All Hands on Deck: The Role of Collaborative Platforms and Lead Organizations in Achieving Environmental Goals

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Abstract

This study examines the effectiveness of collaborative platforms in supporting local collaborations for natural resource management. It also explores how governmental and non-governmental lead organizations adopt differing collaborative implementation approaches and how these variations influence outcomes. Utilizing a natural experiment and a difference-in-differences estimator, we evaluate if the Department of Energy's Clean Cities program functions as a collaborative platform to foster local-level Clean Cities Collaborations across the U.S., thereby improving air quality. Our findings suggest that Clean Cities Collaborations have a substantial and enduring impact on reducing air pollution. A series of subgroup analyses suggests that these environmental improvements are most noticeable in collaborations led by nonprofits and regional government councils, rather than those directed by state and local governments. A complementary content analysis provides exploratory evidence that issue definition, collaborative group structure, and inclusive decision-making processes are crucial managerial factors that contribute to the environmental improvements. These insights pave the way for more effective management of collaborative governance on a larger scale.

Keywords: collaborative platform, lead organization, environmental management, natural experiment

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1 Introduction

Collaborative governance has become an increasingly popular approach for addressing complex and multifaceted issues and achieving more effective and innovative outcomes (Ansell and Gash 2008; Fung 2006). An important question associated with collaborative governance is how to structure and manage collaboration to be more effective, sustainable, and scalable (Ansell and Gash 2008, 2018; Bryson et al. 2015; Emerson and Nabatchi 2015). Specifically, collaborative governance regimes (CGRs) refer to a more institutionalized form of collaborative governance (Emerson and Nabatchi 2015; Emerson et al. 2012). CGRs leverage actors at the local level to collaboratively address issues across organizational and jurisdictional boundaries over a period of time, thereby making positive changes in the local socio-ecological system context (Emerson and Nabatchi 2015; Emerson et al. 2012). In their recent study, Ansell and Gash (2018) proposed the concept of *collaborative platforms*, which document high-level efforts at the national or international level to facilitate multiple local CGRs. This conceptualization sheds light on the development of a coherent and adaptable set of collaborative processes and structures that can be widely applied across jurisdictions for effective collaborative governance (Ansell and Gash 2018).

Despite these theoretical premises, two gaps remain to understand whether and how platform-supported collaborations, or CGRs, generate positive outcomes in diverse contexts. First, existing studies often examine local or regional scale collaborations or utilize cases to comparatively examine collaborative processes and outcomes (Bell and Scott 2020; Yoon et al. 2022). This focused approach limits scholars from exploring the generalizability of collaborative platforms and CGRs and identifying their heterogeneous impacts in various political and social contexts. Second, the literature has yet to conduct a comprehensive analysis of the structural variations of CGRs that exist within the same collaborative platform. Considering that collaborative platforms orchestrate and facilitate but do not mandate local collaborations (Ansell and Gash 2018), collaborations are led by different types of organizations which adjust their collaborative policy goals, leverage varying resources and local stakeholders, and construct decision-making processes differently (Koontz et al. 2004). Specifically, some CGRs are often managed top-down when the lead organization is a government entity, while nongovernmental lead organizations leverage grassroots actions and adopt a bottom-up approach to implementing CGRs (Koontz et al. 2004; Krogh 2020; Lubell 2004). Without comprehending these structural mechanisms and their varying impacts on collaborative outcomes, scholars cannot provide practical recommendations for public managers to effectively employ collaborative platforms as a tool in policy implementation.

To address these challenges, this study asks two research questions: (1) Can collaborative platforms effectively facilitate local collaborations and achieve policy objectives? (2) If so, would collaborations under the same umbrella of a collaborative platform have different collaborative structures and varying outcomes? We investigate the research questions in the context of environmental policy. As a part of the commitment to clean air, the Department of Energy (DOE) introduced the Clean Cities program under the Energy Policy Act of 1992 to reduce gasoline assumption and promote alternative fuels (Department of Energy 2023). The Clean Cities program is a collaborative platform that fosters local collaboration activities, offering informational, technical, and financial resources, and collaborative structures for local collaborations. Local Clean Cities Collaborations (CCCs) are CGRs that adopt the collaborative platform's design rules and processes and tailor them to fit local contexts. State governments, local governments, regional councils, and nonprofit organizations have voluntarily led and initiated CCCs, with support from the Clean Cities platform. CCCs strive to improve air quality by adopting alternative fuel vehicles, installing alternative fuel stations, and engaging in community outreach. Therefore, the collaborative platform of Clean Cities provides an ideal context to compare multiple local collaborations and their outcomes across the nation with the same goals.

We employ three empirical steps to answer our research questions. First, we use a natural experiment and adopt the difference-in-differences (DiD) method, which allows us to identify the causal effects of CCCs on air quality and assess whether CCCs with top-down government-led or bottom-up nonprofit-led approaches perform differently. Second, we incorporate a content analysis to add a more nuanced understanding on how the different lead organizations of CCCs tailor the collaborative mechanisms (i.e., issue definition, resource allocation, group structure, and decision-making process) and implement collaborations distinctively. Finally, we conducted exploratory DiD analysis for each mechanism subgroup identified in the content analysis, aiming to further understand the causal mechanisms of different lead-organization models on environmental impacts.

2 Collaborative Governance in Natural Resources

2.1 Collaborative Governance Regimes

Collaborative governance broadly refers to a set of institutional processes that integrate governmental and non-governmental actors across sectoral, hierarchical, and jurisdictional boundaries, enabling them to work together and carry out public services and provide goods (Ansell and Gash 2018). Academics and practitioners advocate collaborative governance through two arguments: normative and instrumental (Bryson et al. 2015). In the normative argument, collaborative governance promotes diversity in the decision-making process by giving voice to a wider array of public and private interests (Fung 2015; Hong and Page 2004), resulting in inclusive communication among actors, mutual trust, and norms of reciprocity. The mutual trust further facilitates collaborative leadership, shared understanding, and commitment to the process of service delivery (Ansell and Gash 2008; Thomson and Perry 2006). On the other hand, the instrumental argument suggests that collaborative governance is an effective tool to address complex policy and management problems across jurisdictional and sectoral boundaries. In a successful collaborative institution, the transaction costs of coordinating collective actions are lower than free-riding other policy actors (Berardo and Scholz 2010). As Ostrom (1990, 38) argued, when organizations act independently to manage natural resources, "...the net benefits they obtain usually will be less than could have been achieved if they had coordinated their strategies in some way."

To specify actions and institutional arrangements that facilitate collaborative behaviors, Emerson et al. (2012) developed the integrative framework for collaborative governance, in which they introduced the idea of CGR. In this framework, each CGR is a socio-ecological system that involves multiple actors from different sectors, who work collectively around sets of implicit and explicit institutions in a given area to solve cross-boundary policy issues. These institutions include subsidizing network members, coordinating regular meetings, improving participant representation, and performing task oversight (e.g., Jager et al. 2020; Liu and Tan 2022; Mehdi and Nabatchi 2022; Wang et al. 2019). With these institutions, CGRs can effectively promote voluntary efforts among actors and reduce free-riding behaviors in managing natural resources (Emerson and Nabatchi 2015).

Specifically, CGRs facilitate ongoing engagement among their members over a period of time, distinguishing themselves from ad-hoc and temporary collaborations (Emerson and Nabatchi 2015; Mehdi and Nabatchi 2022). While some short-term collaborations have specific goals and disband upon achieving them, CGRs address broader problems with sustained efforts and the ability to govern the issue at the local level. This study follows the CGR framework and uses the term CGR to denote collaborative governance.

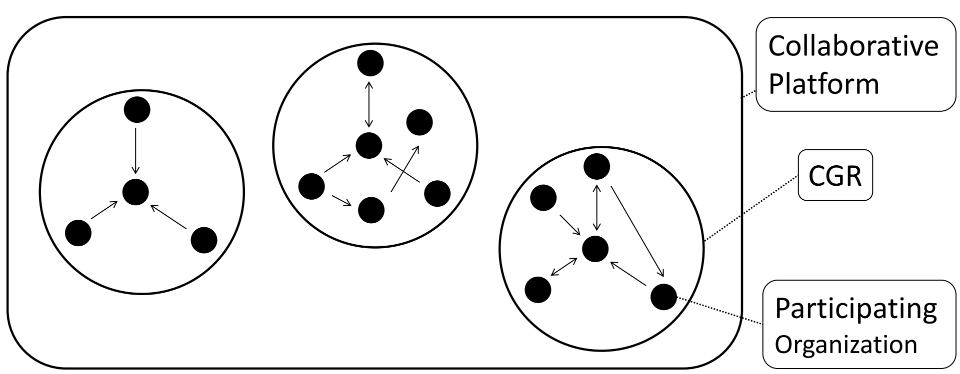
2.2 Scaling-up Effects of Collaborative Platforms

Recently, literature paid attention to the strategic efforts to facilitate CGRs and intentionally deploy multiple CGRs to achieve policy goals in the broader system, which is defined as the "scaling-up effect" of collaborative governance (Ansell and Torfing 2015). Ansell and Gash (2018, 16) theorized this phenomenon and introduced the concept of a "collaborative platform", which is "...organizations or programs with dedicated competencies and resources for facilitating the creation, adaptation, and success of multiple or ongoing collaborative projects or networks." Collaborative platforms are typically managed and sponsored by organizations such as a federal or state agency, funders, and international organizations

(Ansell and Gash 2018). Such platforms facilitate CGRs by catalyzing local actors to form voluntary collaboration and allow for flexibility of collaborative rules in consideration of the local contexts (Ansell and Gash 2008; Bell and Scott 2020). Collaborative platforms provide information and resources to CGRs, while also offering design guidelines for achieving overarching objectives. Simultaneously, these platforms allow CGRs to adapt their governance strategies to complex local contexts and needs. Therefore, institutional rules and network structures in CGRs can be very different even if these CGRs are sharing common policy goals and are supported by the same collaborative platform. This reconfigurability of the platform's institutional rules facilitates the efficient development of collaborative rules, governance structures, and institutional designs (Bell and Scott 2020; Lee 2022).

Considering the above characteristics, the collaborative platform approach offers a structural framework that promotes and supports the sustainable development of CGRs with shared core objectives within a given policy domain, while also scaling up CGRs in various geographical contexts. Taking this macro-level strategy into account is important to understand the outcomes of CGRs on a larger scale. We visualize the relations between CGRs and the collaborative platform in Figure 1, in which the outermost rounded rectangle indicates the collaborative platform, within which are three CGRs. Dark dots within each CGR are participating organizations in the network. Connecting lines between dots indicates different structural connections between organizations.

Figure 1: Illustration of CGRs in a collaborative platform



Although the scaling-up effect of collaborative platforms on CGRs is theoretically promising (Ansell and Gash 2018), we lack empirical evidence to justify the systematic impacts of platform-supported CGRs on policy objectives. Most empirical associations between collaborative governance and environmental outcomes are established in relatively small-scale investigations between CGRs, or do not explicitly connect the idea of the collaborative platform to their analysis (Bell and Scott 2020; Lee 2022; Yoon et al. 2022). Therefore, we propose our first hypothesis to empirically examine the ways in which a collaborative platform supports CGRs in achieving environmental objectives across areas with varying socio-economic contexts.

H1: Areas with collaborative platform-supported CGRs would improve environmental outcomes, compared to those without CGRs.

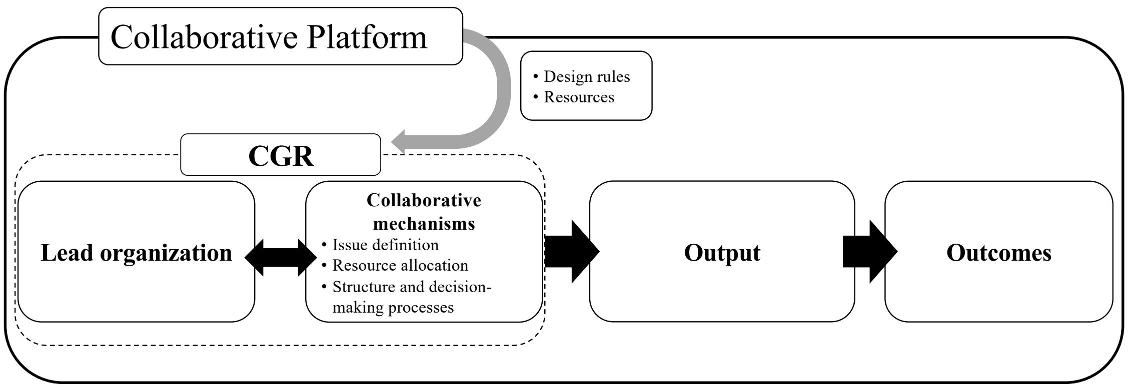
3 Lead Organizations in Collaborative Governance Regimes

Next, we ask a "*why*" question and investigate the mechanisms of a collaborative platform scaling local CGRs, and how some local CGRs have successful outcomes while others do not. Here, we focus on lead organizations in platform-supported CGRs and explore whether lead organizations generate variations in processes and outcomes. A lead organization is a "network broker" which brings stakeholders together to achieve a shared goal, facilitates transactions and coordinates collaborative decision-making processes within CGRs (Provan and Kenis 2008, 234). We argue that lead organizations are likely to shape implementing collaboration and outcomes, mediating between the collaborative platform and CGRs for two reasons. First, lead organizations are not only network brokers but also serve as contact points between the platform and CGR. Lead organizations communicate the platform-level broad goals and objectives to the participants, so that CGRs can develop their targets and plans and generate outputs. Second, lead organizations map out the collaborative decision-making processes and activities (Emerson et al. 2012; Provan and Kenis 2008). Given the determined collaborative structures, CGRs take actions to attain intended outcomes. Therefore, lead organizations streamline local CGRs' structures and processes from infancy to established collaboration. Previous studies have studied that CGRs are led by different organizations from state, local, and special-purpose governments to nonprofit organizations, and they adopt different approaches to implement CGRs (Koontz and Newig 2014; Koontz et al. 2004). Top-down approaches in CGRs are particularly suited to explain how government authorities guide the overall collaborative implementation and provision of resources (Koontz and Newig 2014; Krogh 2020). Conversely, bottom-up approaches emphasize the engagement of various actors and the coordination among them. These approaches are more relevant to local-level and community-based lead organizations (Koontz and Newig 2014; Lubell 2004; O'Toole Jr. 2015).

We examine how the top-down and bottom-up approaches manage CGRs differently in terms of three factors of collaborative mechanisms, following Koontz et al. (2004): a) issue definition, b) resources available for collaboration, and c) group structure and decision-making processes. Issue definition describes how a CGR frames an issue, which establishes a ground for a range of actions carried out by the CGR (Koontz and Newig 2014; Koontz et al. 2004). Based on the collaboratively defined issue, participants build a shared causal theory that certain collaborative solutions would address the problem (Koontz and Newig 2014). Second, resources for collaboration are critical to determining what CGRs can achieve. Human resources refer to dedicated staff as a facilitator or volunteers; technical resources are expertise and knowledge in the issue area; and financial resources are the funds available for actions (Koontz et al. 2004; Steelman and Carmin 2002). Lastly, the group structure is the organizational arrangements of CGRs, and decision-making processes involve the rules to decide participants, design collaborative activities, and aggregate opinions to a group-level decision (Emerson et al. 2012; Koontz et al. 2004). We suggest that these three factors are critical for platform-supported CGRs to achieve their goals as Figure 2 depicts.

Overall, platform-supported CGRs in both top-down and bottom-up implementation approaches tend to show a high degree of similarity in issue definitions. This is primarily because their motivations closely align with the collaborative platform's overarching goals (Ansell and Gash 2018). Below, we focus our discussion on the differences between top-down and bottom-up implementation approaches, specifically in terms of resource allocation and collaborative group structure. We also hypothesize their impacts on collaborative outcomes.

Figure 2: Conceptual framework



3.1 Top-down and bottom-up approaches: governments and nonprofits as lead organizations

Governments often adopt a top-down approach to managing CGRs to leverage local stakeholders and achieve policy goals (Span et al. 2012a,b). Government-led CGRs are likely to have the resources and governments are willing to transfer resources to participants (Scott and Thomas 2017). The key resource that governments wield as lead organizations in CGRs is their legal authority to pursue CGR goals. Governments not only exert legal authority over participants, but also, in the system context outside of CGRs, they can enact policies, programs, and codes to achieve policy goals (Buchanan 2002) that align with the CGR's goals. Governments have the legitimacy to mobilize key stakeholders as well as general citizens to collaborate and take action, which other CGRs often lack (Hui and Smith 2022). Further, governments have administrative and fiscal resources to fund collaborative efforts (Koontz 2006). Public officials may allocate financial resources to support CGRs when necessary, and staff are knowledgeable about external funding opportunities and grant writing, which is transferable to CGR management (Sprague et al. 2019).

Nonetheless, CGRs with top-down approaches may not be successful in activating norms and building more inclusive CGRs. For successful and innovative collaborative efforts, participants should perceive equal decision-making opportunities among members, as this fosters trust and commitment within the CGRs (Johnston et al. 2011). However, when governments lead CGRs, they may utilize the existing administrative structure to reduce collaboration initiation costs (Scott and Thomas 2017). This type of CGR may resemble the hierarchical structure of government institutions, and government actors may exert authority in the decision-making process (Krogh 2020; Moore and Koontz 2003). Therefore, CGRs led by governments are prone to decision-making power disparities among members, which hinder the utilization of the full spectrum of expertise of participants (Doberstein 2016; Vangen and Huxham 2012). Governments may push through decisions even when there is no full consensus or overturn collaborative decisions to achieve the goal of the collaborative platform for the sake of productivity (Provan and Kenis 2008; Rhoads et al. 1999; Schlager and Blomquist 2008; Vermeiren et al. 2021).

In contrast to governments, nonprofits and community-based organizations play significant roles in local collaborative efforts and often lead CGRs bottom-up (Koontz et al. 2004; Valero et al. 2021). Compared to government entities, community organizations generally have relatively less access to resources, which often limits the capacity for action of CGRs. In CGRs with a bottom-up approach, resources are not distributed from the lead organization; rather, resources are collected by participants. Nonprofits' main sources of funding are donations or grants, which are contingent on external actors (Bowman 2011; Carroll and Stater 2009; Rousseau et al. 2020). However, nonprofits often lack the capacity for successful grant writing (Mandeville 2007). Thus, the financial capacity of CGR participants matters as much as that of the lead organizations for bottom-up CGRs to secure funding and sustain operations. In addition, lead organizations with bottom-up approaches may face difficulties in managing internal tensions of collaborations or addressing emerging challenges, which may reduce the participation of other actors (Cornforth et al. 2015). Specifically, having powerful public authorities within the CGRs can be challenging to maintain equal standing among actors. CGRs led by nonprofits often have consultative bodies who feed into major decisions (Cornforth 2012), and governmental actors may have a louder voice than others and be dominant in decision-making processes.

Still, bottom-up CGRs are more successful in activating social norms among participants and facilitating collaborative transactions, realizing the benefits of grassroots governance. Nonprofits can lead CGRs by building and reinforcing social norms such as trust, reputation, and reciprocity, which can be applied to their interactions with other stakeholders in the CGRs (Van Slyke 2007). This can lead to better outcomes since nonprofits focus on the long-term success of the organization and prioritize the interests of all stakeholders, rather than just their own interests (Davis et al. 1997; Jeavons 1994). Furthermore, lead organizations with a bottom-up approach encourage participants to exercise their ownership at equal standings. A successful lead organization in CGRs should be a steward, coordinating diverse interests and mediating uneven power distribution among members (Vermeiren et al. 2021), which nonprofits are likely to be proficient at. Nonprofit organizations with a stewardship culture are more oriented toward collective interests and emphasize harmony among members (Krzeminska and Zeyen 2017). These strong stewardship practices and positive impact on communities can be transferrable to CGRs (Van Puyvelde et al. 2012). Considering the positive and negative aspects of nonprofits as lead organizations, we propose a set of competing hypotheses below.

Considering the positive and negative aspects of governments and nonprofits as lead organizations within CGRs, we propose a set of competing hypotheses below.

H2a: Collaborative platform-supported CGRs that implement the top-down approach improve environmental outcomes more than those employing the bottom-up approach.

H2b: Collaborative platform-supported CGRs that implement the bottom-up approach improve environmental outcomes more than those employing the top-down approach.

4 Context: Clean Cities Program as a Collaborative Platform

The U.S. government has taken nationwide efforts to address climate change and air quality, and one of the key initiatives is the Clean Air Act of 1963, along with a series of (Environmental Protection Agency 2021). The amendment in 1990 marked a significant step in the U.S. government's efforts to reduce emissions from the transportation sector and promote sustainable transportation options. As part of the amendment, the production and use of alternative fuel vehicles have been promoted, including biodiesel, E85, electricity, hydrogen, compressed natural gas, liquefied natural gas, and liquefied propane gas vehicles (Alternative Fuels Data Center 2021).

The DOE initiated the Clean Cities program in 1992, which promotes local collaborations through voluntary governance to implement alternative fuels and infrastructure deployment (Copulos 2005; Gollagher and Hartz-Karp 2013; Hall and Lutsey 2017). The Clean Cities program can be considered a good test case to study the performances of platform-supported CGRs. The Clean Cities program acts as a backbone organization to encourage local CGRs by offering information, technical support, and personnel aid (Bourbon 2016). The Clean Cities Collaborations (CCCs) are CGRs of diverse stakeholders, including private companies, fuel providers, businesses with vehicle fleets, government agencies at the state and local level, and non-profit organizations (Department of Energy 2023).

The Clean Cities program provides resources and design rules necessary for forming local CCCs and collaborating in the implementation of alternative fuels, thereby improving air quality. First, as a collaborative platform, the Clean Cities program supplements local CCCs technical and administrative resources, and funding opportunities. The program provides technical support and decision-making tools for local CCCs to make informed decisions in alternative fuel vehicle purchases, infrastructure siting and maintenance, and the implementation of the most effective projects to reduce emissions (Department of Energy 2023). Also, the Clean Cities program has provided funding opportunities to support projects that contribute to the program goals (Department of Energy 2023). These resources are crucial to initiate and sustain collaborative efforts and improve outcomes.

Second, the Clean Cities program offers both fixed and varied design rules for CCCs. The program requires CCCs to adhere to fixed design rules, such as the identification of core members, the appointment of a coordinator, setting goals, and creating an implementation plan (Bourbon 2016). While following these stable guidelines, the program allows flexibility for each CCC. Any interested actor can be the lead organization, and CCCs are free to decide which stakeholders to involve, geographical scope of target area, and what specific targets for pollution reduction they wish to pursue. As shown in Table 1, CCCs have diverse lead organizations, including state agencies, local governments, regional councils, or nonprofit organizations. Subsequently, stakeholders work together to establish a memorandum of understanding aligned with local circumstances to implement alternative fuels and reduce pollutant emissions, in line with the program's objectives. With the flexibility of design rules, CCCs are similar yet different in terms of structure and management of collaborations as they tailor the rules of the collaborative platform to fit their local contexts. The variation in lead organizations among CCCs presents an opportunity to investigate the hypotheses above, that different lead organizations would have different collaboration implementation approaches.

Table 1: Definition of CCCs different types of lead organizations

Lead organization model	Definition
State-led CCCs	CCCs led by state agencies
Local-led CCCs	CCCs led by city or county governments
Regional-led CCCs	CCCs led by regional planning councils, councils of governments, or metropolitan planning organizations
Nonprofit-led CCCs	CCCs led by nonprofit organizations

Source: National Renewable Energy Laboratory of DOE

CCCs generate similar outputs, even if they have different lead organizations. Each CCC develops an alternative fuel implementation plan that outlines outputs for the deployment of alternative fuels. Key outputs encompass supporting alternative fuel programs, implementing alternative fuels and infrastructure deployment, and conducting community outreach. First, CCCs advocate legislation to improve air quality and adopt alternative fuels. As most of CCCs do, the CCC in South Carolina (led by a state agency) and Denver Metro CCC (led by a nonprofit organization) supported statewide legislation to provide incentive programs for alternative fuel vehicles and infrastructure (Kaiser 1999a; South Carolina Department of Health and Environmental Control 2006). Second, CCCs focus on expanding alternative fuel infrastructure and adopting alternative fuel vehicles. This includes replacing internal combustion engine vehicles with alternative fuel vehicles, installing alternative fueling stations, and upgrading to more fuel-efficient vehicles. For example, Denver Metro CCC (led by a nonprofit organization) used DOE funds to transition governmental fleets to electric vehicles (Kaiser 1999a). The Chicago Area Clean Cities is led by the Chicago city government, builds alternative fuel infrastructure, and purchases alternative fuel vehicles (Kaiser 1999c). Lastly, CCCs implement educational programs, campaigns, and community outreach to promote alternative fuels. For example, Clean Cities Georgia (led by a nonprofit organization) developed decision-making tools to assist local stakeholders in adopting alternative fuels and held workshops (Kaiser 1999b), and Chicago Area Clean Cities have conducted educational campaigns for the community and drivers (Kaiser 1999c).

5 Causal Effects of CCCs on Air Quality

5.1 Data and variables

We conducted an investigation on the effectiveness of the Clean Cities program nationwide in the U.S. The sample population included all counties ($N_{county} = 1,393$) in the 48 adjoining U.S. states[1] that have air quality data available between 1990 and 2020. Air qual-

[1] Alaska, Hawaii, and Washington D.C. were omitted from analysis due to missing data problems of several variables.

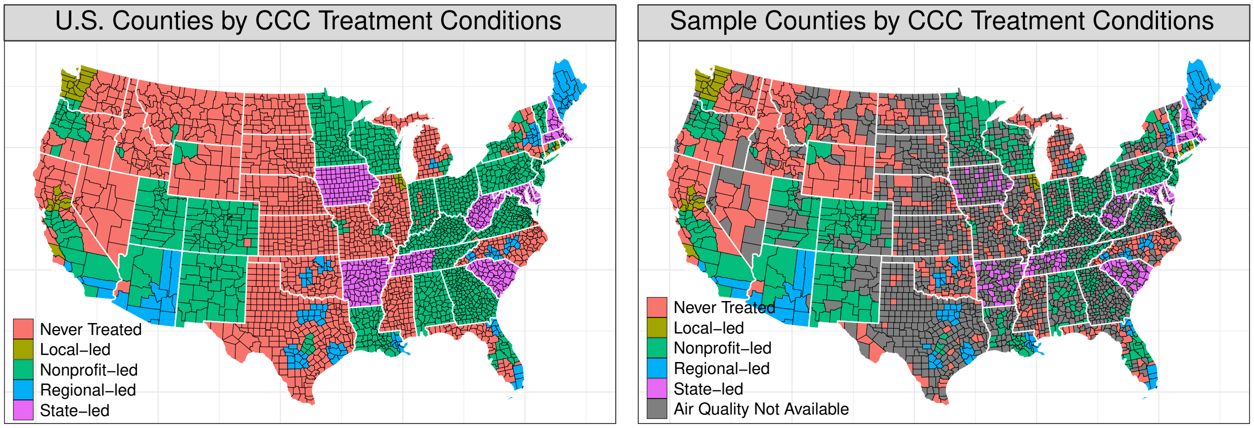
ity data was obtained from the Environmental Protection Agency (EPA). We constructed two dependent variables: annual average air quality index (AQI) and bad days ratio (BDR). The AQI accounts for all air pollutants within a specific geographical area, as defined by the National Ambient Air Quality Standards[2]. AQI ranges from 0 to 500, with a higher value indicating poorer air quality in the county. We present seven maps in Appendix A, showing the U.S. AQI from 1990 to 2020 at five-year intervals. The EPA standard indicates that AQI above 100 is considered unhealthy for public health. Accordingly, we included BDR which measures the ratio of days in which the AQI exceeds 100 for each observed county (Qiu and Kaza 2017).

The treatment variable is the adoption of CCCs, and the data was obtained from the National Renewable Energy Laboratory of DOE. The left panel in Figure 3 displays the snapshot of the entire population of counties with or without CCCs in the conterminous United States in 2020 and the right panel shows the counties included in our sample. In total, our dataset included 910 counties with 80 CCCs and 483 counties that never had CCCs. We constructed a binary variable to indicate whether a county belongs to an active CCC in a given year. As we mentioned above, the DOE categorizes the lead organization of each CCC as: (1) state agency, (2) local government (i.e., municipality or county), (3) regional council (i.e., council of governments, metropolitan planning organization, or regional planning council), and (4) nonprofit organizations. We used this information to compare bottom-up (nonprofit-led) and top-down (government-led: including state agency, local government, and regional council) approaches. Additionally, we conducted a subgroup analysis for each category with different types of lead organizations as part of an exploratory analysis. Appendix B demonstrates the county and CCC sample size in each category.

We also included several covariates that may be associated with air quality. First, we collected county-level demographic variables from the Census Bureau, including population

[2] AQI was derived using the measured concentration level of carbon monoxide, nitrogen dioxide, ozone, sulfur dioxide, particular matter smaller than 2.5 micrometers, particular matter smaller than 10, and lead in the air. Please visit the EPA website to read more detailed information about AQI: https://www.epa.gov/outdoor-air-quality-data/about-air-data-reports

Figure 3: Counties with active CCCs

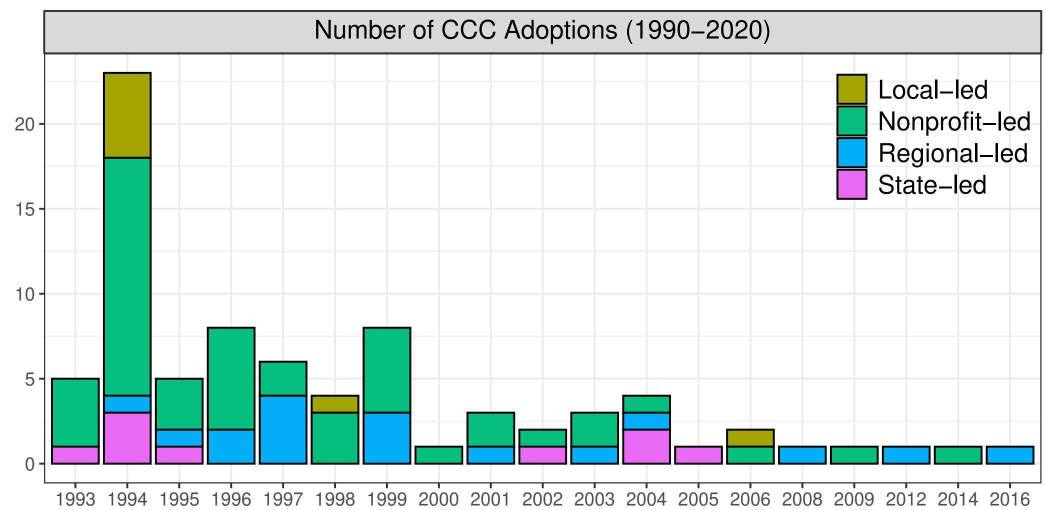


density, the proportion of the white population, and the number of labor force. Second, we included information on key sources of emissions that may affect air quality. We documented the number of businesses in local freight trucking in each county from County Business Patterns. We also included the total number and capacity of electric power generators, and the ratio of hydroelectric- and coal-fueled power generators and capacity in each county using data from Energy Information Administration. Third, we controlled state level regulatory programs to reduce pollutant emissions of stationary sources. We included a variable measuring the number of facilities that are regulated by state-level programs under the Clean Air Act that control pollutant emissions, and a count variable of facilities' Clean Air Act violation history at the state level from the National Emissions Inventory. Fourth, we gathered the number of state-level incentive programs (e.g., tax credits, loans, rebates, tax exemptions, and grants) to facilitate alternative fuel supply and infrastructure deployment from the Alternative Fuels Data Center. Fifth, we included a variable measuring county-level number of nonprofit organizations promoting preservation and protection of the environment from the National Center for Charitable Statistics. Finally, we included two weather variables: annual average temperature and precipitation, obtained from the National Centers for Environmental Information. In Appendix C, we report the descriptive statistics for these variables in the overall sample and each lead organization subgroup.

5.2 Method: Two-stage DiD estimator

The DiD method is the most appropriate approach to identify the causal effects of CCCs on air quality. However, our dataset faces two empirical challenges. First, CCCs have been adopted across the country between 1993 and 2016 (see Figure 4). In this staggered treatment adoption setting, the traditional two-way fixed-effects estimator in the DiD framework yields biased results from heterogeneity in treatment effects across counties that adopted CCCs at different points in time (Goodman-Bacon 2021; Roth et al. 2023). Second, our panel was unbalanced because air quality data is not always available for each county in our 31-year research time span.

Figure 4: Staggered adoption of CCCs



To address both challenges, we employed the two-stage difference-in-differences (2SDiD) estimator developed by Gardner (2022)[3], which has been frequently used in the applied economics literature to combat treatment effects heterogeneity bias in unbalanced panels (e.g., Abouk et al. 2023; Han 2023; Zhang et al. 2023). In the first stage, the outcome variable is regressed on the time-varying covariates and fixed effects using only untreated

[3]We implemented the 2SDiD estimators using `R` package `did2s`, which was developed by Butts and Gardner (2021).

observations. By using only untreated observations to estimate the parameters, this stage is not affected by treatment effect heterogeneity (Gardner 2022). The estimated parameters are then used to residualize the outcome in the second stage, which is regressed on the treatment variable using all observations. The following equations demonstrate our 2SDiD estimator:

$$Y_{i,t} = \delta_i + \theta_t + \phi X_{i,t} + \epsilon_{i,t} \tag{1}$$

In equation 1, $Y_{i,t}$ is the outcome for county i during year t. δ_i is a vector of county-fixed effects and θ_t is a vector of year-fixed effects. $X_{i,t}$ is a vector of covariates. $\epsilon_{i,t}$ is a county-year error term. This equation forms a residualized outcome $\tilde{Y}_{i,t} = Y_{i,t} - \hat{\delta}_i - \hat{\theta}_t - \hat{\phi} X_{i,t}$. In the second stage, this residualized outcome is regressed on a binary treatment indicator in equation 2:

$$\tilde{Y}_{i,t} = \beta \text{Treated}_{i,t} + v_{i,t} \tag{2}$$

$\text{Treated}_{i,t}$ equals to 1 in year t and all subsequent years following the adoption of CCC in county i, otherwise 0. For counties that never implement a CCC, $\text{Treated}_{i,t}$ equals 0 for all periods. Therefore, β is the key coefficient to identify the average treatment effect on the treated units (ATT) in this model. In equation 3, we report the results of dynamic specification in the second stage that regresses the outcome on dummies for the time relative to treatment:

$$\tilde{Y}_{i,t} = \sum_k \left[\beta_k \text{Treated}_i \cdot (t - T_i^* = k)\right] + v_{i,t} \tag{3}$$

This equation is the same as equation 2 except that it interacts the treatment indicator Treated_i with event-study indicators to trace out the time path of treatment effects. T_i^* is the year a CCC adopted in county i and $k = 0$ is omitted as the baseline time. This specification has two purposes. First, it tests the parallel trend assumption that the treatment group and the control group would have experienced parallel changes in air quality over time before CCC interventions. This assumption ensures that the control group serves as a valid counterfactual baseline for evaluating outcomes in the absence of CCC interventions Roth et al. (2023). Second, it examines the dynamic treatment effects each year following the implementation of CCC interventions. Accordingly, we could assess the long-term effects of CCCs.

Finally, we used spatially adjusted standard errors in our 2SDiD models (Blackburn et al. 2020; Conley 1999). This adjustment is necessary because air traveling across county boundaries can potentially lead to spatial autocorrelation. In addition to the above empirical approaches, we assessed the robustness of our 2SDiD models through various sensitivity tests. The results section reports and deliberates these tests.

5.3 Results

5.3.1 Overall effects of CCCs on air quality (H1)

We begin by evaluating H1. Table 2 displays the overall effects of CCCs using 2SDiD estimates for both air quality measures. H1 is supported by the results in models (1) and (2). On average, the adoption of a CCC would reduce AQI by 1.81 points. When using BDR as the dependent variable, the ratio of bad air quality days in a year would be reduced by 1.40 percentage points[4]. In relative terms, CCC adoptions led to a reduction in air pollution by 4% and a decrease in the proportion of bad days by 25% (comparing absolute effects—1.81 points and 1.40 percentage points, respectively—to baseline outcome means), which indicate substantial changes. In addition to the average effects of CCCs on air quality, we also illustrated the dynamic treatment effects of CCCs. Figure 5 displays the event-study plots measure for both AQI and BDR. After 20 years of implementation, CCCs reduced AQI and BDR by 4.16 points and 2.67 percentage points, respectively.

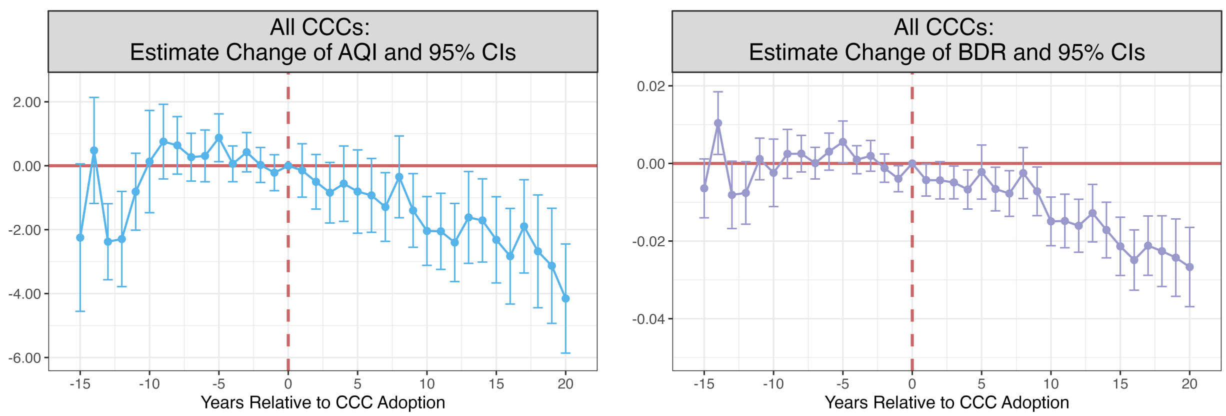
[4] 2SDiD estimates incorporate only the treatment variable in its second-stage model, while covariates are included in the first stage, not the second. This approach typically results in a smaller R^2 compared to other conventional models (Beghelli et al. 2023).

Table 2: 2SDiD estimates: Overall effects of CCCs on air quality

	(1)	(2)
Dependent variable	AQI	BDR
Baseline mean	42.548	0.055
Treated	-1.806	-0.014
	(0.508)	(0.003)
P-value	0.000	0.000
Observation	28,253	28,253
Adj. R^2	0.008	0.025
County FE	Yes	Yes
Year FE	Yes	Yes
Covariates	Yes	Yes

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods.

Figure 5: Dynamic treatment effects of CCCs on air quality: Event study analysis



5.3.2 Top-down and bottom-up effects of CCCs (H2a & H2b)

The subgroup analysis presented in Table 3 and Figure 6 supports H2b over H2a, indicating that bottom-up, nonprofit-led CCCs outperformed top-down, government-led CCCs. Observations in models (3) and (4) compare counties in government-led CCCs (including state-led, regional-led, and local-led CCCs) with counties that never experienced CCCs, while observations in models (5) and (6) compare counties in nonprofit-led CCCs with counties that never experienced CCCs. In model (3), the 2SDiD estimate of AQI is not distinguishable from 0. However, it suggests a 1.40 percentage point reduction in BDR, which represents a 27% reduction in relative terms. The results in models (5) and (6) show that the implementation of nonprofit-led CCCs has reduced both AQI and BDR by 1.78 points and 1.30 percentage points, respectively. These results indicate 4% and 23% reductions in relative terms, respectively.

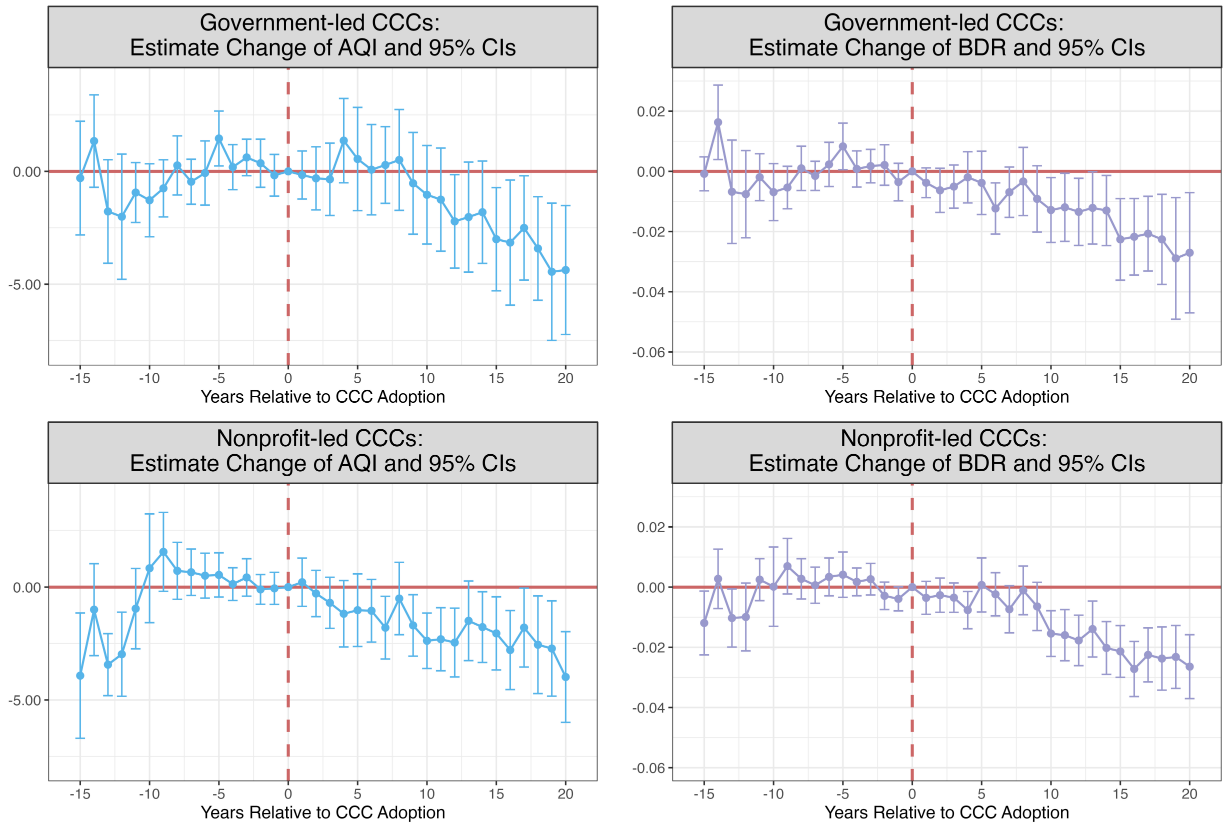
Table 3: 2SDiD estimates: Bottom-up & top-down effects of CCCs on air quality

	Government-led		Nonprofit-led	
	(3)	(4)	(5)	(6)
Dependent variable	AQI	BDR	AQI	BDR
Baseline mean	42.365	0.051	42.658	0.057
Treated	-1.496	-0.014	-1.784	-0.013
	(0.858)	(0.005)	(0.603)	(0.003)
P-value	0.081	0.002	0.003	0.000
Observation	15,655	15,655	21,858	21,858
Adj. R^2	0.006	0.027	0.008	0.024
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods.

Figure 6 displays the event-study plots for both subgroups. In government-led CCCs, the treatment effects on AQI only occurred 15 years after their adoptions, while the treatment effects on BDR stabilized after 10 years. After 20 years, government-led CCCs reduced AQI and BDR by 4.37 points and 2.79 percentage points, respectively. In contrast, the effects of nonprofit-led CCCs emerged more quickly than those of government-led CCCs for both outcomes, and these effects stabilized after the tenth year. After 20 years, nonprofit-led CCCs reduced AQI and BDR by 3.98 points and 2.64 percentage points, respectively.

Figure 6: Top-down & bottom-up CCCs on air quality: Event study analysis



5.3.3 *Analysis of government subgroups*

To comprehend the reasons behind the relative inefficiency of government-led CCCs, we separated them into state-led, regional-led, and local-led CCCs. We further investigated whether heterogeneous effects existed between these governance models. Table 4 displays the results of these analyses.

Overall, we found that the inefficiency in reducing air pollution within government-led CCCs was attributable to state-led and local-led CCCs. Neither of these CCCs produced discernible effects on air quality from 0 in both AQI and BDR. However, regional-led CCCs performed well in both air quality measures (see models 9 and 10), reducing AQI by 4.74 points and BDR by 2.50 percentage points. These results corresponded to relative reductions of 11% and 42%, respectively.

Table 4: 2SDiD estimates: Heterogenous effects of government-led CCCs on air quality

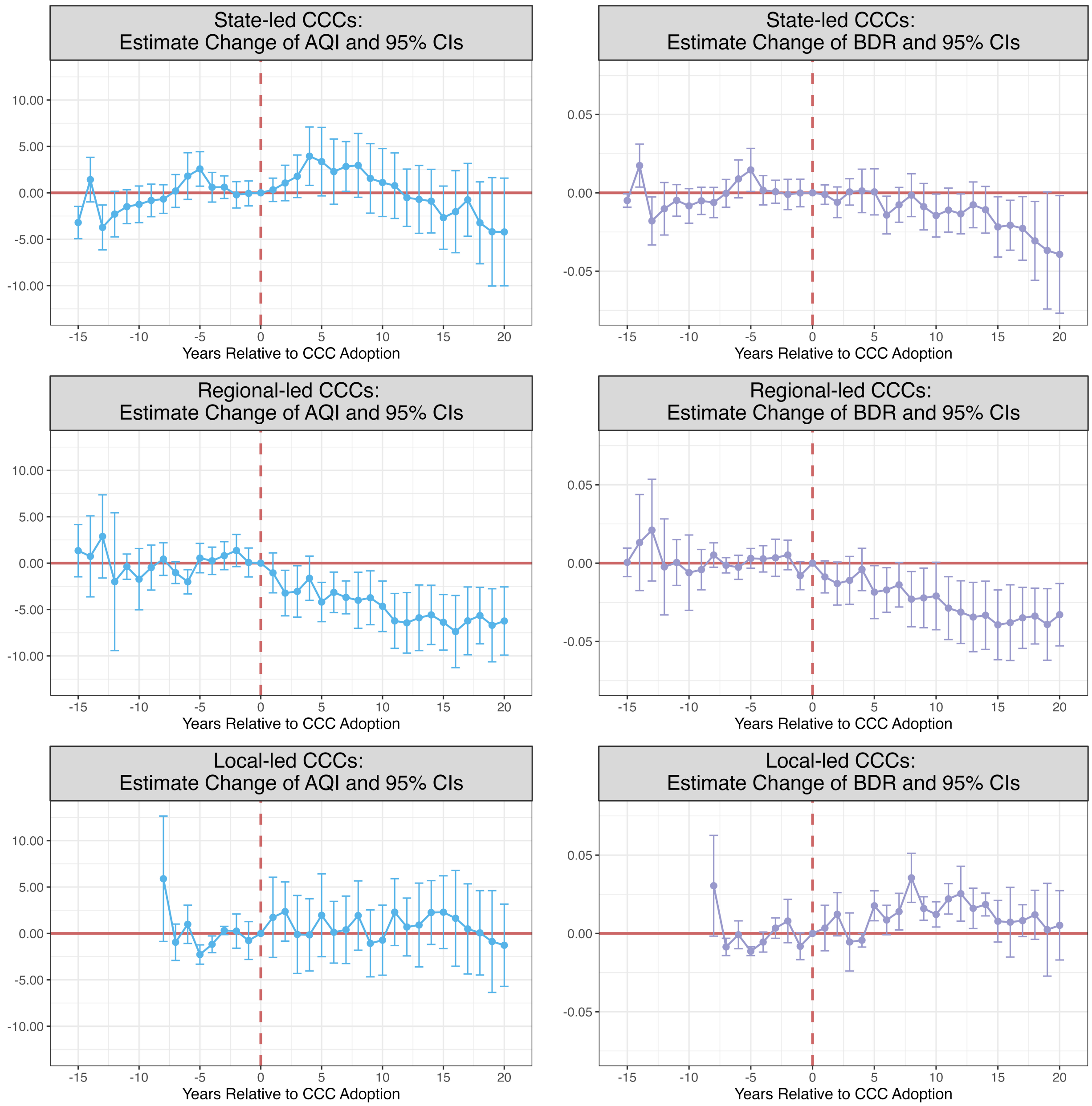
	State-led		Regional-led		Local-led	
	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	AQI	BDR	AQI	BDR	AQI	BDR
Baseline mean	42.107	0.048	43.303	0.059	39.579	0.036
Treated	-0.005	-0.013	-4.736	-0.025	0.627	0.009
	(1.490)	(0.007)	(1.020)	(0.007)	(1.877)	(0.005)
P-value	0.997	0.051	0.000	0.000	0.738	0.091
Observation	12,664	12,664	11,390	11,390	10,121	10,121
Adj. R^2	0.000	0.022	0.033	0.056	0.000	0.006
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods.

Next, we illustrate event-study plots for all subgroups within government-led CCCs in Figure 7[5]. Consistent with the ATTs in Table 4, neither state-led nor local-led CCCs generated any long-term air pollution reduction effect over the 20 years. In contrast, regional-led CCCs were efficient. They began to decrease AQI in the second year after implementation, and the effects stabilized after 4 years. The reduction of BDR occurred and became stable after 5 years. After 20 years, regional-led CCCs reduced AQI and BDR by 6.24 points and 3.29 percentage points, respectively. These long-term effects were even slightly stronger than those of nonprofit-led CCCs.

[5] The event-study plots for local-led CCCs only include estimates from eight years before CCC adoptions. This is because most local-led CCCs were adopted in 1994 and 1998, which is within or less than 8 years from 1990. Although one local-led CCC was adopted in 2006, its sample size is insufficient to provide the statistical power needed for calculating spatially adjusted SEs.

Figure 7: Heterogenous effects of government-led CCCs on air quality: Event study analysis



5.3.4 Robustness checks

In addition to the aforementioned analyses, we conducted several sensitivity tests to assess the robustness of our findings. First, we evaluated the parallel trend assumption in our 2SDiD model, which requires that the differences in air quality between treatment and control counties be generally statistically indistinguishable from 0, relative to the year before

CCC adoptions. The event-study plots in Figures 5, 6, and 7 demonstrate that there was little evidence of systematic differences in pre-trends within our models, particularly for the ten years preceding CCC adoptions. Therefore, the parallel trend assumption was satisfied.

Second, we examined the no-anticipation assumption, which suggests that the treatment has no causal effect before its implementation (Roth et al. 2023). To evaluate this assumption, we conducted a placebo test, assuming that the treatment commences two years earlier than its actual start for each CCC county (Liu et al. 2022). We then applied the same event study strategy as in our main analyses to determine placebo dynamic treatment effects. Appendix D presents the placebo tests. There was little evidence of systematic treatment effects following the placebo CCC adoptions, which supported the no-anticipation assumption.

Furthermore, we replicated our main and subgroup analyses using counties from states that have historically faced significant air quality issues. This analysis is necessary because regional-led and nonprofit-led CCCs may outperform local-led and state-led CCCs, potentially due to having more severe air quality conditions to address prior to the adoption of CCCs. Appendix E shows the 2SDiD models that only include states with a history of poor air quality, findings that closely align with our primary results. Given this similarity, we have less concern about this issue.

6 Comparing Collaborative Mechanisms in CCCs

6.1 Combining content analysis and natural experiment

The above evidence reveals that the nonprofit-led and regional-led CCCs are effective in addressing air quality problems. Regardingly, the top-down and bottom-up dichotomy may not be sufficient to explain the reasons behind the heterogeneity in our results. Therefore, we adopt a two-step strategy to build a nuanced understanding of how and why different lead organizations in CCCs yield varying collaborative outcomes. First, we conduct a content analysis to examine whether the four different lead organizations employ varying collaborative implementation approaches, providing a descriptive analysis across multi-n cases (Honig

2019). We explore the heterogeneity of implementation strategies among organizations beyond the top-down versus bottom-up dichotomy, focusing on three key dimensions: issue definition, resource allocation, group structures and decision-making processes. Second, we perform 2SDiD analysis for each mechanism subgroup. This allows us to compare the causal impacts of these collaborative mechanisms on air quality improvement.

6.2 Case selection and data collection protocol

A list of CCCs was collected on 2022 December, from the National Renewable Energy Laboratory (NREL), which identified 86 operating CCCs. Of the 86 CCCs, 11 were excluded because no archival information was available, or the websites were irrelevant or out of operation. The final sample consisted of 75 CCCs including 9 state-led, 7 local government-led, 16 regional-led, and 43 nonprofit-led CCCs and we collected their documents and archival records (see Appendix F for the complete case list). Instead of selecting a single case that represents each type of lead organization, we examine the whole population of CCCs available. This large-n case selection (Goertz and Haggard 2023; Haggard and Kaufman 2012) lessens the problem of representativeness in the case selection stage.

To identify how each type of lead organization manages CCCs similarly and differently across types, we adopt summative content analysis where we search and define themes across cases and categorize the data (Hsieh and Shannon 2005). Our data collection and analysis process was iterative and simultaneous with theory development from initial coding to focused and theoretical coding (Charmaz 2006). First, two researchers gathered available information to build case summaries on individual CCCs from reports and websites and reviewed them with the broad goal of exploring mechanisms that may differ across CCCs with different lead organizations. Then, we identified a broad theoretical framework to assess following the theoretical discussion in previous studies (Koontz and Newig 2014; Koontz et al. 2004). This initial theoretical framework included overarching categories of issue definition, resources, and group structure and decision-making processes. After narrowing down our scope to three categories, we went through iterative revisions of codes to identify the sub-categories based on observing the case summaries, for a more in-depth and nuanced understanding of the characteristics of each type of lead organization. Then, we established a coding protocol to collect data for each sub-category from the case summaries. Following the protocol, each of the two coders independently coded all 75 cases where three of the sub-categories had inter-coder reliability (Cohen's kappa) under 95%. The authors reviewed cases of disagreement and reached a consensus, where all sub-categories achieved above 96% (see Appendix G). Table 5 summarizes the coding scheme used for content analysis and defines categories.

Table 5: Coding scheme

Overarching categories	Sub-categories	Definition
Issue definition	Collaborative goal	CCCs state air quality and cleaner air quality as a goal
Resource allocation	Mobilize resources externally	Aside from membership fees, CCCs ask for donations and volunteer work from stakeholders or citizens
	Secure funding from the Collaborative platform	CCCs won grants from the Clean Cities program (DOE) to implement projects
Group structure and decision-making processes	Membership is open to apply	CCCs encourage stakeholders to become a member and engage in the collaboration
	Member benefits	Benefits of participating in CCCs
	Member responsibilities	Expected responsibilities and commitments from participants in CCCs
	Cross-sector board of directors	Governing board is cross-sectoral

Issue definition plays a role in mobilizing participants to focus more on a specific policy goal, which shapes collaborative efforts and outcomes (Koontz et al. 2004). We coded whether each CCC states improving air quality as an issue that the collaboration attempts to resolve, which is one of the ultimate goals of the Clean Cities program.

In terms of resources, we focus on financial resources which are critical for any collaborative activities, and measure whether the CCCs raise funding externally (Koontz 2006).

Lead organizations in collaborations play an important role in drawing resources and non-governmental lead organizations are likely to have less access to financial resources (Emerson et al. 2012). Also, obtaining grant funding is an indicator of CCCs to execute projects and sustain collaborations (Sprague et al. 2019). Thus, we measured the number of CCCs who have won the grant at least once provided by DOE's Vehicle Technologies Office to implement alternative fuels and vehicles. We also investigate whether a CCC asks for donations because nonprofit organizations often rely on donations to raise resources (Bowman 2011; Carroll and Stater 2009; Rousseau et al. 2020).

Moreover, we assess group structure and decision-making processes with specific interests in membership rules with four sub-categories of membership openness, member benefits, member responsibilities, and board of governance. For membership openness, whether the membership is open to diverse stakeholders and citizens, or relatively exclusive to the lead organizations and several initial members leads to a different mix of members and collaborative structure (Hardy and Koontz 2009). Some argue that open collaborations facilitate the development of relationships among diverse actors and the creation of innovative solutions (Mandell 2001); while others contend that collaborations based on strong ties and tightly controlled membership are more effective (Verweij et al. 2013). Next, we examine membership benefits, whether a CCC provide benefits to individual participants to attract stakeholders. Expected benefits distribution motivates actors to engage in collaborative governance, which is relevant to membership rules and aggregation of individual preferences (Emerson and Nabatchi 2015; Koontz et al. 2004). Furthermore, our coding scheme includes an assessment of whether a CCC clearly outlines member responsibilities and duties to maintain membership status. By asking members to commit to common goals and take on specific roles and tasks, they become more invested in the collaboration and develop a sense of ownership, which is crucial for fruitful collaborations (Ansell and Gash 2008; Gazley et al. 2010). Lastly, we investigate whether the CCCs have a cross-sectoral board, as successful collaboration depends on the broad spectrum of stakeholders (Fischer and Maag 2019).

6.3 Descriptive analysis: Comparing collaborative mechanisms among lead organizations

We coded our observations and derived basic descriptive statistics of how resources, goals, and group structure differ across types of lead organizations to establish regularities in Table 6.

Table 6: Content analysis results

Categories	Sub-categories	Regional (n=16)	Local (n=7)	State (n=9)	Nonprofit (n=43)
Issue definition	Collaborative goal	9 (56%)	4 (57%)	4 (44%)	34 (79%)
Resource allocation	Ask for donation	1 (6%)	1 (14%)	0 (0%)	29 (67%)
	Awarded funding from DOE	1 (6%)	1 (14%)	4 (44%)	12 (28%)
Group structure and decision-making processes	Membership is open to apply	13 (81%)	4 (57%)	2 (22%)	42 (98%)
	Member benefits	11 (69%)	4 (57%)	2 (22%)	39 (91%)
	Member responsibilities	4 (25%)	1 (14%)	1 (11%)	30 (70%)
	Cross-sector board of directors	3 (19%)	5 (71%)	0 (0%)	33 (77%)

In terms of issue definition, we began by assessing whether CCCs' objectives align with those of the collaborative platform. At the platform level, the Clean Cities program states that reducing vehicle emissions and improving air quality is one of their long-term goals (Department of Energy 2023). A considerable number of CCCs in each lead organization subgroup showed a good alignment with the platform's goals for improving air quality: 44% state-led CCCs, 57% local-led CCCs, 56% regional-led, and 79% nonprofit-led CCCs highlighted improving air quality as the problem they would like to address. Others mentioned goals such as reduction of petroleum consumption (case 11) or increased adoption of alternative fuels (case 45).

Second, CCCs mobilize resources through funding from the collaborative platform or from citizens and stakeholders. State-led and nonprofit-led CCCs won funding from the platform more often than the local-led and regional-led CCCs when measuring the number of CCCs that have won grants at once. In addition, nonprofit-led CCCs were proactive in their efforts to raise resources externally. 67% of nonprofit-led CCCs encouraged donations and volunteers to support their activities. On the other hand, only 1 regional-led and 1 local-led CCCs asked for donations, indicating that government-led CCCs are likely to be more self-sufficient in terms of resources and funding their own activities.

Third, regarding group structure and decision-making processes, nonprofit-led and regional-led CCCs were more open to engage interested parties and stakeholders. 98% nonprofit-led, 81% regional-led CCCs actively sought potential participants. On the other hand, state and local government-led CCCs were less interested in engaging new participants, which rarely described the member benefits and responsibilities.

Also, nonprofit-led and regional-led CCCs highlighted the benefits of collaboration and asked for members' commitments. 91% nonprofit-led and 69% regional-led CCCs explicitly stated the benefits of being collaborative members. Member benefits include technical training and roundtables for peer learning and networking, funding opportunities and webinars, assistance with grant writing, and/or participation in the decision-making of the collaboration. Compared to others, CCCs led by non-profit organizations tend to emphasize the responsibilities of their members more prominently than other lead organizations. Members were expected to make commitments to work with other stakeholders to design activities (case 41) or vote on decision-making processes and serve on sub-committees (case 50).

6.4 Exploratory analysis: Heterogeneous effects of collaborative mechanisms on air quality

The descriptive analysis above suggests plausible correlations between collaborative mechanisms and the improvement of air quality. The better performances of nonprofit-led and regional-led CCCs are associated with their collaborative group structures and inclusive decision-making processes. However, the limited number of observations for state-led and local-led CCCs compared to the other groups might undermine this argument. Consequently, the causal relationship between these mechanisms and air quality outcomes has not yet been confirmed. In response, we conducted an exploratory analysis using 2SDiD, specifically focusing on mechanism subgroups, to further clarify and reinforce our understanding of the collaborative mechanisms within CCCs.

Similar to the other 2SDiD subgroup analyses in this research, we compare counties in CCCs that have ever adopted a specific collaborative mechanism with those that have never experienced CCCs in each mechanism subgroup. Table 7 presents the results for the issue definition subgroup (Panel A, models 13-14), resource allocation subgroups (Panel B, models 15-18), and the group structures and decision-making processes subgroups (Panel C, models 19-26). CCCs in each subcategory within Panel A and C demonstrate significant treatment effects with p-values < 0.05. These results suggest that clear long-term goals, along with more collaborative group structures and inclusive decision-making processes, are key collaborative mechanisms driving air quality improvement. In comparison, the effects of resource allocation capacity are less pronounced in Panel B. In addition, we also report the event-study plots for all mechanism subgroups in Appendix H.

It is important to note that our content analysis findings are exploratory in nature and limited by the scope of our data. We based our observations of CCCs' collaborative processes on publicly available information, which may not provide a comprehensive view from insiders' perspectives. Nevertheless, our analysis provides an initial understanding of how the implementation approaches employed by CGRs within a collaborative platform differ based on the lead organization, and the varying degrees of impacts of collaborative mechanisms in improving air quality.

Table 7: 2SDiD estimates: Heterogenous effects of collaborative mechanisms on air quality

Panel A. CCCs with clear goals

	(13)	(14)
Dependent variable	AQI	BDR
Baseline mean	42.949	0.057
Treated	-2.364	-0.012
	(0.617)	(0.003)
P-value	0.000	0.001
Observation	21,030	21,030
Adj. R^2	0.016	0.020

Panel B. CCCs with resource allocation capacity

	Donation		Funded by DOE	
	(15)	(16)	(17)	(18)
Dependent variable	AQI	BDR	AQI	BDR
Baseline mean	42.678	0.052	38.049	0.040
Treated	-1.108	-0.010	0.233	-0.006
	(0.649)	(0.003)	(1.131)	(0.005)
P-value	0.088	0.002	0.837	0.279
Observation	17,838	17,838	14,940	14,940
Adj. R^2	0.004	0.015	0.000	0.005

Panel C. CCCs with collaborative group structure and decision-making processes

	Open membership		Clear benefits		Clear responsibility		Cross-sector decision	
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Dependent variable	AQI	BDR	AQI	BDR	AQI	BDR	AQI	BDR
Baseline mean	42.816	0.055	43.172	0.058	41.560	0.052	43.330	0.057
Treated	-1.850	-0.013	-1.638	-0.013	-1.427	-0.012	-2.014	-0.014
	(0.493)	(0.003)	(0.509)	(0.003)	(0.665)	(0.003)	(0.550)	(0.003)
P-value	0.000	0.000	0.001	0.000	0.032	0.000	0.000	0.000
Observation	24,086	24,086	23,102	23,102	19,249	19,249	20,261	20,261
Adj. R^2	0.010	0.026	0.008	0.024	0.006	0.023	0.012	0.031

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods. County and state fixed effects as well as covariates are included in all models.

7 Discussion and Conclusion

To advance the scholarship on collaborative governance, this study presents new evidence regarding the relations between a collaborative platform, CGRs led by different types of organizations, and environmental outcomes. Through the natural experiment, we find that the DOE's Clean Cities program served as an effective collaborative platform for fostering local collaboration in pursuit of environmental objectives. Furthermore, the results demonstrate that CCCs led by nonprofit organizations outperformed those led by government entities. A more detailed subgroup analysis of government-led CCCs reveals that state and local government-led CCCs did not significantly impact air pollution levels. However, CCCs led by regional councils achieved outcomes comparable to those of nonprofit-led CGRs. We employ content analysis to further investigate the mechanisms underlying the varying performance of these distinct lead-organization models. Clear goals, collaborative group structures, and inclusive decision-making processes are stronger predictors of environmental improvement than resource allocation. Given that CCCs across various lead-organization models exhibit a similar propensity for clear long-term goals in the Table 6, we suggest that the collaborative group structure and inclusive decision-making process jointly explain why nonprofit-led and regional-led CCCs outperform local-led and state-led CCCs.

This research makes three key theoretical contributions to the field of collaborative governance. First, it directly addresses the question posed by Ansell and Gash (2018, 29): "...how collaborative governance is being promoted and facilitated as a generic policy instrument." This inquiry is crucial for the collaborative governance study and practice, as the field's early development was predominantly reactive in nature, and the practice was mostly at the local level (Ansell and Gash 2008). However, the promotion and scaling of collaborative governance as a more global and proactive policy instrument remain largely unexplored (Ansell et al. 2023). Therefore, this study is the first to establish a generalizable relationship between a collaborative platform, its supported collaborations, and the ensuing collaborative outcomes. By conducting a nationwide analysis, this research confirms that collaborative platforms can effectively scale collaborations to various locations across the country at the macro level. Additionally, the scope of the data collected encompasses not only geographical breadth but also temporal depth. Collaborative efforts are often time-consuming, and their impacts tend to manifest over the long term rather than immediately (Ansell and Gash 2018). However, existing literature seldom includes data spanning a 31-year period, as seen in this study (Siciliano et al. 2021). With this extensive data structure, we observed the long-term effects of collaborative governance on air pollution reduction. This research demonstrates that the collaborative institutional rules, processes, and resources provided by collaborative platforms facilitated the scaling of localized CGRs, ultimately enabling the achievement of cross-boundary environmental objectives over an extended period.

Second, this research answers the question of whether platform-supported CGRs led by different types of organizations yield varying outcomes. This inquiry aligns with Provan and Kenis (2008)'s classic argument that the lead organizations act as brokers within collaborative networks. While diverse types of lead organizations across sectors coordinate CGRs with different purposes and mechanisms (Koontz et al. 2004), systematic comparisons of their impacts on collaborative outcomes have been notably absent. Intriguingly, our subgroup analysis uncovered that the heterogeneity in collaborative outcomes is not solely determined by the public-nonprofit sector dichotomy. Rather, nonprofit organizations and regional government councils were generally more effective CGR leaders in improving air quality. This finding not only contributes to the collaborative governance literature by establishing robust connections between organizational leadership and collaborative outcomes (see also McGuire and Silvia 2009; Silvia 2011), but also enhances the performance comparisons between nonprofit and public organizations. As Andrews et al. (2011) proposed, the scholarship in public administration should re-examine the theoretical relationship between organizational publicness and performance by incorporating additional moderating mechanisms that influence performance beyond the sector labels.

Third, the combination of descriptive content analysis and exploratory 2SDiD focused on mechanism subgroups enhances our understanding of the managerial functions in each lead-organization model that drive collaborative outcomes. Our finding aligns with what previous studies found that clear issue definition is a base for participants to build solutions and address problems more effectively (Koontz and Newig 2014; Koontz et al. 2004). Moreover, accessibility of collaborative membership, clarification of responsibilities and benefits, and inclusive decision-making processes were more prominent in nonprofit-led and regional-led CCCs. These collaborative structures lead to causal impacts on air quality improvement. The capacity of resource allocation has smaller impacts on air quality improvement, compared to issue definition and collaborative group structures. This finding contradicts several studies which found mandated collaboration with top-down resource support to be more effective than self-initiated collaboration (e.g., Bitterman and Koliba 2020; Liu and Tan 2022; Scott 2016). Although nonprofit-led CCCs may not have a stable financial resource stream, they adopt proactive resource mobilization strategies such as leveraging donations, interns, and volunteers to raise both financial and human resources to support their activities. This approach aligns with the purpose of the federal government in utilizing collaborative platforms, which is to leverage untapped, potentially interested parties and citizens (Ansell and Miura 2020). Overall, our content analysis and 2SDiD of mechanism subgroups reveal the core values of collaboration itself: Actively facilitating collaborations, promoting representation in decision-making, and establishing a long-term commitment to shared core goals are essential for healthy collaborations (see also Bryson et al. 2016; Koontz 2006; Mehdi and Nabatchi 2022; Ulibarri 2015).

Beyond its theoretical contributions, this research also offers practical insights for collaborative governance. Our study suggests CCCs often frame their issues differently from the overarching platform-level goals. To effectively tackle specific policy challenges, the collaborative platform may actively manage and closely align CGR-level goals. Furthermore, recognizing that there is no one-size-fits-all solution for policy implementation, public managers within collaborative platforms should tailor resource support to the specific needs of CGRs with varying conditions (Scott and Thomas 2017). For instance, CGRs with limited legal authority and resources may benefit from stronger financial and legal support to ensure their collaborative efforts remain sustainable. Conversely, for CGRs led by organizations with significant political power, collaborative platforms should introduce projects and opportunities that foster improved communication and mutual trust among participants. Lastly, we suggest that lead organizations in CGRs should not only focus on allocating resources and setting policy goals for their participants but also on developing suitable strategies to coordinate collaborative actions among participants. These strategies should facilitate collaboration in everyday tasks and build consensus on sharing benefits and responsibilities among participants.

While this research illuminates the integration of collaborative platforms and CGRs in a study and explores collaborative mechanisms across multiple lead organization models, three limitations warrant attention in future studies. First, the Clean Cities program pertains to the environmental policy domain, and the applicability of findings to other policy contexts remains uncertain. Future research could examine the effectiveness of collaborative platforms and various lead organization models through comparative analysis across different policy areas. Second, this study primarily investigates the scaling-up effects of collaborative governance at the macro level, but a more comprehensive integration of analyses from different levels should be incorporated in future research. An interesting question for the next generation of collaborative governance research is at individual and organizational level, testing how the collaborative behaviors of public managers may influence organizational or CGR-level outcomes. Additionally, our analysis could not control several sources of emissions and bad air quality, such as vehicle ownership or wildfire, due to lack of data. The incorporation of nonpoint source emissions in subsequent studies is recommended to establish the effectiveness of the Clean Cities in improving air quality.

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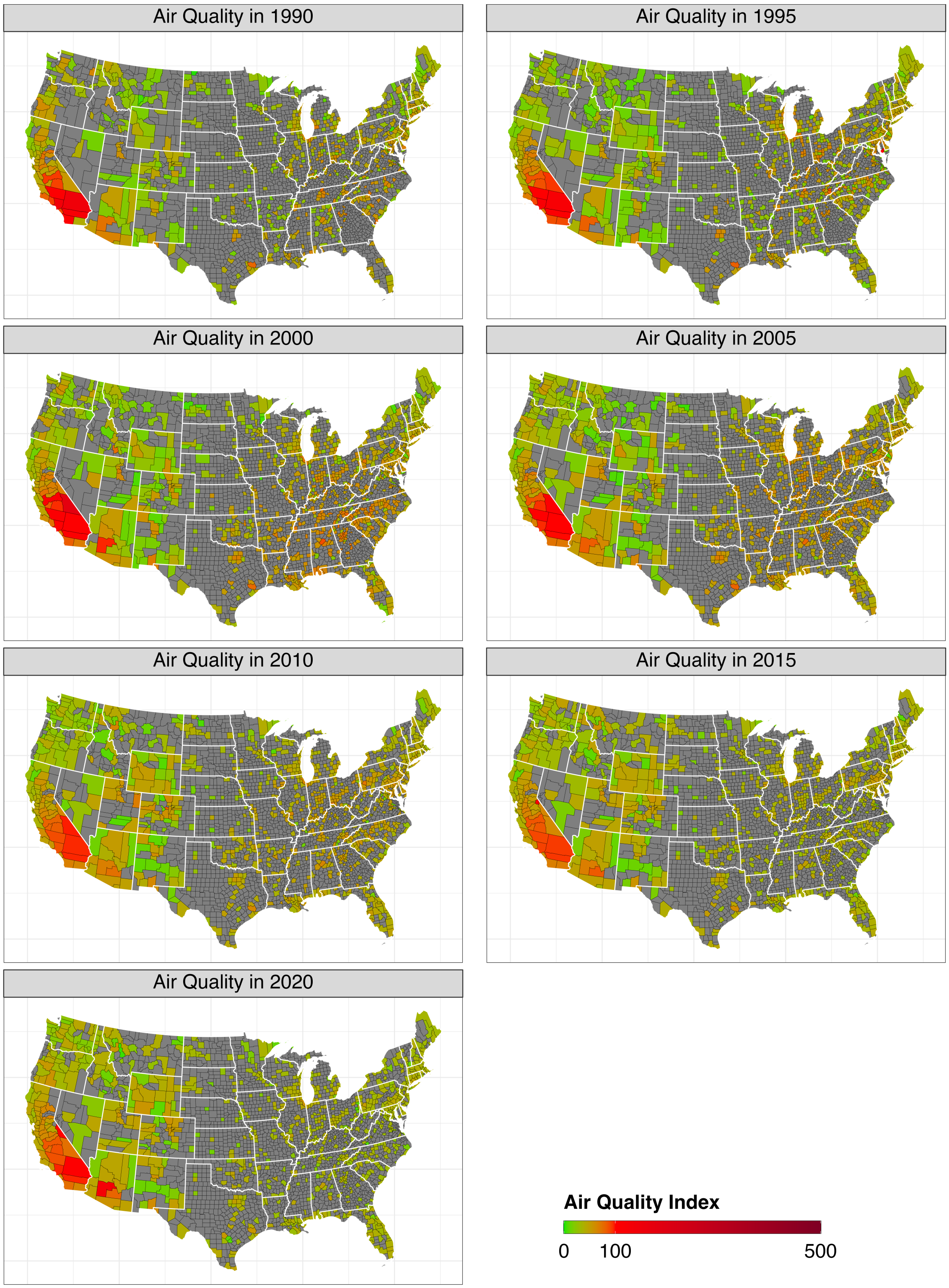
Appendix A U.S. Air Quality Index from 1990 to 2020

Figure A.1: Maps of U.S. air quality index from 1990 to 2020



Appendix B Sampling Counties

Table B.1: Sampling counties in each type of CCC

	N of Counties	N of CCCs
Ever experienced CCCs	910	80
Never experienced CCCs	483	
Ever experienced nonprofit-led CCCs	615	47
Ever experienced government-led CCCs	295	33
Ever experienced state-led CCCs	163	9
Ever experienced regional-led CCCs	101	17
Ever experienced local-led CCCs	31	7

Appendix C Descriptive Statistics

Table C.1: Summary statistics: Full sample

	Observation	Mean	SD	Min	Max
Air quality index	28253	41.49	14.40	1.43	303.85
Bad days ratio	28253	0.03	0.06	0.00	0.69
Population density	28253	496.40	2080.43	0.28	48484.66
White population (ratio)	28253	0.85	0.14	0.18	1.00
Motor freight transportation	28253	33.57	87.97	0.00	2227.00
Labor force	28253	117068.42	254107.80	259.00	5153091.00
Annual temperature (°F)	28253	54.34	8.26	32.62	78.38
Annual precipitation (inch)	28253	3.36	1.36	0.05	11.04
Alternative fuels incentives	28253	0.57	1.01	0.00	6.00
Ratio of hydroelectric power	28253	0.14	0.31	0.00	1.00
Ratio of hydroelectric capacity	28253	0.12	0.30	0.00	1.00
Ratio of coal power	28253	0.07	0.20	0.00	1.00
Ratio of coal capacity	28253	0.11	0.28	0.00	1.00
Total generator	28253	7.51	12.27	0.00	171.00
Total power capacity	28253	454.37	904.20	0.00	9786.00
Regulated facility	28253	370.99	1286.64	0.00	11648.00
Regulation violation	28253	53.71	141.80	0.00	1176.00
Pro-environmental nonprofits	28253	5.91	12.10	0.00	318.00

Table C.2: Summary statistics: Counties ever treated by CCCs

	Observation	Mean	SD	Min	Max
Air quality index	18993	43.39	14.22	2.25	162.38
Bad days ratio	18993	0.04	0.07	0.00	0.69
Population density	18993	625.28	2458.72	0.41	48484.66
White population (ratio)	18993	0.85	0.14	0.18	1.00
Motor freight transportation	18993	41.32	102.81	0.00	2227.00
Labor force	18993	147644.88	296652.84	259.00	5153091.00
Annual temperature (°F)	18993	54.75	7.95	32.62	78.38
Annual precipitation (inch)	18993	3.54	1.31	0.05	11.04
Alternative fuels incentives	18993	0.63	1.04	0.00	6.00
Ratio of hydroelectric power	18993	0.13	0.29	0.00	1.00
Ratio of hydroelectric capacity	18993	0.10	0.27	0.00	1.00
Ratio of coal power	18993	0.07	0.21	0.00	1.00
Ratio of coal capacity	18993	0.12	0.29	0.00	1.00
Total generator	18993	8.43	13.50	0.00	171.00
Total power capacity	18993	504.57	959.63	0.00	9786.00
Regulated facility	18993	505.98	1519.56	0.00	11648.00
Regulation violation	18993	46.44	123.31	0.00	1176.00
Pro-environmental nonprofits	18993	7.13	13.91	0.00	318.00

Table C.3: Summary statistics: Counties ever treated by nonprofit-led CCCs

	Observation	Mean	SD	Min	Max
Air quality index	12598	43.30	14.66	2.25	143.22
Bad days ratio	12598	0.04	0.07	0.00	0.67
Population density	12598	716.93	2932.76	0.41	48484.66
White population (ratio)	12598	0.86	0.14	0.18	1.00
Motor freight transportation	12598	39.36	94.83	0.00	2227.00
Labor force	12598	137315.51	292018.21	259.00	5153091.00
Annual temperature (°F)	12598	53.91	7.72	32.62	75.69
Annual precipitation (inch)	12598	3.41	1.30	0.20	9.83
Alternative fuels incentives	12598	0.61	0.99	0.00	4.00
Ratio of hydroelectric power	12598	0.11	0.28	0.00	1.00
Ratio of hydroelectric capacity	12598	0.09	0.27	0.00	1.00
Ratio of coal power	12598	0.08	0.22	0.00	1.00
Ratio of coal capacity	12598	0.12	0.29	0.00	1.00
Total generator	12598	7.66	12.50	0.00	108.00
Total power capacity	12598	456.30	888.42	0.00	6665.40
Regulated facility	12598	580.98	1689.76	0.00	11648.00
Regulation violation	12598	37.79	95.09	0.00	1176.00
Pro-environmental nonprofits	12598	6.43	13.70	0.00	318.00

Table C.4: Summary statistics: Counties ever treated by state-led CCCs

	Observation	Mean	SD	Min	Max
Air quality index	3404	42.93	11.31	3.59	110.22
Bad days ratio	3404	0.03	0.05	0.00	0.57
Population density	3404	385.32	891.19	9.23	7991.26
White population (ratio)	3404	0.83	0.16	0.26	1.00
Motor freight transportation	3404	25.68	43.58	0.00	422.00
Labor force	3404	98094.71	132763.85	2294.00	932660.00
Annual temperature (°F)	3404	55.39	6.23	37.85	68.08
Annual precipitation (inch)	3404	3.93	0.82	1.65	7.56
Alternative fuels incentives	3404	0.74	1.22	0.00	4.00
Ratio of hydroelectric power	3404	0.16	0.31	0.00	1.00
Ratio of hydroelectric capacity	3404	0.12	0.29	0.00	1.00
Ratio of coal power	3404	0.10	0.24	0.00	1.00
Ratio of coal capacity	3404	0.15	0.32	0.00	1.00
Total generator	3404	8.78	13.06	0.00	171.00
Total power capacity	3404	497.00	777.76	0.00	4071.60
Regulated facility	3404	328.87	676.58	0.00	3290.00
Regulation violation	3404	17.59	37.95	0.00	184.00
Pro-environmental nonprofits	3404	5.76	9.70	0.00	108.00

Table C.5: Summary statistics: Counties ever treated by regional-led CCCs

	Observation	Mean	SD	Min	Max
Air quality index	2130	44.92	15.56	7.63	162.38
Bad days ratio	2130	0.05	0.08	0.00	0.69
Population density	2130	428.23	603.73	3.85	3349.84
White population (ratio)	2130	0.83	0.14	0.21	0.99
Motor freight transportation	2130	51.21	101.71	0.00	1036.00
Labor force	2130	225212.57	364016.07	6944.00	2274172.00
Annual temperature (°F)	2130	60.02	10.03	37.00	78.38
Annual precipitation (inch)	2130	3.45	1.41	0.05	8.53
Alternative fuels incentives	2130	0.48	0.91	0.00	6.00
Ratio of hydroelectric power	2130	0.16	0.31	0.00	1.00
Ratio of hydroelectric capacity	2130	0.09	0.25	0.00	1.00
Ratio of coal power	2130	0.04	0.13	0.00	1.00
Ratio of coal capacity	2130	0.07	0.21	0.00	1.00
Total generator	2130	11.36	16.41	0.00	116.00
Total power capacity	2130	787.59	1392.79	0.00	9786.00
Regulated facility	2130	477.57	1603.94	0.00	11648.00
Regulation violation	2130	129.80	231.77	0.00	1176.00
Pro-environmental nonprofits	2130	9.44	14.70	0.00	132.00

Table C.6: Summary statistics: Counties ever treated by local-led CCCs

	Observation	Mean	SD	Min	Max
Air quality index	861	42.63	13.88	6.16	86.02
Bad days ratio	861	0.04	0.06	0.00	0.31
Population density	861	658.14	922.40	10.20	3793.01
White population (ratio)	861	0.85	0.10	0.52	0.99
Motor freight transportation	861	113.78	260.26	0.00	2018.00
Labor force	861	320016.79	504509.44	8640.00	2742036.00
Annual temperature (°F)	861	51.75	5.25	42.76	64.89
Annual precipitation (inch)	861	4.32	2.17	0.26	11.04
Alternative fuels incentives	861	0.77	1.21	0.00	4.00
Ratio of hydroelectric power	861	0.22	0.35	0.00	1.00
Ratio of hydroelectric capacity	861	0.20	0.35	0.00	1.00
Ratio of coal power	861	0.02	0.05	0.00	0.43
Ratio of coal capacity	861	0.06	0.18	0.00	0.88
Total generator	861	11.94	19.61	0.00	124.00
Total power capacity	861	572.21	1198.77	0.00	7008.60
Regulated facility	861	91.75	98.55	0.00	528.00
Regulation violation	861	87.30	216.13	0.00	1176.00
Pro-environmental nonprofits	861	18.19	22.34	0.00	139.00

Table C.7: Summary statistics: Counties never treated by CCCs

	Observation	Mean	SD	Min	Max
Air quality index	9260	37.15	13.84	1.43	303.85
Bad days ratio	9260	0.02	0.04	0.00	0.52
Population density	9260	201.79	527.78	0.28	5984.23
White population (ratio)	9260	0.86	0.14	0.25	1.00
Motor freight transportation	9260	15.84	28.53	0.00	363.00
Labor force	9260	47175.10	63159.69	358.00	457133.00
Annual temperature (°F)	9260	53.42	8.86	33.30	77.10
Annual precipitation (inch)	9260	2.95	1.38	0.22	9.96
Alternative fuels incentives	9260	0.44	0.92	0.00	6.00
Ratio of hydroelectric power	9260	0.18	0.35	0.00	1.00
Ratio of hydroelectric capacity	9260	0.16	0.34	0.00	1.00
Ratio of coal power	9260	0.06	0.18	0.00	1.00
Ratio of coal capacity	9260	0.09	0.25	0.00	1.00
Total generator	9260	5.40	8.45	0.00	84.00
Total power capacity	9260	339.63	750.03	0.00	9119.40
Regulated facility	9260	62.43	156.80	0.00	1349.00
Regulation violation	9260	70.32	175.84	0.00	1176.00
Pro-environmental nonprofits	9260	3.14	5.32	0.00	61.00

Appendix D Placebo Tests

Figure D.1: Placebo dynamic treatment effects of CCCs on air quality

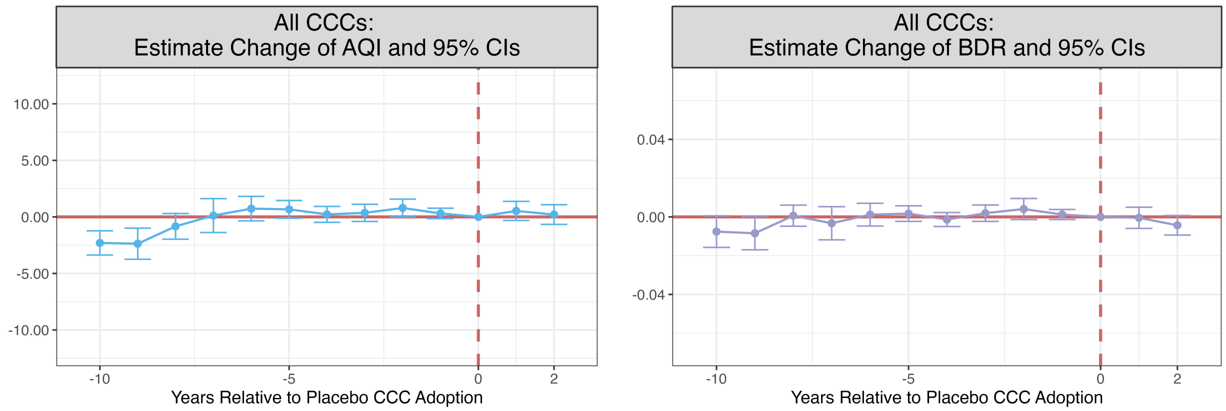


Figure D.2: Placebo top-down & bottom-up CCCs on air quality

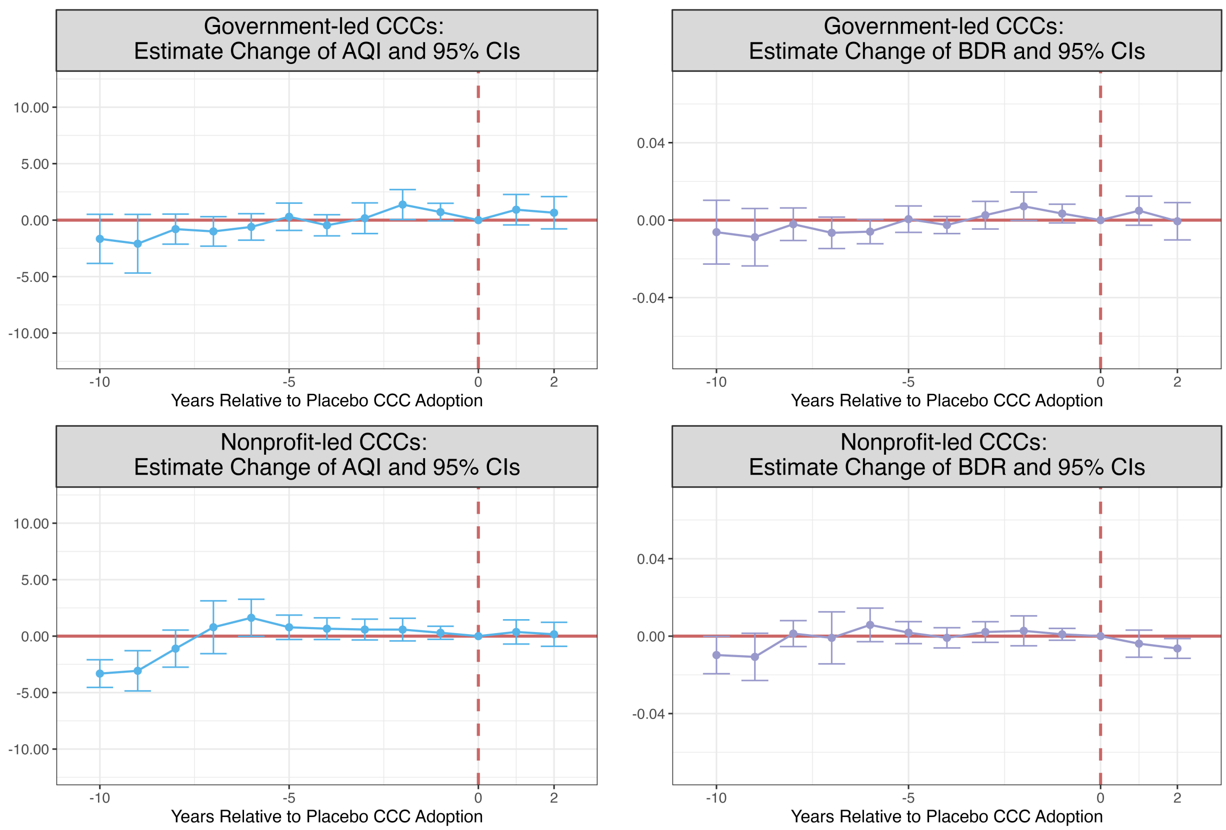
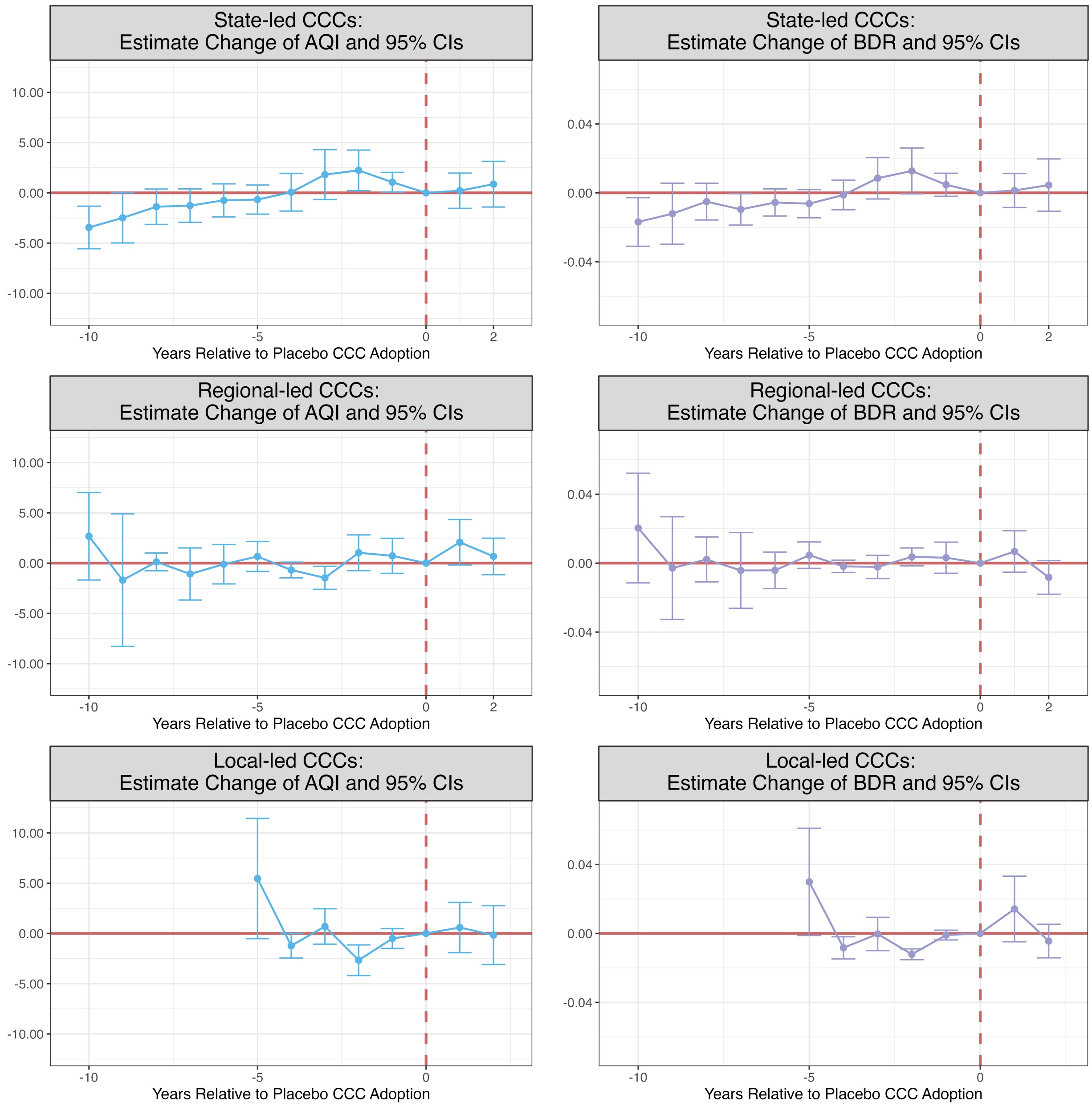


Figure D.3: Placebo heterogenous effects of government-led CCCs on air quality



Appendix E Analysis of States with a History of Poor Air Quality

In this section, we exclude states historically known for better air quality—specifically NM, AZ, OR, WA, CO, UT, NV, ID, WY, MT, ND, SD, ME—and reanalyzing the data using counties with historically poorer air quality.

Table E.1: 2SDiD estimates: Overall effects of CCCs on air quality

	(1)	(2)
Dependent variable	AQI	BDR
Baseline mean	43.548	0.059
Treated	-1.644	-0.014
	(0.558)	(0.003)
P-value	0.003	0.000
Observation	22,490	22,490
Adj. R^2	0.007	0.025
County FE	Yes	Yes
Year FE	Yes	Yes
Covariates	Yes	Yes

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods.

Table E.2: 2SDiD estimates: Bottom-up & top-down effects of CCCs on air quality

	Government-led		Nonprofit-led	
	(3)	(4)	(5)	(6)
Dependent variable	AQI	BDR	AQI	BDR
Baseline mean	43.410	0.055	43.630	0.062
Treated	-1.453	-0.014	-2.780	-0.017
	(1.014)	(0.005)	(0.648)	(0.003)
P-value	0.152	0.005	0.000	0.000
Observation	11,937	11,937	17,023	17,023
Adj. R^2	0.005	0.026	0.021	0.035
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods.

Table E.3: 2SDiD estimates: Heterogenous effects of government-led CCCs on air quality

	State-led		Regional-led		Local-led	
	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	AQI	BDR	AQI	BDR	AQI	BDR
Baseline mean	42.107	0.048	45.376	0.068	46.550	0.062
Treated	0.646	-0.007	-7.691	-0.040	0.116	0.004
	(1.523)	(0.007)	(1.299)	(0.009)	(2.220)	(0.008)
P-value	0.672	0.280	0.000	0.000	0.959	0.591
Observation	9,874	9,874	8,004	8,004	6,999	6,999
Adj. R^2	0.001	0.007	0.081	0.107	0.000	0.001
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Spatially adjusted standard errors are reported in parentheses. Baseline means are mean values of dependent variables for treated counties in pre-intervention periods.

Appendix F CCCs Case Identifiers

Table F.1: Case identifiers

Case ID	CCC Name
1	Arkansas Clean Cities
2	Central Coast Clean Cities
3	Western Riverside County Clean Cities Coalition
4	Los Angeles Clean Cities Coalition
5	Southern California Clean Cities Coalition
6	San Francisco Clean Cities Coalition
7	Sacramento Clean Cities Coalition
8	Connecticut Southwestern Area Clean Cities
9	State of Delaware Clean Cities
10	North Florida Clean Fuels Coalition
11	Southeast Florida Clean Cities Coalition
12	Chicago Area Clean Cities
13	Iowa Clean Cities Coalition
14	Southeast Louisiana Clean Fuel Partnership
15	Maine Clean Communities
16	State of Maryland Clean Cities
17	Massachusetts Clean Cities
18	Greater Lansing Area Clean Cities
19	Granite State Clean Cities Coalition
20	Capital District Clean Communities Coalition (Albany)
21	Land of Sky Clean Vehicles Coalition (Western North Carolina)
22	Centralina Clean Fuels Coalition
23	Triangle Clean Cities (Raleigh, Durham, Chapel Hill)
24	Tulsa Clean Cities
25	Central Oklahoma Clean Cities (Oklahoma City)
26	Palmetto State Clean Fuels Coalition
27	Middle-West Tennessee Clean Fuels Coalition
28	Alamo Area Clean Cities (San Antonio)
29	Houston-Galveston Clean Cities
30	Dallas-Fort Worth Clean Cities
31	Western Washington Clean Cities
32	State of West Virginia Clean Cities
33	Alabama Clean Fuels Coalition
34	Valley of the Sun Clean Cities Coalition (Phoenix)
35	San Diego Regional Clean Cities Coalition
36	Silicon Valley Clean Cities (San Jose)
37	San Joaquin Valley Clean Cities
38	East Bay Clean Cities Coalition (Oakland)

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Table F.1 – Continued from previous page

39	Northern Colorado Clean Cities Coalition
40	Denver Metro Clean Cities Coalition
41	Capitol Clean Cities of Connecticut
42	Greater New Haven Clean Cities Coalition
43	Greater Washington Region Clean Cities Coalition
44	Tampa Bay Clean Cities Coalition
45	Central Florida Clean Cities Coalition
46	Clean Cities-Georgia
47	Sustainable Transportation Coalition of Hawaii
48	Treasure Valley Clean Cities
49	Yellowstone-Teton Clean Cities Coalition
50	South Shore Clean Cities
51	Greater Indiana Clean Cities Coalition
52	Kansas City Regional Clean Cities
53	Kentucky Clean Cities Partnership
54	Louisiana Clean Fuels
55	Ann Arbor Clean Cities Coalition
56	Twin Cities Clean Cities Coalition
57	St. Louis Clean Cities
58	New Jersey Clean Cities Coalition
59	Empire Clean Cities
60	Genesee Region Clean Communities (Rochester)
61	Clean Communities of Central New York (Syracuse)
62	Clean Communities of Western New York (Buffalo)
63	North Dakota Clean Cities
64	Clean Fuels Ohio
65	Columbia-Willamette Clean Cities
66	Rogue Valley Clean Cities
67	Pittsburgh Region Clean Cities
68	Eastern Pennsylvania Alliance for Clean Transportation
69	Ocean State Clean Cities
70	East Tennessee Clean Fuels Coalition
71	Lone Star Clean Fuels Alliance (Central Texas)
72	Utah Clean Cities
73	Vermont Clean Cities
74	Virginia Clean Cities
75	Wisconsin Clean Cities

Appendix G Intercoder Reliability

Table G.1: Intercoder reliability

Sub-categories	Agreement	Cohen's kappa
Collaborative goal	96.00%	0.9071
Ask for donation	100.00%	1
Membership is open to apply	97.33%	0.9071
Member benefits	96.00%	0.8924
Member responsibilities	96.00%	0.9201
Cross-sector board of directors	96.00%	0.9199

Appendix H Event-Study Plots for Mechanism Subgroups

Figure H.1: Dynamic treatment effects of CCCs with clear goals

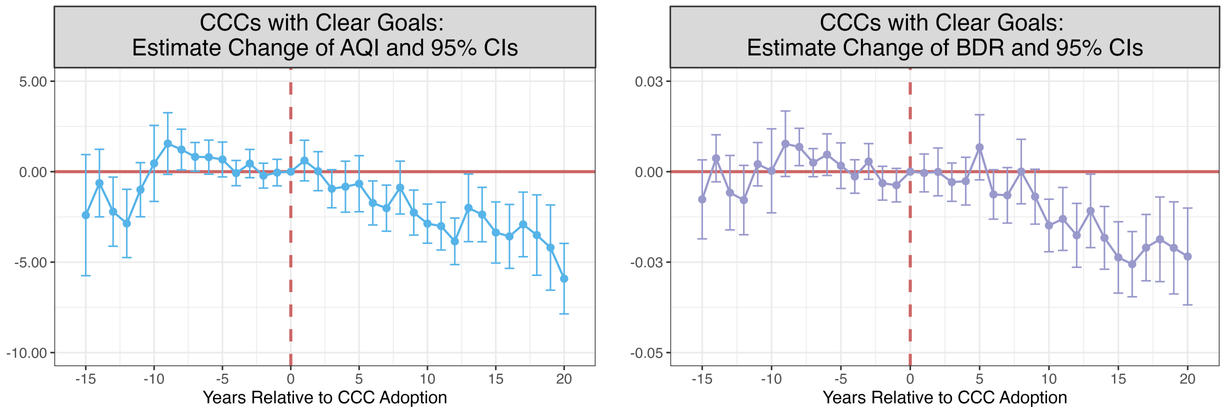

Figure H.2: Dynamic treatment effects of CCCs with resource allocation

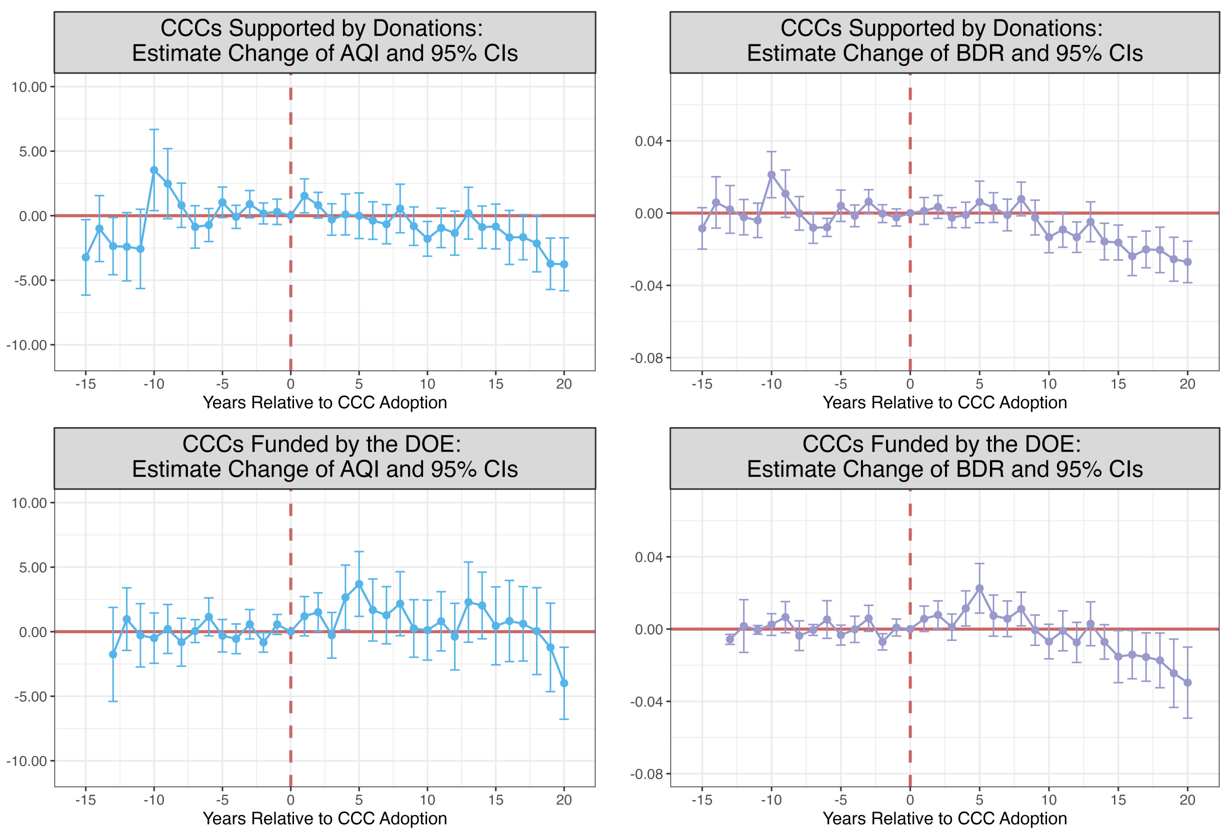

Figure H.3: Dynamic treatment effects of CCCs with collaborative group structures and inclusive decision-making processes