Impacts of Municipal Mergers on Pollution Control: Evidence of River Pollution in Japan

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Abstract

Municipal mergers are widely adopted by policymakers to improve local public services, including pollution control. Municipal mergers can improve environmental quality by internalizing pollution spillovers to neighboring municipalities, but coordination costs and unbalanced political power among pre-merger municipalities can work in the opposite direction. We test this relationship in the context of Japan's large-scale municipal mergers that almost halved the number of municipalities. By using the staggered implementation of municipal mergers and 30-year water quality data, we find that municipal mergers increase water pollution, and the effects persist for about 15 years. Our results point to weaker pollution control through coordination cost and political economy channels.

JEL: D73, Q52, Q53, R11, R58

Keywords: Municipal Merger, Pollution, Water Quality, Negative Externality, Political Economy

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1 Introduction

The appropriate level of decentralization and centralization, i.e., distribution of power between local and central governments, has been long debated in academics (Tiebout, 1956; Oates, 1972; Besley and Coate, 2003). Under decentralized governance, competition among municipalities is hypothesized to ensure Pareto-efficient allocation of local public services, but the allocation can become inefficient when local public services within a jurisdiction have spatial spillover effects on neighbors without inter-jurisdictional coordination (Tiebout, 1956; Oates, 1972; Jannin and Sotura, 2020). One key example of this spillover is a negative externality of weak pollution control on the environmental quality of neighboring municipalities. In accordance with this argument, an increase in local jurisdictions under decentralized governance has been recently shown to negatively affect environmental quality in developing countries (Burgess et al., 2012; Lipscomb and Mobarak, 2016). Then, the question is what will be the environmental effect of the opposite policy, i.e., a decrease in local jurisdictions, which is more prevalent in developed countries. Do fewer, larger-sized municipalities facilitate the internalization of negative externalities, thus improving environmental quality?

In this paper, we examine how municipal mergers, where two or more municipalities combine to form a new municipality, affect river pollution in Japan. Municipal mergers have been widely adopted in 20 developed countries such as Denmark, Germany, France, Japan, and United States. This policy aims to provide local public services with higher quality at a lower cost based on economies of scale — a larger municipality can provide local public services at lower unit costs (OECD, 2014). One may expect that municipal mergers can improve environmental quality because of this more cost-effective implementation of pollution control. This positive effect can be further reinforced by the internalization of pollution spillovers across pre-merger municipalities, as discussed above. On the other hand, coordination costs and unbalanced political power among pre-merger municipalities may hamper the pollution control effort of merged municipalities, leading to the deterioration of environmental quality. The relationship between municipal mergers and environmental outcomes appears ambiguous and deserves careful empirical examination.

We test this relationship in the context of Japan's municipal mergers in the late 1990s to 2000s. This merger policy in Japan has unique characteristics to effectively answer our research question. First, this policy drastically reduced the number of municipalities by about 50%, from 3,238 in 1998 to 1,725 by 2012. This large-scale and universal occurrence of municipal mergers in all prefectures in Japan increases the external validity of our results. Second, municipal mergers occurred over time from 1999 to 2011. We use the staggered implementation of municipal mergers as a setting of quasi-natural experiment to provide causal impacts of mergers on environmental outcomes. Lastly, the universal occurrence of municipal mergers allows us to use water quality data from 3,000 monitoring stations across Japan. We use rich water quality data over 30 years to examine the long-run impact of municipal mergers on water quality.

We investigate the effects of municipal mergers on river water quality by exploiting the staggered implementation of municipal mergers. The existence of both merged municipalities and never-merged municipalities and the variation in the timing of municipal mergers among merged municipalities allow us to adopt difference-in-differences (DID) and event study specifications. Here, we compare the outcomes of municipalities that merged and municipalities that did not merge, as well as comparing the outcomes of municipalities that merged earlier and municipalities that merged later. In this staggered-adoption DID design, simple two-way fixed effects may be subject to the bias which comes from the bad comparison between early merged municipalities and late merged municipalities (Goodman-Bacon, 2021). Thus, we adopt recently-developed alternative estimators (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021) that are robust to this concern as the baseline specification.

Strikingly, we find that municipal mergers do not improve water quality but rather increase river pollution on average by around 6 percent. This negative effect persists for about 15 years in the event study specification. This is a finding that runs counter to the mechanism of the internalization of pollution spillovers. The causality of this effect hinges on the assumption that the treated municipalities and untreated municipalities would move in parallel in the absence of municipal mergers. A plot of raw water quality data comparing never-merged versus merged municipalities shows the parallel pre-trends, and event study plots do not show any differential impacts before the mergers. The results are also robust to an alternative specification when we only use variation in merger timings among municipalities that experienced municipal mergers.

Next, we examine whether the internalization of pollution spillovers is plausible by directly testing the negative externality theory suggested in Lipscomb and Mobarak (2016). We follow their specification to exploit the changes in river distances between monitoring stations and municipality borders. Specifically, we examine how river distances from monitoring stations to their closest upstream and downstream municipality borders affect the water quality. We find that pollution levels do not change as a river flows downstream within a municipality, a pattern inconsistent with the negative externality theory. Without the evidence of the negative externality theory, municipal mergers are unlikely to internalize pollution spillovers and improve water quality. This result is consistent with the negative effects observed in the DID design.

To identify alternative mechanisms of increased water pollution due to municipal mergers, we investigate two mechanisms: (i) weaker pollution control on existing pollution sources due to coordination costs and unbalanced political power among pre-merger municipalities at the *intensive* margin, and (ii) new pollution sources due to increased economic activities and change in land use at the *extensive* margin.

As for the intensive margin mechanism, we first test whether municipal mergers with higher coordination costs lead to larger water pollution because insufficient coordination of public services after mergers can weaken pollution control. We show that pollution increases for "equal-footing" mergers that entail higher coordination costs but not for "incorporating" mergers with lower coordination costs (coordination cost channel).[1] Second, we examine whether incorporated municipalities with smaller political power experience larger water pollution than incorporating municipalities with larger political power, where mayors continue to hold the same position after municipal mergers and thus reduce local public service provision outside their electoral base (political economy channel). We find that incorporated municipalities experience water pollution while incorporating municipalities do not experience water pollution.

To identify pollution sources affected by the intensive margin mechanism, we examine the change in the operation of domestic wastewater in sewage treatment plants, which are operated under the responsibility of municipalities. We do not find statistically significant changes in the water quality of discharge from sewage treatment plants. This null result in the case of domestic wastewater suggests that weaker pollution control has likely affected the emission of industrial wastewater, which is another major pollution source regulated by municipalities through reporting and inspections.

Conversely, the extensive margin mechanism is not supported in our analysis. We examine the impacts of municipal merges on land use around water quality monitoring stations. We do not find effects on any land use classifications, including agriculture, built-up, forest, and non-use.

Therefore, we conclude that municipal mergers can have unintended negative effects on the water quality of rivers when coordination costs among municipalities and neglect of incorporated municipalities weaken pollution control. In the future policy discussion of municipal mergers, we need to incorporate these negative effects as potential costs in the cost-benefit analysis. The policymakers also need to keep in mind that the compositions of municipalities matter for the local public service provision after municipal mergers.

Our paper makes three contributions. First, we contribute to the literature on decen-

[1] Equal-footing mergers involves mergers between municipalities of similar size, with a new municipality name given after the merger. On the other hand, incorporating mergers involves a larger municipality incorporating other smaller municipalities, with the resulting municipality inheriting the name of the incorporating municipality.

tralization and fiscal federalism by showing that spillovers across jurisdictions may not be simply resolved by consolidations of municipalities, and coordination costs and balance of political powers matter. Previous studies show that splits in municipalities exacerbate pollution spillovers along rivers in Brazil (Lipscomb and Mobarak, 2016), and conversely, mergers internalize spillovers of air pollution in China (Wang and Wang, 2021). We find no evidence of this negative externality theory. We instead show that mergers increase river pollution in Japan. Then, we suggest alternative mechanisms, i.e., weaker pollution control due to coordination costs and unbalanced political power among pre-merger municipalities, which should be newly incorporated in the discussion of decentralization.

Second, we contribute to the literature on the impacts of municipal mergers by showing surprising negative effects on the environment. Most previous studies investigate the macroeconomic effects of municipal mergers on local public finance (Hinnerich, 2009; Reingewertz, 2012; Moisio and Uusitalo, 2013; Hirota and Yunoue, 2017; Miyazaki, 2018; Pickering et al., 2020), economic activity (Egger et al., 2018) and determinants of municipal mergers (Weese, 2015). We instead focus on the environmental impacts of municipality mergers, where only a little evidence exists. A particularly relevant paper is Wang and Wang (2021), which showed that township mergers in China internalized the negative externalities of polluting firms and *reduced* emissions by these firms. We complement this paper in two ways: (i) we show that municipal mergers can *increase* pollution and that negative externality theory may not matter in a developed country context; (ii) our 30-year panel data on water quality enables us to examine the long-term impacts of municipal mergers, and we show that the negative impacts of municipal mergers persist for about 15 years.[2]

Third, we broadly contribute to the literature on the causes of and measures against water pollution by providing first causal estimates of the effects of municipal mergers on water

[2] Another relevant paper is Mizunoya et al. (2021) which examined the impacts of municipal mergers on watershed management of the Lake Kasumigaura Basin based on the simulation of a dynamic expanded input-output model. This paper is a case study of one water body and relies on a simulation based on the model. Instead, we examine the causal impacts of municipal mergers across Japan based on the quasi-experimental design.

quality. Past studies have found that water pollution increases with political boundaries (Sigman, 2002; Kahn et al., 2015; Lipscomb and Mobarak, 2016) and sanitation investment without adequate fecal sludge management (Motohashi, 2022). Another set of studies has examined the effectiveness of government interventions in reducing pollution, including water pollution regulations (Greenstone and Hanna, 2014; Keiser and Shapiro, 2019), and court rulings (Do et al., 2018). This paper shows that a decrease in political boundaries, i.e., municipal mergers, can also cause water pollution.

The rest of the paper is organized as follows. Section 2 provides background information on municipal mergers and water quality in Japan. In Sections 3 and 4, we explain the data and empirical strategy, respectively. Section 5 discusses the results. In section 6, we analyze the underlying mechanisms behind our results. Section 7 concludes.

2 Municipal Mergers and Water Quality

2.1 The "Great Heisei Municipal Mergers" in Japan

The "Great Heisei municipal mergers" took place in Japan predominantly in the late 1990s to 2000s. They are large-scale municipal mergers that occurred universally in all prefectures in Japan (Figure 1). The number of municipalities in Japan drastically decreased by about 50% from 3,238 in 1998 to 1,725 by 2012.

The financial incentives under the revisions of the "Act on Special Provisions of the Merger of Municipalities" in 1995 and 1999 played a key role in fostering these municipal mergers.[3] The 1995 revision announced that the purpose of the Act was to push forward municipal mergers and introduced five-year preferential treatment in local tax allocation for merging municipalities. Municipalities, especially those in rural areas, were experiencing dwindling birth rates, aging, and declining population, as well as increasingly difficult fiscal

[3] The Act had been in place since 1965, The focus of the Act was originally on facilitating merger procedures.

conditions following the burst of the bubble economy in the early 1990s. Municipal mergers were seen as a tool to rejuvenate such municipalities.

The 1999 revision further strengthened financial incentives. The above preferential treatment in local tax allocation was extended to 10 years. Furthermore, merged municipalities were now allowed to issue "Special Provision Bonds" for up to 10 years after merging to fund public projects included in their merger proposals. These municipalities were only asked to pay back 30 percent of what they borrowed using these bonds, and the central government paid the remaining 70 percent. The bonds were essentially a 70 percent public project subsidy for merging municipalities. The government initially announced that, in order to be eligible for these benefits, municipalities had to merge by March 2005. However, this was later extended by one year to March 2006 in order to provide more time for municipalities that were struggling to complete mergers by the original deadline.

Thanks to the strong push by these financial incentives, the number of municipal mergers in Japan increased over time from the late 1990s. Figure 2 illustrates the frequency of municipality mergers since 1995. The first merger occurred in 1999 when financial incentives were strengthened. However, merger counts remained low for the next few years. The vast majority of mergers took place between 2004 and 2006. This not only reflects the fact that it can take several years to complete the merger process but also indicates bunching behavior by municipalities to meet the initial and final deadlines of 2005 and 2006, respectively. Municipal mergers continued even after 2006 until 2011. As discussed here, there is a variation in the timings of municipal mergers. Also, the "Great Heisei municipal mergers" were not mandatory for municipalities, so we have a variation between municipalities that experienced municipal mergers and those that did not. We use these variations in the difference-in-differences and event-study specification as explained in Section 4.1.

The municipal mergers under the 1995 and 1999 revisions were not a forced policy. The autonomy of municipalities was respected, and municipalities could choose whether or not to negotiate mergers and which municipalities to negotiate with. The merger process took the following steps. Firstly, "interested" municipalities were to vote and form a panel to discuss potential mergers. Secondly, the panel was to negotiate and formulate merger proposals. Finally, a merger was formally announced and implemented after final voting by the municipalities involved and administrative approval by the prefectural governor and the Minister of Internal Affairs and Communications.

Lastly, municipal mergers can be categorized into two types: "equal-footing" mergers and "incorporating" mergers. The former type involves mergers between municipalities of similar size, with a new municipality name given after the merger. A mayor of the new municipality will be newly elected in the election held after the completion of the municipal merger. On the other hand, "incorporating" mergers involve a larger municipality incorporating other smaller municipalities, with the resulting municipality inheriting the name of the incorporating municipality. A mayor of an incorporating municipality continues to be the mayor of the newly created municipality, while mayors of incorporated municipalities lose their jobs after municipal mergers.

2.2 Water Quality and Pollution Control in Japan

Water quality in Japan is regulated by the Environmental Quality Standards for Water Pollution. One important regulated indicator of water quality is BOD (Biochemical oxygen demand). BOD is the amount of dissolved oxygen needed by aerobic biological organisms to break down the organic material present, which captures the overall level of water contamination from various sources such as domestic, agricultural, and industrial wastewater. These standards set the limit values of BOD to be from 1 up to 10 mg/L in rivers, which depends on the usage of water in a given location.

Under these environmental standards, water quality in Japan has generally improved over time. The average BOD of rivers declined from about 3.5 to 1.5 mg/L from 1979 to 2018 (Ministry of the Environment, Government of Japan, 2019), which are within the range of limit values of BOD. Thus, our analysis examines whether the magnitude of the improvement in the water quality of rivers becomes larger or not after municipal mergers.

The main sources of water pollution can be categorized into three sources: (i) domestic wastewater (sewage), (ii) industrial wastewater, and (iii) agricultural wastewater. Municipalities in Japan are responsible for controlling pollution from domestic wastewater and industrial wastewater. Domestic wastewater is usually treated in sewage treatment plants which are managed by municipalities. Effluent standards on industrial wastewater are enforced through reporting and inspections by prefectures and designated cities.[4] On the other hand, agricultural wastewater is a non-point source that is diffused over a wide area as a result of factors such as precipitation, and thus it is more difficult to control this source. Municipalities do not have an explicit responsibility to control agricultural wastewater.

2.3 How Do Municipal Mergers Affect Water Quality?

Municipal mergers can affect water quality through several channels. One channel which has been examined in the past literature is negative externalities along rivers (Lipscomb and Mobarak, 2016). Lipscomb and Mobarak (2016) develop a theoretical framework where pollution within a municipality located upstream of a river adversely affects other municipalities located downstream. They show that decentralization, i.e., having more municipalities along a river path, worsens water pollution. Based on their model, we may expect that municipal mergers, which decrease the number of municipalities along a river path, would improve water quality in rivers.

The key to the negative externality theory is the spatial pattern of river pollution within a municipality. As in Appendix Figure A1, based on Lipscomb and Mobarak (2016), consider a municipality, which spans an area from 0 to 1 on the horizontal axis, that is located along a river with a population uniformly populated in this area. The river flows from 0 to 1, and thus 0 and 1 are the upstream and downstream municipality borders, respectively. A local

[4] A designated city is a city that has a population greater than 500,000 and has been designated by the ordinance of the Japanese government under the Local Autonomy Law. A designated city is delegated many of the functions normally performed by prefectural governments.

governor chooses how much economic activity to pursue and hence how many pollutants to emit at each point within his/her municipality. Because the local mayor wishes to minimize the negative impact of emissions on his/her population and does not care about people living in other municipalities, including those downstream, he/she will choose to focus most of the economic activity and emissions near the downstream border, 1. Most of his/her population would be living upstream of this point and would not be adversely affected by emissions that take place at this point.

Thus, the Lipscomb and Mobarak (2016) model predicts, among others, that pollution will increase exponentially as the river flows downstream within a municipality and that there will be a structural break in the slope of the pollution function at the municipality border. The latter prediction follows from the fact that emission is high just upstream of a municipality border but is low just downstream of a municipality border. We test the presence of such spatial patterns by using specifications in the spirit of Lipscomb and Mobarak (2016).

In addition to the negative externality theory, we hypothesize that two additional channels, namely the coordination cost channel and the political economy channel, have weakened the pollution control of municipalities. First, as for the coordination cost channel, post-merger surveys indicate a lack of organization and solidarity among municipality officials, including difficulty and delay in policy coordination, as negative consequences of the "Great Heisei Municipal Mergers" (National Association of Towns and Villages, 2008; Nakazawa and Miyashita, 2016). If coordination costs among merging municipalities are high, a newly created municipality will have difficulties in reformulating public services, which were separated by each pre-merger municipality, into newly coherent public services. Thus, the quality of pollution control in merged municipalities with higher coordination costs may deteriorate. In terms of the types of municipal mergers, "equal-footing" mergers between municipalities of similar size are expected to have higher coordination costs than "incorporating" mergers when a large municipality will incorporate other small municipalities. Therefore, we expect that water pollution is substantial in the case of “equal-footing” mergers with higher coordination costs.

Second, as for the political economy channel, municipal mergers can cause unbalanced political power between incorporating and incorporated municipalities in the case of “incorporating” mergers. A mayor of an incorporating municipality continues to be the mayor of the newly created municipality, while mayors of incorporated municipalities lose their jobs after municipal mergers. Because the mayor of the newly created municipality has an electoral base in the former incorporating municipality, he or she may prioritize pollution control in that area. Similarly, post-merger, council members of the new municipality may consist mainly of members from the incorporating municipality. Indeed, reports by the National Association of Towns and Villages note that the voices of people living in incorporated municipalities were not adequately reflected after mergers took place (National Association of Towns and Villages, 2008). As a result, pollution control of incorporated municipalities may be weakened. Thus, we may expect that incorporated municipalities experience larger water pollution due to weaker efforts to control water pollution.

Finally, another channel could be the change in land use, which results from increases in economic activity as suggested by Egger et al. (2018). For example, if enhanced economic activity leads to deforestation and increases in built-up areas, river pollution may increase after mergers due to an increase in industrial wastewater.

3 Data

In this paper, we combine novel datasets on ambient water quality and detailed information on municipal mergers to examine the effects of municipal mergers on water quality. We also use geospatial data, including municipality boundaries and river lines, to identify the changes in distances between monitoring stations and municipality borders and test the negative externality theory.

3.1 Water Quality

The main outcome variable is water quality. We use data from water quality monitoring stations, which are provided by the Ministry of Environment, Government of Japan. These water quality data are originally collected by each prefecture in Japan under Article 15 of the Water Pollution Prevention Act and reported to the Minister of the Environment. Then, the Ministry of Environment publicizes these reported data on its website. These data include yearly average indicators of water quality, which are measured at monitoring stations in Japan. Among multiple water quality indicators, we use the yearly average BOD (Biochemical oxygen demand) as a representative indicator in the analysis. As aforementioned, BOD is a standard measure of water quality that is being monitored under the "Environmental Water-Quality Standard" in Japan. A higher level of BOD values means a higher level of water pollution.

In our analysis, we use balanced panel data of 3,219 water quality monitoring stations along rivers in Japan from 1990 to 2018 (Figure 3). We drop 3,590 stations whose water quality data are partially available during this period to address the concern of endogenous construction of monitoring stations. Thanks to large panel data of thousands of stations across Japan over 30 years, we are able to assess the dynamic impacts of municipal mergers on water quality over a long period.

We complement this dataset with geospatial data of water basins in Japan, provided by the Ministry of Land, Infrastructure, Transport, and Tourism, to identify the basin where a given monitoring station is situated.

3.2 Municipal Merger

The key treatment variable in our analysis is an indicator of whether a municipal merger occurred in the municipality where a given monitoring station is located in a given year. Thus, we obtain data on the timing of municipal mergers and on the involved municipalities from the Ministry of Internal Affairs and Communications. The data allow us to compare the change in water quality between merged municipalities and non-merged municipalities, as well as between municipalities that merged earlier and those that merged later.

This dataset also includes information on the types of municipal mergers ("equal-footing" mergers versus "incorporating" mergers) and whether the municipality is incorporating municipality or incorporated municipality in the case of "incorporating" mergers. We use this information to examine the heterogeneous impacts of municipal mergers by merger types in the analysis of the coordination cost channel and political economy channel.

3.3 River Distance

To test the negative externality theory as in Lipscomb and Mobarak (2016), we calculate the changes in distances between monitoring stations and municipality borders.

As for data sources, we obtain pre-merger (1984) and post-merger (2018) municipality boundary data, provided by Kirimura et al. (2011). We also obtain detailed river node data with elevation information, as well as river line data, provided by the Ministry of Land, Infrastructure, Transport, and Tourism. Lastly, we use the locations of water monitoring stations in the water quality data.

In this analysis of negative theory, we construct two distance variables, U and D, in the spirit of Lipscomb and Mobarak (2016). U refers to the distance along the river from a monitoring station to its closest upstream municipality border. Likewise, D indicates the river distance between a monitoring station and its closest downstream border. U and D require calculating distances along rivers instead of Euclidean distance and judging flow direction.

For constructing U and D, we use the river node data, which contains elevation information, to compute fine-resolution elevation raster data. Based on this elevation data, we identify the upstream-downstream relationships among monitoring stations and municipality borders. Then, we calculate these two distance variables along rivers.[5]

[5] Detailed steps are written in the Appendix C.4.

3.4 Other Municipality Characteristics

We supplement the above information with further data to account for municipality characteristics that might affect both water quality and the likelihood of municipal mergers. Specifically, we use an economic indicator and population.

As an economic indicator, we use "Product shipment values" from 1990 to 2012 from the Census of Manufacture, provided by the Ministry of Economy, Trade, and Industry.

We also use population data from the Census. Because the Census is conducted every five years, we compute the yearly population from 1990 to 2015 based on the linear interpolation of the reported population in 1995, 2000, 2005, 2010, and 2015.

3.5 Data Matching and Sample Construction

For matching water quality data with municipal merger data, we use municipality boundary GIS data provided by the Ministry of Land, Infrastructure, Transport, and Tourism. We first use this boundary data and the GPS coordinates of monitoring stations to identify the latest prefecture and city names of these stations. Then, we match both data based on the latest prefecture and city names. All other data, including water basins and other municipality characteristics, are similarly merged based on the latest prefecture and city names.

After data matching, we construct a balanced panel of 3,219 water quality monitoring stations in 936 cities from 1990 to 2018 for the difference-in-differences specification. The baseline specification in the analysis uses panel data from 1996, 5 years before the first municipal merger was observed in our dataset in 2001. We also conduct robustness checks by using alternative sample periods, (i) 1990-2018 and (ii) 1999-2018, which shows similar results (Appendix Figure A4).

In the specification that uses river distance to test the negative externality theory, we only use monitoring stations that are situated along the river lines that are used in our data construction. We also exclude monitoring stations that are situated either in uppermost cities or downstream cities because one of the distance measures (U or D) cannot be calculated.

We use observations until 2015 since we use population as a control, and population data are available until 2015. Then, the final sample for the river distance specification becomes 700 monitoring stations from 1996 to 2015.

3.6 Summary Statistics

Summary statistics of all variables are shown separately for pre-merger and post-merger periods in Table 1. In the pre-merger periods, merged municipalities (treatment group) are different from non-merged municipalities (control group) in most variables, including product shipment values and population. Although large level differences are observed, we rely on the assumption of parallel trends in the difference-in-differences specification. We test this assumption later in Section 4.1 and Section 5.1. Also, BOD levels decrease in post-merger periods both in treatment and control groups. However, the magnitude of decrease in BOD level is smaller in the treatment group, which implies that municipal mergers cause water pollution. A formal econometric analysis of this impact is conducted in the following sections.

4 Empirical Strategy

We examine the impact of municipal mergers on water pollution in two ways. First, we directly assess the impact of municipal mergers on water pollution by adopting a difference-in-differences model with two-way fixed effects. Simple ordinary least squares (OLS) estimates are subject to bias due to potential endogeneity through potential reverse causality and omitted variables. Municipal mergers could be implemented to better mitigate the water pollution in those municipalities, although this could be highly implausible because the decisions of municipal mergers are said to be primarily based on macroeconomic conditions such as local government budgets. Also, spurious correlations may be caused by omitted unobservables, such as different priorities on water pollution control across municipalities.

Thus, we adopt a difference-in-differences model to deal with potential endogeneity. By including monitoring station fixed effects and basin-year fixed effects, we control for the time-invariant unobservable differences across monitoring stations and secular time trends, which may vary across river basins.

Second, using a specification similar to Lipscomb and Mobarak (2016), we test whether relationships between locations along the river and pollution predicted by the negative externality theory hold in the case of Japan. Similar to the difference in difference specification, we include station-fixed effects and basin-year fixed effects to control for station-specific characteristics that are constant over time and annual trends that vary across river basins.

4.1 Difference-in-Differences Specification

We first adopt a difference-in-differences model with two-way fixed effects:

$$\ln(BOD_{i,t}) = \alpha + \beta_{DID} Merger_{i,t} + \lambda X_{i,t} + \delta_i + \theta_{b,t} + \varepsilon_{i,t} \tag{1}$$

where the dependent variable, $\ln(BOD_{i,t})$, is a log of BOD at monitoring station i in year t. $Merger_{i,t}$ is an indicator variable that switches on and stays on for all subsequent years when a merger takes place in the municipality associated with station i. $X_{i,t}$ is a vector of time-varying control variables, which include a municipality-level economic indicator and population. Given the "bad control" concerns of a variable of population, which may be affected by municipal mergers, we only include an economic indicator as a control in our baseline specification. We include monitoring station fixed effects (δ_i), which control for time-invariant characteristics of each monitoring station, including positions (downstreamness) along rivers. To account for any secular trends in water quality across years, which may vary across river basins, we include year dummies interacted with indicators for each of the river basins b ($\theta_{b,t}$). Lastly, standard errors are clustered at the municipality level, while we also adopt conservative clustering at the basin level for a robustness check.

The coefficient of particular interest is β_{DID}. If municipal mergers decrease river pollution, as negative externality theory would suggest, then β_{DID} should be negative. On the other hand, β_{DID} could be positive if the negative externality theory does not hold, and high coordination costs and unbalanced political power among pre-merger municipalities cause an increase in river pollution.

Note that we examine a staggered policy: municipal mergers took place in different years. Thus, the estimate of β_{DID} in the regression (1) is a weighted average of all possible two-group/ two-period difference-in-differences estimators (Goodman-Bacon, 2021). In other words, the estimate reflects all possible cases with different definitions of treatment and control groups. One case could be comparing monitoring stations in municipalities that experienced mergers (treatment group) with monitoring stations in municipalities that never experienced mergers (control group). Another case could be comparing monitoring stations in municipalities that experienced mergers in early years (treatment group) with monitoring stations in municipalities that experienced mergers in later years (control group).

The difference-in-differences specification hinges on the parallel trend assumption between treatment and control groups. A simple comparison of the evolution of BOD levels between the treatment and control groups already encouragingly shows signs of parallel pre-trends (Figure 4). To empirically test the parallel trend assumption, we adopt the following event-study specification. This specification also allows us to examine the long-run dynamic impacts of municipal mergers up to 17 years.

$$\ln(BOD_{i,t}) = \alpha + \sum_{\tau=-15}^{17} \beta_\tau Merger_{\tau,i} + \lambda X_{i,t} + \delta_i + \theta_{b,t} + \varepsilon_{i,t} \tag{2}$$

where $Merger_{\tau,i}$ is an indicator for each year τ relative to the municipal merger, where τ is normalized to equal zero in the year that the municipal merger was implemented. τ ranges from -15 to 17 in our sample years. For monitoring stations where municipal mergers did not take place, all $Merger_{\tau,i}$'s are set equal to zero. $\tau = -1$ is set as a reference year.

The β_τ's are the parameters of interest. β_τ's should be around zero and statistically insignificant from $\tau = -15$ to $\tau = -2$ to satisfy parallel pre-trends. After $\tau = 0$, β_τ's capture the dynamic treatment effects in the short and long runs.

Recent literature indicates that, in the case of staggered difference-in-differences designs where treatment effects vary over time, standard two-way fixed effect regression estimates and event study estimates are subject to bias. As mentioned above, two-way fixed effect estimates are weighted averages of all possible two-group/ two-period difference-in-differences estimators. However, comparisons between the early merger group (as a control group) and the late merger group (as a treatment group) becomes problematic if treatment effects vary over time, i.e., when we have a trend break rather than a level shift. This comparison leads to bias from negative weights (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). To overcome this issue and obtain unbiased estimates, we apply an alternative estimator of Callaway and Sant'Anna (2021) that is robust to negative weights as the baseline specification throughout this paper.[6] We present the results of Callaway and Sant'Anna (2021) estimator together with the results of two-way-fixed effects specification of the regressions (1) and (2).

Finally, the baseline specification includes a comparison between never-merged municipalities and merged municipalities, where selection bias can be an issue. Given that the primary purpose of municipal mergers is the improvement of local finance and any local public service provision, the selection bias is perhaps not a large concern in this setting. However, as a robustness check, we run the same regressions (1) and (2) by restricting our sample to monitoring stations in municipalities that experience mergers and by considering municipalities that merge early as treatment group and municipalities that merge later as a control group. These municipalities should be more similar and balanced in characteristics because both groups experienced municipal mergers, which are less susceptible to the concern of selection bias. We show that the results are robust to this specification in Section 5.1.

[6] We also adopt estimator of Sun and Abraham (2021) as a robustness check, which leads to the same results as a Callaway and Sant'Anna (2021) estimator and two-way fixed effects specification (Appendix Figure A3).

4.2 River Distance Specification

To formally test the negative externality theory predictions, we investigate spatial patterns of pollution using the following specification:

$$\ln(BOD_{i,t}) = \alpha + \eta_1 \cdot Downstream_{i,t} + \eta_2 \cdot Downstream^2_{i,t} + \lambda X_{i,t} + \delta_i + \theta_{b,t} + \varepsilon_{i,t} \quad (3)$$

We first obtain distances along the river from monitoring station i to its closest upstream municipality border in year t ($U_{i,t}$), and to its closest downstream municipality border ($D_{i,t}$), as outlined in Section 3. We then construct a variable $Downstream_{i,t} = U_{i,t}/(U_{i,t} + D_{i,t})$. $Downstream_{i,t}$ takes a value between 0 and 1, and measures the relative "downstreamness" of a monitoring station within its municipality. The closer the value is to 1, the more downstream a station is within its municipality. As before, $X_{i,t}$ is a vector of control variables consisting of municipality-level GDP and population. Likewise, δ_i and $\theta_{b,t}$ are station fixed effects and basin-year fixed effects respectively. Standard errors are clustered by station.

The coefficients of prime interest here are η_1 and η_2. Negative externality theory predicts that pollution rises at an increasing rate as we go downstream along a municipality, as illustrated in Appendix Figure A1. In such a case, the first and second derivatives with respect to "downstreamness" would both be positive, and we expect a convex relationship with $\eta_1 > 0$ and $\eta_2 > 0$.

A specification following Lipscomb and Mobarak (2016) is also considered:

$$\ln(BOD_{i,t}) = \alpha + \gamma_1 \cdot U_{i,t} + \gamma_2 \cdot U^2_{i,t} + \gamma_3 \cdot D_{i,t} + \gamma_4 \cdot D^2_{i,t} + \lambda X_{i,t} + \delta_i + \theta_{b,t} + \varepsilon_{i,t} \quad (4)$$

where the variables are as explained above. According to negative externality theory, pollution should increase exponentially as the distance from the downstream border gets smaller (i.e., the further downstream within the municipality), so we expect $\gamma_3 < 0$ and $\gamma_4 > 0$. Also, the existence of a structural break in the pollution function at the municipality border implies that γ_1 should be different from γ_3 (Lipscomb and Mobarak, 2016).

5 Results

5.1 Difference-in-Differences Specification

The results of the difference-in-differences specification are reported in Table 2. Panel A uses the Callaway & Sant'Anna estimator, and it is our preferred specification. The results for standard two-way fixed effect analyses are provided for reference in Panel B. Looking at our baseline specification (Column 1) for Panel A, we find that municipal mergers do not improve water quality but rather increase water pollution on average by around 5.7%. The estimates are statistically significant at 1% level. This is in stark contrast to what the negative externality theory and results of Lipscomb and Mobarak (2016) would suggest. The results are robust to more conservative clustering at the basin level (Column 2). They are also robust when we include population in the regression, although population can be "bad control" that is affected by the treatment (Column 3).

The result of the event study specification, using the Callaway and Sant'Anna (2021) estimator, is shown in Figure 5. The estimates for pre-merger years are largely insignificant, which suggests that parallel pre-trends hold. After period 0, which corresponds to the beginning of municipal mergers, statistically significant impacts of increased water pollution are observed. The point estimates increase over time and remain statistically significant for about 15 years, which suggests that the negative impacts on water quality exacerbate in short to medium run after the merger. The point estimates decrease slightly and become statistically insignificant after 15 years, which could suggest that the increase in pollution is being mitigated in the long term. However, it should be noted that estimates become imprecise over time with larger standard errors. These results are due to the smaller sample sizes in the later periods, which reflects the impacts of water monitoring stations that experience mergers earlier.

These results are robust to various specifications. First, the results are robust to alternative estimators (Appendix Figure A3) and alternative sample periods (Appendix Figure

A4). Second, to address the concern of selection bias, we conduct the same analysis only on the sample of municipalities that experience mergers over the sample period. An event study plot (Appendix Figure A2) also points to increasing water pollution due to municipal mergers over time, especially 6 years after municipal mergers. Difference-in-differences results in Appendix Table B1 do not show statistically significant effects of increased pollution, probably because of the shorter periods covered in this specification than in the baseline specification. However, the sign of the coefficients remains positive as in the baseline specification (Columns 1-2).

5.2 River Distance Specification

Table 3 reports the results of the spatial analysis that uses the changes in river distances between monitoring stations and municipality borders. First, the results on the relative downstreamness (regression (3)) are provided in Columns 3 and 4. The coefficients on both downstream indicator and its squared term are both statistically insignificant. Also, the sign of the coefficient for the downstream indicator is positive, which is contrary to the prediction by the negative externality theory.

Second, results for the Lipscomb and Mobarak (2016) specification (regression (4)) in Columns 1 and 2 are not supportive of the negative externality channel either. In our preferred specification with basin-year fixed effects (Column 2), the coefficient of D is again positive and not statistically significant. Furthermore, we cannot reject the equality of the coefficients of U and D when we test the structural break in the pollution function at the municipality border.

In sum, the negative externality channel of Lipscomb and Mobarak (2016) does not hold true in the case of municipal mergers in Japan. This may be partly due to differences between developing/emerging countries (Lipscomb and Mobarak, 2016) and developed countries like Japan. In a developed country case, it may be more difficult or costly to relocate polluting sources (to internalize any externality) after municipal mergers, where for instance, property rights are more rigid, and there is a less available land area for relocation. Null impacts of municipal mergers on land in Section 6.4 are consistent with this explanation.

6 Mechanisms

We find that municipal mergers had negative impacts on water quality and that the negative externality channel is not relevant in our setting. These negative impacts of municipal mergers can be caused by the following two potential mechanisms.

First, municipal mergers can weaken pollution control on existing pollution sources, such as industrial wastewater from existing factories and domestic wastewater from existing sewage treatment plants, at the *intensive* margin. A failure to coordinate effectively (coordination cost channel), or neglect of small, incorporated areas after municipal mergers (political economy channel), could weaken pollution control on these existing sources. We investigate the evidence of this *intensive* margin channel by analyzing the heterogeneous effects of municipal mergers, as well as examining the change in pollution control in sewage treatment plants.

Second, municipal mergers can increase economic activities, as Egger et al. (2018) showed, which could worsen pollution as a result of new emitting sources along rivers, i.e., an increase in pollution at the *extensive* margin. This may, for instance, involve turning forest areas near rivers into industrial and residential areas, which would lead to increases in water pollution from industrial and domestic wastewater. We test this *extensive* margin channel by examining the impacts of municipal mergers on land use patterns.

6.1 Coordination Costs

We test the coordination cost channel by comparing the case of "equal-footing" mergers which entail higher coordination costs, with "incorporating" mergers which have lower coordination costs. We expect that "equal-footing" mergers result in larger water pollution because of higher coordination costs. We estimate the impacts of "equal-footing" mergers by the regression (1) after only keeping the municipalities that have experienced "equal-footing" and never treated municipalities. The same procedure is repeated for the case of "incorporating" mergers.

Columns 1 and 2 in Table 4 reports the impacts of municipal mergers of both types. We find a statistically significant negative impact in the case of "equal-footing" mergers (Column 1). On the other hand, the impact becomes less substantial in the case of "incorporating" mergers (Column 2). The effect is statistically significant only at 10% level, and the magnitude of the effect is reduced to 4.6%. As we have expected, the negative impacts are more substantial in the case of "equal-footing" mergers, which entail higher coordination costs among pre-merger municipalities.

6.2 Political Economy

We also test the political economy channel by comparing the change in water quality of incorporating municipalities with that of incorporated municipalities. We expect that incorporated municipalities experience larger water pollution due to neglect by a mayor originally from the incorporating municipality. We estimate the impacts of municipal mergers in incorporating municipalities by the regression (1) after only keeping the incorporating municipalities and never-treated municipalities. The same procedure is repeated for the case of incorporated municipalities.

Columns 3 and 4 in Table 4 report the results. Incorporated municipalities experience a larger increase in water pollution by about 9%, and this result is statistically significant at 1% level (Column 3). On the other hand, we find no effect for the incorporating municipalities (Column 4). This difference in results aligns with the argument of the political economy channel where incorporated municipalities incur negative effects.

6.3 Weaker Control of Existing Pollution Sources

In the coordination cost and political channels, we show that municipal mergers can weaken water pollution control. Concretely, this could take the form of insufficient treatment of domestic wastewater in sewage treatment plants and industrial wastewater in factories, which are under the responsibility of municipalities (Section 2.2). In an effort to explicitly test the change in pollution control, we examine the change in the quality of treatment of domestic wastewater at sewage treatment plants.

Treated wastewater from sewage treatment plants is discharged into rivers. Hence, if merged municipalities reduce their efforts to treat wastewater, water quality in rivers may deteriorate. This weaker pollution control can occur in the form of delaying the renewal of aging sewage treatment plants, which can inhibit sufficient wastewater treatment at these plants.[7]

To test this possibility, we compute the BOD values of effluent and influent[8] of sewage treatment plants from 1996 to 2017 in Japan. We use the Sewage Statistics compiled by the Japan Sewage Works Association and aggregate plant-level data into municipality-level data by computing the mean of BOD values. In this analysis, we adopt the difference-in-differences specification that is similar to the baseline specification in Section 4.1, although we include municipality fixed effects and cluster the standard errors at the municipality level.

Appendix Table B3 and Appendix Figure A6 report the results of this analysis. We do not find statistically significant impacts of municipal mergers on effluent water quality, which suggest that pollution control efforts are not weakened by delaying renewal. The placebo check, which looks at the impact on influent water quality, also shows null effects as expected. These null results of sewage treatment plants suggest that municipal mergers may cause weaker pollution control on other pollution sources, i.e., either industrial wastewater or

[7] The aging of sewage treatment plants is a growing issue in Japan. More than 80% of sewage treatment plants have been operating for 15 years since their inception and need to be renewed to maintain the quality of wastewater treatment.

[8] Effluent is wastewater flowing out of a sewage treatment plant, while influent is wastewater entering a sewage treatment plant.

agricultural wastewater. However, as discussed in 2.2, agricultural wastewater is a non-point source that is difficult to be controlled by the municipality's policy.

Hence, the results from this analysis on sewage treatment plants, combined with the characteristics of agricultural wastewater as well as the relevance of the coordination cost and political economy channels, offer indirect and suggestive evidence that the most likely source of weaker pollution control is industrial wastewater.

6.4 New Pollution Sources Due to Change in Land Use

We examine the impact of municipal mergers on land use patterns. This analysis is based on the 100-meter raster data of land use in 1991, 1997, 2006, 2009, 2014, and 2016 from the dataset of the Ministry of Land, Infrastructure, Transport, and Tourism. We focus on the land use pattern within the 150-meter buffer from each monitoring station. Land use is categorized into 4 classifications: agriculture, forest, built-up, and non-use. Then, we construct the share of each land use classification and the binary indicator of which land use classification is major for each monitoring station.[9]

Based on the constructed dataset on the shares and binary indicators of 4 land use classifications over 6 periods, we adopt the same difference-in-differences approach as the baseline specification in section 4.1. In this case, the panel data does not cover consecutive years, so we cannot use the Callaway and Sant'Anna (2021) estimator, which requires a balanced panel with consecutive years. Thus, we use the two-way fixed effects specification and Sun and Abraham (2021) estimator.

As shown in Appendix Table B2 and Appendix Figure A5, we do not find statistically significant impacts of municipal mergers on land use patterns (agriculture, built-up, forest and non-use). Thus, the water pollution induced by municipal mergers cannot be explained by this extensive margin channel.

[9] Detailed steps are written in the Appendix C.6.

7 Conclusion

We examine the environmental impacts of municipal mergers, where two or more municipalities combine to form one municipality. Although municipal mergers can facilitate the internalization of pollution spillovers across municipalities, we find that municipal mergers aggravate water pollution.

To document this negative environmental impact, we examine the case of Japan's large-scale municipal mergers in the late 1990s to 2000s, which drastically reduced the number of municipalities by about 50%. Based on 30-year water quality data on more than 3,000 monitoring stations and detailed information on municipal mergers, we investigate the long-run impacts of municipal mergers on water quality.

We adopt two main identification strategies. First, we use variations in the occurrence and timings of municipal mergers to adopt the difference-and-differences and event study specifications. Because simple two-way-fixed effects specification is susceptible to bias in estimates due to negative weights, we also adopt alternative estimators that are robust to this bias. Second, we use the Lipscomb and Mobarak (2016) specification, which directly tests pollution spillovers along rivers based on the negative externality theory. Specifically, we use the change in distances from monitoring stations to their closest upstream and downstream municipality borders along rivers.

Strikingly, we find that municipal mergers increase river pollution by around 6 percent, and this negative effect persists for about 15 years. We also find no evidence of negative externality theory in the river distance specification.

To answer why pollution increased due to municipal mergers, we investigate heterogeneous effects by merger types and involved municipalities. We find that pollution increases in "equal-footing" mergers with higher coordination costs but not so much in "incorporating" mergers with lower coordination costs. We further show that in the case of "incorporating" mergers, incorporated municipalities experience a larger increase in water pollution than incorporating municipalities, whose political power is higher because a mayor there continues to hold the same position after municipal mergers. These results suggest that pollution control becomes weaker due to coordination costs and political economy channels. We specifically investigate the possibility of weaker pollution control in the case of wastewater treatment in sewage treatment plants. The null result of this analysis indirectly suggests that the river pollution may be a result of weaker pollution control on industrial wastewater, which is another major source of wastewater that can be controlled by municipalities.

Our results have several implications for policy and research direction on municipal mergers. First, while proponents emphasize positive impacts on macroeconomic outcomes such as local public finance, municipal mergers can have unintended negative impacts on environmental outcomes. These negative effects should be carefully considered in the cost-benefit analysis of future municipal mergers.

Second, the negative externality narrative of river pollution may not be as relevant in a developed country's case of municipal mergers as in a developing country's case of splits in municipalities. Our results point to the relative significance of coordination cost and political economy channels in the case of Japan. Conducting careful pre-analysis of likely relevant channels and designing relevant countermeasures on a country-by-country basis would be important in mitigating any negative impacts of municipal mergers on water quality. Investigating why the relative importance of each channel differs between developed and developing countries may be an interesting area for future research.

Finally, the negative effects we observed can be similarly present in other policies managed by municipalities, including educational investment and healthcare. The coordination cost and political economy channels can play a role in weakening the implementation of these policies. This may be a topic that will be examined in future studies.

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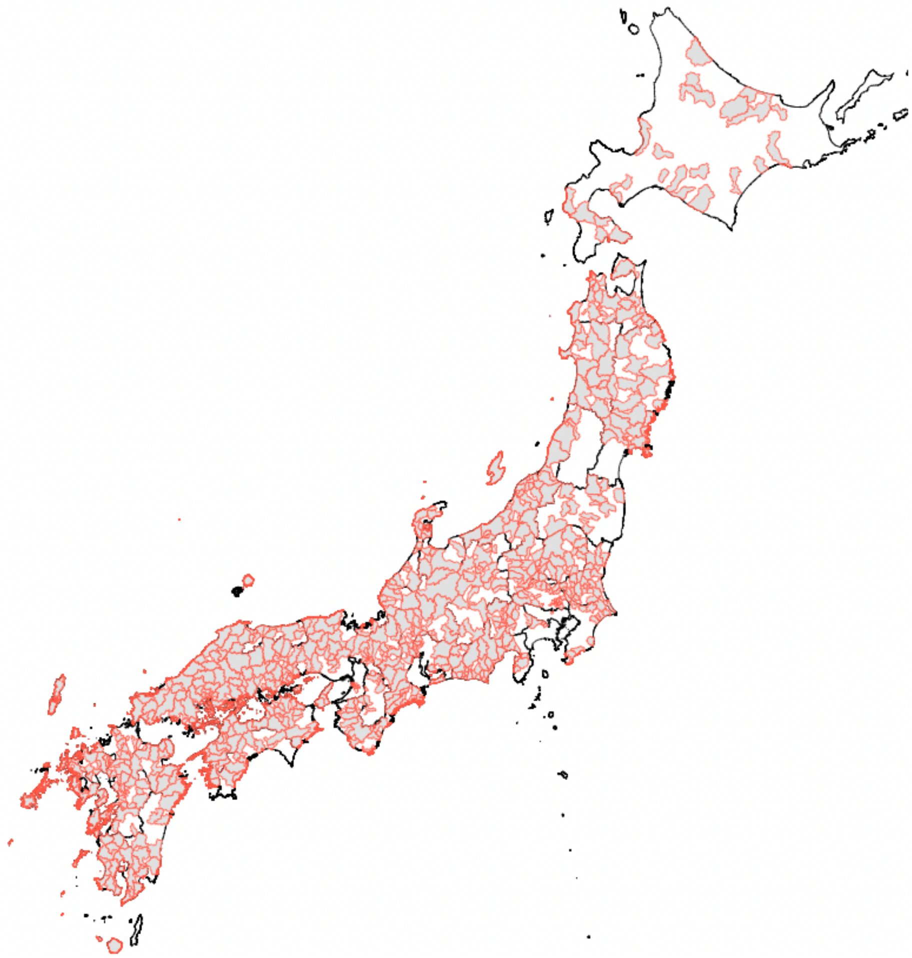

Figure 1: Locations of Municipal Mergers in Japan

Notes: This figure shows the boundaries of municipalities that experienced municipal mergers (red lines surrounding grey areas) and the boundaries of prefectures in Japan (in black).

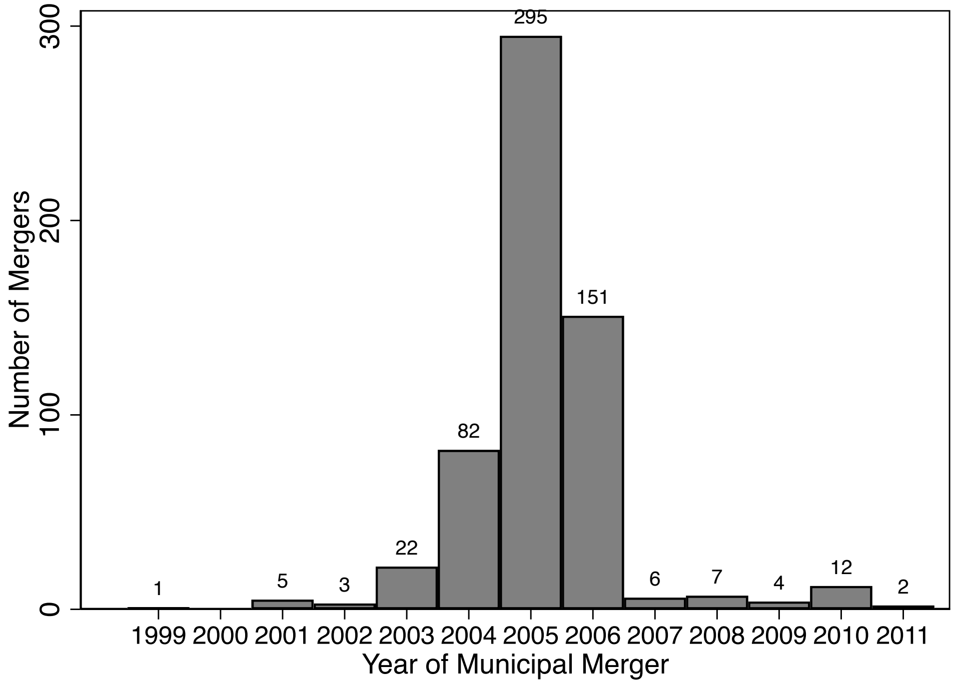

Figure 2: Timing of Municipal Mergers in Japan

Notes: This figure shows the number of municipal mergers by year in Japan based on the merger data of the Ministry of Internal Affairs and Communications. In our analysis, we only use variation of merger years from 2001 to 2011 based on our sample of municipalities along rivers.

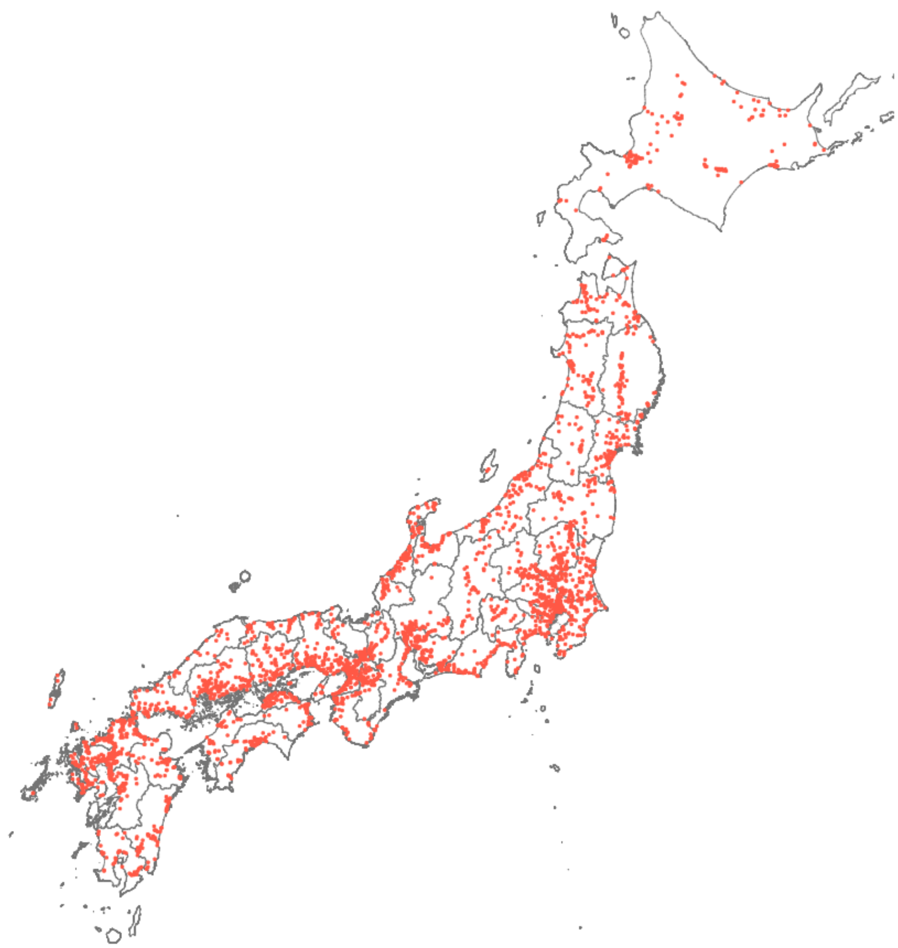

Figure 3: Locations of Water Quality Monitoring Stations in Japan

Notes: This figure shows the locations of water quality monitoring stations (in red) that are included in our sample along rivers based on the data of the Ministry of Environment. Boundaries of prefectures in Japan are also shown (in black).

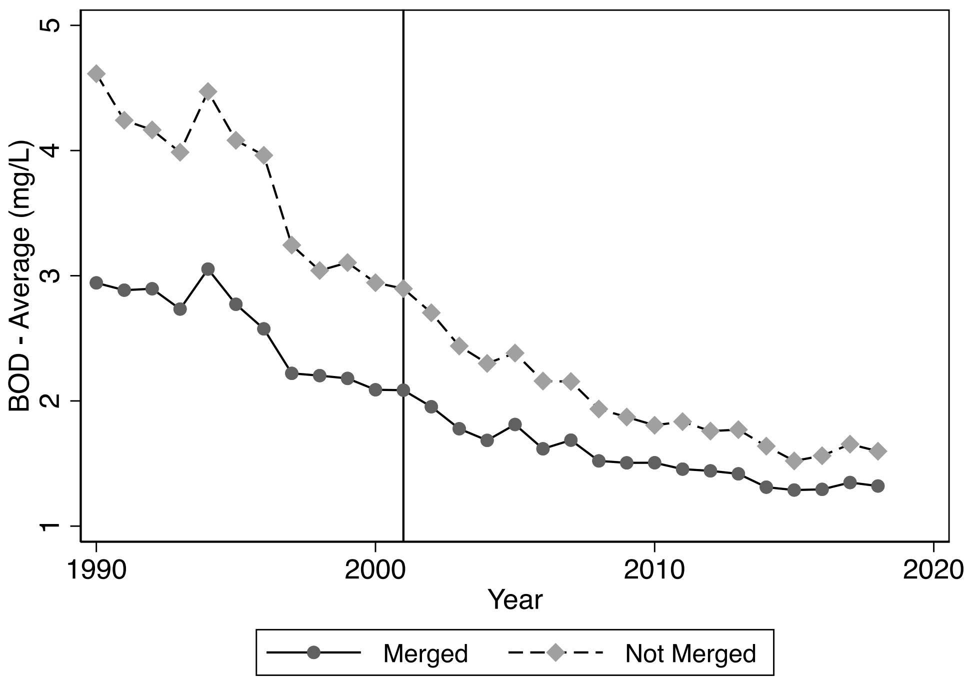

Figure 4: Trends of BOD level in Treatment and Control groups

Notes: This figure compares the changes in average BOD values (mg/L) from 1990 to 2018 between the municipalities which experienced municipal mergers (Merged) and the municipalities which did not experience the mergers (Not Merged). The vertical in 2001 shows the year when the first municipal mergers took place in our sample.

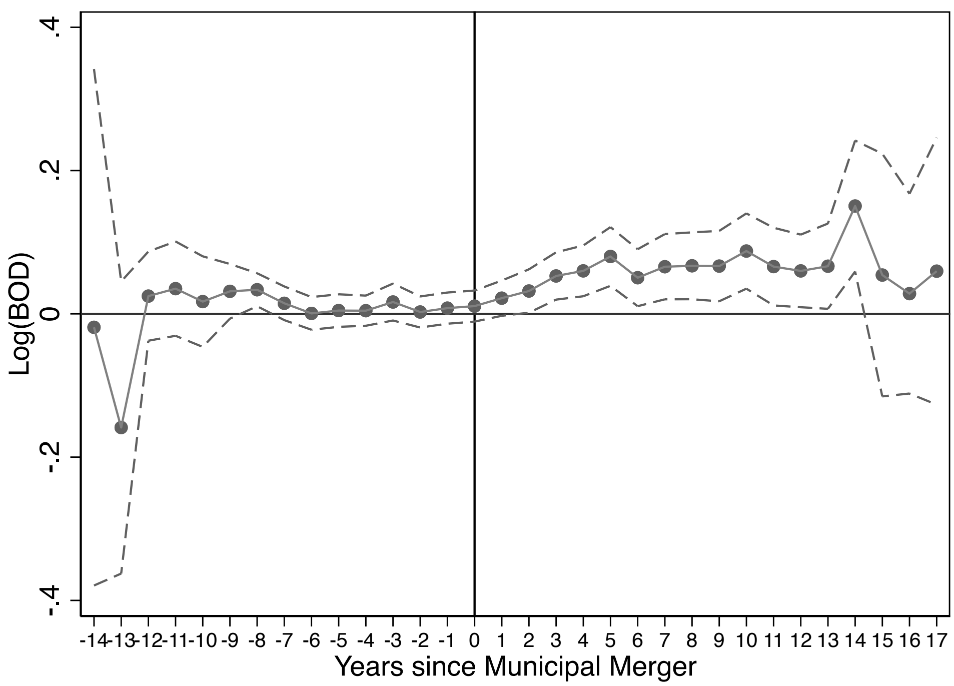

Figure 5: The Dynamic Impact of Municipal Mergers on Water Pollution

Notes: This figure shows the coefficients of the estimators according to the Callaway and Sant'Anna (2021) methodology. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. This specification includes monitoring station fixed effects, year fixed effects, and product shipment values as a control.

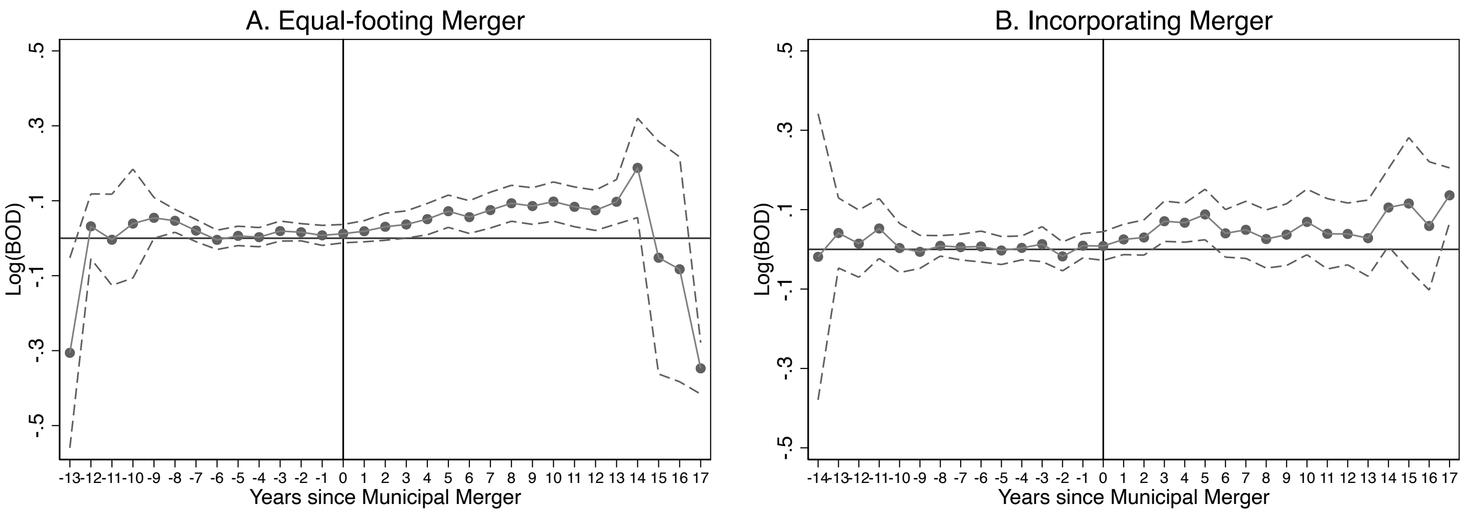

Figure 6: Mechanism on Coordination Cost: Event Study Results

Notes: These figures show the coefficients of the estimators according to the Callaway and Sant'Anna (2021) methodology. Panel A shows the impacts of equal-footing mergers based on the data of these municipalities and never-merged municipalities, while Panel B similarly shows the impacts of incorporating mergers. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. All specifications include monitoring station fixed effects, year fixed effects, and product shipment values as a control.

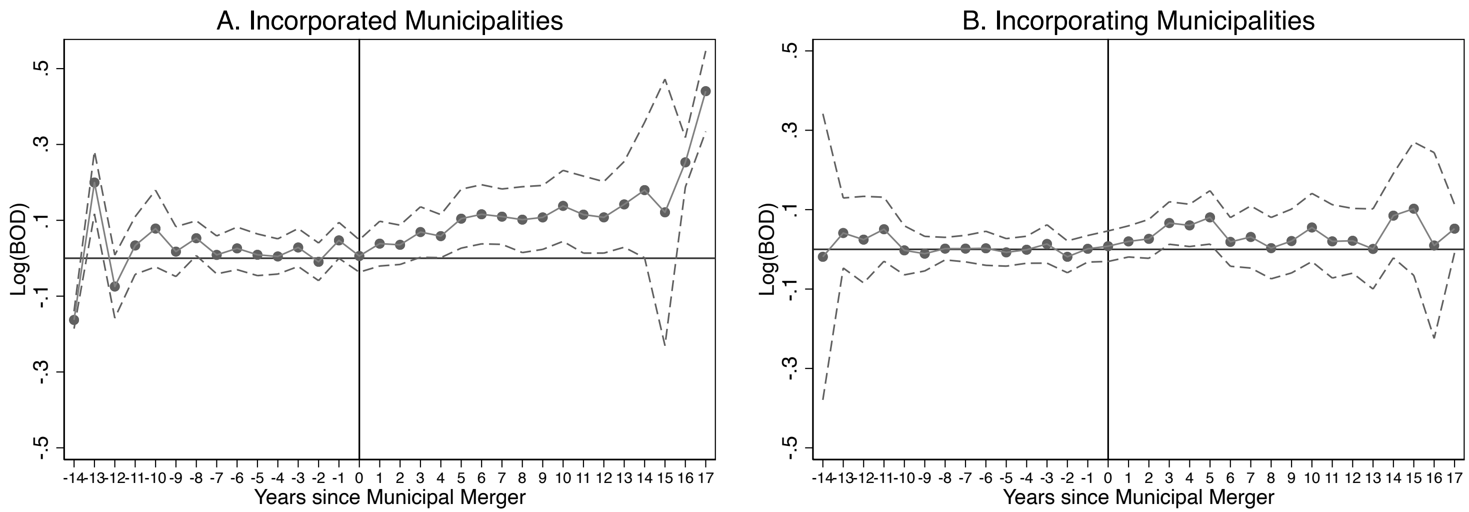

Figure 7: Mechanism on Political Economy: Event Study Results

Notes: These figures show the coefficients of the estimators according to the Callaway and Sant'Anna (2021) methodology. Panel A shows the impacts of mergers in incorporated municipalities based on the data of these municipalities and never-merged municipalities, while Panel B similarly shows the impacts of mergers in incorporating municipalities. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. All specifications include monitoring station fixed effects, year fixed effects, and product shipment values as a control.

Table 1: Summary Statistics

Variable	Means: Not Merged	Means: Merged	Difference	Obs.
Panel A. 1990-2000				
BOD - Yearly average (mg/l)	3.805	2.595	-1.210***	35,706
	(5.172)	(4.956)	(0.264)	
Distance from upstream border to station (km)	4.402	4.161	-0.241	7,700
	(4.741)	(4.899)	(0.461)	
Distance from station to downstream border (km)	3.518	3.914	0.396	7,700
	(4.174)	(4.287)	(0.429)	
Downstream indicator (0-1)	0.554	0.533	-0.021	7,700
	(0.278)	(0.272)	(0.022)	
Product shipment values (100 billion JPY)	2.553	2.974	0.421***	10,461
	(6.197)	(5.775)	(0.117)	
Population (thousand)	100.124	111.504	11.380***	10,285
	(268.369)	(156.001)	(4.366)	
Major land use around stations: Agriculture (0/1)	0.382	0.455	0.072***	10,804
	(0.486)	(0.498)	(0.026)	
Major land use around stations: Forest (0/1)	0.139	0.227	0.088***	10,804
	(0.346)	(0.419)	(0.020)	
Major land use around stations: Buildup (0/1)	0.458	0.311	-0.147***	10,804
	(0.498)	(0.463)	(0.031)	
BOD - Effluent from Sewage Treatment Plants (mg/l)	5.426	7.537	2.111	1,084
	(3.228)	(34.439)	(1.753)	
Panel B. 2001-2018				
BOD - Yearly average (mg/l)	1.999	1.557	-0.442***	58,428
	(2.095)	(1.700)	(0.098)	
Distance from upstream border to station (km)	4.402	6.053	1.651**	10,500
	(4.741)	(8.252)	(0.775)	
Distance from station to downstream border (km)	3.518	5.668	2.149***	10,500
	(4.174)	(7.622)	(0.679)	
Downstream indicator (0-1)	0.554	0.531	-0.023	10,500
	(0.278)	(0.261)	(0.021)	
Product shipment values (100 billion JPY)	2.209	3.066	0.857***	17,118
	(4.963)	(7.284)	(0.095)	
Population (thousand)	104.229	110.711	6.482	14,025
	(285.869)	(161.852)	(3.958)	
Major land use around stations: Agriculture (0/1)	0.266	0.332	0.066***	10,974
	(0.442)	(0.471)	(0.025)	
Major land use around stations: Forest (0/1)	0.132	0.217	0.085***	10,974
	(0.338)	(0.412)	(0.019)	
Major land use around stations: Buildup (0/1)	0.587	0.442	-0.145***	10,974
	(0.492)	(0.497)	(0.031)	
BOD - Effluent from Sewage Treatment Plants (mg/l)	4.120	3.716	-0.404***	4,607
	(3.032)	(3.477)	(0.102)	

Notes: Panel A compares the summary statistics between merged municipalities and non-merged municipalities before municipal mergers started in our sample (before 2001), while Panel B compares the summary statistics since 2001 when the first mergers were observed in our data. The unit of observations of product shipment value, population, and BOD of effluent is the municipality, but it is the station for other variables. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors of differences are clustered at the municipality level when the unit of observations is the station.

Table 2: DID Results - The Impact on Water Quality

	Log(BOD)		
	(1)	(2)	(3)
Panel A: Callaway & Sant'Anna (2021) Estimator			
Merger (= 1)	0.057***	0.057***	0.050***
	(0.018)	(0.018)	(0.016)
Panel B: Two-way Fixed Effects			
Merger (= 1)	0.040**	0.040	0.036**
	(0.018)	(0.024)	(0.017)
Observations	74,037	74,037	63,460
R^2	0.881	0.881	0.889
Number of Stations	3,219	3,219	3,173
Number of Municipalities	936	936	920
Clustered SE at...	Municipality	Basin	Municipality
Station FE	YES	YES	YES
Product Shipment Values	YES	YES	YES
Population	NO	NO	YES
Mean of Dep. Variable	2.659	2.659	2.619

Notes: The coefficients are reported. Standard errors are in parentheses and clustered at the municipality level in Columns 1 and 3 and basin-level in Column 2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All specifications in Panel A include year fixed effects, while all regressions in Panel B include basin-year fixed effects. Mean dependent variables are the mean of BOD values before municipal mergers started in our sample (before 2001) in each specification.

Table 3: Results of River Distance Specification

	Log(BOD)			
	(1)	(2)	(3)	(4)
Distance from upstream border to station (U)	0.010***	0.004		
	(0.003)	(0.003)		
Squared distance from upstream bortder to station (U^2)	-0.000**	-0.000		
	(0.000)	(0.000)		
Distance from station to downstream border (D)	0.002	-0.003		
	(0.004)	(0.005)		
Squared distance from station to downstream border (D^2)	0.000	0.000		
	(0.000)	(0.000)		
Downstream indicator ($U/(U+D)$)			-0.191	-0.215
			(0.230)	(0.225)
Squared downstream indicator ($(U/(U+D))^2$)			0.273	0.334
			(0.212)	(0.224)
Observations	14,000	13,360	14,000	13,360
R^2	0.876	0.915	0.875	0.915
Number of Stations	700	668	700	668
Number of Municipalities	700	668	700	668
Year FE	YES	NO	YES	NO
Basin-Year FE	NO	YES	NO	YES
Station FE	YES	YES	YES	YES
Product Shipment Values	YES	YES	YES	YES
Population	YES	YES	YES	YES
F-stat for U = D	1.631	1.578	-	-
p-value for U = D	0.202	0.209	-	-
Mean of Dep. Variable	2.365	2.401	2.365	2.401

Notes: The coefficients are reported. Standard errors, clustered at station level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Mean dependent variables are the mean of BOD values before municipal mergers started in our sample (before 2001) in each specification.

Table 4: DID Results: Mechanisms on Coordination Cost and Political Economy

	Coordination Cost		Political Economy	
	(1) Equal-footing	(2) Incorporating	(3) Incorporated	(4) Incorporating
Panel A: Callaway & Sant'Anna (2021) Estimator				
Merger (= 1)	0.063***	0.046*	0.091***	0.033
	(0.019)	(0.027)	(0.034)	(0.028)
Panel B: Two-way Fixed Effects				
Merger (= 1)	0.069***	0.006	0.103***	-0.019
	(0.022)	(0.026)	(0.028)	(0.028)
Observations	54,579	48,139	32,568	44,988
R^2	0.885	0.886	0.891	0.887
Number of Stations	2,373	2,093	1,416	1,956
Number of Municipalities	813	598	541	593
Clustered SE at...	Municipality	Municipality	Municipality	Municipality
Station FE	YES	YES	YES	YES
Product Shipment Values	YES	YES	YES	YES
Population	NO	NO	NO	NO
Mean of Dep. Variable	2.671	3.033	3.130	3.144

Notes: The coefficients are reported. Standard errors, clustered at the municipality level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All specifications in Panel A include year fixed effects, while all regressions in Panel B include basin-year fixed effects. Mean dependent variables are the mean of BOD values before municipal mergers started in our sample (before 2001) in each specification.

Appendix

Impact of Municipal Mergers on Pollution Control:
Evidence from Water Quality Change in Japan

Kazuki Motohashi   Michiyoshi Toya

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A Additional Figures

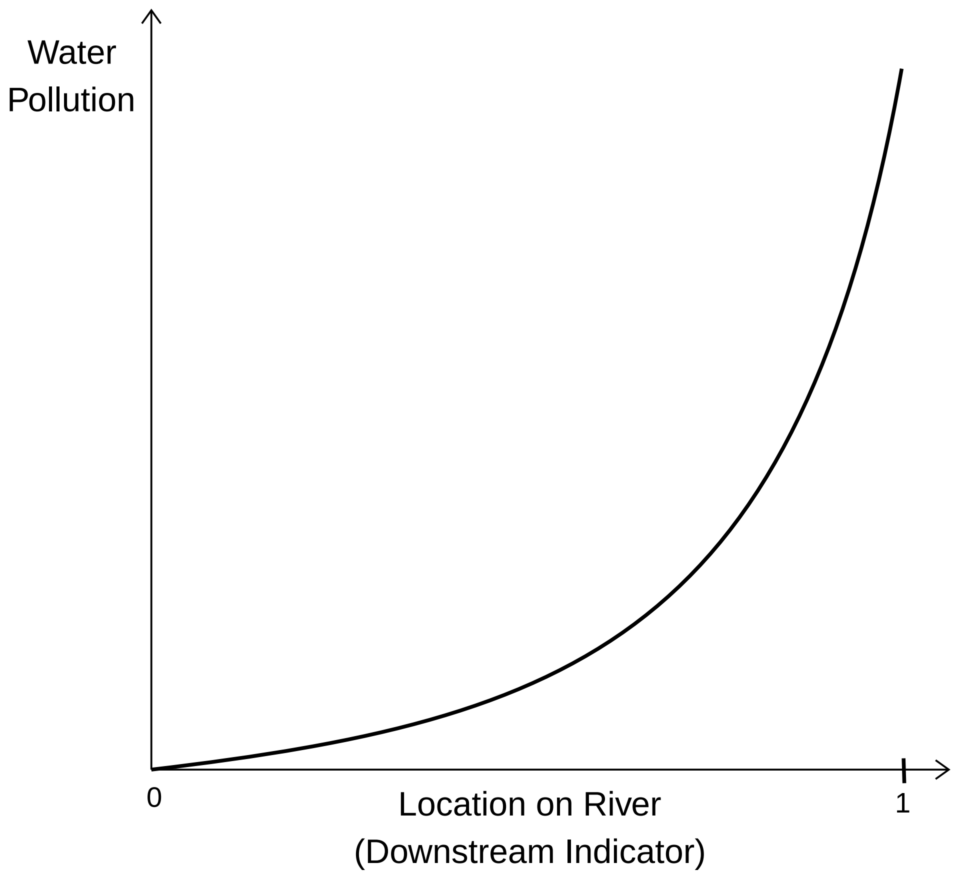

Figure A1: Prediction of Negative Externality Theory

Notes: This figure shows a convex relationship between a downstream indicator and water pollution implied by the negative externality theory of Lipscomb and Mobarak (2016).

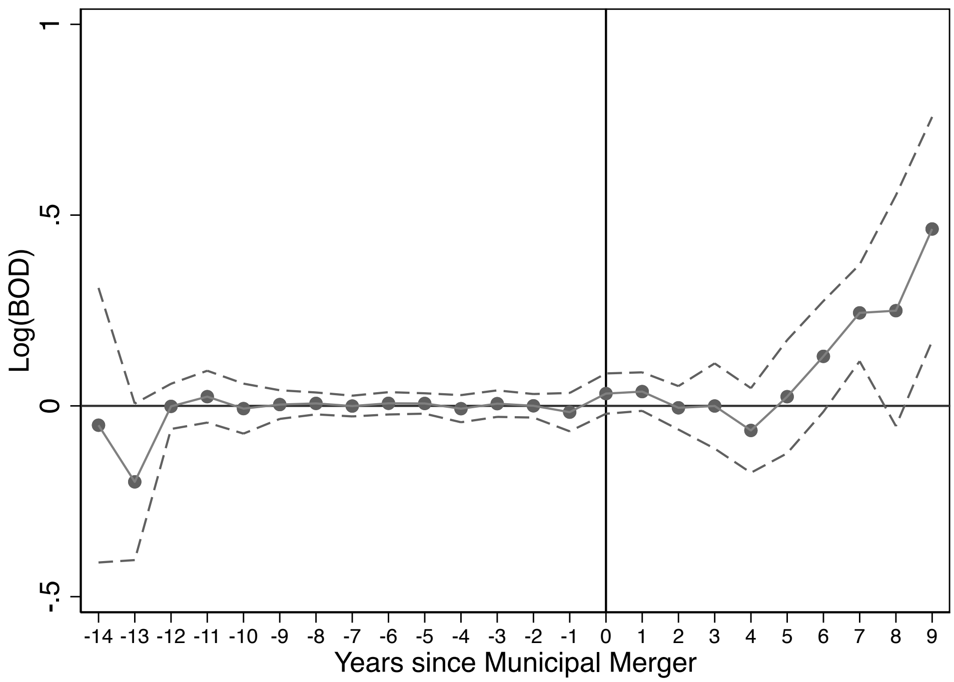

Figure A2: Event Study Results (Early Mergers versus Late Merger)

Notes: The sample is limited to monitoring stations in municipalities that have experienced mergers. (We drop monitoring stations in municipalities that have never merged.) This figure shows coefficients of estimators according to the Callaway and Sant'Anna (2021) methodology. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. This specification includes monitoring station fixed effects, year fixed effects, and product shipment values as a control.

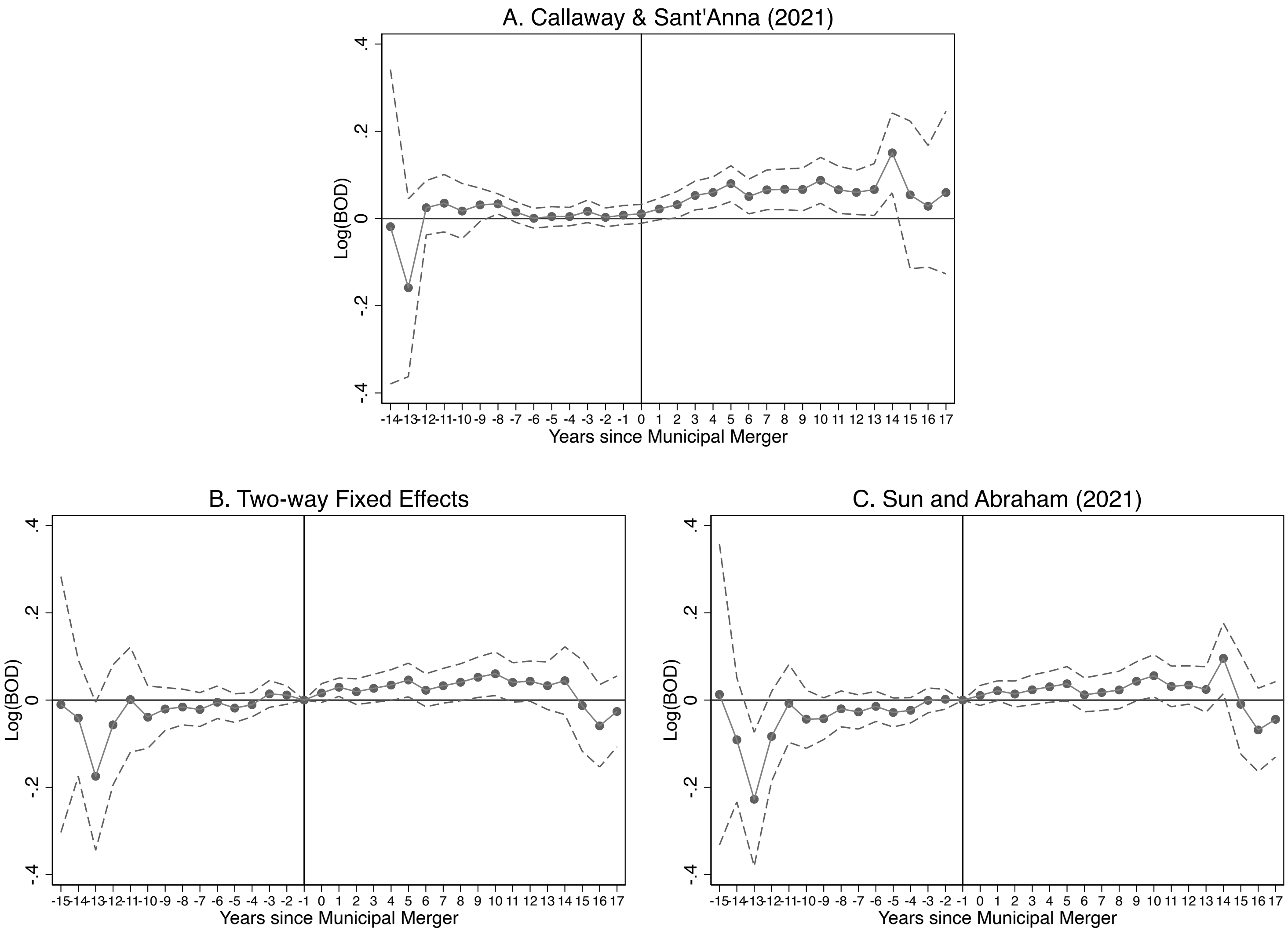

Figure A3: Event Study Results with Alternative Estimators

Notes: These figures compare the event study results among 3 alternative estimators. Panels A, B, and C show the coefficients of the estimators according to the Callaway and Sant'Anna (2021) methodology, two-way fixed effects specification, and the Sun and Abraham (2021) methodology, respectively. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. Panel A includes monitoring station fixed effects, year fixed effects, and product shipment values as a control, while Panels B and C include monitoring station fixed effects, basin-year fixed effects, and product shipment values as a control.

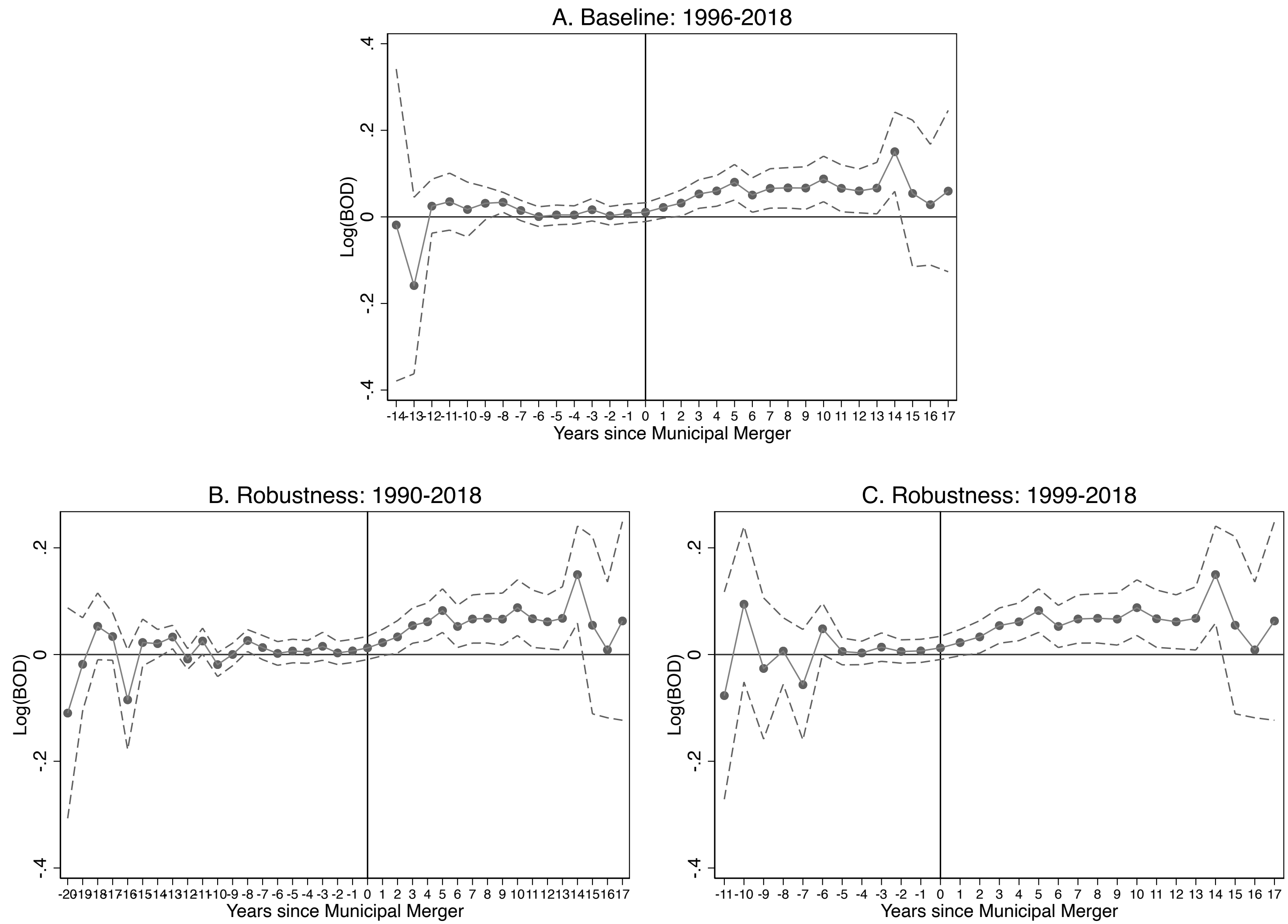

Figure A4: Event Study Results with Alternative Sample Periods

Notes: These figures show the coefficients of the estimators according to the Callaway and Sant'Anna (2021) methodology. Panel A is the baseline specification when the sample years are 1996-2018, while Panels B and C are shown for robustness checks when the sample years are 1990-2018 and 1999-2018, respectively. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. All specifications include monitoring station fixed effects, year fixed effects, and product shipment values as a control.

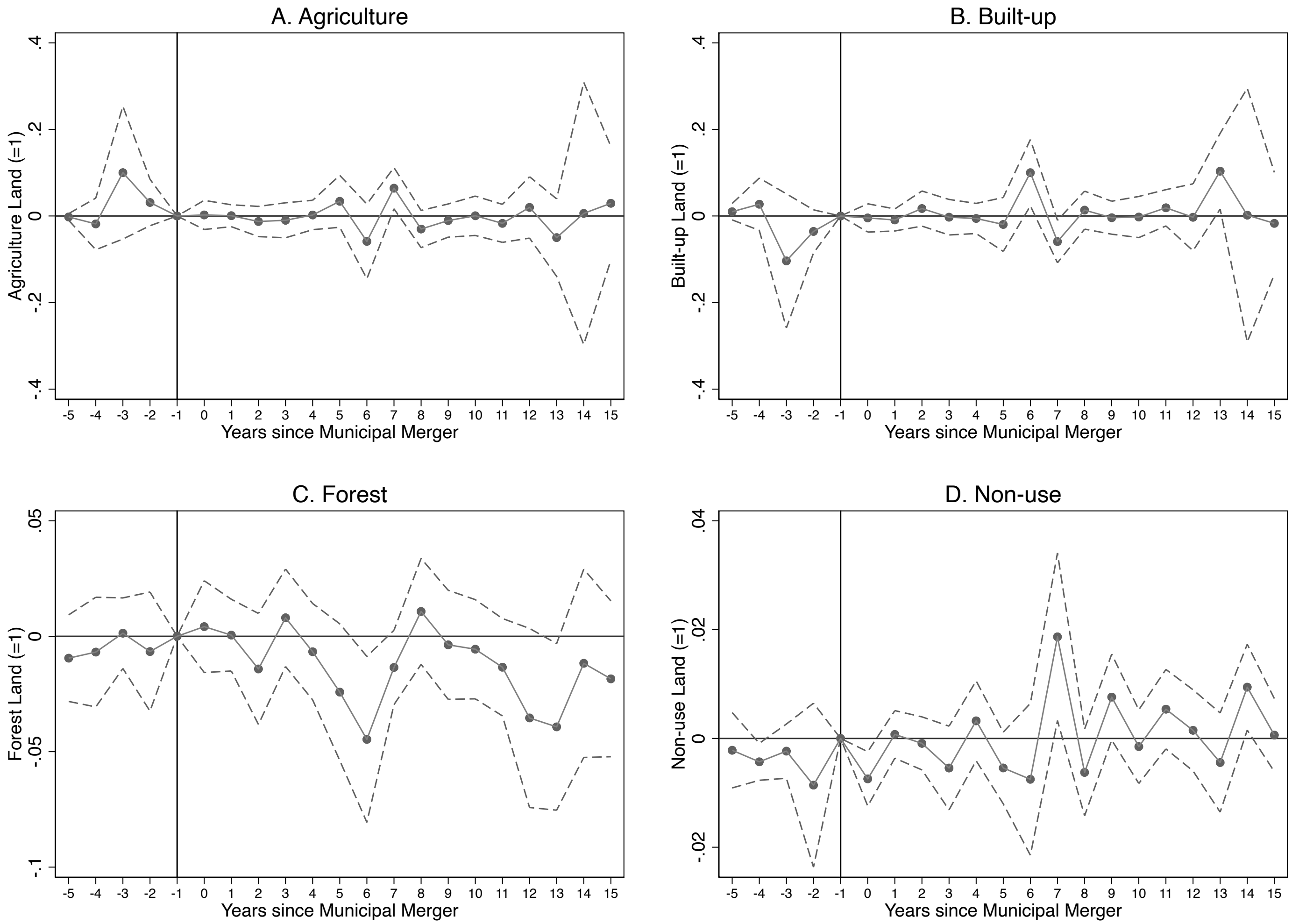

Figure A5: Event Study Results: Change in Land Use

Notes: These figures show the coefficients of the estimators according to the Sun and Abraham (2021) methodology. Four panels show results when the dependent variables are the indicator which takes one if the majority of land use within 150 meters from monitoring stations is the corresponding type. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the municipality level. All specifications include monitoring station fixed effects, basin-year fixed effects, and product shipment values as a control. The coefficients of event time from -4 to -12 are not shown because most of them are dropped in the regressions.

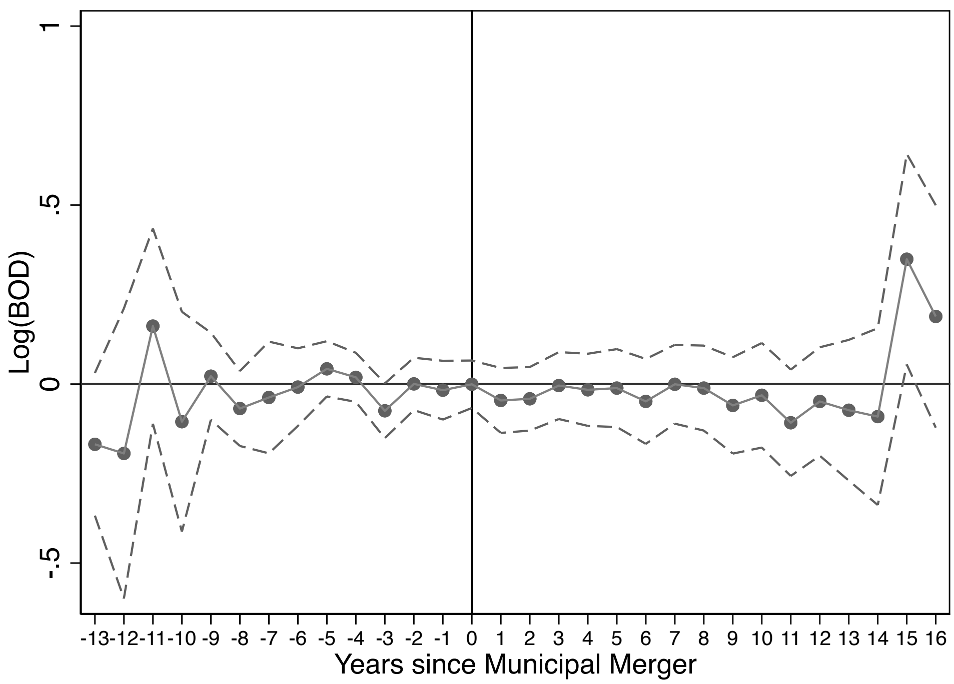

Figure A6: Event Study Results: Wastewater Treatment in Sewage Treatment Plants

Notes: This figure shows the coefficients of the estimators according to the Callaway and Sant'Anna (2021) methodology. The 95% confidence intervals are shown with dashed lines. This specification includes city fixed effects, year fixed effects, and product shipment values as a control.

B Additional Tables

Table B1: DID Results - The Impact on Water Quality (Early Mergers versus Late Mergers)

	Log(BOD)		
	(1)	(2)	(3)
Panel A: Callaway & Sant'Anna (2021) Estimator			
Merger (= 1)	0.011	0.011	-0.005
	(0.031)	(0.033)	(0.030)
Panel B: Two-way Fixed Effects			
Merger (= 1)	0.010	0.010	0.009
	(0.013)	(0.016)	(0.012)
Observations	44,666	44,666	38,840
R^2	0.878	0.878	0.885
Number of Stations	1,942	1,942	1,942
Number of Municipalities	442	182	442
Clustered SE at...	Municipality	Basin	Municipality
Station FE	YES	YES	YES
Product Shipment Values	YES	YES	YES
Population	NO	NO	YES
Mean of Dep. Variable	2.260	2.260	2.260

Notes: The sample is limited to monitoring stations in municipalities that have ever merged. The coefficients are reported. Standard errors are in parentheses and clustered at the municipality level in Columns 1 and 3 and basin-level in Column 2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All specifications in Panel A include year fixed effects, while all regressions in Panel B include basin-year fixed effects. Mean dependent variables are the mean of BOD values before municipal mergers started in our sample (before 2001) in each specification.

Table B2: DID Results: Change in Land Use

	Agriculture		Built-up		Forest		Non-use	
	(1) Dummy	(2) Share	(3) Dummy	(4) Share	(5) Dummy	(6) Share	(7) Dummy	(8) Share
Merger (= 1)	-0.010	-0.002	0.006	-0.003	-0.005	0.001	0.003	0.001
	(0.012)	(0.006)	(0.013)	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)
Observations	13,471	13,471	13,471	13,471	13,471	13,471	13,471	13,471
R^2	0.867	0.953	0.884	0.955	0.919	0.975	0.697	0.768
Number of Stations	2,774	2,774	2,774	2,774	2,774	2,774	2,774	2,774
Number of Municipalities	871	871	871	871	871	871	871	871
Basin-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Station FE	YES	YES	YES	YES	YES	YES	YES	YES
Product Shipment Values	YES	YES	YES	YES	YES	YES	YES	YES
Population	NO	NO	NO	NO	NO	NO	NO	NO
Mean of Dep. Variable	0.383	0.377	0.424	0.411	0.177	0.170	0.006	0.015

Notes: The coefficients are reported. Standard errors, clustered at the municipality level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 1, 3, 5, 7 report results when the dependent variables are the indicator which takes one if the majority of land use within 150 meters from monitoring stations is the corresponding type. Columns 2, 4, 6, 8 report results when the dependent variables are the shares of the area of the corresponding type within 150 meters from monitoring stations. All regressions are based on two-way fixed effects, which include both basin-year fixed effects and monitoring station fixed effects. Mean dependent variables are the mean of dependent variables before municipal mergers started in our sample (before 2001) in each specification.

Table B3: DID Results: Wastewater Treatment in Sewage Treatment Plants

	Effluent Water Quality	Influent Water Quality (Placebo)
	(1)	(2)
	ln(BOD)	ln(BOD)
Panel A: Callaway & Sant'Anna (2021) Estimator		
Merger (= 1)	-0.032	0.035
	(0.046)	(0.032)
Panel B: Two-way Fixed Effects		
Merger (= 1)	-0.065	0.014
	(0.042)	(0.026)
Observations	5,691	5,691
R^2	0.579	0.553
Number of Municipalities	271	271
Municipality FE	YES	YES
Year FE	YES	YES
Station FE	YES	YES
Product Shipment Values	YES	YES
Population	NO	NO
Mean of Dep. Variable	6.782	195.258

Notes: The coefficients are reported. Standard errors, clustered at the municipality level in Panel A, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Mean dependent variables are the mean of BOD values before municipal mergers started in our sample (before 2001) in each specification.

C Data Appendix

C.1 Water Quality

- We obtain the ambient water quality data from 1990 to 2018 from the following data source.
  - Water environment information website (*Mizu kankyo sogo joho site*), Ministry of Environment
  - `https://water-pub.env.go.jp/water-pub/mizu-site/mizu/download/download.asp` (accessed January 24, 2021)
- We use the yearly average BOD values and GPS coordinates of each water quality monitoring station in this dataset.
- We complement this dataset with the geospatial data of water basins from the following data source.
  - Water basin boundary Ver.1.1 (*Ryuikikai/hishusuiiki dai 1.1 ban*), Ministry of Land, Infrastructure, Transport and Tourism
  - `https://nlftp.mlit.go.jp/ksj/gmlold/datalist/gmlold_KsjTmplt-W12.html` (accessed February 6, 2021)

C.2 Municipal Merger

- We obtain the municipal merger data from the following data source.
  - Collection of municipal merger documents (*Shichoson gappei shiryoshu*), Ministry of Internal Affairs and Communications Environment
  - `https://www.soumu.go.jp/gapei/gapei.html` (accessed July 16, 2021)
- We use the following information for all cases of municipal mergers since 1999.
  - Names of newly created municipalities
  - Dates of municipal mergers
  - Names of involved municipalities
  - Types of municipal mergers ("equal-footing" mergers versus "incorporating" mergers)

C.3 Municipality Boundary for Data Matching

- We obtain the municipal boundary data from the following data source.
  - Administrative boundary data (*Gyosei kuiki deta*), Ministry of Land, Infrastructure, Transport and Tourism
  - `https://nlftp.mlit.go.jp/ksj/jpgis/datalist/KsjTmplt-N03.html` (accessed January 16, 2021)
- We use the municipal boundary to identify the latest prefecture and city names of all monitoring stations. Then, we match water quality data with municipal merger data based on the latest prefecture and city names.

C.4 River Distance

C.4.1 Data Source for River Distance

- We obtain river polyline data from the Global Map dataset developed by Geospatial Information Authority(GSI), Ministry of Land, Infrastructure, Transport and Tourism.
  - https://www.gsi.go.jp/kankyochiri/gm_japan_e.html (accessed June 27, 2021)
- We use detailed river node (point layer) data, which includes elevation information, provided by the Ministry of Land, Infrastructure, Transport and Tourism.
  - https://nlftp.mlit.go.jp/ksj/index.html (accessed June 27, 2021)
- We obtain both pre-merger and post-merger municipality boundaries. As such, we use 1984 and 2018 municipality boundary information from the Municipality Map Maker dataset developed by Kirimura et al. (2011).
  - `http://www.tkirimura.com/mmm/` (accessed June 27, 2021)

C.4.2 Construction of River Distance

We construct two distance variables, U and D, based on the following steps.

1. We perform inverse distance weighting (IDW) interpolation on the river node point layer to create a 300-meter raster elevation layer, which is at a finer resolution than readily available DEMs (Digital Elevation Models) and is highly accurate along river paths.
2. We use the river polyline layer and the municipality boundaries layer and intersect them by point to obtain municipality entry/exit points of rivers.
3. We attach elevation information to both the "entry/exit point" layer and the monitoring station layer using the raster feature to point tool.
4. To reduce margins for error, we only focus on monitoring stations that are located within 2km of the river polyline by conducting spatial queries.
5. We build a network based on the river polyline layer and perform a "find the closest facility" analysis to pick the six closest border boundary points along the river for each monitoring station and obtain distances for these routes.
6. We use the elevation information to determine whether each selected border boundary points are upstream or downstream of the monitoring station, after which we find the closest upstream and downstream border boundaries for each monitoring station and finally obtain values for U and D.

C.5 Other Municipality Characteristics

- Product shipment values (*Seizouhin shukka gaku tou*)
  - We obtain the data of product shipment values from two data sources, which cover different periods.
    * 1990-2012: Municipality-level population and economic data (*Shichoson betsu jinko/keizai kankei deta*), Cabinet Office

        · https://www5.cao.go.jp/keizai-shimon/kaigi/special/future/keizai-jinkou_data.html (accessed February 13, 2020)
    * 2013-2018: Census of manufacture (*Kogyo tokei chosa*), Ministry of Economy, Trade and Industry,
        · https://www.meti.go.jp/statistics/tyo/kougyo/result-2.html (accessed June 3, 2021)

- Population
  - We obtain the population data from two data sources, which cover different periods.
    * 1990, 1995, 2000, 2005, 2010: Municipality-level population and economic data (*Shichoson betsu jinko/keizai kankei deta*), Cabinet Office
        · https://www5.cao.go.jp/keizai-shimon/kaigi/special/future/keizai-jinkou_data.html (accessed February 13, 2020)
    * 2015: Census (*Kokusei Chosa*), Ministry of Internal Affairs and Communications Environment,
        · https://www.e-stat.go.jp/stat-search?page=1&toukei=00200521 (accessed June 3, 2021)
  - Because population data are available every 5 years, we conduct linear interpolation to estimate the population for other years.

C.6 Land Use

- We obtain 100-meter mesh raster data of land use in 1991, 1997, 2006, 2009, 2014, and 2016 from the following data source.
  - Land use mesh data (*Tochi riyo saibun mesh deta*), Ministry of Land, Infrastructure, Transport and Tourism
  - https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-L03-b.html (accessed December 6, 2020)
- We compute the numbers of pixels corresponding to the following 4 land use classifications within the 150-meter buffer of each monitoring station[10]. Then, we compute the share of pixels for each classification and the binary land use indicator of whether each classification has the largest number of pixels.
  - Agriculture
  - Forest
  - Built-up
  - Non-use

[10] Although the original data have finer land use classifications, we regrouped them into 4 classifications for the analysis. We also dropped the pixels corresponding to sea and river water.

C.7 Sewage Treatment Plants

- We obtain sewage treatment plants data from 1996 to 2017 from the following data source.
  - Sewage statistics (*Gesui tokei*), Japan Sewage Works Association
  - We obtain this dataset from the Japan Sewage Works Association on July 8, 2021.
- We use data of BOD values of both effluent (wastewater flowing out of a sewage treatment plant) and influent (wastewater entering a sewage treatment plant) in each sewage treatment plant. We then aggregate these data into city-level average BOD values of effluent and influent.