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

Yixin Liu and Chao Tan

Abstract

Can network administrative organizations (NAOs) improve networks' effectiveness to overcome complex social and environmental problems? This is a classical question in collaborative governance. The public management literature examines collaborative outcomes at either the organization (network node) or the entire network level, but lacks "edge level" outcomes to evaluate structured interactions among network actors. Therefore, we investigate collaborative outcomes in an inter-jurisdictional area, which reflects collaborative efforts between local governments. Recently, Guangdong Province in China enacted the River Chief System (RCS), an institutional reform that mandates the provincial government to establish a NAO to coordinate inter-city rivers' management. To assess how well the reform worked to reduce pollution, we employ the synthetic control method using monthly water quality data from 14 river monitoring sites in two neighboring cities. Our results indicate that the reform reduced the inter-jurisdictional river sites' pollution level effectively by 36%. This finding contributes to the collaborative governance theory and provides new evidence on whether the NAO model improves the shared outcomes between local governments.

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

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Introduction

Grouping multiple organizations with different interests into a governance network to achieve shared goals is a topic central to public management scholars (Bodin 2017; Ostrom 2010). Management problems in environmental governance can be described often as interdependent subproblems among network members (Bodin 2017). In fragmented jurisdictions, local governments often face complex social and environmental conditions when governing common pool resources (CPR). Their organizational goals may conflict with shared network-level goals, and unclear responsibilities may aggravate free-riding behaviors among them. This collective action dilemma limits local governments' ability to achieve shared environmental outcomes. In particular, if each local government prioritizes organizational benefits over the network-level benefits, the outcomes for all will be worse in the long-term.

After decades of development, public management scholarship has posited that collaborative governance is a remedy for free-riding behaviors, and therefore, is an effective tool to improve network outcomes. Two major research topics have emerged within this intellectual tradition and the literature on collaborative governance: (1) Motivation and formation of collaborative governance, and (2) outcomes of collaborative governance (O'Toole Jr 2015). This article is consistent with the second topic, which emphasizes the way collaborative governance performs differently in varying social and institutional contexts. In contrast to most of the studies on this topic, which are conducted in Western countries, we investigate collaborative governance and its environmental outcomes in China.

Based upon the premises in the existing environmental management literature, we identify two theoretical gaps in the discussion on forms of collaborative governance and their outcomes. First, scholars often treat collaboration as a broad concept and examine its results, while the treatment of network structure is considered a "black box" (Bitterman and Koliba 2020, 638). Under different institutional conditions, networks form different structures that yield highly varied outcomes. As Provan and Kenis (2008) suggested, network structures can be summarized as three models: Participant-governing network; lead organization-governed network, and network administrative organization (NAO). Therefore, investigating each of these network modes' effectiveness is necessary for public management scholars to study collaborative governance's outcomes.

Second, we lack "edge level" evidence to study collaborative outcomes. 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 entire network ecological system's effectiveness (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 et al. (2016, 914) referred to as "shared core goals" of collaborative governance that "…cannot easily be achieved except by collaborating."

To fill both theoretical gaps, we focus on one specific collaboration mode: The NAO model, and ask the following research question: Compared to non-collaborative governance, can the NAO model improve environmental outcomes in cross-boundary areas?

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 Guangdong provincial government enacted the River Chief System (RCS) at the beginning of 2018 to improve river management and water quality. Before the RCS was enacted, neighboring cities self-governed inter-jurisdictional rivers. Since the RCS has been implemented, the provincial government has become the NAO and coordinates its subordinate city governments' management of inter-jurisdictional rivers. This institutional reform provides a unique opportunity to compare the network effectiveness between a fragmented local governance system and the NAO model.

To evaluate this institutional reform's effect, we collected water quality data from monthly samples during 2017-2018 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. 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. By 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.

Our findings have two major theoretical implications. First, the NAO model is more effective than is fragmented local governance as a method to govern environmental outcomes in inter-jurisdictional areas. Second, this study is the first to use inter-jurisdictional natural resources as the units of analysis to investigate network activities, so our finding adds new "edge level" evidence to the collaborative governance literature.

Background: Jurisdictional Fragmentation and Free-riding Behaviors in China

Limiting opportunistic behaviors is a central issue in environmental governance (Carroll et al. 2018; Konisky and Woods 2012; Sigman 2002). Natural resources such as rivers and air are interconnected across 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 can acquire political and economic benefits from these behaviors in the short run, but the environment overall will suffer continuous harm in the long-term. Conflicts among stakeholders in the inter-jurisdiction will increase, and eventually these conflicts can lead to what Hardin (1968) referred to as "the tragedy of the commons."

Although China has a strong central government and a top-down political system, its environmental management is not coordinated effectively often because of jurisdictional fragmentation among local governments (Guo and Lu 2019). This phenomenon is similar to what Bodin (2017, 4) argued, "Actors do not collaborate with others in management of ecologically interconnected resources more than would be expected by chance." Thus, it is apparent that institutional obstacles limit network actors' collaboration across jurisdictions.

There are two major institutional reasons that contribute to jurisdictional fragmentation in China's environmental management. First, local governments do not have sufficient bottom-up motivations to collaborate with each other in environmental issues. In the Western tradition, local governments' self-organizing networks originated with a democratic assumption: Local preferences and reelection pressures motivate their policy actions (Gerber and Hopkins 2011). For example, two neighboring cities may treat the water pollution problem in a cross-boundary river that flows between them collaboratively because residents from both sides complain about the water quality issue. However, this assumption does not apply in many developing countries with authoritarian governments, where policy decisions are top-down nearly exclusively. In such systems, local officials' policy motivations derive largely from hierarchical competition for promotion: The centralized cadre system (Anderson et al. 2019). Therefore, local officials' responsiveness is weak. A recent field experiment in China Buntaine et al. (2021) conducted revealed this phenomenon. They found that citizens' monitoring contributes no effect to urban waterway's water pollution control, but higher authority government's oversight reduces water pollution significantly. Although this study does not test inter-governmental collaboration, it suggests that China's bottom-up incentive for government action is very limited.

Second, the hierarchical competition for promotion has an adverse side effect on environmental management. Although the Chinese government attempts to improve environmental conditions by including environmental performance in its promotion indicators, this approach ameliorates environmental contamination only within jurisdictions, and can even aggravate free-riding behaviors in cross-boundary areas. Further, high stakes pressure for organizational performance motivates local governments to compete with each other. 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. Thus, local governments are often adversarial and lack sufficient trust and consensus to collaborate on environmental problems in cross-boundary areas. Therefore, simply establishing oversight of local river performance cannot overcome these complexities effectively.

In addition to the fragmented local politics, complex environmental conditions and financial shortcomings are other major challenges for river governance in China (Han et al. 2016). Without effective coordination, combining local governments to form effective collaboration is extremely difficult. In general, high levels of common trust and consensual goals among network actors are keys to achieve a participant-governed network (Provan and Kenis 2008). Although this network mode is common in Western democracies, it is difficult to find in China for the reasons aforementioned. Without a collaborative environment, fragmented local authorities and their opportunistic behaviors have harmed China's interconnected natural resources continuously over the past three decades. These challenges in river governance reflect a classical question Ansell and Gash (2008, 549) asked: "Is collaborative governance more effective than adversarial or managerial governance?"

Theoretical Rationale

To solve the jurisdictional fragmentation problem and end the adversarial governance in managing China's interconnected natural resources, local governance requires a better coordination mechanism. Consistent with China's institutional context, this mechanism should be top-down and have the ability to motivate local governments to achieve common goals. According to Provan and Lemaire (2012, 640), the NAO model "...may be formally established and/or mandated through a top-down process." Unlike a fragmented local system, the NAO model includes an external member that governs the network. This external member can be a person or an organization that supervises, coordinates, and integrates the collaborative actions among network members (Provan and Kenis 2008). In local politics, NAOs can be upper-level government entities that have authority to coordinate policy instruments among lower-level governmental actors (Wang et al. 2019). In this section, we address the NAO model's advantages in overcoming free-riding behaviors in cross-boundary areas. In addition, we introduce the theoretical association between the NAO model and its outcomes from the collaborative governance regime perspective. By theorizing the NAO model's mechanisms to achieve interconnected natural resources management, we provide a comprehensive demonstration of why it is consistent with China's institutional context.

Network Administrative Organization

When interlocal governmental network actors do not have high levels of trust and goal consensus, the NAO model has several advantages over the fragmented system to 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 et al. 2016). For example, Macciò and Cristofoli (2017) found that NAOs with strong managerial leadership support healthcare networks' persistence. They also suggested certain effective leadership practices, such as regular meetings with members, forging agreements between partner organizations, and serving as a mediator among parties. As Provan and Kenis (2008) argued, when the policy problems become more complex, networks are more likely to form a centralized mode to maintain their effectiveness.

The NAO model's second benefit derives from its ability 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 fragmented system is favored less than is the NAO model as a system to monitor 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 ability to monitor performance at both the organizational and network levels, which motivates network members to keep their agreements to accomplish network goals.

Finally, NAOs allocate external resources to subsidize network members, which improves the incentives and competencies in network-level collaboration (Provan and Lemaire 2012). When faced with complex environmental problems, local governmental actors lack financial, technical, and political resources to implement regional policies (Wang et al. 2019). NAOs can not only provide 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) showed that American local agencies are more likely to cooperate with the federal government when they have less total revenue; Wang et al. (2019) found that Chinese regional watersheds' protection relies on the NAO model with upper-level governments' financial subsidies; Bitterman and Koliba (2020) found that the Vermont State government provides financial and human assistance to stormwater projects' local mandated networks.

Collaborative Governance Regime

Although several studies have tested the NAO model's advantages in coordinating complex network activities, 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 organizations, the CGRs, 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 et al. 2019; Scott 2016). Scholars have also investigated outcomes of the entire network's 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 when studying pollution problems in environmental governance, because opportunistic behaviors often occur in cross-boundary areas. One important topic in the environmental policy literature locates the analysis at the jurisdictional borders. If the assumption of inter-jurisdictional political actors' free-riding holds, each government would have different enforcement levels for inner- and inter-jurisdictional pollution. To examine this phenomenon, social scientists use distance indicators of the boundary frequently to measure differences in enforcement. For example, Sigman (2005) studied transboundary spillovers among American states using water monitoring sites within 50 miles of the state boundary as the distance threshold. Her findings suggested that 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) obtained similar findings when they combined the Environmental Protection Agency's (EPA) Toxic Release Inventory data and American counties' characteristics, and found 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 found that when state boundaries bisect the watersheds, federal enforcement provides 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 fragmented local governance 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: When local governments collaborate with each other under the NAO model, the network (compared to a fragmented system) governs environmental outcomes in inter-jurisdictional areas more effectively.

River Chief System: The NAO Model in China

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 establish a river chief office and 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 that spanned multiple counties' boundaries) forced the Wuxi municipal government to rearrange its management model, which coordinated county and district governments to control the water pollution collectively [1]. 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 was implemented, neighboring governments self-governed the management responsibilities for inter-jurisdictional rivers. Since the RCS was implemented, the upper-level government serves as the NAO that governs network activities in these rivers externally. River chiefs have been appointed to four different governmental levels (from high to low): Provincial; city; county, and district (Wang and Chen 2020). Provincial heads are general chiefs for all inter-city rivers in the region, and chief executives of cities, counties, and districts are river chiefs for their own jurisdictions. The government leaders and their departmental agencies form the river chiefs' offices and manage subordinate intergovernmental networks.

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 in coordinating network activities. First, river chiefs facilitate collaborations among local governments. 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). With this mechanism, relationships between local governments change from competitive to collaborative. Local governments responsibilities' in inter-jurisdictional rivers become clear, communication between local governments increases, and most importantly, the RCS consolidates each CGR's shared core goals.

Second, the RCS improves the mechanism of rivers' water quality oversight. Every river receives a water pollutant reduction target. River chiefs monitor their subordinate rivers'

[1] In China's political system, counties and districts are subordinate governments of a city. This hierarchy differs from that in the United States and certain other Western contexts, in which the county is the political subdivision of states.

annual performance and adjust the targets in the following year (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 (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.

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 to serve as external experts and participate in the river management plan design and implementation stages (Li, Tong, and Wang 2020). Hence, both financial and expertise resources improve the network's capacity.

Figure 1 illustrates two alternative configurations of river governance. Panel A shows a non-collaborative local governance system, in which the provincial government provides direct oversight of water quality in each city's rivers. Under this system, cities care about the water quality of rivers within their jurisdictions, but they have less incentive to manage inter-jurisdictional rivers. Panel B shows the river governance under the RCS, in which the provincial government engages actively in river governance and coordinates cities surrounding inter-jurisdictional rivers into effective CGRs.

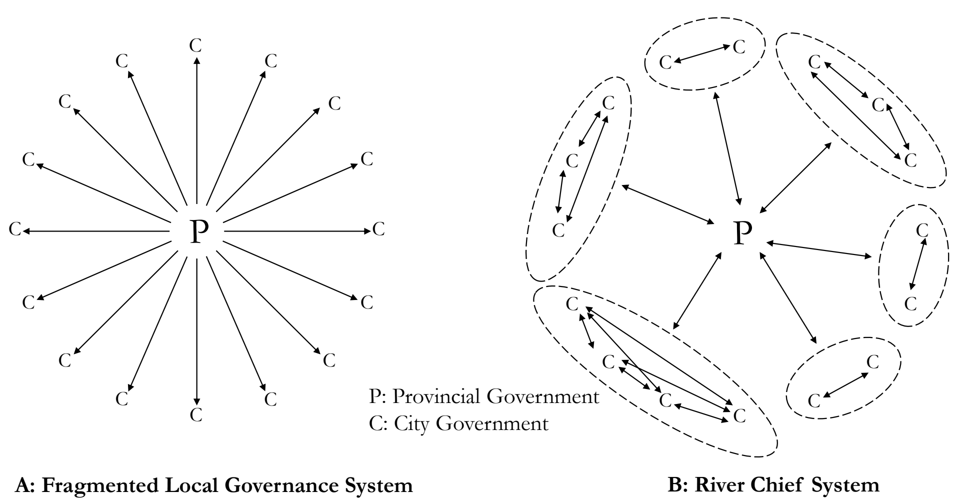

Figure 1: Alternative Network Configuration of River Governance

Empirical Strategy

Case Study: Maozhou River between Dongguan and Shenzhen

Although the RCS has been implemented in many provinces, it is technically difficult for researchers to conduct a large-scale comparison of water quality between inter- and inner-jurisdictional rivers, largely because rivers are often interconnected. Hence, treatments on inter-jurisdictional rivers may spillover to inner-jurisdictional rivers. To overcome this research barrier and investigate collaborative governance's effects on water pollution control causally, we find a special case: Maozhou river, which flows between the two major industrial cities in Guangdong Province: Dongguan City and Shenzhen City. The Maozhou river is located most downstream, close to the marine outfall, and other inner-city rivers in both cities are farther upstream (see Figure 2). This special case improves our research's internal validity, because a downstream river's water quality is unlikely to affect upstream rivers.

Figure 2: Study Area

Note: The red dot is the inter-jurisdictional Maozhou river site, black dots are the inner-jurisdictional control river sites. The yellow area is Changan district, and the pink area is Shajing district. Light blue lines indicate the sample watersheds and black lines are Shenzhen and Dongguan's jurisdictional boundaries.

This case's scope has limitations, but 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. Further, Dongguan and Shenzhen are in the center of the Pearl River Delta Economic Zone, which is the hub of Chinese high-tech and manufacturing industries. While on the one hand, this region has been leading China's economic advancement in the past 40 years, on the other, it has been suffering from severe environmental costs in air and water pollution for a long while (Huang et al. 2017; Yi et al. 2018).

In recent years, both cities' governments have declared policy intentions to solve their water pollution problems, and their inner-city water quality conditions have been improving continuously. However, the water treatment of the inter-jurisdictional Maozhou river continues to underperform, primarily because of industrial pollution discharge. Both Dongguan and Shenzhen have many polluting plants that have been regulated to limit their discharge into inner-city rivers, but could still discharge into the inter-city Maozhou river, in which the managerial responsibility was unclear. Even worse, from the Figure 2 map we can see that Maozhou river is at a downstream location and connects to the marine outfall, where the pollution is discharged directly into the ocean ultimately.

The RCS has been implemented formally in Guangdong Province since the beginning of 2018, and thereafter, the provincial government has coordinated river management with both cities. To resolve free-riding behaviors from both cities' pollution discharge into Maozhou river, the provincial government organized monthly meetings with both municipal governments and county and district governments adjacent to the river. The meetings clarified government authorities' responsibilities, shared information among network members, and coordinated managerial tasks in each period. The major enforcement goal to reduce water pollution was to regulate polluters. Thus, both municipal governments and their subordinate agencies, counties, and districts inspected those polluters' discharge behaviors collaboratively and negotiated with them to identify alternative environmentally sound solutions. Moreover, the provincial government provided financial resources for both cities to coproduce green areas along both banks of the river, which encouraged sustainable development for both cities in that surrounding area.

The 2018 institutional reform affected the inter-city Maozhou river's management model significantly, but theoretically, had no effect on other inner-city rivers, which creates a natural counterfactual for us to compare. City, county, and district-levels' RCSs have been implemented in 10 cities in Guangdong Province since 2015, including Shenzhen and Dongguan, so inner-city rivers' governance responsibility had been clarified by then. The 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 policy actor in the network, with the provincial government as the NAO. This institutional change provides us a unique opportunity to study the provincial government, Maozhou river, and the cities on both sides of the river as an integrated CGR.

Data

Given the short implementation period to date, it is difficult for researchers to collect large-N water performance data for inter-jurisdictional rivers in Guangdong Province. Thus, to obtain a preliminary understanding of the RCS's treatment effect on the cross-boundary area, we collaborated 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 cities.

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 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 in close proximity within the greater Maozhou watershed area. In 2002, the Ministry of Environmental Protection 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 classified all rivers in our sample as level poor V water. Thus, they all have the common target to improve water performance from level poor V to V. Specifically, COD, NH3-N, and TP should be less than 40 mg/L, 2.0 mg/L, and 0.4 mg/L, respectively.

The Synthetic Control Method

The synthetic control method that Abadie, Diamond, and Hainmueller (2010, 2015) ddeveloped matches our time-series cross-sectional water quality data perfectly, in which 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, and treated and control units' characteristics match well rarely. 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 used 17 cities in the Jiangsu province to construct the synthetic Jiangyin city. By comparing the actual and synthetic Jiangyin, they found 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 to the treated unit as possible. With this weighting matrix, we reproduced the synthetic control treated unit that had similar outcomes in the pre-intervention period. Therefore, the difference between the treated unit and synthetic treated unit's outcome indicated the treatment effect. To identify the causal effect accurately, we minimized the mean square prediction error (MSPE) in the pre-intervention period. Appendix A documents the detailed steps in the synthetic control method's causal procedure and the mathematicalal expression of MSPE.

The key in the synthetic control method is to have a lengthy 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). The water quality data from 2017-2018 combined yielded 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) suggested 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). As mentioned above, it is highly unlikely for the RCS intervention to spill over from the most downstream treated site to other upstream control sites.

Measurement of The Water Quality

Using the Ministry of Environmental Protection's (2002) *Environmental Quality Standards for Surface Water* (GB3838-2002), 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: $PI = 1/3(COD/40 + NH_3N/2 + TP/0.4)$. 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 B).

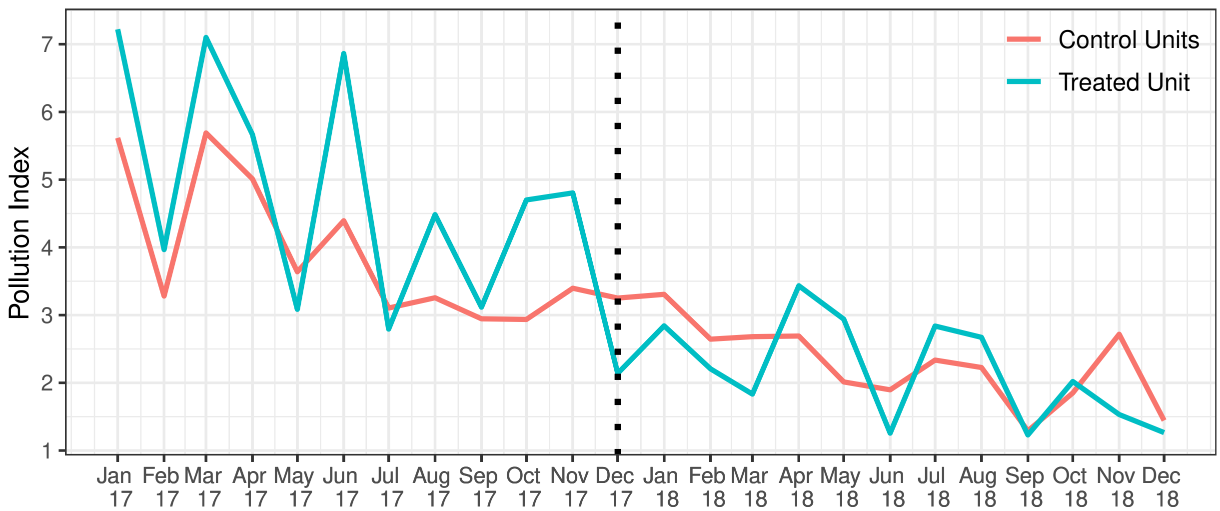

Figure 3: Trends of PI: Treated Unit versus Average Control Units

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).

We collect district-level socioeconomic data in which each river monitoring site is located from Dongguan and Shenzhen's Statistical Yearbooks. The socioeconomic predictors include local population, economy size, and the local government's financial capacity (Konisky and

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 district where a river is located (RMB/per capita)
Gov. revenue per capita	The 2017 annual government revenue per capita in the district where a river is located (RMB/per capita)
Gov. expenditure per capita	The 2017 annual government annual expenditure per capita in the district where a river is located (RMB/per capita)
Population density	The 2017 annual population/area in the district 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 land 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

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. According to 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 districts: Changan district (area = 97.87 km^2, population = 663,800) from Dongguan, and Shajing district (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 unit treated.

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 manually from Google Earth. 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 areas (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.

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

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 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

Next, we summarize the weights 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 A). We label the river sites DG1 to DG6 for the sites in Dongguan and SZ1 to SZ7 for the sites in Shenzhen. Summing these weights of each control site's water quality values, we construct the synthetic treated river site.

Results

The Main Effect of The RCS

Figure 4 displays our main finding on the RCS's treatment effect on reducing pollution in the inter-jurisdictional river site. 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.

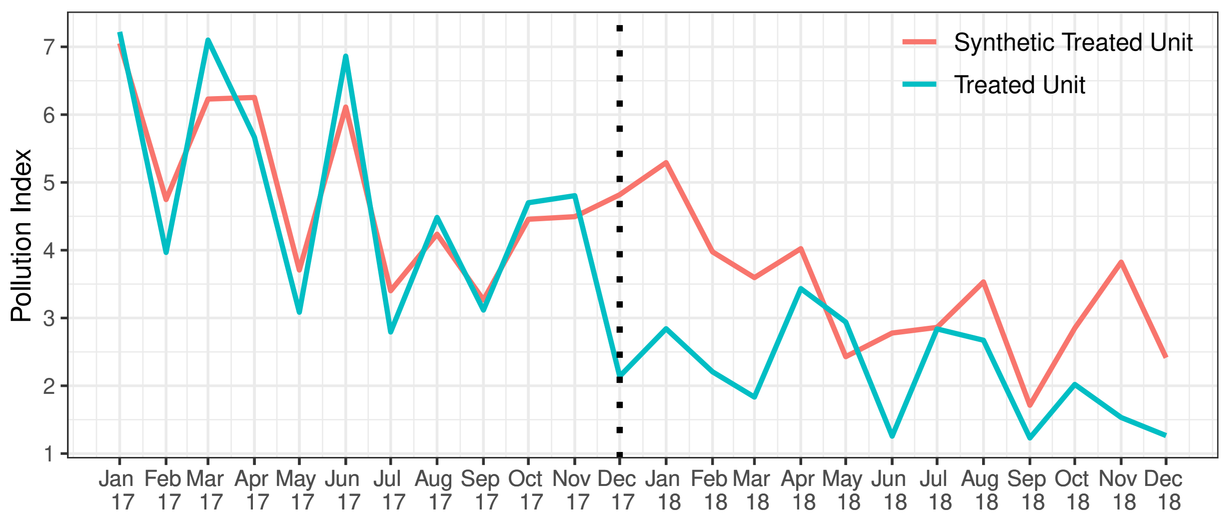

Figure 4: Trends of PI: Treated Unit versus Synthetic Treated Unit

After the RCS was enacted, the inter-jurisdictional river site's water quality improved immediately, and the river's PI was 56% lower than its synthetic control unit in December 2017. However, this pollution reduction effect did not hold consistently in the middle of 2018, but increased again to 48% 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 pattern that differed greatly from its synthetic control unit. Details of each pollutant indicator are provided in Appendix C Figure C1.

The RCS's treatment effect overall is sizeable. Figure 5 reports the average treatment effect on the treated unit (ATT) during the thirteen months post-intervention (December 2017 to December 2018). We estimate the ATT based upon Appendix B equation (2), which is obtained from a t-test of PI between the treated unit and the synthetic treated unit in the post-intervention period. This estimation generates our model's overall effect size. On average, the PI in the actual inter-jurisdictional river site is 1.22 (36%) lower than its synthetic control unit (SE = 0.346, p = 0.0017). The ATT for each pollutant is reported in Appendix C Figure C2.

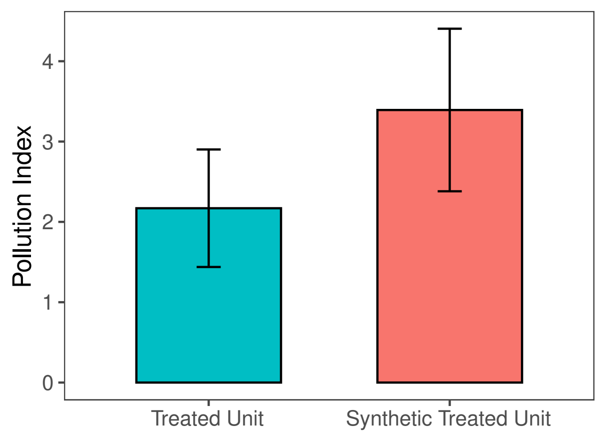

Figure 5: ATT in the Post-Intervention Period

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 reassign 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 illustrates 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 differences in value 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 discard four extreme control units because their pre-intervention MSPEs are more than two times higher than the treated unit.

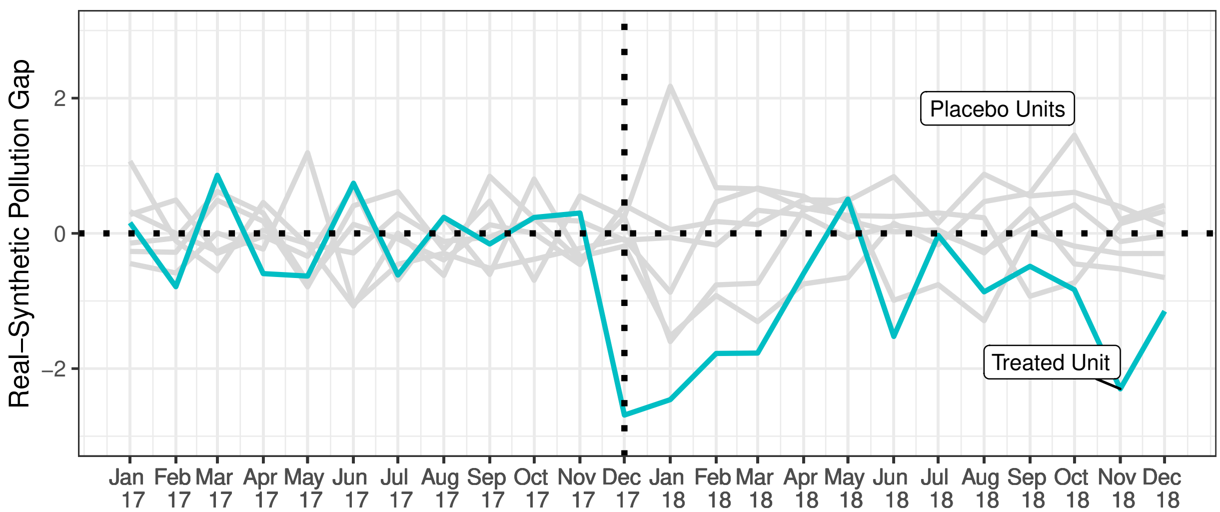

Figure 6: PI Gaps in the Actual Treated Unit and Placebo PI Gaps in Control Units

Next, we employ significance tests with the post- and pre-intervention $\text{MSPE}_{\text{ratio}}$. Figure 7 reports the $\text{MSPE}_{\text{ratio}}$ comparisons between the treated inter-jurisdictional river site and the others. The result demonstrates that the inter-jurisdictional river site's $\text{MSPE}_{\text{ratio}}$ is at least 2.67 times larger than that of any other control site. Not a single control site's $\text{MSPE}_{\text{ratio}}$ is close to the inter-jurisdictional river site. The larger $\text{MSPE}_{\text{ratio}}$ value indicates that the water quality difference between the treated and synthetic control unit increased in the post-intervention period. Therefore, if one assigns the treatment to these data randomly, the probability of obtaining a $\text{MSPE}_{\text{ratio}}$ as large as the inter-jurisdictional river is 1/14 (p = 0.07) [2].

[2] Of note, the comparably large p-value ($0.07 > 0.05$) does not mean our explanatory 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 units with similar characteristics, and the larger sample size may lead to overfitting problems in the comparison.

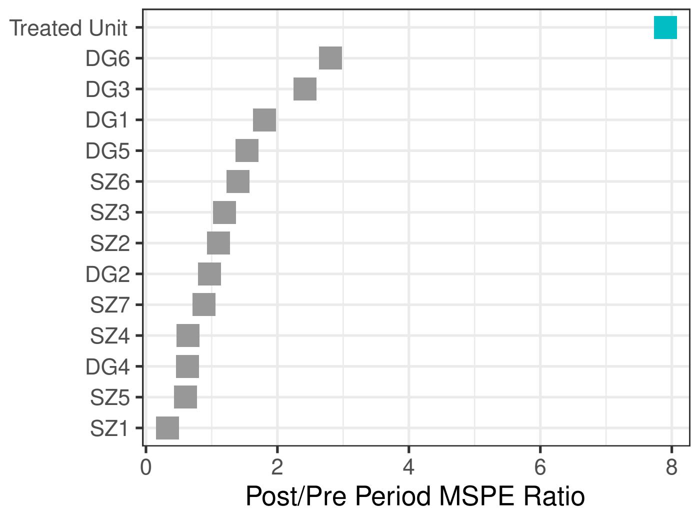

Figure 7: PI $\text{MSPE}_{\text{ratio}}$ of Post-/Pre- Intervention: The Treated and Control Units

We also rerun 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 D. 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 domestic 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 based upon local farmers' individual behavior. Therefore, reducing 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 measures to treat it.

Discussion and Conclusion

Theoretical Implication

By investigating the way shifting from fragmented local governance to the NAO model affects 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 network governance modes and their collaborative outcomes.

By comparing water quality performance before and after the network structure changed from the fragmented system to NAO, we demonstrate that the NAO model is a better strategy to improve environmental outcomes. This finding is consistent with Provan and Kenis's (2008, 236) view that NAO enhances a 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 is the first study in the collaborative governance literature to use an inter-jurisdictional natural resource as the unit of analysis. Our special case overcomes the spillover effect in identification, which has prevented previous studies from comparing management of inter- and inner-jurisdictional natural resources. Performance of interconnected natural resources in cross-boundary areas serves as a bridge between organizational performance and network ecology-level performance. Hence, we refer to it as "edge level" evidence. 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 local governments.

The NAO model's utility we identify in the Maozhou River has implications not only for China, but also has theoretical associations with other countries' contexts. In the United States, Bitterman and Koliba (2020) found that Vermont's state-established mandated networks subsidies improved municipalities' capacity, so they became more competent in controlling water pollution. Vermont's mandated network model outperforms not only non-collaborative networks, but also voluntary collaborative networks. In Australia, a study of bushfire planning Brummel et al. (2012) conducted demonstrated the importance of mandated collaboration in facilitating network members' communication, which is the critical method to maintain high quality services. When the mandated planning was completed, local authorities diminished interorganizational communication. and the networks transformed back to voluntary forms. Combining these findings and the results from our study, the NAO model's ability to facilitate collaboration has been established well in different contexts. Moving beyond this research topic, we suggest that public management scholars need to disentangle the "black box" of collaborative structure continuously as we study network effectiveness. As noted earlier, we should not only examine collaborative governance as a broad concept, but also observe and compare outcomes between different network modes from a closer and more rigorous perspective.

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 are unable to explain several internal mechanisms further, 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 recommend 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 upon 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 should be examined in future studies with samples that can be generalized better. 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. Further, 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 top-down structure is a unique context in which to study mandated networks, the institutional differences between it and democracies becomes a major barrier for scholars to communicate results. As mentioned earlier, 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 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 B Trends of Pollutants

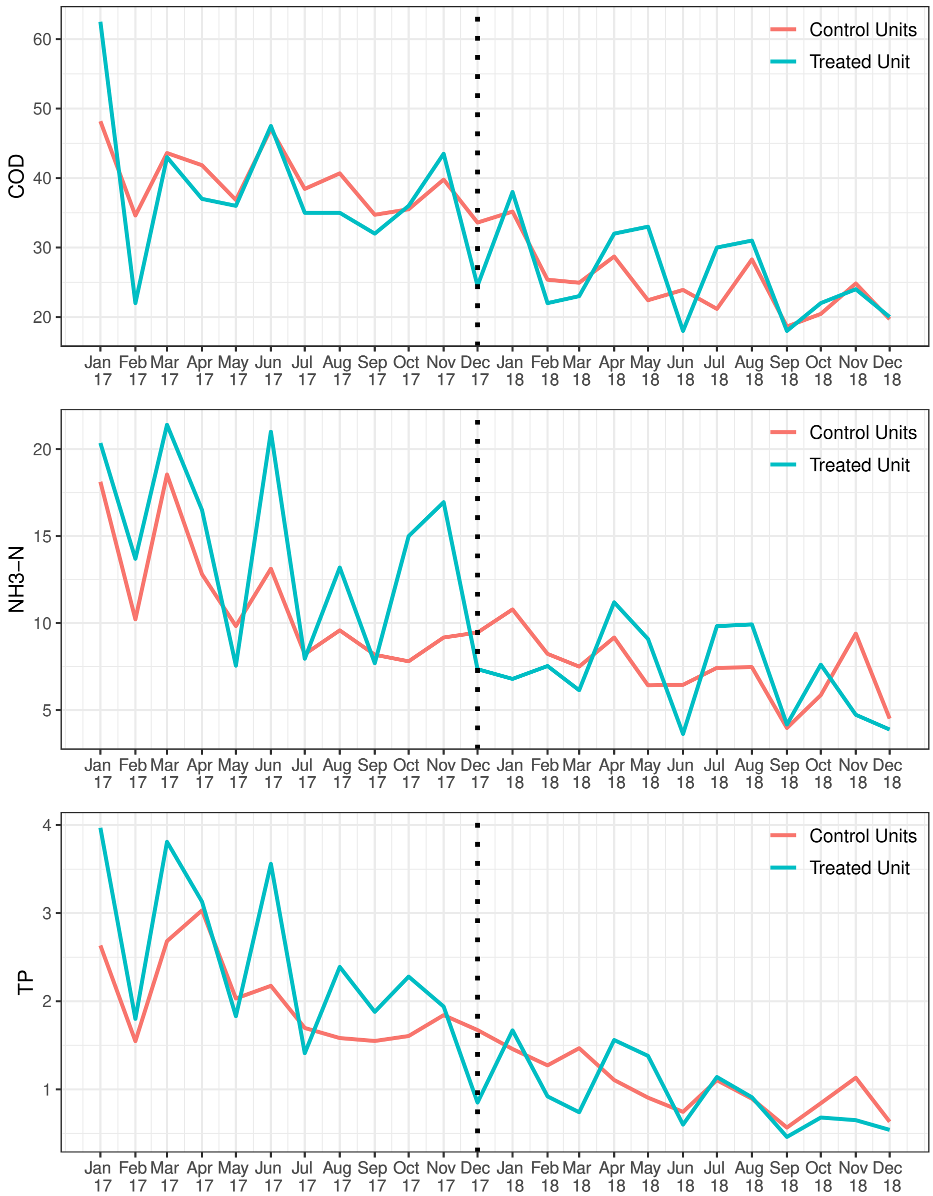

Figure B1: Trends of Pollutants: Treated Unit versus Average Control Units

Appendix C Treatment Effect on Each Pollutant

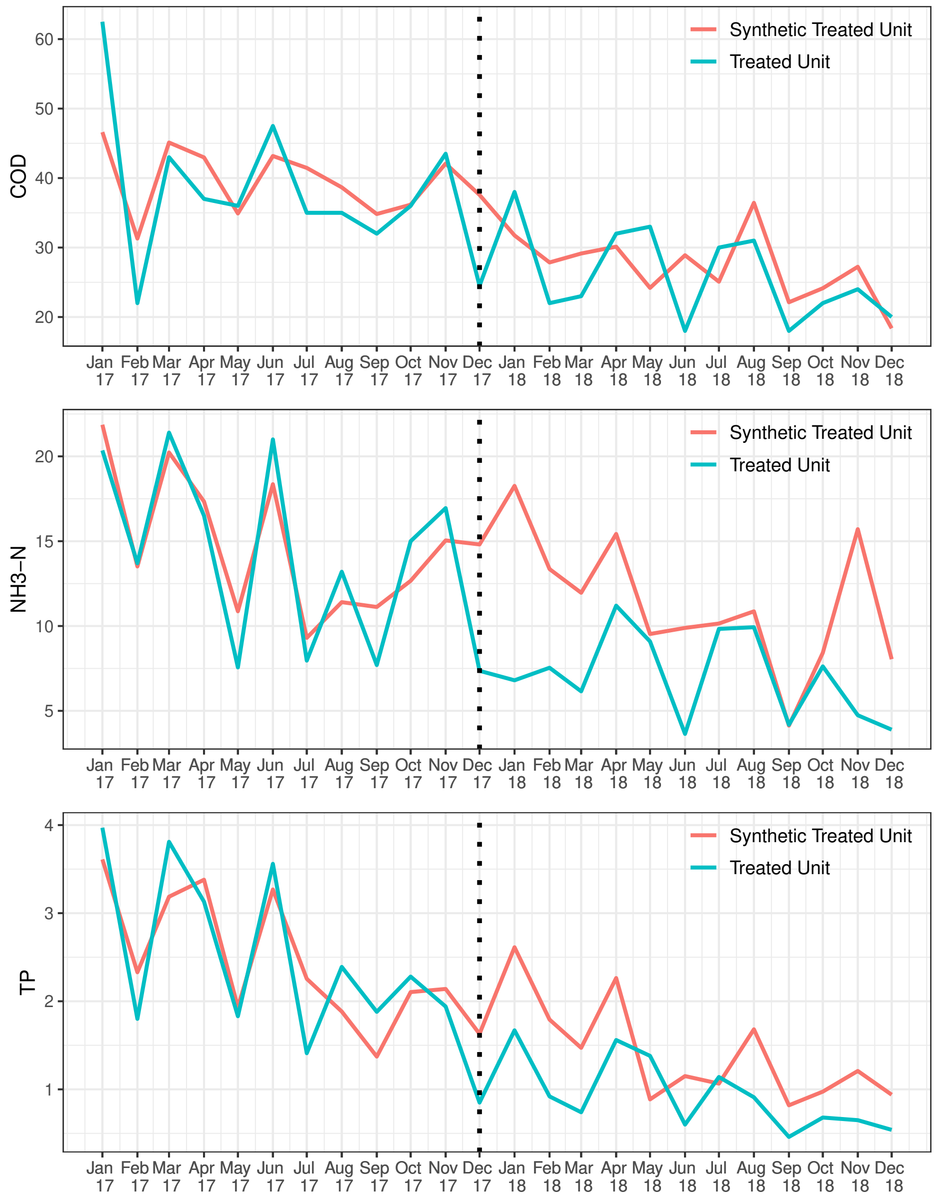

Figure C1: Trends of Pollutants: Treated Unit versus Synthetic Treated Units

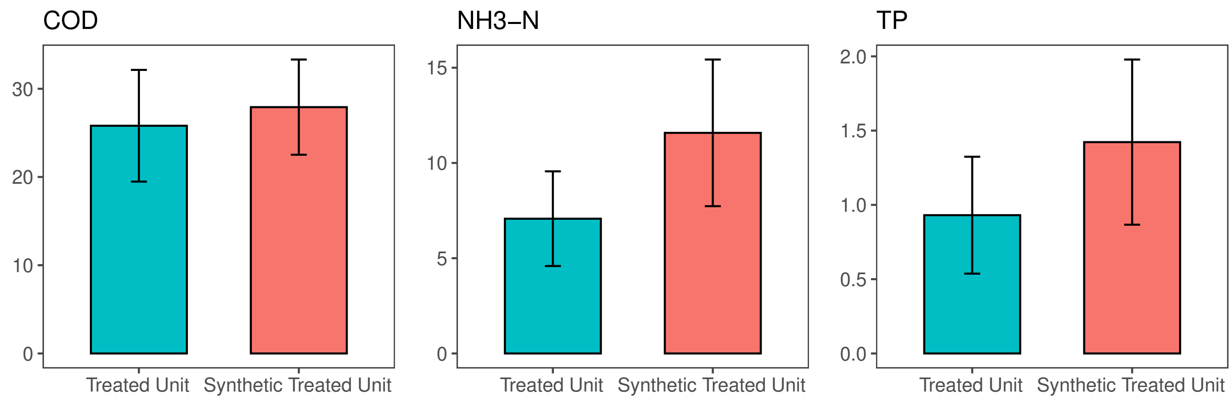

Figure C2: ATT of Pollutants in the Post-Intervention Period

Note:
COD: ATT = 2.11 (8%) (S.E. = 2.307, p-value = 0.369)
NH3-N: ATT = 4.51 (39%) (S.E. = 1.271, p-value = 0.00165)
Phosphorus: ATT = 0.49 (35%) (S.E. = 0.189, p-value = 0.0156)

Appendix D Placebo Test of Pollutants

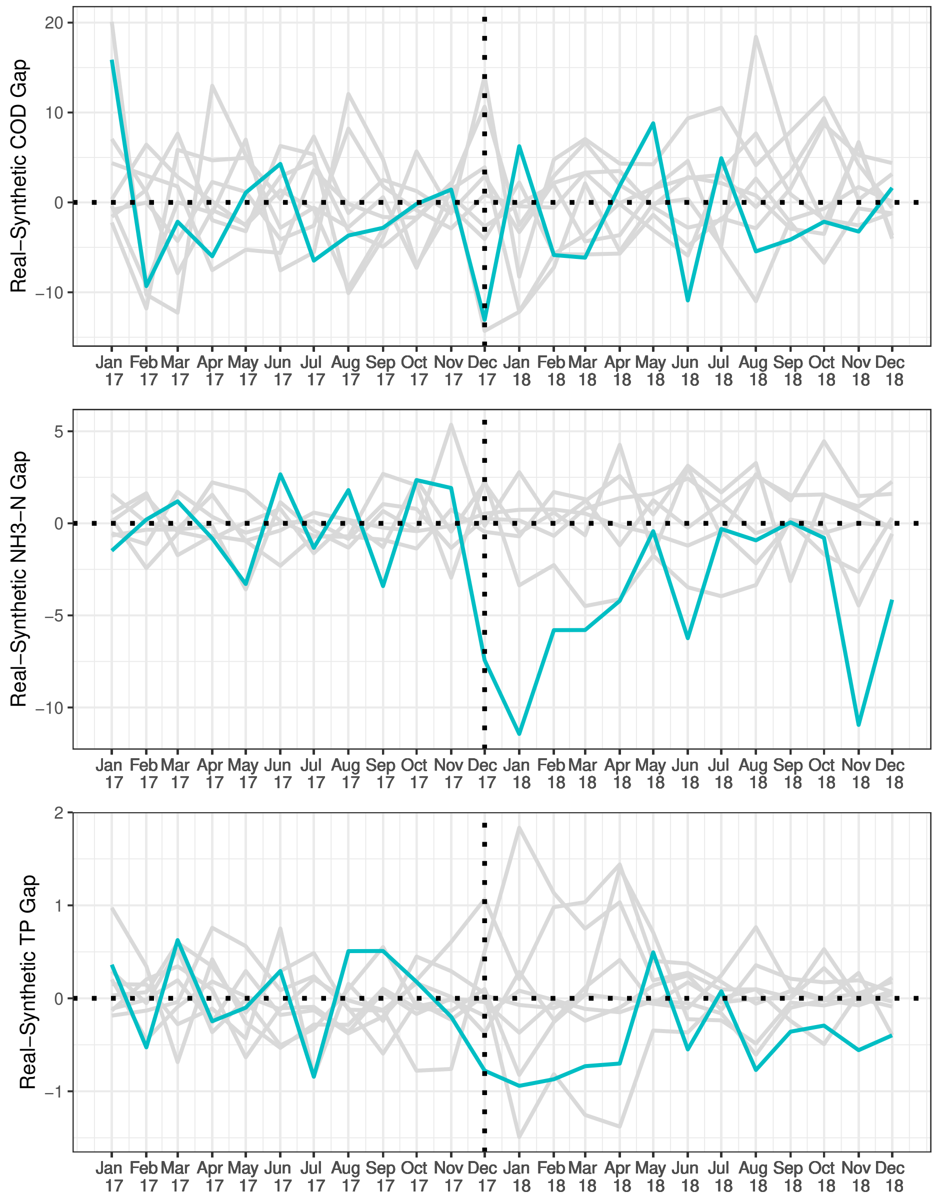

Figure D1: Pollutants Gaps in The Real Treated Unit and Placebo PI Gaps in Control Units

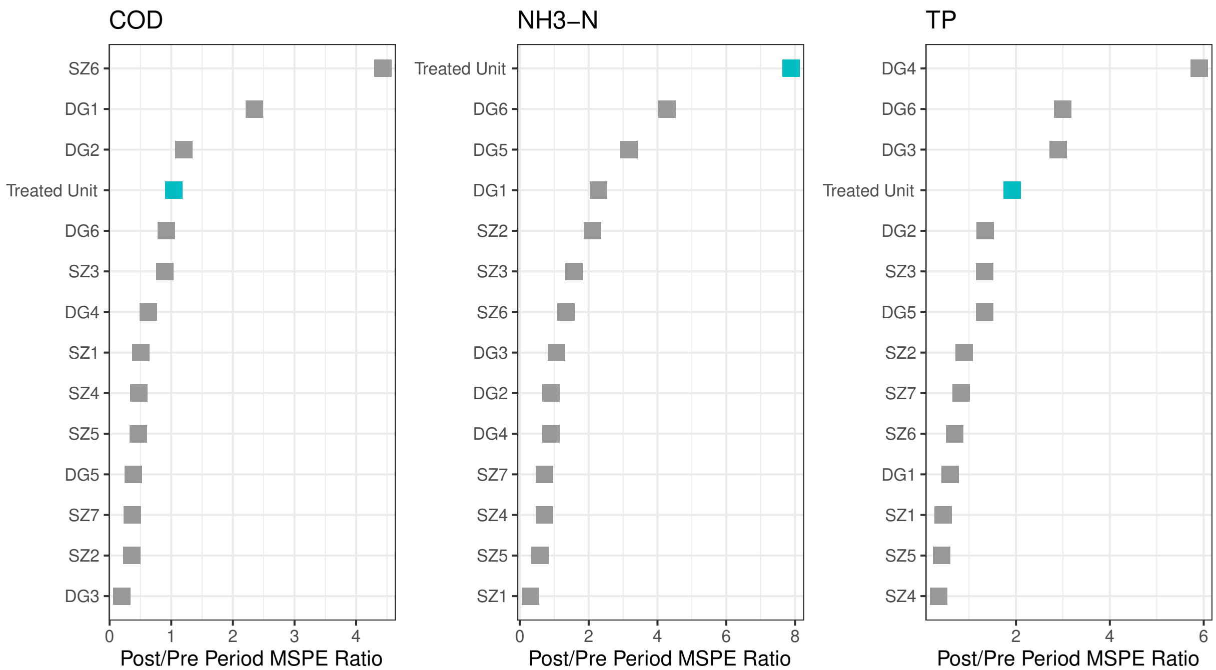

Figure D2: Pollutants $\text{MSPE}_{\text{ratio}}$ of Post-/Pre- Intervention: The Treated and Control Units