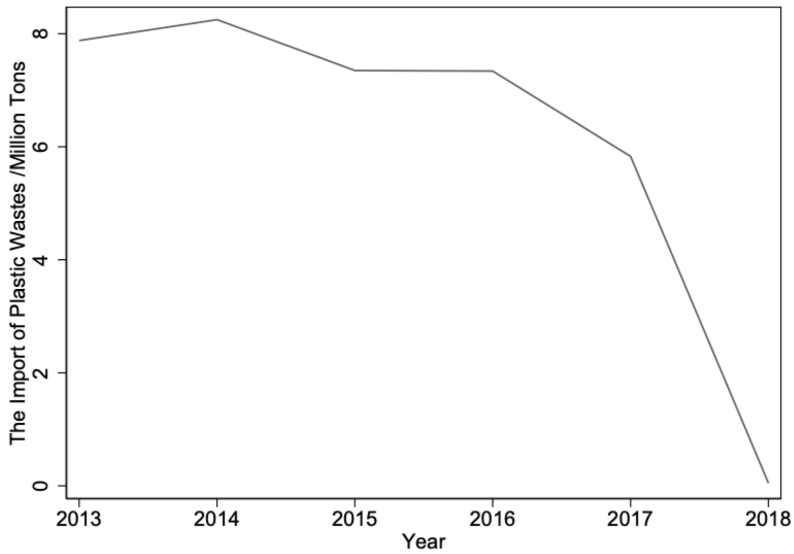

FIGURE 2.2: Import of Plastic Waste by China

Source: China Recycling Industry Report 2019

government set three targets in this policy called the *Implementing Plan for Banning Foreign Trash Imports and Promoting Reform in the Solid Waste Import Management System*. The first target was to reduce the import of solid waste to gradually lessen the environmental damage. The second was to regulate the recycling industry by inspecting illegal behaviors, revising related laws, monitoring smuggling, and promoting job changes. The last was to increase the recycling rate of domestic waste, improve the recycling technology, and build new and cleaner recycling plants.

As a result of this ban, the volume of plastic waste imported to China has greatly reduced. According to the *China Recycling Industry Report 2019* published by Ministry of Commerce of the People's Republic of China (2019), it has reduced from 5.83 million tons in 2017 to 0.05 million tons in 2018, by almost 99% (Figure 2.2). We expect the great reduction would have a noticeable effect on the air quality.

2.3 Methodology and Data

2.3.1 Methodology

We employ a DID method to identify the treatment effects and mitigate possible endogeneity problems (Meyer, 1995). City-level daily 8-hour average ozone concentration (*Ozone*) is used as a dependent variable to estimate the effect of the plastic waste ban. The baseline model is formulated as follows:

$$Ozone_{it} = \alpha_i + \gamma_t + \beta Treatment * Afterban_{it} + X_{it} + \epsilon_{it}, \tag{2.1}$$

where $Ozone_{it}$ denotes the ozone level in city i in day t and *Treatment**Afterban* is the DID indicator that captures the treatment effect. The term is interacted by *Treatment*, which takes one for the cities in the treatment group and takes zero for cities in the control group, and *Afterban*, which takes one after the implementation of the ban and takes zero before the implementation of the ban. We expect the coefficient of the interaction term *Treatment**Afterban* to be negative if the ban reduces the ozone concentration. We also include city fixed effect α_i to control the characteristics of cities and time fixed effect γ_t to capture the seasonal effect of the ozone concentration. X_{it} is a set of control variables including *Max_Temp*, which denotes the daily maximum temperatures, *Wind_Speed*, which denotes the highest wind speed during the day, and a dummy variable *Sunny* for sunny days. We choose these three control variables because we use the maximum 8-hour average ozone concentration covering the daytime, which is affected by the highest temperature, the weather, and the highest wind speed during the daytime. In general, sunshine and high temperature contribute to the formation of ozone while higher wind speed is associated with lower ozone concentration. ϵ_{it} is the error term and the standard errors are clustered at the city level.

We define the treatment group and the control group through the following steps. First, we follow the *The China Recycling Industry Report 2014* (Ministry of Commerce of the People's Republic of China, 2014) and *The China Recycling Industry Report 2016* (Ministry of Commerce of the People's Republic of China, 2016) to locate the treatment group. According to these reports, most of the plastic waste recycling facilities are concentrated in four coastal provinces, Hebei Province, Shandong Province, Zhejiang Province, and Guangdong Province. We think this is reasonable because the plastic waste, as its name suggests, is unwanted garbage to the exporting countries. Compared to the cost of dealing with plastic waste in their own country, it's more beneficial to export the waste to some developing countries, like China. In this sense, the imported price of plastic waste is very low. When plastic waste arrives in the coastal provinces of China, however, transferring the light and bulky plastic waste from coastal provinces to inland provinces is not economically efficient, considering the value of the waste. Therefore, most of the imported plastic waste is supposed to be recycled in these coastal provinces.

Second, for the control group, choosing provinces having similarities to the treatment groups in terms of geographical and economic activities, particularly ozone pollution status, is important. To achieve this goal, we follow the *13th Five-Year Plan for the Prevention and Control of VOCs Pollution*, which gave a list of provinces with heavy ozone pollution that needed to improve their air quality. As all the provinces in the treatment group are listed in this policy, we also choose control groups from the list to keep a similar VOCs pollution status. To balance the dataset, we also choose four provinces for the control group, Henan Province, Anhui Province, Jiangxi Province, and Hunan Province, all of which are in proximity to the provinces in the treatment group. The geographical location of the provinces in the treatment in dark blue and control groups in light green is illustrated in Figure 2.3.

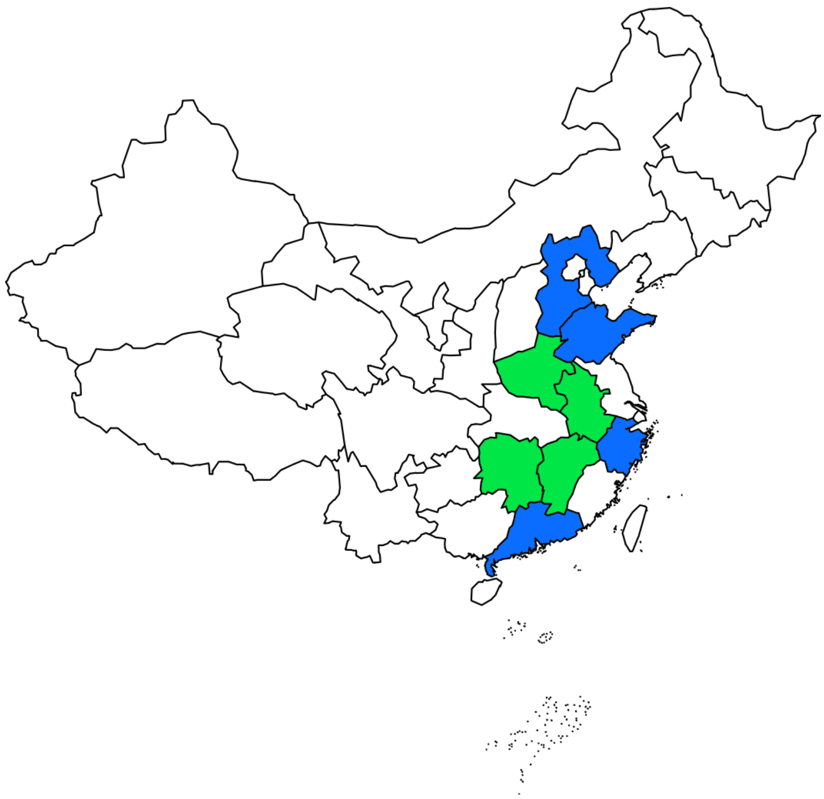

FIGURE 2.3: Control Group (Light Green) and Treatment Group (Dark Blue)

Third, given the complex relationship between ozone concentrations and its precursor emissions, we further consider the ozone-NOx-VOC sensitivity regime to define the treatment and control groups. Cities in the NOx-limited regime may face a higher concentration of ozone if the concentration of VOCs decreases, which could cause a bias. Therefore we follow the ozone photochemical regime plotted by Jin and Holloway (2015) to find cities located in the VOCs-limited and transitional regimes to confirm that the concentration of VOCs contributes to the formation of ozone. Consequently, we have 46 cities from treatment provinces and 31 cities from control provinces.

2.3.2 Data

We use city-level daily data. The data on ozone and other pollutants including PM2.5, PM10, SO2, CO, and NO2 in cities of selected provinces are collected from the China Air Quality Online Monitoring and Analysis Platform.[1] This website collects real-time data on pollutants from the Ministry of Ecology and Environment of China and automatically calculates daily average data. The data for temperature, weather, and wind speed were obtained from Tianqihoubao,[2] which collects historical weather data covering 34 provinces and provides data for 2,290 counties. The baseline research period is from January 1, 2017, to December 31, 2018, spanning one year before and after the import ban. We could not build a balanced dataset because of some data loss and corruption.

Table 2.1 reports the descriptive statistics of the data on pollutants and weather for our baseline analysis. Our dataset comprises 53,234 observations, and the average concentration of ozone is $101.2\mu g/m^3$. As the acceptable concentration of ozone set by the WHO is 100 $\mu g/m^3$ (World Health Organization, 2006), ozone pollution still poses a serious threat to Chinese citizens. As for the weather data, *Max_Temp* takes the real value of the highest temperature in each day at the city level. *Wind_Speed* takes the highest wind speed during the daytime classified by the Beaufort wind force scale at the city level. *Sunny* only takes one when the weather during daytime is sunny and takes zero for any other weather at the city level. The differences in variables between the two groups are insignificant, suggesting the validity of our group selection.

[1] *http://www.aqistudy.cn*
[2] *http://www.tianqihoubao.com*

TABLE 2.1: Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
All					
Ozone ($\mu g/m^3$)	53,234	101.2	50.08	1	586
PM2.5 ($\mu g/m^3$)	53,234	48.19	37.56	2	539
PM10 ($\mu g/m^3$)	53,234	81.55	53.88	4	646
SO2 ($\mu g/m^3$)	53,234	18.69	15.48	1	217
NO2 ($\mu g/m^3$)	53,234	32.90	18.2	2	183
CO (mg/m^3)	53,234	0.9656	0.5280	0.1	11.8
Max_Temp (°C)	53,233	21.99	10.10	-20	41
Wind_Speed (*number*)	53,076	3.277	0.8590	0	12
Sunny (*dummy*)	53,233	0.2706	0.4442	0	1
Treatment Group					
Ozone ($\mu g/m^3$)	32,076	102.2	51.70	1	586
PM2.5 ($\mu g/m^3$)	32,076	45.45	36.88	2	539
PM10 ($\mu g/m^3$)	32,076	79.62	56.48	5	646
SO2 ($\mu g/m^3$)	32,076	15.70	13.56	1	217
NO2 ($\mu g/m^3$)	32,076	36.12	18.73	2	183
CO (mg/m^3)	32,076	0.9505	0.5430	0.1	9
Max_Temp (°C)	32,075	22.15	10.18	-20	41
Wind_Speed (*number*)	32,062	3.365	0.8919	0	12
Sunny (*dummy*)	32,075	0.2938	0.4555	0	1
Control Group					
Ozone ($\mu g/m^3$)	21,158	99.76	47.49	4	316
PM2.5 ($\mu g/m^3$)	21,158	52.36	38.21	3	450
PM10 ($\mu g/m^3$)	21,158	84.47	49.56	4	583
SO2 ($\mu g/m^3$)	21,158	22.23	17.04	1	126
NO2 ($\mu g/m^3$)	21,158	28.02	16.28	2	139
CO (mg/m^3)	21,158	0.9885	0.5037	0.2	11.8
Max_Temp (°C)	21,158	21.74	9.970	-7	40
Wind_Speed (*number*)	21,014	3.142	0.7873	1	7
Sunny (*dummy*)	21,158	0.2352	0.4241	0	1

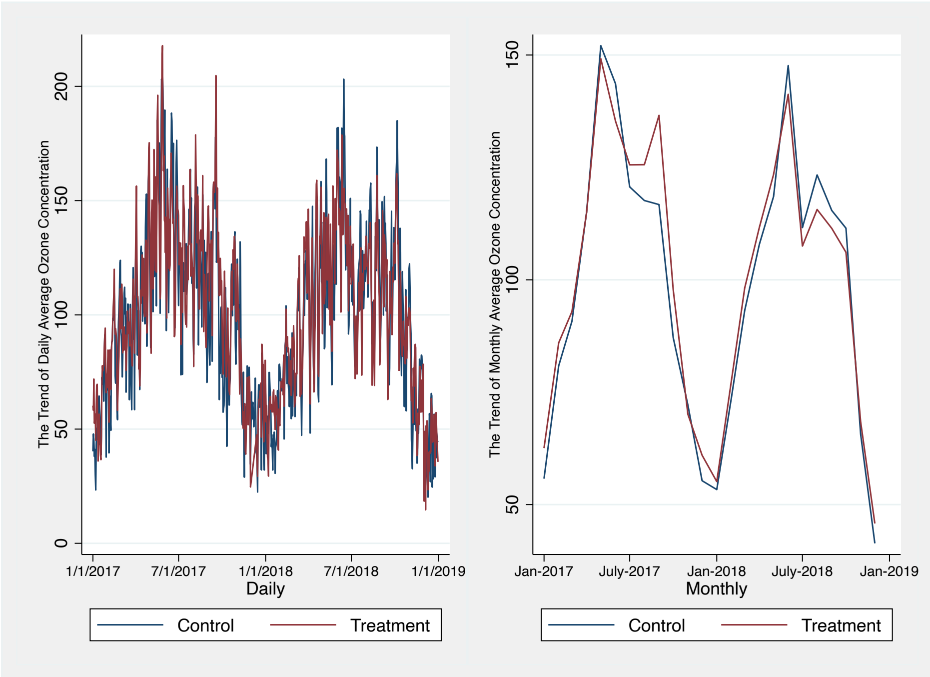

FIGURE 2.4: Daily and Monthly Average Ozone Concentration in Control and Treatment Groups

2.3.3 Common Trend Assumption

One of the most important assumptions of the DID model is the common trend or parallel trend assumption. We provide the trend of the daily average and the monthly average of the ozone concentration in both the control and treatment groups, illustrated in Figure 2.4, as the first evidence to validate this assumption. The daily average ozone concentration indicates a similar trend in each group, while the monthly average shows that the ozone concentration trend in the two groups is parallel most of the time before being treated.

To test the parallel trend assumption further, we adjust our main model to conduct an event study using the following model:

$$Ozone_{it} = \alpha_i + \gamma_t + \sum_{p=-2}^{-12} \beta_p treatment_i * M_p + \sum_{q=0}^{11} \beta_q treatment_i * M_q + X_{it} + \epsilon_{it}, \tag{2.2}$$

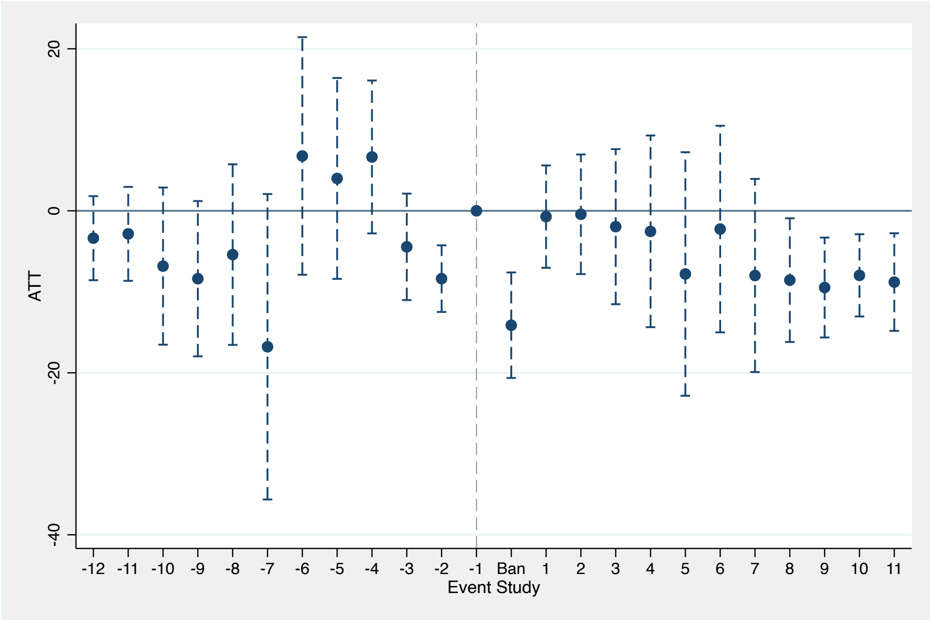

FIGURE 2.5: Event Study for the Daily Ozone Concentration

where *treat* is a dummy variable that equals 1 when the observation is in the treatment area, M_p is a dummy variable for p months before the ban, and M_q is a dummy variable for q months after the ban. The event study covers the entire research period and the reference group is one month before the ban, that is, December 2017. The other settings are similar to our main model including the control variables and fixed effects. The result of the event study is plotted in Figure 2.5 with 95% confidence intervals. The estimations of coefficients in the pre-treated period are not statistically significant, except for the one for November 2017. The figure shows a drop in ozone concentration immediately after the implementation of the ban, although the effect is not statistically significant until the last few months of the year 2018. Overall, the event study provides evidence that the dataset is suitable for performing DID analysis.

2.4 Results and Discussion

2.4.1 Baseline Results

Estimation results are summarized in Table 2.2. [1] We use the model in column (1) as the reference because it includes the control variables and the finer time fixed effects. In this case, the estimation of the coefficient of the DID indicator is statistically significant at the 5% level with a value of approximately -2.9. As the coefficient denotes the average treatment effect on the treated, this result suggests that the import ban reduced the average concentration of ozone by $2.9\mu g/m^3$, which is approximately 2.8% of the average ozone concentration in the treatment area. Coefficients for the control variables have expected signs and are statistically significant. We believe the variable *Max_Temp* and *Sunny* successfully captured the effect of temperature and sunshine on ozone formation, while strong wind speed, which is captured by the variable *Wind_Speed*, could reduce ozone concentration.

These results support our hypothesis that the import ban reduced the recycling activities of plastic wastes that potentially release VOCs into the atmosphere and contribute to ozone pollution. As one of the main targets of the import ban is to improve the local environmental status, the ban achieves this objective by reducing the inputs. However, the estimated impact is only about 2.8%, suggesting that the recycling of plastic wastes might not be a major source of VOCs in the treatment area.

Notably, Unfried and Wang (2022) also investigate the effect of the import ban while leading to a result different from ours. They find a reduction in the concentration of PM2.5 rather than ozone. We believe the reason for it could be the difference in the research settings. For example, we only include cities in the treatment and nearby provinces under VOCs-limited or transitional regimes, which are very likely

[1] We do not include the model using all fixed effects because the month fixed effect and the year fixed effect will cause collinearity with the date fixed effect.

TABLE 2.2: Effect of the Import Ban on the Ozone Concentration

Variables	(1)	(2)	(3)	(4)
Treatment*Afterban	-2.915**	-3.614**	-4.516***	-4.617***
	(1.366)	(1.382)	(1.390)	(1.358)
Max_Temp	5.011***	4.332***		
	(0.331)	(0.207)		
Sunny	4.550***	16.50***		
	(0.864)	(1.182)		
Wind_Speed	-1.569***	-1.797***		
	(0.356)	(0.370)		
Constant	-8.395	26.68***	52.10***	60.05***
	(6.217)	(2.927)	(4.595)	(2.224)
City FE	Y	Y	Y	Y
Date FE	Y	N	Y	N
Month FE	N	Y	N	Y
Year FE	N	Y	N	Y
Observations	53,075	53,075	53,234	53,234
R-squared	0.626	0.510	0.512	0.328
Number of City	77	77	77	77

Robust standard errors clustered at city-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

to suffer from VOCs pollution in our study to better capture the effect of the ban on the ozone concentration, whereas they cover all Chinese prefecture-level cities in their study.

2.4.2 Robustness Analysis

In our baseline analysis, we focus on ozone concentration to estimate the effect of the import ban on plastic waste. In this subsection, we carry out some analyses to prove the robustness of our baseline result. We first extend our research period from 2017 - 2018 to 2016 - 2019 to analyze the effect of the ban in the long run. Next, we change the outcome variables to other pollutants to check the casualty of the baseline analysis.

First, in our baseline analysis, the research period is set from 2017 to 2018, which is one year before the ban and one year after the ban. In this way, we can focus on the effect brought by the ban more clearly and directly considering the uncertainty brought about by longer research periods. The longer research period, however, is effective in evaluating the validity of the policy in the long run and providing further evidence for the common trend assumption. Therefore, we extend the research period to two years before and after the ban, which is from 2016 to 2019. The descriptive statistics for the four-year dataset are provided in Table 2.3. The dataset includes 109,376 observations, and the average concentration of ozone is $99.28\mu g/m^3$, which is slightly lower than the baseline dataset.

Similar to the baseline estimation, we first plot the extended four-year event study with 95% confidence intervals in Figure 2.6 to examine the trend of the two groups. The estimations of coefficients in the pre-treated period are not statistically significant, except for the one for November 2017, which is the same as the event study of the baseline estimation. The extended one, however, shows that the ban is effective during the last few months of 2018 and the first few months of 2019 while getting weaker from then on. The DID regression results for the expended dataset are presented in Table 2.4. The estimation of the coefficient of the DID indicator in column (1) is approximately -3.913 and statistically significant at the 1% level. The impact of the ban during the extended research period is about 3.9%, which is a bit larger than the baseline model. This is mainly because the ban is still effective during the first few months of 2019 as the above event study shows. We think this analysis using an extended research period supports our main analysis and gives evidence of the effect of the ban in the long run.

Second, we run the same model as column 1 in Table 2.2 but using the concentration of PM2.5, PM10, SO2, NO2, and CO as outcome variables. The results are reported in Table 2.5 and we do not find statistically significant results for any of these pollutants. We think these results also support our results as our hypothesis suggests that other pollutants should not or be affected or only marginally affected

TABLE 2.3: Descriptive statistics of the Extended Dataset

Variables	Obs.	Mean	Std. Dev.	Min	Max
All					
Ozone ($\mu g/m^3$)	109,376	99.28	49.83	1	586
PM2.5 ($\mu g/m^3$)	109,376	49.37	39.81	1	703
PM10 ($\mu g/m^3$)	109,376	83.41	57.64	4	886
SO2 ($\mu g/m^3$)	109,376	18.33	15.99	1	217
NO2 ($\mu g/m^3$)	109,376	34.50	18.42	2	183
CO (mg/m^3)	109,376	0.9750	0.5628	0.1	18.4
Max_Temp (°C)	109,361	21.78	10.05	-30	41
Wind_Speed (*number*)	108,992	3.232	0.9483	0	12
Sunny (*dummy*)	109,361	0.2607	0.4390	0	1
Treatment Group					
Ozone ($\mu g/m^3$)	64,933	100.1	51.42	1	586
PM2.5 ($\mu g/m^3$)	64,933	46.44	39.12	1	703
PM10 ($\mu g/m^3$)	64,933	81.13	59.65	4	886
SO2 ($\mu g/m^3$)	64,933	16.47	15.52	1	217
NO2 ($\mu g/m^3$)	64,933	36.38	19.02	2	183
CO (mg/m^3)	64,933	0.9569	0.5808	0.1	18.4
Max_Temp (°C)	64,918	21.96	10.13	-30	41
Wind_Speed (*number*)	64,866	3.317	0.9892	0	12
Sunny (*dummy*)	64,918	0.2861	0.4519	0	1
Control Group					
Ozone ($\mu g/m^3$)	44,443	98.11	47.38	2	316
PM2.5 ($\mu g/m^3$)	44,443	53.66	40.41	3	665
PM10 ($\mu g/m^3$)	44,443	86.75	54.41	4	823
SO2 ($\mu g/m^3$)	44,443	21.04	16.29	1	176
NO2 ($\mu g/m^3$)	44,443	31.76	17.15	2	172
CO (mg/m^3)	44,443	1.001	0.5344	0.1	11.8
Max_Temp (°C)	44,443	21.51	9.912	-7	40
Wind_Speed (*number*)	44,126	3.107	0.8698	1	7
Sunny (*dummy*)	44,443	0.2237	0.4168	0	1

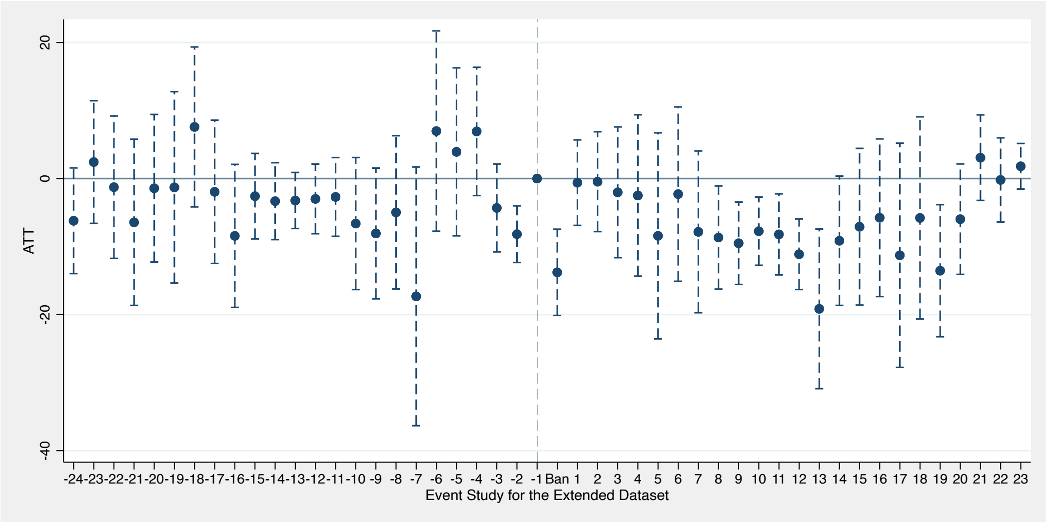

FIGURE 2.6: Event Study for the Extended Dataset

TABLE 2.4: DID Estimation Result of the Extended Dataset

Variables	(1)	(2)	(3)	(4)
Treatment*Afterban	-3.913***	-4.748***	-4.438***	-4.504***
	(1.355)	(1.393)	(1.437)	(1.415)
Max_Temp	4.822***	4.094***		
	(0.313)	(0.193)		
Sunny	5.682***	16.71***		
	(0.825)	(1.305)		
Wind_Speed	-1.148***	-1.161***		
	(0.354)	(0.322)		
Constant	0.757	16.19***	57.22***	47.12***
	(5.392)	(2.698)	(3.267)	(2.120)
City FE	Y	Y	Y	Y
Date FE	Y	N	Y	N
Month FE	N	Y	N	Y
Year FE	N	Y	N	Y
Observations	108,988	108,977	109,376	109,365
R-squared	0.623	0.510	0.513	0.340
Number of City	77	77	77	77

Robust standard errors clustered at city-level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 2.5: Effect of the Import Ban on Other Pollutants

Variables	(1) PM2.5	(2) PM10	(3) SO2	(4) NO2	(5) CO
Treatment*Afterban	0.696	1.930	0.485	0.722	-0.0172
	(1.030)	(1.689)	(0.720)	(0.617)	(0.0245)
Max_Temp	-0.0959	0.725***	-0.0837	0.146*	-0.00989***
	(0.151)	(0.226)	(0.0556)	(0.0786)	(0.00194)
Sunny	-3.506***	-1.272	1.043***	0.631*	-0.0420***
	(0.770)	(1.076)	(0.294)	(0.321)	(0.0127)
Wind_Speed	-2.807***	-2.109***	-0.999***	-2.846***	-0.0467***
	(0.354)	(0.490)	(0.177)	(0.246)	(0.00674)
Constant	165.3***	219.9***	46.47***	77.76***	2.790***
	(8.246)	(11.76)	(2.724)	(2.621)	(0.191)
City FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Observations	53,075	53,075	53,075	53,075	53,075
R-squared	0.517	0.501	0.366	0.562	0.441
Number of City	77	77	77	77	77

Robust standard errors clustered at city-level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

by the import ban.

2.4.3 Heterogeneous Effects

In this subsection, we explore the heterogeneity in the treatment effect to better understand the impact of the import ban. We first investigate if the effect of the ban varies as time evolves. Next, we explore the difference in effects among cities with higher or lower baseline ozone concentrations. Further, we examine the difference between harbor cities and inland cities.

First, the effect of the ban may not appear immediately because many companies are supposed to keep stock of recyclable materials to maintain a stable supply. Even if the import of plastic waste is banned, many recycling firms can keep processing plastic waste using stocks for some periods. Thus, the effect of the ban may change with time.

TABLE 2.6: Time Effect of the Import Ban

Variables	Ozone
Q1	-2.107
	(1.907)
Q2	-1.001
	(2.726)
Q3	-3.053
	(2.996)
Q4	-5.553**
	(2.551)
Max_Temp	5.015***
	(0.336)
Sunny	4.524***
	(0.872)
Win_Speed	-1.581***
	(0.351)
Constant	-8.401
	(6.207)
City FE	Y
Date FE	Y
Observations	53,075
Number of City	77
R-squared	0.626

Robust standard errors clustered at city-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Therefore, we divide the DID indicator *Treatment*Afterban* into 4 variables (Q_1, Q_2, Q_3, Q_4) to capture the change during the four quarters in one year. The variables Q_1, Q_2, Q_3, and Q_4 take a value of 1 when they are in the first, second, third, and fourth quarters of the year 2018, respectively. Hence, the model is represented as follows:

$$Ozone_{it} = \alpha_i + \gamma_t + \beta_1 Q_{1it} + \beta_2 Q_{2it} + \beta_3 Q_{3it} + \beta_4 Q_{4it} + X_{it} + \epsilon_{it}. \tag{2.3}$$

The result is presented in Table 2.6. Although the estimation of the coefficients of Q1, Q2, and Q3 are negative, the coefficients are not statistically significant. However, the coefficient of Q4 is negative, statistically significant at the 5% level, and larger in value than those in the other quarters. This result indicates that the effect of the ban was not so strong during the first three quarters of 2018, and the effect of the ban appeared in the last quarter of 2018. Both of the event studies plotted for the baseline analysis and the robustness analysis also provide a similar trend. We believe this is because the stock of plastic waste could maintain the recycling process for a while until the material was consumed. Alternative plastic waste sources such as domestic plastic waste, however, will offset the effect of the ban afterward.

Second, we examine if the ozone pollution status before the implementation of the ban influences the effects of the ban. For example, areas with higher average ozone concentrations in the treatment group might suffer more from the VOCs exhaust released by plastic waste recycling, and therefore, the effects might be larger in those areas. To verify this hypothesis, we conduct a sub-sample analysis with the cities where the ozone concentration before the ban is higher than the average value. After the resampling, we have 26 cities in the treatment group and 17 cities in the control group.

The result is reported in table 2.7. In this analysis, we obtain a negative but not statistically significant result: the import ban does not have a significant impact on the ozone concentration in heavily polluted areas. We believe this is reasonable as the recycling of plastic wastes might not be a large source of VOC pollution in these cities.

Last, we compare the impact among cities with and without ports. As most of the plastic wastes are imported by ship and the transportation costs compared to the value of these plastic wastes are high, we believe considerable plastic wastes are recycled in coastal cities with ports. Thus, the harbor cities in the treatment areas are very likely to experience a larger effect from the ban. Therefore, we use the cities with harbors in the treatment group and keep the control group the same as before. After this resampling, we have 21 cities in the treatment group and 32 cities in the control group. Furthermore, we use cities with big harbors (Harbors with over 10,000,000 tons total trading amount per year) in the treatment group to confirm our expectations.

TABLE 2.7: Effect of the Import Ban in Heavy Polluted Areas

Variables	Ozone
Treatment*Afterban	-2.886
	(1.943)
Max_Temp	4.985***
	(0.411)
Sunny	2.040**
	(0.927)
Wind_Speed	-1.189**
	(0.507)
Constant	-5.936
	(4.890)
City FE	Y
Date FE	Y
Observations	29,358
Number of City	43
R-squared	0.776

Robust standard errors clustered at city-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The result is reported in table 2.8. The estimation of the coefficients for the DID indicator *Treatment*Afterban* is still negative and statistically significant. Compared to our baseline result, the coefficient of the DID indicator *Treatment*Afterban* has a larger absolute value in both columns. This result supports our hypothesis that the import ban indeed has a larger effect on the harbor cities where a substantial amount of plastic wastes are recycled.

2.5 Conclusion and Implications

In this study, we investigated the effects of the ban on the import of plastic waste on air quality using China's city-level daily ozone concentration data. First, we tested the common trend assumption by event study. The results of our baseline DID model suggested that the ban might help reduce the ozone concentrations in the treatment area where many plastic recycling firms are located. The estimated coefficients indicated that the ban contributed to a decrease in the ozone concentration in the treatment group by approximately $2.9\mu g/m^3$. Second, we extended our

TABLE 2.8: Effect of the Import Ban on Harbor Cities

Variables	(1) Cities with Ports	(2) Cities with Big Ports
Treatment*Afterban	-3.312*	-5.466**
	(1.810)	(2.038)
H_Temp	5.070***	5.127***
	(0.207)	(0.256)
Sunny	5.595***	3.624***
	(1.064)	(1.119)
Wind	-1.984***	-1.404***
	(0.402)	(0.438)
Constant	-11.22*	-12.24*
	(5.946)	(6.326)
City FE	Y	Y
Date FE	Y	Y
Observations	35,693	27,975
R-squared	0.610	0.668
Number of City	52	41

Robust standard errors clustered at city-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

research period to two years before and after the ban and examined the effect of other pollutants to provide further evidence supporting our baseline results. Furthermore, we tested the coefficients among different quarters of the treated year of 2018. Combined this result with the event study for the extended research period, we found that the ban was only effective during the last few months of 2018 and the first few months of 2019. Our heterogeneous analysis also demonstrated that the effect of the ban on areas heavily polluted by ozone was weaker while the effect on harbor cities was larger. In summary, we captured the environmental effects caused by the ban in our research settings.

The data availability prevents us from implementing a more detailed analysis. As we could not capture the exact location and the situation of the plastic recycling firms and workshops, defining the treatment and control groups at the exact city level or even the monitoring-point level is challenging. We also do not know the exact share of VOCs emitted by the plastic waste recycling firms which could have led to more precise results. Despite these limitations, our approach allowed us to examine the impact of the import ban in a simple framework.

We believe that in the long run, the import ban will lead to an increase in the recycling of domestic plastic waste. Therefore, the effect that we found might be temporal because of a possible increase in the supply of recyclable materials from domestic waste. For instance, several large cities in China, such as Shanghai, have already started waste sorting in 2019. This will increase the domestic supply of recyclables, reviving the domestic plastic waste recycling industry. To maintain the local air quality, however, the ban might not be enough. We think the plastic waste recycling industry needs to transform its process by adopting new technologies, which could be supported by policymakers.

Chapter 3

Do Municipal Mergers Reduce the Cost of Waste Management? Evidence from Japan

3.1 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. 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, we examine the case study of the Great Heisei Consolidation in Japan by applying difference-in-differences (DID) methods and propensity score matching (PSM). 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, 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 on MSW management costs. Second, we develop a novel methodology that processes the data at the pre-merger level rather than the post-merger level used in many previous studies. This allows us to maintain the number of observations and is also suitable for applying propensity score matching. Third, we use a 20-year dataset for most Japanese municipalities, which provides more convincing results and enables us to explore heterogeneity between types of mergers as well as between municipalities that are members of waste management associations and those that are not. 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. Furthermore, the results from heterogeneous analysis also suggest that some municipalities, particularly small municipalities merged by absorption, benefitted from economies of scale, showing a 10% 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 chapter is organized as follows. Section 2 introduces the background of our study. Section 3 explains the dataset and models used in our analyses. Section 4 presents and discusses our empirical results. Our conclusions and policy implications are reported in Section 5.

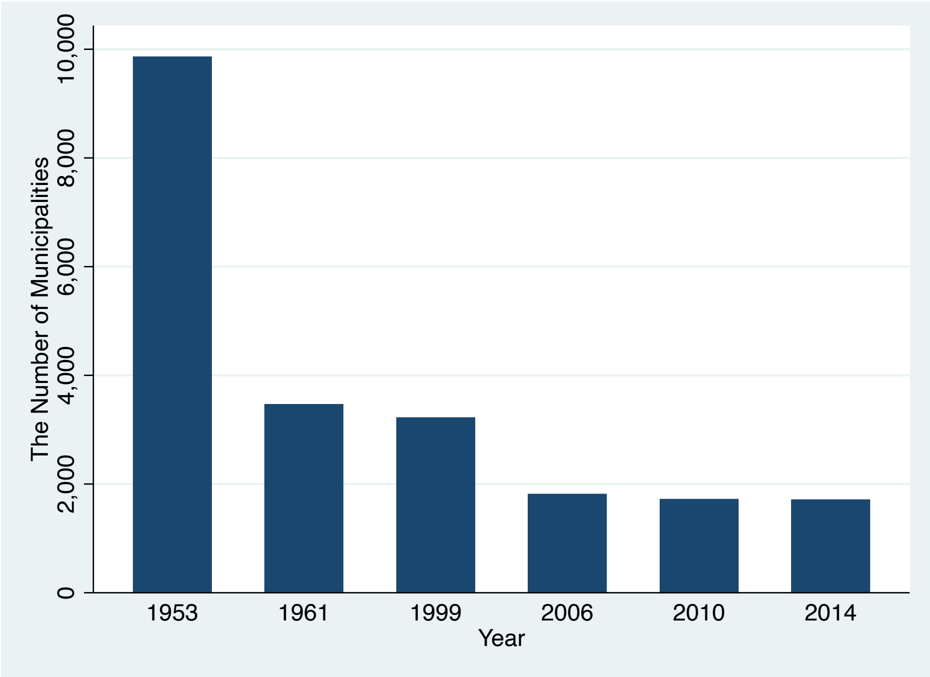

FIGURE 3.1: Number of Municipalities in Japan

Source: Ministry of Internal Affairs and Communications of Japan, 2021

3.2 Background

3.2.1 The Great Heisei Consolidation in Japan

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 in Japan. 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). The Consolidation can be divided into two stages, before and after the merger regulation was amended during this period. As a result, the number of municipalities in Japan reduced from 3,229 in 1999 to 1,821 in 2006 when the first stage ended and to 1,727 when the second stage finished in 2010 (Figure 3.1).

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). There were two types of mergers in the Great Heisei Consolidation: absorptions, in which a large municipality absorbs a smaller one or several smaller ones, and fusions, in which a new municipality is created by the consolidation of municipalities. Approximately 85% of the mergers realized during the Great Heisei Consolidation were fusions. In Section 4, we compare the effect on waste management costs between these two types of mergers. 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.

3.2.2 MSW Management in Japan

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 municipality expenditure for waste management by imposing the recycling fees on producers and consumers, the total cost of waste management remains substantial. Figure 3.2 shows the total MSW management

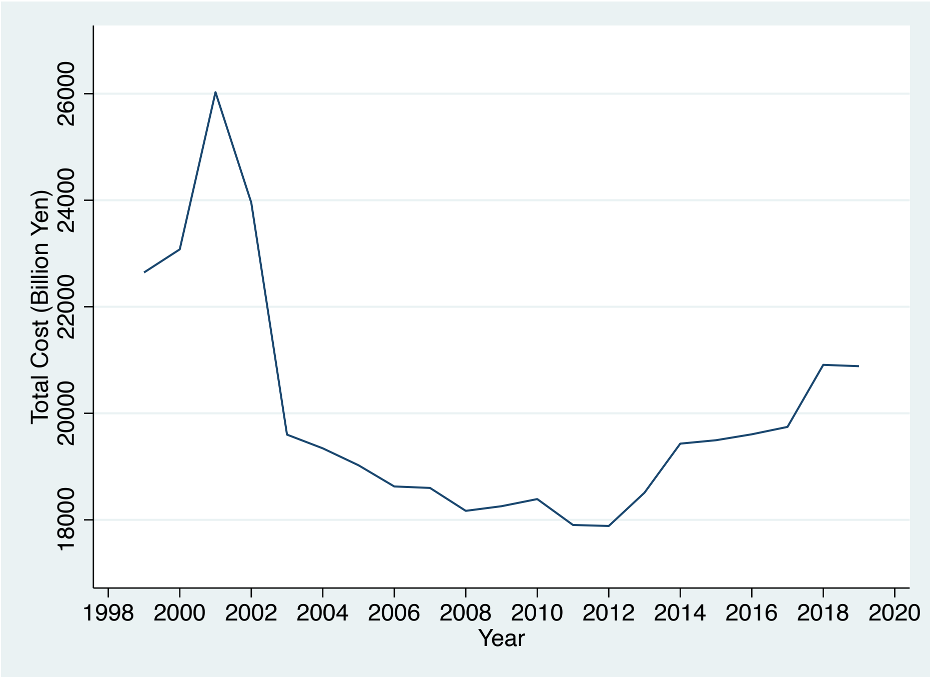

FIGURE 3.2: The Total Cost of MSW Management in Japan

Source: MOE of Japan, 2021

cost in Japan over time. In the 2019 fiscal year, Japan spent 2,089 billion yen on processing 42.7 million tons of MSW, including 415 billion yen on construction costs and 1,552 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.[1]

Local municipalities are responsible for the management of MSW in Japan. Long before the Great Heisei Consolidation, many municipalities formed waste management associations with neighboring municipalities to collectively address 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, here were 450 such waste management associations in 2018. In Section 4, we explore whether the estimated effect of municipal mergers varies by the membership of the associations. Moreover, MSW

[1]One US Dollar is approximately one hundred and ten Japanese Yen as of January 1, 2019.

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 MSW 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.

3.3 Data and Methodology

3.3.1 Data

We use data 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. The total cost can be divided into the processing and management cost and the construction cost. We cannot divide it further because of the existence of the contributions to waste management associations which do not have any further details during the early periods. Owing to data availability, we exclude some municipalities such as Tokyo Special Wards, municipalities that suffered from the Great East Japan Earthquake, and those with corrupted data.

Regarding municipal mergers, we obtain data on changes to the municipal codes from the Portal Site of the Official Statistics of Japan and manually merge the data into the waste management dataset. We use municipalities that merged in 2004 and 2005 as the treatment group and those that did not merge between 1999 and 2018 as the control group.[2] Approximately 85% of the mergers in this period were carried out in 2004 and 2005 given the strong fiscal measures from the central government during the first stage of the Consolidation as described in the previous section.[3]

The final dataset used for the analysis contains 1,548 municipalities in the post-merger dataset and 2,867 municipalities in the pre-merger dataset over the 20-year period. Here, the post-merger level 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. The pre-merger level means that the number of municipalities is based on the municipalities before their mergers, and their data after merging take the same value as the newly formed municipalities as if they still exist.

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. We also calculate the MSW management costs per capita for the robustness check.

3.3.2 Baseline DID model

Following previous studies, we use the post-merger dataset as our baseline analysis to handle the treatment group as if they had already merged before their actual merger. This is also helpful to capture the change in the efficiency of the treatment group from the pre- to post-merger periods.

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

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

TABLE 3.1: Descriptive Statistics of the Post-Merger Dataset

Variable	Obs.	Mean	Min	Max	Std. Dev.
All					
Total (1000*Yen*/*ton*)	30,960	47.1	0	6434	70.9
Processing&Management (1000*Yen*/*ton*)	30,960	38.3	0	624	24.0
Construction (1000*Yen*/*ton*)	30,960	7.27	-1.12	6343	64.0
DID Indicator (*dummy*)	30,960	0.22	0	1	0.41
Treatment Group					
Total (1000*Yen*/*ton*)	9,340	41.9	0	580	27.0
Processing&Management (1000*Yen*/*ton*)	9,340	34.8	0	580	16.9
Construction (1000*Yen*/*ton*)	9,340	5.82	-1.12	503	18.9
DID Indicator (*dummy*)	9,340	0.72	0	1	0.45
Control Group					
Total (1000*Yen*/*ton*)	21,620	49.4	0	6434	82.8
Processing&Management (1000*Yen*/*ton*)	21,620	39.8	0	624	26.3
Construction (1000*Yen*/*ton*)	21,620	7.86	-0.65	6343	75.5
DID Indicator (*dummy*)	21,620	0	0	0	0

Table 3.1 reports the descriptive statistics of the baseline model. The average processing and management cost per ton is approximately 34,800 yen in the treatment group and 39,800 yen in the control group. The average construction cost per ton is approximately 5,820 yen in the treatment group and 7,860 yen in the control group.

We adopt a Difference-in-Differences 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:

$$y_{it} = \alpha_i + \gamma_t + \beta D_{it} + \epsilon_{it} \tag{3.1}$$

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.

3.3.3 Common Trend Assumption

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:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p=-2}^{-5} \beta_p treat_i * N_p + \sum_{q=0}^{13} \beta_q treat_i * N_q + \epsilon_{it}, \tag{3.2}$$

where *treat* is a dummy variable that equals 1 when the observation is in the treatment group, N_p is a dummy variable for p years before the merger, and N_q is a dummy variable for q years after the merger. More particularly, N_{-5} indicates the year 1999 for those merged in 2004 and the year 2000 for those merged in 2005. N_{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 effect α_i and year fixed effect γ_t are included similar to the baseline model.

The results of the event study are plotted in Figures 3.3 to 3.5 with the responding 95% confidence interval provided. First, these figures show a similar trend before mergers, whereas 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. These results provide supportive evidence that the parallel trends assumption appears reasonable.

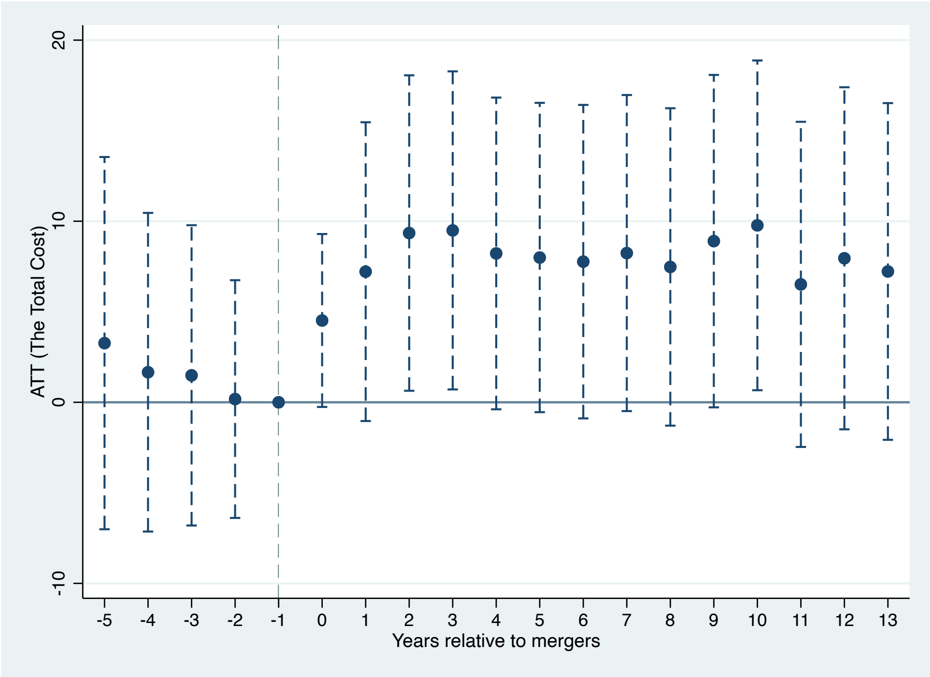

FIGURE 3.3: Event Study Analysis of the Total Cost of the Baseline Model

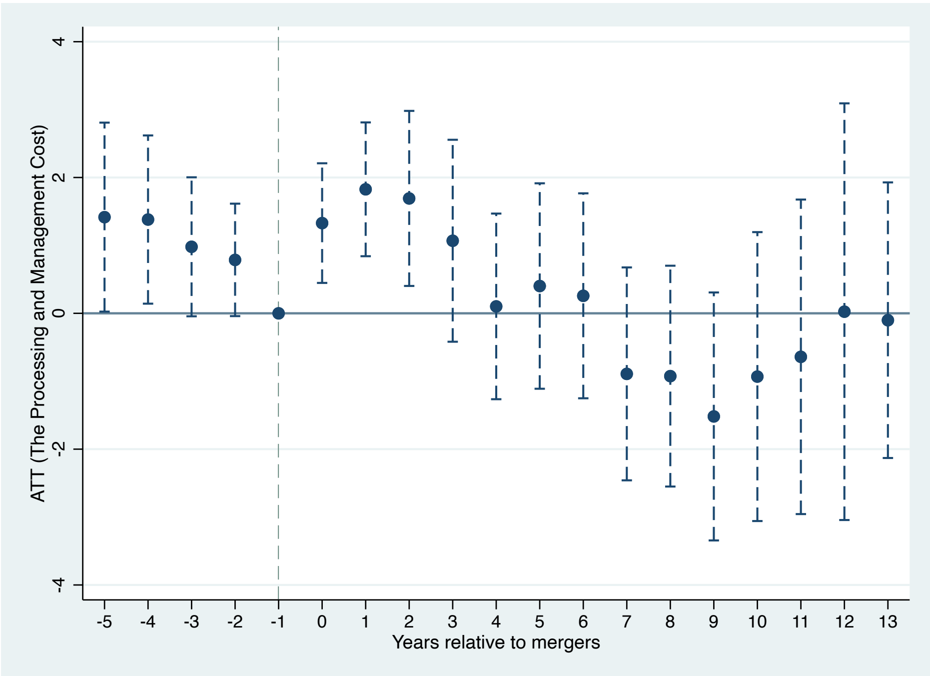

FIGURE 3.4: Event Study Analysis of the Processing and Management Cost of the Baseline Model

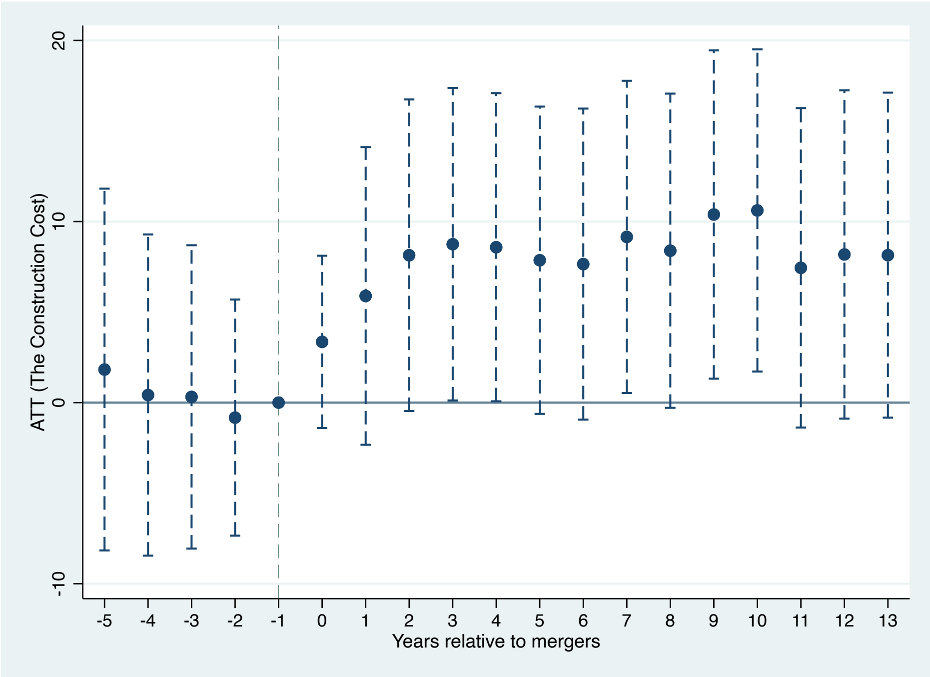

FIGURE 3.5: Event Study Analysis of the Construction Cost of the Baseline Model

3.3.4 PSM-DID model

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). The PSM-DID method introduced by Heckman et al. (1997) has been used by many studies when sample selection bias is not negligible. However, two reasons discourage us from using the post-merger dataset in the PSM-DID analysis. The first is related to the covariates necessary to calculate the propensity score. If we used the post-merger dataset in the PSM-DID analysis, it would not be possible to use certain variables (e.g., the debt expenditure burden ratio) to match the covariates because of aggregation difficulties (i.e., we cannot simply aggregate data measured by the ratio). However, it is critical to include variables describing fiscal conditions such as the debt expenditure burden ratio for the matching process because one major motivation behind mergers is to improve the resulting municipality's fiscal conditions. The second reason is that the post-merger dataset merges the treatment group municipalities even before they actually merge, whereas we do not adopt a similar process in the control group. Therefore we will be matching municipalities that were not even in existence yet with existing ones if we use the post-merger dataset. For the sake of uniformity, it would be better to apply a similar procedure to the control group as the treatment group.

3.3.5 The Virtual Merging Method

Based on these difficulties in implementing PSM using the post-merger dataset, we develop a new method that fully utilizes the pre-merger dataset. In this approach, we merge the control group virtually just as in the treatment group, as shown in Figure 3.6. The difference is that the mergers in the treatment group are real ones, which are expected to bring about changed outcomes (e.g., economies of scale), whereas the mergers in the control group are hypothetical. Through this virtual merging approach, the variables of the municipalities in the treatment group always take the real value during the pre-merger period and we can maintain symmetry in the data compilation process between the treatment and control groups, which is more balanced than simply merging the observations only in the treatment group. This approach also retains a larger number of observations than the post-merger dataset, although both the post- and pre-merger level datasets inevitably create hypothetical outcome variables.

We virtually merge the control group data according to the following steps. First, we summarize the distribution of merging patterns in the treatment group by the number of municipalities in one merger and the frequency of each merger pattern by year. Table 3.2 reports the merger patterns of the municipalities in our dataset. Following the distribution in Table 3.2, we merge the municipalities in the control group hypothetically. In our case, the sample size of the control group is approximately 60% of the treatment group. For replication, we use the same seed to

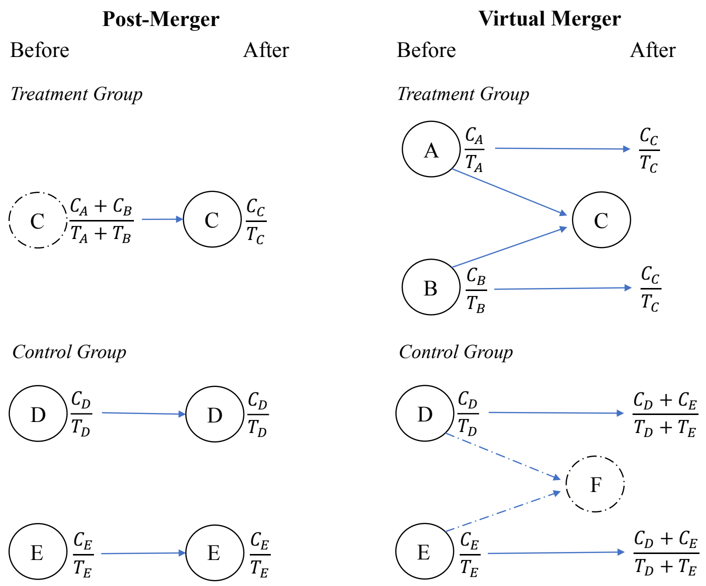

FIGURE 3.6: Difference between the Post-Merger and Virtual Merger Data

generate random numbers for each municipality, virtually merge the control group 100 times using the pattern, and then take the averages of the outcome variables, which are the processing and management cost per ton, the construction cost per ton, and the total cost per ton.

Table 3.3 reports the descriptive statistics of the virtual merger dataset. The average processing and management cost per ton is approximately 35,400 yen in the treatment group and 35,100 yen in the control group. The average construction cost per ton is approximately 6,150 yen in the treatment group and 6,910 yen in the control group. The difference between the treatment and control groups is smaller in the virtual merger dataset than in the baseline post-merger level dataset.

3.3.6 Matching Techniques

Following previous studies (Hirota and Yunoue, 2017; Suzuki and Sakuwa, 2016), we use seven covariates to predict the probability of being assigned to the treatment

TABLE 3.2: Numbers of Municipalities Involved in One Merger

Pattern	(1) Municipal Mergers in 2004	(2) Municipal Mergers in 2005
2 Municipalities	59	128
3 Municipalities	55	86
4 Municipalities	30	39
5 Municipalities	20	24
6 Municipalities	17	5
7 Municipalities	6	10
8 Municipalities	8	3
9 Municipalities	5	1
10+ Municipalities	4	5

TABLE 3.3: Descriptive Statistics of the Virtual Merger Dataset

Variable	Obs.	Mean	Min	Max	Std. Dev.
All					
Total (1000Yen/ton)	57,340	43.1	0	3749	46.1
Processing&Management (1000Yen/ton)	57,340	35.3	0	580	16.7
Construction (1000Yen/ton)	57,340	6.44	-1.12	3511	41.3
DID Indicator ($dummy$)	57,340	0.45	0	1	0.5
Treatment Group					
Total (1000Yen/ton)	35,680	42.8	0	1193	32.4
Processing&Management (1000Yen/ton)	35,680	35.4	0	580	18.9
Construction (1000Yen/ton)	35,680	6.15	-1.12	1124	24.7
DID Indicator ($dummy$)	35,680	0.72	0	1	0.45
Control Group					
Total (1000Yen/ton)	21,660	43.4	0	3749	62.5
Processing&Management (1000Yen/ton)	21,660	35.1	0	439	12.17
Construction (1000Yen/ton)	21,660	6.91	0	3511	59.3
DID Indicator ($dummy$)	21,660	0	0	0	0

TABLE 3.4: Descriptive Statistics of the Variables Used for the Matching

Variable	Obs.	Mean	Min	Max	Std. Dev.
Debt burden ratio	2,867	12.29	0.29	25.03	2.82
Population	2,867	35,666	195.5	3,263,734	125,838
Population over 65	2,867	4,798	61	336,041	14,205
Population density	2,867	5.51	0.01	142	11.6
Agriculture sales	2,867	3,334.344	0	58,028	3,921
Manufacturing sales	2,867	92,626	0	8,156,606	338,327
Commercial sales	2,867	149,150	22.5	70,185,775	1,682,669

group: the debt expenditure burden ratio, population, population over 65 years old, population density, sales for the agriculture sector, sales for the manufacturing sector, and sales for the commercial sector. We obtain this data from the Portal Site of the Official Statistics of Japan and present the summary statistics in Table 3.4. Owing to data availability, these variables are averages of several years before our research period. The debt expenditure burden ratio and sales for the agriculture sector are the averages from 1989 to 1998. Population, population over 65 years old, and population density 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. We adopt the Epanechnikov kernel function to perform the matching and generate the weights.

We also run event study analyses for the PSM-DID model after matching, as shown in Figures 3.7 to 3.9. We again find similar trends for the treatment and control groups in the pre-merger period. For the municipalities in the treatment group, the total and construction costs increase following the merger. The processing and management cost decreases slightly, but the coefficient is not statistically significant.

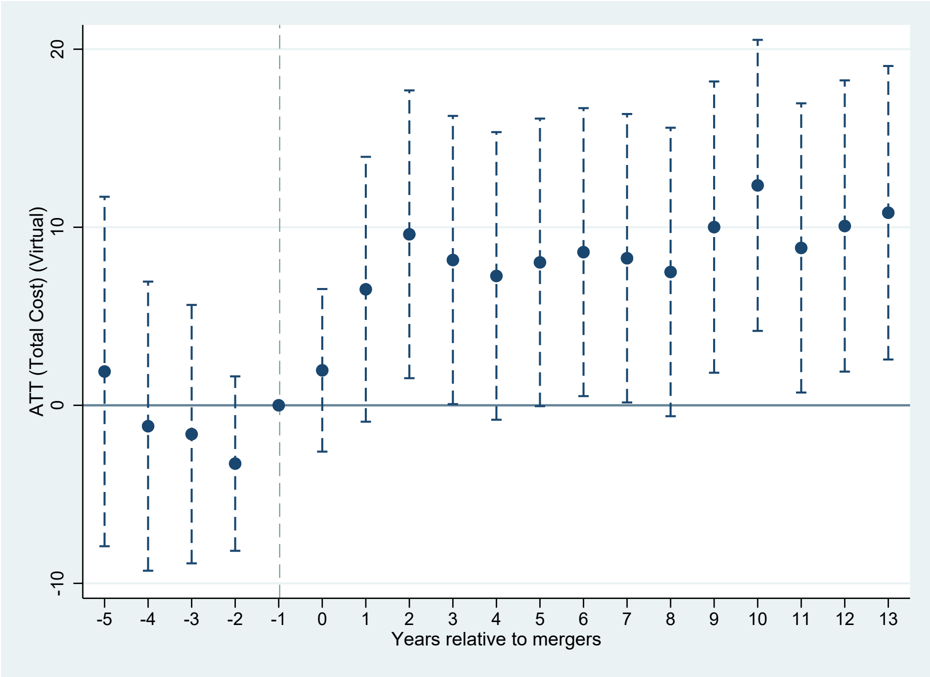

FIGURE 3.7: Event Study Analysis of the Total Cost in the PSM-DID Model

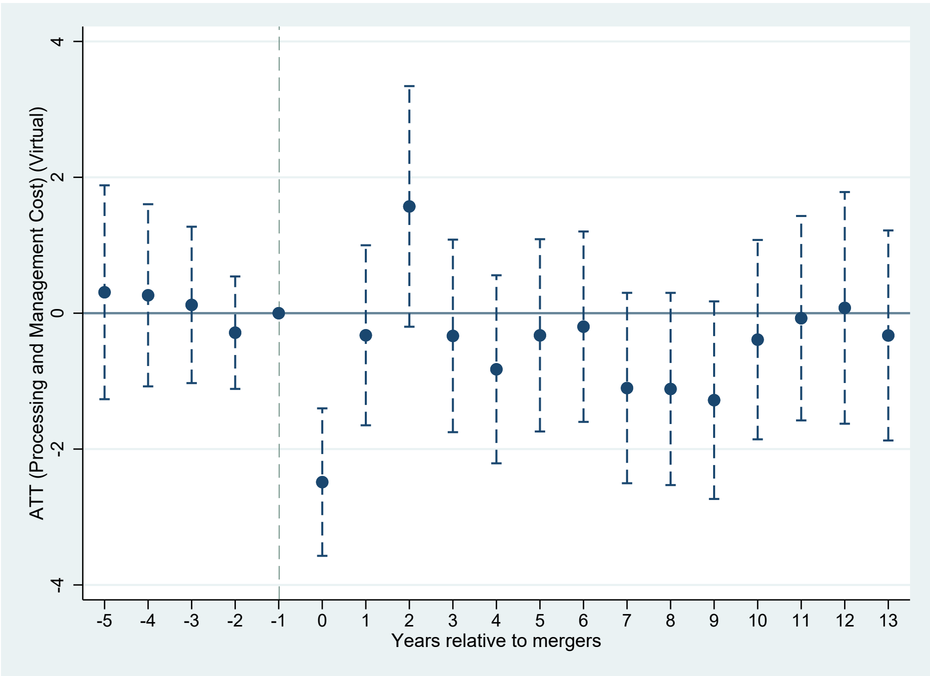

FIGURE 3.8: Event Study Analysis of the Processing and Management Cost in the PSM-DID Model

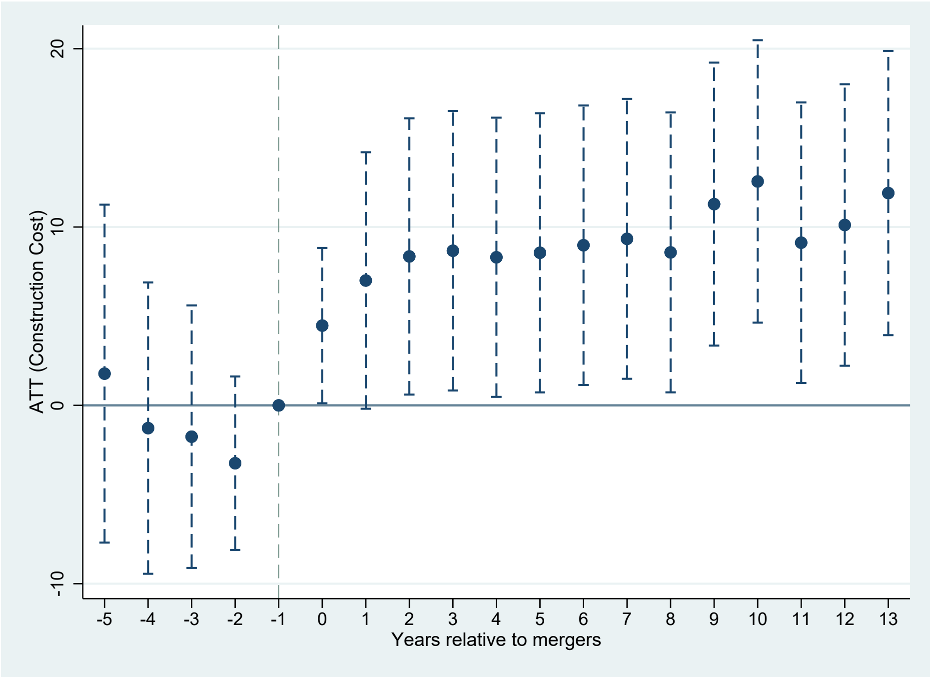

FIGURE 3.9: Event Study Analysis of the Construction Cost in the PSM-DID Model

3.4 Results and Discussion

3.4.1 Baseline Model

Table 3.5 reports the results of our baseline estimation. 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 6,150 yen per ton, whereas that in the construction cost is 7,400 yen per ton. Compared with the control mean, they are 15% and 94%, respectively. Although the coefficient of the processing and management cost per ton is negative, it is small in magnitude and insignificant, suggesting that a merger may not bring about economies of scale.

TABLE 3.5: Results of the Baseline Model

Variable	(1) Total	(2) Processing and Management	(3) Construction
D	6.15***	-0.947	7.42***
	(2.00)	(0.69)	(1.94)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Obs.	30,960	30,960	30,960

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3.6: Balancing Test for the PSM

Variables	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|
Debt burden ratio	U	12.275	12.322	-1.6		-0.43	0.665
	M	12.273	12.419	-5.1	-210.6	-1.54	0.123
Population	U	24843	53333	-20.6		-5.93	0.000
	M	24037	23297	0.5	97.4	0.32	0.749
Population over 65	U	3803.4	6422.5	-16.9		-4.82	0.000
	M	3693.8	3514.3	1.2	93.1	0.64	0.520
Population density	U	3.3402	9.0421	-45.4		-13.17	0.000
	M	3.3287	3.1632	1.3	97.1	0.85	0.395
Agriculture sales	U	3137.1	3656.3	-12.9		-3.45	0.001
	M	3131.7	3165.7	-0.8	93.5	-0.30	0.768
Manufacturing sales	U	66137	1.4e+05	-19.7		-5.39	0.000
	M	64537	63537	0.3	98.6	0.13	0.898
Commercial sales	U	80374	2.6e+05	-9.5		-2.80	0.005
	M	76168	63480	0.7	93.0	0.62	0.532

3.4.2 Virtual Merging Model

This subsection uses the PSM-DID approach to address the sample selection bias in municipal mergers. Table 3.6 reports the balancing test results for the PSM, showing that the differences between the treatment and control groups are insignificant after the matching. The biases between the treatment and control groups after the matching are within 10% for all the variables, which confirms the effectiveness of the matching.

Table 3.7 reports the estimation results of the PSM-DID approach. Similar to the baseline model, we find that the coefficients of the treatment indicator for the

TABLE 3.7: Results of the PSM-DID Model

Variable	(1) Total	(2) Processing and Management	(3) Construction
D	8.82***	-0.864	9.82***
	(2.43)	(0.78)	(2.16)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Obs.	57,340	57,340	57,340

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

total and construction costs are positive and statistically significant at the 1% level. However, the coefficients are larger than those of the baseline model because of the difference between the pre- and post-merger level datasets. In this case, the total cost increases by approximately 8,200 yen per ton, and the construction cost rises by 9,820 yen per ton after the merger. Compared with the control mean, they are 19% and 142%, respectively. The coefficient of the treatment indicator for the processing and management cost per ton is still insignificant. The results of our PSM-DID analysis are thus consistent with those of our baseline model, providing supportive evidence that minimal economies of scale resulted from the Great Heisei Consolidation.

3.4.3 Robustness Check

To check the robustness of the baseline results, we employ the cost per capita as an alternative dependent variable. Assuming the waste generated per capita should not change much before and after merging, it can be used as an alternative outcome variable. The outcome variables are the total cost per capita, the processing and management cost per capita, and the construction cost per capita. As shown in Table 3.8, the results are qualitatively similar to our baseline and PSM-DID model analyses. The coefficients of the treatment indicator for the total and construction

TABLE 3.8: Robustness Check

Variable	(1) Total per capita	(2) P & M per capita	(3) Construction per capita
D	2.510***	0.127	2.474***
	(0.611)	(0.182)	(0.613)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Obs.	30,960	30,960	30,960

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

costs per capita are positive and statistically significant at the 1% level. The results of the robustness check indicate a 2,510 yen increase in the total cost per capita and a 2,474 yen increase in the construction cost per capita for municipalities in the treatment group after the merger, whereas the coefficient for the processing and management cost per capita is still insignificant.

3.4.4 Subsample Analysis

Merger Type

This subsection investigates the difference between the two types of mergers in the Great Heisei Consolidation: fusions and absorptions. 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. Hence, we divide the treatment group 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 3.9 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

TABLE 3.9: Results by Merger Type

Variable	Total			Processing and Management			Construction		
	Baseline	Fusion	Absorp.	Baseline	Fusion	Absorp.	Baseline	Fusion	Absorp.
D	6.15***	6.95***	2.79	-0.947	-0.429	-3.28***	7.42***	7.70***	6.43***
	(2.00)	(2.03)	(2.40)	(0.69)	(0.75)	(0.88)	(1.94)	(1.96)	(2.32)
Municipal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	30,960	29,260	23,320	30,960	29,260	23,320	30,960	29,260	23,320

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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. This result is similar to Blesse and Baskaran (2016) who also studied the difference between the two types of mergers and found that the annexation type of merger (what we called absorption-type merger in this study) is more effective in reducing costs. This implies that smaller municipalities are likely to achieve economies of scale and obtain a boost in efficiency when absorbed by larger municipalities. Nevertheless, the coefficient of construction cost remains positive and significant, as in the other models.

Membership of Waste Management Associations

As noted in Section 2, many municipalities in Japan provide MSW services jointly with neighboring municipalities by forming a waste management association. The waste management association typically plays a proactive role in MSW management, and the cost is allocated to member municipalities. In practice, many municipalities that merged in the Great Heisei Consolidation were members of the same waste management association even before the mergers. It is worth investigating whether the treatment effect differs between those who joined these associations and those who did not because it would be difficult for merged municipalities to pursue further cost reduction if they had already formed an association and made

TABLE 3.10: Results by Membership of Waste Management Associations

Variable		Total			Processing and Management			Construction	
	Baseline	Attend	Never	Baseline	Attend	Never	Baseline	Attend	Never
D	6.15***	2.17**	21.5**	-0.947	-0.395	0.194	7.42***	2.72***	22.0**
	(2.00)	(1.06)	(9.32)	(0.69)	(1.03)	(2.33)	(1.94)	(0.86)	(9.55)
Municipal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	30,960	25,700	5,260	30,960	25,700	5,260	30,960	25,700	5,260

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

efforts for efficient service provisions. Hence, we divide the dataset into municipalities with association membership and those without, based on whether the municipalities paid contributions to a waste management association at least once during our research period.

The estimated results in Table 3.10 show that the coefficients of the treatment indicator for the total and construction costs per ton remain positive and statistically significant in all the columns. However, there is a large difference in the size of the coefficients between these groups. The estimated treatment effect for member municipalities is 10 times smaller than that for non-members. As we further discuss in the next subsection, the result supports our hypothesis that the increase in construction cost is caused by the new projects of merged municipalities because association members often operate shared facilities and do not need to construct new infrastructure.

3.4.5 Discussion

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, the subsample analysis by merger type shows the possibility that smaller municipalities achieved economies of scale to some extent by being absorbed into larger municipalities. We can interpret our findings as follows.

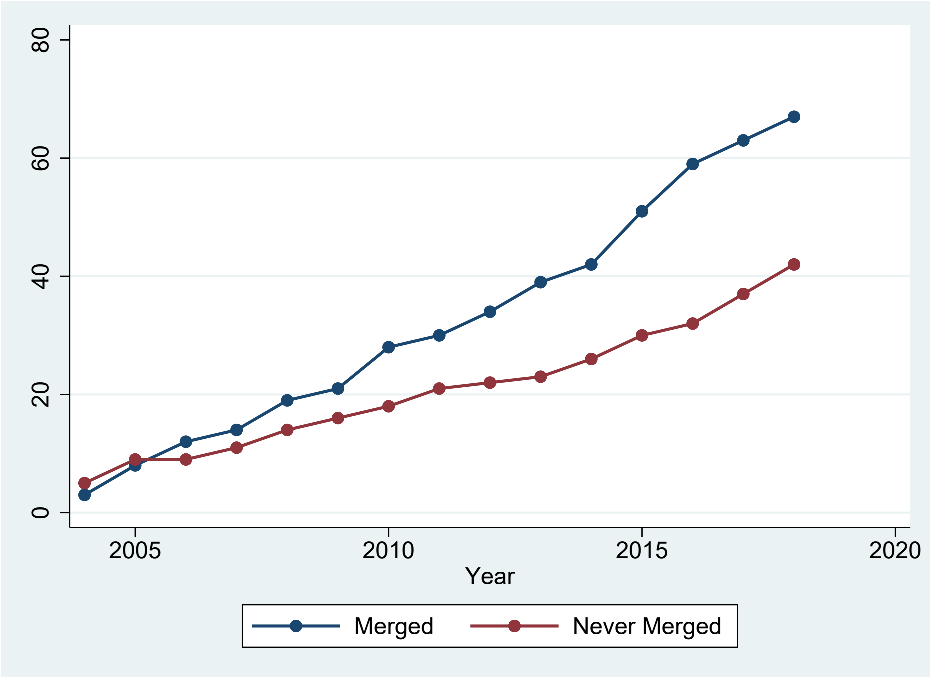

FIGURE 3.10: Numbers of Incinerators Built by Merged and Never Merged Municipalities

First, 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 that merged during the first stage could issue these special bonds to build waste processing facilities for the newly formed municipality. Figure 3.10 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 evidence for the increase in the construction cost. In addition, our results regarding the membership of waste management associations suggest that the increase in cost is lower for members than for non-members. Another interpretation is that members had already built large joint incinerators before the merger, and their demand for new incinerators might be lower than non-member municipalities.

Second, contrary to our expectations, we find that the municipal mergers brought about minimal economies of scale. We only identified subsequent cost reductions for absorption-type mergers, suggesting that economies of scale in MSW management had already been achieved for most municipalities—even before the municipal mergers took place. Many less efficient municipalities achieved economies of scale by joining waste management associations and/or promoting privatization, whereas some larger municipalities had achieved economies of scale alone. Therefore, only small municipalities improved waste management cost efficiency through municipal mergers.

3.5 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. First, we created a post-merger dataset and applied the DID method as our baseline analysis, finding no evidence for the scale economy in waste management cost realized by the Great Heisei Consolidation. By contrast, the result from the sub-sample analysis shows that absorption-type mergers did achieve some subsequent cost savings.

Furthermore, we found an increase in construction costs among merged municipalities, suggesting that the special bonds for mergers helped the construction of new waste processing facilities, particularly for those that had never belonged to a waste management association. The higher number of incinerators built in merged municipalities also provided supportive evidence. We checked the robustness of our results by using the MSW management costs per capita as an alternative dependent variable and obtained a similar result.

Lastly, we developed a new method to process the data and create a virtually merged dataset based on the pre-merger level. Our PSM-DID analysis based on the new approach lent further support to our conclusion. The virtual merging method is attractive because it treats the treatment and control groups equally and allows researchers to use pre-merger data for PSM-DID analysis.

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

Chapter 4

Reduce, Recycle, and Municipal Mergers: The Effect of the Great Heisei Consolidation on Waste Management

4.1 Introduction

People are generating waste every day, from small things such as used plastic bottles and containers, leftovers, unwanted clothes, and outdated electronics to large things like broken bicycles, furniture, and home appliances. The World Bank Group estimates that the world generates 2 billion tons of municipal solid waste annually and expects that volume to grow to 3.4 billion tons by 2050 (Kaza et al., 2018). As a result, there are great concerns about how to deal with those wastes economically and environmentally. Municipal solid waste management has been a major challenge for cities to achieve sustainable development (Saeed et al., 2009; Chifari et al., 2017). The United Nations also set up the Sustainable Development Goals (SDGs) in 2015, which put sustainability in first place.

As Japan's landmass is limited which causes difficulties when finding landfill disposal sites, municipal solid waste management is greatly highlighted in Japan. The 3Rs (Reduce, Reuse, Recycle) aimed to reduce the generation of waste has been promoted country-widely based on the policy called *Basic Law for establishing a Circular Society* since 2000. Meanwhile, many industrialized countries have deployed broad municipal merger reforms in the belief that larger municipal units can increase efficiency in public service provision in recent decades (Fox and Gurley, 2006; Blesse and Baskaran, 2016). A similar scenario also happened in Japan such as the Great Heisei Consolidation which reduced about 45% of the municipalities. And we are curious if municipal mergers could promote the 3Rs, particularly the reduction of waste and the recycling of waste as well.

In this study, we want to answer the question of whether municipal mergers could improve municipal solid waste management by reducing the generation of waste and promoting the recycling of waste. In particular, we examine the case study of the Great Heisei Consolidation in Japan by applying difference-in-differences (DID) methods. The Japanese Ministry of the Environment provides a very detailed database on municipal solid waste management from 1999 to date that covers both the pre-merger and post-merger periods, which fits our needs perfectly.

The contributions of our study can be summarised as follows. First, although some studies shed light on the 3Rs in Japan, few focus on the resulting effect of the Great Heisei Consolidation. We are one of the first to apply the DID method to the effect of mergers on municipal waste management as far as we know. Second, we apply both OLS and GLM models to the DID method for a variety of outcome variables that we are interested in. Third, we include the analysis of plastic waste as the pollution of plastic waste has been a global problem. Last, we use a 20-year dataset for most of the Japanese municipalities which is supposed to provide more convincing results.

The estimation results of our study indicate that the Great Heisei Consolidation may not contribute to the reduction of municipal solid waste and little promote the recycling of municipal solid waste. Our estimation expects an 11.8 kg per capita annual more total municipal solid waste in the merged municipalities compared to those never merged. In addition, the value would be 13.0 kg considering the announcement effect. We also find out that the merged municipalities are 20.1% more likely to not charge for the disposal of combustible waste and 25.0% more like to not charge for the disposal of incombustible waste. The number of waste separation categories is higher in the merged municipalities by 0.56 types which is not a big deal compared to the change in the charging policy. Furthermore, we test the municipal mergers' effect on plastic waste, getting the result that municipal mergers result in a lower amount of recycled plastic waste in merged municipalities with no contribution to the collection of plastic waste.

Among the existing literature, few focus on the effect of municipal mergers on waste management. Shimamoto (2019) examines the factors that impact municipal solid waste per capita and the recycling rate at the prefecture level in Japan. The author found that the female population and senior citizen population tend to have a lower waste per capita while higher gross domestic product and higher educational attainment result in a higher waste per capita. As the author studied at the prefecture level, the effect of municipal mergers is not analyzable. Chifari et al. (2017) analyzed the Japanese MSW management system and estimate the cost elasticity with respect to the waste volumes at three treatment stages: collection, processing, and disposal. They observed economies of scale at all three stages. As they only used the dataset of 2010, they could not capture the effect of the Great Heisei Consolidation as well. Tsuzuki et al. (2018) considered the effect of municipal mergers when studying unit-based pricing, which is a type of waste charging policy by adding a dummy variable to capture the effect. They actually found out that the Great Heisei Consolidation might increase waste generation but they were not able to give a detailed reason for it.

The remainder of this chapter is organized as follows. Section 2 introduces the background of our study. Section 3 explains the dataset and models used in our analyses. Section 4 presents and discusses our empirical results. Section 5 concludes.

4.2 Background

4.2.1 The Great Heisei Consolidation in Japan

The Great Heisei Consolidation formally started in 1999 with the enforcement of the Special Municipal Mergers Law. 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). The Special Municipal Mergers Law, however, is a carrot-and-stick policy. 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).

The Great Heisei Consolidation is mainly divided into two stages. The first stage is from 1999 to 2006 while the second stage is from 2007 to 2010. The main difference between the first and second stages is that the municipalities merged in the first stage will receive larger fiscal measures than the second stage. Therefore, most of the municipalities merged in the first stage. The number of municipalities in Japan reduced from 3,229 in 1999 to 1,821 in 2006 when the first stage ended and to 1,727 when the second stage finished in 2010.

There are also mainly two types of mergers: absorptions, in which a large municipality absorbs a smaller one or several smaller ones, and fusions, in which a new municipality is created by the consolidation of several municipalities. Approximately 85% of the mergers realized during the Great Heisei Consolidation were fusions.

Before the actual implementation of municipal mergers, the municipalities which were going to merge together would organize a consolidation conference or council to discuss the details of the municipal merger. According to the Ministry of Internal Affairs and Communications (2005), we calculated the average establishment date of the consolidation conference before the target merging date and it is about one and a half years. As there could be lots of negotiation and coordination in order to deal with the difficulties and achieve their joint goals, we believe there could be an impact on the waste management policies in the newly formed municipalities.

4.2.2 Municipal Solid Waste Management in Japan

Japan has been implementing policies for promoting the 3Rs (Reduce, Reuse, Recycle) and investing lots of resources in recycling due to the relatively limited landmass in Japan. In the fiscal year 2019, Japan spent 2,089 billion yen on processing 42.7 million tons of municipal solid waste. There are also a series of laws enacted to reduce waste generation and promote recycling, such as the Container and Packaging Recycling Law in 1995, the Home Appliance Recycling Law in 1998, the Basic Law for Establishing a Circular Society in 2000, and the End-of-life Vehicle Recycling Law in 2002 (Honma, 2021).

Local municipalities are responsible for the management of solid waste in Japan and municipalities could 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 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.

Municipalities, however, have to make a choice, when they plan to merge with other municipalities with different waste management policies. Whether they are determined to follow existing policies from the merging municipalities or make completely new waste management policies, there is a great chance that the waste management policies could change. And we think the key lies in the coordination and negotiation during the consolidation conferences. For example, Mitoyo City, Kagawa Prefecture is formed by the municipal merger of Mino, Nio, Saita, Takase, Takuma, Toyonaka, and Yamamoto in 2005. While the newly formed Mitoyo City charges for the disposal of combustible wastes, Nio, Takase, and Yamamoto did not charge for the disposal before the merger. As a result, Mitoyo City reports that the combustible waste had been reduced by 11.47% compared to the same month last year (Mitoyo City, 2006).

4.3 Data and Methodology

4.3.1 Data

We get most of our data from the Annual Survey of Municipal Solid Waste (Ministry of the Environment of Japan, 2022). This survey covers all municipalities in Japan and includes detailed information on municipal solid waste management such as the amounts of different kinds of waste, the population involved, the charging policy for different kinds of waste, the collection of different kinds of waste, and the number of waste separation categories. Because of data availability and integrity, we exclude some municipalities such as Tokyo Special Wards, municipalities that suffered from large earthquakes such as the Great East Japan Earthquake, and those with corrupted data.

We also obtain data on changes to the municipal codes from the Portal Site of the Official Statistics of Japan and manually merge the data into the waste management dataset regarding the information on municipal mergers. We use municipalities that merged in 2004 and 2005 as the treatment group and those that did not merge between 1999 and 2018 as the control group.[1] Approximately 85% of the mergers were carried out in 2004 and 2005, given the strong fiscal measures from the central government during the first stage of the Consolidation as described in the previous section.[2]

One of the most difficulties in this research is how to handle municipal mergers. Here, we process the dataset at the post-merger level. The post-merger level means that we take the municipalities in merged status no matter whether it is before or after mergers. In this way, the number of municipalities is the same as the number of municipalities after their mergers. Their data before merging take the aggregated value as if they already merged during the pre-merger period. For dummy variables and count variables, we take their average and make a fractional dataset.

Table 4.1 reports the descriptive statistics of the baseline model. There are 1,531 municipalities in the dataset and the research period is twenty years. The average annual waste per capita is approximately 337 kg in the treatment group and 343 kg in the control group. The average number of waste separation categories is 9.985 in the treatment group and 9.754 in the control group. We think the difference between the control group and treatment group is minor and the dataset is balanced.

There is still something to be noted, though. First, we use the sum of waste collected by municipalities and recyclables collected by civil groups from households

[1] We exclude municipalities that merged in other years and those that merged two or more times from the sample.

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

as the total waste and the sum of waste collected by municipalities from households only and recyclables collected by civil groups from households as the household waste. We then divide the waste by the population involved for the data of waste per capita. Second, the indicators for waste management policies such as charging and collecting are fractional dummy variables. They take one for positive, zero for negative, and fractional values in the pre-merger periods. We also exclude the municipalities which never changed their policies to avoid collinearity, as their dummy variables always take one or zero. Third, as there has been a limitation to the records of data on the number of waste separation categories in the early research periods, we exclude the municipalities which ever reached the limitation to the records in the early periods. Last, the amount of recycled plastic waste including all the plastic containers, white trays, and other plastics. This is because we do not have detailed data on the earlier research periods.

4.3.2 Baseline DID Design

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

$$y_{it} = \alpha_i + \gamma_t + \beta D_{it} + \epsilon_{it} \tag{4.1}$$

The variable y denotes the outcome variables. D is a dummy variable as the DID indicator that captures the treatment effect. It will take one for treated municipalities in the post-merger periods and zero otherwise. 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 given municipalities. ϵ_{it} is the

TABLE 4.1: Descriptive Statistics

Variable	Obs.	Mean	Min	Max	Std. Dev.
All					
Annual Waste Per Capita (*ton*)	30,620	0.341	0.008	2.960	0.108
Annual Household Waste Per Capita (*ton*)	30,620	0.256	0.008	1.376	0.069
Charging for Combustible Waste (*dummy*)	13,900	0.606	0	1	0.475
Charging for Incombustible Waste (*dummy*)	13,060	0.561	0	1	0.482
Waste Separation Categories (*numeral*)	18,540	9.807	1	31	4.265
Annual Recycled Plastic Waste Per Capita (*ton*)	30,620	0.0035	0	0.1000	0.0055
Annual Recycled PET Bottles Per Capita (*ton*)	30,620	0.0018	0	0.0914	0.0016
Collection of Plastic Waste (*dummy*)	23,280	0.712	0	1	0.443
Treatment Group					
Annual Waste Per Capita (*ton*)	9,100	0.337	0.130	1.058	0.078
Annual Household Waste Per Capita (*ton*)	9,100	0.248	0.083	0.943	0.051
Charging for Combustible Waste (*dummy*)	5,360	0.624	0	1	0.447
Charging for Incombustible Waste (*dummy*)	5,380	0.511	0	1	0.467
Waste Separation Categories (*numeral*)	4,240	9.985	2	24	4.136
Annual Recycled Plastic Waste Per Capita (*ton*)	9,100	0.0034	0	0.0833	0.0056
Annual Recycled PET Bottles Per Capita (*ton*)	9,100	0.0016	0	0.0872	0.0013
Collection of Plastic Waste (*dummy*)	7,940	0.720	0	1	0.421
Control Group					
Annual Waste Per Capita (*ton*)	21,520	0.343	0.008	2.960	0.119
Annual Household Waste Per Capita (*ton*)	21,520	0.260	0.008	1.376	0.075
Charging for Combustible Waste (*dummy*)	8,540	0.594	0	1	0.491
Charging for Incombustible Waste (*dummy*)	7,680	0.597	0	1	0.491
Waste Separation Categories (*numeral*)	14,300	9.754	1	31	4.302
Annual Recycled Plastic Waste Per Capita (*ton*)	21,520	0.0036	0	0.1000	0.0055
Annual Recycled PET Bottles Per Capita (*ton*)	21,520	0.0019	0	0.0914	0.0017
Collection of Plastic Waste (*dummy*)	15.340	0.709	0	1	0.454

error term. Standard errors are clustered at the municipality level.

4.3.3 Alternative GLM models

Although we use OLS to estimate some of our baseline models, we also use other estimation approaches when the dependent variables are dummy variables and count variables. In this sense, we intend to estimate the binary outcome variables using a Probit model and estimate the count outcome variable using a Poisson model. Our dataset, however, is a fractional one resulting from the way we handle the municipal merger data which causes difficulties when estimating them using the conventional Probit model and Poisson model.

To solve this problem, we follow Papke and Wooldridge (1996) to employ a fractional Probit regression by the generalized linear model using the Probit link function as the alternative method. We also employ a fractional Poisson regression by GLM model using the Poisson link function as well. For reference, we still provide the conventional OLS estimations in the results.

4.3.4 Event Study

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 and provide analyses of the time effect, we adjust our main model to implement an event study using the following OLS model:

$$y_{it} = \alpha_i + \gamma_t + \sum_{p=-2}^{-5} \beta_p treat_i * N_p + \sum_{q=0}^{13} \beta_q treat_i * N_q + \epsilon_{it}, \tag{4.2}$$

where *treat* is a dummy variable that equals 1 when the observation is in the treatment group, N_p is a dummy variable for p years before the merger, and N_q is a dummy variable for q years after the merger. More particularly, N_{-5} indicates the

TABLE 4.2: The Effect of Municipal Mergers on Waste Per Capita

VAR	(1) Total Municipal Solid Waste	(2) Waste from Households Only
D	0.0118***	0.0105***
	(0.0031)	(0.0023)
Municipal FE	YES	YES
Year FE	YES	YES
Treatment Group	455	455
Control Group	1,076	1,076
Observ	30,620	30,620

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

year 1999 for those merged in 2004 and the year 2000 for those merged in 2005. N_{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 for those merged in 2004 or 2004 for those merged in 2005. Municipality fixed effect α_i and year fixed effect γ_t are included similarly to the baseline model.

4.4 Results and Discussion

4.4.1 Waste Per Capita

Table 4.2 reports the result of our estimation of the municipal mergers' effect on the waste per capita. The estimated coefficients of both the two outcome variables are statistically significant and positive. This indicates that the waste per capita of the merged municipalities is higher than that of the non-merged municipalities. We can interpret from the results that the residents in merged municipalities are generating about 11.8 kg per capita annually more waste than non-merged municipalities, which responds to 3.5% of the total waste. For the waste only coming from households, the value is about 10.5 kg per capita annually. This result is consistent

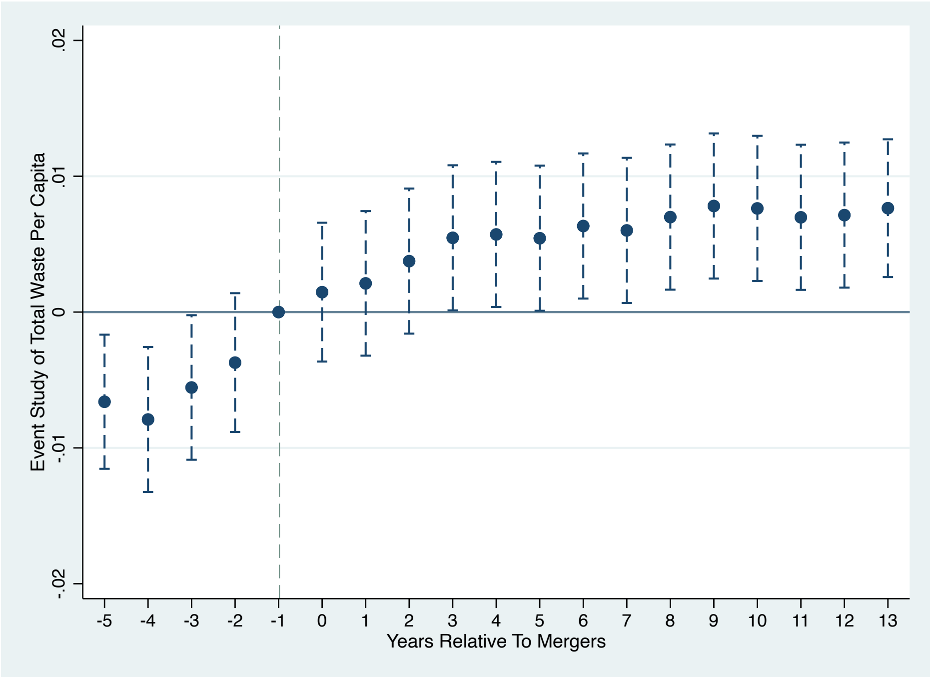

FIGURE 4.1: Event Study of Total Waste Per Capita

with Tsuzuki et al. (2018) who also captured an increase in the waste generation of the merged municipalities.

The result of the event study is plotted in Figure 4.1 with the responding 95% confidence interval provided. Although we think there is a difference before and after the merger, the pre-merge period already shows a somewhat increasing trend. We think there could be a sort of announcement effect in this case. Municipal mergers are not determined of a sudden and there is a lot of coordination and preparation in the consolidation conferences before the mergers' actual implementation. Residents should be aware of the mergers long before their municipalities merged with the others. Therefore, the influence of the mergers may also show up earlier than the actual mergers.

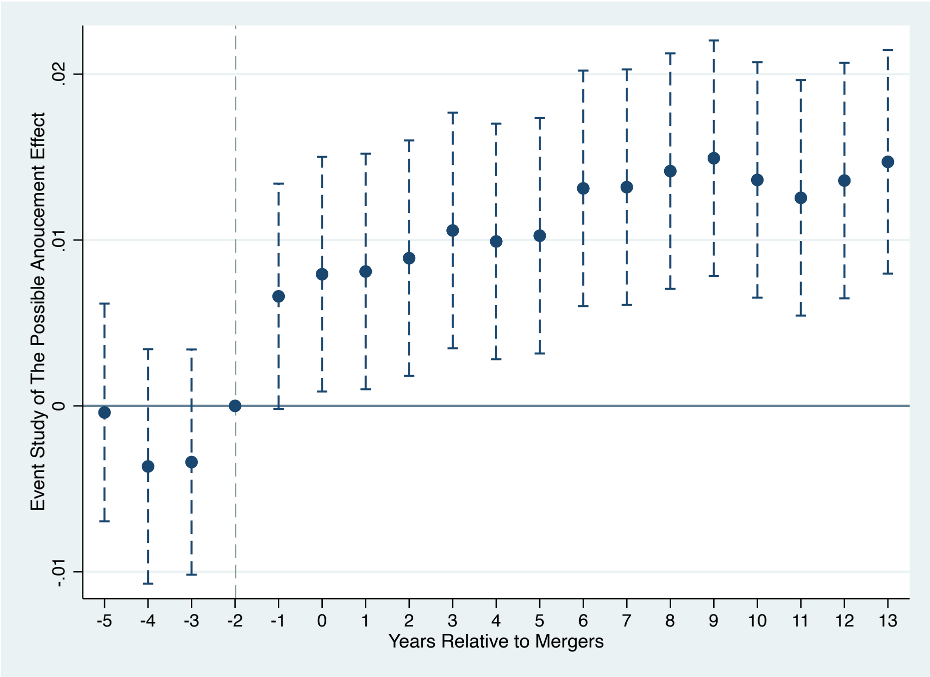

FIGURE 4.2: Event Study of Possible Announcement Effect

4.4.2 Announcement Effect Exploration

To take the announcement effect into consideration, we change the reference year of the event study to two years before the municipal mergers. This is because the average establishment date of the consolidation conference before the target merging date is about one and a half years, which we calculated in Section 2. We assume most of the residents should be aware of municipal mergers and changes in policies at least one year before the actual implementation. The result is plotted in Figure 4.2. We think we successfully captured the announcement effect in this way since there is a notable difference before and after the municipal mergers.

Considering the existence of the announcement effect, we change the treatment year to one year before the actual year of the mergers and carry out the DID analysis again. The result is reported in Table 4.3. The estimations of both the coefficients are still significant and positive while both the value are larger than the baseline

TABLE 4.3: The Effect on Waste Per Capita Considering Announcement Effect

VAR	(1) Total Municipal Solid Waste	(2) Waste from Households Only
D	0.0130***	0.0112***
	(0.0031)	(0.0023)
Municipal FE	YES	YES
Year FE	YES	YES
Treatment Group	455	455
Control Group	1,076	1,076
Observ	30,620	30,620

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

model. This result indicates that the residents in merged municipalities are generating about 13.0 kg per capita annually more waste than non-merged municipalities, which responds to 3.8% of the total waste, and the value of waste from households only is about 11.2 kg per capita annually.

This result is kind of interesting because it seems that people show different attitudes toward waste reduction or maybe environmental protection just because of municipal mergers if we only look at this result. To explain the mechanism behind this phenomenon, we further examine the differences in the waste charging policies among the merged and never-merged merged municipalities.

4.4.3 Charging Policies for Combustible and Incombustible Waste

We focus on the charging policy of combustible and incombustible waste as both two kinds of waste are the most common wastes generated from daily life, supposing no one throws furniture and home appliances every day. Table 4.4 reports the result of the estimation of the municipal mergers' effect on the waste charging policies. One thing to be noted is that we exclude municipalities that never changed their policies during our research period to avoid collinearity.

TABLE 4.4: The Effect of Municipal Mergers on Charging Policies

VAR	(1) Combustible			(2) Incombustible		
	OLS	Probit	Marginal	OLS	Probit	Marginal
D	-0.260***	-1.014***	-0.201***	-0.293***	-1.215***	-0.250***
	(0.327)	(0.168)	(0.033)	(0.019)	(0.166)	(0.032)
Municipal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Treatment Group	268	268	268	269	269	269
Control Group	427	427	427	384	384	384
Observ	13,900	13,900	13,900	13,060	13,060	13,060

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Our estimation results show a statistically significant and positive effect from both the OLS and fractional Probit (GLM) model. We can interpret from the result that about 20.1% to 26% more of the merged municipalities tend to not charge for combustible waste compared to those never-merged municipalities. For the charging of incombustible waste, the value is about 25% to 29.3%. As for previous studies showing charging for waste will decrease the generation of waste (Usui and Takeuchi, 2013; Sasao, 2000), we think this result is consistent with the increase in waste per capita.

The result of the event study analysis is plotted in Figure 4.3 with the responding 95% confidence interval provided. Although there is a trend of not charging for combustible waste even before the mergers, we could still spot a significant jump before and after mergers. As for the possible reason for the trend in the pre-merger period, we think the coordination and preparation for municipal mergers should be responsible for this, too. Some municipalities might unify their policies before they merge to make the merging process more smooth. Unlike the waste per capita, waste management policies, however, are made up officially, so it is not supposed to have an announcement effect here. Therefore, we could still capture the impact right after the municipal mergers except for those municipalities that changed their

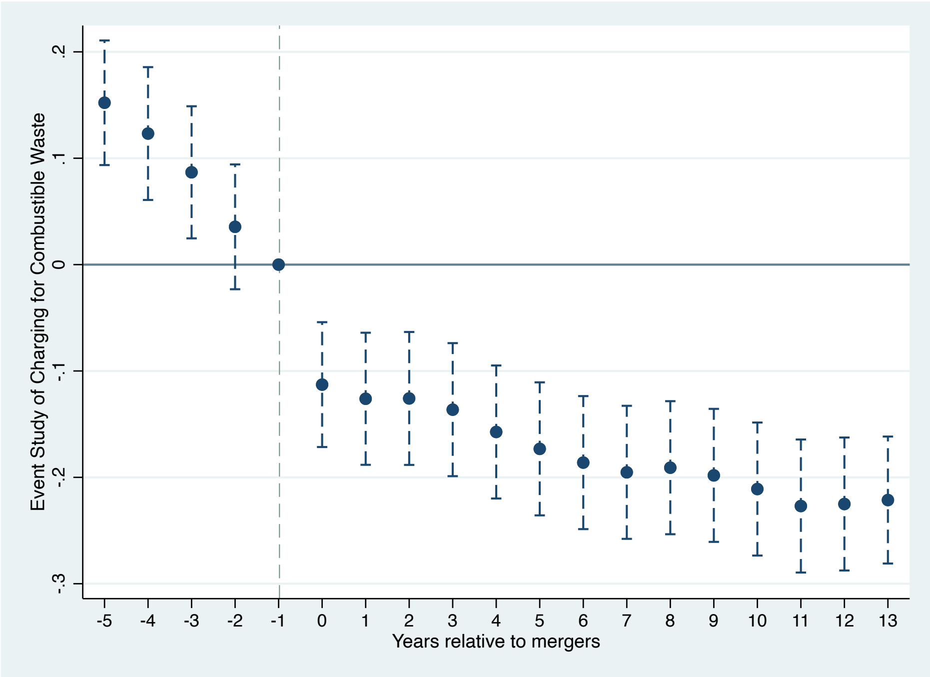

FIGURE 4.3: Event Study of Charging for Combustible Waste

policies before official mergers.

4.4.4 The Number of Waste Separation Categories

Except for the charging of waste, another important thing for the residents when they dispose of waste is the waste separation rules. Municipalities are able to make their own waste separation rules, and generally, more detailed waste separation is supposed to improve recycling. Table 4.5 shows the result of the effect of municipal mergers on waste separation. Here, we use the number of waste separation categories as the outcome variable.

Our estimation shows a statistically significant and positive result both in the OLS and Poisson model. This result indicates that compared to the municipalities never merged, the merged municipalities are likely to increase the number of separations by 0.53 to 0.56 types, or by about 5.4% to 5.7%. The event study of waste

TABLE 4.5: The Effect of Municipal Mergers on Waste Separation

VAR	(1) OLS	(2) Poisson	(3) Marginal
D	0.534**	0.057**	0.557**
	(0.244)	(0.023)	(0.230)
Municipal FE	YES	YES	YES
Year FE	YES	YES	YES
Treatment Group	212	212	212
Control Group	715	715	715
Observ	18,540	18,540	18,540

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4.6: The Effect of Municipal Mergers on Plastic Waste

VAR	(1) Plastic Waste	(2) PET Bottles	(3) Collection of Plastic Waste	
			OLS	Probit
D	-0.0005**	-0.0001***	-0.005	0.022
	(0.0002)	(0.00004)	(0.021)	(0.132)
Municipal FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Treatment Group	455	455	397	397
Control Group	1,076	1,076	767	767
Observ	30,620	30,620	23,280	23,280

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

separation is plotted in Figure 4.4 with the responding 95% confidence interval provided, and we can notice the difference before and after the merger.

This result shows that municipal mergers could improve waste recycling in some aspects, as residents need to separate more categories of waste after municipal mergers. The effect, however, is small for about only 0.56 types, which is very easily offset by the effect of changes in the charging policies of waste.

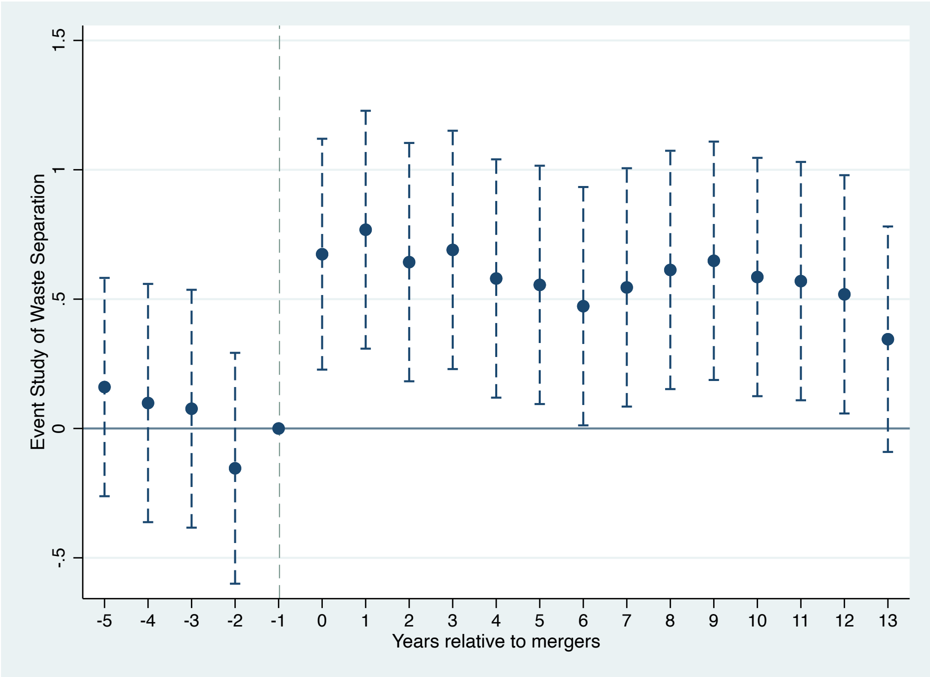

FIGURE 4.4: Event Study of Waste Separation

4.4.5 Plastic Waste

Plastic pollution has been a severe global problem (Ritchie and Roser, 2018). Therefore, whether plastic waste could be more properly recycled is another concern in this study. We measure this question by focusing on the amount of recycled plastic per capita and whether the municipalities collect plastic waste from households. We report the result of the amount of recycled plastic per capita and the collection status of plastic waste (including white trays, plastic containers, and other plastics) in Table 4.6. To be noted, the result of recycled plastic waste per capita was adjusted for the announcement effect, which means the treatment time is one year before actual mergers. We also did not include the collection status of PET bottles here because in our dataset a twenty-year average of 92.9% municipalities are collecting PET bottles while the twenty-year average of plastic waste is only about 64.7% [3].

[3]This value is different from the descriptive statistics because we include the municipalities always with the same value (never changed their policies) here.

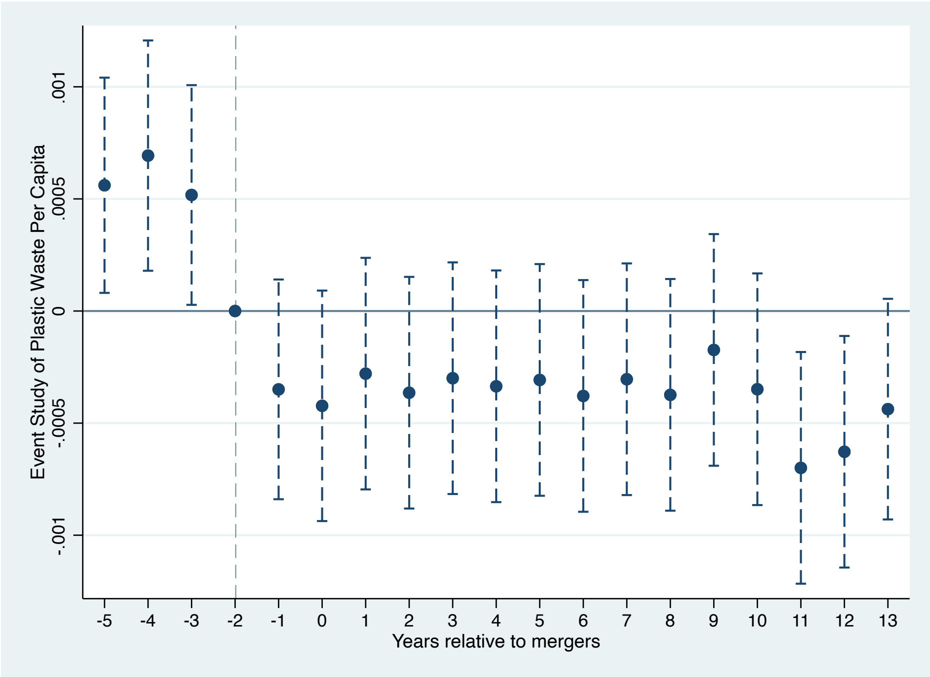

FIGURE 4.5: Event Study of Plastic Waste Per Capita

The estimated coefficients are statistically significant and negative for both plastic waste per capita and PET bottles per capita, while not statistically significant for the collection of plastic waste. These results indicate that while municipal mergers do not have an effect on the collection of plastic waste, mergers have a negative impact on the recycled amount of plastic waste. The event study is also plotted in Figure 4.5 with the responding 95% confidence interval provided and we can see the difference between before and after mergers.

4.4.6 Discussion

The analyses above give a consistent and robust result that the Great Heisei Consolidation does not contribute to the reduction of waste while little contributes to the recycling of waste as well. We think the lower rate for charging combustible waste and incombustible waste in the merged municipalities is the main reason for the higher waste generation. Although there is an increase in the number of waste separation types, the percentage is low and the effect could be easily offset by the effect of not charging for the combustible and incombustible waste. Furthermore, we find that the recycled amount of plastic waste is lower in the merged municipalities. We can infer from this result that there are residents who throw plastic waste away together with combustible waste after the charges for combustible waste have been canceled, which further proved the effect of not charging for combustible waste is larger than the effect of adding waste separation categories.

As the reasons for the higher rates of not charging for waste in the merged municipalities, we think the coordination during the consolidation conferences before the implementation of municipal mergers could be responsible. If a municipality with policies of charging for the disposal of waste merged with others that do not charge for it, we believe the most smooth way is to abort the charging policy as people just like free things and are not willing to pay if they do not need to. Adding just 0.56 kinds of waste separation, however, seems not that painful to the residents and perhaps reflects, at least, some efforts to promote recycling and environmental protection.

4.5 Conclusions

Through the case study of the Great Heisei Consolidation in Japan, we examined whether municipal mergers could reduce annual waste per capita and promote recycling. First, our baseline DID estimation shows an 11.8 kg or 3.5% higher annual total waste per capita in the merged municipalities compared to those never merged. We also find a possible announcement effect in this case through the event study and the value would be 13.0 kg or 3.8% considering the announcement effect.

Second, fewer merged municipalities charge for combustible waste and incombustible waste compared to the municipalities never merged which we think caused the increase in the annual waste per capita. Specifically, both the OLS and GLM model give over 20% effects from the municipal mergers. We believe that the reason for the fewer charging lies in the coordination as non-charging policies would be more acceptable to the residents, resulting in smoother municipal mergers. As for other waste management policies, we found an 0.56 or 5.7% increase in the waste separation categories of the merged municipalities compared to municipalities never merged. Though we think the effect is minor compared to the effect of non-charging policies, this still shows a kind of effort toward recycling and environmental protection.

Furthermore, we put our interest in plastic waste and found out that the amounts of recycled plastic waste and PET bottles after municipal mergers are lower than those never merged municipalities. We think the change to non-charging policies should be responsible for this phenomenon. The result also shows that municipal mergers did not contribute to the recycling of plastic waste either. Based on the findings, we conclude that municipal mergers perhaps do not lead to strict waste management policies but looser ones instead. Policymakers should be careful of this when planning municipal mergers if a more sustainable and environmentally friendly society is their target.

Chapter 5

Conclusions

This thesis studied some indirect effects of policies related to waste management through three case studies. The effects of China's solid waste import ban on local air pollution, the effect of Japan's Great Heisei Consolidation on the cost of municipal solid waste management, and the effect of Japan's Great Heisei Consolidation on the reduction and recycling of municipal solid waste.

First, controlling polluting activity by limiting the input rather than directly controlling the facilities is effective, at least in the short run, through the investigation of China's solid waste import ban. Our results suggest the import ban may contribute to the reduction of ozone concentration in the treatment area while the effect might be temporal if the domestic recycling rate increases afterward.

Second, municipal mergers might not always bring economies of scale to municipal solid waste management through the case study of Japan's Great Heisei Consolidation. Our results suggest that most merged municipalities did not show a sign of a reduction in processing and management cost except for some small municipalities merged with other big municipalities. The fiscal measures from the national government, however, could increase the construction cost because of the construction of new facilities.

Lastly, municipal mergers could lead to looser waste management policies, resulting in higher waste generation per capita also through the case study of the

Great Heisei Consolidation. Our results suggest that more municipalities ever merged changed to not charge for the disposal of waste than the municipalities never merged. The recycling of plastic waste is not promoted as well. The number of separation catagories, however, is higher among the merged municipalities which might be a kind of effort to embrace sustainability, though the effect could not be that large.

This thesis extends the literature on waste management by looking at some indirect effects of policies. The conclusion could be drawn that not only the direct effect but also the indirect effect of the policies should be considered and evaluated when making policies.

Bibliography

Al-Salem, S., Lettieri, P., and Baeyens, J. (2009). Recycling and recovery routes of plastic solid waste (psw): A review. *Waste Management*, 29(10):2625–2643.

Allers, M. A. and Geertsema, J. B. (2016). The effect of local government amalgamation on public spending, taxation, and service levels: Evidence from 15 years of municipal consolidation. *Journal of Regional Science*, 56(4):659–682.

Almond, D., Chen, Y., Greenstone, M., and Li, H. (2009). Winter heating or clean air? unintended impacts of china's huai river policy. *American Economic Review*, 99(2):184–90.

Atkinson, R. (2000). Atmospheric chemistry of VOCs and NOx. *Atmospheric Environment*, 34(12-14):2063–2101.

Bel, G., Fageda, X., and Mur, M. (2014). Does Cooperation Reduce Service Delivery Costs? Evidence from Residential Solid Waste Services. *Journal of Public Administration Research and Theory*, 24(1):85–107.

Blesse, S. and Baskaran, T. (2016). Do municipal mergers reduce costs? Evidence from a German federal state. *Regional Science and Urban Economics*, 59:54–74.

Blom-Hansen, J., Houlberg, K., and Serritzlew, S. (2014). Size, Democracy, and the Economic Costs of Running the Political System. *American Journal of Political Science*, 58(4):790–803.

Brooks, A. L., Wang, S., and Jambeck, J. R. (2018). The chinese import ban and its impact on global plastic waste trade. *Science Advances*, 4(6):eaat0131.

Cao, J., Garbaccio, R., and Ho, M. S. (2009). China's 11th five-year plan and the environment: Reducing so2 emissions. *Review of Environmental Economics and Policy*, 3(2):231–250.

Cao, Z., Chen, Q., Li, X., Zhang, Y., Ren, M., Sun, L., Wang, M., Liu, X., and Yu, G. (2019). The non-negligible environmental risk of recycling halogenated flame retardants associated with plastic regeneration in china. *Science of The Total Environment*, 646:1090–1096.

Chen, D. M.-C., Bodirsky, B. L., Krueger, T., Mishra, A., and Popp, A. (2020). The world's growing municipal solid waste: trends and impacts. *Environmental Research Letters*, 15(7):074021.

Chifari, R., Lo Piano, S., Matsumoto, S., and Tasaki, T. (2017). Does recyclable separation reduce the cost of municipal waste management in Japan? *Waste Management*, 60:32–41.

China Economic Daily (2018). Blocking foreign garbage completely. http://paper.ce.cn/jjrb/html/2018-05/28/content_363586.htm (in Chinese).

Fox, W. F. and Gurley, T. (2006). *Will Consolidation Improve Sub-National Governments ?* Policy Research Working Papers. The World Bank.

Greenstone, M., He, G., Li, S., and Zou, E. Y. (2021). China's war on pollution: Evidence from the first 5 years. *Review of Environmental Economics and Policy*, 15(2):281–299.

He, J., Liu, H., and Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in china. *American Economic Journal: Applied Economics*, 11(1):173–201.

He, Z., Li, G., Chen, J., Huang, Y., An, T., and Zhang, C. (2015). Pollution characteristics and health risk assessment of volatile organic compounds emitted from different plastic solid waste recycling workshops. *Environment International*, 77:85–94.

Health Effects Institute (2019). State of global air 2019. special report. *Boston, MA: Health Effects Institute.*

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, 64(4):605–654.

Heyes, A. and Zhu, M. (2019). Air pollution as a cause of sleeplessness: Social media evidence from a panel of chinese cities. *Journal of Environmental Economics and Management*, 98:102247.

Hirota, H. and Yunoue, H. (2017). Evaluation of the fiscal effect on municipal mergers: Quasi-experimental evidence from Japanese municipal data. *Regional Science and Urban Economics*, 66:132–149.

Honma, S. (2021). Cost efficiency of recycling and waste disposal in Japan. *Journal of Cleaner Production*, page 11.

Huang, D.-Y., Zhou, S.-G., Hong, W., Feng, W.-F., and Tao, L. (2013). Pollution characteristics of volatile organic compounds, polycyclic aromatic hydrocarbons and phthalate esters emitted from plastic wastes recycling granulation plants in xingtan town, south china. *Atmospheric Environment*, 71:327–334.

Huang, Q., Chen, G., Wang, Y., Chen, S., Xu, L., and Wang, R. (2020). Modelling the global impact of china's ban on plastic waste imports. *Resources, Conservation and Recycling*, 154:104607.

Jin, X. and Holloway, T. (2015). Spatial and temporal variability of ozone sensitivity over china observed from the ozone monitoring instrument. *Journal of Geophysical Research: Atmospheres*, 120(14):7229–7246.

Jin, Y., Andersson, H., and Zhang, S. (2016). Air pollution control policies in china: A retrospective and prospects. *International Journal of Environmental Research and Public Health*, 13(12):1219.

Kaza, S., Yao, L. C., Bhada-Tata, P., and Van Woerden, F. (2018). *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*. Washington, DC: World Bank.

Lazarevic, D., Aoustin, E., Buclet, N., and Brandt, N. (2010). Plastic waste management in the context of a european recycling society: Comparing results and uncertainties in a life cycle perspective. *Resources, Conservation and Recycling*, 55(2):246–259.

Meyer, B. D. (1995). Natural and Quasi-Experiments in Economics. *Journal of Business & Economic Statistics*, 13(2):151–161.

Ministry of Commerce of the People's Republic of China (2014). China recycling industry report 2014. http://images.mofcom.gov.cn/ltfzs/201406/20140618113317258.pdf.

Ministry of Commerce of the People's Republic of China (2016). China recycling industry report 2016. http://images.mofcom.gov.cn/ltfzs/201605/20160525144948127.doc (in Chinese).

Ministry of Commerce of the People's Republic of China (2017). China recycling industry report 2017. http://ltfzs.mofcom.gov.cn/article/date/201705/20170502568040.shtml (In Chinese).

Ministry of Commerce of the People's Republic of China (2019). China recycling industry report 2019. http://images.mofcom.gov.cn/ltfzs/201911/20191111161709299.pdf(in Chinese).

Ministry of Ecology and Environment of China (2017a). One of the results of the campaign to fight against illegal behaviors of the firms recycling imported solid wastes. https://www.mee.gov.cn/gkml/sthjbgw/qt/201707/t20170722_418355.htm (In Chinese).

Ministry of Ecology and Environment of China (2017b). Report on the state of the ecology and environment in china 2017. https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/201805/P020180531534645032372.pdf (in Chinese).

Ministry of Ecology and Environment of China (2018). Report on the state of the ecology and environment in china 2018. https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/201905/P020190619587632630618.pdf (in Chinese).

Ministry of Internal Affairs and Communications (2005). The establishment status of the legal merger council. https://www.soumu.go.jp/gapei/gapei3.html (In Japanese).

Mitoyo City (2006). The amount of combustible waste is reduced though the joint efforts. *Kouhou Mitoyo*, https://www.city.mitoyo.lg.jp/material/files/group/6/3gatugo-12.pdf (In Japanese).

Moisio, A. and Uusitalo, R. (2013). The impact of municipal mergers on local public expenditures in finland. *Public Finance and Management*, 13.

Papke, L. E. and Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11(6):619–632.

PRC Central Government (2017). The results of the campaign to fight against illegal behaviors of the firms recycling imported solid wastes. http://www.gov.cn/xinwen/2017-07/29/content_5214447.htm (in Chinese).

Qu, S., Guo, Y., Ma, Z., Chen, W.-Q., Liu, J., Liu, G., Wang, Y., and Xu, M. (2019). Implications of china's foreign waste ban on the global circular economy. *Resources, Conservation and Recycling*, 144:252–255.

Reingewertz, Y. (2012). Do municipal amalgamations work? Evidence from municipalities in Israel. *Journal of Urban Economics*, 72(2-3):240–251.

Ritchie, H. and Roser, M. (2018). Plastic pollution. *Our World in Data*. https://ourworldindata.org/plastic-pollution.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70 (1):41–55.

Saeed, M. O., Hassan, M. N., and Mujeebu, M. A. (2009). Assessment of municipal solid waste generation and recyclable materials potential in Kuala Lumpur, Malaysia. *Waste Management*, 29(7):2209–2213.

Sasao, T. (2000). An analysis on the impact user fees for waste service and separate collections have on waste reduction. *Journal of the Japan Society of Material Cycles and Waste Management, 2(1), 1-10.*

Sharholy, M., Ahmad, K., Mahmood, G., and Trivedi, R. (2008). Municipal solid waste management in indian cities – a review. *Waste Management*, 28(2):459–467.

Shimamoto, K. (2019). Determining factors of waste management in japan. *Theoretical and Empirical Researches in Urban Management*, 14(3):62–76.

Silvestre, H. C., Marques, R. C., Dollery, B., and Correia, A. M. (2020). Is cooperation cost reducing? An analysis of public–public partnerships and inter-municipal cooperation in Brazilian local government. *Local Government Studies*, 46(1):68–90.

Sun, M. (2019). The effect of border controls on waste imports: Evidence from china's green fence campaign. *China Economic Review*, 54:457–472.

Suzuki, K. and Sakuwa, K. (2016). Impact of municipal mergers on local population growth: An assessment of the merger of Japanese municipalities. *Asia Pacific Journal of Public Administration*, 38(4):223–238.

Tsai, C.-J., Chen, M.-L., Chang, K.-F., Chang, F.-K., and Mao, I.-F. (2009). The pollution characteristics of odor, volatile organochlorinated compounds and polycyclic aromatic hydrocarbons emitted from plastic waste recycling plants. *Chemosphere*, 74(8):1104–1110.

Tsuzuki, K., Yokoo, H., and Suzuki, A. (2018). Effects of unit-based pricing on municipal solid waste :considering the effects of the municipal mergers. *Journal of the Japan Society of Material Cycles and Waste Management*.

Unfried, K. and Wang, F. (2022). Importing air pollution? evidence from china's plastic waste imports. *IZA Discussion Paper Series, No. 15218*.

Usui, T. and Takeuchi, K. (2013). Evaluating unit-based pricing of residential solid waste: A panel data analysis. *Environmental and Resource Economics*, 58(2):245–271.

Viard, V. B. and Fu, S. (2015). The effect of beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics*, 125:98–115.

World Bank (2022). The global health cost of pm2. 5 air pollution: A case for action beyond 2021. *The World Bank Group*.

World Health Organization (2006). Who air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: Global update 2005: Summary of risk assessment.

Yamashita, K., Yamamoto, N., Mizukoshi, A., Noguchi, M., Ni, Y., and Yanagisawa, Y. (2009). Compositions of volatile organic compounds emitted from melted virgin and waste plastic pellets. *Journal of the Air and Waste Management Association*, 59(3):273–278.

Yokomichi, K. (2017). The Development of Municipal Mergers in Japan. *Up-to-date Documents on Local Autonomy in Japan No. 1. Council of Local Authorities for International Relations*, Institute for Comparative Studies in Local Governance, National Graduate Institute for Policy Studies, http://www.clair.or.jp/j/forum/honyaku/hikaku/pdf/up-to-date_en1.pdf.

Zhang, D. Q., Tan, S. K., and Gersberg, R. M. (2010). Municipal solid waste management in china: Status, problems and challenges. *Journal of Environmental Management*, 91(8):1623–1633.

Zhang, X., Chen, X., and Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences*, 115(37):9193–9197.