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

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Abstract

Can network administrative organizations (NAOs) improve networks' ability to solve complex social and environmental problems? This is a classical question in collaborative governance. The public management literature examines collaborative outcomes at either the organization or the entire network level, but has not addressed "edge level" outcomes to evaluate structured interactions among network actors. Therefore, we investigate outcomes in an inter-jurisdictional area that reflect collaborative efforts between local governments. Recently, Guangdong Province in China enacted the River Chief System, an institutional reform that mandates the provincial government to establish a NAO to coordinate intercity rivers' management. To assess how well the reform has 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% in the following year. This preliminary 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

The question, "Is collaborative governance more effective than adversarial or managerial governance?" (Ansell and Gash 2008, 549) is central to public management. However, combining multiple organizations with different interests into a governance network to achieve shared goals is difficult (Bodin 2017; Ostrom 2010). Management problems in environmental governance can be described often as interdependent subproblems among network members (Bodin 2017). Local governments often face complex social and environmental conditions when governing common pool resources in fragmented jurisdictions. 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 and leads adversarial competition. 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 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 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 (Milward and Provan 1998). As Provan and Kenis (2008) suggested, network structures can be summarized as three models: Participant-governed network; lead organization-governed network, and network administrative organization (NAO). Therefore, investigating each of these network models' effectiveness is necessary for public management scholars to study collaborative governance's outcomes properly.

Second, we lack "edge level" evidence of 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 form of collaboration: The NAO model, and extend Ansell and Gash's (2008) question into our 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's river chief office 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 during 2017-2018 from monthly samples of 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 water pollution control in the inter-jurisdictional river. 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.

Theoretical Rationale

Collaborative Efforts at Network Edges

Do networks really work? Public policy and management scholars have studied networks seriously for more than two decades (O'Toole Jr 1997; Provan and Milward 2001). When networks are treated as dependent variables, scholars have conducted research on network nodes, edges, and entire networks. These studies focus respectively on actors that participate in network activities (e.g., Leach and Sabatier 2005), connections between network units (e.g., Berardo and Lubell 2016; Dixon and Elston 2020), and networks' structures overall (e.g., Yi 2018). However, when networks are considered independent variables, the existing literature has documented network outcomes at only the levels of nodes and entire networks, but has failed to analyze the middle ground: network edges.

This is a surprising omission because edges constitute connections between network actors that indicate collaborative efforts directly. Network edge is the path to connect two actors (Patty and Penn 2017). Different policy areas have no consensus of how to measure network edges, and we argue that this is one of the reasons that scholars examine network outcomes in different levels. For example, schools in public education networks are connected by sharing teaching materials and information, so measuring collaborative outcomes at the level of network nodes (students' achievement in each school) is appropriate (Meier and O'Toole Jr 2003); health providers in public health networks are connected by co-delivering services to the same patients, so measuring collaborative outcomes at the level of entire networks (patients' aggregated outcomes in the network system) is appropriate (Provan and Milward 1995). In environmental policy networks, common pool natural resources are network edges to connect interlocal governments. Although understanding organizational and entire network level outcomes are both important, we should extend theoretical discussion on network activities and their outcomes on natural resources in transboundary areas. Studying collaborative efforts in connecting areas between two jurisdictions can deepen our knowledge on how to balance organizational self-interests and collective actions in the broader network (Provan and Lemaire 2012).

To fill this theoretical gap, we elaborate the theoretical connections between network activities at the level of edges and their environmental outcomes. In the following sections, we first use the collaborative governance regime (CGR) framework to demonstrate why studying collaborative performance at the edge level is important in complex social ecological systems. Second, we introduce the concepts of models in network governance and explain the way the NAO model motivates and coordinates network actors to pursue shared goals at network edges collaboratively. Finally, we test our hypothesis by connecting the theoretical foundations of NAOs to our empirical research case: River governance in China.

The Collaborative Governance Regime Framework

Natural resources such as rivers and air are distributed across multiple political jurisdictions. Given this environmental context, collaborations to achieve shared core goals among local government authorities are required to overcome the collective action dilemma. Network scholars use "regime" to describe the complex social ecological systems associated with inter-jurisdictional natural resources (Emerson et al. 2012). Accordingly, the CGR framework is designed to analyze the outcomes of collaborative governance embedded in such systems.

Emerson et al. (2012, 6) defined CGR as "…the particular mode for, public decision making in which cross-boundary collaboration represents the prevailing pattern of behavior and activity." If we view inter-jurisdictional environmental issues as collective action problems in CGRs, the units of analysis of collaborative outcomes should include participant organizations, the CGRs, and target goals (Emerson and Nabatchi 2015). These three levels of analysis correspond to the units of analysis in network research: Participant organizations are network nodes; the CGRs are network edges, and target goals are established for the entire network. Abundant studies of collaborative performance in environmental governance have set their units of analysis on participant organizations (e.g., Bitterman and Koliba 2020; Scott 2016) and 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). Indeed, this level of analysis is central to network governance because network actors are assumed to be interdependent, and the outcomes of interdependency should be attractive to more public management scholars (Agranoff 2007).

Using CGRs as the units of analysis is even more critical when studying environmental pollution problems in complex social ecological systems: Opportunistic behaviors often occur in cross-boundary areas, which are the connections and network edges between neighboring governments. Local governments have responsibilities to reduce environmental contamination within their jurisdictions, 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). These "gaming in the boundary" effects demonstrate the existence of adverse inter-jurisdictional externalities, which occur in many environmental policy areas such as river, air, and wind power (Helland and Whitford 2003; Monogan III et al. 2017; Sigman 2005). As Bodin (2017, 4) argued, "Actors do not collaborate with others in management of ecologically interconnected resources more than would be expected by chance." If scholars and governments do not develop effective management tools to mitigate these adverse inter-jurisdictional externalities, adversarial competitions would eventually lead to what Hardin (1968) referred to as "the tragedy of the commons."

Modes of Network Governance

Networks and collaborative governance are often seen as management tools to overcome collective action dilemmas in managing common pool resources. As we mentioned at the outset, there are three modes of networks in collaborative governance: Participant-governed networks; lead organization-governed networks, and the NAO model (Provan and Kenis 2008). Participant-governed networks require high levels of common trust and consensual goals among network actors, while lead organization-governed networks are more centralized. In these latter networks, a core network member with sufficient resources and legitimacy to lead network activities coordinates key decisions (Provan and Kenis 2008), and network participants share the same goal with the lead organization. Participant-governed networks and lead organization-governed networks are both common in health and human services. Organizations in these policy areas often reach consensus that building community capacity is essential to deliver services, so the participant-governed networks are feasible (Chaskin 2001). Lead organization-governed networks are applicable when organizations demand that a core organization manages clients' flow and resources efficiently (Provan and Kenis 2008).

Among the three modes, the NAO model is the most centralized form and has an external member (not one of the network participants) that coordinates network activities (Provan and Kenis 2008). When network participants have little trust in each other and have different organizational interests, they may not be motivated to participate in voluntary collaboration or allow a lead organization to coordinate network activities. In such cases, a mandated external network broker could be a solution to reduce transaction costs in collaboration (Provan and Milward 2001). Managing common pool natural resources is the policy area that interlocal network actors often distrust and leads them to compete with each other. Without proper regulations or collaborative mechanisms, they spillover pollutants to, and extract resources from, neighboring jurisdictions. Compared to the other two modes, the NAO model is the most effective tool to achieve network-level competency, and is used often to address complex inter-jurisdictional problems (Provan and Kenis 2008).

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. These advantages include coordinating formal collaboration, providing oversight, and allocating resources (Provan and Kenis 2008; Wang et al. 2019).

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). 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, as a system to monitor task quality, a fragmented system is favored less than is the NAO model (Provan and Kenis 2008). Finally, NAOs allocate external resources to subsidize network members, which improves the incentives and competencies in network-level collaboration (Provan and Lemaire 2012). NAOs 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).

Although the theoretical premises above show NAOs' effectiveness in managing natural resources, we lack evidence of its capacity to solve free-riding problems in cross-boundary areas. To overcome the free-riding problem, the recent RCS reform in China is an attempt to switch the fragmented system to the NAO model in river governance. This institutional experiment offers an ideal context for us to compare the effectiveness of the NAO model and the fragmented system in governing inter-jurisdictional natural resources. Next, we introduce the environmental management in China

Jurisdictional Fragmentation in China

As Li et al. (2016) suggested, "China can be characterized as a fragmented authoritarian country." It has a top-down political structure in which the central government is the primary policymaker and local governments implement policy. This central-local relationship is consistent with the classic principal-agent dilemma. The central government controls local governments by overseeing the environmental performance within their jurisdictions, which provides the opportunistic structure for local governments to practice free-riding behaviors in inter-jurisdictional areas (Li et al. 2016). In the following paragraph, we provide two explanations for this phenomenon.

First, local officials' policy motivations derive largely from the hierarchical promotion system: The centralized cadre system (Anderson et al. 2019), in which local government officials' promotions are based upon their performance. This system stimulates interlocal competition rather than voluntary collaboration, and the competition for promotion has an adverse side effect on environmental management (Guo and Lu 2019). Although the Chinese government attempts to improve environmental conditions by including environmental performance in the promotion criteria, this approach ameliorates environmental contamination only within jurisdictions, and can even aggravate free-riding behaviors in cross-boundary areas (Cai et al. 2016). Further, high stakes pressure for organizational performance motivates local governments to game the system and discharge pollutants to neighboring jurisdictions (Anderson et al. 2019; Zhang and Cao 2015). In river governance, the central government measures local governments' performances by reading the pollution index from water monitoring stations. To compete with other governments and win the promotion game, city governments discharged on average 57% more pollutants to their downstream neighbors between 1999 and 2010 (He et al. 2020). These 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 collaboratively address environmental problems in cross-boundary areas.

Second, 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 nearly all policy decisions are top-down. In such systems, higher-level governments appoint local officials, so they are accountable to their higher governments, but less responsive to citizens (Li et al. 2016). A recent field experiment in China that Buntaine et al. (2021) conducted revealed this phenomenon: Higher authority governments' oversight reduces water pollution more effectively than citizens' monitoring. This study suggests that China's bottom-up incentive for government action is very limited.

Without a collaborative environment, fragmented local authorities and their opportunistic behaviors have harmed China's interconnected natural resources continuously over the past three decades (Zhang et al. 2018). Although the central government is often seen as the enabling factor to facilitate policy implementation, we suggest that it has less control of environmental conflicts in inter-jurisdictional areas. With little mutual trust and consensus, local governments have high transaction costs in forming voluntary collaboration, so the NAO model with a central broker may be more efficient in policy implementation (Iborra et al. 2018).

River Chief System: The Mandated NAO Model in China

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. The RCS is an institutional attempt to implement the NAO model in China that appoints the leading officials in higher governments as "river chiefs" for inter-jurisdictional rivers. River chiefs are required to establish NAOs: the river chief offices, which work closely with their subordinate local governments and coordinate river quality management with multiple sectors and agencies (Liu et al. 2019).

The river chief offices correspond to the definition of NAO in managing river governance networks. 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. In public-sector networks, this external member is often the "...central, local administrative entity" that supervises, coordinates, and integrates the collaborative actions among network members (Provan and Milward 2001, 419). River chief offices are created by upper-level governments and serve as the external coordinator of local government networks. They do not implement local services or policy regulations directly, but coordinate local governments' network activities. As Kenis and Provan (2009, 448) suggested, "Government run NAOs are generally set up (by mandate) when the network first forms, to stimulate its growth through targeted funding and/or network facilitation and to ensure that network goals are met." Accordingly, the river chief offices change fragmented local governance networks to highly centralized forms designed to achieve the network goals that improve water quality in inter-jurisdictional rivers (Wang et al. 2019).

Given these characteristics, the RCS uses the unique top-down mandated approach to establish external brokers: river chief offices to coordinate river governance networks. Its implementation also follows the Chinese approach to experimental governance. This innovation can be traced back to 2007, the time of the water supply crisis in Wuxi City, Jiangsu province (Wang and Chen 2020). An 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 . Since then, the central government has recommended the RCS to other areas. At the end of 2016, 16 of 31 mainland Chinese provinces had adopted the RCS fully or in part. 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.

The key mechanisms of the RCS reflect the NAO model's major advantages in coordinating formal collaboration, performing oversight, and allocating resources. First, river chiefs coordinate formal collaborations among local governments. They hold regular meetings with lower-level government leaders and coordinate actions directly among other departmental agencies, such as the water affairs bureau, environmental protection, agriculture, land and resources, and financial departments (Liu et al. 2019; Wang and Chen 2020). Formal collaborations have proven to be important mechanisms of NAOs that improve networks' capacity. For example, Macciò and Cristofoli (2017) used regular meetings and standard operating rules to measure formalized coordination mechanisms in Switzerland's homecare networks, and found that these mechanisms enhanced network endurance and performance significantly. Similarly, a study of Australian bushfire planning (Brummel et al. 2012) conducted demonstrated the importance of mandated collaboration in facilitating organizational representatives' communication. Through the mechanism of formal collaboration, 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 performance oversight. Every river receives a water pollutant reduction target. River chiefs monitor their subordinate rivers' 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. These performance oversight activities reflect Provan and Milward's (2001, 418) idea that "...NAO is both agent of the community and the principal of the network participants." The river chief offices' performance oversight differs from the central government's traditional oversight. In the RCS, the performance information is not only a criterion for promotion or punishment, but is used to revise future management plans as well. As the principals that engage strongly with agents in the performance management process, the river chief offices fill the principal-agent information gaps and restrict opportunistic behaviors.

Third, the river chief offices 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 et al. 2020). The NAO model's advantage in resource allocation has been examined in other contexts. For example, Whetsell et al. (2020) found that the model enhanced pooling resources and reduced cooperation costs for innovation in the US semiconductor industry. Similarly, Bitterman and Koliba (2020) found that the state-established NAO enhanced local government networks' ability to allocate funds, which therefore improved their environmental performance. Taking advantage of these insights, the RCS's capacity to allocate resources reflects the NAO model's advantage in solving "…external demands and needs are being faced by the network" (Provan and Kenis 2008, 240).

The advantages of the RCS described above demonstrate its ability to mitigate the transaction costs of participating in collaboration by reducing information asymmetry, task complexity, and power asymmetry (Hindmoor 1998; Williamson 1981). Formal collaboration and regular meetings with local governments reduce information asymmetry, and these mandated mechanisms help local governments forge contracts and achieve common goals. Performance oversight reduces collaboration risks from task complexity and provides goal guidance. Finally, resource subsidies balance power asymmetry between local governments and provide external support that stabilizes the network.

In summary, river chief offices are NAOs that "…are committed to network-level goals and have a strategic involvement with the network as a whole" Provan and Kenis (2008, 240). 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). However, these studies focused on water quality within jurisdictions, such as counties and cities, but did not capture the RCS's core goal: water pollution reduction in inter-jurisdictional rivers. Therefore, we conduct a case study of inter-jurisdictional river governance in China to test the following hypothesis.

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.

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 farthest downstream, close to the marine outfall, and other inner-city rivers in both cities are farther upstream (see Figure 1). This special case improves our research's internal validity, because a downstream river's water quality is unlikely to affect that of upstream rivers.

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 China's high-tech and manufacturing industries. While on the one hand, this region has led China's economic advancement in the past 40 years, on the other, it has suffered severe environmental costs in air and water pollution for a long while (Yi et al. 2018).

Figure 1: 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.

In recent years, both cities' governments have declared their intentions to solve their water pollution problems, and their inner-city water quality conditions have improved 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 can still discharge into the inter-city Maozhou river, in which the managerial responsibility has been unclear. Even worse, from the Figure 1 map we can see that Maozhou river is located downstream and connects to the marine outfall, where ultimately, the pollution is discharged directly into the ocean.

The RCS has been implemented formally in Guangdong Province since the beginning of 2018, and the provincial river chief office has coordinated river management with both cities since then. To resolve free-riding behaviors in both cities' pollution discharge into Maozhou river, the provincial river chief office 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 river chief office 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 river chief office 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 et al. (2010, 2015) developed 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 compromised 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, and it has become popular in environmental studies in recent years (e.g. Bueno and Valente 2019; Maamoun 2019; Sun et al. 2019). 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.

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 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 root mean square prediction error (RMSPE) in the pre-intervention period. Appendix A documents the detailed steps in the synthetic control method's causal procedure and the mathematical expression of RMSPE.

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 construct 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.

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

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 2 displays the PI trends for the treated unit and the control units' mean before and after the RCS was enacted (trends for each pollutant shown in Appendix B).

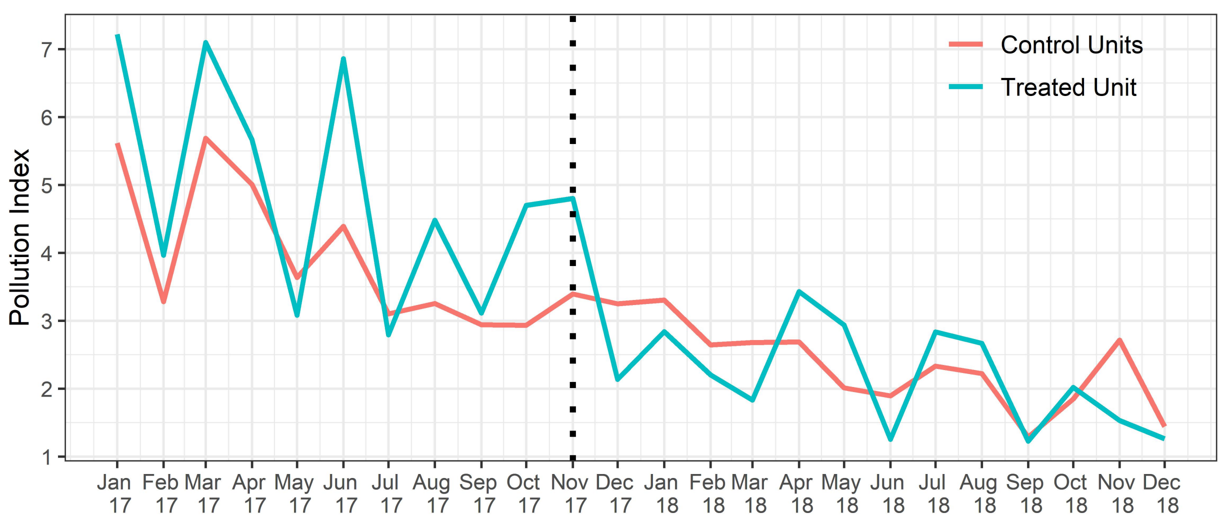

Figure 2: Trends of PI: Treated Unit versus Average Control Units

Measurement of Predictors

According to the formal justification, we select valid predictor variables to construct a synthetic control unit comparable to 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	
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)
District water supply	The 2017 annual water supply in the district where a river is located (10,000m^3)
Environmental predictors	
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)
Residential 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

We collect district-level socioeconomic data for each river monitoring site's location from Dongguan and Shenzhen's Statistical Yearbooks. The socioeconomic predictors include local population, economy size, district water supply, 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 values comparable to the predictors above. According to the definition of common pool resource, 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 of 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, residential, 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	91170.05	94896.41
Gov. revenue per capita	4977.57	4968.03	6449.14
Gov. expenditure per capita	5901.28	8347.39	10980.78
Population density	0.62	0.28	0.38
District water supply	7174.00	4079.77	5876.15
River flow rate	10.67	10.75	8.46
Industrial land use	2.26	1.49	1.73
Residential land use	0.13	0.07	0.30
Agricultural land use	0.39	0.16	0.19
Avg. PI in spring	6.10	6.08	4.86
Avg. PI in summer	5.21	5.40	4.35
Avg. PI in fall	3.46	3.61	3.10
Avg. PI in winter	4.75	4.51	3.17

Note: Pre-intervention MSPE = 0.302

Table 2 compares the pre-intervention predictors' means for the treated river site, the synthetic treated river site, and the donor sample mean. We can see clearly that the treated unit's predictor values are more similar to the synthetic unit than is the donor sample average, which suggest that our synthetical control weighting is successful. Moreover, these data show the particularity of our case in China. Our sampling districts have higher GDP per capita than the 2017 national average (59,660 RMB)[1]. In addition, industrial land use is the major

[1]This data is from the website of The World Bank.

land use in the areas of our sampling river sites. As contrast, industrial and residential land use are more balanced in general Chinese cities (Liu et al. 2014). Combining these two regional variables and the level poor V water quality in the sampling rivers, our case shows the trade-off between manufactural based economic development and environmental protection, which is a common problem for many economic developed areas in China (Du and Yi 2021). Therefore, this regional characteristic makes our case salient and have policy implications to river governance in other regions in China.

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

Unit Name	Synthetic Control Weight
DG1	0.056
DG2	0.011
DG3	0.090
DG4	0.000
DG5	0.007
DG6	0.503
SZ1	0.000
SZ2	0.086
SZ3	0.247
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 the weights of each control site's water quality values, we construct the synthetic treated river site.

Results

The Main Effect of The RCS

Figure 3 displays our main finding on the RCS's treatment effect in 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 is implemented, which indicates that our predictors achieve a good match between the treated unit and its synthetic control counterfactual in the pre-intervention period.

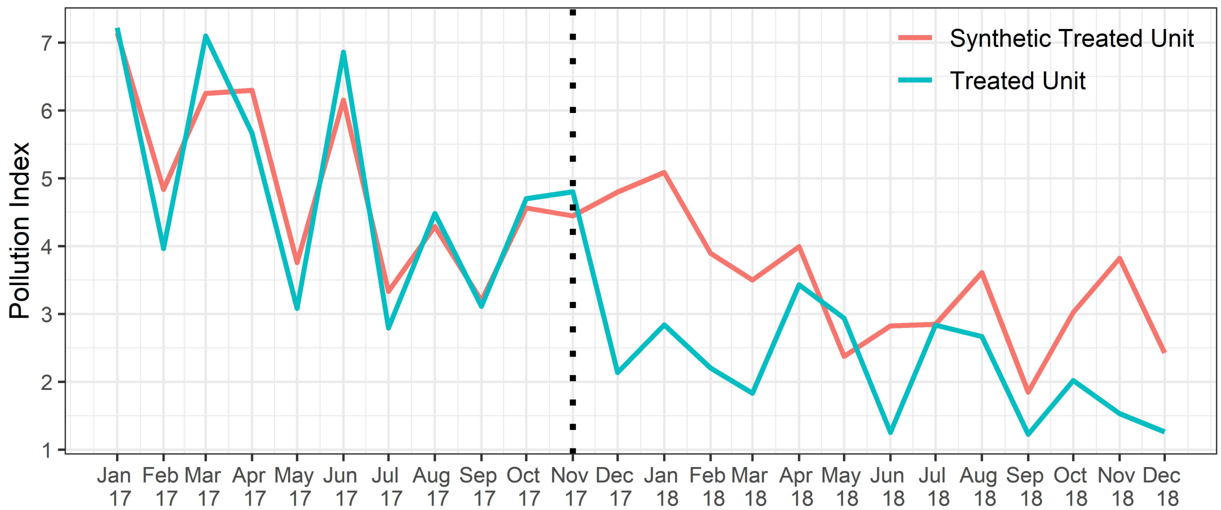

Figure 3: Trends of PI: Treated Unit versus Synthetic Treated Unit

After the RCS was enacted, the inter-jurisdictional river site's water quality improved immediately, and the river's PI was 55% lower than its synthetic control unit in December 2017. However, this pollution reduction effect did not remain consistent in the middle of 2018, but increased again to 48% at the end of the year. Water temperature, different human activities in dry and wet seasons, and the Spring Festival between January and February all contribute to this seasonal fluctuation of water quality (Crosa et al. 2006; Razali et al. 2020; Wu et al. 2016). However, these environmental and social factors apply to all river sites in our sample, so they do not harm the internal validity of this study. If we measure each pollutant separately, NH3-N and TP show similar patterns, but with different magnitudes of fluctuation. COD's pattern does not differ greatly from its synthetic control unit. Details of each pollutant are provided in Appendix C.

The RCS's treatment effect overall is sizeable. Figure 4 reports the mean 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 A equation (1), which is obtained from a t-test of the 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 = 0.33, p = 0.001). The ATT for each pollutant is reported in Appendix C.

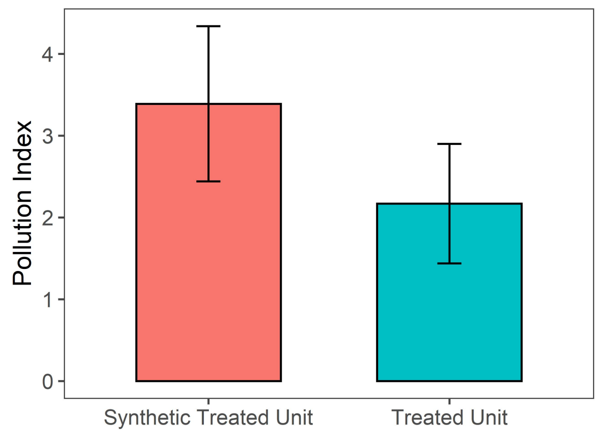

Figure 4: ATT in the Post-Intervention Period

In-place 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 placebo tests from both in-place and in-time dimensions (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.

In the in-place placebo test, we reassign the treatment to other control units in the donor pool to see whether they have effects similar to that in the inter-jurisdictional river site. Figure 5 shows that the treatment effect of the treated inter-jurisdictional river site (green line) is greater 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 RMSPEs are more than twice as high as the treated unit.

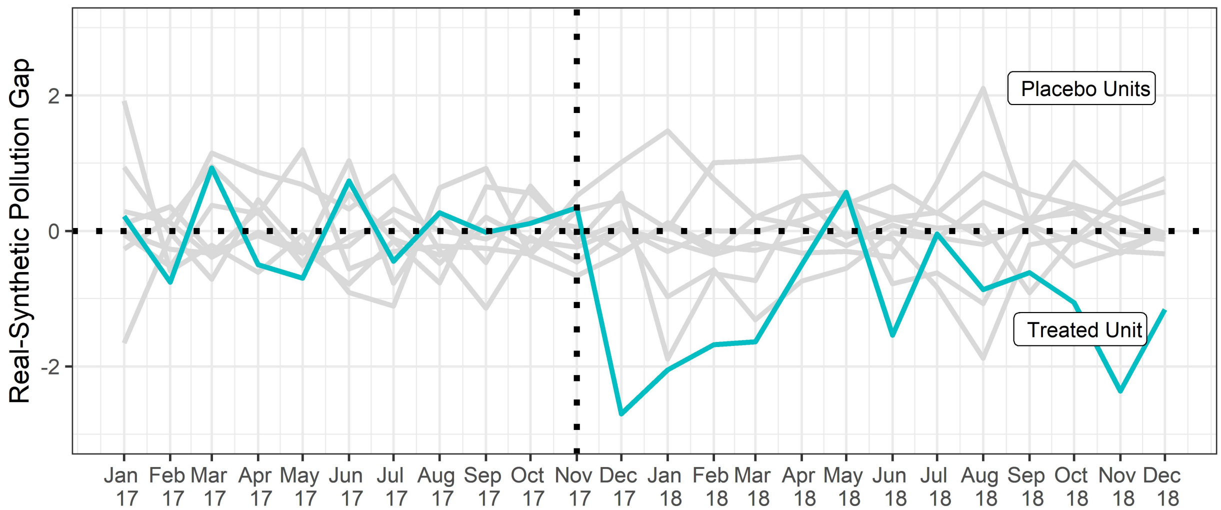

Figure 5: PI Gaps in the Actual Treated Unit and Placebo PI Gaps in Control Units

Next, we employ significance tests with the post- and pre-intervention $\text{RMSPE}_{\text{ratio}}$. Figure 6 reports the $\text{RMSPE}_{\text{ratio}}$ comparisons between the treated inter-jurisdictional river site and the others. The result demonstrates that the inter-jurisdictional river site's $\text{RMSPE}_{\text{ratio}}$ is at least 1.44 times larger than that of any other control site. Not a single control site's $\text{RMSPE}_{\text{ratio}}$ is close to the inter-jurisdictional river site. The larger $\text{RMSPE}_{\text{ratio}}$ 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 $\text{RMSPE}_{\text{ratio}}$ as large as the inter-jurisdictional river is $1/14$ ($p = 0.07$).

We also rerun the in-place placebo test for each pollutant and obtain a similar result for NH3-N, 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,

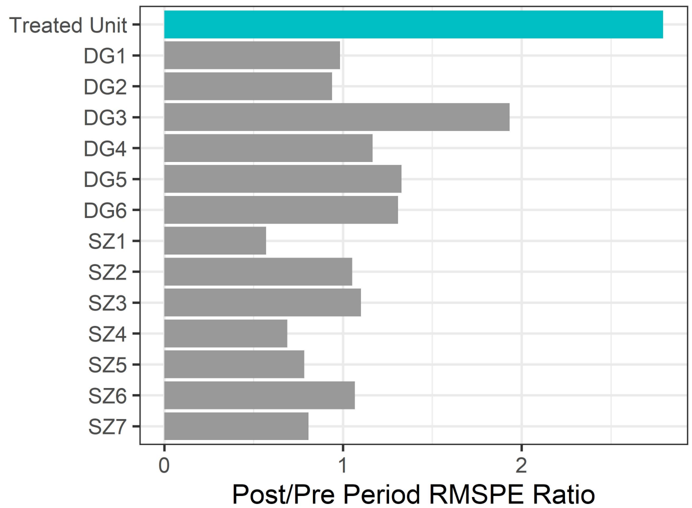

Figure 6: PI $\mathrm{RMSPE}_{\mathrm{ratio}}$ of Post-/Pre- Intervention: The Treated and Control Units

NH3-N indicates primarily industrial sewage and domestic wastewater, and TP indicates largely 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 that of the other two pollutants.

Comparing the reduction in COD and NH3-N, we suggest that the targeted performance is a moderating variable in our case[2]. Although we do not find a significant decline in COD, it is lower than 40 mg/L (the targeted performance) during most of the time points. In comparison, NH3-N experiences a clear decline after the RCS's implementation, but it had not yet achieved the targeted 2 mg/L goal at the end of 2018. This heterogeneity demonstrates that local governments' collective actions are conditional on pollutants' targeted performances. Interlocal collaborations mitigate water pollution continuously until the inter-jurisdictional river site achieves its targeted performance.

[2]Most synthetic control studies have only one treated unit and several control units in the sample. Therefore, it is difficult to involve moderating or mediating variables in the model because of the lack of statistical power. Rather than adding interaction terms into the model, we adapt Lu et al.'s (2021) strategy to conduct the pollutant subgroup analysis to discuss the potential moderating variable: targeted performance.

In-time Placebo Test

The RCS has a rapid effect after it is implemented. To evaluate whether the RCS or some confounding factors before November 2017 actually determine the pollution reduction, we conduct an in-time placebo test (Abadie 2019). We rerun the model with the treatment beginning point assigned to the middle of the pre-intervention period: June 2017. We apply the same predictors in our main analysis to construct our synthetic control unit, but only include the PI's mean values in spring (January, February, and March) and summer (April, May, and June).

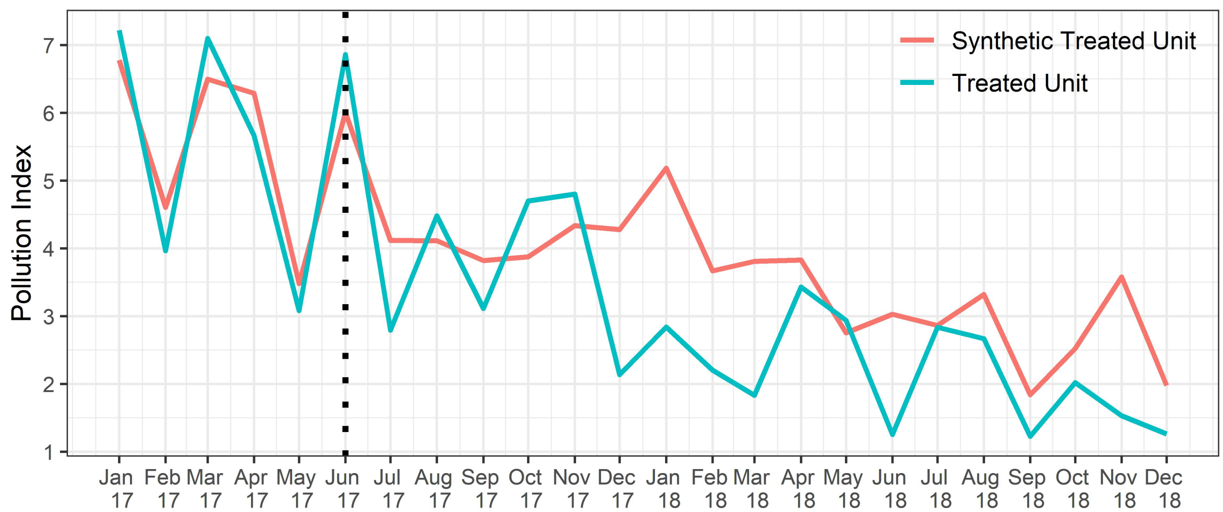

Figure 7: Placebo Time Trends of PI: Treated Unit versus Synthetic Treated Unit

Figure 7 displays the result, which demonstrates two important features. First, we do not observe a continuously sharp PI decrease from July to November 2017. The random walk pattern prior to the actual intervention timing allows us to be concerned less about a pretreatment confounding effect. Second, a clear PI gap between the synthetic and treated unit emerges around December 2017, and this is the case even when we exclude information on the actual timing of the RCS implementation. This evidence enhances the credibility of our estimator of the RCS intervention in November 2017. Although a one-year pre-intervention period appears to be short, the in-time placebo test offers convincing evidence that our synthetic control estimator has potential predictive power (Abadie et al. 2015). Appendix E reports the in-time placebo tests for all pollutants, which yield results similar to that of PI.

Discussion and Conclusion

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. 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. By formalizing network coordination, performing oversight, and allocating external resources, the NAO enhances collaborations among network actors and ultimately improves environmental outcomes.

One goal of our analysis is to provide empirical evidence of the outcomes of collaborative efforts in the cross-boundary area. To the best of our knowledge, this is the first study in the collaborative governance literature that uses 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 local governments cannot achieve long-term beneficial outcomes for the entire network unless they 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.

While our case study in China offers direct evidence for ways to govern rivers in a complex institutional environment, it has general implications for network governance modes and their collaborative outcomes as well. As aforementioned, the RCS reflects several of the NAO model's advantages in mitigating the transaction costs of collective actions. These advantages are also established well in other countries. Formal collaboration, including regular meetings, contract-based agreements between local governments, and facilitating policy processes, are all strategies used frequently in advanced democracies (Brummel et al. 2012; Macciò and Cristofoli 2017). The RCS's performance oversight approach to closing the principal-agent information gap is also applicable in other countries. In particular, if NAOs can collect citizens' opinions on environmental performance actively and use this information to motivate local governments' collaborative behaviors, NAOs would become Provan and Milward's 2001 ideal: Agents of communities and principals of subordinate governments. Finally, RCS's ability to allocate resources brings external resources to networks and reduces the power imbalance problem between local governments. The importance of resource support has been discussed in other cases, such as Vermont's state-municipal mandated networks (Bitterman and Koliba 2020) and the United States' government-led semiconductor industry networks (Whetsell et al. 2020).

In addition to the theoretical contributions above, we suggest that public management scholars need to open and explore the "black box" of collaborative structure continuously as we study network effectiveness. As noted earlier, we must examine not only collaborative governance as a broad concept, but also observe and compare outcomes between different network modes from a closer and more rigorous perspective. Therefore, this study's findings and limitations provide new research opportunities for scholars of collaborative governance.

With respect to collaborative mechanisms, we encourage network scholars to investigate their direct effects on network outcomes. Based upon the aggregated data structure, this study focuses on detecting the RCS institutional reform's treatment effect overall, but is unable to explain several internal mechanisms further, such as formalized coordination, supervised performance, and external resource allocation. If scholars can develop in-depth research collaborations with NAOs and be involved in the design of policy implementation, they can gain closer access to each mechanism and isolate it from other variables in the analysis. Some studies have conducted surveys and interviews with policy insiders to associate specific network mechanisms with perceived network performance (e.g., Lubell et al. 2017; Wang et al. 2019). If survey data can be combined with actual performance measures like pollution reduction in this study, we could explore collaborative mechanisms and compare their effects on network outcomes in different network modes further.

To reach conclusions that can be generalized and extend the research scope, we suggest that future studies collect data over longer periods with larger sample sizes. The existing literature on collaborative performance often relies on cross-sectional data from comparative case studies of only a few comparable networks. Although our panel data detect the effect of network mode change, we focus on only one river governance network in the policy subsystem with the data available in two years. This research scope is comparably smaller and shorter than other environmental analysis studies. We expect to see our research design replicated with multiple inter-jurisdictional river sites over a longer period, in which the network research community can explore the dynamic associations between environmental outcomes and network evolution/dissolution (Siciliano et al. 2021). Moreover, such augmented data will allow scholars to discuss network structures' mediation and moderation effects when the treatment effects of collaboration may be heterogenous in different conditions.

In addition, cross-cultural studies should be central in public network analysis. In our Chinese case, the top-down structure and fragmented authoritarian system are unique attributes that may not be applicable to other countries. River chief offices imposed by senior governments may have greater power in performance oversight and resource allocation than

NAOs in other countries. Therefore, we encourage scholars to test our hypothesis in different institutional environments and compare the structural differences between NAOs in China and other countries, as a comparative perspective will allow the network research community to elaborate the collaborative governance theory further.

In a broader sense, this article contributes to the collaborative governance theory in understanding mandated networks' effectiveness in governing cross-boundary environmental resources. Further, using the synthetic control method allows us to overcome the interdependence problem in network research. Our novel identification strategy and positive evidence offer new research opportunities to study collaboration outcomes at network edges.

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Supplemental Information

Contents

Appendix A Causal Identification

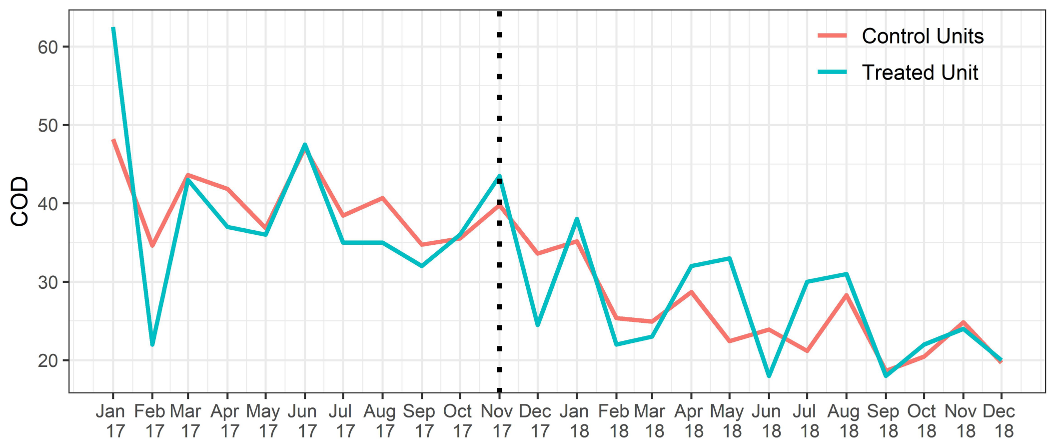
We follow Abadie et al.'s (2010; 2015) steps to demonstrate the synthetic control method's causal procedure. First, we have a sample of $J+1$ units. $J=1$ is the treated unit and $J=(2,...,J+1)$ is the donor pool of control units. All $J+1$ units have $T=T_0+T_1$ time points, T_0 and T_1 are the pre-intervention 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 root mean square prediction error (RMSPE) in the pre-intervention period. The interpretation of RMSPE is the lack of fit between the treated unit and its synthetic control part in the pre-intervention period: $RMSPE=(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{1t}-\sum_{J=2}^{J+1}w_j^*Y_{jt})^2)^{\frac{1}{2}}$. For more discussions of the RMSPE, please read (Abadie et al. 2015).

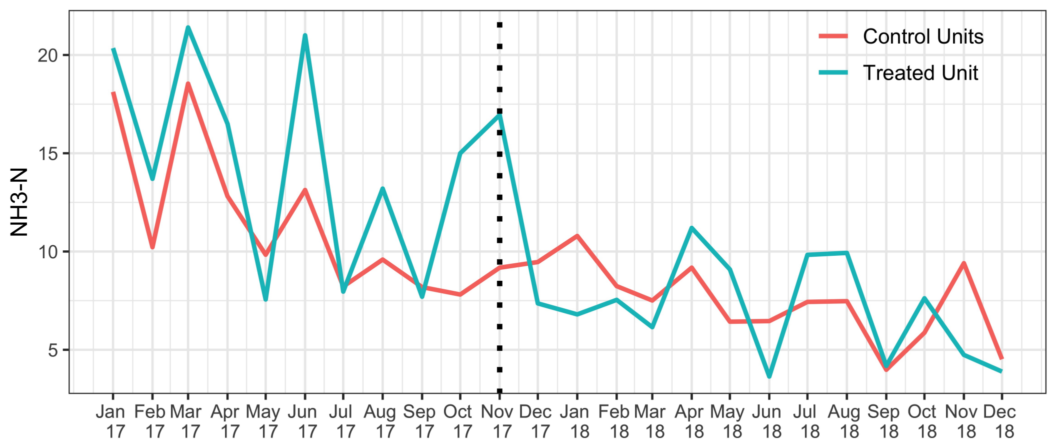
Let Y be the outcome variable, and we can identify:

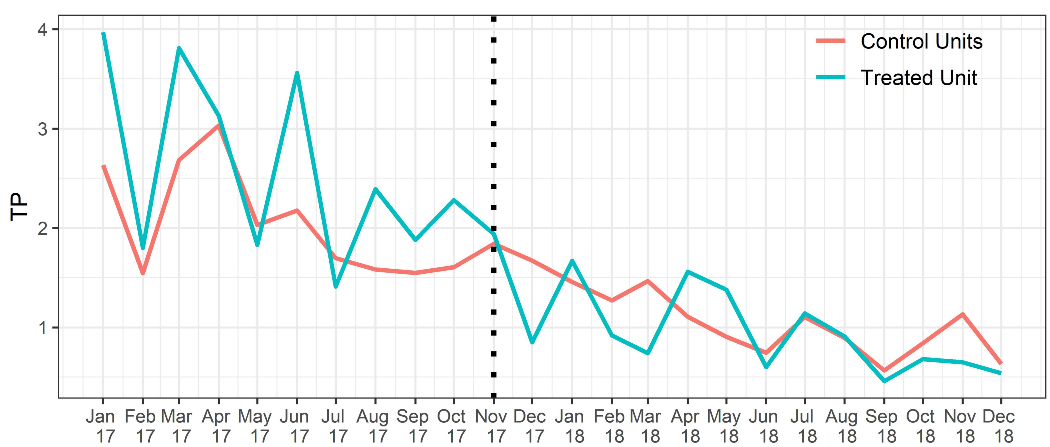
$$\hat{\alpha}_{1t}=Y_{1t}-\sum_{i=2}^{J+1}\mathbf{W_j^*}Y_{jt}, t=T_1 \tag{1}$$

$\hat{\alpha}_{1t}$ 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.

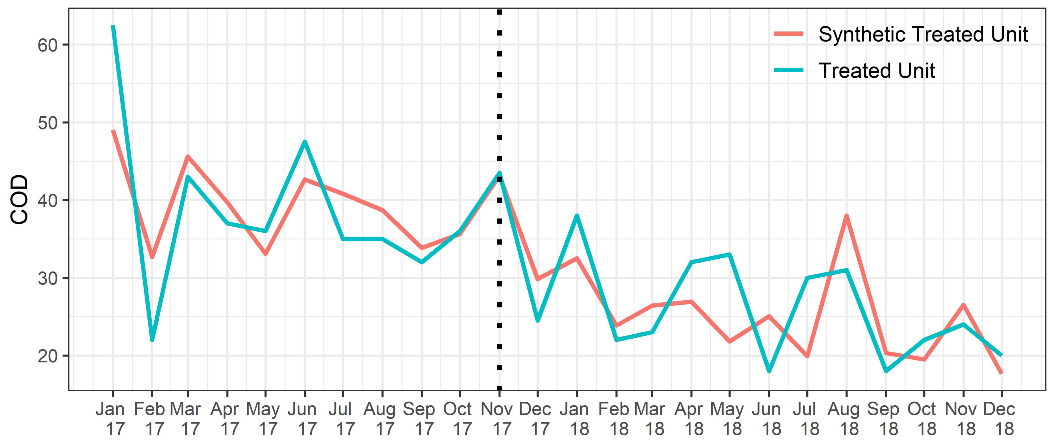
Appendix B Trends of Pollutants

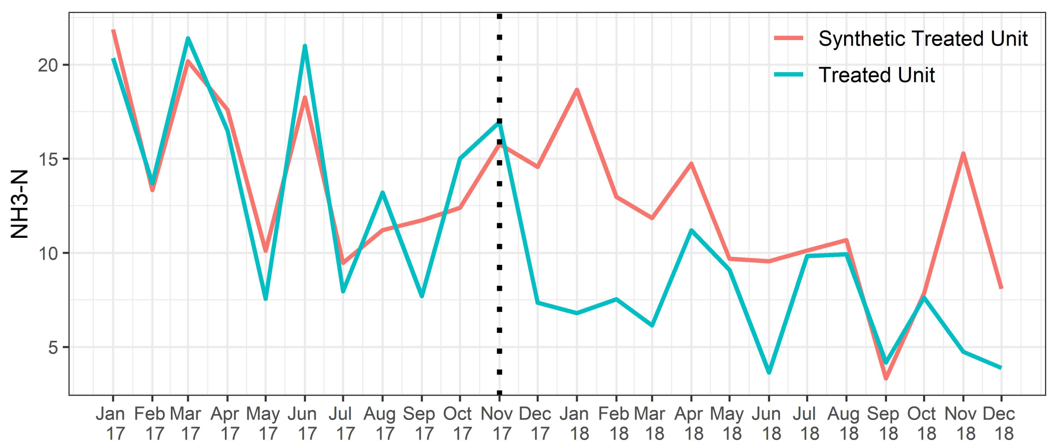


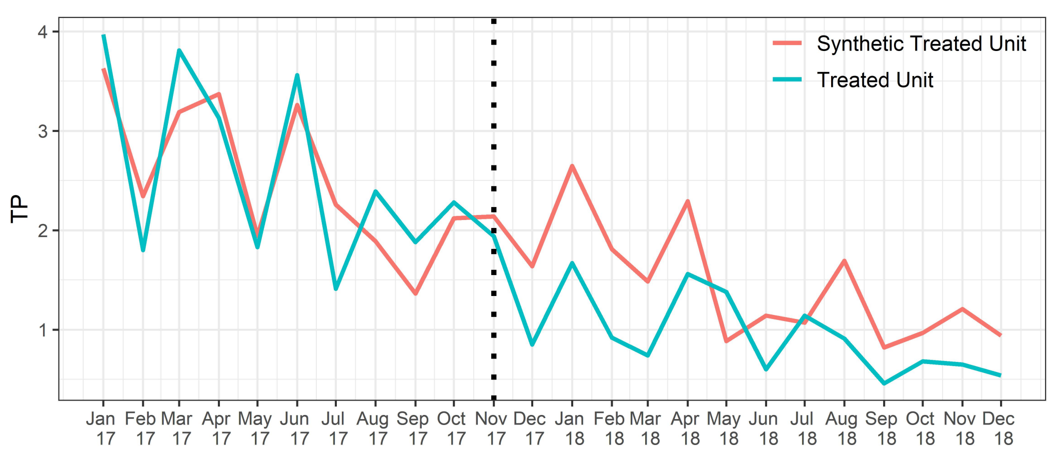


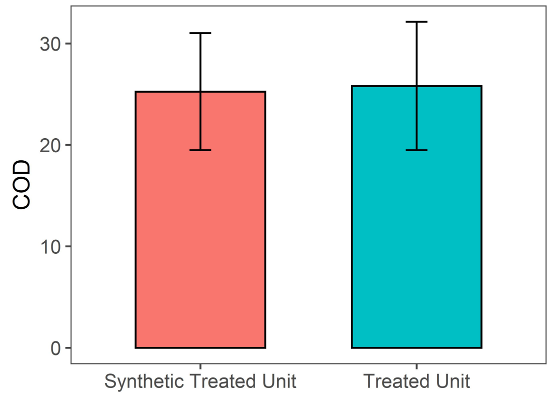


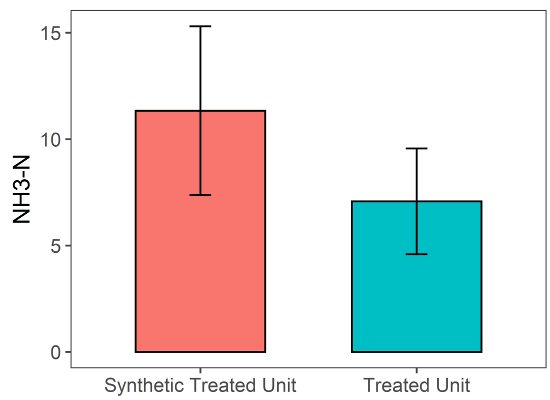
Appendix C Treatment Effect on Each Pollutant

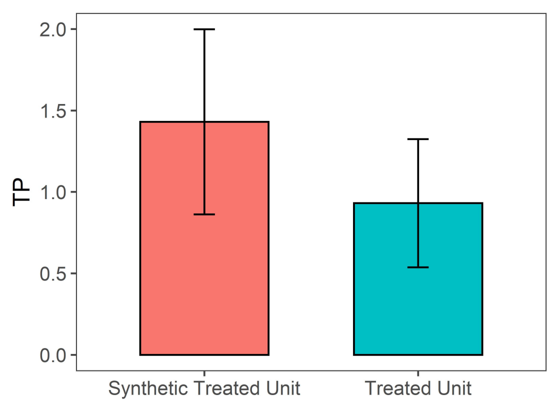






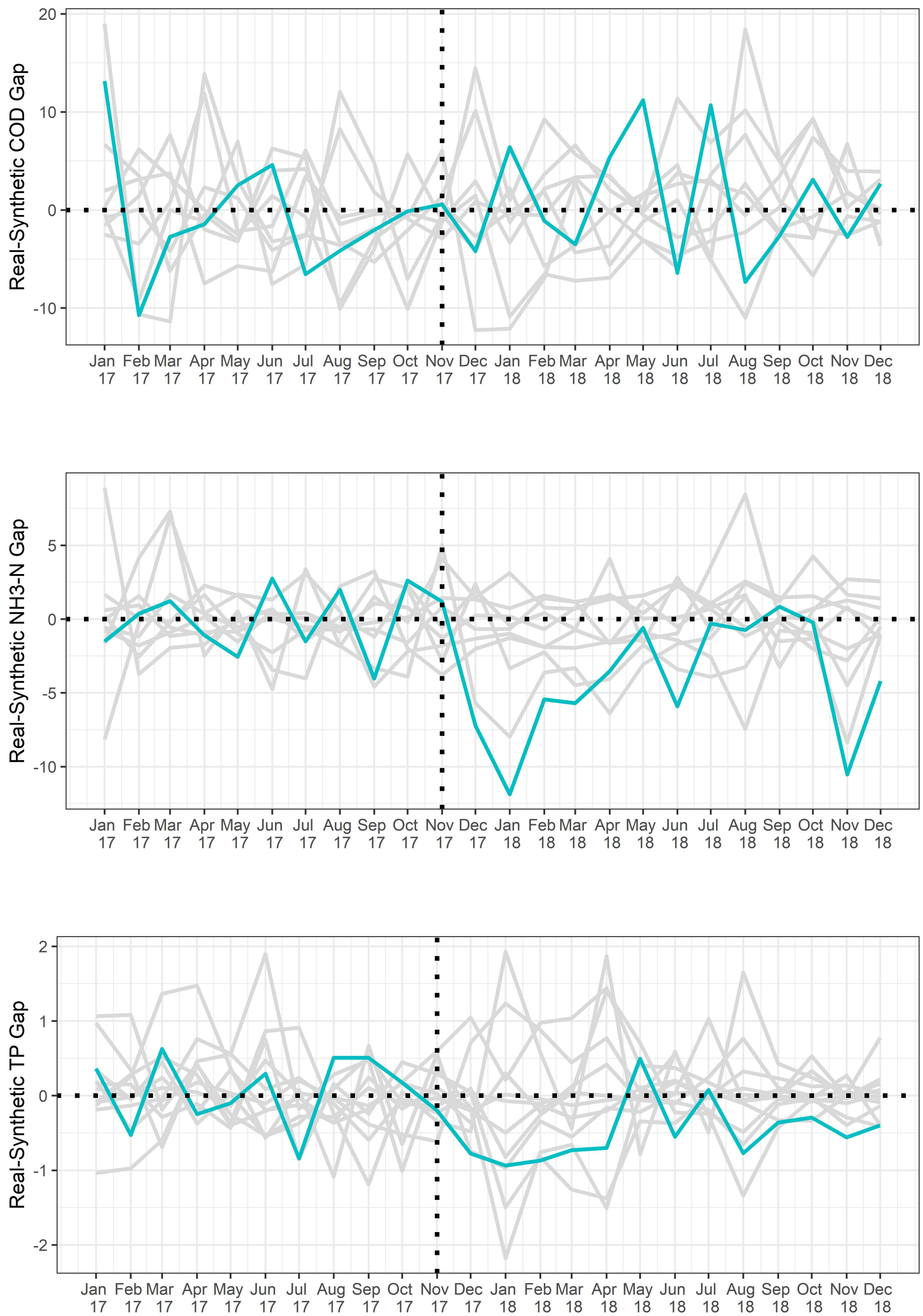






Note:
COD: ATT = 0.55 (1%) (S.E. = 2.38, p-value = 0.82)
NH3-N: ATT = 4.26 (38%) (S.E. = 1.30, p-value = 0.00)
Total Phosphorus: ATT = 0.50 (35%) (S.E. = 0.19, p-value = 0.02)

Appendix D In-place Placebo Test of Pollutants



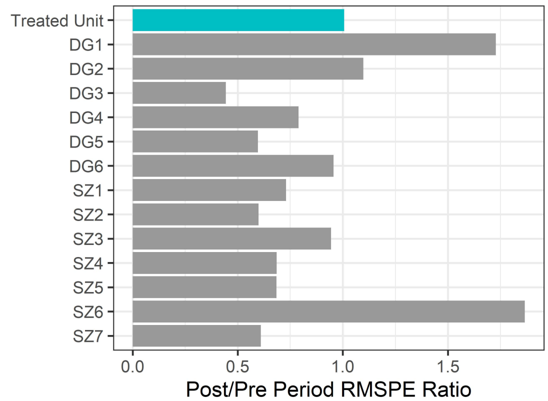


Figure D1: COD

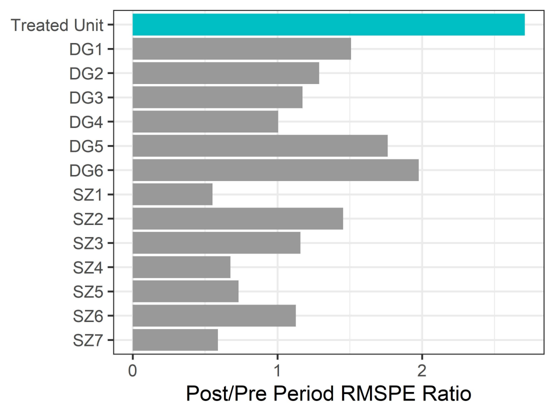


Figure D2: NH3-N

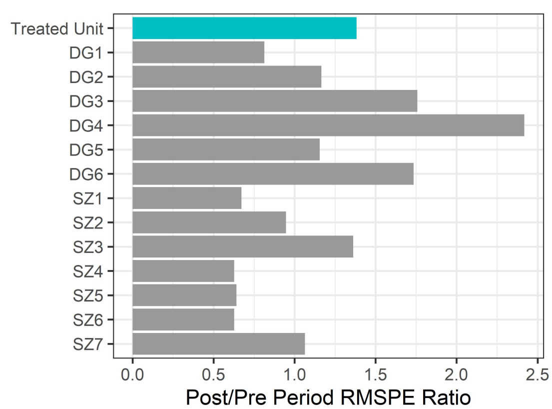


Figure D3: TP

Appendix E In-time Placebo Test of Pollutants