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Do municipal mergers reduce public expenditure? Evidence from the MTE approach

Tsuyoshi Goto*

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Abstract

This study examines whether municipal mergers reduce public expenditure by examining the marginal treatment effect (MTE) of municipal mergers. Extant papers in the literature have paid little attention to bias from self-selection among municipal mergers or to heterogeneity in the treatment effects of the mergers. Corresponding to these issues, we use the instrumental variables used in Miyazaki (2018) [Applied Economics, 50(10), pp. 1108-1121] and estimate the MTEs of the mergers. From the estimated MTEs, we construct several estimands, and we show that the municipal mergers resulted in an increase in public expenditure on average. Moreover, we confirm that the local average treatment effect (LATE) was quite large from FY2006 to FY2015, although it decreased suddenly in FY2016, when some incentives that promoted the mergers ended. This implies that the incentives offered by the national government negated the cost reductions resulting from the municipal mergers.

Keywords: Marginal treatment effect & Municipal merger & Cost reduction

JEL Classification: H72 & H73 & H77

1 Introduction

Over the past 50 years, many countries have experienced mergers among their local governments. One of the aims of such mergers is to increase the efficiency of local governments and to enjoy the benefits associated with economies of scale.

However, whether the consolidation of governments results in administrative efficiency is controversial. In theory, the integration of governments may entail economies of scale and the internalization of externalities among municipalities, while it may make it costly for municipalities to provide public services that reflect local preferences.(Alesina and Spolaore, 1997; Bolton and Roland, 1997; Dur and Staal, 2008; Ellingsen, 1998) Therefore, municipalities face a trade-off when deciding whether to merge. This implies that if mergers are optional, municipalities are likely to select into mergers on the basis of gains; i.e., municipalities decide to merge if the merger is beneficial for them.

In empirics, the results of analyses of public expenditure and the consolidation of governments are diverse, as Table 1 shows. As Blesse and Baskaran (2016) points out, one of the reasons for these diverse

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(1) Author(s)	(2) Data	(3) Method of analysis	(4) Voluntary or Compulsory	(5) (Total) Expenditure
Reingewertz(2012)	1999–2007 data of Israel	DID	Voluntary	Reduced
Blom-Hansen et al. (2014)	2005-2011 data of Denmark	DID	Voluntary	Reduced ※ 1
Allers and Geertsema(2016)	2002-2013 data of Netherlands	DID	Voluntary	Unchanged ※ 2
Blesse and Baskaran(2016)	1995–2010 data of Brandenburg state in Germany	DID	Voluntary	Unchanged
			Compulsory	Unchanged ※ 3
Miyazaki(2018)	2000, 2005 and 2010 data of Japan	FE-IV	Voluntary	Increased ※ 4
Drew et al. (2021)	2014-2020 data of New South Wales state in Australia	DID	Compulsory	Increased

Table1 Empirical studies on public expenditure and government consolidation

Source: Author's own synopsis. Notes: Empirical studies on public expenditure and government consolidation are summarized. *1 The authors call their outcome variable "administrative costs", while it seems to refer to total costs. *2 The authors also report that mergers reduce administrative expenditure. *3 The authors also report that compulsory mergers reduce administrative expenditure. *4 The author uses current expenditure instead of total expenditure.

results may be the self-selection into mergers by local governments. If each local government selects into consolidation based on its gains or losses from doing so, only local governments that obtain gains choose to consolidate. In light of this, some papers, such as Blesse and Baskaran (2016) and Tricaud (2021), point out that the unobserved heterogeneity in the net gains from consolidation may generate different estimation results when mergers are optional, while such unobservables may be less problematic for compulsory mergers.

Another reason for the diversity in the results may be the methods used for identification and the estimands for the analysis. As table 1 shows, many papers in this literature try to estimate the average treatment effect on the treated (ATT), which in many papers is derived through a difference-in-differences (DID) analysis. Allowing for heterogeneity in the treatment effects, the estimated ATTs should be strongly affected by the self-selection issue since the treated municipalities are likely to select into consolidation. The usage of other estimands, for example, the local average treatment effect (LATE), makes it difficult to compare the empirical results within the literature. Since the different estimands indicate the treatment effect on different treatment subjects, if the treatment effects are heterogeneous across treatment subjects, the estimated results should be different depending on the estimation method.

In this paper, we examine local government consolidation as an effective policy for reducing public expenditure using a novel estimation—the estimation of the marginal treatment effect (MTE). By focusing on the MTE, we can overcome the self-selection issue and can estimate several different estimands.

This paper uses data on Japanese municipalities, which underwent a series of mergers in the 2000s. Municipal mergers in Japan were formally optional but were induced by the central government through carrot-and-stick policies. Since the estimation of the MTE requires an IV that affects selection into consolidation but does not have an impact on the outcome, we utilize one of the policies, the gradual reduction in unconditional grants for those municipalities with small populations in FY2002, as an IV following Miyazaki (2018). We examine whether consolidation reduced public expenditure using postmerger data, and the IV satisfies the exclusion restriction since we control for the current population as in Miyazaki (2018).

This paper has three main findings. First, obtained from the Japanese municipal data, the estimated average treatment effect (ATE), average treatment effect on the untreated (ATUT), and ATT show that the consolidation increased the expenditure of municipalities by between 0% and 18%, while the corresponding figure in terms of the LATE is very high at 20%. This suggests that the heterogeneity by estimand is substantial. Since the LATE focuses on compliers, i.e., those treated subjects that would not have chosen to be treated without the effect from the policy used as the IV, the results suggest that the treatment effects are heterogeneous across subjects and that the municipalities selected into consolidation.

Second, we examine the policy effect by year and find that while the magnitude of the estimated LATEs during FY2006-2015 were approximately 0.2, the corresponding figures after FY2016 were half that size. Since the central government offered benefits to merged municipalities for a decade after the mergers and municipalities had to merge by FY2006 to receive the benefits, this result also suggests that the policies of the central government amplified the increase in public expenditure caused by the municipal mergers.

Third, we find that the increase in public expenditure caused by the municipal mergers is visible even more than ten years after the mergers. Since this result can be confirmed for the ATE, ATT, ATUT, and LATE, this suggests that the municipal mergers in Japan increased public expenditure regardless of the treatment subjects.

These findings imply that the treatment effects from the consolidation are heterogeneous across treatment subjects and that the estimated results are diverse depending on the estimands. Considering that existing studies in the literature use several different estimation methods, a significant part of the differences in their results may be explained by the fact that the estimands that they focused on are different.

Regarding the policy implications, this paper shows that the consolidation of local governments increases public expenditure and that the incentives used to promote municipal mergers amplify the increase in public expenditure. Moreover, in the context of Japanese municipal mergers, this paper provides a novel policy implication: the increase in public expenditure caused by municipal mergers was approximately 20% in terms of the LATE, which corresponds to the results in Miyazaki (2018), and was 2%∼12% in terms of the ATE.

While this paper mainly contributes to the literature on the consolidation of local governments, the method used in this paper is heavily dependent on the literature on policy evaluation for self-selection into policies.

To derive the MTE, we use the framework for the generalized Roy model developed in the series of works by Heckman and Vytlacil (Eisenhauer, Heckman, and Vytlacil, 2015; Heckman and Vytlacil, 1999, 2005, 2007). This model allows for heterogeneity in potential outcomes over unobserved resistance to consolidation, and these heterogeneous potential outcomes are characterized as marginal treatment responses (MTRs) and as the MTE over the heterogeneity. In this framework, we can derive several estimands from MTRs and MTE following Mogstad, Santos, and Torgovitsky (2018) and can examine whether consolidation reduces public expenditure.

Estimation under this framework requires an IV that affects only the selection decision but does not affect the outcomes. The novel features of this framework are that the estimation allows for self-selection into treatment and that we can infer several estimands because they can be expressed as weighted averages of the MTEs or MTRs (Mogstad, Santos, and Torgovitsky, 2018). Therefore, this framework is suitable for situations where local governments can opt to merge. We contribute to the literature on government consolidation and public expenditure by suggesting heterogeneous treatment effects and deriving several estimands using the MTE framework.

The remainder of the paper consists of five sections. Section 2 provides background information on Japanese municipal mergers in the 2000s. The analytical method and framework are discussed in Section 3. Section 4 explains the data and presents the findings of the empirical analysis. Section 5 discusses the results of the empirical analysis. Finally, Section 6 concludes.

2 Background

2.1 Local governments in Japan and their revenue sources

Japan is a decentralized country with respect to its public expenditure. Municipalities provide basic public services such as public utilities, primary education, and sanitation. The municipal revenue consists mainly of taxes, grants, and bonds.

Local tax account for approximately 30% of the revenue in the general account, and most tax revenues come from resident taxes and property taxes. Grants from the national government also account for 30% of the revenue in the general account. The main national grants are the local allocation tax (LAT)[*1] and national treasury disbursements (NTDs). The LAT is an unconditional grant. The NTD is an earmarked subsidy. Debt financing is conducted by issuing local bonds, which accounts for 10% of the revenue in the general account.

2.2 Municipal mergers in Japan

In Japan, municipal mergers are optional for municipalities. Although the national government promoted mergers for many years to encourage greater efficiency among municipalities, the number of municipalities decreased by only 5% from FY1965 (3392 municipalities) to FY1999 (3229 municipalities). In FY1999, the national government started to employ "carrot-and-stick" policies to provide strong incentives for municipalities to merge and enacted a law that prescribed the distribution of the incentives for mergers from FY1999 to FY2005.

Regarding the carrots, the national government offered several measures to promote mergers. The main incentive was the LAT incentive. The LAT is an unconditional grant that can be utilized for general purposes. Since the amount of the LAT is calculated by the national government depending on the socioeconomic conditions of the municipalities, and the amount of the LAT per capita tends to fall as

[*1] Although the local allocation tax has a confusing name, the name comes from the fact that the national government collects the tax and allocates it to local governments.

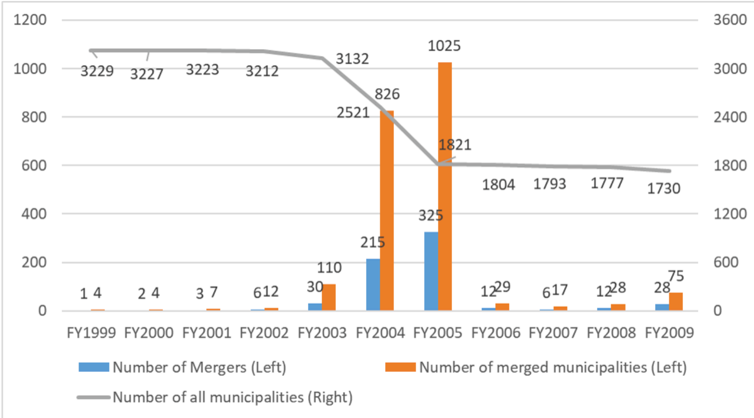

Figure1 Changes in the number of municipalities.

Source: Data from Ministry of Internal affairs and Communications (2016)

the population increases, small municipalities and rural municipalities are sometimes heavily dependent on the LAT as a revenue source. Therefore, expecting a reduction in the LAT, municipalities were reluctant to merge before FY1999. However, the national government guaranteed that the reduction in the LAT would be suspended for 15 years and that merged municipalities would receive the same LAT amount for at least 10 years after the merger. From 10 years to 15 years after the merger, the national government implemented transitional measures, and the amount of the LAT was reduced but was guaranteed to be larger than under the ordinary criteria. (See Figure 2)

Another incentive was the issuance of special-purpose municipal bonds (the special-bond issuance). In FY1999, the national government allowed merged municipalities to issue bonds that could be used to finance up to 95% of the expenditures related to the consolidation, and 70% of the repayment costs were paid by the national government. Several expenditures, such as expenditures on the construction of infrastructure, parks, and new facilities for the merged municipalities and expenditures on events that facilitated the integration of the merged municipalities, were considered to be expenditures related to consolidation. At first, the special-bond issuance was allowed for 10 years after the mergers. However, to accelerate reconstruction after the Great East Japan Earthquake in 2011, the national government postponed the expiration of the policy and allowed merged municipalities in the area affected by the earthquake to issue such bonds for 20 years after their mergers and other merged municipalities to issue them for 15 years after their mergers.

These incentives were available to municipalities that merged between FY1999 to FY2005. As a result, many municipalities merged during that period, as Figure 1 shows.

The national government also used a "stick" policy to promote mergers. That is, the reduction in the LAT ("*Dankai-hosei*" in Japanese) beginning in FY2002 and the amount of the reduction was determined according to population, as Table 2 shows. (Ministry of Internal affairs and Communications, 2002) Since municipalities with small populations could expect a large reduction in the LAT, they had a stronger incentive to merge.

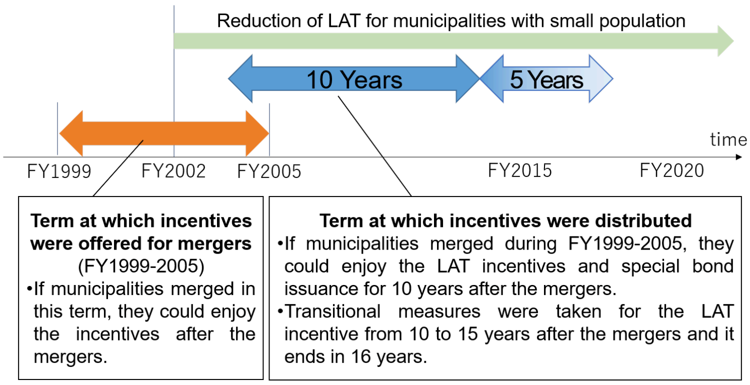

Figure2 Timeline of "carrot-and-stick" policies

Source: Ministry of Internal affairs and Communications (2016)

Population	Reduction in LAT (yen)	Reduction in LAT per capita (yen)	IV
1000	8,000,000	8,000	I
4000	18,000,000	4,500	II
8000	17,000,000	2,125	III
12,000	17,000,000	1,416.7	III
20,000	17,000,000	850	III
30,000	10,000,000	333	IV

Table2 Reduction in LAT

Source: Ministry of Internal affairs and Communications (2002)

For both the carrot and the stick policies, the national government utilized the municipalities' incentive to increase their LAT payments to induce them to merge. In particular, such an incentive should have been effective for municipalities with small populations since their LAT payments were expected to fall if they did not merge but to be constant if they did merge, although the LAT for municipalities with large populations would not have been reduced even if they did not merge (Weese, 2015; Miyazaki, 2018).

2.3 Empirical issue of voluntary mergers

The aim of this paper is to examine whether the consolidation of local governments reduces public expenditure, focusing on municipal mergers in Japan. However, as explained in the previous section, the municipal mergers in Japan were strongly influenced by the national government despite being formally optional. This implies that local governments might select into consolidation based on their gains or losses from the consolidation and that consolidation would be an endogenous treatment.

To address this issue, Miyazaki (2018) utilizes the reduction in the LAT for small municipalities as IVs. He creates categorical dummy variables that equal one for nonmerged municipalities depending on their populations in FY2002 and uses those variables as IVs for the nonmerged municipalities. For the merged municipalities, he employs the share of merging municipalities in each category as IVs: for example, if a category 1 municipality and a category 2 municipality merged, the variables for categories 1 and 2 each equal 0.5 for the merged municipality. By controlling for the current population, these categorical variables should not be correlated with the total expenditure per capita after the mergers. Therefore, we adopt this approach.

However, a simple analysis with the IVs based on a two-stage least squares (2SLS) regression captures a limited treatment effect called the LATE. Since the LATE represents the treatment effect only on subjects who change their behavior depending on the value of the IV (i.e., compliers), we cannot evaluate whether municipal mergers in Japan as a whole increase public expenditure. To overcome this shortfall, we conduct a MTE analysis, which uses IVs, and derive several estimands that address the self-selection issue, as follows.

3 Estimation Framework

In this section, we briefly explain the estimation framework. Our framework is based on the generalized Roy model, which is characterized by heterogeneity in municipalities' gains from merging.

3.1 Setup

Consider a representative resident who must decide whether his municipality will merge ($j = 1$) or will remain independent ($j = 0$). A binary variable $D = \{0, 1\}$ equals one if the representative chooses consolidation. We use G_i to denote the total expenditure of municipality $i = 1, \cdots, N$ The relationship between the observed outcome (G_i) and the potential outcomes ($G_{i,j}$) for $j = \{0, 1\}$ is

$$G_i = DG_{i,1} + (1 - D)G_{i,0}. \tag{1}$$

Following Brinch, Mogstad, and Wiswall (2017), we assume that $G_{i,j}$ can be decomposed into two parts, one that contains an unspecified function of the observables X and another that consists of the unobservables $U_{i,j}$, as follows:

$$G_{i,j} = \mu_{i,j}(X) + U_{i,j}. \tag{2}$$

Here, $\mu_{i,j}(X)$ is the unspecified function of observables X and $U_{i,j}$ are unobservables with $E[U_{i,j}|X = x] = 0$. We call eq. (2) the "outcome equation".

The resident obtains indirect utility S_j from choice j and chooses consolidation if $S_1 - S_0 > 0$. We assume that the net benefit of consolidation $S_1 - S_0$ is also a function of the observables and unobservables as follows:

$$S_1 - S_0 = \nu(W) \perp\!\!\!\perp V, . \tag{3}$$

We assume that $S_1 - S_0$ is weakly separable between the observables $W = X, Z$ and the unobservables V, following Heckman and Vytlacil (1999), Heckman and Vytlacil (2005) and Mogstad, Santos, and Torgovitsky (2018). This equation is called the "selection equation". X represents the observable covariates that are common to the outcome equation, and Z represents the IVs. V is the unobserved disutility from choosing $j = 1$. We assume that the representative resident chooses to merge $D = 1$ when the net benefit of consolidation is positive, $S_1 - S_0 > 0$.

Moreover, we make the following assumptions:

Assumption 1. $(U_{t,0}, U_{t,1}, V) \perp\!\!\!\perp Z|X$, where $\perp\!\!\!\perp$ denotes conditional independence.

Assumption 2. V is continuously distributed, conditional on X.

Under Assumption 1, instrument Z is independent of the potential outcomes and unobservables in the selection equation when conditioned on X. Assumption 2 implies that the distribution of V is continuous. Note that this does not impose any particular distributional assumption on V. Using $F_V(.)$ to denote the cumulative distribution function of V, eq. (3) implies that the propensity score for choosing consolidation is

$$P(X, Z) \equiv Pr[D = 1|X, Z] = F_V(\nu(X, Z)). \tag{4}$$

We define $U \equiv F_V(V) \in [0, 1]$ to show the quantiles of the resident's unobserved distaste for consolidation, where V is the unobserved disutility from consolidation. We use p to denote a concrete value of U in what follows.

3.2 Estimands

Based on this setup, we define the MTE following Heckman and Vytlacil (1999) and Heckman and Vytlacil (2005):

$$G^{MTE}(x, p) = E[G_{i,1} - G_{i,0}|X = x, U = p]. \tag{5}$$

The MTE can be interpreted as the ATE for subjects with observables X and unobservable disutility for consolidation U. Using the MTE, we can consider the heterogeneity in the treatment effect for observables X and unobservables U. If the relationship between the MTE and X is examined, we can see whether an observable of type x induces more or fewer behavioral responses to treatment than other observables[*2].

Moreover, we define the MTR following Mogstad, Santos, and Torgovitsky (2018):

$$\begin{aligned} m_0(x, p) = E[G_{i,0}|X = x, U = p] = \mu_0(x) + E[U_{i,0}|U = p, X = x] \\ m_1(x, p) = E[G_{i,1}|X = x, U = p] = \mu_1(x) + E[U_{i,1}|U = p, X = x]. \end{aligned} \tag{6}$$

Since it is known that the identification of $E[U_{i,0}|U = p, X = x]$ requires some rigid restrictions on the data, we assume the separability assumption from Brinch, Mogstad, and Wiswall (2017) as follows:

Assumption 3: $m_j(x, p)$ is separable between X and U. That is, $E[U_{i,j}|X = x, U = p] = E[U_{i,j}|U = p]$.

Applying this assumption, $m_j(x, p)$ can be written as $m_j(x, p) = \mu_j(x) + k_j(p)$, where $k_j(p)$ is defined as $k_j(p) \equiv E[U_{i,j}|U = p]$. Using the MTRs, Mogstad, Santos, and Torgovitsky (2018) show that several estimands can be written in the following form:

$$\beta^* \equiv E[\int_0^1 m_0(x, p)\omega_0(w, p)dp] + E[\int_0^1 m_1(x, p)\omega_1(w, p)dp], \tag{7}$$

where $\omega_j(w, u)$ is the weighting function for $j \in \{0, 1\}$, $W = w(= \{x, z\})$ and $U = u$. By changing the weighting functions as shown in Table 3, we can derive various estimands.

[*2] For example, changes in municipal expenditure in response to changes in the average income level can be checked.

Estimand	Expression	$\omega_0(w,p)$	$\omega_1(w,p)$
Average Treatment Effect (ATE)	$E[G_{i,1}-G_{i,0}]$	1	1
ATE on the Treated (ATT)	$E[G_{i,1}-G_{i,0}\vert D=1]$	$-\omega_1(w,p)$	$\frac{1[p\leq p(w)]}{P(D=1)}$
ATE on the Untreated (ATUT)	$E[G_{i,1}-G_{i,0}\vert D=0]$	$-\omega_1(w,p)$	$\frac{1[p\geq p(w)]}{P(D=0)}$
Local ATE (LATE) $U\in(\underline{p},\bar{p})$	$E[G_{i,1}-G_{i,0}\vert U\in(\underline{p},\bar{p}))$	$-\omega_1(w,p)$	$\frac{1[p\in(\underline{p},\bar{p})]}{\bar{p}-\underline{p}}$

Table3 Estimands and weighting functions

Source: Mogstad, Santos, and Torgovitsky (2018).
Note: We can derive the target estimand by substituting the listed weighting functions $\omega_0(w,u)$ and $\omega_1(w,u)$ into eq. (7). Since the LATE is the average treatment effect for those who are shifted into treatment when the instrument is shifted from z to z', $\underline{p}$ and $\bar{p}$ are defined as $\underline{p}=p(x,z)$ and $\bar{p}=p(x,z')$, respectively, for the LATE for $U\in(\underline{p},\bar{p})$.

For the estimands listed in Table 3, we can simplify (7) as

$$\beta^* = E[\int_0^1 (m_0(x,p)-m_1(x,p))\omega_1(w,p)dp]. \tag{7'}$$

3.3 Estimation of MTE

In this subsection, we briefly explain the procedure for estimating the MTR and MTE. Please see Brinch, Mogstad, and Wiswall (2017) for details. Consider the conditional means of $G_{i,j}$ for a given $X=x$, $P(W)=p$, and $D=j$ for $j=\{0,1\}$. Since we have sample data for $G_{i,j}, X, P(W)$, and D, we can construct the sample analogs of the conditional means. Using eqs. (2) and (6) and Assumption 3, this can be expressed as

$$\begin{aligned} E(G_{i,0}|X=x,P(W)=p,D=0) &= \mu_0(x)+E[U_{i,0}|U\geq p] \\ &= \mu_0(x)+K_0(p) \quad (8) \\ E(G_{i,1}|X=x,P(W)=p,D=1) &= \mu_1(x)+E[U_{i,1}|U<p] \\ &= \mu_1(x)+K_1(p), \quad (9) \end{aligned}$$

where $K_0(p)$ and $K_1(p)$ are $E[U_{i,0}|U\geq p](=\frac{\int_0^p E[U_{i,0}|U=p]}{p})$ and $E[U_{i,1}|U<p](=\frac{\int_p^1 E[U_{i,1}|U=p]}{1-p})$, respectively. By differentiation with respect to p, we can derive $k_0(p)=-\frac{\partial K_0}{\partial p}(1-p)+K_0(p)$ and $k_1(p)=\frac{\partial K_1}{\partial p}p+K_1(p)$.

Although the shape of $K_j(p)(j=0,1)$ is unknown, we consider a cubic approximation, and the approximated $K_j(p)$ can be expressed as

$$\begin{aligned} \hat{K}_1 &= \sum_{l=1}^{3}\pi_{1l}\frac{p^l-1}{l+1} \\ \hat{K}_0 &= \sum_{l=1}^{3}\pi_{0l}\frac{p(1-p^l)}{(1-p)(l+1)}, \end{aligned} \tag{10}$$

where $\pi_{jl}(j=0,1)$ is the coefficient for the lth power of p. Using the sample data, we can derive several $E(G_{i,j}|X=x,P(W)=p,D=j)=\mu_j(x)+K_j(p)$ conditional on X. For example, $E(G_{i,j}|X=x,P(W)=p,D=j)=\mu_j(x)+\hat{K}_j(p)$ and $E(G_{i,j}|X=x,P(W)=p',D=j)=\mu_j(x)+\hat{K}_j(p')$ can be derived by changing the value of Z. Since three unknown parameters π_{jl} should be derived for each $j = 0, 1$ from (10), if we have several points for p for each j, we can estimate $\hat{K}_j$. This implies that the variation in Z creates many values for $P(X, Z) = p$ in the range of $U = [0, 1]$. In the estimation, we limit the range of U to cover the common support for $P(X, Z|D = 0)$ and $P(X, Z|D = 1)$.

Using the specification in (10), we can also derive an approximated $k_j(p)$: $\hat{k}_j(p) = \sum_{l=1}^{3} \pi_{jl}(p^l - \frac{1}{l+1})$. In addition, since the usual regression model assumes the linearity of the regression equation, we assume that $\mu_j(x) = x\beta_j$. Therefore, the estimated MTR and MTE are, respectively,

$$\begin{aligned} m_0(x, p) &= x\beta_0 + \sum_{l=1}^{3} \pi_{0l}(p^l - \frac{1}{l+1}) \\ m_1(x, p) &= x\beta_1 + \sum_{l=1}^{3} \pi_{1l}(p^l - \frac{1}{l+1}) \end{aligned} \tag{11}$$

and

$$m(x, p) = x(\beta_1 - \beta_0) + \{\sum_{l=1}^{3} \pi_{1l}(p^l - \frac{1}{l+1}) - \sum_{l=1}^{3} \pi_{0l}(p^l - \frac{1}{l+1})\}. \tag{12}$$

4 Data and analysis

4.1 Data

In this study, we employ data on Japanese municipalities from FY2006 to FY2018 since the series of mergers ended in FY2005, and the most recent available data is for FY2018. The data sources, units, and summary statistics for the variables are shown in Tables 4 and 5 in Appendix 1.

We set the outcome variable, $G_{i,j}$, to be the log-valued total expenditure per capita. As covariates, X_{it}, we use population, average income, population of elderly individuals, population of young people, foreign population, and land area as the covariates in the baseline analysis. We use logged values for all of these covariates following Miyazaki (2018). Moreover, we also add dummy variables that show the category of the municipalities, such as city or village, in the later analyses.[*3]

For the IVs, we create four categorical dummy variables that equal one depending on the population in FY2002: these are variables that indicate municipalities with populations less than 1000 (hereafter, category 1), 1000-4000 (category 2), 4000-8000 (category 3), and 8000-30000 (category 4) (See Table 2). Following Miyazaki (2018), while we directly use these variables for nonmerged municipalities, we employ the share of merging municipalities in each category as IVs: for example, if a municipality with 500 people and a municipality with 9000 people merged, the variables for category 1 and 4 each equal 0.5 for the merged municipality. Since, by controlling for the current population, these categorical variables should not be correlated with the total expenditure per capita after the merger, these variables should satisfy the exclusion restriction, i.e., Assumption 1. Moreover, considering that the amount of the LAT payment was expected to be reduced for smaller municipalities, as Table 2 suggests, and the smaller municipalities

[*3] These consist of four dummy variables: a city dummy, special city dummy, core city dummy, and designated city dummy. In Japan, administrative responsibilities are different for these four categories of cities and for villages/towns.

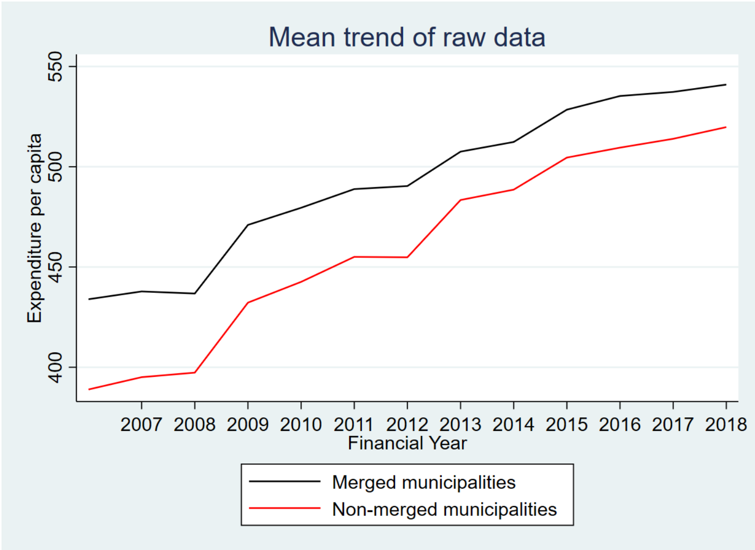

Figure3 Trend in total expenditure per capita

Note: The average trend in total expenditure per capita for merged and nonmerged municipalities are shown as a black line and a red line, respectively. Merged municipalities here are municipalities that merged during FY1999-2005, and nonmerged municipalities are all other municipalities. We did not control for any variables in creating this figure.

should have been more willing to merge, our instrumental variables satisfy the monotonicity assumption. We also check the weakness of the IVs by using a probit regression in the first-stage analysis, and find that the instruments are not weak.*4

Before the analysis, we check the trends in the outcomes using the data. Figure 3 shows the average trend in the total expenditure per capita for merged and nonmerged municipalities. At a glance, the trends for merged and nonmerged municipalities seem to be parallel, and the growth in the expenditures of merged municipalities is slightly less than that in nonmerged municipalities. However, the causal effect of mergers cannot be determined from this figure. Therefore, we examine the causal effect as follows.

4.2 Analysis results

4.2.1 Estimation of the MTEs and MTRs

In the analysis, we conduct the MTE analysis year by year.*5 In doing so, we derive annual treatment effects and observe their transition.*6 In this section, we show the results of the analysis for FY2010 as an example.*7

Figure 5 shows the estimated MTE for FY2010. The MTE is defined for each value of unobserved

*4 We report the hypothesis test results for the IVs in the first-stage regression in Table 6.

*5 This is because the MTE analysis was developed for cross-sectional data, and panel data analysis methods are underdeveloped.

*6 Although we can pool the data for analysis, since such an analysis would fail to show the transitions in the treatment effects, we do not do so.

*7 We show the results for the other years in the appendix.

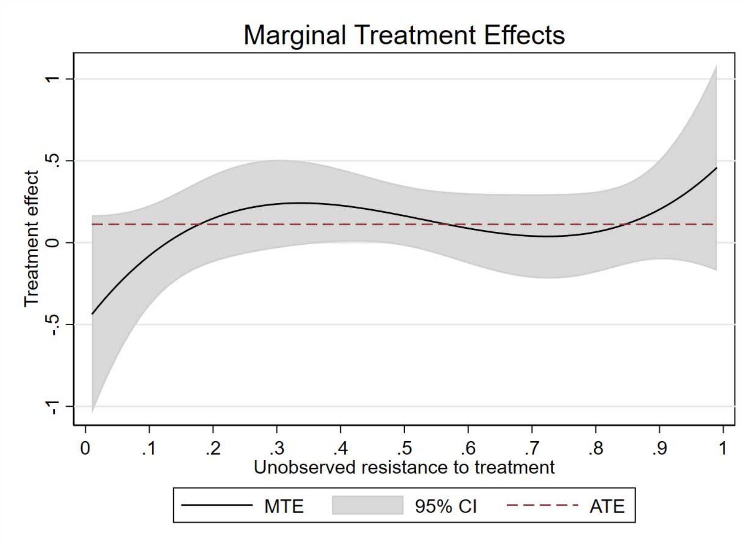

Figure4 MTE over unobserved resistance to treatment in FY2010

Note: The MTE and ATE are shown as a black solid line and a red dotted line, respectively. The dark shaded area indicates the 95% confidence intervals for the MTE. The estimated MTE here is $\hat{m}(x,p) = x(\hat{\beta}_1 - \hat{\beta}_0) + \{\sum_{l=1}^{3} \hat{\pi}_{1l}(p^l - \frac{1}{l+1}) - \sum_{l=1}^{3} \hat{\pi}_{0l}(p^l - \frac{1}{l+1})\}$ and the horizontal line corresponds to p.

resistance, and the graph shows that municipalities with a high degree of resistance to merging tend to have a large MTE, although the values of the MTE are not significantly different from 0 across the entire range. This suggests that there is heterogeneity in the treatment effects over unobserved resistance to merging.

We can confirm the heterogeneity in the treatment effects in the other years by observing Figure 13 in the appendix. The shapes of the MTE graphs are different for each year. For example, the figures show that from FY2006 to FY2011, the MTEs for municipalities that are highly resistant tend to be small, while from FY2016 to FY2018, those for municipalities with low levels of resistance tend to be small. This suggests that the effect of mergers can vary as time passes. This is natural considering that the incentives for the mergers offered by the national government were time-limited measures and that the LAT incentive, one of the main incentives, began to decrease starting ten years after the merges, as Figure 2 shows.

Moreover, Table 6 in the appendix shows the estimated coefficients for eqs. (6). The results show that the estimated coefficients for population and its square, land area, and the constant are similar in value between the nonmerged and merged municipalities . However, the coefficients for the other covariates sometimes take on different values. Moreover, the estimated π_{Dl}s, $(D \in \{0,1\}, l \in \{1,2,3\})$, are not significantly different from 0. Considering that the values of the MTEs are not significantly different from 0, this result is natural. Although the estimated π_{Dl}s are insignificant, the estimand from (7') may be significant due to the weighting. Therefore, we show the results from the estimation of the estimands in the next subsection.

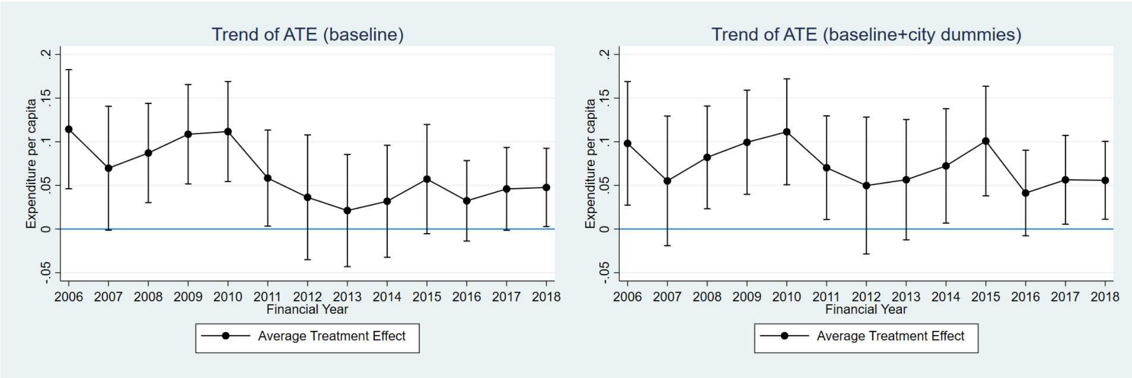

Figure5 The estimated ATEs for each year

Note: The estimated ATEs for each year are shown. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. the estimated ATEs are calculated with eq. (7') as follows:

$$ATE = E[\int_0^1 (m_0(x,p) - m_1(x,p))dp].$$

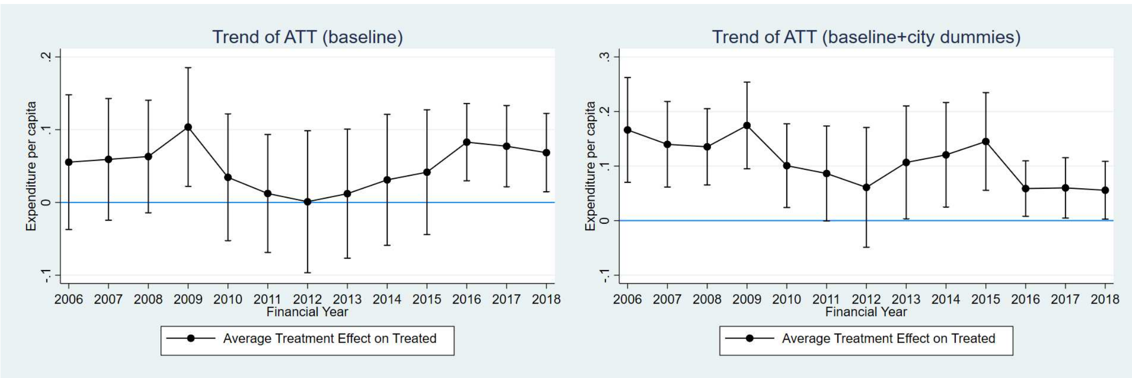

Figure6 The estimated ATTs for each year

Note: The estimated ATTs for each year are shown. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. the estimated ATTs are calculated with eq. (7') as follows:

$$ATT = E[\int_0^1 (m_0(x,p) - m_1(x,p))\frac{1[p \leq p(w)]}{P(D=1)}dp].$$

4.2.2 Estimation of several estimands

Figures 5, 6, 7, and 8 show the estimated ATE, ATT, ATUT, and LATE, respectively, for each year. The results are also summarized in Tables 7 and 8 in the appendix. The left panel of each figure shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. Since the shapes of both graphs

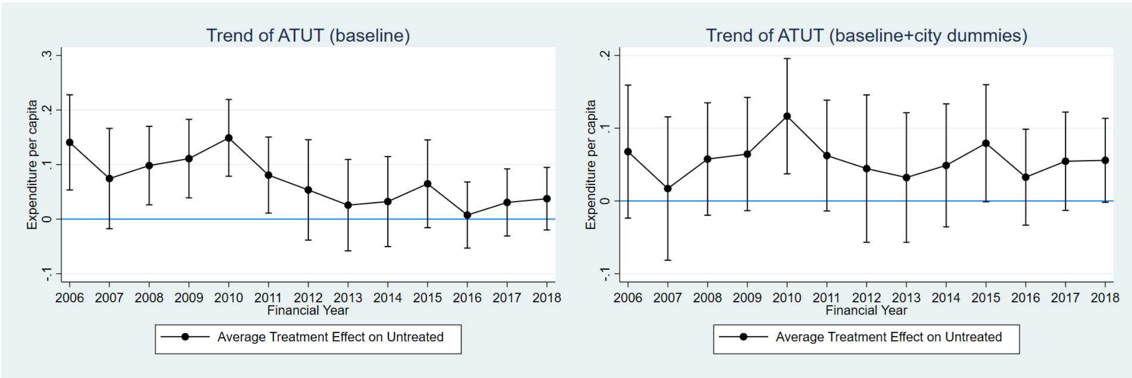

Figure7 The estimated ATUTs for each year

Note: The estimated ATUTs for each year are shown. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. the estimated ATUTs are calculated with eq. (7') as follows:

$$ATUT = E[\int_0^1 (m_0(x,p) - m_1(x,p)) \frac{1[p \geq p(w)]}{P(D=0)} dp].$$

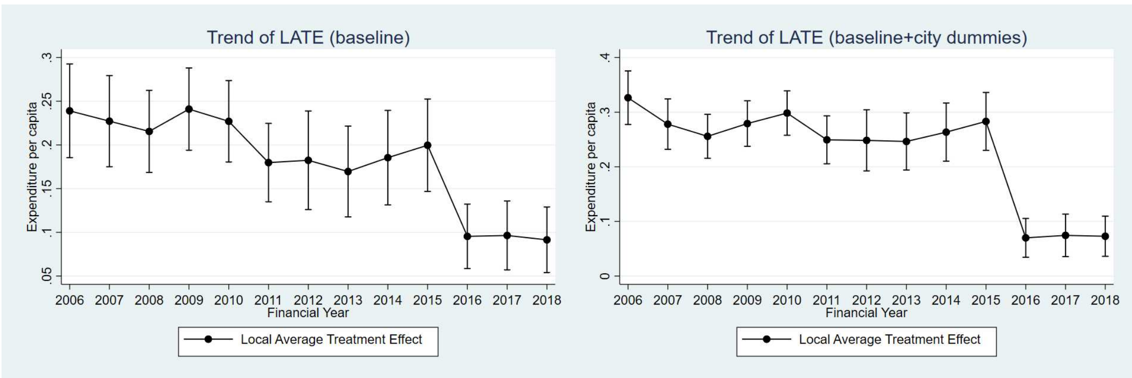

Figure8 The estimated LATEs for each year

Note: The estimated LATEs for each year are shown. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. The estimated LATEs are calculated with eq. (7') as follows:

$$LATE = E[\int_0^1 (m_0(x,p) - m_1(x,p)) \frac{1[p \in (\underline{p}, \bar{p})]}{\bar{p} - \underline{p}} dp).$$

seem similar, the results of the baseline analysis are robust in the sense that the trends in the estimands do not vary with the addition of covariates.

Figure 5 and Tables 7 and 8 show that the point estimates for the ATE in the baseline analysis range from 0.02 to 0.12, and some of the estimates are not significantly different from 0. This indicates that if all municipalities merged, total expenditure per capita would increase by 2%∼12% on average. Even if city dummies are added, the estimates fall within this same range. Therefore, the results seem to be robust. We can roughly observe that the estimates from FY2006 to FY2010 are large, while they are approximately 0 after FY2011. This may be because the merged municipalities paid the initial cost to launch their new municipalities just after their mergers.

The point estimates for the ATT are shown in Figure 6 and Tables 7 and 8. The magnitudes of the ATTs in the baseline analysis range from 0 to 0.09. The estimates from the analysis with city dummies are larger than the baseline estimates and range from 0.05 to 0.18. Considering that the estimates including control variables reflect comparisons of municipalities within the same population category, this may be because the expenditures for merged municipalities were relatively large within the same category of municipalities. The results indicate that the merged municipalities increased their total expenditure per capita by 0%∼18% after merging. Since the DID estimand is the ATT, this result differs from the results in many extant papers, and we observe an increase in total expenditure due to Japan's municipal mergers.

The point estimates for the ATUTs are shown in Figure 7 and Tables 7 and 8. The magnitudes of the ATUTs range from 0.02 to 0.15 in the baseline analysis and from 0.03 to 0.12 in the analysis with city dummies. The results indicate that the nonmerged municipalities would have increased their total expenditure per capita by 2%∼15% if they had merged.

Comparing the estimates for the ATEs, ATTs, and ATUTs, the magnitudes are not significantly different in most years. This implies that the heterogeneity in the treatment effects on the merged and nonmerged municipalities is not very large. From these results, the heterogeneity in the treatment effects seems to be a trivial issue. However, the point estimates for the LATEs shown in Figure 8 and Tables 7 and 8 clearly indicate different results from those for the ATEs, ATTs, and ATUTs. The values are large, ranging from approximately 0.2 from FY2006 to FY2015 in the baseline analysis and suddenly decreasing to approximately 0.1 from FY2016 to FY2018. Similar results can be seen in the analysis with city dummies. Since the LATE shows the treatment effect on the compliers, i.e., the treatment subjects that would not have chosen to be treated without the incentives from the policy used as an IV, the results mean that those municipalities induced to merge by the reduction in the LAT increased their expenditure by approximately 20% from FY2006 to FY2015 due to their mergers.

Although compared to the other estimates, the LATE estimates seem to be pretty large, they are actually in line with the results of an extant paper, Miyazaki (2018), since he reports that the increase in current expenditure estimated using the fixed-effects instrumental variable (FE-IV) approach is approximately 0.2. Considering that the FE-IV estimation generates a LATE (Chabe-Ferret, 2022), our results capture the same effect as Miyazaki (2018).[*8]

[*8] In addition, Miyazaki (2018) reports a gradual reduction in the treatment effect using data up to FY2010, and we

Why do the estimated LATEs take on such large values? Considering that the LATE captures the treatment effect on those municipalities induced to merge by the reduction in the LAT and that these municipalities would not have merged without that reduction, these municipalities were likely to be affected by the carrot-and-stick policies implemented by the national government. In other words, these municipalities were likely to select into consolidation based on the gains from the incentives to merge, and they enjoyed those incentives more than the other municipalities. In addition, taking into account that the national government guaranteed that merged municipalities would receive the same LAT payment for at least 10 years after their merger, the sudden reduction in the LATE in FY2016 is natural because FY2016 is exactly 11 years after the last year during which municipalities must merge to be eligible to receive the incentives.

Finally, we find that, more or less, the increase in public expenditure after municipal mergers can be seen even more than ten years after the mergers. Because this is true for the ATEs, ATTs, ATUTs, and LATEs, this suggests that the municipal mergers in Japan increased public expenditures regardless of the treatment subjects.

The results shown in this subsection imply that the municipalities selected into consolidation based on their gains or losses and that the increase in public expenditure was caused by the incentives to merge offered by the national government.

4.3 Robustness check

As a robustness check, we add a different set of variables to the set of IVs: average income and the population of elderly individuals, young individuals, and foreign individuals in FY2002.[*9] These variables should have an impact on the determination of mergers, while they should be uncorrelated with expenditure per capita after the mergers when the covariates for the time of the merger are controlled for. Therefore, the exclusion restriction is satisfied for these variable. In addition, it is expected that the reduction in average income and the increase in the population of elderly, young, and foreign individuals will result in an increase in public expenditure because it implies an increase in the number of individuals cared for by the municipality. Including these additional variables generates additional variation in the propensity scores given that aside from the covariates, the categorical variables were the unique source of variation in the propensity scores.

The results of the estimation are shown in Figures 9, 10, 11, and 12 in the appendix. These results are very similar to the results from the models that use only the four categorical variables and suggest the robustness of the main results. Considering that the estimated ATEs range between 0.02 and 0.12 and that this is the same range as in the baseline model, we can conclude that Japan's municipal mergers slightly increased public expenditure on average. Moreover, since all LATE results show a sudden reduction in FY2016, we can infer that the distribution of merger incentives, which last until FY2015, increased the expenditure of compliers, i.e., municipalities that switched their behaviors due to

observe a similar trend in our estimation results.

[*9] We do not use the population in FY2002 because it is clearly correlated with the four categorical dummy variables that are used as IVs and it absorbs the variation captured by the categorical variables.

the merger incentives.

5 Discussion

The results in this paper show that total expenditure per capita increased by 2%∼12% on average according to the ATE for Japan's municipal mergers in the 2000s. However, many extant papers report that the consolidation of local governments reduces or does not change expenditures, as Table 1 shows. What, then, accounts for this difference? In fact, answering this question is impossible because the institutional background and several features of the local governments, such as the population of their jurisdictions and their roles, are totally different across papers. However, by showing the results for different estimands, we indicate that the selection into mergers affects public expenditure as Blesse and Baskaran (2016) and Tricaud (2021) suggest since our estimation of the LATEs suggests that the increase in public expenditure by compliers was much larger than that of other municipalities.

The results also imply that we should take care regarding which estimand we focus on. Although Miyazaki (2018) reports a large increase in public expenditure after mergers using Japanese data, his estimand, the LATE, clearly differs from the ATE. In other words, focusing on the different estimands leads to different results even if the same data are used. This paper shows that the increase in public expenditure after mergers in Japan was modest in terms of the ATE.

Regarding the effect of municipal mergers in terms of reducing costs, since the LATEs capture the treatment effect on those municipalities that were likely to select into consolidation based on the gains from the incentives of the mergers and LATEs were suddenly reduced in FY2016, the result of LATEs indicates that the increase in public expenditure was driven by the incentives to merge provided by the national government. This implies that these incentives to merge might amplify the increase in public expenditure even if the government consolidation itself has a cost reducing effect. Therefore, when the national government wants municipalities to merge, it should be careful in its use of incentives to merge.

6 Conclusion

This study examines whether municipal mergers reduce public expenditure using the MTE of municipal mergers. Extant papers in the literature have paid little attention to bias from the self-selection into municipal mergers or to the heterogeneity in the treatment effects of the mergers. Corresponding to these issues, we use the IVs used in Miyazaki (2018), estimate the MTEs of the mergers, and show that the total expenditure per capita increased by 2%∼12% after the mergers according to the ATE. Although this paper uses the MTE to examine several estimands for public expenditure, more sophisticated methods may be available. To obtain further insights into municipal mergers, more research is needed.

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7 Appendix

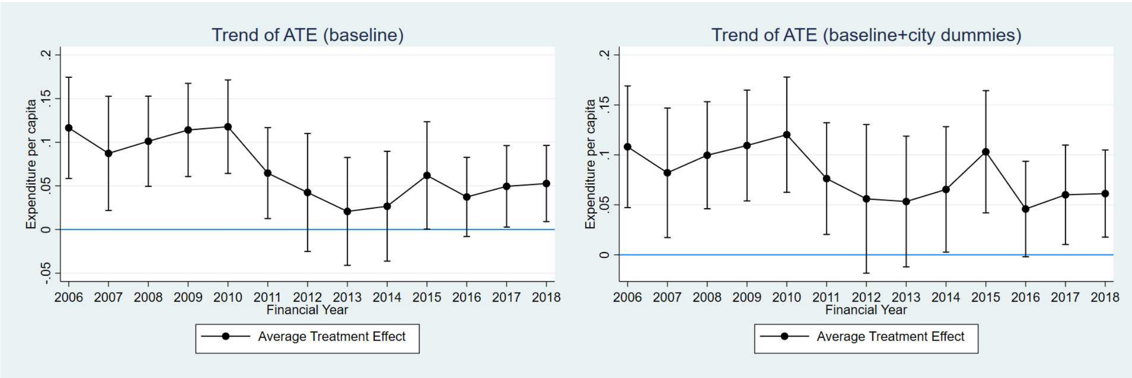

Figure9 The estimated ATEs when new IVs are added for each year

Note: This figure shows the estimated ATEs when we set the four categorical dummy variables, the average income, and the population of elderly, young, and foreign individuals in FY2002 as IVs for each year. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. The estimated ATEs are calculated with eq. (7') as follows:

$$ATE = E[\int_0^1 (m_0(x,p) - m_1(x,p))dp].$$

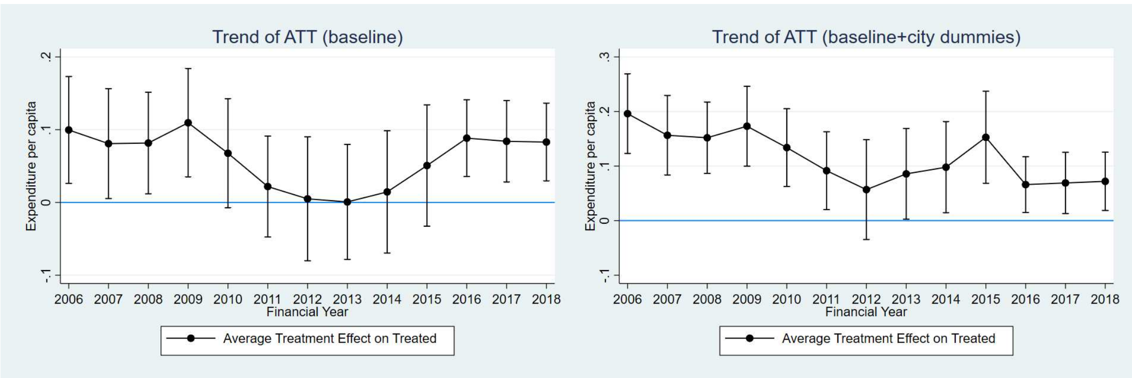

Figure10 The estimated ATTs when new IVs are added for each year

Note: This figure shows the estimated ATTs when we set the four categorical dummy variables, the average income, and the population of elderly, young, and foreign individuals in FY2002 as IVs for each year. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. The estimated ATTs are calculated with eq. (7') as follows:

$$ATT = E[\int_0^1 (m_0(x,p) - m_1(x,p)) \frac{1[p \leq p(w)]}{P(D=1)} dp].$$

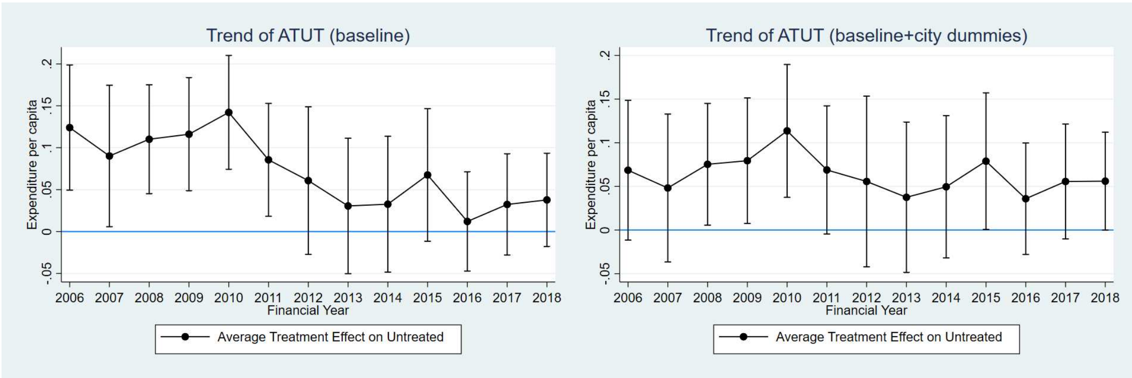

Figure11 The estimated ATUTs when new IVs are added for each year

Note: This figure shows the estimated ATUTs when we set the four categorical dummy variables, the average income, and the population of elderly, young, and foreign individuals in FY2002 as IVs for each year. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. The estimated ATUTs are calculated with eq. (7') as follows:

$$ATUT = E[\int_0^1 (m_0(x,p) - m_1(x,p)) \frac{1[p \geq p(w)]}{P(D=0)} dp].$$

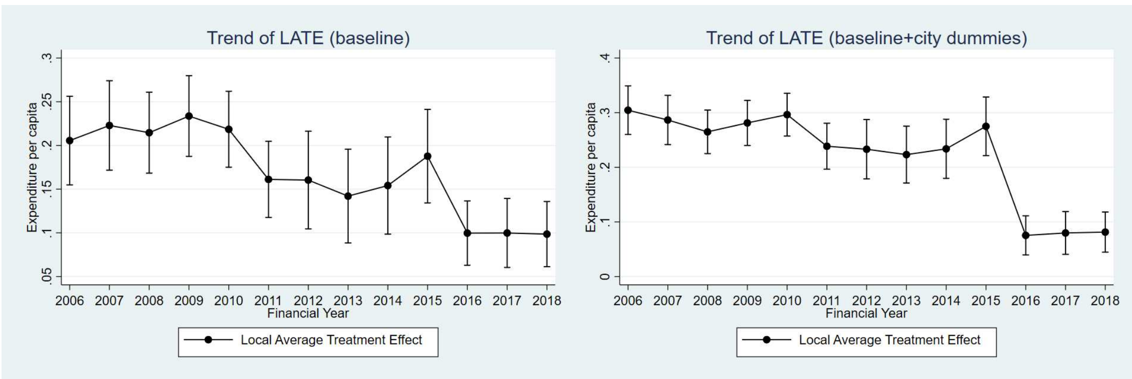

Figure12 The estimated LATEs when new IVs are added for each year

Note: This figure shows the estimated LATEs when we set the four categorical dummy variables, the average income, and the population of elderly, young, and foreign individuals in FY2002 as IVs for each year. The left panel shows the results when we use the covariates in the baseline analysis, and the right panel shows the results when city dummies are added to the covariates in the baseline analysis. The vertical black lines show the 95% confidence intervals based on standard errors clustered at the municipality level. The estimated LATEs are calculated with eq.(7') as follows:

$$LATE = E[\int_0^1 (m_0(x,p) - m_1(x,p)) \frac{1[p \in (\underline{p}, \bar{p}]]}{\bar{p} - \underline{p}} dp].$$

VARIABLES	Source	Unit
Exp per capita	The Survey of Local Public Finance	Thousand yen
Pop	Population survey based on Basic Resident Register	
Young pop	Population survey based on Basic Resident Register	
Elderly pop	Population survey based on Basic Resident Register	
Foreign pop	Population survey based on Basic Resident Register	
Area	Land area of municipality	Hectare
Income	The Survey of Municipal Residential Tax	Thousand yen
City	The Survey of Local Public Finance	Dummy
Special city	The Survey of Local Public Finance	Dummy
Core city	The Survey of Local Public Finance	Dummy
Designated city	The Survey of Local Public Finance	Dummy

Table4 Variables and data sources

	Merged municipalities			Nonmerged municipalities		
VARIABLES	N	Mean	SD	N	Mean	SD
Exp per capita	6,461	556.3	250.0	13,567	699.4	668.5
Pop	7,547	210,288	508,607	15,819	59,419	216,013
Young pop	7,547	27,697	70,961	15,819	7,857	28,053
Elderly pop	7,547	54,623	118,614	15,819	14,017	47,204
Foreign pop	7,547	842.3	2,307	15,819	760.6	4,035
Area	6,461	113,094	186,100	13,569	14,526	19,727
Income	6,461	1,078	231.5	13,567	1,147	326.3
City	7,547	0.629	0.483	15,827	0.285	0.452
Special city	7,547	0.0256	0.158	15,827	0.0161	0.126
Core city	7,547	0.0368	0.188	15,827	0.0142	0.118
Designated city	7,547	0.00742	0.0858	15,827	0.00885	0.0936

Table5 Summary statistics

	FY2006		FY2007		FY2008		FY2009		FY2010	
	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged
Pop	-2.083***	-1.899***	-2.114***	-2.016***	-2.143***	-1.745***	-2.216***	-1.914***	-2.449***	-2.257***
SE	0.153	0.323	0.153	0.340	0.154	0.323	0.148	0.330	0.175	0.346
Income	0.129***	0.108	0.147***	0.424*	0.094**	-0.012	0.076*	-0.030	0.110***	-0.037
SE	0.042	0.089	0.043	0.221	0.042	0.086	0.041	0.085	0.041	0.085
Elderly pop	0.210***	0.632***	0.214***	0.878***	0.212***	0.625***	0.242***	0.708***	0.371***	0.822***
SE	0.063	0.126	0.065	0.177	0.067	0.136	0.066	0.140	0.076	0.147
Young pop	0.264***	0.410**	0.275***	0.544***	0.281***	0.307**	0.277***	0.345**	0.354***	0.479***
SE	0.078	0.162	0.074	0.178	0.073	0.154	0.070	0.152	0.074	0.151
Foreign pop	-0.015	-0.031*	-0.005	-0.052*	0.000	-0.011	0.003	-0.018	-0.007	-0.020
SE	0.010	0.018	0.009	0.027	0.009	0.016	0.009	0.016	0.008	0.017
Area	0.118***	0.134***	0.123***	0.134***	0.121***	0.123***	0.117***	0.117***	0.124***	0.120***
SE	0.008	0.017	0.008	0.018	0.007	0.016	0.008	0.016	0.008	0.016
Pop2	0.068***	0.030***	0.068***	0.019**	0.069***	0.028***	0.071***	0.031***	0.072***	0.034***
SE	0.003	0.007	0.003	0.009	0.003	0.007	0.003	0.007	0.004	0.007
Cons	14.199***	11.703***	14.162***	8.564***	14.681***	11.957***	15.256***	12.705***	15.450***	13.838***
SE	0.489	1.203	0.486	2.266	0.473	1.091	0.463	1.100	0.536	1.199
Pi1	2.276	1.856	-0.991	-0.149	-1.810	0.560	-0.970	0.737	-3.345	1.787
SE	3.814	5.573	2.079	3.165	2.091	3.195	3.587	5.214	2.692	4.078
Pi2	-7.012	-7.104	0.758	0.505	2.767	-1.668	0.179	-2.080	5.126	-6.039
SE	8.765	13.022	4.417	7.181	4.459	7.255	8.683	12.789	5.904	9.345
Pi3	4.947	5.833	-0.105	-0.370	-1.407	1.298	0.891	1.565	-2.475	4.543
SE	5.699	8.587	2.676	4.674	2.683	4.686	5.664	8.462	3.591	5.985
First stage	124.2		167.3		146.7		145.5		90.73	

	FY2011		FY2012		FY2013		FY2014		FY2015	
	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged
Pop	-1.955***	-1.803***	-1.764***	-1.396***	-1.749***	-1.318	-1.777***	-1.397***	-1.519***	-1.494***
SE	0.149	0.306	0.189	0.426	0.170	0.378	0.164	0.361	0.162	0.365
Income	-0.054	-0.231**	-0.289***	-0.618**	-0.185***	-0.421**	-0.070	-0.256**	-0.036	-0.213*
SE	0.043	0.092	0.101	0.277	0.067	0.177	0.057	0.125	0.052	0.117
Elderly pop	0.140**	0.575***	-0.064	0.284	0.006	0.327	-0.008	0.383**	-0.116	0.417**
SE	0.071	0.139	0.096	0.242	0.085	0.203	0.082	0.185	0.080	0.189
Young pop	0.200***	0.397***	0.122	0.251	0.150**	0.223	0.165**	0.231	0.052	0.235
SE	0.068	0.139	0.079	0.170	0.071	0.151	0.065	0.142	0.066	0.147
Foreign pop	-0.008	-0.012	0.013	0.029	-0.006	-0.011	-0.017	-0.024	-0.025**	-0.023
SE	0.010	0.019	0.015	0.035	0.012	0.024	0.015	0.026	0.012	0.022
Area	0.126***	0.132***	0.132***	0.148***	0.134***	0.147	0.135***	0.147***	0.133***	0.142***
SE	0.007	0.015	0.008	0.017	0.008	0.016	0.008	0.015	0.008	0.015
Pop2	0.068***	0.028***	0.071***	0.029***	0.066***	0.026***	0.067***	0.026***	0.065***	0.029***
SE	0.003	0.006	0.004	0.008	0.003	0.007	0.003	0.007	0.003	0.007
Cons	15.344***	13.773***	16.959***	15.734***	15.913***	13.937***	15.340***	13.027***	14.617***	13.226***
SE	0.471	1.116	0.710	1.929	0.559	1.390	0.587	1.325	0.557	1.319
Pi1	-5.314	-1.167	-2.069	-2.192	-0.271	-2.801	-1.167	-2.552	-2.146	-1.981
SE	3.297	5.103	5.060	7.724	5.393	8.208	5.076	7.603	4.460	6.819
Pi2	10.681	2.046	1.567	4.136	-1.898	6.258	1.299	5.280	3.676	3.279
SE	7.655	12.379	11.105	17.923	11.650	18.845	11.182	17.485	10.042	16.042
Pi3	-6.433	-1.419	-0.024	-2.531	1.995	-4.272	-0.371	-3.382	-2.022	-1.767
SE	5.047	8.521	6.932	11.915	7.131	12.411	6.934	11.446	6.323	10.643
First stage	89.79		90.33		88.95		90.20		92.40	

	FY2016		FY2017		FY2018	
	Nonmerged	Merged	Nonmerged	Merged	Nonmerged	Merged
Pop	-1.684***	-1.824***	-1.805***	-2.222***	-1.793***	-2.331***
SE	0.167	0.352	0.161	0.342	0.164	0.338
Income	0.026	-0.281**	0.047	-0.263**	0.088	-0.272**
SE	0.053	0.116	0.053	0.116	0.056	0.111
Elderly pop	-0.057	0.346**	0.009	0.469***	0.050	0.545***
SE	0.083	0.172	0.086	0.171	0.088	0.179
Young pop	0.149**	0.312**	0.185***	0.430***	0.199***	0.472***
SE	0.066	0.136	0.063	0.129	0.064	0.129
Foreign pop	-0.046***	-0.007	-0.054***	-0.017	-0.057***	-0.005
SE	0.015	0.024	0.016	0.026	0.015	0.024
Area	0.141***	0.137***	0.137***	0.134***	0.136***	0.122***
SE	0.007	0.015	0.007	0.016	0.007	0.017
Pop2	0.066***	0.045***	0.068***	0.052***	0.065***	0.052***
SE	0.003	0.006	0.003	0.006	0.003	0.006
Cons	14.482***	15.302***	14.637***	16.490***	14.062***	16.763***
SE	0.575	1.269	0.551	1.163	0.582	1.158
Pi1	1.134	-2.957	0.803	-2.560	1.191	-1.839
SE	3.852	5.596	3.850	5.532	3.780	5.412
Pi2	-5.287	8.397	-4.575	6.975	-5.532	4.486
SE	9.872	14.475	10.085	14.552	9.891	14.214
Pi3	4.633	-6.112	4.203	-4.876	4.768	-2.845
SE	6.802	10.079	7.054	10.230	6.936	10.006
First stage	225.6		227.4		228.6	

Table6 The estimated coefficients from eq. (6) for each year

Note: The estimated coefficients from (6) are listed. Since the MTRs are defined separately for the treated and untreated groups, the estimated results are listed separately for nonmerged and merged municipalities. The row titled "First stage" shows the value of the χ^2 statistic, which corresponds to the F value in OLS, under the joint hypothesis that the coefficients on the four categorical instrumental variables are zero in the first stage probit regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FY2006	FY2007	FY2008	FY2009	FY2010	FY2011	FY2012	FY2013	FY2014	FY2015
ATE	0.116***	0.0873**	0.101***	0.114***	0.118***	0.0647*	0.0425	0.0207	0.0267	0.0620*
	(0.0296)	(0.0333)	(0.0263)	(0.0272)	(0.0273)	(0.0266)	(0.0345)	(0.0315)	(0.0321)	(0.0313)
ATT	0.0996**	0.0809*	0.0817*	0.110**	0.0676	0.0219	0.00497	0.000687	0.0145	0.0507
	(0.0375)	(0.0385)	(0.0356)	(0.0380)	(0.0382)	(0.0354)	(0.0435)	(0.0403)	(0.0429)	(0.0425)
ATUT	0.124**	0.0902*	0.110***	0.116***	0.142***	0.0856*	0.0608	0.0306	0.0326	0.0675
	(0.0381)	(0.0430)	(0.0331)	(0.0344)	(0.0346)	(0.0343)	(0.0449)	(0.0412)	(0.0413)	(0.0403)
LATE	0.206***	0.223***	0.215***	0.234***	0.218***	0.161***	0.160***	0.142***	0.154***	0.188***
	(0.0259)	(0.0261)	(0.0236)	(0.0236)	(0.0222)	(0.0222)	(0.0285)	(0.0274)	(0.0283)	(0.0273)
N	1654	1654	1654	1654	1654	1654	1654	1654	1654	1654

	(11)	(12)	(13)
	FY2016	FY2017	FY2018
ATE	0.0373	0.0495*	0.0527*
	(0.0231)	(0.0238)	(0.0223)
ATT	0.0884**	0.0841**	0.0830**
	(0.0269)	(0.0286)	(0.0272)
ATUT	0.0120	0.0323	0.0377
	(0.0302)	(0.0308)	(0.0283)
LATE	0.0997***	0.0998***	0.0985***
	(0.0188)	(0.0201)	(0.0190)
N	1654	1654	1654

Standard errors clustered at the municipality level are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table7 The estimated values for the estimands in the baseline model for each year

Note: The estimated values for the estimands are listed. They are calculated from the baseline model and based on eq. (7').

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FY2006	FY2007	FY2008	FY2009	FY2010	FY2011	FY2012	FY2013	FY2014	FY2015
ATE	0.108***	0.0821*	0.0996***	0.109***	0.120***	0.0763**	0.0560	0.0533	0.0654*	0.103***
	(0.0310)	(0.0330)	(0.0273)	(0.0283)	(0.0294)	(0.0285)	(0.0379)	(0.0333)	(0.0320)	(0.0312)
ATT	0.196***	0.156***	0.152***	0.173***	0.134***	0.0915*	0.0569	0.0857*	0.0979*	0.153***
	(0.0372)	(0.0372)	(0.0333)	(0.0373)	(0.0364)	(0.0364)	(0.0467)	(0.0424)	(0.0426)	(0.0431)
ATUT	0.0685	0.0482	0.0753*	0.0794*	0.114**	0.0688	0.0556	0.0375	0.0495	0.0789*
	(0.0408)	(0.0432)	(0.0355)	(0.0367)	(0.0388)	(0.0374)	(0.0499)	(0.0439)	(0.0416)	(0.0399)
LATE	0.305***	0.287***	0.265***	0.281***	0.296***	0.239***	0.233***	0.223***	0.234***	0.275***
	(0.0227)	(0.0230)	(0.0203)	(0.0210)	(0.0199)	(0.0214)	(0.0277)	(0.0266)	(0.0276)	(0.0273)
N	1654	1654	1654	1654	1654	1654	1654	1654	1654	1654

	(11)	(12)	(13)
	FY2016	FY2017	FY2018
ATE	0.0458	0.0601*	0.0613**
	(0.0244)	(0.0254)	(0.0222)
ATT	0.0660*	0.0691*	0.0720**
	(0.0261)	(0.0286)	(0.0273)
ATUT	0.0359	0.0556	0.0560
	(0.0326)	(0.0336)	(0.0286)
LATE	0.0753***	0.0798***	0.0814***
	(0.0182)	(0.0200)	(0.0187)
N	1654	1654	1654

Standard errors clustered at the municipality level are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table8 The estimated values for the estimands in the model with city dummies for each year

Note: The estimated values of the estimands are listed. They are calculated from the model with city dummies and based on eq. (7').

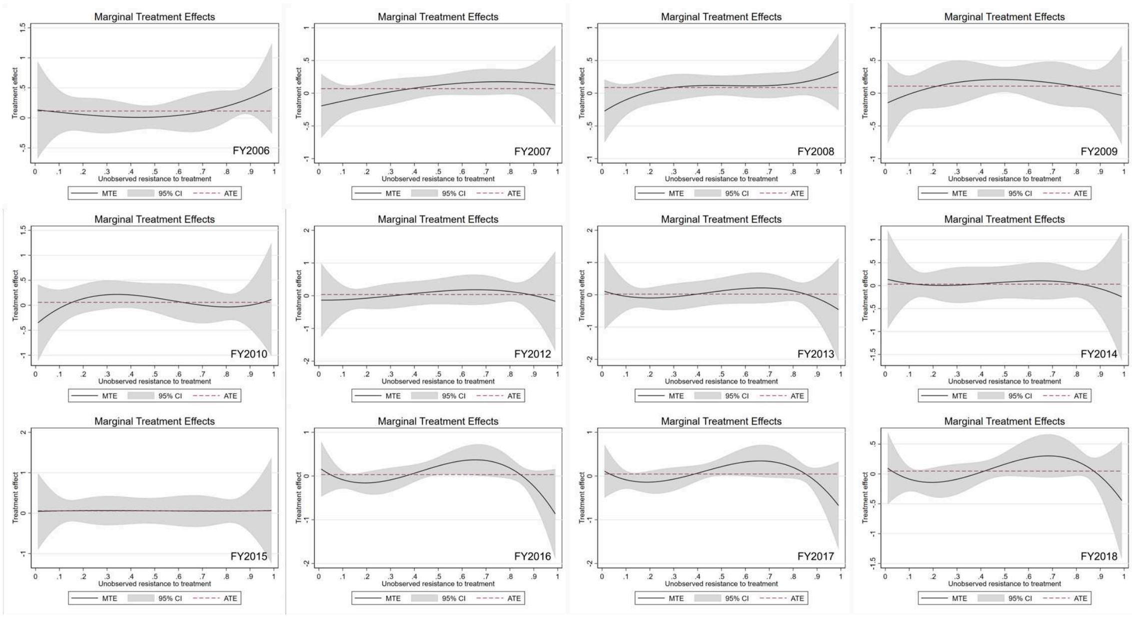

Figure13 MTE over unobserved resistance to treatment in FY2006-2018 (excluding FY2010)

Note: The MTEs and ATEs are shown as the black solid line and red dotted line, respectively. The dark shaded area shows the 95% confidence intervals for the MTEs. The estimated MTE here is $\hat{m}(x,p) = x(\hat{\beta}_1 - \hat{\beta}_0) + \{\sum_{l=1}^{3} \hat{\pi}_{1l}(p^l - \frac{1}{l+1}) - \sum_{l=1}^{3} \hat{\pi}_{0l}(p^l - \frac{1}{l+1})\}$, and the horizontal line corresponds to p.