The Effectiveness of Network Administrative Organization in Governing Inter-jurisdictional Natural Resources

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Word Count: 6971

Abstract

Is participant-governed network or network administrative organization (NAO) more effective in overcoming complex social and environmental problems? This is a classical question in collaborative governance. However, previous studies have examined collaborative outcomes at either the organization or the entire network level, which do not closely enough to observe structured interactions among network actors. Therefore, we investigate collaborative outcomes at an inter-jurisdictional area, where reflects collaborative efforts between local governments. Recently, China enacted the River Chief System (RCS), a nationwide institutional reform that requires provincial governments to establish NAOs to coordinate inter-city rivers' management. We employ the synthetic control method using monthly (2017-2018) water quality data from 14 river monitoring sites in two neighboring cities. Our results suggest that the reform reduced the inter-jurisdictional river site's pollution level effectively by 36%. However, its effect size is larger at the beginning and end of a year, but smaller in the middle. This evidence advances our knowledge of collaborative governance, but also raises concern about a mandated network's overdependence on performance oversight conducted only once annually.

Keywords: Network administrative organization, Environmental management, Common pool resource, Synthetic control

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We thank Frances Berry, Mark Buntaine, Can Chen, Daniel Fay, Chien-shih Huang, Anastasia Semykina, Tian Tang, and Chengxin Xu for feedbacks during different stages of this project. We thank excellent research assistance from Hui Chen. We are also grateful to insightful comments from participants at the 2020 Annual Conference of the South Political Science Association and Online seminar series on Environmental Politics and Governance.

Introduction

Grouping multiple organizations with different interests into a governance network to achieve shared goals is a central topic to public management scholars (Bodin 2017; Ostrom 2010). In environmental management, environmental problems can be described often as interdependent subproblems among network actors (Bodin 2017). Policy actors often face complex social and environmental conditions in governing common pool resources (CPR). Network members' organizational goals may conflict with shared network-level goals, and unclear responsibilities may aggravate free-riding behaviors among them. These collective action dilemmas limit the self-governing network's capacity to achieve shared environmental outcomes. In particular, if each network member outweighs organizational benefits over the network-level benefits, everyone will be worse off in the long-term.

Under different levels of complexity, networks form different structures to overcome the collective action dilemma. As Provan and Kenis (2008) suggest, network structures can be summarized as three modes: Participant-governing network; lead organization-governed network, and network administrative organization (NAO). When social and environmental complexities increase, trust and goal consensus among network members decrease, and then the network structure is more likely to transform from a participant-governing network to the other two. In the process of overcoming complex social problems, these more centralized mandated network modes provide stronger network capacity than does the participant-governing network.

Based on these premises, the existing environmental management literature has two theoretical gaps in discussing forms of collaborative governance and their outcomes. First, scholars often examine one network mode's effectiveness, but rarely test the way the evolution from one mode to another affects environmental and social outcomes (Bitterman and Koliba 2020; Wang et al. 2019). Second, we lack "edge level" evidence to study network performance. Most of the outcome measurements of collaborative governance are either at the organizational or network level. These units of analysis help us understand each network participant's productivity and the effectiveness of the entire network ecological system (Scott 2015, 2016; Yi 2018). However, the central arenas of collaborative actions in environmental management are cross-boundary areas that require multiple network members to manage them collectively (Emerson and Nabatchi 2015). Studying environmental outcomes in cross-boundary areas reflects what Bryson, Ackermann, and Eden (2016, 914) refer to as "shared core goals" of collaborative governance that "cannot easily be achieved except by collaborating." To fill both theoretical gaps, we ask the following research question: Can environmental outcomes in cross-boundary areas be improved effectively when the network structure transforms from a participant-governing network to the NAO model?

Our study answers this question by investigating water pollution control in an inter-jurisdictional river in China. China has a long history of suffering from water pollution as a trade-off with its economic development, and local governments game and free ride each other in environmental governance. In the case of rivers, the inner-city rivers' water quality is often better than that in cross-boundary rivers. To resolve this governance dilemma, the central government enacted the River Chief System (RCS) at the beginning of 2018 to improve river management and water quality. Before the RCS was enacted, inter-jurisdictional rivers were participant-governed by neighboring cities. Since the RCS has been implemented, provincial governments have become the NAOs that coordinate and supervise their subordinate city governments' management of inter-jurisdictional rivers. This institutional reform provides us a unique opportunity to compare the network effectiveness between a participant-governing network and the NAO model.

To evaluate this institutional reform's effect, we collected 2017-2018 monthly water quality data from fourteen river quality monitoring sites in the two most important industrial cities in Guangdong province, Shenzhen and Dongguan. Thirteen of our sample river sites are in inner-city locations in either city, and one treated river site is at the two cities' inter-jurisdictional boundary. Although this small-N comparative study does not offer a generalizable conclusion, the synthetic control method allows us to identify the causal relation between the RCS institutional reform and improvement in the inter-jurisdictional river water quality in the study area. Comparing the water quality patterns between this inter-jurisdictional site and its synthetic control counterfactual before and after the RCS was implemented, we find that the RCS institutional reform improved the inter-jurisdictional river water's quality significantly. However, this effect is unstable and changed during the implementation year, which raises certain institutional concerns.

Our findings have two major theoretical implications. First, the NAO model is more effective than is the participant-governing network as a method to govern environmental outcomes in inter-jurisdictional areas. Second, the NAO model's overdependence on performance supervision may lead to unstable outcomes.

Theoretical Rationale

Participant-governed Network and Free-riding Behaviors

The participant-governed network is the most common form in environmental management, which relies on participatory actors' self-governing communication to manage CPR (Provan and Kenis 2008). Participant-governed networks' effectiveness often requires high levels of common trust and consensual goals among network actors. However, neither requirement is easy to achieve, particularly when organizational interests conflict with network-level shared interests. As Bodin (2017, 4) argue, "Actors do not collaborate with others in management of ecologically interconnected resources more than would be expected by chance." Institutional obstacles limit network actors' collaboration across jurisdictions. With low common trust and goal consensus, fragmented local authorities have many opportunities to game, betray, and free-ride other network actors.

Therefore, limiting such opportunistic behaviors is a central issue in environmental governance (Carroll, Konisky, and Reenock 2018; Konisky and Woods 2012; Sigman 2002). Natural resources such as rivers and air are interconnected by multiple political jurisdictions. Local governments have responsibilities to reduce environmental contamination within their jurisdiction, but they lack incentives to control pollution spillovers to their neighbors. Even worse, local governments may "free ride" their neighbors strategically by discharging pollutants to them (Konisky and Woods 2010). Local governments could gain political and economic benefits from these behaviors in the short run, but the environment overall would suffer continuous harm in the long-term. Conflicts among stakeholders in the inter-jurisdiction would increase, and eventually these conflicts can lead to what Hardin (1968) referred to as the tragedy of the commons.

Network Administrative Organization

Unlike a participant-governed network, an external member governs the network in the NAO model. This external member can be a person or an organization that supervises, coordinates, and integrates the collaborative actions among network actors (Provan and Kenis 2008). In local politics, NAOs are often upper-level government entities that have imposed authority to mandate policy instruments toward lower-level governmental actors (Wang et al. 2019).

When interlocal governmental network actors do not have high levels of trust and goal consensus, the NAO model has several advantages over the participant-governed network that reduce free-riders in cross-boundary areas. First, NAOs coordinate and facilitate interorganizational activities to achieve network-level objectives (Isett and Provan 2005). As a goal-directed approach, NAOs shape policies to reduce conflicts among network actors, simplify the action process, and formalize coordination mechanisms (Macciò and Cristofoli 2017; Saz-Carranza, Iborra, and Albareda 2016). For example, Macciò and Cristofoli (2017) find that NAOs with strong managerial leadership support healthcare networks' endurance. They also suggest certain effective leadership practices, such as regular meetings with members, forging agreements between partner organizations, and serving as a mediator between parties. As Provan and Kenis (2008) argue, when the policy problems become more complex, networks are more likely to evolve from a participant-governed network to a centralized network form to maintain the network's effectiveness.

The NAO model's second benefit derives from its power to monitor network performance and minimize opportunistic behaviors. As a feasible strategy to unify network actors to achieve network-level objectives, NAOs often set task standards for actors and evaluate them periodically (Wang et al. 2019). In governing cross-boundary environmental resources, tasks are often highly interdependent and difficult to accomplish unilaterally. Thus, a participant-governed network is favored less than is the NAO model in monitoring task quality (Provan and Kenis 2008). This issue can be even more serious when actors perceive that collaboration is contradictory to their organizational goals (Saz-Carranza et al. 2016). Therefore, in addition to coordinating actors' network activities, NAOs also have the power to monitor performance at both the organizational and network levels, which motivates network members to keep their agreements to accomplish network goals.

Finally, NAOs provide external resources to subsidize network members, which improves the incentives and competencies in network-level collaboration (Provan and Lemaire 2012). When face with complex environmental problems, local governmental actors lack financial, technical, and political resources to implement regional policies (Wang et al. 2019). NAOs can provide not only resources to assist local actors, but also satisfy external demands for networks, such as buffering macro-level environmental shocks, lobbying and fundraising externally, and building networks' external legitimacy (Provan and Kenis 2008). Resource capacity is one of the most critical reasons for local governments to collaborate with higher-level governments. Scholars have found evidence for this phenomenon in different contexts: Mullin and Daley (2009) show that American local agencies are more likely to cooperate with the federal government when they have less total revenue; Wang et al. (2019) find that Chinese regional watersheds' protection relies on the NAO model with upper-level governments' financial subsidies, and Yi and Cui (2019) suggest that when the ratio of water spending over city spending becomes higher, Chinese cities are more likely to establish a centralized water affairs bureau to manage city's subordinate water departments.

Collaborative Governance Regime

Although the NAO model's advantages in coordinating complex network activities have been tested repeatedly, its effectiveness in governing cross-boundary environmental resources has yet to be explored. If we view inter-jurisdictional collaboration on environmental issues as an integrated collaborative governance regime (CGR), the units of analysis of collaborative outcomes include participant organization, the CGR, and target goals (Emerson and Nabatchi 2015). Abundant studies of collaborative performance in environmental governance have set their units of analysis on participant organizations (e.g. Bitterman and Koliba 2020; Park, Krause, and Feiock 2019; Scott 2016). Scholars have also investigated outcomes for the entire network with its target goals (Scott 2015; Yi 2018). However, we lack evidence from examinations of CGR's collective productivity in "...the arena for structured interactions among its participants" (Emerson and Nabatchi 2015, 726). This level of analysis is central to network governance in public administration, and it should be attractive to more public management scholars (Agranoff 2007).

Using CGRs as the units of analysis is even more critical in studying pollution problems in environmental governance, because opportunistic behaviors often occur in cross-boundary areas. One important stream of environmental policy literature locates the analysis at the jurisdictional borders. If the free-riding assumption of inter-jurisdictional political actors holds, each government would have different enforcement levels between inner- and inter-jurisdictional pollution. To examine this phenomenon, social scientists often use distance indicators of the boundary to measure differences in enforcement. For example, Sigman (2005) study transboundary spillovers among American states using water monitoring sites within 50 miles from the state boundary as the distance threshold. Her findings suggest that the free-riding behaviors are stronger when the water monitoring stations are closer to the boundaries even with the federal Clean Water Act regulation. Helland and Whitford (2003) have similar findings when they combine the Environmental Protection Agency's (EPA) Toxic Release Inventory data and American counties' characteristics, and find that the facilities' pollutant emissions are higher in counties that border other states. Recently, Carroll et al. (2018) constructed a new dataset of 6,000 U.S. state regional environmental offices and find that when state boundaries bisect the watersheds, federal enforcements provide better treatments than do regional offices' efforts. In contrast, when the watersheds are interconnected among in-state counties, fragmented regional offices provide better responses to pollution spillovers.

Given the poor environmental outcomes in cross-boundary areas, setting the units of analysis at CGRs is crucial to understand collaborative governance. Therefore, we compare the participant-governing network and the NAO model's effectiveness in environmental management. Moreover, the inter-jurisdictional natural resource is our action arena. Its environmental quality reflects the shared core goal among participating organizations and captures "...what is ordinarily meant by collaborative advantage" (Bryson et al. 2016, 914).

Hypothesis: After the structure is transformed from a participant-governed network to the NAO model, the local government network is more effective in governing environmental outcomes in inter-jurisdictional areas.

Context

Governing Inter-jurisdictional Rivers in China

In this study, we use the case of inter-jurisdictional river management in China to explore whether the NAO model can improve cross-boundary area water quality. China has suffered in the long-term from river pollution's adverse effects (Zhang, Chen, and Guo 2018), and its hierarchical political system provides a good context in which to study local-level opportunistic behaviors and the mandate network's effectiveness.

As mentioned earlier, a self-organizing, participant-governed network has limited ability to cope with complex and inter-jurisdictional environmental problems, because of the need for high trust and goal consensus among actors. More importantly, local governments' self-organizing behaviors originated with a democratic assumption: Local preferences and reelection pressure motivate their policy actions (Gerber and Hopkins 2011). However, this assumption is not applied in many developing countries with authoritarian governments, where policy decisions are largely top-down (Ye 2009). In such systems, local officials' policy motivations derive largely from the hierarchical competition for promotion: The centralized cadre system (Anderson et al. 2019). Lacking a democratic institutional background, participant-governed networks have worse outcomes in river management in developing countries than in the United States (She et al. 2019), and centralized and mandated networks are preferred more in the former countries.

Including environmental performance in the promotion indicators and clarifying each jurisdiction's responsibility is a way to ameliorate the environmental contamination within jurisdictions, but it cannot solve the free-riding behaviors in cross-boundary areas. High stakes pressure for organizational performance motivates local governments to compete with each other. Thus, they often lack sufficient trust and consensus to collaborate on environmental problems in cross-boundary areas. To game the system, local governments may discharge pollutants to neighboring jurisdictions, report false performance information, and reduce enforcement efforts (Anderson et al. 2019; Cai et al. 2016; Zhang and Cao 2015). These rat race competitions destroy trust between local governments and increase upper-level governments' difficulties in monitoring local behaviors. In addition, the fragmented local politics, complex environmental conditions, and financial shortcomings are other major challenges for river governance in China (Han et al. 2016). Therefore, simply establishing oversight of local river performance is not effective to overcome these complexities.

River Chief System

The RCS is an institutional attempt to implement the NAO model in China, which employs the leading officials in senior governments who are appointed as "river chiefs" for inter-jurisdictional rivers. These river chiefs must work closely with their subordinate local governments and coordinate river quality management with multiple sectors and agencies (Liu et al. 2019).

This innovation can be traced back to 2007, the time of the water supply crisis in Wuxi City, Jiangsu province (Wang and Chen 2020). The explosion of blue algae in Taihu Lake (a large lake across multiple counties' boundaries) forced the Wuxi government to rearrange its management model, which coordinated county and town governments to control the water pollution collectively. Since then, this model has diffused to other areas in China. At the end of 2016, 16 of 31 mainland Chinese provinces had adopted the RCS fully or in part.

Before the RCS's implementation, the management responsibilities for inter-jurisdictional rivers were negotiated between neighboring governments. Since the RCS was implemented, the upper-level government serves as the NAO to manage these rivers. River chiefs have been appointed to four different governmental levels (order from high to low): Provincial, city, county, and township (Wang and Chen 2020). Provincial heads are general chiefs for all inter-city rivers in the region, and chief executives of cities, counties, and townships are river chiefs for their own jurisdictions. The government leaders and their departmental agencies form the River chiefs offices and manage subordinate intergovernmental networks (see Figure 1).

Several studies have shown the RCS's contributions in improving river water quality (Liu et al. 2019; She et al. 2019; Wang and Chen 2020). The key elements of the RCS reflect the NAO model's major advantages. First, river chiefs facilitate the policy process. They hold regular meetings with lower-level government leaders and coordinate actions among other departmental agencies, such as the water affairs bureau, environmental protection, agriculture, land and resources, and financial departments directly (Liu et al. 2019; Wang and Chen 2020).

Second, the RCS sets clear performance thresholds for rivers. Every river receives a water pollutant reduction target. River chiefs monitor their subordinate rivers' monthly performance and include the annual performance as criteria for local cadre promotion (She et al. 2019). The RCS also surveys residents' opinions about water quality near their residences and encourages them to report pollution on the part of firms or government entities (Buntaine, Zhang, and Hunnicutt 2020; Wang and Chen 2020). For example, the river chief office provides an online billboard for residents to upload daily information about their observations of the river (Wang and Chen 2020).

Third, river chiefs provide resources to help subordinate governments manage rivers, and often have a special fund that supports the implementation of water pollution reduction measures (She et al. 2019). In addition, they may also invite university professors as external experts to participate in the river management plan design and implementation stages (Li, Tong, and Wang 2020). Hence, both financial and expertise resources improve the network capacity. Figure 1 depicts the RCS's institutional structure.

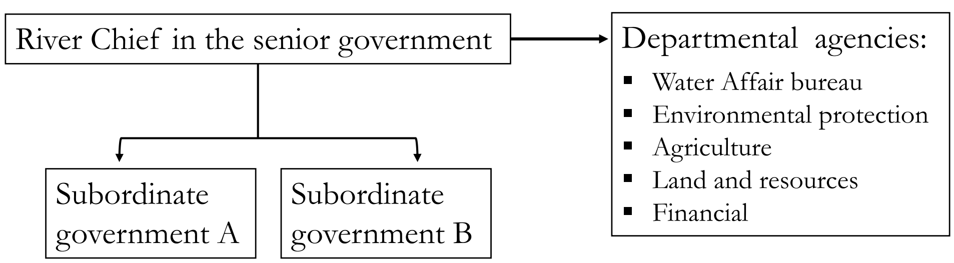

Figure 1: Institutional Arrangement of RCS

Although the RCS has abundant successful experiences in managing rivers, as aforementioned, its effectiveness in mitigating water pollution in inter-jurisdictional rivers is empirically unknown. Most of the studies above have employed participant organizations (cities) as the units of analysis, which limits our knowledge of environmental outcomes at the CGRs level. Therefore, this study innovatively designates an inter-city river site as the treated unit and compares its performance with similar inner-city river sites in the same region to examine whether the RCS implementation affects its change in water quality over time.

Empirical Strategy

Data

The RCS has been implemented formally in all provinces in China since the beginning of 2018. Given this short implementation period to date, it is difficult for researchers to collect nationwide large-N water performance data for inter-jurisdictional rivers. To obtain a preliminary understanding of the RCS's treatment effect on cross-boundary area, we collaborate with the Guangdong Research Institute of Water Resource and Hydropower (GRIWRH) to obtain two years (2017-2018) of monthly river water quality panel data from the two major industrial cities in Guangdong province, Shenzhen and Dongguan (Figure 2). Using a case study strategy, we move a small step forward from previous studies by comparing the participant-governing network and NAO models in an inter-jurisdictional river's governance.

Figure 2: Study Area

Note: The red dot is the inter-jurisdictional Maozhou river site. The yellow area is Changan town, and the pink area is Shajing town. Light blue lines indicate the sample watersheds and black lines are jurisdictional boundaries of Shenzhen and Dongguan. Full geographical information of each river site is reported in Appendix A.

These data include three major water quality indicators: Chemical oxygen demand (COD); ammonia nitrogen (NH3-N), and total phosphorus (TP) from fourteen rivers' water monitoring sites in both cities. Among them, thirteen sites are located in the inner-city (seven sites are in Shenzhen, six in Dongguan). In addition, one river site, the Maozhou river in the Gonghe village monitoring station, lays on the inter-jurisdictional boundary between Shenzhen and Dongguan. All fourteen rivers have severe water pollution problems and are located closely within the greater Maozhou watershed area. As of 2002, the Ministry of Environmental Protection has categorized water quality performance into six levels (from good to bad): I, II, III, IV, V, and poor V (Yan et al. 2015). The provincial government has classified all rivers in our sample as level poor V water. Thus, they all have the common target to ameliorate water performance from level poor V to V. Specifically, COD, NH3-N and TP should be lower than 40 mg/L, 2.0 mg/L, and 0.4 mg/L, respectively, and a river must pass all three indicators' standards to achieve its target performance.

The 2018 institutional reform affected the inter-city Maozhou river's management model largely, but theoretically, had no effect on other inner-city rivers, which creates a natural counterfactual for us to compare. City, county, and township-levels' RCSs have been implemented in 10 cities in Guangdong province, including Shenzhen and Dongguan, since 2015, so inner-city rivers' governance responsibility had been clarified by then. The 2018 institutional reform shifted the responsibility to manage inter-city rivers from neighboring cities to the provincial government beginning in 2018 (Wang and Chen 2020). Since then, every city can be viewed as a single participant organization in the network, and the provincial government as the NAO. This institutional change provides us a unique opportunity to study the provincial government, Maozhou river, and its cities on both sides as an integrated CGR.

Although this case study has limitations in its scope, it still serves as a valuable reference for other inter-jurisdictional rivers in China. As one of the most important economically-developed provinces, Guangdong's economy is greater than that of any other province in China. Shenzhen and Dongguan are in the center of the Pearl River Delta Economic Zone, which is the hub of Chinese high-tech and manufacturing industries. On the one hand, this region has been leading China's economic advancement in the past 40 years, but on the other, it has been suffering from the severe environmental costs of air and water pollution for a long while (Huang et al. 2017; Yi et al. 2018). In recent years, both cities' governments have policy intentions to solve the water pollution problems, and their inner-city water quality conditions have been improving continuously in recent years. However, the water treatment of the inter-jurisdictional Maozhou river continues to fail to meet its target performance.

The Synthetic Control Method

The synthetic control method Abadie, Diamond, and Hainmueller (2010, 2015) developed matches our panel water quality data perfectly, where we have only one treated unit and multiple control units in the sample.

In small-N case studies, the comparability among different cases is tainted by likely unobserved confounding variables. Treated and control units' characteristics rarely match well. Hence, it is difficult to conduct statistical falsification. The synthetic control method is a remedy for this problem. This method's major property is that it combines all comparative control units and weights them on the treated unit in the pre-intervention period. This method has become popular in environmental studies in recent years (e.g. Bueno and Valente 2019; Maamoun 2019). Most relevant to our study, Sun et al. (2019) applied this method to investigate the Chinese green credit policy in Jiangyin. They use 17 cities in the Jiangsu province to construct the synthetic Jiangyin city. By comparing the actual and synthetic Jiangyin, they find that the policy motivated firms to reduce COD discharges effectively.

The treated unit in this study is the inter-jurisdictional Maozhou river monitoring site, while other inner-city river sites in the sample are our control units. After constructing them as the synthetic Maozhou river site, this synthetic control unit reproduces the treated unit without the treatment effect in the post-intervention period. Comparing the time-series patterns between the actual treated unit and the synthetic control unit after the treatment assignment is better than simply comparing each unit in the pool (Abadie et al. 2010).

We used both socioeconomic and environmental covariates to construct a weighting matrix, which made the control units' characteristics as similar as possible to the treated unit. With this weighting matrix, we reproduced the synthetic control treated unit that have similar outcomes in the pre-intervention period. Therefore, the outcome difference between the treated unit and synthetic treated unit indicated the treatment effect. To accurately identify the causal effect, we minimized the mean square prediction error (MSPE) in the pre-intervention period. Appendix B documents detailed steps of the synthetic control method's causal procedure and mathematic expression of MSPE.

The key in the synthetic control method is to have a sizeable pre-intervention period, a comparable donor pool of control units, a set of time-constant predictors, and an effective treatment cut-off point (Abadie 2019). Combining the water quality data from 2017-2018, we have 24 time points in total. Although the RCS was enacted at the beginning of 2018, the provincial government finalized dividing the inter-jurisdictional rivers' work arrangement with its subordinate governments at the beginning of November 2017. Therefore, we use January to November 2017 as the pre-intervention period. Further, Abadie et al. (2015) suggest that the donor pool units' characteristics should be as similar as possible to those of the treated unit. In this sense, all river sites and their corresponding jurisdictions in our sample are from two cities in a small region. Thus, we are less concerned about interpolation biases. In addition, the synthetic control method has the no-interference assumption, which requires the intervention to have no spillover effects on control units (Abadie 2019). In our sample, the treated Maozhou river site is the most downstream, close to the marine outfall. Therefore, it is theoretically unlikely for the RCS intervention to spill over from the most downstream treated site to other upstream control sites (Appendix A shows a map that includes all study sites' locations).

Measurement of The Water Quality

Referred to as the *Environmental Quality Standards for Surface Water* (GB3838-2002) by the Ministry of Environmental Protection (2002), we build our main dependent variable with the comprehensive water pollution index (PI) (Liu et al. 2019; Yan et al. 2015). In the following formula, C_i contains i categories of pollutants (mg/L), and S_i represents each pollutant's corresponding target standard.

$$PI = \frac{1}{n} \sum_{i=1}^{n} \frac{C_i}{S_i} \tag{1}$$

In this case, we weight the pollutant values on the level V target standards: $PI = 1/3(COD/40 + NH_3N/2 + P/0.4)$. In addition, we also measure the effect of the RCS's implementation on each pollutant separately. Figure 3 displays the PI trends for the treated unit and the average of the control units before and after the RCS was enacted (trends for each pollutant shown in Appendix C).

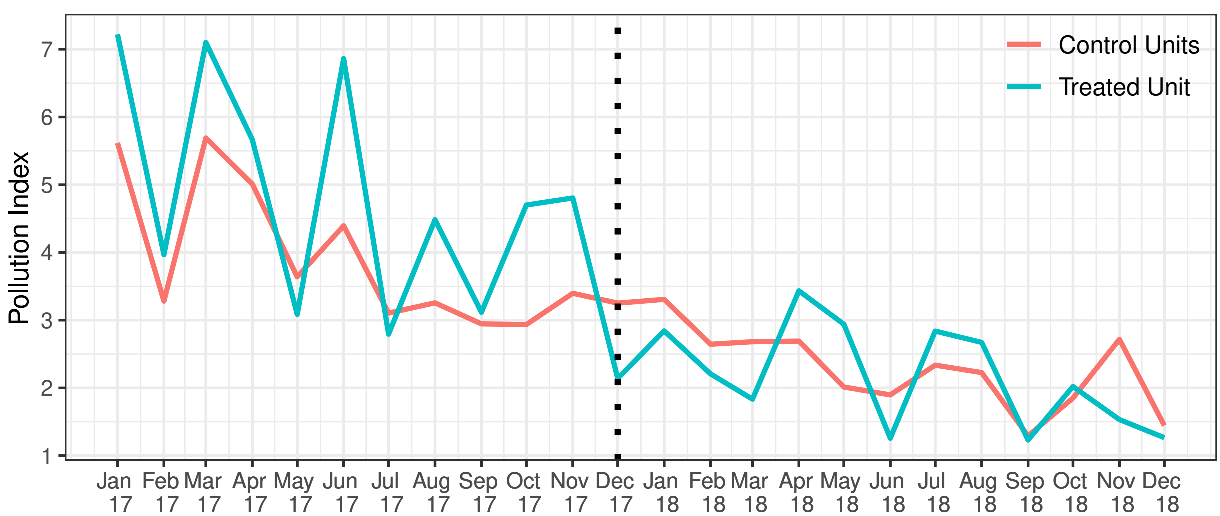

Figure 3: Trends of PI: Treated Unit versus Average Control Units

Measurement of Predictors

According to the formal justification, we select valid predictor variables to construct a comparable synthetic control unit for the treated unit (Table 1). Both the local socioeconomic and environmental conditions affect River water quality (Scott 2015, 2016).

Table 1: Predictors for the Water Quality

Variable Name	Variable Description
Socioeconomic predictors	**Township level**
GDP per capita	The 2017 annual Gross Domestic Product per capita in the town where a river is located (RMB/per capita)
Gov. revenue per capita	The 2017 annual government revenue per capita in the town where a river is located (RMB/per capita)
Gov. expenditure per capita	The 2017 annual government annual expenditure per capita in the town where a river is located (RMB/per capita)
Population density	The 2017 annual population/area in the town where a river is located (10,000 people/1km^2)
Environmental predictors	**Site level**
River flow rate	The 2017 annual average water velocity at the water monitoring site point
Industrial land use	Area in the one-kilometer radius circle (km^2)
Agricultural lane use	Area in the one-kilometer radius circle (km^2)
Water quality in Spring 2017	The average water quality in January, February and March 2017
Water quality in Summer 2017	The average water quality in April, May and June 2017
Water quality in Fall 2017	The average water quality in July, August and September 2017
Water quality in Winter 2017	The average water quality in October and November 2017

We collect township-level socioeconomic data from Dongguan and Shenzhen's Statistical Yearbooks in which each river monitoring site is located. The socioeconomic predictors include local population, economy size, and the local government's financial capacity (Konisky and Woods 2012; Scott 2015, 2016; Sun et al. 2019). As a river in the inter-jurisdictional area, our treated unit provides a challenge in constructing comparable values that match the predictors above. By the definition of CPR, the Maozhou river at the Gonghe village monitoring site does not belong to either Shenzhen or Dongguan's administrative territory, but is located in the center of two similar sized adjacent towns: Changan (area = 97.87 km^2, population = 663,800) from Dongguan, and Shajing (area = 66.69 km^2, population = 360,300) from Shenzhen. For this natural setting, we average the values from each of the two areas' socioeconomic predictors to approximate the socioeconomic predictors for the treated unit.

We also collect environmental data for each river monitoring site. The annual river flow rate is obtained from GRIWRH and the authors collected land use data from Google Earth manually. To measure the local land use condition precisely, we employ the areal appointment technique with ArcGIS to construct a one-kilometer radius circle and calculate each water monitoring site's industrial and agricultural area (Konisky and Woods 2010). In addition, river water quality fluctuates seasonally according to different weather conditions. Thus, we include the mean values of the water quality in each of the four seasons in the pre-intervention period.

The Table 2 compares the pre-intervention predictor means for the treated river site, the synthetic treated river site, and the donor sample average. We can see clearly that the treated unit's predictor values are more similar to the synthetic unit than is the donor sample average.

Table 2: Water Quality Predictor Means in the Pre-intervention Period

	Treated Unit	Synthetic Unit	Donor Sample
GDP per capita	90154.55	91940.43	94896.41
Gov. revenue per capita	4977.57	5056.92	6449.14
Gov. expenditure per capita	5901.28	8160.74	10980.78
Population density	0.62	0.30	0.38
River flow rate	10.67	11.16	8.46
Industrial land use	2.26	1.38	1.73
Agricultural land use	0.39	0.34	0.19
Avg. PI in spring	6.10	6.02	4.86
Avg. PI in summer	5.21	5.37	4.35
Avg. PI in fall	3.46	3.64	3.10
Avg. PI in winter	4.75	4.48	3.17

Note: Pre-intervention MSPE = 0.300

Next, we summarize the weights that have been assigned to each river site in the donor pool (Table 3). These weights describe their similarity to the treated river site according to the socioeconomic and environmental predictors matrix. In total, all weights sum to one (see mathematic expression in Appendix B). We label the river sites as SZ1 to SZ7 for the districts in Shenzhen, and DG1 to DG6 for the districts in Dongguan. Summing these weights of each control site's water quality values, we constructed the synthetic treated river site.

Table 3: Weights in the Synthetic Inter-jurisdictional River Site

Unit Name	Synthetic Control Weight
DG1	0.041
DG2	0.000
DG3	0.206
DG4	0.000
DG5	0.001
DG6	0.414
SZ1	0.005
SZ2	0.092
SZ3	0.240
SZ4	0.000
SZ5	0.000
SZ6	0.000
SZ7	0.000

Results

The Main Effect of The RCS

Figure 4 displays our main finding on the RCS's treatment effect on the inter-jurisdictional river site pollution reduction. We can see clearly that the synthetic inter-jurisdictional river site's PI is very similar to that of the actual treated river site before the RCS was implemented, which indicates that our predictors achieved a good match between the treated unit and its synthetic control counterfactual in the pre-intervention period.

After the RCS was enacted, the inter-jurisdictional river site's water quality improved immediately, and the inter-jurisdictional river's PI was 55.61% lower than its synthetic control part in December 2017. However, this pollution reduction effect did not hold consistently in the middle of 2018, but increased again to 47.59% at the end of the year. If we measure each pollutant indicator separately, NH3-N and TP showed similar patterns, but with different magnitudes of fluctuation. COD did not show a much different pattern than its synthetic control unit. Details of each pollutant indicator are included in Appendix D Figure D1.

The outcome pattern fluctuated. We control the seasonal effects in our weighting model, so a possible explanation of the outcome fluctuation is the mechanism of local cadre pro-

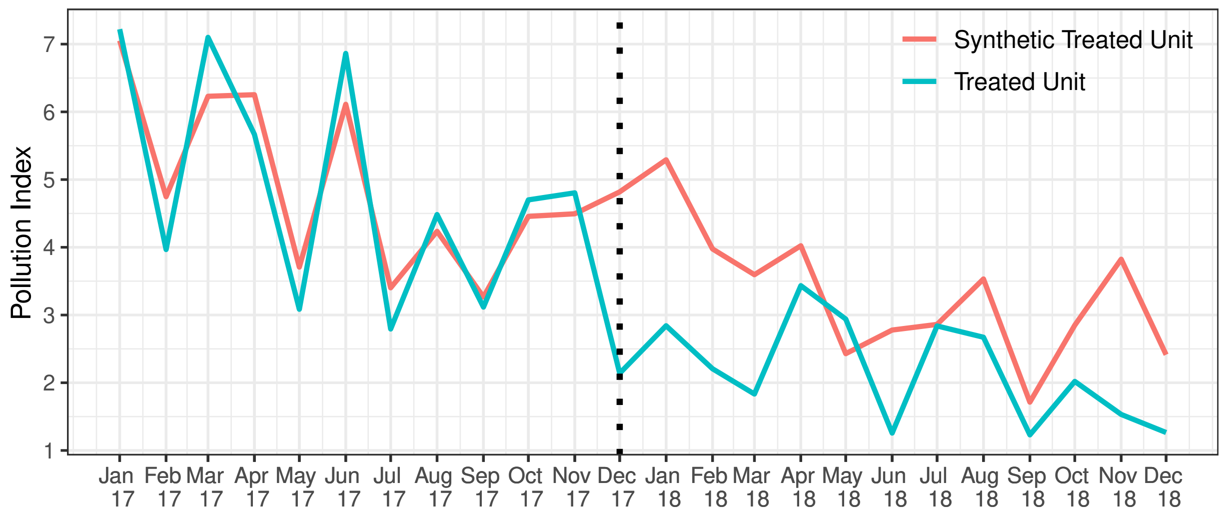

Figure 4: Trends of PI: Treated Unit versus Synthetic Treated Unit

motion. The promotion evaluation system records only annual average water quality as the indicator for the local government's river management performance. Therefore, local governments have a stronger shared motivation to improve the water quality at the end of the year.

Although water quality has not improved steadily, the RCS's treatment effect overall is sizeable. Figure 5 reports the average treatment effect on the treated unit (ATT) during the post-intervention thirteen months (December 2017 to December 2018). On average, the PI in the actual inter-jurisdictional river site is 1.22 (36.04%) lower than its synthetic control unit (S.E. = 0.346, $p = 0.0017$). ATT for each pollutant is reported in Appendix D Table D2.

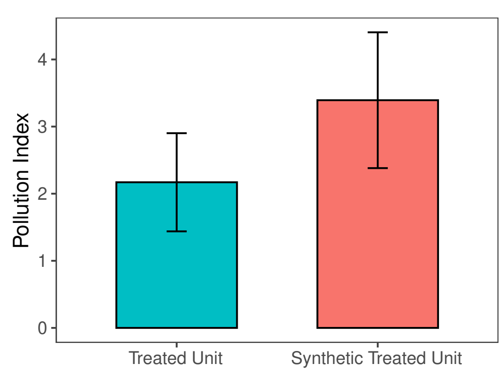

Figure 5: ATT in the Post-Intervention Period

Placebo Test

Conventional regression-based studies often test hypotheses by comparing results with the benchmark significance levels, but the small-N synthetic control approach relies on a placebo test (Abadie et al. 2010). We reassigned the treatment to other control units in the donor pool to see whether they result in effects similar to that in the inter-jurisdictional river site.

First, Figure 6 demonstrates that the treatment effect of the treated inter-jurisdictional river site (green line) was larger than that of other river sites with placebo assignments (grey lines). The distances between these lines and the horizontal dashed line are the value gaps between each river site and its synthetic control counterfactual. The vertical dashed line is the RCS implementation period. Following Abadie et al.'s (2010) recommendation, we discarded four extreme control units because their pre-intervention MSPEs were more than two times larger than the treated unit.

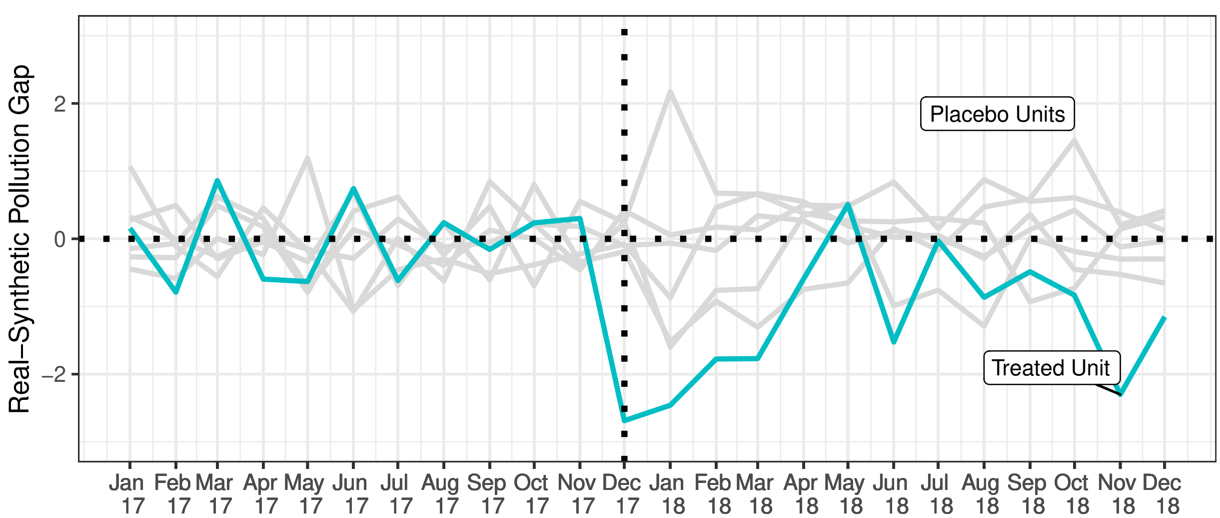

Figure 6: PI Gaps in The Real Treated Unit and Placebo PI Gaps in Control Units

Next, we employ significance tests with the post- and pre-intervention $\mathrm{MSPE}_{\mathrm{ratio}}$. Figure 7 reports the $\mathrm{MSPE}_{\mathrm{ratio}}$ comparisons between the treated inter-jurisdictional river site and the others. The result demonstrates that the inter-jurisdictional river site's $\mathrm{MSPE}_{\mathrm{ratio}}$

is at least 2.67 times larger than that of any other control site. Not even one control site's $MSPE_{ratio}$ is close to the inter-jurisdictional river site. The larger $MSPE_{ratio}$ value indicates that the water quality gap between the treated and control unit increased in the post-intervention period. Therefore, if one assigns the treatment to these data randomly, the probability of obtaining a $MSPE_{ratio}$ as large as the inter-jurisdictional river is $1/14 = 0.07$ (p-value)[1].

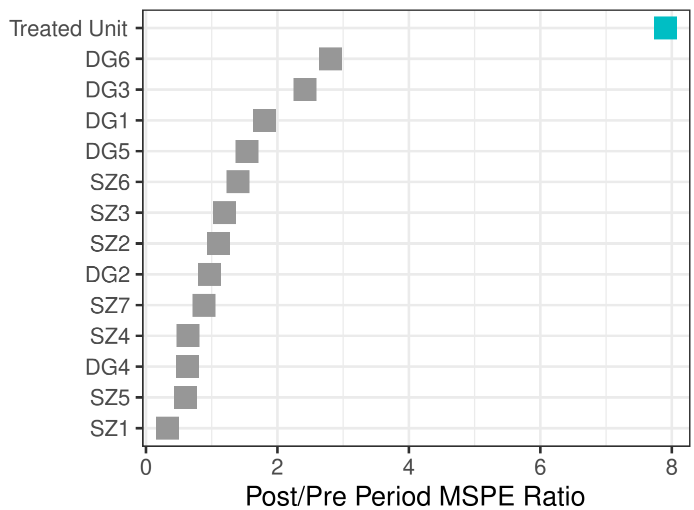

Figure 7: PI $MSPE_{ratio}$ of Post-/Pre- Intervention: The Treated and Control Units

We also reran the placebo test for each pollutant indicator, and obtain a similar result for NH3-N as the PI, but COD and TP fail to pass the $p = 0.1$ threshold. These results suggest that the RCS effect is significant for NH3-N, but largely not for COD or TP. We report these results in Appendix E. Various human activities' effects and pollutants' different corresponding target performances can explain these heterogenous results. COD indicates industrial wastewater, NH3-N indicates primarily industrial sewage and life wastewater, and TP indicates primarily agricultural pollution from fertilizers (Ministry of Environmental Protection 2002). Governments can reduce COD and NH3-N by regulating polluting industries. However, agricultural fertilization is local farmers' individual behavior. Therefore, reducing

[1]Of note, the comparably large p-value ($0.07 > 0.05$) does not mean our explainatory power is weak, because the total sample size in the donor pool determines the probability of significance largely. According to Abadie et al. (2015), researchers often need to restrict the donor pool to those with similar characteristics units, and the larger sample size may lead to overfitting problems in the comparison.

the TP level often requires longer than the other two pollutants. Moreover, COD in the inter-jurisdictional river site is lower than 40 mg/L (the target performance) during most of the study time frame, which explains why governments have not implemented aggressive treatments of it.

Discussion

Theoretical Implication

By investigating the way transforming from participant-governance to the NAO model relates to water pollution control in a cross-boundary area, we advance our knowledge of collaborative governance's effectiveness. When facing different public problems, the optimal collaborative strategies also differ. While our case study in China offers direct evidence for ways to govern rivers in a complex institutional environment, it also has general implications for the modes of network governance and their collaborative outcomes.

By comparing water quality performance before and after the network structure changed from the participant-governing mode to NAO, we find that the NAO model is a better strategy to improve environmental outcomes in the cross-boundary area. This finding is consistent with Provan and Kenis's (2008, 236) view that NAO enhances network's capacity to deal with "unique and complex network-level problems and issues." As we discuss at the outset, river management often includes social and environmental complexity that a single organization cannot possibly manage. With formalized network coordination, strict performance supervision, and external resource provision, the NAO enhances collaborations among network actors and ultimately improves environmental outcomes.

One intent of our analysis is to provide empirical evidence of collaborative efforts in the cross-boundary area. To the best of our knowledge, this study is the first in the collaborative governance literature to use an inter-jurisdictional natural resource as the unit of analysis. Performance of interconnected natural resources in cross-boundary areas serves as a bridge between organizational performance and network ecology-level performance. Controlling environmental quality within a jurisdiction is fundamentally important for every local government, but we cannot achieve long-term beneficial outcomes for the entire network overall unless local governments coordinate to solve pollution problems on their shared borders jointly. To study why collaborative governance succeeds or fails, we must disentangle network members' shared outcomes. Therefore, our findings contribute to the collaborative governance theory, and provide new evidence to determine whether the NAO model improves the shared outcomes between two local governments.

Although our results support the NAO model's effectiveness in general, the fluctuating time trend raises some institutional concerns. The RCS treatment effect is stronger at the beginning and end of the post-intervention period than in the middle. Our empirical model does not observe the RCS's internal mechanisms, so here we provide a post hoc exploratory analysis as an indirect explanation of our findings. One of the possible reasons for the fluctuating pattern is that performance supervision determines the treatment effect strongly. Although formalized network coordination and external resource provision are written explicitly in the RCS law documents, local governments care more about their annual performance in the centralized cadre promotion system (She et al. 2019). This leads to a theoretical concern for the mandated network mode of collaboration: The RCS is overly-reliant on top-down supervision, but relies less on communication, coordination, and other functions of network activities. Similar to Huang's (2014) suggestion, the NAO model has power asymmetry. It strengthens vertical connectivity between NAOs and network actors, but weakens horizontal information sharing among them.

In addition, public opinion may be symbolic in the policy process. As aforementioned, the RCS collects residents' daily opinions about their water quality nearby. If governments listened to these opinions timely and carefully, the water quality improvement should be more stable. Buntaine et al.'s (2020) field experiment address this in part. They find that disseminating river performance to upper-level government rather than the public is more useful in motivating local governments to control pollution. Based on this insight and our implicit findings, the way to improve the RCS and other centralized NAOs' accountability may be an important research topic in the future.

Limitation and Future Research Agenda

This research makes a unique contribution to the study of inter-jurisdictional collaborative behaviors, but it faces three main limitations. First, we focus on detecting the RCS institutional reform's treatment effect overall, but lack further explanation of several internal mechanisms, such as formalized coordination, performance supervision, and external resource provision. We have no opportunity to access the communication process among network actors, polluting firms' regulation activities, or financial input for the RCS. Therefore, exploring and comparing major determinants of the policy output within the NAO model is beyond our research scope. To overcome this limitation and improve our knowledge of NAO, we suggest that future research use diverse research methods, such as qualitative interviews with policy insiders and surveys with stakeholders about their collaborative experiences.

This study's second limitation is its small research scope. Based on the data available, we focus our analysis on only one inter-jurisdictional river site and its nearby inner-jurisdictional river sites. Thus, our findings' external validity and generalizability should be examined in a future nationwide study. Moreover, environmental governance is not a short-term effort, so we also hope to examine the RCS's treatment effects during a longer time period. Upon more careful consideration, we expect to see our research design replicated with data with much larger sample sizes in both cross-sectional and time-series dimensions.

Finally, the research context is another limitation. Although China's authoritarian structure is a special context in which to study mandated networks, the institutional differences between it and democracies becomes a major barrier for scholars to communicate results. We encourage scholars to test our hypothesis in other institutional environments and compare the structural differences between NAOs in China and other countries to develop the collaborative governance theory further.

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Supplemental Information

Contents

Appendix A Study Sites

Figure A1: Treated And Control River Sites

Appendix B Causal Identification

We follow Abadie et al.'s (2010; 2015) steps to demonstrate the synthetic control method's causal procedure. First, we have a sample of $J+1$ units. $J=1$ is the treated unit and $J=(2,...,J+1)$ is the donor pool of control units. All $J+1$ units have $T=T_0+T_1$ time points, T_0 and T_1 are the pre-intervention and post-intervention periods. To construct the synthetic control unit, we apply a weighting average of samples in the donor pool: $\mathbf{W}=(w_2,...,w_J+1)'$ with $(0 \leq w_j \leq 1)$. To select the best value of $\mathbf{W}$, we match the synthetic control unit's characteristics so they are similar to those of the treated unit. To obtain this, we include $\mathbf{X_1}$ $(k \times 1)$ vector of time-constant variables for the treated unit in the pre-intervention period, and $\mathbf{X_0}$ as the $k \times J$ matrix of the same time-constant variables for the control units. Then, we can construct the synthetic control unit by minimizing $\|\mathbf{X_1}-\mathbf{X_0}\mathbf{W}\|$ to obtain the $\mathbf{W}^*$ (between 0 and 1), which minimizes the mean square prediction error (MSPE) in the pre-intervention period. The interpretation of MSPE is the lack of fit between the treated unit and its synthetic control part in the pre-intervention period: $MSPE=\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{1t}-\sum_{J=2}^{J+1}w_j^*Y_{jt})^2$. For more discussions of the MSPE, please read (Abadie et al. 2010).

Let Y be the outcome variable, and we can identify:

$$\hat{\alpha}_{1t}=Y_{1t}-\sum_{i=2}^{J+1}\mathbf{W_j^*}Y_{jt}, t=T_1 \tag{2}$$

$\hat{\alpha}_{1t}$ estimates the average treatment effect on the treated unit $J=1$. Y_{1t} and $\sum_{i=2}^{J+1}\mathbf{W_j^*}Y_{jt}$ are the outcomes of the treated unit and its synthetic control counterfactual in the post-intervention period.

Appendix C Trends of Pollutants

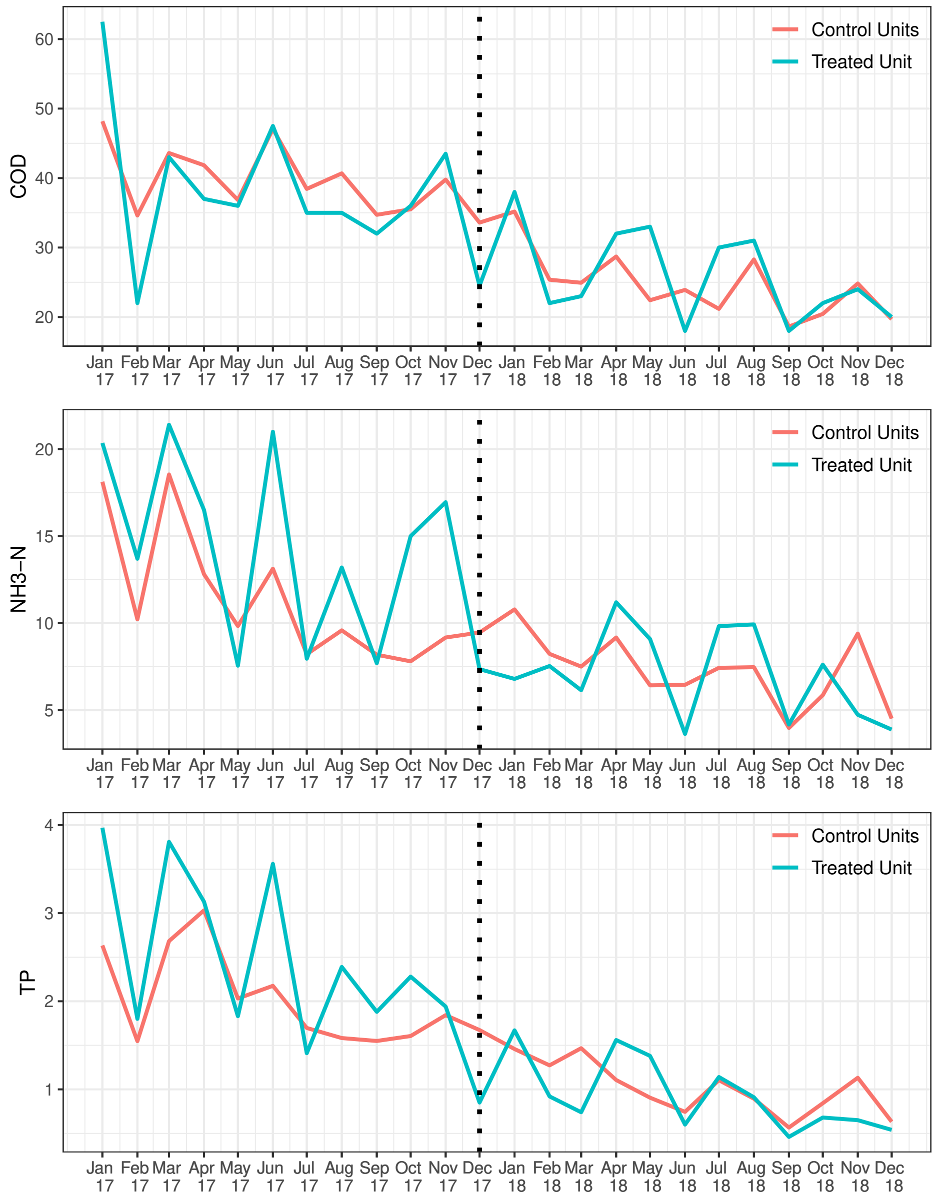

Figure C1: Trends of COD/NH3-N/TP: Treated Unit versus Average Control Units

Appendix D Treatment Effect on Each Pollutant

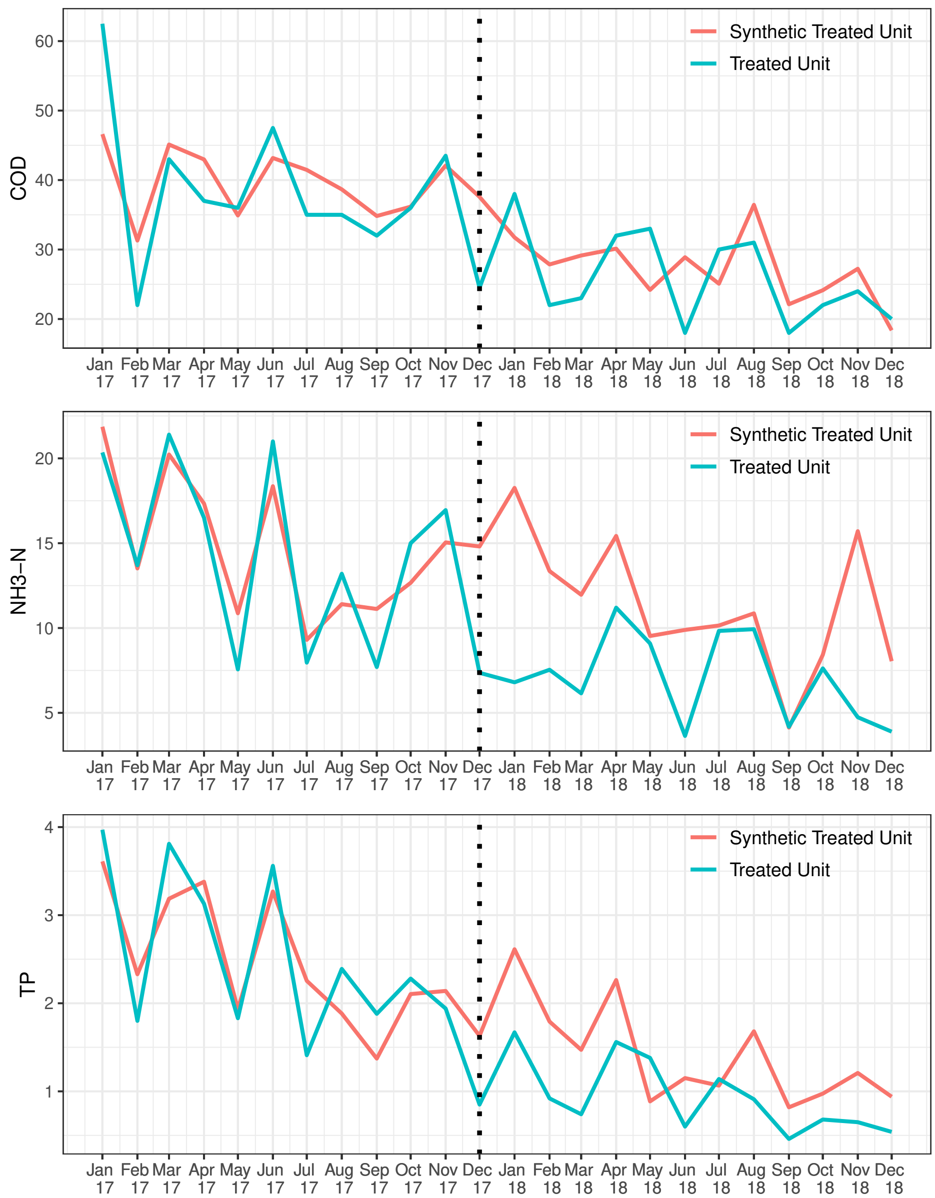

Figure D1: Trends of COD/NH3-N/TP: Treated Unit versus Synthetic Treated Units

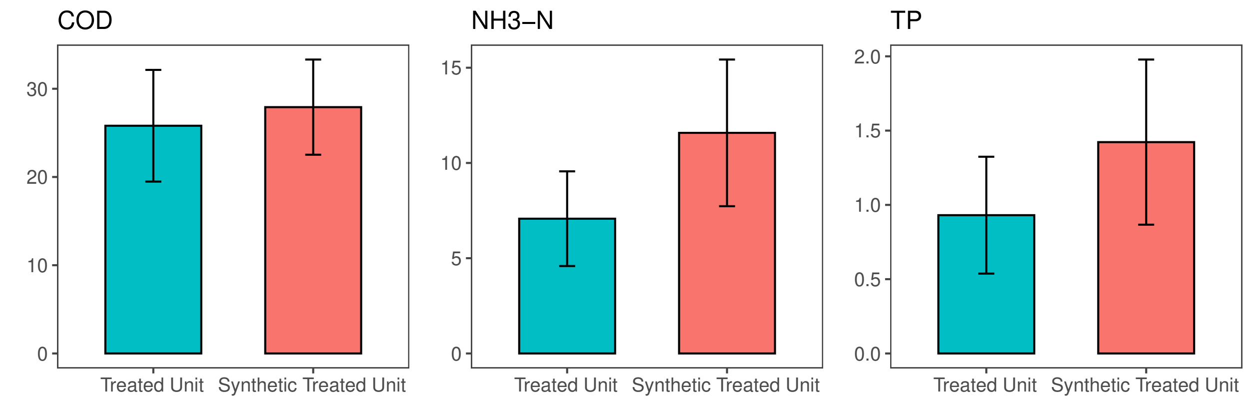

Figure D2: ATT of COD/NH3-N/TP in the Post-Intervention Period

Note:
COD: ATT = 2.11 (7.56%) (S.E. = 2.307, p-value = 0.369)
NH3-N: ATT = 4.51 (38.90%) (S.E. = 1.271, p-value = 0.00165)
Phosphorus: ATT = 0.49 (34.57%) (S.E. = 0.189, p-value = 0.0156)

Appendix E Placebo Test of Pollutants

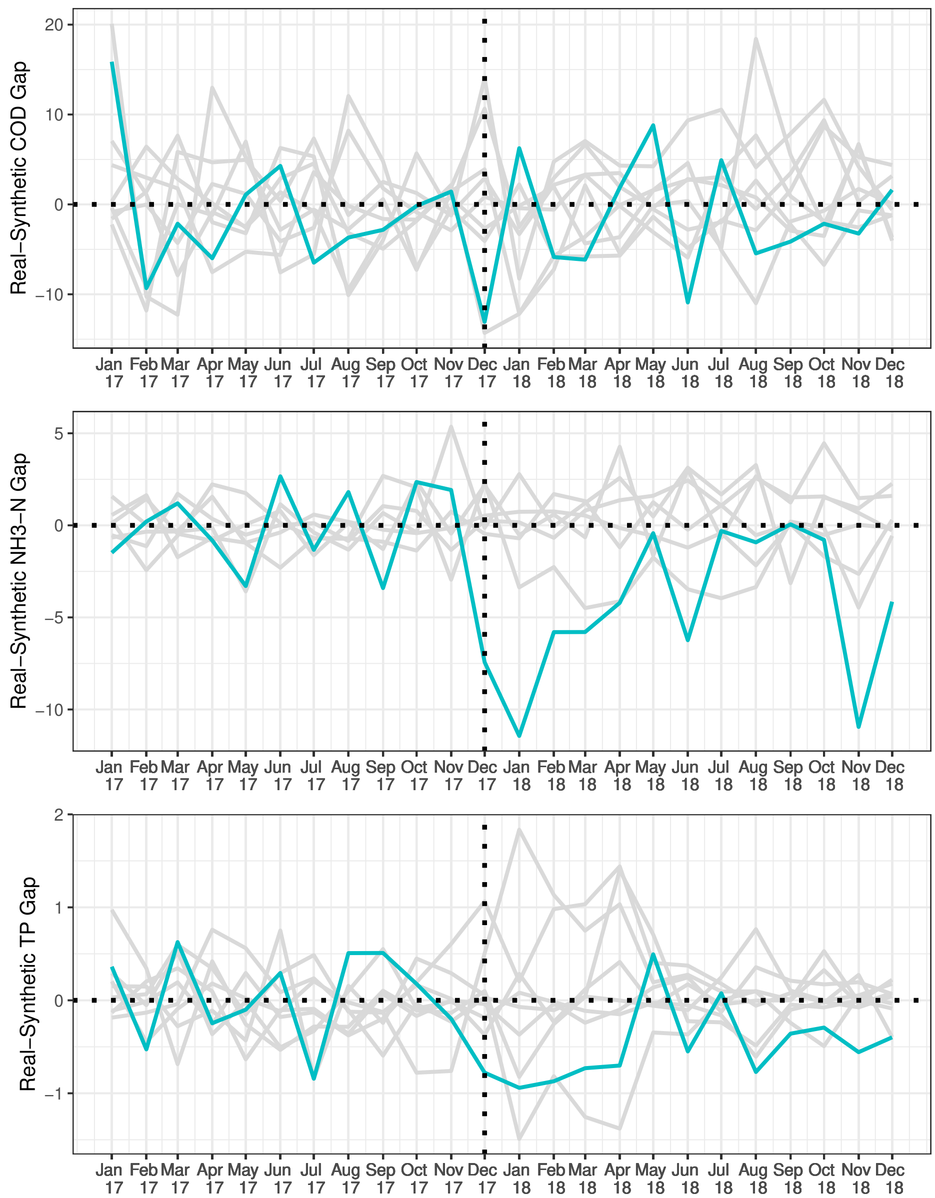

Figure E1: COD/NH3-N/TP Gaps in The Real Treated Unit and Placebo PI Gaps in Control Units

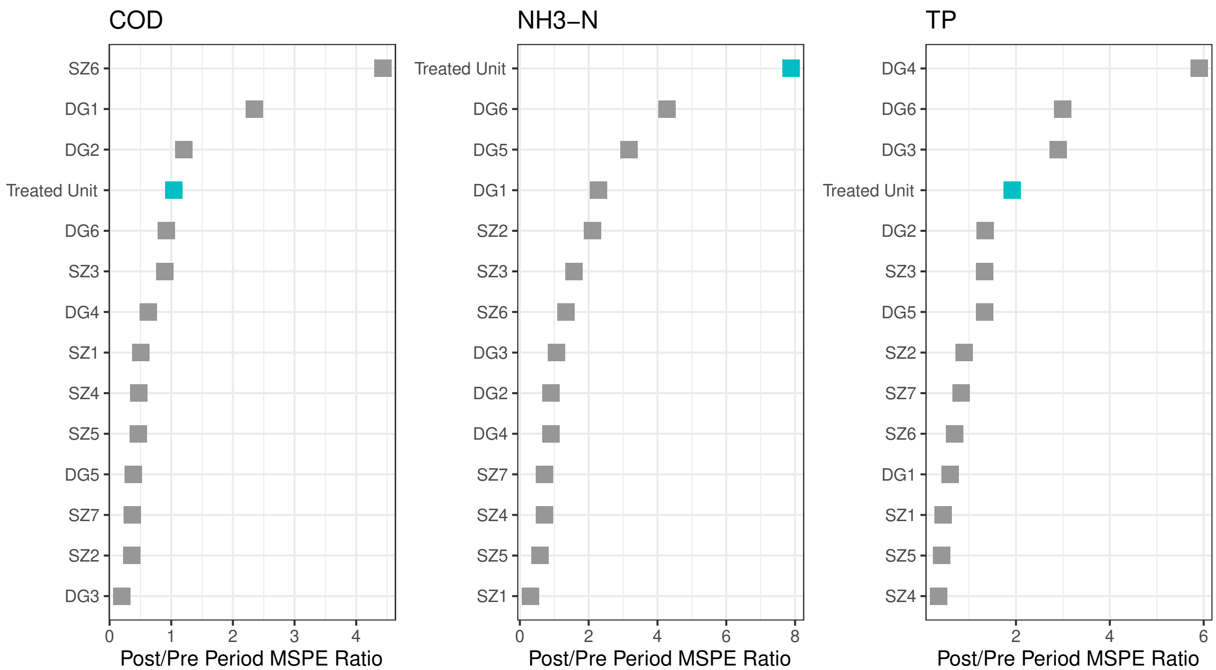

Figure E2: COD/NH3-N/TP $\text{MSPE}_{\text{ratio}}$ of Post-/Pre- Intervention: The Treated and Control Units