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Leveraging System Context to Understand Collaborative Systems in Modern Public Management

Catherine Annis

Abstract

Complex and boundary-spanning problems like overpopulation, hunger, pandemics, homelessness, and environmental degradation occur more frequently now than ever (Bynander & Nohrstedt, 2019; Criado & Guevara-Gómez, 2021; Huang, 2020; Kapucu, 2015; Getha-Taylor, 2007; Jayasinghe et al., 2022). Policymakers increasingly address these challenges through interorganizational collaboration (Isett et al., 2011). Countries worldwide now use collaborative governance to respond to such wicked problems (Jayasinghe et al., 2022; Huang, 2020; Megawati et al., 2020). Despite growing in popularity, gaps remain in understanding collaborative governance at scale.

In this dissertation, I present research on the interconnected nature of collaborative governance initiatives in the United States by studying the units that carry out collaborative governance in modern public management: collaborative governance regimes (CGRs). A CGR is "a particular mode of, or system for, public decision-making in which cross-boundary collaboration represents the prevailing pattern of behavior and activity" (Emerson et al., 2015, p. 18). Collaborative systems occur when multiple CGRs operate within or across policy arenas in a defined geography or jurisdiction (Annis et al., 2020). I explore the contexts that collaborative systems operate within. System context refers to "the broad and dynamic set of surrounding conditions that create opportunities and constraints for initiating and sustaining CGRs (Emerson & Nabatchi, 2015a, p. 232). Studying the system context is essential because collaboration does not occur in a vacuum. System context factors can create opportunities for or constraints on CGRs that influence their processes and performance. I show the existence of collaborative systems in the U.S. and ask, what leverage can be gained by exploring the broader system contexts of collaborative systems?

I present studies of collaborative systems consisting of hundreds of interconnected CGRs in practice today to uncover lessons about collaborative governance at scale. In Chapter One, I detail a collaborative system operating in Oregon in a facilitative system context for collaborative governance. Oregon's system context features state support and legislation that supports the CGRs there (Cochran et al., 2019). In Chapter Two, I examine the context of the COVID-19 pandemic to understand collaborative governance when an unexpected crisis occurs. I analyze adaptation in two community referral networks whose system context is unstable due to the pandemic's onset. In Chapter Three, I do not examine the characteristics of a collaborative system; instead, I study the association between states' broader system contexts and formal CGR registration to that state.

I find that collaborative systems exist and can be measured. Chapter One explores representation in a collaborative system in Oregon. The results reveal a high amount of membership overlap among CGRs, even across sectors. This high level of membership overlap has resulted in a tightly interconnected collaborative system in Oregon. It should alert leaders to probe whether a diverse set of actors are substantively represented across the system because the same actors appear in CGRs repeatedly.

In Chapter Two, I examine what leverage analysts can gain from looking at collaborative systems in a system context impacted by a crisis. I do this by studying two community referral networks in a U.S. state where the system context was unstable due to the onset of the COVID-19 pandemic. I document that community referral networks adapted to changes in supply and demand for services during the pandemic's emergence. I find organizational tenure and resource munificence contributed to CGR's adaptability during the crisis. Rather than going through the lead organization governance model with the coordination center directing ties, organizations saw greater returns to modifying the governance structure for faster service delivery to locate and serve clients directly and more quickly during the early days of the pandemic. I find flexible governance structures can buffer CGR member exit during crises. In Chapter Three, I analyze collaborative governance in Medicare to show how researchers can understand CGRs' broader system context. Chapter Three demonstrates how leaders and managers can use data analytics to understand CGRs, system context factors, and outcomes.

I draw four conclusions from the three essays. First, I conclude that researchers and practitioners can gain leverage by examining the system context of collaborative systems, including public management insights on steering collaborative systems for large-scale policy implementation. Second, my results indicate that studying collaborative systems and their contexts allows scholars to contribute to a concise theory of collaborative governance that transcends disciplines. Third, I find that managers can enhance the success of CGRs by focusing on their governance structures and the entities that support them. Fourth, my results show that scholars can gain leverage in understanding collaborative systems and broader system contexts using various data types and methodologies, including qualitative methods, network analysis, and econometrics. The broad range of data types and methodologies available to understand collaborative governance is good for scholarship and practice. When leaders know system context conditions, they become better equipped to manage the current and changing conditions that influence their work (Emerson & Nabatchi, 2015a).

LEVERAGING SYSTEM CONTEXT TO UNDERSTAND COLLABORATIVE SYSTEMS IN MODERN PUBLIC MANAGEMENT

by

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For my family

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Introduction

Governing is no longer just driven by hierarchies exercising top-down power. Multiple organizations now work together to address problems by exercising horizontal power. Public managers share decision-making authority with other actors when designing and implementing public policy. Other actors include nonprofits, private organizations, and other governments. Scholars refer to this trend as collaborative governance. Currently, little research considers the system context and interdependence of multiple collaborative governance arrangements where collaborative governance occurs or explores their use across policy areas (Emerson & Nabatchi, 2015a).

In this dissertation, I focus on the system contexts that surround multi-level and cross-sector collaborative initiatives. I aim to understand the structures and processes of collaborative arrangements as systems and how these systems the environments of these systems influence them. I contribute to the public administration literature on collaborative governance at the system level by asking the over-arching research question: *What leverage can be gained by examining the broader system context in which collaborative systems are embedded?*

In this introduction, I overview the key concepts that I address. I begin this introductory chapter by first providing a background where I define relevant terms. I follow the background with a statement of the problem I address and a rationale for my work. I then overview the scope and significance of the topic of collaborative systems before describing the dissertation structure. I provide more detailed definitions, illustrations, and examples throughout the chapters.

Background

Evidence from a growing body of literature suggests that such interorganizational partnerships are promising mechanisms for improving public service delivery (for a systematic overview of interorganizational partnerships from the network governance literature, see Provan et al., 2007). The concept of collaboration as a form of governing also increased in scale and scope over the last 30 years as the public sector shifted from more traditional government models toward less centralized governance models (Salamon, 2011). In efforts to understand collaboration, researchers began to want to understand how actors work horizontally rather than in the top-down hierarchical structures by which public agencies were typically known (Salamon, 2011). The research on collaboration to solve public problems developed over time and is now popularly termed collaborative governance.

Collaborative Governance

Collaborative governance is the decision-making and management that occurs when governmental and nongovernmental agencies work together to achieve mutually beneficial results (Emerson & Nabatchi, 2015a). Throughout this chapter, I refer to the units that carry out collaborative governance as collaborative governance regimes (CGRs). A CGR is "a particular mode of, or system for, public decision-making in which cross-boundary collaboration represents the prevailing pattern of behavior and activity" (Emerson et al., 2015, p. 18). Governments turn to interorganizational partnerships like CGRs when they feel they can solve a problem or deliver a good more effectively with others than they could alone (Emerson & Nabatchi, 2015a). The research on collaborative governance has grown exponentially over the past three decades, primarily focusing on collaborative processes. For example, studies show that elements related to leadership (e.g., Ansell & Gash, 2008; O'Leary & Bingham, 2007; O'Leary et al., 2012) and resources (e.g., Thomson & Perry, 2006; Vangen & Huxham, 2005) are critical for building capacities for joint action amongst actors. Collaborative governance research also includes the system contexts in which collaborative governance occurs (Emerson & Nabatchi, 2015a). Actors collaborate within complex contexts influenced by governing systems, other actors, and resources.

System Context

System context describes the characteristics of the environment surrounding collaboratives, such as any history of conflict or the political and legal structures surrounding an issue. Such characteristics can include political, legal, socio-economic, environmental, and other factors acting as facilitators or barriers to collaboration (Emerson & Nabatchi, 2015a, p. 27). For example, the system context describes the material, social, and cultural circumstances in which interactions form. The broader system context potentially enables and constrains collaboration. System context factors can also create barriers to the processes and productivity performance of CGRs (Emerson & Nabatchi, 2015a).

I draw on network literature to inform collaborative governance. Evidence shows links between system context, collaborative structures, processes, and outcomes. First, researchers find evidence that system context can influence network structures (Ansell & Miura, 2020; Atouba & Shumate, 2015; Fafchamps & Gubert, 2007; Pugel, 2021; Sapat et al., 2019). In addition, neither CGRs nor their broader system contexts are static. Change and adaptation can occur on a large or small scale in the system context (Emerson & Nabatchi, 2015a). Changing environments means the system context can affect how CGRs adapt and, at the same time, remain stable enough to meet their collaborative governance goals. Second, there is growing evidence that there is a relationship between system context and collaborative processes (Ansell & Gash, 2008; Dressel et al., 2020; Emerson et al., 2012; Emerson & Nabatchi, 2015a; Moreno & Gonçalves, 2021; Smeets, 2017; van der Horst, 2018). Third, research finds a relationship between system context and collaborative outcomes (Dressel et al., 2020; Bitterman & Koliba, 2020). For example, scholars find regulatory system context factors positively associated with collaborative performance (Bitterman & Koliba, 2020). Such links between system context and collaborative structures, processes, and outcomes motivate the importance of studying the system contexts of the units carrying out collaborative governance today.

Collaborative System

Structural, affiliation, and relational information can reveal how CGRs interconnect to become collaborative systems. Collaborative systems occur when multiple collaborative arrangements operate within or across policy arenas in a defined geography or jurisdiction (Annis et al., 2020). Johnson, Fortune, and Bromley (2017, p. 112) describe a system as “a collection of interacting elements, with them all affecting and being affected by the behavior of the whole.” The challenge in studying systems is that systems can be easy to recognize but difficult to define. Scholars have ascertained two fundamental elements of complex systems as (1) many interacting parts and (2) emergent properties, meaning the emergence of non-random patterns (Morel & Ramanujam, 1999). This work scales up research on collaboration by studying how many CGRs may be a part of a distinct system. It contributes to knowledge on whether and how CGRs connect in a networked space in meaningful ways. In Chapter One, I provide a detailed overview of the collaborative system concept, including an illustrated example of one’s structure.

Statement of the Problem

Jurisdiction-spanning problems are increasing and becoming more complex (Bynander & Nohrstedt, 2019; Criado & Guevara-Gómez, 2021; Huang, 2020; Kapucu, 2015; Getha-Taylor, 2007; Jayasinghe et al., 2022). Network governance scholars find that interorganizational partnerships and collaboration are now standard tools for policy development and implementation (Isett et al., 2011). Meanwhile, research continues to document how collaborative governance is occurring to manage crises (Bynander & Nohrstedt, 2019; Criado & Guevara-Gómez; Getha-Taylor, 2007; Guevara-Gómez, 2021; Huang, 2020; Jayasinghe et al., 2022; Kapucu, 2015). In addition, collaborative approaches continue to increase in practice and are therefore essential to understand and evaluate (Carboni et al., 2022; Shumate, 2022).

My work fills gaps in the public administration literature on collaborative governance in different system contexts. Currently, little research considers the system context and interdependence of multiple CGRs or explores their use across policy areas (Emerson & Nabatchi, 2015a). Gaps remain in how collaborative arrangements' system contexts may relate to a collaborative system's structure. Ananda and Proctor (2013, p. 97) highlight "calls for a closer examination of contexts that are conducive to the success of collaborative initiative." As collaborative strategies rise, governments must understand how to sustain and replicate successful collaborative governance initiatives. The answer may lie in understanding how CGRs interact with one another and their environments.

A systems science approach, that is, one that considers the interdependencies and nested features of subsystems or networks, can provide the methodologies, models, and tools necessary to examine the complex nature of collaboration. However, such approaches remain underutilized in collaborative governance scholarship. One reason is that collaborative governance scholars focus more on processes than structure. However, as data on collaborative arrangements become more available, I see evidence of collaborative systems taking shape.

To better understand governance, scholars identify the need for studies that use data from multiple sources at multiple levels of analysis and employ methods capable of utilizing these multiple data inputs. For example, scholars highlight a need for more research on the multi-level nature of governance to enhance understanding of the repositioning of government (Jilke et al., 2019). I answer such calls to contribute to a congruent theory of governance by examining the collaborative systems concept.

Research Questions

This research focuses on collaborative governance arrangements in different areas of the United States. My key research question is, what leverage can be gained by examining the broader system context in which collaborative systems are embedded? To answer this, I address sub-questions. The first two chapters examine collaborative systems in U.S. states. Both systems include collaborative units from various policy domains (i.e., education, economic development, health, and more. In Oregon, the collaborative system under study serves Oregon residents. In Chapter One, I ask, what factors drive the structure of the state-sponsored collaborative system operating in Oregon? What are the implications? In Chapter Two, the collaborative system serves U.S. veterans and military families. I address the question: How do collaborative referral networks adapt to changes in the supply and demand of services at the onset of COVID-19? In the third chapter, I observe collaborative governance in the U.S. healthcare sector that services beneficiaries enrolled in the Medicare Shared Savings Program (MSSP). How can researchers identify and measure the characteristics of CGRs, their broader system contexts, and their outcomes? The studies offer evidence on collaborative governance from 2013-2020. I uncover the leverage gained by examining the broader system contexts of collaborative systems and CGRs.

Research Aims

My research has four key aims. The first is to define the collaborative system as the larger institutional context or networked space in which collaborative arrangements are embedded and understand whether collaborative systems exist and currently operate in practice.

A second aim is to understand how CGRs function systematically, including how they interact with other CGRs, how their system contexts influence them, and the CGRs to which they are systematically connected. A third aim is to fill gaps in the collaborative governance literature by utilizing large-N data sources and mixed methods. Fourth, I aim to uncover how scholars and practitioners can leverage system context to make evidence-based decisions when steering collaborative systems and implementing collaborative governance policy at scale. Overall, this work aims to understand how looking at collaborative systems and their broader system contexts enhance knowledge of collaborative governance.

This dissertation includes three studies. The first two chapters uncover information about the system context of collaborative systems. First, I examine how membership overlaps drive the structure of a state-connected collaborative system in Oregon. Oregon features a system context with favorable political and financial conditions that plausibly affect the linkages of collaborative units across policy sectors. Next, I research the ability of a veteran-serving collaborative system in a U.S. state to adapt to a substantial change in case quantity and needs during the COVID-19 pandemic. I examine how this collaborative system with a lead-organization governance structure reacts when its system context is shocked, leading to uncertainty, instability, and rapid change, including changes in the supply of and demand for services. In Chapter Three, I examine associations between state system context characteristics and the number of CGRs forming in that state. The third chapter explores the characteristics of the system context associated with formal CGR registration in that state.

Significance for Research

The collaborative system concept fits into the literature that underpins the collaborative governance concept in that it downplays the roles of individual actors and highlights the broader processes taking place in contexts that set the conditions for collaboration. As the state decentralizes, the importance of understanding relationships increases as jurisdictional boundaries lessen. Scholars can understand public service providers through the relationships, overlaps, and connections between various units that make up the whole. Studies show that structural arrangements, such as the size of an interorganizational network and the extent of resource exchanges within, can shape behavior, determine performance, and structure relationships with external actors (e.g., Blair, 2002).

This dissertation asserts that public management can include broader units of analysis to understand CGRs and the collaborative system through the collaborative system concept. For example, applying network methodologies can allow researchers to understand collaborative structures at multiple levels of analysis to accurately capture the true nature of dependence within them (i.e., Carboni, 2015). Roberts (2019) points out that a broadening understanding of intragroup interactions can lay the foundation and be the link toward better research that answers the big questions of public administration. In addition, I use qualitative techniques, network analysis, and econometrics to offer novel insights and recommendations on how to understand the collaborative systems operating in the public sector today. For example, recent literature reviews find that few articles use network analysis techniques and suggest remedies related to applying advanced network analysis tools and underutilized quantitative methods to large-scale data in network research (Kapucu et al., 2017; Lecy et al., 2014).

Significance for Practice

States and federal governments now use collaborative governance as a policy tool to deliver services (Huang, 2020; Jayasinghe et al., 2022; Megawati et al., 2020; Putzel, 2003).

Findings from collaborative systems research reveal to practitioners how to best support them. For example, research insights can offer practical contributions by indicating whether there are entities that are likely much more efficient for the transfer and diffusion of knowledge and resources across multiple collaborative arrangements. Such insights allow scholars and managers to indicate how information or resource diffusion occurs across policy domains.

I build an understanding of the innovative tools and strategies developed to enhance collaboration within and across sectors and examine the modern ways organizations work together to address complex issues. Establishing the collaborative system concept is timely for practice because policymakers already use collaborative arrangements as policy tools. Therefore, taking a bird's-eye view of systems can help practitioners identify challenges and opportunities for improvement. For example, suppose there are correlations between government agency participation and poor collaborative outputs or outcomes. In that case, research can help probe where the challenge might lie, such as the over-representation of specific organizations across the system might be worth exploring.

Dissertation Structure

I provided my work's background, rationale, scope, and significance here. Next, I present Chapter One, where I measure the contribution of structural factors in a collaborative system in Oregon. In Chapter Two, I study how collaborative referral networks adapted to changes in the supply and demand for services during COVID-19 in a southeastern U.S. state. In Chapter Three, I identify and measure the characteristics of CGRs, their broader system contexts, and their outcomes. In the final chapter, I summarize the findings generated on collaborative systems and their broader system contexts as they relate to collaborative governance literature in public administration.

Chapter One: Measuring Representation and the Contribution of Structural Factors in the Collaborative System

By Catherine Annis, Julia Carboni, Tina Nabatchi

Abstract

Policymakers use collaborative governance regimes (CGR) and collaborative platforms to include diverse stakeholders in policy development and implementation. CGRs are multi-stakeholder forums with shared decision-making. Collaborative platforms are entities that support the development and work of multiple CGRs. I introduce the concept of the collaborative system as a way to understand links across multiple CGRs and collaborative platforms. The premise of collaborative governance is that it will be inclusive of diverse stakeholders and result in policies and programs that are responsive to stakeholder interests. However, limited evidence about substantive representation in collaborative governance exists (Koski et al., 2016). Extant studies tend to focus on a single or small number of CGRs, limiting the generalizability of findings.

I conduct a large N empirical study of collaborative governance representation in this chapter. I focus on how CGRs are linked in the collaborative system to understand the diversity of actor representation. Using descriptive network analysis and exponential random graph modeling (ERGM), I analyze data from 242 CGRs operating across five policy areas in the U.S. State of Oregon, a leader in using collaborative governance to address complex problems. My work offers theoretical contributions to collaborative governance literature by developing the concept of the collaborative system and examining the structure of representation across the system. I find many membership overlaps between CGRs and collaborative platforms in the collaborative system indicating a limited set of actors are present in the collaborative system,

raising questions about the representativeness of these arrangements. I conclude with insights for future studies.

Introduction

Scholars and practitioners premise collaborative governance on the representation of the interests of multiple actors. Collaborative governance should ensure that actors advocate for affected actors' interests, whether by themselves or proxy (Emerson & Nabatchi, 2015a; Leach, 2006). Relative to other organizational designs like bureaucracies, actors design collaborative governance initiatives so that those who have a stake in the outcomes of a public decision-making process can access a seat at the table in decision-making about public problems. Theoretically, representation is essential to collaborative governance, and systematic under-representation of affected stakeholders impairs meaningful collaboration (Carboni et al., 2017; Koski et al., 2016)

In this study, I focus on the State of Oregon, a national leader in using collaborative governance to address complex problems, such as natural resource disparities, over the last 30 years (Cochran et al., 2019). I examine representation by analyzing overlaps in membership that form the collaborative system operating in the state. A collaborative system is the larger networked space in which collaborative governance regimes (CGRs) and collaborative platforms are embedded. CGRs are modes of public decision-making in which the primary pattern of behavior is cross-boundary collaboration (Emerson & Nabatchi, 2015a). A collaborative platform is an organization or program with dedicated competencies to facilitate the creation, success, and scale of multiple CGRs to reach collaborative governance goals (Ansell & Gash, 2018). I perform exponential random graph modeling (ERGM) to understand how membership overlap shapes Oregon's collaborative system of CGRs and collaborative platforms in terms of how factors contribute to observed patterns in representation.

Policymakers and public managers increasingly use CGRs and platforms as policy solutions, highlighting the need to understand them and their interconnected nature in depth

(Ansell & Gash, 2018; Emerson & Nabatchi, 2015a; Yoon et al., 2022). CGRs are comprised of multiple actors - typically organizations - collaborating to meet a common goal. I explore the interconnected nature of CGRs and their platforms using data on 242 CGRs[1] from the Oregon Atlas of Collaboration (OAC). I test hypotheses about representation through an analysis of membership overlap. I consider the impact of membership overlap on representativeness in the collaborative system (Yoon et al., 2022; Annis et al., 2020). Oregon is a prime state to examine such questions because it features a system context with favorable political, socio-economic, and financial conditions for statewide collaboration across policy areas and regions (Cochran et al., 2019).

Collaborative systems may contain cross-CGR and cross-collaborative platform linkages through common members (Annis et al., 2020). While scholars now know much about interorganizational collaboration within CGRs, knowledge gaps remain in how CGRs might interconnect in a larger system. To address this gap, I answer two research questions:

RQ1: How do I conceptualize and measure collaborative systems?

RQ2: How do I measure representativeness within and across CGRs in collaborative systems?

Analysis reveals a collaborative system with many membership overlaps between CGRs, suggesting that there is limited representation of stakeholder interests. I provide insights for future studies that include decision-making rules for CGR member selection. I also contribute to the collaborative governance literature by examining representation in collaborative systems'

[1] Yoon and colleagues' (2022) descriptive analysis of the OAC dataset during the same study period drops one CGR from the unit of analysis based on missing data. I replaced the missing observation with the correct data and kept the CGR observation. My choice to keep the observation explains the differences in sample sizes between the two studies.

structures. My study provides lessons on collaborative governance design for other states utilizing collaborative governance.

I structure this chapter as follows. First, I define terms. Second, I provide a literature review of representation in collaborative governance. Third, I discuss my measures and analyses, presenting a visual map and network analysis of Oregon's collaborative system. I then present and discuss the ERGM analysis and conclude with implications for management and practice.

Collaborative Governance Regimes, Collaborative Platforms, and Collaborative Systems

Governments increasingly engage in collaborative governance or "the processes and structures of public policy decision-making and management that engage people across the boundaries of public agencies, levels of government, and/or the public, private, and civic spheres to carry out a public purpose that could not be otherwise accomplished" (Emerson & Nabatchi, 2015a, p. 18). Collaborative governance includes shared decision-making authority with nonprofits, private organizations, citizens, and other governments in public policy development and implementation. While collaborative governance is a popular research topic, there is little work on how collaborative governance efforts interconnect to form larger systems. Before I offer hypotheses, I define the following terms: collaborative governance regimes, collaborative platforms, collaborative systems, and the broader system context.

Collaborative Governance Regimes

A collaborative governance regime (CGR) is "a particular mode of, or system for, public decision-making in which cross-boundary collaboration represents the prevailing pattern of behavior and activity" (Emerson et al., 2015, p. 18). CGRs can be considered the smallest unit of analysis to describe an entity within which actors collaborate for public decision-making. I focus on externally directed CGRs, meaning they are mandated by legislation or agency action or induced with incentives like funding requirements (Emerson & Nabatchi, 2015a).[2]

Collaborative governance has become a popular policy tool, and policymakers use CGRs across numerous policy domains (e.g., Yoon et al., 2022). Scholars recently developed the collaborative platform concept to address the spread of CGRs beyond localized efforts to more institutionalized efforts that engage multiple CGRs across geography or policy area (Ansell & Gash, 2018). The collaborative platform concept complements the idea of CGRs while also acting as a next step in understanding and modeling collaboration (Ansell & Gash, 2018; Yoon et al., 2022).

Collaborative Platforms

Scholars are scaling up research on collaboration in the collaborative governance literature through conceptualizing “collaborative platforms,” the organizations or frameworks that convene or direct multiple collaboratives. A collaborative platform is “an organization or program with dedicated competencies and resources for facilitating the creation, adaptation, and success of multiple or ongoing collaborative projects or networks” (Ansell & Gash, 2018, p. 20). Platforms serve as “boundary organizations” (Guston, 2001) and mechanisms for coordinating the efforts of multiple CGRs working across geographies in the same policy field or toward similar ends. In other words, collaborative platforms serve as an overarching body for coordinating diverse and semi-independent CGRs into an interacting system, though they can vary in how they support CGRs. For example, while some platforms provide funding and

[2] CGR type can change over time. Many of the CGRs in Oregon’s collaborative system began as self-initiated or independently convened and later became externally directed due to legislation or funding requirements (Yoon et al., 2022).

information, others mandate types of participation and the rules of collaboration for multiple CGRs (Yoon et al., 2022).

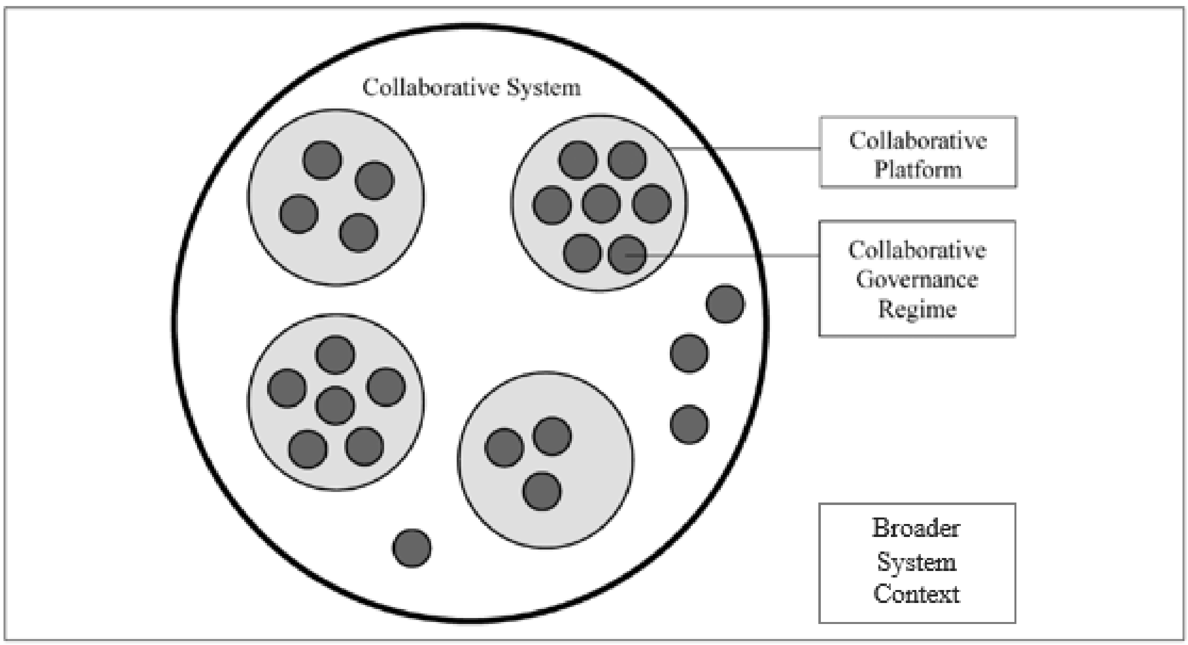
Despite their growing use in practice, there is limited research on the use of collaborative platforms (for examples, see Nambisan, 2009; Bitterman & Koliba, 2020; Lee, 2022), and platforms exhibit properties that are not yet well understood (Ansell & Gash, 2018; Yoon et al., 2022). Platforms are a foundation for understanding a broader collaborative system. However, the concept focuses on the organizations convening or directing CGRs (Ansell & Gash, 2018). A CGR can, and many do, exist outside of a supporting collaborative platform but may systematically connect in a more extensive system through other factors, such as overlapping membership.

Collaborative Systems

Contemporary research trends aim to understand the characteristics and outcomes of CGRs systematically (Jilke et al., 2019). Perhaps the most intuitive units that connect CGRs, within and beyond the platform level, are the overlapping individuals and organizations that link various collaboratives through their participation and membership. If such linkages beyond the collaborative platform level exist, they are not yet well understood. Missing from the field of collaborative governance are theory and empirics in the broader system encompassing CGRs and platforms. It is important to understand how CGRs are linked to each other because it is likely that membership overlaps will influence the outputs and outcomes of CGRs, much like nonprofit board interlocks are theorized to influence nonprofit governance (Bloch et al., 2020; Yoon, 2020; Yoon, 2021).

Simply put, a system is “a collection of interacting elements, with them all affecting and being affected by the behavior of the whole” (Johnson et al., 2017, p.112). I define a collaborative system as the larger networked space in which CGRs and collaborative platforms are embedded. Figure 1 shows an example of a collaborative system containing four collaborative platforms, each containing a varying number of CGRs. The collaborative system lens allows scholars to scale up research on collaboration and understand whether and how CGRs may be connected.

Figure 1: Example of a Collaborative System and Broader System Context



Adapted from Annis, Carboni, and Nabatchi (2020) and Yoon, Fields, Cochran, and Nabatchi (2022)

Collaborative systems may contain cross-CGR and cross-collaborative platform linkages through sharing common members. CGR characteristics, such as the platforms or contexts they operate within, can influence membership overlaps that affect the structure of the entire collaborative system. I theorize CGRs have connections to other CGRs within their platforms and to CGRs outside of their collaborative platforms rather than operating in silos.

I draw on network literature to develop hypotheses and tools to examine collaborative governance structures. Although collaborative governance and network structure are distinct research streams, the two are complementary. As data on collaborative structures become more available, researchers can use network data and methods to focus on the structure of collaborative governance regimes. Large N research on collaborative governance is starting to appear due to newly available data and methods. Examples include collaboration in the State of Oregon (Cochran et al., 2019; Yoon et al., 2022), U.S. Medicare reform (Centers for Medicare & Medicaid Services, 2022a), and community-based referral networks (Carboni et al., 2022; Gibson et al., 2022; Shumate, 2022). However, current research focuses little on understanding the structure and governance of collaborative systems or the contexts in which they operate.

Broader System Context

System context describes the characteristics in which collaboratives are embedded. Such characteristics can include political, legal, socio-economic, environmental, and other factors that enable and constrain collaboration (Emerson & Nabatchi, 2015a, p. 27). Examples of system context factors include environmental problems, whether leadership and the broader community have favorable views of collaborative governance, and the number of resources to begin and sustain collaborative governance initiatives.

The system context and the collaborative system are distinct concepts. The system context describes the environmental conditions of CGRs, collaborative platforms, and collaborative systems (Emerson & Nabatchi, 2015a). Meanwhile, the collaborative system concept describes a collection of connected collaborative units, such as CGRs and platforms, all affecting and being affected by the whole system's behavior. Examples of changes to the system context include elections, the passage of new legislation, the introduction of a new problem, changes in resources, or other changes to the broader environmental context. Such changes can occur in contexts where collaborative systems exist, which can facilitate or hinder collaboration within CGRs, platforms, and collaborative systems.

Context informs scholarly understanding of collaborative systems because it describes the circumstances in which interactions form (Kooiman, 2003). Currently, little research considers the system context and interdependence of multiple CGRs or explores their use across policy areas (Emerson & Nabatchi, 2015a). Gaps remain in how CGRs' system contexts may influence a collaborative system's structure (Emerson & Nabatchi, 2015a). Network researchers posit that understanding the contexts in which interorganizational networks operate is important for effective public sector management (Huang & Provan, 2007; O'Toole & Meier, 2004; Provan & Milward, 1995; Provan & Sebastian, 1998). I contribute to the new wave of public administration research on governance by using CGRs as units of analysis to understand a networked system of multiple collaborations (Annis et al., 2020; Yoon et al., 2022) and the representation within. This chapter examines membership overlaps in CGRs in a collaborative system.

Literature Review

The premise of collaborative governance is to connect diverse actors with different priorities and goals to represent different stakeholder interests to solve problems together that they could not solve alone (Ansell & Gash, 2008; Emerson & Nabatchi, 2015a). Literature on democratic governance discusses representation in traditional governmental forms (Bishu & Kennedy, 2019). Collaborative governance scholarship focuses much less on the topic, though research is growing (see Beierle & Konisky, 2001; Carboni et al., 2017; Emerson & Nabatchi, 2015a; Koski et al., 2016; Koski et al., 2018; Leach, 2006; Siddiki et al., 2015). Research may be limited because people commonly assume that collaborative governance processes are inherently representative, given that representation is meant to be a salient component of collaborative function (Ansell & Gash, 2008; Emerson & Nabatchi, 2015a; Koski et al., 2016). However, scholars find that CGRs suffer from under-representation in practice, where CGR participants represent some organizational actors much more than others (Carboni et al., 2017; Koski et al., 2018).

Such findings show that representation in CGRs, collaborative platforms, and collaborative systems is a topic worth pursuing. In this work, I study representation in a collaborative system by analyzing membership overlaps across CGRs in Oregon. I discuss this in further detail below, followed by a review of representation in collaborative governance. I conclude the literature section by drawing on network concepts to demonstrate how scholars can measure representation in collaborative systems.

Network researchers in public administration first studied public service provision in interorganizational and multi-actor arrangements in the 1990s (e.g., Milward & Provan, 2000; Provan & Milward, 1995). Today, researchers apply network analysis methods to reveal structural patterns and characteristics in CGRs, including representation among actors, such as organizations (e.g., Carboni et al., 2017). I use network analysis methods to understand representation in collaborative governance processes (Carboni et al., 2017). However, while those authors examined representation at the CGR level, I focus on the collaborative system level. I operationalize the collaborative system as a network of networks to better understand stakeholder representation, including the most central actors. Understanding who participates within and across CGRs provides a tool to evaluate inclusivity (Carboni et al., 2017).

Understanding the values represented in collaborative governance settings is important (Beierle & Konkisky, 2001). Some of the most salient dimensions for evaluating representativeness include understanding the strength of different perspectives in CGRs, such as local versus national perspectives, rural versus urban perspectives, and environmental versus economic perspectives (Leach, 2006). If actors are over-represented and more central in a collaborative system, under-represented actors' points of view can be disenfranchised, marginalized, or non-existent altogether. When such under-representation occurs, it lowers the legitimacy of CGRs and signals problems with the collaborative design and processes, which potentially affect output (Carboni et al., 2017). To address under-representation, authors recommend scholars study the causes and solutions of under-representation and examine whether specific groups are not having their interests represented (Carboni et al., 2017). Doing so will likely generate benefits. For example, engaging diverse interests benefited watershed CGRs by leading actors to have a broader commitment to the CGR (Emerson & Gerlack, 2014). In the next section, I discuss common ways representation is defined and studied.

Representation in Collaborative Governance

Two types of representation typically are studied in the literature on representation in collaborative governance: descriptive representation and substantive representation. In this chapter, I study the more commonly analyzed concept of descriptive representation in a collaborative system, thus extending the literature beyond single CGRs. Scholars measure descriptive representation by considering those with access to the collaborative process (Carboni et al., 2017; Koski et al., 2016). Scholars use descriptive representation as a measure of diversity that allows scholars and practitioners to understand who has a seat at the table (Carboni et al., 2017). While descriptive participation does not reveal details of how members engage in collaborative planning, processes, or outputs, it is an effective concept for understanding which stakeholders have formal access to collaborative governance processes (Koski et al., 2016).

“Formal membership is a useful and valid way for describing which of the various stakeholders who have a vested interest in the topic or the work of a collaborative are represented therein” (Koski et al., 2016, p. 2).

Substantive representation is not directly examined in my analysis but is still worth noting. In the political science literature, substantive representation has to do with reflecting the interests of those involved (Pitkin, 1967). Collaborative governance scholars use the term to describe who engages meaningfully in a process rather than just counting who is at the table. Substantive representation occurs when collaborative processes, goal setting, and outputs represent diverse stakeholders (Koski et al., 2018); however, being a formal member of a CGR does not guarantee that actors will participate meaningfully (Carboni et al., 2017). Authors examine a food policy council CGR. They measure substantive representation by examining what actors attend meetings and what actors participate in meeting discussions (Carboni et al., 2017). Their results show CGR participants varied in their substantive representation, concluding that collaborative governance process diverges from its inclusive design in practice. Although substantive participation is out of the purview of this analysis, these findings confirm that it is a mistake to assume that all collaborative governance processes are inherently representative. My findings motivate further research on representation in collaborative systems (Koski et al., 2016).

Beyond describing and contrasting different types of representation, case studies reveal that challenges in representation occur in practice, further providing evidence of the over-representation of some actors versus others within CGRs (Carboni et al., 2017; Koski et al., 2016; Koski et al., 2018; Leach, 2006; Siddiki et al., 2015). Findings from this line of research show important differences in descriptive representation in collaborative design versus who ends up at the table (Koski et al., 2018). Under-representation is not always the case, however. In a representative sample of 76 watershed partnerships, CGRs featured well-balanced partnerships regarding the number of participants representing major interest sectors (Leach, 2006). However, respondents felt the watersheds were under representative of the local population, despite them being entities where collaborative public management took place (Leach, 2006). Research suggests that "groups can only be as diverse as they are designed to be" (Koski et al., 2018, p. 16), meaning the structural design of groups affects their ability to be diverse and representative (Koski et al., 2018; Siddiki et al., 2015). The finding suggests that research on representation can inform best practices for CGRs, collaborative platforms, and even collaborative system designs to increase the chances of being representative. The limited research and examples of mixed findings motivate a need for more research on representation. Currently, most collaborative governance research focuses on the CGR level. No research looks at representation in collaborative governance at the collaborative platform or system level. I contribute to the literature by examining patterns of representation in a collaborative system.

Measuring Representation in Collaborative Systems

To ask more nuanced questions about representation within and across CGRs in the collaborative system, I examine CGR membership overlaps through membership overlaps. I construct an affiliation network that assesses common membership overlaps rather than a sociomatrix that examines interorganizational or interpersonal relationships. An affiliation network is an appropriate form of analysis because I can use membership overlaps to understand whether the overrepresentation of actors exists in the system. Over-representation indicates the system may be too reliant on a small set of actors rather than representing a diverse set of actors.

Membership overlap provides a measure of how often actors, in my case organizations, are formal members in more than one CGR, allowing scholars to understand descriptive representation at a system level. If CGR members overlap repeatedly, the CGR system highly represents those actors. If I do not see many overlaps, I might surmise that the system represents many stakeholder interests. To set a baseline for understanding whether a collaborative system represents a diversity of interests, one can look to policy area proximity and geographical proximity.

CGRs working in different policy areas (e.g., education, public safety, health, natural resources, and economic development) have distinguishing characteristics (Lee & Hung, 2022; Shakirova, 2020). In collaborative systems bounded by geography, a limited number of actors have expertise within a policy area. Although CGRs can gain an additional organizational member in various ways, I expect being in the same policy area can facilitate connections. For example, there may be only 600 organizations with policy expertise in the education sector of a state or regional boundary. Two education CGRs may experience more shared membership overlap due to the finite nature of education-focused organizations. I would expect that if members overlap, it is likely among CGRs that are policy area proximate. Therefore, I hypothesize that more overlaps occur among policy area proximate CGRs than not policy area proximate CGRs. I hypothesize:

Hypothesis 1: There are greater membership overlaps in CGRs in the same policy area than in CGRs that are not in proximate policy areas.

Similarly, actors who join CGRs often have geography-specific missions, especially in the natural resource sectors (e.g., Cochran et al., 2019). It is plausible that simply being in the same geographic area can facilitate overlaps because a limited number of regional experts focus on a geography-specific issue. Therefore, I expect to see more overlaps among geographically proximate CGRs than CGRs that are not geographically proximate.

Hypothesis 2: There are greater membership overlaps in geographically proximate CGRs than in CGRs that are not geographically proximate.

Collaborative platforms strategically connect, scale, and mobilize CGRs to achieve desired outcomes and can establish direct connections between CGR members (Ansell & Miura, 2020). Collaborative platforms can alter the structure of a collaborative system by influencing overlaps among CGRs. I expect to find a positive association between collaborative platform participation and CGR membership overlap, given that collaborative platforms' purpose is to bring together CGRs working on the same issues. For example, in my case study of interest in Oregon, the state agency responsible for the platform may be involved in every CGR within as a function of its platform oversight role. CGRs linked to the same collaborative platform are likely to have membership overlaps because the platform may choose from the same set of actors. Even though I expect to find overlap due to platform orchestration (i.e., state agencies), exploring the magnitude is important. Combined with the mixed methods design, I can see whether orchestration is the only driver of overlaps within platforms. If I find reasons beyond oversight and orchestration, then forming hypotheses about collaborative platforms to understand representation is warranted.

Hypothesis 3: There are greater membership overlaps between CGRs in the same collaborative platform than among CGRs that are not within the same collaborative platform.

I answer salient questions about representation in collaborative governance practice and descriptively learn who is most central to collaborative governance arrangements in a collaborative system. First, testing these hypotheses provides information about whether the system represents diverse interests. Second, testing these hypotheses helps me uncover whether specific factors systematically drive the representation patterns I observe (Carboni et al., 2017). Finally, my research helps to address the common critique of the collaborative governance field being too policy-specific (Frederickson et al., 2015; Wachhaus, 2012). It does so by applying network analysis methods to broaden analyses on collaborative governance operating at different levels across policy domains. This work is the first to empirically test the collaborative system concept to understand: How do I conceptualize and measure networked spaces in collaborative systems? Second, how do I measure representativeness within and across CGRs in large collaborative systems?

Empirical Setting: Oregon State Government

Oregon is now a leader in formally using collaborative governance as a policy tool to solve public problems and deliver services (Cochran et al., 2019). Oregon's politicians, stakeholders, and community leaders come together across sectors to identify how to solve their shared challenges through collaborative governance. The State of Oregon legislates collaborative governance in five policy areas within the state (natural resources, education, public safety, health, and economic development). In total, 242 CGRs formally connect to the state and operate across 13 platforms in these policy areas.[3] Recent research highlights the importance of examining representation in Oregon's collaborative system. Researchers led focus groups to understand Oregon's collaborative system. They found that the State of Oregon and collaborative

[3] The 242 CGRs does not include the unknown number of self-initiated and independently convened CGRs and other collaborative platforms also operating in Oregon.

platform members want to ensure participant diversity and inclusiveness in processes (Cochran et al., 2019), showing that practitioners there recognize the need for representative collaboration and evaluations of whether there is systematic over-representation of specific groups.

Even though I analyze externally directed CGRs, it does not necessarily mean the State or some other external entity controls membership decisions. I do not have data on how each CGR chooses its members. Therefore, I do not know where the locus of decision-making lies. It can occur at the CGR level, the platform level, or another way. Therefore, I look at observable membership overlap across CGRs generally. It is worth noting that I expect some over-representation in Oregon. Oregon's collaborative platforms influence membership overlap, given that the purpose of the platforms is to bring together CGRs working on the same issues. The state agency responsible for the collaborative platform may be involved in every CGR within the platform as a function of its platform oversight role.

The data for this project come from the Oregon Atlas of Collaboration (OAC) project, an inventory, and a catalog of the externally directed CGRs and collaborative platforms in Oregon's collaborative system. It is a cross-sectional dataset that includes regime-level information on structural characteristics (i.e., features of each CGR), physical geography (i.e., spatial information about CGR locations and the range of operations), and social geography (i.e., network information about the participating individuals, organizations, and collaborative platforms).

Data

I perform network analysis, including exponential random graph modeling (ERGM), using Oregon's collaborative system using the OAC dataset. My sample includes the complete list of CGRs formally connected to the state of Oregon by 2019. Oregon organizes and supports CGRs through collaborative platforms. If a CGR was not externally directed *and* part of a platform, I did not include it in my analysis. Researchers collected data using a web scraping method, and data collection ran from October 2018 to October 2019.

Researchers selected participant and organizational variables based on lists published on the CGRs' websites. The lists included board members, committee members, and people hired as employees for a CGR. People who simply participated in meetings were not included in the database because the OAC's goal is to portray formal members accurately. For the analysis, I extracted, cleaned, and analyzed data from CGRs in the OAC database (N=242)[4] and how they may overlap by the unique organizations that serve on them (N=4,751)[5]. I provide summaries of the data relative to the collaborative system structure at the CGR level in Table 1.

To measure CGR membership overlap, I created unique IDs at the organization level, giving each organization one unique ID, regardless of how many people indicated membership. For example, when the data show three people from one organization participating, that organization is counted only as one unique observation in the dataset. Some citizens were unaffiliated with any organization or indicated they were self-employed (private landowners, judges, attorneys). I treat these instances as unique organizations because these citizens are unconnected to any organization in the data but still serve as members on CGRs. I include them because they count as unique overlaps. To perform my analyses, I transformed a two-mode matrix where CGRs and organizations are the modes to a one-mode matrix where CGRs are the only nodes, and overlapping organizations are the weighted ties between them (Carboni, 2015). The total membership overlaps in the one mode matrix come out to N=7,794.

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[4] These numbers represent the population of CGRs and their corresponding collaborative platforms that are formally connected to the State of Oregon, but do not capture all the collaboratives in Oregon. An unknown number of self-initiated and independently convened CGRs and other collaborative platforms also operate in Oregon.

[5] My sample differs from Yoon et al.'s (2022) descriptive analysis of the OAC dataset during the same study period in two ways. First, I chose to include organizations and those individuals who are unaffiliated with any organization so that I can analyze all membership overlaps. Second, I impute the median for continuous variables and report "Unknown" for missing categorical variables, whereas Yoon and colleagues chose to drop CGRs where data was missing.

Measures

I define my key measures in this section: policy area, geographic proximity, and collaborative platform. *Policy area* is an attribute variable that represents the sector of the collaboratives. CGRs can fall into five categories: economic development, education, health, natural resources, and public safety. I operationalize *geographic proximity* as the primary region in which the CGR operates. I follow five regional boundaries outlined by Oregon's Department of Transportation (Oregon Department of Transportation, n.d.).

I also hypothesize that *collaborative platform* influences membership overlaps because the platform may choose from the same actors. I expect to find that the collaborative platform variable influences membership overlap, given that the platform's purpose is to bring together CGRs working on the same issues. The state agency responsible for the collaborative platform may be involved in every CGR within the platform because platforms have an oversight role in Oregon. I still choose to include the collaborative platform measure as an independent variable rather than a control because I am interested in the magnitude of CGR overlaps associated with platforms in Oregon as a key focus of this analysis. I operationalize *platform membership* as a unique numerical code. Platform membership represents the collaborative platform to which each CGR belongs. For example, 12 CGRs belong to the "STEM Hubs" collaborative platform. As such, these CGRs would share a unique code.

Table 1: Collaborative System Descriptive Statistics

Measure	Sub-Measure	Count	$\bar{x}$ (SD)	Min	Max
Funding Type					
	Federal Funds	12			
	State Funds	109			
	Local Funds	2			
	NGO Funds	5			
	Private	1			
	Public Mix	20			
	Public/Private Mix	50			
	Unsure	43			
Platforms		13			
Policy Area					
	Economic Development	20			
	Education	41			
	Health	19			
	Natural Resources	126			
	Public Safety	36			
Region					
	Portland Metro	33			
	Willamette Valley & North Coast	74			
	Southwestern Oregon	47			
	Central Oregon	37			
	Eastern Oregon	45			
	Unsure	6			
Geographic Scope					
	Local-Multiple jurisdiction	177			
	Local-Single jurisdiction	64			
	Unsure	1			
Size (# of Members)			19.1 (31.2)	2	382
Staff (# FTE Staff)			2.22 (3.84)	0	40
Date of Formation			2007 (8.4)	1977	2019
Observations		242	242	242	242

To better understand whether policy area proximity, geographic proximity, and the extent to which platforms explain membership overlap patterns in the collaborative system more than by chance, I control for other CGR characteristics that may also influence membership overlap. I include variables on geographic scope, founding date, funding type, CGR size, collaborative platform, and staff. I operationalize *geographic scope* as whether CGRs span one jurisdiction or span across multiple jurisdictions within the state. Geographic scope has to do with the spatial distribution of CGRs (Yoon et al., 2022). I measure CGR *founding date* as the identified start date of the collaborative when members finalized ground rules or the date of the first agreement document. It describes a CGR's initiation year. In some instances, the year might be before the state passed legislation mandating collaboration. I control for the founding date because it is plausible that similarities in CGR age drive membership overlap between CGRs, and I want to account for it in my analysis. I operationalize CGR *funding type* as the primary stream of funding the CGR uses. Funding sources are categorized as local funding, state funding, federal funding, NGO funding, private funding, a mix of public funding, a mix of public-private funding, and unknown. I include funding type as a control because CGRs' resources likely influence collaborative membership overlaps, such as through membership based on a collaborative's access to certain resources. *Collaborative size* describes the number of members participating in each CGR. I control for the size of a CGR because it can influence overlaps as well. For example, larger CGRs have more opportunities for CGRs to share members. I control for the number of CGR full-time equivalent (FTE) staff. Researchers pulled *Staff* data from the CGR website staff lists. The CGR website often listed part-time people as 0.5 FTE and full-time people as 1.0 FTE. If the website was not clear on how many staff there were, but it was clear from the site that there was a coordinator and I could see their name, then I input 1.0 FTE. If the website listed a staff person, but that person's FTE status was unclear, I input 1.0 FTE for that person. I control for the number of CGR staff because platforms or the State of Oregon can employ staff on multiple CGRs, which can influence membership overlap.

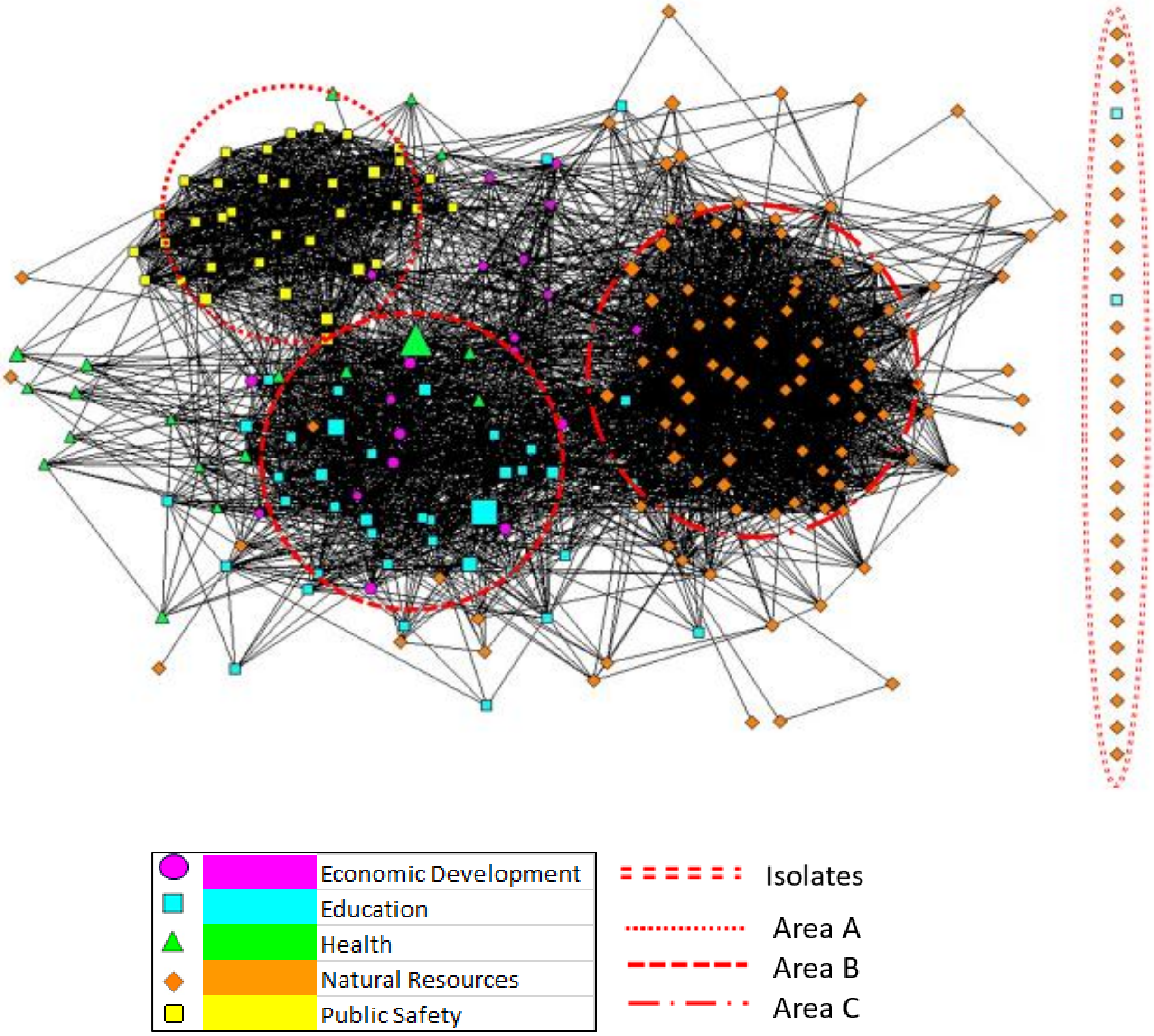
Analysis

I use a mixed methods approach to answer my research questions: How do I conceptualize and measure networked spaces in collaborative systems? How do I measure representativeness within and across CGRs in large collaborative systems? First, I provide a visual network map of the system, followed by a descriptive network analysis. Next, I describe my ERGM method and model selection process before presenting my results.

Network Graph and Descriptive Network Analysis

I first present a visualization of the collaborative system's network graph produced by a CGR-to-CGR one-mode adjacency matrix, where weighted ties represent the number of overlapping members (Figure 2). A CGR's size dictates the size of its node. The larger the node, the more members are in the CGR. I represent the policy domain that each CGR falls into through the color and shape of the node. Line thickness represents the number of overlapping members. I find evidence of over-representation. Figure 2 shows that 78% of the CGRs interconnect in the collaborative system through membership overlap across policy areas.

Figure 2: One-Mode Network Map with Attributes



CGR nodes (N= 242)

I see 28 CGR nodes in the Isolates circle in the left periphery, meaning that only 28 CGRs do not have at least one overlapping member with any other CGR. From the current data, I do not have a sense as to why these 28 CGRs do not have overlapping membership with other CGRs in the system. I can tell, however, that the isolates come from the natural resources and education policy domains. They vary in size. Area A, Area B, and Area C visually reveal patterns in the levels of overlap across policy domains. In Area A, it is apparent that overlapping member organizations tightly connect public safety CGRs. In addition, public safety CGRs tend to overlap with other public safety CGRs. In contrast, Area B in Figure 2 reveals that economic development, education, health, and in a small part, natural resource CGRs appear to make up a heterogeneous group in a collaborative system, revealing that CGRs overlap even when they are not from the same policy area.

The network graph in Figure 2 shows systematic patterns of overlaps across policy areas. A few natural resource CGRs tightly connect in Area B of this visualization of the system. However, most natural resources CGRs overlap with other natural resource CGRs, represented by Area C. Certain areas of the network graph show more homogeneity than others. The homogeneity suggests CGRs from the same policy area drive membership overlaps in these regions of the map. The following section presents my descriptive network analysis of whole and subgroup measures to gain further insights into the collaborative system.

Clusters

To better understand the visual maps, I perform whole and sub-group analyses of the collaborative system using UCINET. Table 2 shows Oregon's externally directed collaborative system is large (CGR nodes= 242) with many unique membership overlaps (N=4,751) and many total membership overlaps (N=7,794). As I can see from the total membership overlaps row, membership overlap occurs more than in one-off instances. I discuss the descriptive statistics more in-depth, interpreting the whole network measures first, followed by the subgroup-level measures below.

Table 2: System and Subgroup Level Measures

Network Level Measure	**Value**
CGR Nodes	242
Unique Membership Overlaps	4,751
Total Membership Overlaps	7,794
Average Distance	2.041
Subgroup Level Measure	**Value**
Connectedness	0.782
K-core Index	38

Table 1 reports the average CGR size = 19.13 members.

I calculate whole network measures to understand the overall collaborative system. Average distance is a way to measure collaborative system cohesion. It is the average number of steps along the shortest paths for all possible pairs (Watts & Strogatz, 1998). An average distance of two shows that you can reach any CGR in two steps, further suggesting the collaborative system experiences high membership overlap. A benefit of a low average distance, however, is that it means there is potential for a high efficiency of information diffusion. Nodes that are a short distance from other nodes facilitate the quick transfer of information (Borgotti & Li, 2009) and can reduce the costs of information diffusion. My results highlight opportunities to strategically disseminate knowledge, innovation, and other resources efficiently by identifying the most centralized

CGR members throughout the collaborative system. I explore the system further through subgroup analyses.

To understand the sub-group level, I examine connectedness and the k-core index in Table 2. A connectedness score of 0.78 reveals that the OAC is not a fragmented network of CGRs. It shows that 78% of the actors in the collaborative system can reach one another by any path. The k-core measure displays smaller interconnected cluster areas in the collaborative system by identifying tightly interlinked groups (Torab & Ganesh, 2021; Wasserman & Faust, 1994). The k-core is "a maximal group of entities, all of which are connected to at least *k* other entities in the group" (Torab & Ganesh, 2021, p. 37). My k-core index value varies between one and thirty-eight, with one being the least integrated subgroup and 38 being the most. I find that the most integrated group, the group with the k-core index of 38, consisted of 70 CGRs. I provide a complete list of the 70 CGRs in Appendix 1. Interestingly, the CGRs come from diverse policy areas and platforms and form a large, tightly interconnected group through shared membership. The finding suggests the collaborative system in Oregon is a dense network.

Next, I compute an average tie strength between CGRs by policy area (Table 3). I sum all of the tie strengths, counted by how many organizational members overlap between them. I then calculate an average for each policy group. My analysis shows that the most CGR-to-CGR membership overlaps were within CGRs' respective policy domains for economic development (2.99), natural resources (0.80), and public safety (2.23). Interestingly, health and education had the highest tie strength between one another (1.24), rather than within their policy areas, unlike the other groups. Table 3 confirms my suspicions about Area B of the network map above. Membership overlaps occur between CGRs of different policy areas, especially in the health and education domains. However, these findings suggest CGRs most frequently experience membership overlap within the same policy area.

Table 3: Average Tie Strength

	Economic Development	Education	Health	Natural Resources	Public Safety
Economic Development	**2.989**	0.488	0.553	0.187	0.192
Education	0.488	1.013	**1.241**	0.105	0.105
Health	0.553	**1.241**	1.135	0.059	0.313
Natural Resources	0.183	0.106	0.058	**0.773**	0.03
Public Safety	0.192	0.105	0.313	0.03	**2.265**

I present the highest average tie strength across groups in bold.

The visual appearance of the network map and the descriptive network analyses demonstrate that I tend to see overlaps based on the CGR policy area. Now I know more about how the collaborative system is structured. I present my statistical tests of the hypotheses using ERGM in the following section.

Exponential Random Graph Modeling

I perform my estimation using exponential random graph modeling (ERGM) (Frank & Strauss, 1986; Pattison & Wasserman, 1999; Robins et al., 2007; Wasserman & Pattison, 1996) using Maximum Pseudo Likelihood Estimates (MPLE) (Hunter et al., 2008). ERGMs produce estimates by simulating many random networks that are the same size as the observed network and determining whether the structure is random or systematically associated with predictor variables (Atouba & Shumate, 2014). I use ERGM analysis to examine the collaborative system in Oregon and test hypotheses related to policy area and geographic proximity to uncover drivers of membership overlap and understand representation.

The purpose of ERGM is to understand local selection forces that influence the global structure of a networked system (Hunter et al., 2008). ERGM allows us to go beyond traditional network analysis techniques used in public administration, which are descriptive (Frank & Strauss, 1986; Pattison & Wasserman, 1999; Robins et al., 2007; Wasserman & Pattison, 1996) to using probability distributions to make predictions. ERGMs are useful for studying collaborative systems. They allow researchers to infer whether network substructures are more or less commonly observed than what is expected by chance, allowing researchers to develop models on how sub-network structures combine to form whole networks beyond random connections (Robins et al., 2007). For a comprehensive overview of ERGMs, see Shumate and Palazzolo (2010).

Model Development and Selection

I fit the model so the ERGM can properly simulate random networks like mine to produce accurate estimates. I start with a null model. Throughout, I examine the Bayesian Information Criterion (BIC) each model produces. The BIC reports how well the model estimates the data (Dziak et al., 2020). Lower BIC values reflect models better able to predict that data. Table 4 presents the model development process. The null model, model 1, is an ERGM model with no nodal covariates. The null model reported BICs of 20,862. In models 2-5, I examine the contribution of added covariates detailed in the measures section. I settle on model 5, which has the lowest BIC and includes the full set of terms for my analysis. Including the full set of terms improves model fit to a small degree.[6]

[6] The ERGM package which I use to estimate the ERGMs presented in this chapter also provides the Akaike Information Criterion (AIC) and a corrected version of the AIC (AICC), but I report the BIC since it tends to prefer simpler models (Dziak et al., 2020).

Table 4: Bayesian Information Criteria (BICs) for Model Development and Selection

Model	BIC
1 (Null Model)	20862
2	20848
3	20835
4	20829
5	**20803**

In addition to the BIC model selection process, I ran goodness-of-fit tests, available in Appendix 2. The goodness-of-fit tests show model 5 fits the model statistics, degree, and path distance parameters well. However, the model does not show a good fit for simulating the common neighbors that two already connected CGRs have. Common neighbors represent local clustering in the collaborative system, so the model struggles to simulate instances when an organization that is already a member on two CGRs becomes a member of a third CGR due to the number of overlapping members within the original two). Network scholars refer to this phenomenon as k-triangles. Estimating k-triangles is a high-order estimation beyond the scope of this analysis. However, it is important to note that this does lower the accuracy of my results. I discuss the implications and solutions for future research to address this in the discussion and Appendix 2. Overall, the lowered BIC in the model selection process and the good fit for model statistics, degree, and average path length demonstrate my chosen model's ability to generate many networks like the collaborative system in Oregon. Fitting the model allows us to perform statistical analyses and draw conclusions about the drivers of membership overlap using ERGM analysis.

Results

Table 5 displays the results of the ERGM. For a more straightforward interpretation, I report coefficients as odds ratios. The results show a negative and statistically significant coefficient for the edges terms. CGRs were less likely than chance to have membership overlap, meaning that the overlaps in Oregon's collaborative system are not likely formed at random. Various factors influence CGR-to-CGR membership overlap. In line with previous research, the edges result is not surprising given the large number of nodes (Atouba & Shumate, 2014). The edges parameter also controls for the sparseness of the large collaborative system to avoid the large number of absent ties inhibiting the other parameters from being modeled (Atouba & Shumate, 2014).

Table 5: ERGM Results

	Maximum Pseudo Likelihood Estimate (MPLE)		Standard Error (SE)	Conditional Odds Ratio	
Edges	-1.43	***	0.03	-0.19	***
Policy Area Proximity (H1)	-0.07		0.05	-0.48	
Geographic Proximity (H2)	0.01		0.04	0.50	
Collaborative Platform (H3)	0.52	***	0.06	0.63	***
Geographic Scope	-0.13	***	0.03	-0.47	***
Founding Date	0.01		0.05	0.50	
Funding Type	-0.04		0.03	-0.49	
CGR Size	0.10		0.07	0.53	
Staff	-0.02	***	0.003	-0.49	***

Significance: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 6 reviews the hypotheses in light of the results. The non-significant coefficient for Hypothesis 1 shows that I cannot draw conclusions about the relationship between policy area proximity and membership overlap from this ERGM. The non-significant coefficient for Hypothesis 2 shows that I cannot draw conclusions about the relationships related to geographic proximity and membership overlap from my model either. Various reasons may explain why I did not find support for Hypotheses 1 and 2 in the ERGM analysis. Hypothesis 1 posits greater membership overlaps in policy-area proximate CGRs than in CGRs that are not policy-area proximate. Hypothesis 2 posits that I would expect to see more overlaps in geographically proximate CGRs than in CGRs that are not geographically proximate. The lack of support for Hypotheses 1 and 2 might result from some imprecision in ERGM, which could explain the slight improvement in the BIC. The imprecision may stem from the poor fit for k-triangles when fitting my model. Finally, based on the findings in my network graphs, it is apparent that membership overlaps occur by policy area. However, the reason I do not find significance may be because other variables drive the structure to a much greater extent than policy area proximity or geographic proximity.

I find support for Hypothesis 3, which models the extent to which collaborative platforms influence membership overlap. Hypothesis 3 states that there are greater membership overlaps between CGRs in the sample platform than among CGRs that are not within the same collaborative platform. The relationship was positive and significant at the 1% level. CGRs had 0.63 higher odds of having shared membership overlaps when part of the same collaborative platform than CGRs that were not part of the same platform. I am not surprised by this finding, given the structure of Oregon's collaborative system of externally directed CGRs and the responsibilities of the platforms within it. However, I am interested in the magnitude here, which is telling. The results reveal that CGRs that join platforms have a 63% chance of gaining membership overlaps with other CGRs in the same platforms. Therefore, it is not necessarily guaranteed (a 100% chance) CGRs will experience within-platform overlaps, but the odds are high. In the discussion section, I discuss these findings further in conjunction with my other analyses.

Table 6: Results by Hypothesis

Hypotheses	Results
Hypothesis 1: There are greater membership overlaps in policy area proximate CGRs than in CGRs that are not policy area proximate.	Fail to reject the null hypothesis
Hypothesis 2: I would expect to see more overlaps in geographically proximate CGRs than in CGRs that are not geographically proximate.	Fail to reject the null hypothesis
Hypothesis 3: There are greater membership overlaps between CGRs in the sample platform than among CGRs that are not within the same collaborative platform.	Significant

I find geographic scope and staff attributes were significantly related to membership overlap. First, the model shows a negative coefficient on the geographic scope model statistic, meaning CGRs were 0.47 lower odds of having organizational members already serving on CGRs characterized by the same geographic scope. The finding indicates that CGRs that span multiple jurisdictions are significantly less likely to have membership overlap with other multi-jurisdictional CGRs. Similarly, this finding indicates that CGRs that span single jurisdictions are significantly less likely to have membership overlap with other single-jurisdictional CGRs.

Second, I find significance for an inverse relationship between the control covariate of FTE staff and overlapping membership overlap between CGRs. CGRs with more staff were 0.49 times lower odds of sharing membership overlap with other CGRs in general, meaning higher-staffed CGRs had a lower tendency to have membership overlap with other CGRs in the collaborative system. Finally, a lack of significance shows I cannot draw conclusions about CGR control variables related to age, funding type, and size and their influence on CGR membership overlap.

My results show that, of my hypothesized variables, only collaborative platforms significantly influenced membership overlap in the collaborative system. I cannot reject the null hypotheses in favor of the alternative hypotheses for policy area or geographic proximity. However, I find collaborative platform proximity positively influences membership overlap, while geographic scope similarities negatively influence membership overlap. I also find a negative relationship between staff and membership overlaps among CGRs. I discuss these results in further detail in the following section.

Discussion

I summarize this section's main findings by answering my two research questions. I discuss the practical implications of each. Then, I discuss the study in light of limitations, research implications, and future directions.

Main Finding 1: How do I conceptualize and measure collaborative systems?

The descriptive network analyses reveal a tightly connected collaborative system through high membership overlap. The collaborative system had an overall connectedness score of 78%. The short average distance of two between all possible pairs means that the structure of Oregon's collaborative system may lead to inequities in representation but also may facilitate a high efficiency of information diffusion and exchange due to membership overlap. The level of overlap I find through the network maps and descriptive statistics suggests Oregon's collaborative system has an over-representation of certain actors. The average tie strength measure revealed that most CGR-to-CGR membership overlaps were within CGRs' respective policy domains. Appendix 1 provides a list of the 70 most over-represented actors in the collaborative system, identified by the k-core index measure. In accordance with previous findings, my research demonstrates the value of using network analysis to reveal the structural patterns and characteristics in collaborative arrangements, including representation (Carboni et al., 2017). Over-representation of actors has implications for collaborative governance. The premise of collaborative governance is that it represents interested stakeholders. When CGRs across the state have many common members, I must ask whether the system represents stakeholder interests. I discuss these findings further below.

Main Finding 2: How do I measure representativeness within and across CGRs in large collaborative systems?

My work informs scholarship and practice about whether a collaborative system represents diverse interests. I define a collaborative system as the larger networked space in which CGRs and collaborative platforms are embedded. I find and measure a highly connected system by applying network tools and methods to the OAC database. I use network maps as a tool to visualize the system. Methods include network measures of average distance, k-core indices, and average tie strength. The large number of overlaps indicates that the system may not be diverse. I probe further to understand drivers of membership overlap patterns at the system level using ERGM analysis. I expected that policy area and geography would positively influence membership overlaps at the system level because of the geographically bounded nature of Oregon's collaborative system or externally directed CGRs.

Given that there are only so many experts in the state, I expected I might see the same organizational actors serving on CGRs repeatedly within policy domains and regions. However, I cannot rule out that policy area (H1) or geographic proximity (H2) drives the structure of the collaborative system through membership overlaps beyond what may occur by chance. The lack of support for the hypotheses may indicate that the system represents a diverse set of voices and that policy area or geographic proximity factors do not drive membership overlaps. Based on how interconnected the system is, I find it more believable that the lack of support for the first two hypotheses is due to variables like number of staff and geographic proximity being more associated with overlap, and I find evidence of this. For example, despite some of the CGRs being geographically specific, meaning they only focus only within one region, I found an inverse relationship between geographic scope and CGR membership overlap. A plausible explanation for this finding is that decision-makers for CGRs that are smaller in scope, such as single-jurisdiction CGRs that are not geographically specific, may be incentivized to choose organizations that are already serving in multi-jurisdiction spanning CGRs.

Literature suggests that becoming connected to collaborative arrangements that span multiple jurisdictions can increase the scope of efforts, help smaller collaborative arrangements realize the benefits of economies of scale through shared costs, and maximize the return on their time and resources (Andrews & Entwistle, 2010; Warner & Bel, 2008). Meanwhile, decision-makers for multi-jurisdiction CGRs may have overlapping members with smaller CGRs due to their localized expertise, such as knowledge of the physical and social geography of the location where the problem they are trying to address occurs (Emerson & Nabatchi, 2015a). However, I cannot confirm the mechanisms behind the significant result but highlight it for future research. I only study the structure of the collaborative system and cannot draw conclusions on stakeholder motivations.

I find that collaborative platforms influence overlaps (H3). Such overlap was expected, given that the platform's purpose is to bring together CGRs working on the same issues. Therefore, the same government agency might serve on all CGRs within a platform for oversight. However, the network graphs and descriptive network statistics show membership overlap occurs beyond the organizations' serving on multiple CGRs on behalf of the platforms. Overlapping organizations came from all policy domains. Appendix 1 provides a list of the actors that overlapped most frequently. For example, platforms are policy domain specific, yet the results show that CGRs overlap across policy domains (i.e., health and education). The k-index analysis supports this, revealing the most integrated group of CGRs consists of 70 CGRs overlapping across multiple policy domains. My study highlights a limitation related to reliance on collaborative platforms to orchestrate the structure of a collaborative system. The results highlight the tradeoff between reliance on collaborative platforms and systematic representation. Over-reliance on platforms can lead a system to consist of the same actors repeatedly serving on CGRs. Finally, the high connectedness score and the heterogenous groupings in the network graph also support that it is not only platforms driving over-representation. Membership overlaps occur beyond the platform level. Overall, I see many overlaps through common members in the system. However, I cannot comment on the extent that over-representation occurs because I only have data on state connected CGRs, and I do not know the universe of actors. I surmise that some over-representation is very likely occurring, which may mean the system represents a limited number of stakeholder interests due to instances of over-representation being inherent in the collaborative system. In addition, not all CGRs experienced overlap, so I find platform-orchestrated overlap is not guaranteed.

The results answer my research questions by showing how to conceptualize and measure networked spaces in collaborative systems. My results suggest network analysis methods provide a great deal of insight into the existence and structure of collaborative systems. Next, I discuss the practical implications of these results.

Implications for Policy

The establishment of the collaborative system concept has many implications for practice. Policymakers use CGRs and collaborative platforms as policy tools to develop and implement public policy. Public stakeholders' increasing reliance on collaborative governance signals that governments value scaling up and organizing collaborative activities (Ansell & Gash, 2018; Centers for Medicare & Medicaid Services, 2022a; Cochran et al., 2019; Shumate, 2022). Using a systems lens can help practitioners identify challenges and opportunities for improvement.

The Oregon case highlights opportunities for those interested in strategically managing collaborative systems. For example, leaders interested in learning the best ways to disseminate and route resources across collaborative systems might consider performing this type of analysis on existing systems. In doing so, they can identify the most centralized CGRs and platforms and efficiently manage the system through central actors. By orchestrating overlaps, managers can use network measures to bridge gaps in fragmented systems. For example, k-core indices allow stakeholders to see the names of the CGRs that make up the least and most integrated sub-groups. Such information is beneficial to close representation gaps in collaborative systems, such as when leaders want to connect isolates to the main component for easier information diffusion and orchestration of the whole. Alternatively, stakeholders can use network analysis techniques to determine whether collaborative systems experience overlaps in members to gauge representation. For example, too much membership overlap signals there may be a lack of diverse participation in collaborative governance practices (Carboni et al., 2017; Koski et al., 2018). When collaborative governance over-represents some actors, it lowers the legitimacy of CGRs and signals problems with the collaborative design and processes, potentially affecting output (Carboni et al., 2017). Overall, applying network analyses to collaborative systems allows policymakers and managers to know more about the structure of their collaborative systems and whose values the systems represent. Insights into collaborative systems can inform strategic decisions to reach desired goals.

Based on my findings, I recommend that policymakers and managers encourage CGRs to assess diverse membership rosters, including those actors who can think about complex problems from different perspectives and bring their unique experiences, expertise, and values to the CGR. Leaders can legitimize their initiatives by facilitating diverse descriptive and substantive engagement in deliberative processes (Beierle & Carboni et al., 2017; Emerson & Nabatchi, 2015a; Konisky, 2001; Koski et al., 2016; Koski et al., 2018; Leach, 2006; Siddiki et al., 2015). In these ways, practitioners can enhance representation in CGRs by connecting diverse actors with different priorities and goals (Ansell & Gash, 2008; Emerson & Nabatchi, 2015a).

Limitations

My research is not without limitations. My analysis does not include the CGRs outside of those externally directed by the state. However, these missing CGRs may have membership overlap with CGRs within the collaborative system under examination here. However, understanding the bounded network of CGRs occurring in Oregon is a contribution given that studies at the whole system level are lacking, in large part due to the difficulty of collecting relational data (Robins et al., 2004). A second limitation is that I used a cross-section of data on CGRs in Oregon in 2019.

While analyzing how a collaborative system changes over time is undoubtedly valuable, this snapshot of the collaborative structure allows researchers to understand how CGRs are interconnected. Therefore, it allows us to begin to theorize what using CGRs as a policy tool might mean for public service delivery in the governance era. Third, goodness-of-fit tests show my model does a poor job of simulating k-triangles. Although estimating k-triangles is beyond this analysis's scope, it suggests endogenous network terms, such as triadic closure, may be missing to measure transitivity and clustering of membership overlaps further.[7] However, the model does properly fit the model statistics, degree, and path distance parameters. In addition, adding my model statistics to the null model improved the ERGM estimation, and I chose the model with the lowest BIC to improve model accuracy. To address this, I provide a detailed discussion of k-core clusters and map the network in the chapter in Appendix 2. Given these factors, I feel comfortable reporting the results. Fourth, the results are not generalizable beyond the CGRs in Oregon. However, it sets a baseline for conceptualizing and measuring collaborative systems. It brings up essential considerations for representative participation.

Implications for Research and Future Directions

To address my study limitations, I suggest three avenues for future research. First, I suggest future work revisit theory to uncover what omitted endogenous network terms drive k-

[7] When I include triadic closure in my model (not shown), the BIC greatly lowered, however, the model failed the goodness-of-fit tests. Future research my try to add triadic closures using a different set of variables to illuminate best model fit.

cliques in the Oregon collaborative system, which may improve overall model fit and the accuracy of the results. Given my non-significant results around Hypotheses 1 and 2, I also suggest future research further test for relationships between CGR member overlap and geographic proximity and policy area proximity. Furthermore, I find significant evidence that higher-staffed CGRs had a lower tendency to have membership overlap with other CGRs. Given the lack of prior research on the topic, I can merely speculate why more staff would be associated with less membership overlap between CGRs. I suggest that future research study this relationship to add context.

Now that I established the interconnected structure of a collaborative system, the next step is to consider how to refine and advance it. I rely on the integrated theory of collaborative governance to develop the collaborative system concept (Emerson & Nabatchi, 2015a) and encourage future research to continue to apply network analysis methods to this framework to test collaborative governance theory empirically. I suggest scholars utilize advances in network methodologies to understand two-mode and even three-mode networks to examine the collaborative system at multiple levels of analysis to accurately capture the true nature of interdependence (i.e., Carboni, 2015; Fararo & Doreian, 1984).

Similar to previous work, I conclude that measuring who participates allows collaborative governance researchers to evaluate the inclusivity of collaborative governance (Carboni et al., 2017). My findings are valuable as the structural design of groups affects their ability to assess diversity and representativeness (Koski et al., 2018; Siddiki et al., 2015). I recommend three next steps for furthering this line of work. First, researchers can further this work by determining what interests collaborative initiatives serve by delving into which actor representation. Second, here I analyze descriptive representation, and I recommend future research determine what actors are more substantively represented than others to uncover who engages meaningfully in a process, rather than just counting who is at the table (Carboni et al., 2017; Koski et al., 2016). A third next step is to determine why CGR membership overlaps occur. While it is beyond the scope of this study, decision rules for entry need to be studied to add more nuance to understanding systems. For example, researchers can explore where decision-makers are satisficing using the lens of bounded rationality (Simon, 1997). Based on bounded rationality, it is plausible that those tasked with membership decisions satisfice and choose actors already serving on CGRs with whom they are familiar to avoid risk and to make decisions quickly without perfect information. In doing so, decision-makers may choose familiar actors to serve as members of CGRs again and again. Future research on this topic may clarify why I observe collaborative system over-representation.

As data becomes available beyond the organizational level, research can continue to reveal how CGRs interconnect or fragment. Such a research agenda provides an avenue for understanding the wide variation in rules, procedures, organization, and performance outcomes that characterize the decentralized state (Rainey, 2014). Such an agenda also answers Ansell and Gash's (2018) call for increased research on how actors use collaborative governance as a generic policy instrument.

Conclusion

Oregon's use and support of collaborative governance initiatives make it a uniquely facilitative system context for CGRs and collaborative platforms to carry out their work, not only in silos but also through CGR-to-CGR overlaps that have system-level impacts on structure. Scholars contribute to collaborative governance theory by studying the processes and factors that drive groups as they arrange in "arrays of negotiation, implementation, and service delivery"

(O’Toole, 2000, p. 276). My research used the Oregon Atlas of Collaboration dataset, situated the concept of the collaborative system in the public administration literature, and established that there is a collaborative system operating in Oregon. I perform descriptive network analysis techniques to uncover the embeddedness of collaborative arrangements in wider systems and whether there are challenges to representation within. My findings reveal the tendency of CGRs to have high levels of membership overlap with other CGRs serving within the same platform but across different geographic scopes drives the system’s structure. My findings also show that representation is a challenge that system leaders should address.

My findings raise questions about representation in collaborative governance. If collaborative systems reveal high overlap among separate CGRs, it raises questions about whether the CGRs within represent stakeholder interests. Too much membership overlap may signal a lack of diverse participation, which is antithetical to the principles of collaborative governance.

Overall, this work shows the utility of the collaborative system concept. Observing the collaborative system is timely, as new data for research on CGRs and collaborative platforms continues to increase in scale and scope. It is important to understand more integrated systems of collaborative governance efforts, such as CGRs and collaborative platforms, connecting and working together in a collaborative system. Developing and examining the collaborative system concept through the integrated framework for collaborative governance allows CGR members, platform leaders, and other external directors and stakeholders to view the collaboratives they are in as embedded and evolving within a larger system (Emerson & Nabatchi, 2015a). Such information about collaborative system structure can help public managers evaluate their satisfaction with the centralization or diffuseness of the system. Structural information can also provide insights into adjusting the system and determining actionable steps to ensure equitable participation. Such research has important implications for policy design, implementation, and outcomes by considering how government and nongovernment actors can develop strategic relationships to achieve beneficial policy outcomes for the communities they serve.

Chapter Two: CGR Adaptation During COVID-19

By Catherine Annis

Abstract

In this chapter, I research the ability of a veteran-serving collaborative system in a U.S. state to adapt to a substantial change in case quantity and needs during the COVID-19 pandemic. I examine how this collaborative system with a lead-organization governance structure reacts when its system context is shocked, leading to uncertainty, instability, and rapid change, including changes in the supply of and demand for services. I explore collaborative governance regime (CGR) adaptation immediately following stay-at-home orders during the pandemic. CGRs are entities where cross-boundary collaboration represents the prevailing pattern of behavior and activity to make public decisions (Emerson et al., 2012). I study community referral networks that meet the criteria of CGRs. The two community referral networks operate in a U.S. state where the system context was unstable due to the pandemic's onset. I use Temporal Exponential Random Graph Modeling (TERGM) (Robins & Pattison, 2001) and qualitative methods to explore how CGRs adapt to substantial changes in times of crisis. I find reciprocity significantly explains behavior in both CGRs. Lead organizations were more likely to send referrals between organizations where they previously originated in one organization and then were accepted in the other. In the same vein, organizations were more likely to accept referrals from organizations that had previously accepted their referrals, orchestrated by the lead organization (Provan & Kenis, 2007). In one CGR, the amount of time an organization was part of the collaboration was positively associated with lead organization-coordinated referral-sending activity. My work contributes to collaborative governance theory and practice by testing the viability of adaptation from the integrated framework for collaborative governance (Emerson & Nabatchi, 2015a, 2015b).

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Human Subjects Protection

This human subjects research obtained joint IRB approval from Northwestern University (Institution A) and Syracuse University's (Institution B) IRB Offices on June 23, 2020 (Study Number: STU00212731).

Introduction

Increasingly, health-related emergencies, such as Zika, Ebola, and COVID-19, present policymakers and public managers with the dilemma of choosing the most effective public service provision models to minimize the public impact (Jayasinghe et al., 2022; O'Flynn, 2020). Public actors manage complex societal problems through collaboration among organizations (Davies & Blanco, 2022). The onset of the COVID-19 pandemic in 2020 and predictions of more frequent future pandemics demonstrate the importance of actors working across organizational boundaries (Andrew et al., 2020). In this introduction, I discuss collaborative governance management during a crisis and motivate my use of community referral networks.

Collaborative governance is "the process and structures of public policy decision-making and management that engage people across the boundaries of public agencies, levels of government, and/or the public, private, and civic spheres to carry out a public purpose that could not otherwise be accomplished" (Emerson et al., 2012, p. 18). Research continues to document how collaborative governance functions during a crisis (Bynander & Nohrstedt, 2019; Criado & Guevara-Gómez, 2021; Getha-Taylor, 2007; Huang, 2020; Jayasinghe et al., 2021; Kapucu, 2015). Rapid change can disrupt stakeholder groups engaging in collaborative governance (Shumate & Cooper, 2022), and rapid change is a feature of crisis contexts.

Collaborative governance regimes (CGRs) are "a particular mode of, or system for, public decision making in which cross-boundary collaboration represents the prevailing pattern of behavior and activity among autonomous participants who have come together to achieve some collective purpose defined by one or more target goals" (Emerson & Nabatchi, 2015a, p. 18). Public managers use CGRs to develop and implement policy. I treat CGRs as networks for this analysis. The concepts come from distinct literature streams. Networks are "groups of three or more legally autonomous organizations that work together to achieve not only their own goals but also a collective goal" (Provan & Kenis, 2008, p. 231). Collaborative governance includes shared decision-making authority with nonprofits, private organizations, citizens, and other governments in public policy development and implementation. Therefore, all CGRs consisting of three or more actors are networks, but not all networks are CGRs. In this study, I specifically examine community referral networks through which at least one or more public actors have granted some decision-making authority. Referral networks are "systems of relationships among organizations that allow them to direct people (e.g., clients) to the appropriate services that are not available at their own facility" (Gibbons & Samaddar, 2009, p. 352). Patient referral relationships between providers can symbolize collaboration. Scholars can examine referrals as interaction data to move beyond simply understanding whether clients receive a service to a more nuanced understanding of the referral process, such as whether referral relationships persist over time. As such, referrals can represent the mechanisms associated with changes in network connectivity, which uncover and promote network transformation processes (Amati et al., 2019).

Despite the increasing use of CGRs, there is limited research on collaborative governance in different system contexts. There is also limited research on how leadership adapts and steers CGRs in response to crises. Gaps also remain in how CGRs adapt and evolve in rapidly changing system contexts. System context describes the contextual characteristics of CGRs' environments, including political, legal, socio-economic, environmental, and other influences that enable and constrain collaboration (Emerson & Nabatchi, 2015a, p. 27). To address this, I examine CGR's adaptation to shift in the system contexts of two regions within one U.S. state immediately before and after the emergence of COVID-19. I address the research question: *How did community referral networks adapt to changes in the supply of and demand for services during the emergence of COVID-19?*

To adapt means to make fit, often by modification. Adaptation leads to change, and organizational attributes and power systems influence the dynamics of change (Karemere et al., 2015). This research focuses on the changing relationships within one form of CGR. I examine community referral networks that utilize public resources and collaborate to implement public policy. Community referral networks are entities where public actors work with community-based organizations to meet common goals through goal setting, referral activity, and information sharing (Carboni et al., 2022). While not all referral networks are CGRs, the community referral networks I study in this chapter meet the criteria of CGRs. They bring stakeholders together to collaborate to address a public need that one organization cannot address alone. In this study, I examine networks focused on improving the quality of life for veterans and military families in their communities. The networks are part of a collaborative initiative that systematically brings together public, private, and nonprofit organizations to meet this goal. Therefore, I deem them collaborative networks. Public managers use collaborative networks to deliver services where public policy or management challenges require multiple organizations to address a problem or support clients with complex needs (Carboni et al., 2022; Jang et al., 2016; Milward & Provan, 2006; Popp et al. 2014). I discuss in more detail how they meet the definition of CGRs in the study context section.

Increasingly, public managers and policymakers use referral networks to integrate health and human services better and collaborate to meet common goals (Carboni et al., 2022). In the U.S., it is common for individuals to be referred from one organization to another to acquire the total number of services they need (Shumate, 2022), highlighting the importance of understanding referral behavior in human services during crises. By examining referral patterns between actors, I show how the COVID-19 pandemic disrupted the relational patterns among organizations within CGRs in real time and how CGR leaders and members adapted. I examine how a collaborative system adapted to the environmental shock of the pandemic through referral patterns.

My research focuses on two veteran-serving community referral networks. They are part of AmericaServes, the first collaborative initiative that systematically brings together public, private, and nonprofit organizations to provide services to veterans and their families across the U.S. AmericaServes is a collaborative system. Collaborative systems occur when multiple collaborative arrangements operate within or across policy arenas in a defined geography or jurisdiction (Annis et al., 2020). In 2020, AmericaServes consisted of eight networks. I limit the scope of this collaborative system to two CGRs systematically connected within their state by the AmericaServes program.

The two CGRs under study each use a lead organization. In networks with lead organization governance, an organization that handles "all major network-level activities and key decisions are coordinated through and by a single participating member, acting as a lead organization" (Provan & Kenis, 2007, p. 235). The CGRs of focus are highly centralized and depend on a lead organization who is a network member to orchestrate referral connections and steer the regimes to achieve their goals of improved community outcomes for veterans and their families (Provan & Kenis, 2007). In answering how community referral networks adapted during the emergence of COVID-19, I contribute to the limited literature on collaborative systems by examining how lead organizations' managed CGRs during a crisis (Ansell & Gash, 2018).

I also contribute to research by applying underutilized methods and data to examine collaboration in public administration. I statistically analyze real-time interaction data that comes directly from the system components of referral networks (Annis et al., 2022). System log data is scraped directly from communication technology platforms. In addition to accurate, dynamic data, system log data provides a nuanced picture of how the networks serve clients in real-time. I also contribute to public administration scholarship using Temporal Exponential Random Graph Modeling (TERGM) to analyze CGRs over time. I answer calls for more sophisticated methods and longitudinal analysis to document change and evolution using network analysis in public administration (Kapucu et al., 2017; Lecy et al., 2014).

I begin this chapter with an overview of the literature, laying out the research questions and hypotheses. I describe the system context that surrounds the CGRs. Next, I present the thematic analysis and TERGM network analysis method, followed by an overview of the results. The discussion section integrates the qualitative and quantitative findings to gain a complete picture of how networks adapted to the emergence of COVID-19. I conclude with a discussion of implications for researchers and public managers.

Literature Review

This literature review is structured as follows. First, I describe the integration of collaborative governance and crisis management literature. Second, I discuss the distinction between collaborative governance and network works of literature, explaining how and why I treat CGRs as collaborative networks. Third, present research on how differences in governance structures can influence CGRs' ability to adapt during crises. I present the viability of adaptation as a key metric to understand whether CGRs adapted satisfactorily at the onset of COVID-19 and detail how scholars can measure adaptation by looking at interactions between actors. I conclude the literature review by laying out the hypotheses.

Disaster sociology was the first discipline to publish research on how independent units cooperate to eliminate service delivery fragmentation during times of crisis in the 1960s (Gillespie & Colignon, 1993; Bynander & Nohrstedt, 2019). Over time, advances in public management and related disciplines contributed to the knowledge of collaborative governance in crisis contexts. Scholars continue to expand knowledge of crisis management to encompass more adaptive and flexible system designs using collaborative strategies (Farazmand, 2007). Meanwhile, collaborative public management and crisis management literature continue to integrate (Bynadnder & Nohrstedt, 2019).

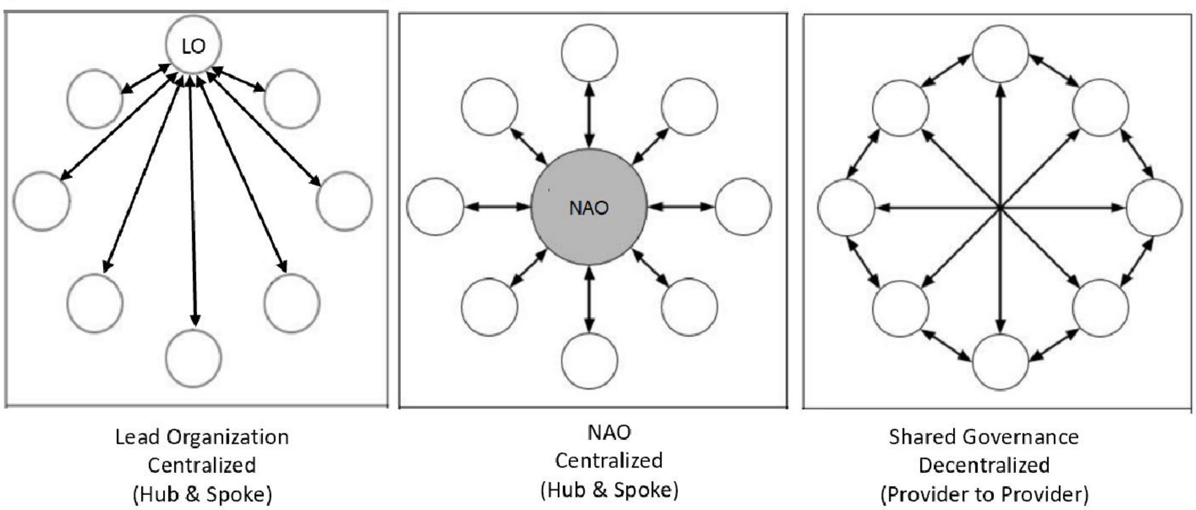
To understand how CGRs adapt in crises, scholars can draw from the network governance literature. Collaborative governance and network governance are two distinct but complementary research streams. They have been parallel tracks of scholarship in understanding the decentralization of the state. Collaborative governance tends to be more interested in the processes used for cross-boundary work, and network research tends to be more interested in the structures used for cross-boundary work. While the two tracks recognized each other, scholars have shown a tendency to work in parallel rather than in concert. Both sets of literature highlight the mixed economy involved in producing the “common good” for the public, where close collaborative agreements occur among individuals, organizations, and institutions in the public, nonprofit, and for-profit sectors (Morgan & Cook, 2014). However, only recently have scholars in the two tracks started to explore the structural properties of collaborating groups and the multi-level nature of the hollow state. Given the rich body of work on collaborative governance arrangements and single networks, there is a ripe opportunity for network and collaborative governance scholars to stop working in silos and start further integrating theoretical streams.

Decisions about governance structure can put collaboratives on different trajectories as they change and evolve (Emerson, 2018). The network governance literature provides three key governance types: shared governance structure, lead organization structure, and NAO structure (Provan & Kenis, 2007). The main difference between the three structures in referral networks is that actors can send referrals directly between providers in the decentralized model. In contrast, referrals must go through the lead organization or the NAOs, who then sends them to the appropriate provider in centralized models. I examine two networks that use a lead organization structure, meaning a single network participant takes on the role of a lead organization and governs the entire network (Provan & Kenis, 2007). Lead organization governance structure differs from the NAO structure, where "a separate administrative entity… is set up specifically to govern the network and its activities…The network broker [that] plays a key role in coordinating and sustaining the network" (Provan & Kenis, 2007, p. 236). Rather than having an external actor govern the network, the lead organization is a participant. Lead organization governance structure also differs from shared governance structure networks, where the network is decentralized and fully governed by the organizations within it rather than one participant or an external entity orchestrating (Figure 3).

Figure 3 shows the similarities and differences between a lead organization structure, an NAO structure, and a shared governance structure. When networks are highly centralized, where interactions occur by and through a single organization, they form a hub and spoke structure, as shown in the first two panels. Although organizations still interact in models such as these, the lead organization or the NAO is the centralized orchestrator of ties and activities (Provan & Kenis, 2007). The main difference between the first two panels is that the NAO is designated in darker gray because it is an outside entity and is not part of the provider network. The third panel shows a decentralized, shared governance structure where peer-to-peer ties are the predominant mode of activity.

The hub and spoke model that NAOs and highly centralized lead organizations create may lead to bottlenecks in community referral networks during rapid change. A bottleneck is a situation that stops a process or activity from progressing. In such instances, lead organizations and NAOs may have less capacity to fulfill their roles in integrating service provision, particularly when system context conditions change (Provan & Kenis, 2007). Lead organization and NAO-governed networks' formal nature hinders their ability to adapt to change compared to less-centralized shared governance models (Provan & Kenis, 2007). Provan and Kenis (2007) posit that lead organization and NAO-governed networks are more stable than shared governance networks due to their formalized nature. However, lead organization and NAO-governed networks are less flexible because participating organizations do not constantly shape and reshape the CGRs like in shared governance models.

Figure 3: Network Governance Structures



Adapted from Kenis and Provan (2009)
LO = Lead Organization, NAO = Network Administrative Organization

A network's structural form can its performance and some network governance structures are better suited to achieving specific outcomes than others (Kenis & Provan, 2009). Scholars and practitioners can use any measure to evaluate network performance (Kenis & Provan, 2009).

Therefore, scholars can explore how network governance relates to outcomes like network goal attainment, productivity, survival, stability, and resilience during abrupt change. These outcomes relate to the concept of the viability of adaptation from the collaborative governance literature. The viability of adaptation concept provides information about how to measure collaborative network viability over time. Viability of adaptation measures the continuing capacity of collaborative arrangements to add value above and beyond individual participant efforts (Emerson & Nabatchi, 2015a). It is a useful term to study for the networks under study in this chapter because they follow the lead organization model. Authors find that "The weakness of the [lead organization] model is that the lead organization may have its own agenda and can readily dominate the other network members, causing resentment and resistance. In addition, because the lead organization takes on many of the activities of governing the network, network members can readily lose interest in network-level goals and focus instead on their own self-interest, undermining the viability of the network" (Kenis & Provan, 2009, p. 448). Therefore, it is important to understand whether the lead organization structure increases or diminishes network viability in crisis contexts.

The dynamic nature of CGRs means that they are adaptable. Viability of adaptation is a concept included in the integrated framework for collaborative governance (Emerson & Nabatchi, 2015a, 2015b; Emerson et al., 2012). The integrated framework for collaborative governance synthesizes conceptual frameworks, research findings, and knowledge from practice to model collaborative governance (Emerson et al., 2012). The framework posits that collaborative actions lead to intermediate or end outcomes, and these outcomes, in turn, lead to adaptation. Adaptation can occur on a large or small scale in the system context, in the CGR itself, and in its member organizations. Therefore, viability of adaptation describes how well participating organizations manage to adapt and, at the same time, remain stable enough to carry out their missions. Examining the viability of adaptation allows researchers to assess the productivity performance of CGRs over time (Emerson & Nabatchi, 2015b). To study network adaptation, I test the viability of adaptation.

A CGR reaches an equilibrium of adaptation when there is perceived stability of participants' ongoing mission and accomplishments, such as evidence of ongoing contributions by CGRs to participants or improvements in interorganizational partnerships (Emerson & Nabatchi, 2015b). Authors measure the viability of adaptation through evidence of CGR contributions to achieving goals (e.g., dedicated staff, resource acquisition, and resource sharing). Researchers also assess the viability of adaptation using evidence of continued CGR to contribute to achieving targeted goals (Emerson & Nabatchi, 2015b). I utilize this framework to understand how CGRs adapted to the COVID-19 pandemic.

There will likely be changes in the levels of connectivity within community referral networks that I can attribute to the onset of the pandemic (Karemere & Macq, 2014; Karemere et al., 2015; Li et al., 2021; Wang et al., 2021). Care organizations are highly responsive to issues that draw public attention, such as pandemics (Li et al., 2021). A highly visible public issue can help CGRs and the organizations within them attract more attention and resources, allowing them to respond better to needs. Moreover, community referral networks use referrals to strategically manage clients and important relationships on referral technology systems during crises. For example, Wang, Hao, and Platt (2021) found that organizations' communication moved from scarce to active. Their networks increased connectivity as they coordinated crisis response during the early stages of COVID-19. The finding shows organizations use referral activity as a strategic action during crises. Researchers examine the determinants of adaptation by analyzing the interactions between providers and network leadership (Karemere et al., 2015). For example, Karamere and colleagues (2015) find that crisis emergence led to the sudden departure of providers and changes in service delivery, including a decrease in care activities. Their results also show crisis emergence led to changes in the dynamic interactions between actors, with experienced actors leaving the care system. These studies motivate the research question: *How did community referral networks adapt to changes in the supply of and demand for services during the emergence of COVID-19?*

Collaborative governance scholars widely accept that effective leadership mitigates the chances of failure (Emerson, 2018; Emerson & Nabatchi, 2015a; O'Leary et al., 2012). Failure to adapt can look like the inability to continue collaborating, mismanagement during a crisis, or even total collaborative dissolution (Farazmand, 2007; Shumate & Cooper, 2022). For example, researchers found management failures during the Hurricane Katrina crisis at the local, state, and federal levels when leaders poorly implemented collaborative governance initiatives (Farazmand, 2007). Some authors view the evolution of collaboratives as a function of the evolution of each organization's adaptation strategies within it (Koza & Lewin, 1999). When CGR members leave or stop participating, collaborations can become unstable and involve high dissolution rates. Such exit or non-participation emerges when member organizations prioritize strategic intents that differ from the collaborative arrangement (Koza & Lewin, 1999). Research suggests this instability of relationships is associated with the inability to adapt (Koza & Lewin, 1999).

The amount of time spent in collaboration is an important element to consider when modeling CGR referral network activity and the viability for adaptation. According to the integrated framework of collaborative governance, organizations build the capacity for joint action by collaborating over time. Actors build their capacity for joint action through procedural arrangements, leadership, knowledge, and resources. The capacity for joint action is ‘‘a collection of cross-functional elements that come together to create the potential for taking effective action’’ and serve ‘‘as the link between strategy and performance’’ (Saint-Onge & Armstrong, 2004, p. 19; adapted by Emerson et al., 2012, p. 14). The capacity for joint action increases as organizations continue to work with one another, establish procedural arrangements, build knowledge, establish resources, and overcome early transaction costs of collaboration (Emerson, 2018). Time in a collaborative is a significant predictor of collaborative ties (Atouba & Shumate, 2014). Previous research on the AmericaServes collaborative system finds organizational tenure is positively associated with the formation of referral ties in one CGR but negatively associated with referral tie formation in another, suggesting that additional research is needed to clarify the relationship (Annis et al., 2022). To expand the literature and test hypotheses for networks responding to shocks, I test the hypothesis:

Hypothesis 1: Organizations with longer network tenure are more likely to be active in the referral network during a crisis.

Studies observe that organization size is related to referral activities (Amati et al., 2019; Francetic et al., 2021). For example, Amati, Lomi, and Mascia (2019) find that referral events flow to larger hospitals and that larger facilities receive rather than send referrals. Francetic, Tediosi, and Kuwawenaruwa (2021) support these findings. Their results suggest that attributes related to organizational size are associated with more referrals between actors, highlighting organizational characteristics as necessary when comparing networks and their activity. Boje and Whetten (1981) suggest that larger organizations are less constrained in receiving and sending client referrals and carry more influence than smaller organizations. However, recent research by Annis and colleagues (2022) finds mixed results regarding the number of programs and referrals organizations receive in the AmericaServes collaborative system. While these pieces of literature illuminate associations between organization size and referral behavior, the characteristic of size might play a different role in an adaptive context. For example, researchers focusing on standalone organizations rather than organizational behavior within CGRs, find larger for-profit and nonprofit organizations have greater resources and prestige in place to buffer the negative impacts of a crisis than small organizations of the same type (Penrose, 2000; Guth, 1995). Cloudman and Hallahan (2006) find larger organizations engaged in more crisis preparedness activities. I focus on organizational referral sending and receipt in a community referral network during COVID-19; in this context, I may not see the same results. Testing the relationship between organization size and referral network tie behavior during COVID-19 can help clarify the relationship and contribute knowledge on network adaptation in rapidly changing contexts. To expand the literature and test hypotheses for networks responding to shocks, I test the hypothesis:

Hypothesis 2a: Organizational size is positively associated with tie behaviors through organization referral origination during a crisis.

Hypothesis 2b: Organizational size is positively associated with tie behaviors through lead organization referral routing decisions during a crisis.

I also examine the unique number of services and referral network adaptation. Research finds that organizations with more services can hold influence in the network and send and receive referrals at a higher rate than organizations with fewer services (Boje & Whetten, 1981; Whetten & Aldrich, 1977). Other research supports this notion, finding an association between collaborative ties and the number of services an organization offers (Fulton, 2016). Compared to organizations that have a lower mix of programs, meaning a lower number of unique programs offered, organizations offering more services have more opportunities to input clients in their CGR's network and to receive referrals for clients from the lead organization. For example, an organization offering food assistance, education, and employment programs has a higher service mix than an organization only focusing on food assistance programs. I expand the literature by testing the relationship between service mix and referral tie behaviors in networks responding to shocks.

Hypothesis 3a: Organizational service mix is positively associated with tie behaviors through organization referral origination during a crisis.

Hypothesis 3b: Organizational service mix is positively associated with tie behaviors through lead organization referral routing decisions during a crisis.

Authors view environmental discontinuities as positively associated with organizational reliance on network participation and adaptation (Koza & Lewin, 1998; Lewin et al., 1999, Wang et al., 2021). Network adaptation is associated with positive whole network effects, such as stability, continued ability to deliver on shared goals, and continued collaboration, which may lead to increased resource acquisition (Wang et al., 2021). Scholars write that "stability can be achieved when network effects dominate potential returns from opportunism" **(**Koza & Lewin, 1999, p. 652). The scholars posit that networks achieve stability when organizations work together as a cohesive whole CGR unit rather than focusing primarily on their organizational priorities. CGRs successfully adapt when they are viable and resilient during changing conditions, meaning CGRs adapt when they produce outputs, outcomes, and other CGR-related work in light of changing circumstances (Emerson & Nabatchi, 2015a). Suppose the AmericaServes CGRs remained operational and continued to build joint capacity during the emergence of the pandemic crisis. In that case, I expect they would have higher viability of adaptation and an improved likelihood of reaching an equilibrium of adaptation (Emerson & Nabatchi, 2015a, 2015b).

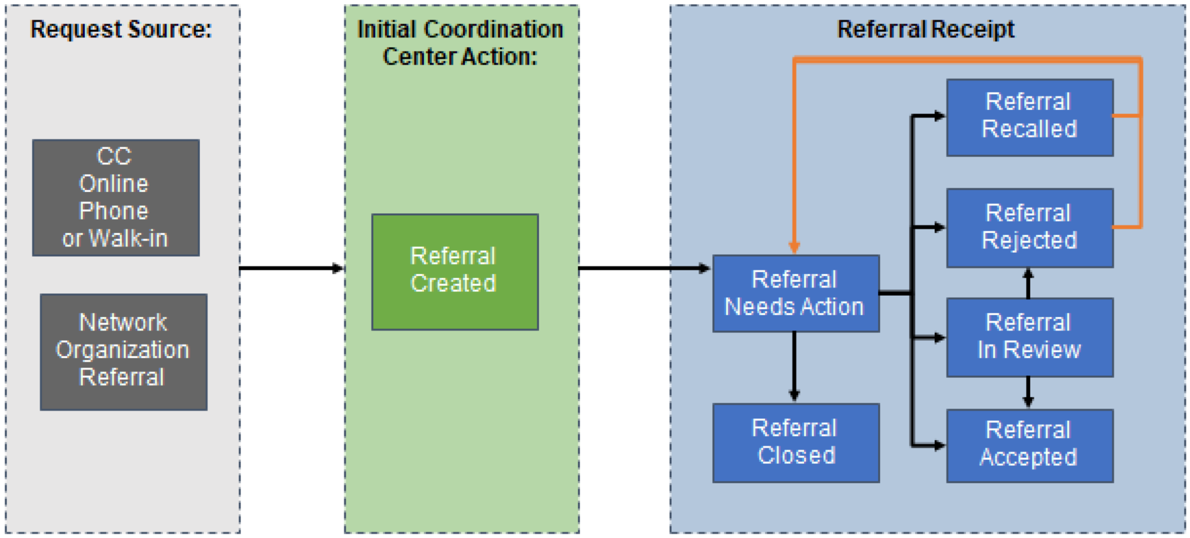
Study Context

This chapter focuses on two AmericaServes networks. These networks are veteran-serving community referral networks operating within the same U.S. state. The AmericaServes program creates a continuum of care among service providers to increase access to services for veteran families, such as housing and shelter, employment, social and spiritual enrichment, benefits navigation, income support, individual and family support, legal support, wellness, health, mental health, and food assistance. The program utilizes a novel referral network technology and the strategy of using coordination centers as lead organizations to achieve increased client accessibility, identify and address co-occurring needs, and generate individual and community-level outcomes via enhanced collaboration. In this section, I describe the AmericaServes referral process in detail. Then I focus on the CGR context, where I describe the units of analysis. I motivate the study by offering details on the population of interest, U.S. veterans, and how they were affected by the pandemic. Following that, I discuss the state that the study takes place in and how it was impacted by and responded to COVID-19 during the study period.

Coordination centers are lead organizations in the AmericaServes community referral networks under study. The centers employ intake specialists and care coordinators that link clients to appropriate providers. The coordination center is a central organizational actor that manages the intake and referral of all clients, allowing the providers in each network to focus on providing. The coordination center centralizes knowledge of services, requirements, eligibility, documentation, and more in one organization. In turn, this helps reduce care gaps in the area (Gibson et al., 2022). AmericaServes' provider members constantly collaborate. For example, the coordination center frequently brings providers together in meetings to share data and decide how to collaborate to meet their shared goals. They work together to address the public issue of improving the quality of life for veterans and their families. This approach moves these community referral networks to be higher in the collaborative spectrum as CGRs, where cross-boundary collaboration represents the prevailing pattern of behavior and activity to make decisions (Emerson et al., 2012). The coordination centers achieve cross-boundary collaboration by facilitating the trust and interdependencies necessary to produce outcomes of collaborative action and social impact (Shumate & Cooper, 2022; Emerson & Nabatchi, 2015a).

Figure 4 details how the coordination centers control referral flows in the networks. The networks I study in this chapter use the centralized hub and spoke model structure. Client referrals can originate from the coordination center's online, phone, or in-person platforms. Alternatively, referral requests can originate from providers. Providers cannot directly send referrals to and from one another. All referrals must go through the coordination center, which routes them based on client needs, eligibility, and provider capacity.

Figure 4: Referral Process Flow Diagram



CC is an acronym for coordination center. This figure provides a simplified overview of the AmericaServes process to show the coordination center's role in referral activity.

There are three key benefits of the coordination centers being centralized hubs. The first benefit is that the coordination centers track metrics on provider participation, capacity, and eligibility requirements so that the providers can focus on providing. Second, the coordination centers facilitate collaboration among the provider members and promote service accessibility by integrating care. Third, the coordination center employees specialize in client intake and identifying co-occurring needs. The cons are that the coordination center imposes formality and stability rather than flexibility, which may hinder the networks' ability to adapt to change (Provan & Kenis, 2007). Since all referrals go through the coordination center, there are no opportunities for direct peer-to-peer referral ties and activity in the community referral networks under study. If an event hinders their capacities, the coordination centers may struggle to integrate service provision (Provan & Kenis, 2007).

CGR Context

I examine adaptation in two operating within the same state: CGR 1 and CGR 2. CGR 1 covers a state's central area where over 150,000 veterans reside. CGR 2 encompasses western counties, and approximately 90,000 veterans are in its geographic area. I chose these community referral networks because they share a state system context and have similar characteristics, including the same governance structure that features a coordination center as the centralized hub (lead organization structure). The community referral networks aim to produce social impact for the state's veterans and their families, and organizations work together within them to generate population-level improvements in the quality of life of veterans and military families.

System Context: Population

Statistics reveal U.S. veterans faced heightened threats of catching COVID-19 and becoming severely ill (Feyman et al., 2022). Veterans are at high risk because they tend to be older than the general population, with a median age of 65 (U.S. Census Bureau, 2018). Veterans also tend to have more comorbidities that put them at heightened risk for severe COVID-19 compared to the general population, such as hypertension and diabetes (Feyman et al., 2022). A recent study found that morbidity among VA-connected veterans increased by 16% in 2020, the first year of the COVID-19 pandemic (Feyman et al., 2022). The pandemic also highlighted behavioral health needs. Statistics show an increase in veteran calls to suicide prevention hotlines during the pandemic. For example, Veteran Crisis Line experienced a 12% increase in call volume at the pandemic's onset (Wentling, 2020).

Veterans also face heightened economic threats that the pandemic exacerbated. Although veteran homelessness has been steeply declining since 2009, veteran homelessness increased between 2019 and 2020. Although this increase was by less than 1% (U.S. Department of Housing and Urban Development, 2021), the switch in direction is concerning. The Bureau of

Labor Statistics reported that veteran unemployment increased from 4.1% in March 2020 to 11.7% in April 2020 (U.S. Bureau of Labor Statistics, 2020). This increase reflects the effects of the COVID-19 pandemic (The Institute for Veterans and Military Families, 2020). Despite veterans receiving some of the best public benefits in the country, systemic gaps in healthcare and financial support remain (Feyman et al., 2021). Before the pandemic, the AmericaServes CGRs were already working to address this fragmentation, putting them in an opportunistic position to address changing veteran needs during the pandemic.

System Context: State

This chapter examines two AmericaServes CGRs operating in a southeastern U.S. state. There is limited public data on the pandemic's effect on veterans by state. However, pre-pandemic statistics show the state of interest had a veteran unemployment rate of 4.0% before the pandemic in 2019. In addition, 7.0% of the state's veterans lived in poverty, and approximately 798 homeless veterans resided there in 2019 (Veterans Data Central, 2019). The study period ran from January 1st to May 1st of 2020 to capture the emergence of the pandemic.

The state recorded its first COVID case on March 3rd, 2020, and logged over 10,923 COVID cases, 547 COVID hospitalizations, and 399 COVID deaths during the study period (Public Press, 2020). Public schools closed in both networks on March 23rd, 2020. The state government issued shutdown orders for retail, the inside of bars and restaurants, personal-care businesses, and recreational and entertainment businesses for CGR 1's region on March 31st, 2020, and CGR 2's region on April 4th, 2020. The trends show COVID cases, hospitalizations, and deaths increased in the state population during COVID emergence. Therefore, I expect that the pandemic shock negatively impacted veterans in the state and that the CGRs under study had to adapt to meet the changing client needs among changing system context factors. I use a mixed-method approach to explore how community referral networks adapted during the emergence of COVID-19.

Data

The first case of COVID appeared in the southeastern state of interest in March 2020. I look at two points in time. The pre-COVID period uses data from January 2020-February 2020 and the COVID emergence period used data from April 2020-May 2020. The quantitative panel data comes from de-identified system logs from the referral network technology. System log data are time-stamped interactions among organizations scraped from information communication technology platforms and do not require survey or interview participation. The data is unique because many researchers do not use it for network analysis. Scholars more commonly use interview and survey methods for network analysis. System log data are more accurate than survey or interview data because researchers do not rely on subject recall since information and communication technology (ICT) collects the data. ICT automatically collects, aggregates, and stores real-time logs of inter-organizational activities, including referrals and other connection points (Itkin et al., 2019; Landauer et al., 2020). The data provide nuanced information on how network services to clients in real-time. Network members and leaders can use that information to target their interactions to improve program implementation and service delivery. I use system data to perform network analysis to increase my study's reliability and understand the flow and evolution of interactions within the networks. The system log data allow me to capture complex networks' dynamic and evolving properties in real-time (Annis et al., 2022). I contribute to network literature by using this unique data source.

The panel includes the full sets of referral interactions for referrals that completed the whole process, from the opening of a referral to the acceptance of a referral. All referrals go through the coordination center, which sends them to a provider to deliver services. For conciseness, I interpret the analyses by discussing the organizations where referrals originated as referral senders, and I describe the organizations that accepted referrals as referral receivers.

The qualitative data comes from interviews with key coordination center managers and care coordinators within each network. I integrate system log data with interview data to inform patterns observed in the quantitative data. In doing so, I aim to uncover how the networks adapted to their changing system contexts. Integrating the findings allows me to understand how political, legal, and socio-economic factors in the system context impacted the networks and whether these factors enabled and constrained their collaboration during the study period (Emerson & Nabatchi, 2015a).

Methodologies

I divide the methodology section into two parts. First, I describe the temporal exponential graph model (TERGM) methodology. Next, I discuss the supplemental thematic analysis I perform to interpret the TERGM results better and add context to the study findings.

Temporal Exponential Graph Model (TERGM)

To explore the research questions and hypotheses, I examine network dynamics using TERGM (Robins & Pattison, 2001). Network dynamics are changes in the state of ties among a set of nodes (Shaefer & Marcum, 2017). I measure referral relations at the dyad level, meaning I measure relations between organization nodes (i.e., between care providers) (Schaefer & Marcum, 2017). The TERGM enables temporal data analysis by accommodating inter-temporal dependence in longitudinally observed networks so I can understand how provider relationships have changed over time (Shaefer & Marcum, 2017). TERGMs provide information on how past referral interactions contribute to observed network features. Since I use panel data, I use conditional maximum likelihood estimation (CMLE) for fitting the network model. I model dynamic network processes using observations of the whole network at two points using the same node-set. The strategy I describe remains the gold standard approach for temporal network data (Morris et al., 2015).

I analyze the formation and persistence of ties to understand the factors influencing the coordination center to connect two organizations through a referral relationship. I refer to referral-sending behavior, or outgoing ties, as *Activity*. I refer to referral receipt, or incoming ties, as *Popularity*. I model the likelihood of activity and popularity of providers based on organizational attributes to model the likelihood of organizations, including the coordination center, to send and receive referrals in both periods. *Edge Formation* tracks the formation of ties between pre-COVID and COVID emergence. It is the fraction of empty dyads in the pre-COVID period that formed a tie by the emergence period (Morris et al., 2015). Edge Persistence describes the number of times a coordination center connects a specific pair of organizations through referrals.

Simply put, persistence measures the number of referral ties from $t - 1$ to t, pre-COVID to COVID emergence, respectively (Leifeld et al., 2018). I examine two different persistence effects. First, the more referrals that originate from a focal Organization A get sent by the coordination center to Organization B, the more likely that the coordinate center will continue to send referrals that originate from Organization A to Organization B. Second, the more a provider Organization A receives referrals that originated from Organization B, the more likely the provider Organization A is to continue to receive future referrals that originated from Organization B.

Within the formation and persistence models, I analyze the likelihood of reciprocal referral connections appearing over time. *Reciprocity* represents how many referrals are mutually returned. For example, if a referral originates in Organization A and the coordination center sends it to Organization B, then Organization B's referrals tend to end up in Organization A due to coordination center routing. This interaction constitutes a reciprocal relationship. I also examine activity and popularity based on *Organization Tenure*, *Organization Size*, and the number of *Unique Programs* to test the hypotheses and determine whether these attributes influence tie formation or persistence. An organization's number of years in the network is organization tenure. An organization's number of programs acts as a proxy for organization size. The unique programs variable is binary, denoting whether an organization has an above-average number of unique programs offered for its network. The unique programs measure allows me to capture the diverse program mix of organizations to understand how this might influence tie formation during the pandemic.

Thematic Analysis

To enhance understanding and increase the internal validity of the analysis, I perform a supplementary thematic analysis on transcripts from interviews with three key coordination center employees at two points in time. Doing so also helps me tease out what coordination center employees perceive as network effects that have come from the pandemic and what effects they perceived to have not come from the pandemic when interpreting the TERGM results.

I collected data with a team from the Maxwell School of Citizenship and Public Affairs at Syracuse University and Northwestern University's Network for Nonprofit and Social Impact. In the first interviews, I asked respondents to discuss the pre-COVID period. I asked the respondents to discuss the COVID emergence period in the second set of interviews. I interviewed the same coordination center managers and care coordinators both times. Pre-

COVID interviews began in August 2020, and COVID interviews took place in November 2020. The research team tailored each interview protocol using data-driven findings from the community referral network in which that participant belonged (see Appendix 3 for a sample interview protocol).

In the pre-COVID interview, I asked respondents general background questions about their work with the referral system and how they made decisions about referrals. Then, I asked respondents to discuss a series of tables and graphs of what was found in the system log data to inform my understanding. Finally, I asked respondents to discuss information from January and February, before the first COVID case in the state, and to try to save information about how COVID affected them until the second interview. In the second interview, I asked respondents to tell me generally how COVID affected their work and why similar or different referral patterns emerged during the COVID period.

In both periods, I asked about efficiency (time to accept, time to care) and decision referral rules that dictate how actors route referrals throughout the network. I asked about isolates, that is, what organizations were not active in the network, to correctly identify and remove long inactive organizations from the TERGM network analysis. I also asked about the coordination center rules and the perceived role of the coordination center. These elements vary from network to network and relate to how a network responds and adapts to crises. I asked interviewees about the technology, such as workarounds and what the referral system technology does not capture. Finally, I asked about typical veteran needs that co-occur and why a referral case might go unresolved when the coordination center sends it to a provider. I use this qualitative analysis to corroborate and understand the quantitative findings. In the COVID-19 emergence interviews, I added additional questions to the interview protocol about COVID-19 changes, changes in communication and outreach protocols to clients and providers, changes in process, leadership responses, provider responses, and staffing changes. I performed thematic analysis by reading pre-COVID and COVID interview transcripts to identify patterns in meaning across the transcript data. I supply the coding scheme that emerged for the team and my efforts in Appendix 4.

Descriptive Statistics

In this section, I present descriptive statistics in two ways. First, I use system log data to quantitatively understand the averages and counts of measures in both periods. Next, I present network maps and descriptive statistics to understand the dyadic interactions and changes.

The descriptive statistics in Table 7 show that the two networks are similar. Both CGRs operate in the same collaborative system in the same state and have organizations of similar tenure, number of unique programs, and size. The organizational tenure row shows organizations in both had an average time collaborating of about three years. The organizational size row indicates that each organization's average number of programs is approximately six. An average of six shows that most organizations provide multiple programs, but it does not indicate whether these programs are diverse across service areas. For example, an organization may have six housing-related programs. To better understand program type distribution, the last row in Table 7 shows organizations' average number of unique programs per CGR. I find that organizations in CGR 1 have an average of three unique programs, and organizations in CGR 2 have an average of four unique programs.

Table 7 also shows that both CGRs experienced a decline in clients and total referral ties in COVID emergence. During a crisis event, one might expect that clients would need more services to address needs that stem from a pandemic. However, this was not the case regarding referral volume in the months following COVID emergence in this system context.

Table 7:Descriptive Statistics

	CGR 1 Pre-COVID	CGR 1 Emergence	CGR 2 Pre-COVID	CGR 2 Emergence
Organization Level				
Mean Organization Tenure (Years)	3.16	3.16	2.79	2.79
Range	0-7	0-7	0-7	0-7
Mean Organization Size	5.51	5.51	5.92	5.92
Range	0-43	0-43	0-43	0-43
Mean Organization Unique Programs	3.37	3.37	3.74	3.74
Range	0-22	0-22	0-22	0-22
Network Level				
Total Ties (Edges)	59	35	101	50
Total Reciprocal Ties	12	8	15	5
Total Providers	75	75	79	79
Total Number of Clients[8]	233	171	185	120
Median Time to Accept a Referral (Days)[9]	1.83	3.83	4.92	4.39

The CGR-level results in Table 7 indicate CGR 1's ties declined from 59 to 35, a 40% change. CGR 2 also showed less referral interaction, with ties declining from 101 to 50, a 51% change. The descriptive statistics also reveal that both networks experienced a decrease in the coordination center facilitating reciprocal referral relationships between periods. The changes were more prominent in CGR 2, which experienced a 66% decrease in reciprocal ties. The decrease in reciprocal ties suggests the coordination centers changed their referral patterns during the COVID emergence period. I may observe the change in reciprocal ties because an event

[8] The number of clients row displays the total number of clients per period in each network. Edges are disproportionally lower than the number of clients because I limit the sample to completed referral service episodes. I provide ranges where applicable.
[9] The AmericaServes system log data that the research team requested aggregated time to accept a referral at the network level, so I do not include the range in Table 7.

disrupted the development of exchange and trust between the coordination center and providers in the network (Molm, 2010). It may also reflect changing demands or provider availability.

Given that I see a fall in clients in both networks during the COVID emergence period, fewer clients may be driving the decline in total referral and reciprocal ties. The number of clients served fell by 26% in CGR 1 and 35% in CGR 2. The table shows that no providers formally left or were added to the networks during the study period.

The median time to accept a referral row shows that the networks differed in efficiency, measured by changes in their median time to accept a referral (Gibson et al., 2022). In CGR 1, it took providers three times as long to accept a referral during COVID emergence compared to its pre-COVID period. The difference in time to accept means it took providers a median of two additional days to accept a referral during the COVID emergence time. However, providers in CGR 2 experienced the opposite. CGR 2 members accepted referrals half a day faster during COVID. I follow Gibson and colleagues' (2022) suggestion to be wary when comparing networks to one another using aggregate efficiency measures since the services across networks differ in their levels of complexity. I may not be reasonably comparable using a mean efficiency measure. For example, if CGR 1 has more health service referrals and CGR 2 has more food assistance referrals, CGR 1 will appear less efficient because health services take longer to coordinate and deliver than food assistance. The qualitative interview data that I discuss later in this chapter allow me to understand these differences in depth, considering differences in service complexities.

The decreases in ties, clients, and reciprocal ties across the collaborative system, as well as efficiency differences between the CGRs, suggest that understanding the environmental shocks of COVID on community referral networks is worth pursuing. The decrease in ties and clients is especially interesting since the number of providers with formal membership in the networks stayed the same. The analyses below help uncover why these patterns emerged.

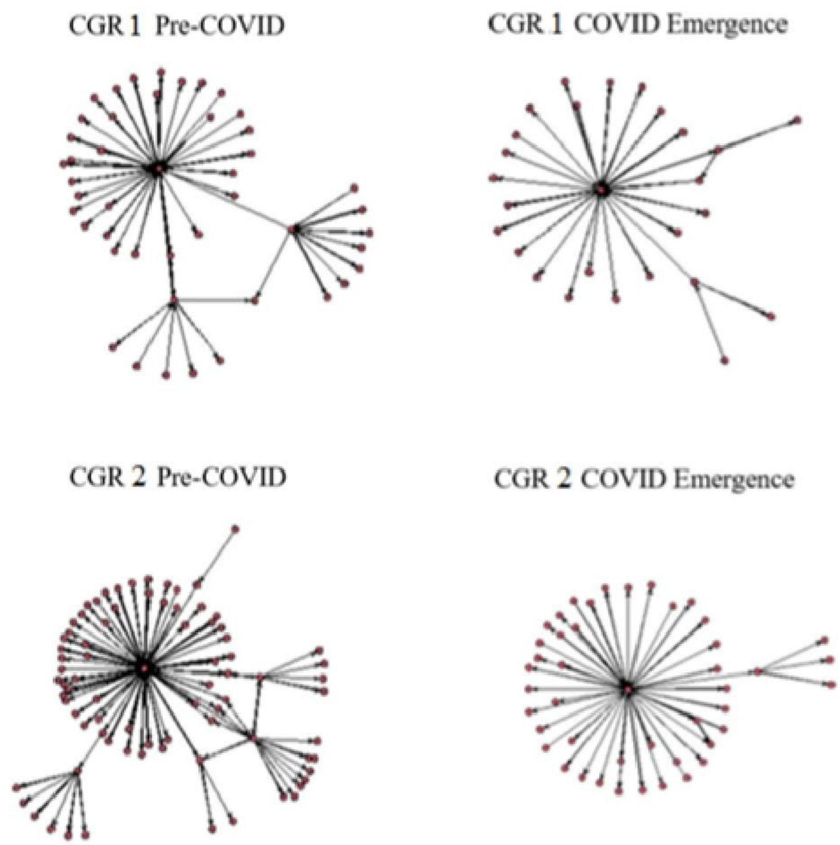
Network Maps to Visually Represent Referrals

Figure 5 illustrates the CGRs' network structures during the pre-COVID and COVID emergence periods. Arrows pointing toward nodes indicate where the coordination sent referrals and where they were accepted, indicating popularity. Arrows pointing away from nodes show where referrals originated, which could be from the coordination center or a provider organization. I call these instances of referral activity. The figures do not display the intermediate step of organizations sending referrals to the coordination center to then be directed out. Despite this, the figures show that the coordination center was at the center of many ties in both networks. On average, referrals originated from the coordination center 56% of the time in CGR 1 and 79% of the time in CGR 2 across the study period. The dense number of ties surrounding the coordination center in the center demonstrates that the coordination center was the main contributor of activity in both networks, inputting clients into the referral network in both periods. The coordination center was a prominent originator of referrals in both periods, which makes sense given the coordination center's role as intake specialists and lead organization. However, the lack of other actors so central to the network means providers are not contributing to client intake and referral activity on a large scale. The AmericaServes program encourages providers to intake clients and input referrals into the network to ensure the CGRs meet veteran-related service goals.

The branched-out areas of the network components indicate that providers were a source of referrals 33% of the time on average across the two networks, which highlights provider participation. These branched-out nodes represent referral relationships occurring where the referral originates and ends up in provider organizations outside the coordination center. CGR 1 had 23% fewer referrals originate from providers than CGR 2, on average.

CGR 1 saw a reduction of 4% in referrals that originated from the coordination center in the emergence period. CGR 2 saw an increase of referrals that originated in the coordination center of 3.2% during COVID. These opposite statistics motivate the qualitative analysis later in this chapter. The qualitative results will help me understand why referral origination from the coordination centers differed between networks during the pandemic's onset. It appears referrals that involve the coordination center form and persist more than referrals that do not originate at or end up in the coordination center, even in the COVID emergence period. The finding suggests that the coordination center may have had more stability and higher viability of adaptation than the providers in the networks.

Figure 5: Structures During Pre-COVID and COVID Emergence



The number of total ties is greater in the pre-COVID period in both networks because providers temporarily shut down, showing that there are a higher number of referrals during the pre-COVID period. The descriptive statistics in Table 7 support this finding, showing that there were 40% fewer referral ties in CGR 1 and approximately 51% fewer ties in CGR 2 during the COVID emergence period. The overall decrease in provider ties suggests that the onset of COVID-19 in the CGRs' system context played a role in the networks' change. The sparse networks during COVID emergence compared to pre-COVID also call into question providers' ability to continue to contribute to the achievement of targeted goals in their CGRs, and as such, their ability to reach an equilibrium of adaptation (Emerson & Nabatchi, 2015b). I further explore these propositions using qualitative analysis and TERGM results.

Qualitative Results

I perform a supplemental thematic analysis to disentangle what network changes occurred because of the pandemic as opposed to other factors and to build a more accurate picture.[10] Table 8 provides the count of coded excerpts from the coordination center manager and employee interviews from both periods. The interview data and the distribution of code counts into their respective thematic categories show that COVID-19 was not the only influencer of referral activity in the networks but was a large contributor.[11]

The data shows the pandemic shock to the system context led providers and the coordination center to respond. Both CGRs experienced changes in provider capacity. The coordination center employees explained how organizations responded to the pandemic. For example:

> *"Most organizations have either shut down, limited their activity, [or] limited their engagement with clientele or with other providers. It's providers that we rely on for these services."* (Participant 1, CGR 2, COVID Emergence).

> *"Their services themselves as a whole didn't change, just their ability to be able to serve those needs."* (Participant 2, CGR 2, COVID Emergence).

[10] I cannot make claims about the representativeness of prevalent patterns from the interview data. For example, interviewees discuss organizations that received more money or changed processes during COVID emergence, but I do not have a total count of how many organizations in the networks received more money or shifted operations from the interview data. I only have counts of the frequency that themes emerged. I discuss the implications and remedies for future research in the limitations section.

[11] I expect to see at least one count in each COVID-19 related column in Table 8 because I asked interviewees to answer questions about changes in communication protocols or channels, changes in process, leadership responses, outreach to clients, and provider responses during COVID emergence.

Table 8: Qualitative Analysis Descriptive Statistics

	CGR 1 Pre-COVID	CGR 1 Emergence	CGR 2 Pre-COVID	CGR 2 Emergence
Decision referral rules	105	9	17	26
Client-factors	6	0	5	12
Documentation for decision rules about referrals	1	0	4	10
Organization-based factors	52	9	0	2
System-based factors	10	0	12	3
Effectiveness of the coordination center	0	6	8	3
Isolates	34	3	21	7
Role of the coordination center	19	13	22	0
Rules about timing	6	1	41	9
Technology codes	36	11	6	7
Time to care factors	9	4	1	0
Unresolved cases	0	0	4	1
COVID-19 changes	.	51	.	48
Changes in communication protocols or channels	.	3	.	5
Communication changes in the coordination center	.	3	.	1
Changes in process	.	3	.	9
Leadership responses	.	1	.	2
Outreach to clients during COVID-19	.	5	.	4
Provider responses	.	14	.	8
Staffing changes	.	3	.	2

Values represent unique counts representing the frequency of excerpts coded per period. The bolded text represents parent nodes which include sub-node aggregate counts.

In both CGRs, providers disengaged, not only from the CGRs but altogether. The descriptive statistics show no providers formally left the CGRs. However, the interviews reveal that many providers stopped operating during COVID emergence, lowering the supply of services. Providers' ceasing operations led to challenges for the coordination center, which connects veterans to services and coordinates the CGR.

In CGR 1, interviewees attributed the lowered referral count in the emergence period to a decrease in service demand, lowered provider capacity, and provider shutdown (i.e., benefits navigation for veterans). CGR 2's coordination center also reported that they created and sent fewer referrals due to the onset of the pandemic, which helps explain the decrease in ties observed in the network maps and descriptive statistics above.

Respondents discussed the impact of providers temporarily closing and not picking up referrals in the CGRs. For example, County Veteran Service Offices temporarily closed their doors in both regions due to decreased organizational capacity, decreasing the number of benefits navigation services provided.

> *"One that jumps out to me is that significant decrease again from pre-COVID to pandemic with [veteran] benefits, which again, it's at first glance, that's really surprising, but then through thinking about it, it makes sense with our benefits providers kind of shutting doors or shutting down during that time and having significantly decreased capacity. So, I think that's what we would expect to see across many of these [services] is a decrease in the number of services being provided from pre-COVID to COVID times."* (Person 1, CGR 1, COVID Emergence).

Some organizations did not close. Instead, they changed the way they did their work. For example, a legal service provider in CGR 1 took on a more prominent role of helping clients get on unemployment when a sharp rise in unemployment arose in the state's system context due to COVID. The coordination center in CGR 1 tracked this legal organization's shift in process. It connected an expanded set of clients to the legal organization, demonstrating how provider evolution can lead to network adaptation (Koza & Lewin, 1999) and, in this case, CGR adaptation.

“<Legal Organization Name> took on a large role of helping people with their unemployment paperwork and applications. And we had a difficult time in <State> because so many people were applying for unemployment. It was taking a very, very long for people to achieve some sort of resolution with that. And <Legal Organization Name> stepped in, and it was able to help with that. So, they received a number of referrals as well.” (CGR 1, Person 1, COVID Emergence).

The coordination centers and some providers sought grant money to fill gaps and address changes in demand. Meanwhile, new grant funding lines became available to allow organizations to adapt and respond to the crisis. According to the interviews, some organizations secured these grant resources to buffer the impacts of COVID-19 on the local community. For example, employees from both CGRs reported that provider shutdowns left the homeless population, including veterans, “without anywhere to turn” (Person 1, CGR 2, COVID Emergence). This development in the system context led to a flow of grant resources. A respondent discussed how more money led to a shift in the provider’s processes.

“More money hit the fan. More resources came for emergency housing. And so, another provider of ours shifted their model from getting them permanent supportive housing into getting them into crisis beds… they sort of shifted their mission to fill those emergent beds to help quarantine the people. So, they went away from helping somebody get permanent supportive housing and looking at self-sufficiency. And they walked away from that… and shifted their efforts through some other grants and through the city to open up an additional shelter that had a better model of social distancing inside this huge Civic Center.” (Person 2, CGR 2, COVID Emergence).

The qualitative results reveal the tendency for reciprocity between dyads. Interviewees point out that referrals that originate in the coordination centers end up in organizations that operate under the same umbrella organization as the coordination center (henceforth, sister organizations) and vice versa. I find evidence that these organizations are large, more established in the network, and offer a broad mix of services. For example, when the coordination center in

CGR 2 cannot find a better provider, they tend to send to their sister organizations, as displayed by the following quote:

> *"I use the terminology of we are a self-licking ice cream cone because [CGR 2] is housed within <Umbrella Organization Name>. So, we have so many…direct service needs that I provide to the community, whether it be food from my mothership, housing, employment, utility assistance. So, because we're such a gorilla and I provide those services, oftentimes when those needs come in, when there's no other providers engaged, it's easier for us to send it to ourselves. Essentially, we say to ourselves, to our mothership, and they provide that service...because we are so deep and our breadth is so large that we're able to provide those services quicker because it is our organization. And we're not as reliant on other entities that may not be operating at full capacity."* (Person 1, CGR 2, COVID Emergence)

It is important to remember that referrals can originate from all organizations in the network, not just the coordination center. Still, they go through the coordination center if another organization is the receiver. The qualitative data suggest the coordination center and its sister organizations account for a high proportion of the reciprocal relationships during the COVID period. They led reciprocal ties for two reasons. First, the coordination center is the principal originator and receiver of referrals. Second, the coordination center remained active during the COVID period, with both CGRs' coordination centers' day-to-day practices remaining stable and not changing greatly. A key socio-economic factor contributed to their stability. In their local system context, CGR 1, CGR 2, and their sister programs were deemed essential services by government officials.

> *"I think that for us here, it really didn't affect my business operations, right? Like we were deemed essential early on by the governor [and] by the cities that we operate in. We were deemed essential."* (Person 1, CGR 2, COVID Emergence)

The findings suggest that the quantity and reciprocity of referral ties relate to resource munificence. The coordination centers and their sister providers had the incentive and permission to continue serving veterans during the pandemic. Therefore, they had a greater ability to input clients into the network and receive referrals. Thus, they had more opportunities for the coordination center to drive their reciprocal relationships during the study period, especially during COVID-19. My findings align with scholars' proposition that network effectiveness and stability are most likely in resource-rich environments and least likely in resource-scarce environments (Milward & Provan, 2000). Those providers that had grant funding from the government before COVID and were given even more during COVID had higher viability of adaptation. However, grant parameters did not change and restricted the types of services they could offer and how they delivered them. The grant parameters encouraged the coordination centers to continue their normal referring patterns rather than branching out. The coordination center did not send referrals to more unique service providers or facilitate new referral ties between organizations with whom they would not usually form ties, as was reflected in the network visualizations above. These qualitative results contribute to answering the hypotheses on whether organizational attributes like reciprocity, unique services, and quantity of services may impact tie formation and persistence in referral behavior in the quantitative results.

"COVID happened, and we were deemed essential. And so, like any other pandemic or emergency crisis that happens, the government throws resources at it, right? And so, in this case, we got thrown a lot of money. The community got thrown a lot of money to support and assist with this with little to no guidance or change on the parameters of our grants." (Person 1, CGR 2, COVID Emergence)

Numerous times, the interview data suggested a positive relationship between organizational tenure and continued CGR participation during COVID. The data also suggests a relationship between organizational tenure and having a close relationship with lead organization leadership in the coordination centers. For example, CGR 2 reported that an above-average tenure organization changed its mission to do more on-the-ground outreach to veterans using drive-through resource fairs, job fairs, and food distribution, and even invited coordination center staff to be a part of those events. In another example, CGR 2's interviewee reported that an organization with six years in the network pivoted to meet needs during the pandemic. The coordination center sent referrals to organizations with above-average network tenure to respond to urgent needs during the COVID emergence period.

> *"But one in particular that really stands out to me is <Organization Name> as an employment provider, and really a career transition provider has gone from teaching a single class a month, traveling, physically driving to different parts of <State Name> to meet with clients and teach a class for a week at a time and do it once a month to now teaching typically two classes per month to clients from, at this point, all over the world…So, in this situation, the pandemic has really opened up doors because it has forced that evolution in the way that the service is provided, which has made it possible to reach a greater number of people than we were previously capable of."* (Person 1, CGR 1, COVID Emergence)

> *"One of our communities has really been trying to wrap their arms around the community and trying to embrace this quasi-new normal that we're in. So <Organization Name>, for example, has done quite a few drive-through resource fairs where it's either a job fair with employers who have, you know, have openings right now, or Friday, they had a resource fair. So different organizations in the community came together. They passed out food boxes for individuals. And so, our staff have been really fortunate to be a part of those events."* (Person 2, CGR 2, COVID Emergence)

According to the interviews, it became more challenging to understand provider capacity when face-to-face meetings ceased among CGR members during COVID.

> *"Pre-COVID, we would hold what I call…round tables and focus groups. So, we would host meetings… and we would sit down and talk and say, hey, what's working? What's not working, apples to apples? What are you measuring? What are we measuring? And not only is it just for us, but it is for the other partners are working with each other organically out of the system and the community. It would allow transparency across the board to sort of say, what's your capacity right now? What do your grants look like right now? Who is your new staff right now?"* (Person 1, CGR 2, pre-COVID)

> *"Before we were more dialed into each organization through the network, and because we weren't meeting in person, that sort of went away."* (Person 1, CGR 2, COVID Emergence)

Meanwhile, client urgency for certain services increased. Organizational flexibility to change service delivery processes and reach veterans on the ground contributed to tie formation and persistence during the pandemic. Coordination center interviewees felt that providers adapted to changing needs in the community, such as feeling unsafe going to the grocery store to get food during COVID.

> *"It was those referrals for food, for immediate clothing, for immediate transportation. And so, we were connecting those initially."* (Person 2, CGR 2, COVID Emergence).

The qualitative results help answer the research question: How did referral networks in a U.S. state adapt to changing supply of and demand for services during the emergence of COVID-19? The thematic analysis shows that most providers stopped operating or using the network to deliver services. That is why I observe a lower quantity and less diverse referral ties at the pandemic's onset. The results suggest that the coordination centers and their sister organizations drive reciprocal network ties in both periods. The data also suggests that organizations with established relationships, trust, and experience in the network through longer tenure could acquire more grant resources, stay functioning, and shift their processes to reach people in need if their funding models allowed it.

In line with Emerson and Nabatchi (2015), interviewees attributed adaptability to political and socio-economic factors in the state and local system contexts. Social and political decisions to deem specific organizations as essential and economic decisions to provide them with increased funds to meet changing demands allowed some organizations to increase their viability of adaptation. These organizations represent the nodes that could adapt and remain stable in the networks during the pandemic's onset. The patterns that emerged in the thematic analysis corroborate the network maps and descriptive statistics. In the following section, I use TERGM analysis to test my hypotheses on what factors drove coordination center referral decisions during COVID emergence.

TERGM Results

Table 9 presents the TERGM results. The edge rows can be interpreted as the intercept in a simple linear regression and help control for the network's density. The results show the coefficients for reciprocity in both networks' formation models are significant. I transform the coefficients representing the log odds of tie formation into odds ratios to interpret the results. In CGR 1, organizations were 80.47 times more likely to have the coordination center facilitate reciprocal referral ties between organizations. In CGR 2, organizations were 62.48 more likely to have the coordination center facilitate reciprocal referrals.

Organizations were more likely to accept referrals from organizations that had previously accepted their referrals, orchestrated by the lead organization (Provan & Kenis, 2007). The finding helps answer the research question of how referral networks adapted during the emergence of COVID-19. During the COVID-19 emergence, referral relationships were more likely to form when the coordination center closed mutual dyads.

Hypothesis 1 posits that organizations with longer network tenure are more likely to be active in the referral network during a crisis. I found a significant result in CGR 2's Formation model on referral-sending behavior for organizations with longer organizational tenure, meaning that in CGR 2, organizations who were part of the collaboration for more extended amounts of time were more likely to be active in the network. They were more active in that they more often created referrals and sent them to the coordination center, which then sent the referral out to the appropriate provider. Thus, I find a statistically significant difference in outgoing referral tie formation associated with organizations' tenure in the network compared to those organizations that have been in the CGR for less time.

Next, I transform the coefficient. The results show that organizations that have been in the community referral network longer have a 2.30 increased likelihood of creating and sending a referral to the coordination center. The finding shows more tenured organizations are more likely to form a referral tie relationship compared to organizations with lower tenure in the network. Given the significant result in CGR 2 but not CGR 1, my results partially support Hypothesis 1.

Neither the total number of programs nor whether organizations had an above-average number of unique programs were found to be significant for incoming or outgoing tie formation in this model. I do not find significance reciprocity or any organizational covariates to be significant for persistence in the CGRs in this analysis. Therefore, I do not find support for Hypothesis 2a, that organizational size is positively associated with tie behaviors through organization referral origination during a crisis. It also means that I do not find support for Hypothesis 2b, that organizational size is positively associated with tie behaviors through lead organization referral routing decisions during a crisis. I also do not find support for Hypothesis 3a or 3b. Hypothesis 3a stated that organizational service mix is positively associated with tie behaviors through organization referral origination during a crisis. Hypothesis 3b posited that organizational service mix is positively associated with tie behaviors through lead organization referral routing decisions during a crisis.

Table 9: TERGM Models

	CGR 1	CGR 2
Formation Models		
Network Structure		
Edge	-5.38*** (1.27)	-9.72*** (1.76)
Reciprocity	4.39*** (0.73)	4.13*** (0.72)
Receiver Effects (Popularity)		
Organization Tenure	-0.57 (0.30)	0.18 (0.43)
Organization Size	0.01 (0.05)	-0.03 (0.36)
Organization Unique Programs	0.32 (0.75)	-0.68 (1.69)
Sender Effects (Activity)		
Organization Tenure	0.09 (0.25)	0.83** (0.39)
Organization Size	0.07 (0.10)	0.08 (0.32)
Organization Unique Programs	n/a	2.12 (0.39)
Persistence Models		
Network Structure		
Edge	0.19 (0.98)	-1.43 (1.20)
Reciprocity	0.50 (0.75)	0.43 (0.78)
Receiver Effects (Popularity)		
Organization Tenure	0.13 (0.16)	0.19 (0.23)
Organization Size	0.03 (0.03)	-1.87 (1.06)
Organization Unique Programs	-0.70 (0.55)	0.44 (0.34)
Sender Effects (Activity)		
Organization Tenure	-0.26 (-1.03)	0.44 (0.34)
Organization Size	-0.08 (0.05)	-0.51 (0.41)
Organization Unique Programs	-0.15 (0.72)	1.74 (1.51)

Standard errors are in parentheses.

Significance codes: $p<.001$ ‘***’ $p<.01$ ‘**’ $p<0.05$ ‘*’

Table 10: Results by Hypothesis

Hypotheses	Results
Hypothesis 1: Organizations with longer network tenure are more likely to be active in the referral network during a crisis.	Fail to reject the null hypothesis for CGR 1 Significant for CGR 2
Hypothesis 2a: Organizational size is positively associated with tie behaviors through organization referral origination during a crisis.	Fail to reject the null hypothesis
Hypothesis 2b: Organizational size is positively associated with tie behaviors through lead organization referral routing decisions during a crisis.	Fail to reject the null hypothesis
Hypothesis 3a: Organizational service mix is positively associated with tie behaviors through organization referral origination during a crisis.	Fail to reject the null hypothesis Significant
Hypothesis 3b: Organizational service mix is positively associated with tie behaviors through lead organization referral routing decisions during a crisis.	Fail to reject the null hypothesis

Various reasons may explain why I did not find support for Hypotheses 2a, 2b, 3a, and 3b in the TERGM analysis. First, limited research on changes in tie behaviors within CGRs during crisis shocks underpins the hypotheses. Second, the lack of support for Hypotheses 2a, 2b, 3a, and 3b might signal imprecision in the TERGM. For example, the choices I made for modeling the relationships, such as choosing formation and persistence models rather than looking at tie dissolution, may have introduced imprecision.[12] Third, changes in tie behavior for larger

[12] Dissolution tracks the dissolution of ties and its output represent factors which influence tie dissolution (Hoffman, n.d.).

organizations or organizations with more diverse service mixes may occur in the long term, and perhaps not enough time has passed. Finally, based on research by Gibson and colleagues (2022), I may find support for hypotheses if I perform a subgroup analysis of referral behavior where I disaggregate by service type. I further discuss this in the limitations section below.

Discussion

My guiding research question is, how did community referral networks adapt to changes in supply and demand for services during the emergence of COVID-19? I provide an overview of the results and the implications of each. I then discuss the overall study in light of limitations, future research, and practical implications. Hypothesis 1 posited that organizations with longer network tenure are more likely to be active in the referral network during a crisis. I found this relationship significant in CGR 2 but not in CGR 1. Therefore, I find partial support for Hypothesis 1.

Hypothesis 2a posited that organizational size is positively associated with tie behaviors through organization referral origination during a crisis. Hypothesis 2b stated that Organizational size is positively associated with tie behaviors through lead organization referral routing decisions during a crisis. Hypothesis 3a states that organizational service mix is positively associated with tie behaviors through organization referral origination during a crisis. Hypothesis 3b posited that organizational service mix is positively associated with tie behaviors through lead organization referral routing decisions during a crisis. I could not reject the null in favor of the alternative hypothesis for Hypotheses 2a, 2b, 3a, or 3b.

My results highlight supply-side factors which contributed to and inhibited CGRs' viability for adaptation. First, I find that CGRs became less stable due to temporary provider exit and less flexible governance structures, leading to lower member participation in crisis. Second, I find that the abrupt cessation of face-to-face interactions dealt a great blow to the CGRs' viability of adaptation through lowered opportunities to build shared motivation. Third, organizational factors contributed to some members being more adaptable and willing to continue in the CGR than others, including organizational tenure and relation to the coordination center. I discuss leadership factors that contribute to the success of collaborative governance in crisis management and suggest management strategies considering the findings.

In line with Karemere and colleagues (2015), I find that crisis emergence led to the sudden departure of providers. First, CGRs became less stable due to temporary provider exits and less flexible governance structures, leading to lower member participation in crisis. Informal member exit decreased care activities because CGR members were not participating in the care system. For many providers, the returns to focusing on organizational priorities, such as employee health and safety, were higher than the returns of continued participation in the CGRs (Koza & Lewin, 1999).

Other providers stayed open but participated less in the CGR. The network maps, descriptive statistics, and qualitative interviews reveal that several CGR members remained open but worked around the community referral network. Their choices suggest that the organizations were frustrated with referral network responses to the pandemic. Rather than going through the hub-and-spoke, lead organization-governed community referral network model with the coordination center directing ties, organizations saw greater returns to modifying their service delivery to locate and serve clients directly and more quickly. Changes in client demands, including urgency with employment, food assistance, and housing service types, also drove provider decisions to work outside of the CGRs. Lower participation changed how the CGRs performed. Lower participation also broke down some of the coordination centers' functions, creating difficulties for these lead organizations to fulfill their duties (Provan & Kenis, 2007) and for providers to continue to build joint capacity as a cohesive unit (Emerson et al., 2012; Emerson & Nabatchi, 2015a).[13] AmericaServes coordination centers could no longer effectively perform their key roles as lead organizations orchestrating ties and directing the CGRs. Temporary provider exit and lowered member participation made CGRs less stable and viable for adaptation.

Second, the abrupt cessation of face-to-face interactions affects the CGRs' adaptation viability through reduced opportunities to collaborate effectively. The breakdown inhibited the meetings where providers came together for collaborative governance. It became more difficult for the CGR members to develop shared motivation, that is, the interpersonal elements of trust and motivation of getting people to work together (Emerson et al., 2012; Emerson & Nabatchi, 2015a). The coordination center routes referrals based on the information from those meetings, including network goals, eligibility requirements, and provider capacity. Coordination center employees could not as efficiently and accurately gauge these metrics to make informed CGR management decisions, leaving the CGRs in precarious positions at a time when efficient coordination mattered most to adapt. Pandemic shocks can affect CGRs' ability to build the shared motivation needed to keep members involved and lead organizations functioning correctly.

My third key finding is that well-known providers, such as the coordination centers, their sister organizations, and those organizations with an above-average tenure in the network, remained active and were better able to adapt to the changing system context during COVID emergence. The TERGM results provide further insight, revealing two interesting drivers of formative ties: reciprocity and organizational tenure. The reciprocity results show coordination

[13] Joint capacity describes when actors come together to solve something that they cannot solve alone and therefore must build additional capacity to get work done (Emerson & Nabatchi, 2015a).

centers tended to route referrals between familiar partners. Referral relationships were more likely to form when the coordination center closed mutual dyads in both CGRs. The coordination centers were more likely to send referrals between organizational dyads where they previously originated in one organization and were accepted in the other.

Similarly, organizations were more likely to accept referrals from organizations who had previously accepted their referrals, orchestrated by the coordination center lead organization. The finding suggests that the hub and spoke structure facilitates a feedback loop, with the lead organizations tending to route referrals between familiar partners. Reciprocal relationships occurred frequently but only involved a handful of providers. Many of these providers are part of the same umbrella organization as the coordination centers. These providers also had large grants before COVID while receiving additional large grants when COVID emerged and were deemed essential by the state government. A CGR that has a predominance of reciprocated ties over asymmetric connections may be more “equal” or “stable” than one with a predominance of asymmetric connections (Hanneman & Riddle, 2005). Despite the significant TERGM results for reciprocity in both CGRs, the descriptive statistics show that during the COVID emergence period, reciprocity decreased in both CGRs. The results imply that the CGRs became less stable overall.

My partial confirmation of Hypothesis 1 on organizational tenure shows that during COVID emergence, organizations with higher organizational tenure were more likely to create referrals in one of the CGRs. The findings show that older organizations in the CGR 2 were significantly more likely to originate and send referrals to the coordination center during COVID emergence than organizations in the network for less time. Organizations that had been in CGR 2 for more extended amounts of time adapted by straying from their normal processes to do increased on-the-ground outreach in conjunction with the coordination centers and pivot service delivery to meet the change in demands. Unlike some other members, these organizations continued using CGR's referral system. Strong relationships between organizations and the coordination centers increase the chances of longer-tenured organizations' participation in CGRs, encouraging greater CGR ability to adapt during crises.

The network leadership of the coordination centers contributed to the networks' viability of adaptation by acquiring resources, utilizing the remaining supply of organizations, and leaning on organizations with higher tenure. Leadership also contributed to network viability of adaptation by supporting provider organizations as they adapted, such as when they changed outreach strategies to target clients and meet changing demands in the changing context. At the collaborative system level, state leadership supported the CGRs as solutions to buffer the negative impacts of the COVID-19 crisis by deeming central organizations from the CGRs as essential and providing them with grant funding. The findings suggest that those who want to increase the success of collaborative governance in crisis management should focus on leadership factors of collaboration.

CGR decision-makers should choose governance structures that meet their needs and facilitate integration but also leave room for flexibility in times of crisis (Provan & Kenis, 2007). Opening the possibility for CGRs to decentralize and create allowances for provider-to-provider referrals may avoid hub and spoke bottlenecks during urgent crises (Provan & Kenis, 2007), even if this is only temporary. Lead organization managers should be careful not to perpetuate feedback loops through referral ties between only a few providers, who end up being the most active in the CGRs.

Lead organization managers can also create more stable and equal community referral networks by encouraging all members to increase referral activity through increased client intake and referral-sending behaviors. Network leaders should continue encouraging members to create referrals and input veterans into the system. Doing so will improve CGR member activity and help the CGRs meet their overall goals through improved identification of clients in need and an increased ability to identify and address whether they have co-occurring needs. In this case, the CGRs' goals revolved around the improved quality of life and lowered system fragmentation for veterans and their families.

Future Research

Future research should examine sending and receiving referral patterns by service type (Gibson et al., 2022). For example, coordination centers focused on helping organizations meet urgent client needs during COVID emergence, such as food assistance and passing out supplies. Interviewees indicated that sometimes, these highly urgent and less complex services were the quickest to address (Gibson et al., 2022). Conversely, housing services were an urgent need that took longer to deliver due to pandemic changes. Organizations housed homeless clients in hotels and civic centers for extended periods, negatively affecting their efficiency metrics. Gibson and colleagues' (2022) work also determines that efficiency differs by service type complexity (i.e., housing versus food). The authors conclude that efficiency can significantly vary across AmericaServes networks. Due to this, I suggest future research investigate how crises affect efficiency and other performance metrics by service type.

Another future research direction is further testing the impact of resource munificence on network adaptation. In line with Li and colleagues (2021), I observe that the highly visible public issue of the COVID-19 pandemic helped some organizations to attract more public attention and resources. Organizations that remained stable and central to the CGRs in COVID emergence also reportedly received grant resources. These organizations had some of the most stable ties during COVID-emergence, supporting the notion that additional resources increase the viability of adaptation. According to the integrated framework of collaborative governance, increases in funding can improve the viability of adaptation in a CGR. Funding improves viability by facilitating improved joint capacity, such as by allowing CGRs to have the slack resources to accomplish more together than they could individually (Emerson & Nabatchi, 2015a; Emerson & Nabatchi, 2015b; Emerson et al., 2012). The findings support previous evidence that resource munificence helps build ties. Slack resources help organizations manage tie turnover, which occurs when established relationships dissolve (Bunger & Huang, 2019). To increase stability and equality in the network, the coordination center should use its hub position to generate more reciprocal ties between a more expansive array and a more diverse group of CGR members (Hanneman & Riddle, 2005). In doing so, the coordination center lead organizations can buffer future impacts of unexpected crises on the CGRs they govern.

Limitations

My research is not without limitations. First, I focus on community referral networks and their referral behaviors at two points. Future studies can broaden my analysis to examine adaptation at different points during the COVID-19 pandemic. Adding more periods can improve the robustness of the analysis by revealing more historical patterns. The mixed methods approach, especially the interviews, helped me remedy some concerns about what patterns I can attribute to the pandemic's onset. Second, the case study design does not allow me to claim that these results apply to broader populations beyond contingent examples, such as similar CGRs operating in the same program. However, the case study design helps uncover and refine collaborative governance theory about the viability of adaptation in collaborative dynamics that apply to many cases, even though the effects of such mechanisms can differ from one case context to the next (George & Bennett, 2005). In addition, my work features high internal validity due to having the full roster of provider and system log data during the study period and validating the results through a mixed-method design. Third, the system log data does not show the provider activity occurring outside the network, but this does not mean it is not occurring. The qualitative results help remedy this, with coordination center interviewees providing information on member service delivery outside the referral system technology. However, a fourth limitation is that it is difficult to ascertain the representativeness of prevalent patterns from the interview data. For example, interviewees discuss organizations that received more money or changed processes during COVID emergence. Still, I do not have a total count of how many organizations in the CGRs received more money or shifted operations from the interview data. To enhance future analysis, I suggest future researchers interview providers and collect data on changes in provider-level funding resources and procedural patterns over time. Despite this limitation, the findings speak to the benefits of mixed-method research. The qualitative data allowed a deeper understanding and informed interpretation of the quantitative results. Using system log data directly from the CGRs' ICT platforms allowed me to analyze CGR change over time, contributing to the public administration field.

Conclusion

In this chapter, I discuss veteran networks. Veterans have complex needs (Carboni et al., 2022; Feyman et al., 2021; Wentling, 2020). The findings can inform community referral networks and CGRs that cater to helping other groups that experience complex needs. For example, the results from this research can inform other collaboratives operating globally (Emerson, 2018; Shumate & Cooper, 2022). The results are timely as policymakers in Washington continue to call for collaborative approaches to a broad range of human services (Butler & Sheriff, 2021; Shumate, 2022).

As environments evolve from stable to increasingly chaotic, actors use collaborative initiatives as an integral element of their adaptation strategies (Koza & Lewin, 1999). Policymakers and managers can benefit from ensuring CGRs are funded across their life course to mitigate CGR instability and inflexibility in crises. When faced with an unexpected disaster, CGR leaders can strategically attract attention and resources to stabilize ties, improve joint capacity, and ultimately create adaptable networks during times of heightened public attention to a crisis (Emerson et al., 2012; Emerson & Nabatchi, 2015a, 2015b; Li et al., 2021).

In this work, I highlight the importance of managers staying aware of changes in the legal, political, and socio-economic factors in their CGR's system contexts. The findings suggest that those who want to increase the success of collaborative governance in crisis management should focus on leadership factors of collaboration (Shumate & Cooper, 2022). The research findings align with the widely accepted notion that leadership is critical to collaborative governance (Emerson & Nabatchi, 2015a; Emerson, 2018; O'Leary et al., 2012; Lee et al., 2010). The CGRs in this stud survived the initial pandemic's shock due to leadership's understanding of the political and socio-economic factors in their state and local systems contexts, such as changes in demand, increases in grant funding, and the political categorization of essential services. CGR leadership can also increase CGR viability for adaptation by encouraging reciprocal relationships and motivating long-term provider participation to deepen organizational buy-in and trust through organization tenure.

Research on network adaptation informs the work of collaboratives in a time where collaborative approaches to a broad range of human services continue to increase (Butler & Sheriff, 2021; Shumate, 2022; Carboni et al., 2022). My work fills gaps in the public administration literature on how actors use collaborative governance in different system contexts.

I show how CGRs can be more flexible by focusing on the governance structure types that help support them, such as lead organizations. Rapidly changing system contexts are increasing, and leaders can be ready by understanding how to adapt and steer collaborative systems in response to crises.

The findings contribute to knowledge and work in network governance, service delivery, and adaptation during shocks. From a network governance perspective, I illuminate how networks with centralized network governance operate and adapt during major disasters. Authors assert that addressing complex issues requires more than meeting individual organizations' goals. It requires collective action and governance (Provan & Kenis, 2007). My findings show that forming and maintaining interorganizational interactions is critical for community referral networks to adapt and be resilient during shocks. Network decision-makers can benefit from choosing governance structures that meet their needs and facilitate integration while also leaving room to use more flexible governance structures in times of crisis.

Chapter Three: CGRs, System Contexts, and Outcomes: The Case of Medicare ACOs

By Catherine Annis

Abstract

I utilize the integrative framework for collaborative governance (Emerson & Nabatchi, 2015a) to examine collaborative governance regimes (CGRs), their broader system context, and an outcome of interest. I ask, how can scholars identify and measure the characteristics of CGRs, their broader system contexts, and their collaborative outcomes? I explore the question in the context of Accountable Care Organizations (ACOs) in U.S. Medicare. I use descriptive and inferential statistics on two representative samples of Medicare ACOs and Medicare beneficiaries. I find that, by using secondary data more traditionally reserved for program evaluation and policy analysis, analysts can garner rich insights on CGRs, their broader systems contexts, and important outcomes to their beneficiaries.

Introduction

ACOs are networks of providers (i.e., physicians, hospitals, and others involved in patient care) that collaborate through a unified governance structure that assume the risk for the quality and total cost of the care they deliver (Kocot et al., 2015). In this chapter, I apply the integrative framework for collaborative governance to the literature on Medicare Accountable Care Organizations (ACOs) to explore collaborative governance. Scholars use the integrated framework to identify what is common to most cases of collaborative governance and provide a theoretical foundation to explore themes from scholarly literature (Emerson & Nabatchi, 2015a). I study Medicare ACOs using three elements of the framework: collaborative governance regimes (CGRs), the broader system context, and a collaborative outcome.

Collaborative governance regimes (CGRs) are “a particular mode of, or system for, public decision making in which cross-boundary collaboration represents the prevailing pattern of behavior and activity among autonomous participants who have come together to achieve some collective purpose defined by one or more target goals” (Emerson & Nabatchi, 2015a, p. 18). Broader system context refers to “the broad and dynamic set of surrounding conditions that create opportunities and constraints for initiating and sustaining CGRs,” (Emerson & Nabatchi, 2015a, p. 232). Outcomes include “the intermediate changes in conditions necessary to reach target goals and the resulting effects of accomplishing these goals” (Emerson & Nabatchi, 2015a, p.84). To explore systematic links between broader system contexts, CGRs, and collaborative governance outcomes, I ask the question:

RQ1: How can researchers identify and measure the characteristics of CGRs, their broader system contexts, and their collaborative outcomes?

Using the integrative framework, I contribute to the foundation of knowledge for studying collaborative governance that scholars can use to assess collaborative governance across cases (Bultema et al., 2020; Emerson & Nabatchi, 2015a). I also contribute to research on ACOs as collaborative governance initiatives, where a limited number of scholars have begun to explore this topic (Addicott & Shortell, 2014; Shortell et al., 2010). I contribute to practice by opening questions about CGR selection in some state markets relative to others. I also contribute to practice by exploring differences in a collaborative governance outcome using a matched treatment and comparison group design.

Collaborative Governance and Medicare ACOs

Current U.S. healthcare reform under the Affordable Care Act (ACA) points to increased collaboration as a policy solution to improve public healthcare. The ACA frames collaboration as a solution to close gaps and increase the effectiveness of U.S. health resources through better access, convenience, and timeliness of care delivery for patients at lowered costs (Feinstein, 2014; Petty, 2017). The ACA grants decision-making authority on health care policy implementation to ACOs participating in the Centers for Medicare & Medicaid Services' (CMS) Medicare Shared Savings Program (MSSP), henceforth Medicare ACOs. Technically, Medicare ACOs are separate legal entities from the providers they govern. Rather than integrating the policies and procedures from multiple participants, the ACO and its governing body work together to "determine what uniform policies and procedures to apply across the ACO" (Department of Health and Human Services, 2015, p. 32717).

I use the definition of CGRs to develop criteria to understand whether I can study ACOs as collaborative governance initiatives (Emerson and Nabatchi, 2015). The definition includes the following elements: (1) CGRs consist of autonomous participants, (2) cross-boundary collaboration represents the predominant mode for the conduct, decision-making, and activity, and (3) actors come together to achieve some collective purpose defined by one or more target goals. Medicare ACOs meet the first criterion that CGRs consist of autonomous participants.

HHS grants ACO participants flexibility in how they will interact and govern themselves (Department of Health and Human Services, 2015), and provider participation in an ACO is purely voluntary (Centers for Medicare and Medicaid Services, 2011).

ACOs meet the second criterion that cross-boundary collaboration represents the predominant mode for conduct, decision-making, and activity. Stakeholders involved in the legislative design of Medicare ACO reported, “there must be strong collaboration among multidisciplinary team members to ensure care coordination and patient-centered care” (Department of Health and Human Services, 2011, p. 67808). However, it is unclear whether HHS enforces cross-boundary collaboration since ACO participants have flexibility in designing their governance models. Still, HHS mandates the shared governance structure of ACOs to facilitate cross-boundary collaboration as the predominant mode for decision-making. The ACO model suggests a governance structure and accountability processes individuals and organizations operate collaboratively within the overarching ACO boundary (Addicott & Shortell, 2014). In this chapter, I assume that ACOs meet these standards.

Finally, Medicare ACOs meet the third criterion of a CGR: autonomous participants come together to achieve a collective purpose defined by one or more target goals. ACOs are provider-driven, and stakeholders voluntarily come together to achieve the goals of better care for individuals, better health for populations, and lower growth in expenditures (Department of Health and Human Services, 2011). The ACA incentivizes collaboration through Medicare ACOs because no one organization can generate better health for populations or lower growth in U.S. healthcare expenditures alone.

I further classify ACOs as formalized CGRs (Emerson & Nabatchi, 2015a). Formalization in the collaborative governance literature refers to the structure of collaborative arrangements for developing and implementing joint activities using shared resources (Ansell & Gash, 2008). Medicare ACOs are formal CGRs because they feature formal and informal rules, protocols, and structures to manage their interactions over time (Emerson & Nabatchi, 2015a). For example, ACOs are registered legal structures with a unique taxpayer identification number and must be legally recognized and authorized to conduct business under state laws (CFR § 425.20).[14]

I classify Medicare ACOs as CGRs based on the criteria outlined above. CMS does not require that Medicare providers remain exclusive to one ACO (American Academy of Family Physicians, 2011). Providers technically can belong to multiple Medicare ACOs, and some do, meaning that membership overlap exists (Medicare Payment Advisory Commission, 2020). It is worth mentioning that Medicare ACOs make up a collaborative system under these criteria. A collaborative system is the larger networked space in which collaborative governance regimes (CGRs) and collaborative platforms are embedded (Annis et al., 2020). However, membership overlap and the connections between ACOs are out of the purview of this analysis. In this chapter, I focus on Medicare ACOs and their system contexts. In the following section, I describe the framework I use to study Medicare ACOs as collaborative governance initiatives.

The Integrative Framework for Collaborative Governance

I apply literature on ACOs to the integrative framework for collaborative governance to overview how ACOs function as collaborative entities (Emerson & Nabatchi, 2015a). The integrative framework for collaborative governance includes the major concepts needed to understand how collaborative governance works (Figure 6). The framework considers the broader system context that enables and constrains collaboration, such as the history of conflict

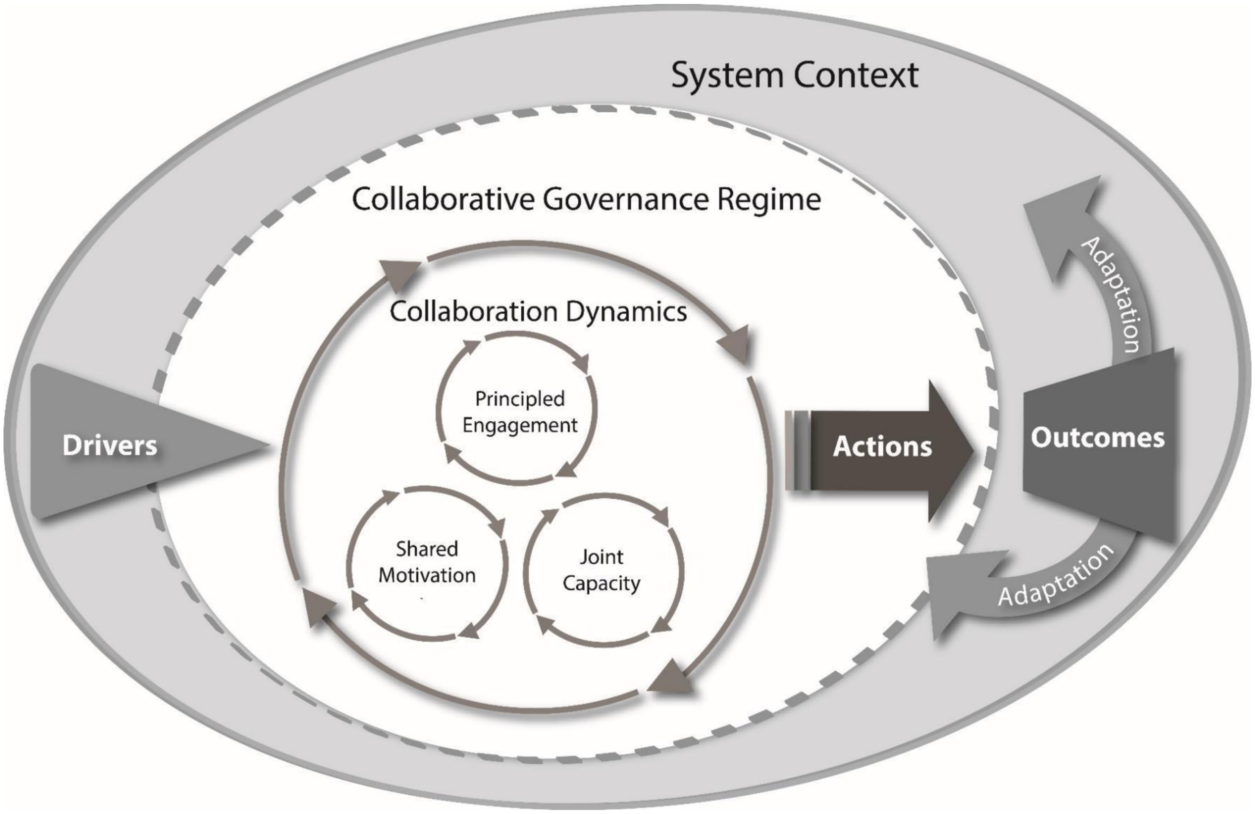
[14] ACOs can operate across state lines, and in some instances, are registered to states they may not practice health in. I discuss further in the discussion section.

or the political and legal structures surrounding the issue. The drivers of collaboration, uncertainty, interdependence, leadership, and consequential incentives emerge from the system context. When at least one of these drivers is present, the integrative framework predicts the formation of a CGR (Emerson & Nabatchi, 2015a).

Actors participating in the CGR engage in collaboration dynamics, the active collaboration processes occurring within formed CGRs. The collaboration dynamics are principled engagement, shared motivation, and joint capacity. Principled engagement encompasses the behavioral elements of how people interact. Shared motivation describes the interpersonal elements of trust, mutual understanding, and internal legitimacy that can motivate and justify continuing engagement. Finally, joint capacity is the additional capacity for collective work when people come together to solve something they cannot solve alone.

Approaches that foster principled engagement build shared motivation and increase joint capacity, allowing CGRs to define the actions the CGR will take, referred to in the framework as the shared theory of change. A shared theory of change is the shared goals and strategy to address them developed through the progressive cycling of discovery, definition, deliberation, and determination during collaboration dynamics. The shared theory of change is “the strategy that the group will use to achieve its collective purpose and common goals” (Emerson & Nabatchi, 2015a, p. 80).

Figure 6: The Integrative Framework for Collaborative Governance



Source: Emerson and Nabatchi, 2015, p. 27

Collaborative actions develop from collaboration dynamics and the shared theory of change. Collaborative actions are "the intentional efforts undertaken as a consequence of the collective choices made by a CGR during collaboration dynamics" (Emerson & Nabatchi, 2015a, p. 82). These actions lead to outcomes, and outcomes lead to adaptations in the system context, such as new laws around an issue or the changing nature of a resource or condition. Adaptations can also lead to changes within the CGR itself, such as changing strategy or inviting new actors to the table. Due to frameworks like this, there is now extensive literature about enabling effective processes at the CGR level. In this chapter, I identify and measure the characteristics of CGRs, their broader system contexts, and their collaborative outcomes in the U.S. healthcare context of Medicare ACOs.

System context factors can create opportunities for or constraints on CGRs that influence their processes and performance. Studies find system context factors are associated with CGR dynamics and CGR outcomes (Dressel et al., 2020). Evidence shows that system context factors can positively and negatively influence collaboration dynamics- the collaboration processes occurring within CGRs (Dressel et al., 2020). For example, environmental scholars find a positive relationship between the social-ecological context variables of larger geographic areas and pronounced fluctuations in forage availability on the collaboration dynamic of CGR time investments. The authors also find that high-land use diversity and the density of other species existing in the system context were counterproductive to the CGRs they were studying's outcomes of interest. Such findings align with previous conclusions that the system context can create barriers to collaboration dynamics and productivity performance of CGRs (Ansell & Gash, 2008; Dressel et al., 2020; Emerson & Nabatchi, 2015a). Previous findings also show that management performance can be improved by anticipating and adapting strategies to address counterproductive system context factors on CGR performance (Emerson & Nabatchi, 2015a). Since system context factors can be associated with collaborative governance outcomes, they are essential to consider when evaluating the potential or actual work of CGRs (Dressel et al., 2020).

I also explore CGR outcomes. CGR outcomes include "the intermediate changes in conditions necessary to reach target goals and the effects of accomplishing these goals" (Emerson & Nabatchi, 2015a, p. 84). Outcomes matter to CGRs, their participants, their beneficiaries, and scholars who study CGRs, among other stakeholders (Emerson & Nabatchi, 2015a). CGR outcomes can be explicit and intended results as well as indirect, unintended, or unanticipated effects, and outcomes may be "physical, environmental, social, economic, and/or political" (Emerson & Nabatchi, 2015a, p. 84). The perceived importance of an outcome differs by audiences (Emerson & Nabatchi, 2015a; Gray, 2000), and CGRs vary in their theories of change and collaborative actions. Even if CGRs are similar, they can vary in the outcomes that they think matter and the outcomes that they realize.

Performance assessments can influence CGR actions. Ideally, CGR performance evaluations focus on outcomes in the resource or service conditions targeted for improvement that are of value to CGR participants, the organizations represented by the participants, and the direct and indirect beneficiaries of the targeted resource or services (Emerson & Nabatchi, 2015a). However, it may not always be the case that stakeholders assess CGR performance on outcomes that are valuable to all three groups. Studying outcomes also allows scholars to deduce whether a CGR influences an outcome of interest and whether that outcome is an indirect, unintended, or unanticipated effect of CGR. Studying outcomes are important because CGR actions can produce intended or unintended consequences (Emerson & Nabatchi, 2015a).

I provide an overview of how analysts and managers can use descriptive and inferential statistics to understand CGRs and whom they serve. In the next section, I walk through an empirical example of how to identify relevant system context factors that may be associated with CGR registration to a state. I also examine whether being the beneficiary of a CGR is associated with changes in an outcome of interest.

Empirical Example

I use three empirical analyses in this section to explore CGRs, their broader system contexts, and outcomes. First, I examine whether state system context characteristics are associated with the number of CGRs registered in that state. Second, I measure the direction and magnitude of the outcome measure of medication nonadherence in the Medicare landscape, both broadly and within a group of CGRs. Third, I use propensity score matching estimation to understand whether being a beneficiary of a CGR is associated with different medication nonadherence outcomes that may be attributed, at least partly, to the collaborative governance processes occurring within.

ACOs

Medicare ACOs have the authorized authority to implement policy goals laid out by the ACA, including goals related to fostering collaboration and coordination of healthcare providers (Addicott & Shortell, 2014; Shortell et al., 2010). Despite the decision-making authority granted by the federal government to Medicare ACOs through the MSSP scholars know little about the over 500 Medicare ACOs operating across the U.S. from a collaborative governance perspective (Daly, 2020). Using the CGR lens in health care is important as recent research finds that increased collaboration has resulted in a more aligned system of organizations collaborating toward population health improvement in a U.S. region (Bultema et al., 2020). Research on collaborative governance at scale is valuable as collaborative reforms and initiatives continue to rise, especially in healthcare. Few scholars examine ACOs as collaborative governance initiatives to fill this gap (for exceptions, see Addicott & Shortell, 2014; Shortell et al., 2010). In Medicare ACOs, cross-boundary collaboration is the predominant behavior at the governance level (i.e., in the provider-led board meetings). For example, the Medicare ACO model mandates shared governance and emphasizes voluntary participation, provider representation, and shared decision-making to facilitate clinical integration. Medicare requires participating ACOs to have governing bodies that represent all the service provider members and must even include some beneficiaries served by the ACO in its governance (McGuireWoods, 2011). Organizations and beneficiaries within the ACO must have at least 75% control of the governing body (McGuireWoods, 2011). [15] [16]

The integrated framework for collaborative governance posits that CGRs often exist within hierarchies, operate using market-based approaches, and function as networks (Emerson & Nabatchi, 2015a). Operationally, Medicare ACOs are groups of physicians, hospitals, and other healthcare providers that work together to provide higher-quality care at lower costs while working together to develop strategies and meet agreed-upon target outcomes collectively. In many ways, ACOs are similar to Medicare Health Maintenance Organizations (HMOs) in that those beneficiaries' health insurance plans are limited to coverage from providers in the network. Both ACOs and HMO patients are primarily Medicare beneficiaries, meaning that patients are 65 or older. However, ACOs and HMOs differ because only people with Original Medicare can be assigned to a Medicare ACO (Medicare Part A, Part B, and Part D). Individuals are not eligible for a Medicare ACO if they have a Medicare Advantage Plan (i.e., Medicare Part C, Medicare Part D Advantage), like in an HMO or a Preferred Provider Organization (PPO) (Centers for Medicare & Medicaid Services, n.d.). Also, ACOs do not constrain patient freedom of choice, which occurs under HMOs.

Broader System Context: State Health

The system context landscape in healthcare is changing in ways that lean into collaborative governance. Increasingly, health system actors collaborate to meet the changing

[15]The remainder may be controlled by entrepreneurial management companies, health plans or other stakeholders participating in the ACO.

[16]Participating organizations must have a meaningful financial or human investment commitment to the ACO's clinical integration to contribute to its success. For example, the ACO must have an infrastructure, such as information technology, that enables the ACO to evaluate its initiatives and give feedback to the provider members to help reach their common goals (McGuireWoods, 2011).

expectations and priorities in the health sphere (Figueroa et al., 2019). For example, U.S. public health initiatives now focus more on improving social determinants of health, working across sectors, and engaging more diverse communities than in the past. Public reforms like the ACA and private sector payment policies increase interdependence between providers, such as between physicians and hospitals (Colla et al., 2016). These trends have led health stakeholders to view collaboration as a necessary component to meet the goals of modern health system transformation (Bultema et al., 2020).

Hospital systems facilitate interdependencies among diverse providers (Bell, 1994). The economic argument for ACOs is that providers are willing to collaborate given aligned incentives (Medicare Payment Advisory Commission, 2019). From a collaborative governance perspective, people are motivated to collaborate only when key actors recognize interdependences (Emerson & Nabatchi, 2015a, p. 46). Researchers posit that hospitals are often well-positioned to engage providers across sectors (Colla et al., 2016). ACOs are more likely to form in markets with more sophisticated technology, which is often a characteristic of teaching hospitals (Colla et al., 2016). Previous research finds that ACOs tend to form and enroll beneficiaries from markets with more sophisticated technology and sicker patients with higher healthcare bills (i.e., teaching hospitals) (Colla et al., 2016).

In 2015, a study found that 20% of US hospitals were in an ACO, and 63% of ACOs included hospitals. Qualitative research showed hospitals had higher availability of start-up resources and advanced data sharing. Hospitals were also well-positioned to engage providers across sectors (Colla et al., 2016). The findings suggest that key hospital actors, such as influential leaders, play an essential role in Medicare ACO development. From an ACO perspective, influential leaders may view states with more hospitals as having a facilitative system context. I hypothesize:

Hypothesis 1: States with more hospitals have a greater number of Medicare ACOs registered than states with fewer hospitals.

ACO stakeholders must consider how to improve care coordination and reduce avoidable service utilization, as well as other factors that could affect its performance (DeLia et al., 2012). Local context factors, like local market dynamics, local practice patterns, health system capacity, concentrations of market power, and healthcare reforms, influence health system performance (Fisher & Corrigan, 2014). For example, researchers find that regional growth rates in spending affect the potential of their ACO to receive shared savings from Medicare (DeLia et al., 2012). CMS rewards Medicare ACOs based on how well they reduce spending relative to the per capita healthcare spending growth.

Aspects of the MSSP program incentivize ACO patient selection, whether intentional or not (Medicare Payment Advisory Commission, 2020). For example, advisors warn that Medicare ACOs may select more high-cost beneficiaries (i.e., sicker patients) at baseline. They warn that ACO may then disproportionally shift out those high-cost beneficiaries in later years by removing high-cost clinicians from the ACO or having high-cost clinicians bill under a TIN that is not part of the ACO (Medicare Payment Advisory Commission, 2020). These practices can lead to unwarranted shared savings payments to an ACO because it will appear that the ACO lowered spending when the ACOs could be showing lower spending due to patient selection (Medicare Payment Advisory Commission, 2020). These warnings display that the current

Medicare ACO system incentivizes patient selection because of allowances in the flexibility of provider billing (Medicare Payment Advisory Commission, 2020).

There is evidence of ACO selection into specific markets in the health policy literature. Researchers find that hospitals belonging to ACOs have more clinically complicated patients than other hospitals (Colla et al., 2016). Patients undergoing treatment at ACO-affiliated hospitals are sicker and tend to have more extended inpatient stays than patients in non-ACO hospitals (Colla et al., 2016). Two potential explanations exist for the correlation between ACO enrollment and sicker patients. First, ACOs tend to have more teaching hospitals and hospitals which offer a more comprehensive selection of services than nonteaching hospitals or hospitals offering fewer services (Colla et al., 2016). Sicker patients may seek hospitals with technological innovations and service mixes. Alternatively, incentives may drive the higher enrollment of sicker patients among ACO hospitals than non-ACO hospitals.

Following this logic, I hypothesize that ACOs form in markets with sicker Medicare patients whose medical bills cost more because it may be easier to demonstrate change after beginning operations in these more extreme environments. I expect to see at least some enrollment in states with a higher median age because Medicare is mainly for people 65 and older, so I test other health variables, like obesity rate, to see if a relationship with sicker patients exists beyond patient age. I must note that another reason for a potential correlation between ACOs and sicker patients may be that ACOs in the MSSP have modest incentives to record more diagnoses in their claims reporting than local patients served by providers not participating in the MSSP (McWilliams et al., 2018). The integrative framework for collaborative governance posits that consequential incentives are a CGR driver and that these incentives emerge from the broader system context. Given the evidence that ACO formation has taken place where it may be easier to meet quality and cost targets (Lewis et al., 2013), I hypothesize the following:

Hypothesis 2: States with worse population health outcomes have a greater number of Medicare ACOs registered than states with less severe population health outcomes.

The Outcome of Interest: Medication Nonadherence

Medication nonadherence is a substantial public health problem that is of major focus in recent U.S. healthcare reform (Pitcock & Fink, 2019). Adherence is defined as “the extent to which patients take medications as prescribed by their health care providers” (Osterburg & Blaschke, 2005, p. 487). In this subsection, I motivate the importance of studying the outcome of medication nonadherence. I then offer a literature review of medication nonadherence and ACOs to support my hypotheses.

Why Scholarship and Practice Should Care About Medication Nonadherence

High drug prices lead some patients to make decisions that can negatively impact their health, including forgoing costly drugs, which may increase healthcare costs in the long term. For example, researchers find that poor drug adherence significantly contributes to increased hospitalizations and medical service utilization in the United States (Desai et al., 2019; Goldman et al., 2007; McDonell & Jacobs, 2002). Nonadherence to medicine is common (Goldman et al., 2007; Minemyer, 2018; Pew, 2018; Rose, 2018) and is found to be associated with increased medical service use (Desai et al., 2019; Goldman et al., 2007; McDonell & Jacobs, 2002) and increased health systems costs (Desai et al., 2019; Goldman et al., 2007; Offord et al., 2013; Watanabe et al., 2018). Of the nearly 60% of Americans taking a prescription drug in 2018, more than a third of Americans said they skipped a prescription or took less than the prescribed dose in the past 12 months due to cost (Pew, 2018).

Scholars began researching patient adherence to treatment in the late 1960s, finding that adherence leads to more favorable patient outcomes than nonadherence (for a meta-analysis, see DiMatteo et al., 2002). Increasing drug adherence significantly increases health system cost savings through significantly lowered hospitalization and rehospitalization rates (Dubois et al., 2012; Encinosa et al., 2010; Rosen et al., 2017; Sokol et al., 2005). Using pill counts to measure adherence, Rich and colleagues (1996) found that elderly congestive heart failure patients with greater than 90% adherence to the medication had lower readmission rates in one month than those with lower than 90% medication adherence. Researchers also find hospitalization rates were lowest for diabetes, hypertension, hypercholesterolemia, and congestive heart failure patients with high adherence levels (Sokol et al., 2005). Researchers find increased adherence leads to healthier patients who are hospitalized less often, which will then be reflected in better health system performance (Dubois et al., 2012; Encinosa et al., 2010; Joynt et al., 2011), especially in older adults (Murray et al., 2004). Such evidence suggests better medication adherence rates can contribute greatly to cost offsets through their role in preventing hospitalizations.

This relationship extends beyond physical health. Scholars also find that better adherence rates improve health for behavioral health patients and ultimately reduce health care spending. An overview of the literature found that poor or non-adherence to antipsychotic medications was consistently associated with higher hospitalization costs (Offord et al., 2013; Sun et al., 2007). Research shows poor or non-adherence to medications for behavioral health occurs in public health plans. Research studying Wisconsin and California public health insurance recipients found an association between poorly adhering behavioral health patients and higher hospital costs (Gilmer et al., 2004; Svarstad et al., 2001).

Scholars write that collaborating with ACOs helps health organizations achieve desirable outcomes, like controlling costs, remaining innovative, increasing patients served, and improving services in the changing healthcare delivery system (Gong et al., 2015). Health scholars and policy stakeholders expect accountable care models to manage patients well because of collaboration (Bultema et al., 2020; Gong et al., 2015; Shortell et al., 2010). Scholars who study healthcare reform and accountable communities of health (ACH) find organizations throughout the study region became more engaged, less siloed, and better connected due to the efforts of the collaborative health initiative (Bultema et al., 2020).[17] However, scholars know little about the collaborative structure of ACOs and how it relates to outcomes. I focus on the problem of medication nonadherence among patients in the U.S. I choose this problem because improving medication adherence is a targeted issue at the Department of Health and Human Services, the Department of Justice, the Federal Trade Commission, the Food and Drug Administration, and in the White House. Increasing medication adherence is also a focus of recent state and federal legislation, including the Patient Right to Know Drug Prices Act (S. 2554 – 115th Congress) and the Know the Lowest Price Act (S. 2553 – 115th Congress).

Medicare ACOs and Medication Nonadherence

There is a growing trend for ACOs to have pharmacists staffed to act as consultants and medication managers and help ACOs meet their two primary objectives: achieving quality

[17] Although ACOs differ from accountable communities of health (ACH) because ACOs focus on provider-to-provider collaboration, rather than provider and community collaboration, both models have been established on the foundation that governance and accountability operate in tandem to support the shared aims of improving quality and containing costs. In addition, both models impose governance structure and mechanisms of accountability where providers operate collaboratively within an overarching framework (Addicott & Shortell, 2014; Bultema et al., 2020).

benchmarks and saving money (Barlas, 2011; Vos MacDonald, 2018). ACOs increasingly staff pharmacists to enhance prevention and reduce avoidable health service utilization and readmissions (Gaspero, 2016). However, their prevalence is unclear. Some researchers assert most ACOs do not engage or integrate pharmacists meaningfully (Gaspero, 2016), and estimates put ACOs that use staff pharmacists at 63% (Vos MacDonald, 2018). ACO pharmacists' key role is counseling patients to ensure they take their medications correctly (Gaspero, 2016; Medical Billers and Coders, n.d.). If nonadherence to medication is a prevalent problem in Medicare, I expect ACOs lower medication non-adherence. If ACOs do mitigate harms that lead to low adherence rates of medications, this suggests ACOs are doing what they are supposed to be doing.

No previous studies use the integrated framework for collaborative governance to examine ACOs, and there is limited collaborative governance research on ACO outcomes. However, studies show growing evidence of integrated accountable care systems providing superior care at the same or lower cost per capita than less-integrated delivery forms (Shortell et al., 2010; Tollen, 2008). For example, Medicare patients in physician-led integrated delivery systems saw better outcomes in cost of care, number of hospital days, number of intensive care days, hospital costs, and physician costs than patients in other settings (Shortell et al., 2010; Sterns, 2007). These findings show measurable improvements in accountable care initiatives as an effective approach to aligning organizations across boundaries, showing measurable improvements in health system engagement, cohesion, and connectivity. Therefore, I expect that being in the ACOs group is associated with lower medication nonadherence scores. I expect to see an effect because of previous evidence that more integrated Medicare programs with shared accountability mechanisms tend to manage patients well because of collaboration and the integrated nature of their work. Researchers posit that improving interactions between patients, healthcare providers, and the healthcare system will have the greatest effect on improving medication adherence compared to other initiatives (Osterberg & Blaschke, 2005). To understand the relationship, I hypothesize:

Hypothesis 3: Beneficiaries in ACOs will experience lower medication nonadherence than if they had not been in an ACO.

I may not find a relationship between medication adherence and ACO enrollment for three reasons. First, I may find no treatment effect because all Medicare ACOs are relatively young. For example, CMS Medicare Public Use File data show that the average age of ACOs by 2020 was approximately six years. It could be that the ACOs are aware of medication nonadherence and its consequences but have yet to address it because the providers are focusing on other collaborative activities. The integrative framework for collaborative governance posits that CGRs can face limited capacity at their outset. They may initially only choose simpler actions, such as focusing on new management practices, enacting new policy measures, deploying staff, monitoring implementation, enforcing compliance, and other tasks (Emerson & Nabatchi, 2015a). Medication nonadherence may be further down the line in Medicare ACOs' "strategic sequences" of how they will carry out actions over time. I may not see any relationship between ACO enrollment and medication nonadherence due to limited capacities. For example, CGRs can have limited capacity in their early stages and may initially focus on actions that are easy first steps to take (Emerson & Nabatchi, 2015a). Medication nonadherence is not an outcome for which Medicare ACOs are evaluated in their performance assessments by CMS. Therefore, ACOs may use their resources to target other metrics through collaborative action.

Second, educating patients about the dangers of medication nonadherence may take time to result in significant changes in patient behavior. It may be that Medicare ACOs do address medication adherence in their theories of change and resulting collaborative actions, but the result will be long-term rather than short-term effects on the outcome. Third, it may be that ACOs use ineffective approaches to address medication nonadherence. In the following sections, I present my analyses.

Data

This study aims to understand the state system contexts associated with Medicare ACO formation and registration in each state. I use data from the Medicare Current Beneficiary Survey Public Use Files (MCBS PUF) and the Medicare Shared Savings Program Public Use Files (MSSP PUF). My variables on state health measures come from the Health Resources and Services Administration (HRSA) and the Agency for Healthcare Research and Quality (AHRQ). State demographic data come from U.S. Census Data, and data on state crime rates come from FBI data. State political data come from the Correlates of State Policy Project to control for variables that may influence differences in ACO formation across states from 2013-2019.

The MCBS is a nationally representative sample of the Medicare population collected by CMS (Centers for Medicare & Medicaid Services, 2022b). The MCBS PUF gives unique identifiers to respondents every year and, therefore, a cross-section rather than a panel like the full MCBS. The MCBS sampling strategy targets the population of Medicare Part A and Part B enrollees as of December 31 of the sample-selection year. The survey uses a three-stage cluster sample design, with the sampling frame specified for Medicare beneficiaries utilizing a five percent sample of CMS administrative enrollment data.[18] Medicare administrative enrollment data contain information on every individual entitled to Medicare. Its sampling design provides nearly equal probabilities of selection samples of beneficiaries within each sampling stratum (Centers for Medicare & Medicaid Services, 2017). The rigorous sampling design of the MCBS produces national estimates of the entire Medicare population each year, including representative estimates of Medicare ACOs during the study period. Given its nationally representative nature, the MCBS PUF allows me to make inferences about the Medicare ACO beneficiaries at the national level. The MCBS links self-report and administrative data for every respondent. I use self-report measures of medication nonadherence.

I also use national administrative data from the MSSP Public Use Files for performance years 2013-2019. The MSSP files are a rich panel dataset updated annually by CMS with data about the complete list of ACOs operating in the MSSP each year. I use administrative data from the MSSP for two analyses. First, I use the MSSP files to study correlations between system context conditions and ACO formation by state between 2013 and 2019. Second, I use the MSSP data to understand the magnitude of medication nonadherence in Medicare. I then perform propensity score matching estimation. I aim to understand the effect of ACO treatment on the treated as it pertains to the effect of ACO enrollment on medication nonadherence compared to statistically similar individuals not exposed to ACO treatment.

Measures

To understand which hypothesized factors of the broader system context relate to new CGR registration in a state, I study the *Annual Number of ACOs by State* as my dependent

[18] The MCBS oversamples Hispanic beneficiaries and beneficiaries aged 85 and over to ensure sufficient sample sizes for analyses (Centers for Medicare & Medicaid Services, 2022b).

variable. It measures the number of Medicare ACOs within a state between 2013 and 2020. I use four variables to understand state health market trends and to examine their relationship to Medicare ACO growth: *Number of Hospitals, Obesity Rate*, *Median Age*, as well as *Total Population with Medicare Health Insurance*. I also include *Violent Crime Rate* as a proxy for violent injuries that may lead to more hospitalizations and health service utilization. I use a political variable called *Democratic Governor* that describes partisan control of a state each year. I also use two variables to understand the relationship between state economic trends and ACO registration *State Tax Revenue* and *Income per Capita*.

For the two outcome analyses, *ACO Enrollment* is my key independent variable. The enrollment variable comes from the MCBS. I use three self-report items from the MCBS survey as my dependent variables. I follow Zivin and colleagues (2009) and use MCBS variables to measure non-adherence to medicine: self-reports of (1) skipping doses, (2) reducing doses, and (3) not obtaining a prescription. The MCBS uses the measures in Table 10 to collect data on prescription drug use. While there are more precise ways to measure levels of adherence, researchers found that asking individuals about times they did not take their medicine is a satisfactory and useful way to gauge individuals' medication nonadherence (Osterberg & Blaschke, 2005). For the propensity score analysis, I match on demographic variables of age and sex. I also match on the health measure of the number of inpatient stays an individual had in a given year to try and control for selection differences in groups to control for the confounder of differences in health that likely influences group assignment.[19]

[19] Although ACO selection primarily occurs at the provider level (Appendix 6), I do not match variables at the provider level because the MCBS only includes beneficiary-level data for medication nonadherance.

Table 11: MCBS Items on Medication Nonadherence

Item Label	Question
Did Not Get Their Prescription	During (CURRENT YEAR), were any medicines prescribed for you that you did not get? Please include refills of earlier prescriptions as well as prescriptions that were written or phoned in by a doctor.
Skipped Doses to Make Last Longer	Please tell me how often during (CURRENT YEAR) you have done any of the following things. Have you often, sometimes, or never… skipped doses to make the medicine last longer?
Did Not Fill Prescription Due to Cost	Please tell me how often during (CURRENT YEAR) you have done any of the following things. Have you often, sometimes, or never decided not to fill a prescription because it cost too much?

Adapted from Medicare Current Beneficiary Survey (MCBS) 2013 Access to Care Public Use File Codebook

Sample

The first analysis examines an unbalanced panel of states with Medicare ACOs participating in them from 2013-2019. I study states as the unit of analysis to understand associations between the number of ACOs in a state and system context factors related to health capacity, population health, demographics, state politics, and state tax revenue. The sample includes 49 states observed across seven years (N=314). I use censored data. If there are years when a state has zero Medicare ACOs, it will not show up in the dataset for that year (occurs for 29 state years). I include all states except Hawaii or Wyoming due to a lack of data on Medicare ACOs in those states.

I use the taxpayer identification number to link ACOs to states. Although ACOs provide services to states both within and outside of the state they are registered in, knowing the state ACOs registered their taxpayer identification numbers is important for understanding their system context. For example, state laws, cultures, and customs can dictate the institutional parameters by which formalized CGRs must abide, which can ultimately affect the performance of the collaboratives (Emerson & Nabatchi, 2015a).

For my second analysis, which looks at collaborative governance outcomes, my sample frame consists of MCBS respondents. It includes those flagged as beneficiaries enrolled in MSSP ACOs in 2013, 2015, and 2016 (N= 6,293) and all other Medicare beneficiary respondents not enrolled in an ACO (N=32,794). These three years are the only years where the MCBS Public Use Files flag the MSSP ACO population. I dropped missing data, including values where respondents answered, “I don’t know,” and the respondent refused to answer. I drop 6% of the original study sample due to missing values. My final study sample for Analysis 2 equals 36,752 observations, consisting of 5,919 ACO beneficiaries and 30,833 non-ACO beneficiaries.

Methods

I perform three analyses to answer the research question of how scholars identify and measure the characteristics of CGRs, their broader system contexts, and their outcomes. First, I use random-effects regression modeling to understand associations between characteristics of a state’s broader system contexts and the number of ACOs registered. Researchers can use either fixed-effect or random-effect models when units of analysis cluster by groups (Bryk & Raudenbush, 1992). I find almost identical results of the models in terms of the estimated direction of the relationships and the statistical significance of the coefficients, suggesting that my estimates are good across specifications and lend some confidence in my ability to make inferences. I also ran a Hausman test to compare fixed with random effects in STATA. The results indicate that the random effects are preferred over the fixed effects for the count of ACOs dependent variable. Therefore, I present the results from the random-effects model in the following section.

Second, I analyze contingency tables to understand the direction and magnitude of medication nonadherence in ACOs. The representative nature of the MCBS survey allows me to make inferences about the magnitude of medication nonadherence in the U.S. Medicare ACO and non-ACO populations during the study period. Third, I use stratified propensity score matching to account for some of the selection bias from patient selection into groups. Medicare does not randomly assign patients to ACOs, and selection bias occurs when two groups have different mean potential outcomes (Cunningham, 2022).

The central idea of matching is that if I match each treated participant to a nontreated individual using a vector of matching variables, I can then compare the average of the dependent variable of the treated with the average dependent variable on the matched nontreated participants. The resulting difference is an estimate of the sample average treatment effect on the treated (ATT) (Rosenbaum & Rubin, 1983). Propensity score matching acts as a treatment-effect estimator and reweights the observational data to achieve experimental-like balanced covariates (Rosenbaum & Rubin, 1983). I consider that matching cannot control for unobserved selection bias. Unobserved heterogeneity always holds the potential to bias effect estimation. I match on the variables age, sex, and the number of inpatient hospital discharges in a year. I choose to match inpatient stays per year to take into consideration the potential confounder of health. Among ACO beneficiaries, the ones skipping medications may be in better health than the ones not skipping medications. Research finds that sicker patients are more motivated to adhere to their treatment plans than healthier patients, who may not feel it is as necessary to adhere to their medication correctly (i.e., people who are diagnosed but may feel symptomless) (Villar, 2021). I account for patient health in my analyses because it could be that the worse the health of the ACO patient, the better the odds that they will adhere to their medicine. In other words, the greater the patient's health, the greater their nonadherence to medication due to potential perceptions of less severe consequences amongst healthier individuals rather than some collaborative aspect of being a beneficiary of an ACO.[20] However, the potential confounder of health is only a problem if it also correlates with being in an ACO. In the next section, I present the three analyses.

Descriptive Statistics

In this section, I present the descriptive statistics for all three analyses. In the first analysis, I explore the association between state characteristics and the number of Medicare ACOs in that state from 2013-2019. Table 12 reveals that U.S. states in my sample had an average of nine Medicare ACOs a year across the study period. States had an average of 107 hospitals during the study period and an average obesity rate of 30%. States had an average violent crime rate of 364 violent crimes per 100,000 people, or 0.3%. States had an average population of approximately 126 million people with Medicare insurance. The median age was 38, with a range of 30 to 45. On average, state tax revenues varied greatly, with a median of approximately 26 million and a range of 1.04 million to 188.24 million, suggesting there are outliers in the dataset. Finally, 39% of the state years in the dataset had Democratic governors. The variation in state characteristics motivate the study. They show states have different local attributes that may relate to ACO registration.

[20] One way to address whether confounding is occurring would be to account for contact an individual has with their ACO care coordinator. Unfortunately, the MCBS PUF data does not track individual engagement with care coordinators. Another way to account for confounding is to generate a scatterplot of the relationship between number of medications a patient takes and adherence rates and look for nonlinearities. Unfortunately, the MCBS PUF does not include a measure of medication counts.

Table 12: State Context and Medicare ACOs

Variable	Means	SD	Median	Min.	Max.
Number of ACOs by State	9.12	9.53	6	1	50
Number of Hospitals	107.30	83.14	93	7	528
Obesity Rate	30.35	3.74	30.3	20.2	40.8
Violent Crime Rate (per 100,000)	363.91	135.59	358.3	102.6	842.8
Population with Medicare (thousands)	1261.94	1420.22	884.87	79.82	12333.67
Median Age	38.42	423	38.5	30.1	45
State Tax Revenue (millions)	20.58	25.97	12.28	1.04	188.24
Democrat Governor (binary)	.39	.49	.	0	1
N= 314					

I analyze states as cases from 2013-2019 in Analysis 1. The number of ACOs is aggregated into a variable to represent how many were in each state in a given year. The minimum number of ACOs by state is one because zeros are dropped for 29 state years in the sample.

Table 13 provides an overview of the MSSP ACO sample compared to the non-ACO sample. I calculate differences in proportions. Table 13 shows the means of the ACO group are significantly different from those of the non-ACO group for many of my variables of interest. I examine the outcome variables for medication nonadherence in each group individually to draw inferences about the outcome of medication nonadherence in the Medicare ACO and Medicare populations. For Analysis 2, I use these samples to generate a contingency table.

In Analysis 3, I use a matched sample design so that I can make comparisons between the groups. After matching, I lost 6% of the sample size of the original data for the ACO group and an average of 24% of the comparison group for variables related to medication nonadherence. I lost between 6%-27% for variables related to health diagnoses for the treatment group and 8%-23% in the comparison group (Appendix 7).

Table 13: Beneficiary-Level Sample Comparisons

Variable	ACO (%)	Non-ACO (%)	Differences Pre-Propensity Score Matching
Age			***
<65	14.11	18.00	.
65-75	32.05	34.55	.
>=75	53.84	47.45	.
Sex			***
Male	44.23	46.36	.
Female	55.77	53.64	.
Race			.
Black (non-Hispanic)	6.89	10.85	***
White (non-Hispanic)	81.79	72.88	***
Hispanic	6.54	10.30	***
Other	4.78	5.96	***
Education			***
Less than High School	14.73	21.10	.
High School or Vocational	35.73	36.47	.
More than High School	49.54	42.43	.
Marriage Status			***
Married	50.79	48.91	.
Not Married	49.21	51.09	.
Income			***
< 25,000 $	37.93	46.39	.
Health Controls			
≥ 1 Inpatient Stay	17.50	9.81	***
Did Not Get Their Prescription	6.61	6.10	No significant difference
Skipped Doses to Make Last Longer	5.71	5.42	No significant difference
Did Not Fill Prescription Due to Cost	9.47	9.77	No significant difference
N= 36,752	30,833	5,919	

I determine differences using difference in proportions hypothesis tests.

Results

Analysis 1: ACOs and the Broader System Context

Table 15 presents the results of the broader system context analysis. I find support for Hypothesis 1 that states with more hospitals have a greater number of Medicare ACOs registered than states with fewer hospitals. A one-hospital increase in a state is associated with 0.049 additional ACOs during the study period. I find support for Hypothesis 2 that states with worse population health outcomes have a greater number of Medicare ACOs registered than states with less severe population health outcomes. The results also show a significant positive relationship between the state obesity rate and the number of ACOs. A one percent increase in a state's obesity rate is associated with .468 additional ACOs registered to a state during the study period. I find a positive association between state median age and ACO registration. An increase of one year in a state population's median age is associated with 0.90 additional ACOs registered to a state over the study period. ACOs tend to register in states with an older share of adults, which makes sense given that Medicare primarily services the elderly. The magnitude is relatively large—a one-year increase in median age relates to almost one full additional ACO to that state. The magnitude paired with the obesity rate result signifies that this relationship is worth further exploration about potential ACO selection.

Despite finding support for health-related variables of age and obesity rate, I cannot reject the null in favor of the alternative hypothesis for the relationship between the number of people with Medicare public health insurance in a state and the number of Medicare ACOs. The result is surprising because, to be eligible for and remain in the MSSP, ACOs must keep a threshold of 5,000 Medicare beneficiaries. Hence, I expected to find a positive relationship between publicly insured people and the number of state ACOs. I cannot reject the null in favor of the alternative hypothesis for the variable violent crime rate. I include the violent crime rate as a proxy for injuries related to violence that may be associated with rates of health service use. Given my model, I cannot rule out that I am seeing this coefficient due to chance.

Table 14: System Context and ACO Registration by State (2013-2019)

State Characteristics	Number of ACOs by State per Year
Total Hospitals	.049***
	(.011)
Obesity Rate	.468***
	(.123)
Violent Crime Rate (per 100,000)	.004
	(.004)
Population with Medicare Insurance (thousands)	.000
	(.000)
Median Age	.90***
	(.30)
State Tax Revenue (millions)	.141***
	(.036)
Democrat Governor	-.471
	(.648)
Constant	-49.68***
	(11.46)
Observations	314
Number of States	48

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I control for other state characteristics that can plausibly influence the formation and sustainability of Medicare ACOs: state taxes and the governor's political party. I find a significant positive relationship between state revenue and the number of Medicare ACOs. Every additional million in state revenue is associated with 0.14 additional ACOs registered in that state. So, the magnitude is relatively small. It may be that when providers consider where they will register their ACO, they factor in state resources, opting for states with more resources. I cannot reject the null in favor of the alternative hypothesis for the political party of a state's governor. There may be a relationship between partisan control of a state governor's office and ACO formation. The coefficient is negative and about 0.47. However, given my model, I cannot rule out that I am seeing this coefficient due to chance.

The associations between state characteristics and the number of Medicare ACOs in a state over time show ACOs registered to states with greater hospital capacity and states with worse population health in terms of obesity rates and median age. I also find support for the notion that more ACOs register in states that have higher tax revenues. My findings motivate further probing into whether stakeholders responsible for ACOs may select specific markets with more favorable system context factors. I discuss the findings further in the paper's discussion section and how they highlight the role of broader system context factors and collaboration drivers in the context of CGR formation as posited by the integrated framework for collaborative governance.

Analysis 2: Prevalence of Medication Nonadherence among Medicare Beneficiaries

The first two rows of Table 16 indicate growing barriers to receiving pharmaceuticals between 2013 and 2016 for all Medicare beneficiaries. The first row shows that from 2013 to 2016, an average of 6.6% of Medicare ACO respondents were prescribed medicines by a doctor that they did not get. The magnitude is quite large when applied to the total number of beneficiaries enrolled in Medicare ACOs each year, approximately 414,250 beneficiaries in the MSSP population for that year.

Table 15: Beneficiary Medication Nonadherence Behaviors

Percent of respondents who indicated that they often or sometimes….	2013	2015	2016	Average	% Change 2013-2016
Had medicines prescribed that they did not get					
ACO	6.63	6.16	7.01	7.01	.38
Non-ACO	5.45	6.30	6.68	5.45	1.23
Skipped doses to make the medicine last longer					
ACO	5.29	5.24	6.36	5.63	1.07
Non-ACO	5.12	5.56	5.64	5.34	0.52
Decided not to fill a prescription because it cost too much					
ACO	10.32	9.18	10.05	9.85	-0.27
Non-ACO	9.11	9.65	9.71	9.49	0.6
No. of ACO Beneficiaries	3,675,263	7,270,233	7,884,058	6,276,518	
No. of Non-ACO Beneficiaries	51,530,975	51,023,962	51,934,423	51,496,453	

N=36,752 beneficiaries (MCBS PUF sample)

Data on national counts for the ACO beneficiary population come from the MSSP PUF. Data on national counts for the non-ACO beneficiary population come from CMS (2020). I subtract the ACO beneficiary count from the total enrollees to populate the final row number of non-ACO Medicare beneficiaries.

The number of Medicare ACO beneficiaries who were prescribed medicines by a doctor that they did not get rose very slightly, 0.38%, between 2013 and 2016. Given that there were, on average, 6.28 million beneficiaries enrolled in MSSP ACOs between 2013 and 2016, this slight increase indicates a growth of approximately 23,851 additional ACO beneficiaries indicating they did not get the medicines prescribed to them in 2016 compared to 2013. Table 16 also reveals that, on average, 5.6% of MSSP ACO respondents skipped doses of their prescription medicine to make the prescription last longer, equating to approximately 332,655 during the study period. Reports of skipped doses increased by 1.1% between 2013 and 2016 for ACO respondents. It may seem that 1.1% is not a large growth. Still, it equates to approximately

69,042 additional ACO beneficiaries in the population not adhering to their medicine so that it would last longer in 2016 compared to 2013. Table 12 also indicates an incremental negative trend in cost barriers to receiving pharmaceuticals for ACO beneficiaries. On average, 9.9% of ACO beneficiaries did not fill a prescription because it cost too much, equating to an estimated 621,375 beneficiaries enrolled in MSSP ACOs per year.

Analysis 2 reveals that medication nonadherence is a health outcome variable that Medicare ACOs may want to target if they are not doing so already. The magnitude of beneficiaries who reported medication nonadherence during the study period suggests drug adherence is an outcome that can be improved and should be addressed for all Medicare enrollees. The finding motivates the propensity score estimation. Is being in the treatment group, that is, being an ACO beneficiary, significantly associated with differences in medication nonadherence outcomes?

Analysis 3: Propensity Score Estimation

Table 17 shows the results of the stratified propensity score estimation. Hypothesis 3 posits that being in an ACO is associated with the odds of an individual changing their medication nonadherence behaviors in either direction. Therefore, my test is a two-sided hypothesis test. If the absolute value of the test statistic is greater than the critical value of 1.96, then I reject the null hypothesis in favor of the alternative. I find that the average treatment effect on the treated difference is incremental in all three measures of medication nonadherence. I also cannot reject the null in favor of the alternative hypothesis. Therefore, I do not find support for Hypothesis 3, that beneficiaries in ACOs experience lower medication nonadherence than if they had not been in ACOs.

Table 16: Stratified Propensity Score Estimation

	ATT	se	t	N_1	N_0
Patient did not get Rx	-0.002	0.006	-0.365	5919	24675
Skipped doses to make Rx last	-0.003	0.003	-0.785	5907	24687
Did not fill Rx due to cost	0.004	0.005	0.773	5919	25167

N_1= Number of treated. N_0= Number of controls. The number of treated and comparisons refers to those individuals who were effectively matched by the stratified propensity score matching method. Bootstrapped standard errors.

Table 18 overviews my hypothesis test findings. In Analysis 1, my random-effects model shows that I can reject the null in favor of the alternative hypothesis that states with more hospitals have a greater number of Medicare ACOs registered than states with fewer hospitals. I also see that states with lower population health have more ACOs registered. For example, the results for the variables obesity rate and median population age are positive and significant. These support the possibility that ACOs may select markets with conditions more conducive to showing better performance. I discuss my results in the following section. In Analysis 2, I do not test hypotheses. I explore the outcome of medication nonadherence by examining contingency tables by ACO membership and medication nonadherence proportions per year on a representative sample of ACO beneficiaries. On average, 6.6% of Medicare ACO respondents were prescribed medicines by a doctor that they did not get, 5.6% of ACO beneficiaries skipped doses of their prescription medicine to make the prescription last longer, and an estimated 9.9% of ACO beneficiaries did not fill a prescription because it cost too much during the study period. Analysis 3 uses a propensity score matching design to test Hypothesis 3. Hypothesis 3 posits that beneficiaries in ACOs experience lower odds of medication nonadherence than if they had not been in an ACOs. My goal of the analysis is to understand if there are significant ATT effects of being in the ACO group on a beneficiary's odds of changing their medication adherence behaviors. I cannot reject the null in favor of the hypothesis for Hypothesis 3.

Table 17: Results by Hypothesis

Hypotheses	Results
Hypothesis 1: States with more hospitals have a greater number of Medicare ACOs registered than states with fewer hospitals.	Statistically different from zero
Hypothesis 2: States with worse population health outcomes have a greater number of Medicare ACOs registered than states with less severe population health outcomes.	Statistically different from zero
Hypothesis 3: Beneficiaries in ACOs experience lower odds of medication nonadherence than if they had not been in an ACOs.	Cannot reject the null in favor of the alternative hypothesis

Discussion

This chapter aims to understand CGRs, their broader system contexts, and their association with outcomes that may be important for the populations they serve. I ask the research question, *how can scholars identify and measure the characteristics of CGRs, their broader system contexts, and their collaborative outcomes?* I answer it using the integrated framework for collaborative governance. The framework highlights CGRs, their broader system context, and their outcomes as important elements to study to understand collaborative governance. I relate my findings to collaborative governance and health policy literature in this section. I overview my main finding, limitations, and avenues for future research. I then discuss implications for policy and research.

Main Finding 1

Using random-effects modeling, I demonstrate how scholars can identify and measure associations between state system context characteristics and the number of formal CGRs registered to that state over time. Examining changes in the number of CGRs registered to a jurisdictional boundary over time allows scholars to understand what system context characteristics may facilitate CGR formation and work and what system context characteristics correlate with CGR deterrence.

Increasingly, U.S. healthcare reform incentivizes providers to collaborate to meet the changing priorities (Figueroa et al., 2019). The ACA financially incentivizes provider interdependence, which has grown over the past decade (Colla et al., 2016). Analysis 1 shows the number of Medicare ACOs grew from 2013 to 2019, which is in line with Medicare reports that the number of ACOs has grown over the past decade (Centers for Medicare & Medicaid Services, 2022a).

My results support the integrative framework. The associations address whether CGRs select into markets based on system context factors is worth further analysis. I find a positive association between the number of hospitals and the number of Medicare ACOs in a state over the study period. Previous research finds that hospitals make good ACO partners due to their higher availability of start-up resources and advanced data sharing (Colla et al., 2016). My finding supports the notion that ACOs are more likely to form in markets with more sophisticated technology, which is often a characteristic of teaching hospitals (Colla et al., 2016). According to the integrative framework for collaborative governance, CGR drivers emerge from the system context, which can increase the likelihood of CGR formation (Emerson & Nabatchi, 2015a). The findings suggest that hospital actors, such as influential leaders, may play an important role in Medicare ACO development. Researchers posit that hospitals are often well-positioned to engage providers across sectors (Colla et al., 2016). From an ACO perspective, influential leaders may view states with more hospitals as having a facilitative system context. Hospital systems facilitate interdependencies among diverse providers (Bell, 1994), which can drive collaboration. People are motivated to collaborate only when key actors recognize interdependences (Emerson & Nabatchi, 2015a), and hospitals can align economic incentives for providers by bringing providers together to form an ACO.

The MSSP offers the consequential incentive of shared savings for Medicare ACOs who can demonstrate meeting performance benchmarks. My findings support the notion that the consequential incentives can lead to preferences in registering an ACO to some state health markets over others. My random-effects model shows that a larger number of ACOs register in states with more obese and older patients. Previous literature also finds a relationship between ACOs and sicker patients (Colla et al., 2016). Experts warn ACOs may strategically choose markets with sicker patients who generate higher healthcare bills (Medicare Payment Advisory Commission, 2020). Enrolling sicker patients can set a high baseline which can help ACOs show lowered spending more easily later (Medicare Payment Advisory Commission, 2020). However, I may find the relationship between ACOs and older patients simply because Medicare primarily services the elderly. Future research can clarify the mechanisms behind the result. My model does not find a positive association between the number of ACOs registered to states with more Medicare-insured people as expected. I am surprised by this finding because I theorized that initiating leaders recognize that, to receive the incentive of shared savings, ACOs must meet enrolled Medicare beneficiary thresholds. The Medicare finding goes against previous work that shows ACO formation occurs where it may be easier to meet quality and cost targets (Lewis et al., 2013). However, the significant health variables support the conclusion that ACO formation occurs where it may be easier to achieve target goals (Lewis et al., 2013). From a collaborative governance perspective, my results suggest that scholars can apply theory to the integrative framework's elements of broader system context and collaboration drivers to predict the level of formal CGR registration to or deterrence from the jurisdiction of interest.

Main Finding 2

The second part of my analysis focused on outcomes. I use contingency tables to show CGR beneficiaries' medication nonadherence levels. My findings reveal that concern about medication nonadherence in Medicare ACOs is warranted. Medicare ACOs saw nonadherence rates between 6-10% on average, which equates to hundreds of thousands of Medicare ACO beneficiaries in the population not adhering to their medicine, sometimes due to cost or to make their medicines last longer. For example, an approximate average of 445,632 Medicare ACO beneficiaries did not get their prescribed medicines during the study period. Medication nonadherence grew in the study period for all measures except one. The ACO group saw a decrease in the measure "decided not to fill a prescription because it cost too much" during the study period.

I also use stratified propensity score analysis to estimate whether I can associate being in the CGR treatment group, meaning a beneficiary of an ACO, with differences in the outcome of interest. I cannot reject the null in favor of no difference, which may suggest that the ACOs under examination do not prioritize the outcome of medication nonadherence in their theories of change or resulting collaborative actions. However, I can only speculate why I do not observe a significant difference in medication nonadherence among the treated. A lack of CGR prioritization of an outcome can occur for various reasons. For example, CGRs face limitations in their capacity. They may see more benefit to focusing on alternative outcome measures, such as measures the MSSP evaluates and to which they have greater incentives tied (Emerson & Nabatchi, 2015a). Medication nonadherence is not a performance outcome tied to shared savings by the MSSP. ACOs may direct their attention elsewhere, meaning medication nonadherence is an outcome that might be less proximate to the collaborative actions that are taking place. CGRs' performance evaluations can shape CGR actions, outputs, and outcomes (Emerson & Nabatchi, 2015a).

The lack of significance of the CGR treatment effect on the treated for medication nonadherence could suggest that CGRs address the outcome of interest, but the effects are difficult to realize in the short term. For example, educating patients about medication nonadherence may take a while to result in significant changes in behavior. Additionally, collaborative action changes over time. A CGR may not affect an outcome of interest due to limited capacities. For example, CGRs can have limited capacity in their early stages and may initially focus on actions that are easy first steps to take (Emerson & Nabatchi, 2015a). Medication nonadherence may be further down the line in Medicare ACOs' strategic sequences of how they will carry out actions over time (Emerson & Nabatchi, 2015a). I may also find no treatment effect because all Medicare CGRs were relatively young during the study period (2013-2016), just a few years old. The MSSP program launched in 2012. It could be that the ACOs are aware of the issue but must focus on other actions, such as addressing new management practices, enacting new policy measures, deploying staff, monitoring implementation, enforcing compliance, or other tasks (Emerson & Nabatchi, 2015a). It could also be the case that ACOs are trying to address medication nonadherence, but their strategies do not work. Further research will clarify the treatment effect of ACO enrollment on the treated.

Health policy stakeholders expect ACOs to manage patients well due to the collaboration mechanism. Previous work proposes improving interactions within healthcare systems will improve medication adherence (Osterberg & Blaschke, 2005). My findings support looking further into researcher suspicions that ACOs may not be engaging or integrating pharmacists meaningfully (Gaspero, 2016), even though estimates put ACOs that use staff pharmacists at 63% and growing (Vos MacDonald, 2018). Being unable to reject the null hypothesis may suggest that the CGRs need to reevaluate their collaboration dynamics, theory of change, or collaborative actions to increase their effectiveness in creating significant differences in this outcome if they truly value it (Emerson & Nabatchi, 2015a). Giving attention to the collaboration dynamics can help rework or clarify a CGR's theory of change and enhance a CGR's ability to carry out collaborative actions (Emerson & Nabatchi, 2015a).

Future Research

In the context of ACOs, research tends to focus on outcomes related to shared savings and improvements in quality (for an overview, see McWilliams et al., 2018). I offer a novel contribution by studying system context and CGR concepts from the integrated framework. Due to data limitations, I do not study the processes of collaboration occurring within ACOs. Collaborative actions, in my analysis, are a black box. Therefore, it is difficult to assess how proximate the outcome of medication nonadherence is to the collaborative action of the CGRs.

The integrative framework for collaborative governance recognizes that CGR outcomes can be intended. The framework also recognizes that outcomes can be indirect, unintended, or unanticipated (Emerson & Nabatchi, 2015a). Even if medication nonadherence falls into the latter category, it is still an interesting outcome to explore from a research standpoint. According to my findings, medication nonadherence is a prevalent problem in the Medicare population, including Medicare ACO beneficiaries. Analysis 2 shows that the problem exists at a concerning magnitude, yet Analysis 3 does not provide evidence of a difference. However, the lack of significance in Analysis 3 does not mean there is no effect. Future research should further examine the relationship.

Data on the actual processes of collaboration can illuminate the findings, but such data remain limited for CGRs in the health field (Shortell et al., 2010). To fill gaps, I recommend future work enhance knowledge on the drivers of CGR formation, collaboration dynamics, CGRs actions and theories of change, and adaptation (Emerson & Nabatchi, 2015a). Researchers in accountable healthcare study the CGR drivers of incentives (Addicott & Shortell, 2014; Bultema et al., 2020; Shortell et al., 2010), interdependence (Bultema et al., 2020; Fisher & Corrigan, 2014; Shortell et al., 2010), interconnectedness (Figueroa et al., 2019), or uncertainty. In accountable care, some scholars directly or indirectly study collaboration dynamics related to principled engagement (Bultema et al., 2020; Gong et al., 2015), shared motivation (Addicot & Shortell, 2014; Shortell et al., 2010), or joint capacity (Gong et al., 2015). However, the work suffers from data limitations. Health policy stakeholders can greatly benefit from research that generates primary data on the collaborative aspects of accountable care initiatives. Managers can learn a great deal from surveys that measure less commonly studied integrated framework elements. For example, despite federal leaders pushing for more collaboration between providers, Medicare ACOs do not base performance evaluations on aspects of collaboration or negotiation between actors (Gong et al., 2015; Shortell et al., 2010). Lack of measurement of collaborative factors results in little consensus on how to achieve successful collaboration and system alignment in health care practice. The lack of measurement of collaborative processes also leaves scholars and practitioners with little evidence to guide them as they choose which approach best fits their needs (Bultema et al., 2020). More data on collaborative dynamics, CGR's theory of change, and CGR action can help measure outcomes of value to the CGR's participants, the participant's organizations, and beneficiaries. More data on collaborative processes can help uncover questions about "which outcomes matter and to whom they matter," which is a "question of ongoing interest to those who study the performance of CGRs" (Emerson & Nabatchi, 2015, p. 84).

Implications

My analysis is important for practice and scholarship. Actors form CGRs to address public problems, requiring stakeholders to understand the surrounding conditions that aggravate or help resolve the problems that CGRs aim to address (Emerson & Nabatchi, 2015a). While the primary purpose of this exercise is to understand CGRs better, I also contribute to health policy literature by studying medication nonadherence in Medicare populations. Hospitals face challenges in identifying patients at risk for avoidable admissions (Rosen et al., 2017), and interventions that aim to reduce hospital admissions or improve adherence are complex and expensive to employ (Donzé et al., 2013; Osterberg & Blaschke, 2005). Medication nonadherence is a desirable factor to target to reduce avoidable inpatient admissions because it is a modifiable risk factor that individuals can reduce and control through altered behavior (Ada, 2022; Rosen et al., 2017). The number of Medicare ACOs has grown since the launch of the MSSP in 2012 (Centers for Medicare & Medicaid Services, 2022a). Preliminary findings are especially critical for those concerned with evaluating the effectiveness of ACOs. Some researchers already assert that improved pharmaceutical adherence will lead to increased positive financial outcomes for ACOs through lowered spending (Vos MacDonald, 2018). HHS grants ACOs flexibility in network governance. Therefore, ACOs have control over designing and implementing interventions to address medication nonadherence. However, it is important to consider what entity would bear the cost of care delivery changes. If addressing medication non-adherence requires new cost outlays from hospitals, it makes sense that ACOs would not want to introduce new costs to member providers when there is fat elsewhere to trim. Future research should explore who bares the cost of ACO medication adherence initiatives.

My results alert practitioners that medication nonadherence is a problem that exists among their beneficiaries. It is plausible that medication nonadherence could be lowering ACO performance metrics in the long term. Being associated with a Medicare ACO does not appear to correlate with differences in medication adherence proportions. It may be because Medicare ACOs focus on outcomes tied to shared savings and other consequential incentives. Equipped with my findings, Medicare ACOs may consider probing the relationships further and adjusting their shared theories of change if warranted. Generally, I recommend CGR stakeholders consider whether there is value in focusing on outcomes beyond their primary performance evaluations. “Outcomes matter not only to scholars who study CGRs but also to the CGR as a whole, to their participants, and to their parent organizations and constituencies, and to its potential beneficiaries” (Emerson & Nabatchi, 2015, p. 84)

Conclusion

Studies on collaborative governance in health help inform decision-makers about the vital role of collaborative partnerships in system transformation (Bultema et al., 2020). Collaborative governance research can aid managers in aligning organizations within sectors and provide evidence to guide evaluations of changing systems. In this work, I bolster scholarly understanding of how researchers and analysts can observe and test theories on CGRs. I address the question, how can researchers identify and measure the characteristics of CGRs, their broader system contexts, and their collaborative outcomes? I conclude that the integrated framework and econometric methods on representative samples allow scholars to draw conclusions about CGRs. For example, I exploit ACOs' taxpayer-identification numbers and find associational support for the notion that ACOs select areas with more hospitals and higher-cost patients. Future research can uncover a great deal of insight into the role of CGRs' broader system contexts and outcomes when studying collaborative governance.

Conclusion

This dissertation aims to answer the overarching research question: What leverage can be gained by examining the broader system context in which collaborative systems are embedded? I find and study the existence of collaborative systems in the U.S. In this section, I conclude the dissertation. First, I summarize the key findings from each chapter by explaining what I expected to see versus what I found. Second, I overview the conclusions which I draw from my research. Third, I explain why my research is important for researchers and practitioners. Fourth, I make recommendations for future research, followed by recommendations for practitioners. In my final paragraph, I round off the dissertation with closing remarks.

Summary of Key Findings

In Chapter One, I detail a collaborative system operating in Oregon that has a facilitative system context for collaborative governance. Oregon's system context features state support and legislation supporting externally-directed CGRs there (Cochran et al., 2019). In Chapter Two, I examine the context of the COVID-19 pandemic to understand collaborative governance when an unexpected crisis occurs. I analyze adaptation in two community referral networks in a U.S. state where the pandemic created instability in the system context. In Chapter Three, I study the broader system contexts and the outcome of medication nonadherence in Medicare ACOs in the United States.

First, I expected that collaborative systems exist and can be conceptualized and measured. I find this to be true. CGRs and collaborative platforms are a common occurrence in today's public landscape. In Chapter One, my coauthors and I theorized that CGRs could overlap through shared members. The Oregon case study demonstrated that CGRs experience membership overlap, which can be quite frequent, opening questions about collaborative system representation.[21] I hypothesized that policy area and geography would positively influence membership overlaps at the system level because of the geographically bounded nature of Oregon's externally directed collaborative system. Given there are only so many experts in the state and within regions within the state, I expected to see the same organizational actors serving over and over within their policy domain and region. However, I do not find statistical evidence that policy area or geographic proximity drives the structure of the whole collaborative system through membership overlaps. Instead, geographic scope, number of staff, and shared collaborative platform membership were positively and significantly associated with overlap. Chapter One reveals a tightly collaborative system connected through high membership overlap. The high level of membership overlap suggests leaders should probe whether the same actors appearing as members of CGRs hinders substantive representation.

In Chapter Two, I examine what leverage analysts can gain from looking at collaborative systems in a system context impacted by a crisis. I do this by studying two community referral networks in a U.S. state where the system context was unstable due to the pandemic's onset. Chapter Two documents how community referral networks adapted to changes in the supply of and demand for services during the emergence of COVID-19. My results highlight factors that contributed to and inhibited CGRs' viability for adaptation. I find organizational tenure and resource munificence contributed to CGR's viability of adaptation. I expected tenure, size, and diversity of service mix to help organizations buffer the changes in supply and demand brought on by the pandemic. I only support the hypothesis that organizations with longer network tenure were more likely to remain active during the COVID period than organizations who collaborated in the CGR for less time. However, the findings only support the hypothesis in one of the two

[21] I coauthored Chapter One with Dr. Julia L. Carboni and Dr. Tina Nabatchi.

AmericaServes community referral networks. I also observe that resources contribute to CGR's viability of adaptation. Organizations that remained stable and central to the CGRs in COVID emergence reportedly received grant resources and were deemed essential by the government.

Chapter Two revealed that community referral networks did experience changes in both the supply and demand of service due to COVID-19 shocking the system context of the state in which they reside. The pandemic shock affected the supply of services. First, I find that CGRs became less stable due to temporary provider exit and less flexible governance structures, leading to lower member participation in crisis. Second, I find that the abrupt cessation of face-to-face interactions among providers dealt a great blow to the CGRs' viability of adaptation through lowered opportunities to build shared motivation. Third, organizational factors contributed to some members being more adaptable and willing to continue in the CGR than others, including organizational tenure and relation to the coordination center. The pandemic shock also affected the demand for services. I find client demands did change, including urgency with employment, food assistance, and housing service types, which also drove provider decisions to work outside the CGRs. These changes in the demand for services affected providers. Rather than going through the hub-and-spoke, lead organization-governed community referral network model with the coordination center directing ties, organizations saw greater returns to modifying their service delivery to locate and serve clients directly and more quickly.

Chapter Three measures the association between states' broader system context characteristics and the number of Medicare ACOs registering in that state over time. Because the MSSP offers consequential incentives, I expect to find that Medicare ACOs register into markets with more favorable system context conditions, such as those with opportunities for interdependence (i.e., states with more hospitals and beneficiaries who have Medicare insurance). Due to consequential incentives of shared savings, I also expect to find that ACOs register to markets with more conditions that allow them to demonstrate reductions in spending more easily. I find an inverse association between Medicare ACOs registered to a state and population health (i.e., higher obesity rate, higher median age). I also find ACO enrollment positively associated with state resources that align incentives and foster interdependence (i.e., more hospitals and more resources through tax revenue). My results suggest that scholars can operationalize the integrative framework's elements of broader system context and collaboration drivers to predict the level of formal CGR registration to or deterrence from the jurisdiction of interest.

Overarching Conclusions

My first conclusion is that researchers and practitioners can gain a great deal of leverage by examining the broader system contexts of collaborative systems. Scholars and managers can learn much about system contexts by examining collaborative systems. By studying the system context, researchers gain the leverage to identify real-world CGRs. By studying the collaborative system concept, such as by geographically mapping collaborative systems or understanding the composition of clients the systems serve, analysts can also garner insights about the broader system context. Studying the system contexts and the collaborative systems are valuable avenues to generate rich insights into collaborative governance in modern public management.

My second overarching conclusion is that the integrative framework for collaborative governance and the collaborative system concept allow researchers to contribute to a concise theory of collaborative governance, no matter the discipline or the field. By looking at a broad range of contexts, I find support for the position that the integrative framework allows researchers to contribute to a concise theory of collaborative governance, no matter the discipline or the field. For example, in Chapter One, I apply the integrative framework to CGRs from public safety, education, health, natural resources, and economic sectors interconnected as one collaborative system in Oregon. Chapter Two focuses on a collaborative system with a wide range of veteran-serving organizations participating as members of two CGRs. Although chapter thee focuses on provider-to-provider collaboration in the health sector, the providers in the MSSP include healthcare payers, pharmacists, physicians, nurses, mental health specialists, hospital administrators, and more. No matter the discipline, the integrative framework is useful for analyzing and interpreting collaborative governance arrangements (Emerson et al., 2012; Emerson & Nabatchi, 2015a).

My third overarching finding is that managers can enhance the success of CGRs by focusing on their governance structures and the entities that support them. My dissertation fills gaps in the public administration literature on how actors use collaborative governance in different system contexts. Chapter Two shows how CGRs can be more flexible by focusing on their governance structures. The first two chapters show how managers can enhance the success of CGRs by focusing on the CGRs themselves, their governance structures, and the entities that help support them, such as collaborative platforms (Chapter One) and lead organizations (Chapter Two). As rapidly changing system contexts increase, leaders can be ready by understanding how to adapt and steer collaborative systems in response to crises.

Finally, my fourth conclusion is that analysts can gain leverage in understanding collaborative governance in modern public management using a wide range of data types and methodologies. Analysts can gain leverage in understanding collaborative systems using a wide range of data types and methodologies. For example, in Chapter One, I analyze a cross-section of secondary data from the OAC using network analysis techniques. I visually and descriptively reveal the structure of Oregon's collaborative system and draw conclusions about its level of descriptive representation. In Chapter Two, I use a mixed methods design by collecting primary qualitative data from interviews with CGR coordinators and generating a quantitative panel from the system-log data of the AmericaServes network, the collaborative system under study.[22] I analyze these data using thematic analysis and stochastic network modeling. In Chapter Three, I analyze a pooled cross-section of data and panel data on Medicare. Both datasets are publicly available representative samples policy analysts use for traditional CMS program evaluation. For example, Chapter Three shows that quantitatively analyzing system contexts allows managers to infer what states are more conducive to CGRs than others based on characteristics of state system contexts. Chapter Three also presents an analysis of an outcome that, I argue, should be of interest to the CGRs under study (i.e., medication nonadherence in Medicare ACOs).

I demonstrate that scholars can address different questions with system log data. Analyzing system log data is an important opportunity for the field, as new public management has proliferated data systems designed to promote accountability and efficiency (Greve, 2015), such as community referral networks. I highlight several advantages of this observed real-time interaction data. It allows scholars to examine large samples and dynamically analyzing real-time interactions alongside the informant-based data. I suggest scholars pair system log data with informant data to garner rich insight about networks. Utilizing these data together opens public administration scholars to a more nuanced understanding of management interventions to achieve network effectiveness. I contribute to the field of public administration by using this novel data source for network analysis.

[22] I performed data collection with a team from the Maxwell School of Citizenship and Public Affairs at Syracuse University and Northwestern University's Network for Nonprofit and Social Impact.

Importance for Practice

This dissertation research is important because there is evidence of collaborative systems beginning to take shape, such as in Oregon (Cochran et al., 2019; Annis et al., 2020; Yoon et al., 2022) and in nationwide community referral networks (Carboni et al., 2022; Shumate et al., 2022; Gibson et al., 2022). Despite the growth of widescale collaborative governance, the current scholarship focuses little on the structure and governance of collaborative systems or their contexts.

My research also demonstrates the value of studying the structural patterns and characteristics in collaborative arrangements, including representation. Examining collaborative systems and their system contexts allowed me to provide support for the notion that CGRs are not always inherently representative (Carboni et al., 2017; Koski et al., 2018) and talk about how the over-representation of actors has implications for collaborative governance. The premise of collaborative governance is that it is a process that represents interested stakeholders. When CGRs across the state have many common members, I must ask whether stakeholder interests are genuinely represented or if CGRs experience performative stakeholder representation.

Recommendations for Future Research

I recommend researchers apply various methodological tools to study collaborative systems. In this work, I show that researchers can use thematic analysis, network analysis, descriptive statistics, and inferential statistics to study collaborative systems. Future work can exploit variation from the staggered implantation of policies or pandemic onsets in system contexts to expand on my studies using causal analyses and generate more generalizable findings.

I also offer data recommendations for future research. The collaborative governance field faces challenges related to limited data, despite the growth of collaborative governance across disciplines. For example, network analysis is a promising way to study collaborative governance, but researchers must consider the difficulties of collecting relational or affiliate data (Robins et al., 2004). The difficulty of data collection has led to it being common to have only a single case study or a few cases of comparisons of collaboration across networks (O'Malley & Marsden, 2008; Provan et al., 2007). As data on collaborative arrangements become more available, researchers can use network data and methods to focus on the structure of collaboration at scale (Powell et al., 2005, p. 1133). Researchers can also analyze CGR system logs or public use file data that use rigorous sampling methods to get a representative sample of the population of interest. Both data types are promising ways to address current data limitations while meeting internal and external validity standards. My strongest recommendation is for scholars to continue to collect primary data guided by the elements outlined in the integrated framework to uncover novel insights into collaborative governance. Finally, more research on CGR adaption can enhance scholarly understanding of how various conditions influence CGRs over time (Emerson & Nabatchi, 2015a). When leaders know system context conditions, they can understand how current and changing conditions might influence their work (Emerson & Nabatchi, 2015a). Future research that assesses the productivity performance of CGRs over time will be valuable to the field.

Recommendations for Practice

First, I recommend managers use a wide range of tools to identify, understand, and make informed decisions around collaborative systems. The integrative framework for collaborative governance is useful for recognizing and categorizing the different elements of collaboration. Both qualitative and quantitative methods are useful for generating insights about real-world CGRs and collaborative systems.

Second, I recommend that managers focus on orchestrating interorganizational interactions. It is better to manage connections than to expect highly connected collaborative systems to be the most desirable. For example, I find that forming and maintaining interorganizational connections is critical for CGR community referral networks to adapt and be resilient during shocks in Chapter Two. However, in Chapter One, I show how too much membership overlap can signal poor representation in a collaborative system. Context certainly matters when thinking about ideal levels of interconnectedness or overlap in collaborative systems.

The research findings align with the widely accepted notion that leadership is critical to collaborative governance (Emerson & Nabatchi, 2015a; Emerson, 2018; O'Leary et al., 2012; Lee et al., 2010). The findings suggest that those who want to increase the success of collaborative governance in crisis management should focus on leadership factors of collaboration (Shumate & Cooper, 2022). For example, this work highlights the importance of managers staying aware of changes in the legal, political, and socio-economic factors in their CGR's system contexts. As another example, this work demonstrates that leaders can benefit from ensuring CGRs are funded across their life course to mitigate CGR instability, bottlenecks, capacity issues, and inflexibility in crises. When faced with an unexpected disaster, CGR leaders can strategically attract attention and resources to stabilize ties, improve joint capacity, and ultimately create adaptable networks during heightened public attention to a crisis.

Research Contributions

While there is a contemporary trend toward understanding the characteristics and outcomes of the groups of organizations carrying out collective action, most research in public administration focuses on outcomes for individuals or traditional organizations (Roberts, 2018). Less is understood about broader scales of research, such as groups of organizations as systems that aim to produce population-level outcomes. Assessing the system context in which collaboratives are embedded allows researchers to understand what factors can impact their productivity and performance (Emerson & Nabatchi, 2015a). I build knowledge of the structure and characteristics of collaborative systems by showing how there are multiple collaborative units within them and how they connect and overlap across traditional boundaries, such as jurisdictions and policy domains. I contribute to theories on how collaboration occurs at the societal level and theories that aim to understand interactions among multiple system components (Jilke et al., 2019).

I detail the leverage that scholars gain from examining their broader system contexts. Specifically, I analyze the factors which drove the structure of the externally directed collaborative system operating in Oregon as of 2019 in the first chapter. I also demonstrate how to measure a collaborative system by examining how two AmericaServes collaborative referral networks adapted to changes in supply and demand of services at the onset of COVID-19 using data from January 2020-February 2020 and April 2020-May 2020 in the second chapter. Finally, I explore broader system context characteristics associated with Medicare ACO registry to a state and the outcome of medication nonadherence in the Medicare Shared Savings Program from 2013-2016 in the third chapter.

I find support for the notion that "the network literature can contribute much more to [scholarly] understanding of CGRs" (Emerson & Nabatchi, 2015, p. 211). My findings support existing evidence that the structural components of networks are inherently related to the governance of collaborative work and vice versa (Provan & Kenis, 2008; Siddiki et al., 2015). I contribute to integrating the collaborative governance and network disciplines, which have only recently begun talking to one another and cross integrating their research streams. I use theory and variables from both fields to contribute to ‘‘illuminating the structure of collective action" (Powell et al., 2005, p. 1133). I integrate the research streams by examining the structure and governance of whole organizational networks. In doing so, I answer calls for more studies on the multi-level nature of governance to build theories and understand the government's repositioning in the hollow state (Jilke et al., 2019).

My dissertation adds knowledge to the field of public administration about governance structures in crises. I contribute to network governance and collaborative governance literature by exploring how collaborative networks with a lead organization structure work to remain viable during a crisis. I highlight an important tradeoff between the formality, legitimacy, and efficiency of lead organization structures and the flexibility of decentralized governance structures. In line with previous research, I find that “because the lead organization takes on many of the activities of governing the network, network members can readily lose interest in network-level goals and focus instead on their own self-interest, undermining the viability of the network” (Kenis & Provan, 2009, p. 448) and that may even be a bigger threat in crisis contexts.

Concluding Remarks

My dissertation answers the call for approaches that study the multi-level nature of governance and enhance theory and understanding of the repositioning of government (Jilke et al., 2019). My findings enhance scholarly understanding of governance in practice by looking at three real collaborative systems and hundreds of CGRs operating in the real world. My work also contributes to the calling for more studies that use data from multiple sources at multiple levels of analysis. I use multiple data sources and analyze multiple levels of collaborative systems, including clients, CGR workers, organizations (CGR members), and CGRs as units of analysis. I also respond to the need for more research that employs methods capable of utilizing these multiple data inputs. I use network analysis, econometrics, and thematic analysis methods on system log data, network data, panel data, pooled cross-sectional and cross-sectional data, and interview data. I answer calls for an ambitious research agenda to build a congruent theory on governance by establishing the collaborative systems concept and contributing knowledge to the integrated framework for collaborative governance (Emerson & Nabatchi, 2015a).

Taking a bird's-eye view of systems can help practitioners identify challenges and opportunities for improvement in collaborative governance. Scholars continue to contribute to a greater understanding of policymakers' and managers' innovative policies, tools, and strategies for collaboration in modern public management. The more scholarship examines the modern ways organizations work together to address complex issues, the more we can learn about our interconnected world.

Appendices

Appendix 1: The 70 CGRs with Highest K-Core Index Score

The k-core measure displays smaller interconnected cluster areas in the collaborative system by identifying tightly interlinked groups (Torab & Ganesh, 2021; Wasserman & Faust, 1994). The k-core is "a maximal group of entities, all of which are connected to at least *k* other entities in the group" (Torab & Ganesh, 2021, p. 37). My k-core index value varies between 1 and 38, with 1 being the least integrated subgroup and 38 being the most. I find that the most integrated group, the group with the k-core index of 38, consisted of 70 CGRs. I provide a full list of the 70 CGRs who all have an index of 38 here. Interestingly, the CGRs come from diverse policy areas and platforms and yet form a large, tightly interconnected group through shared membership.

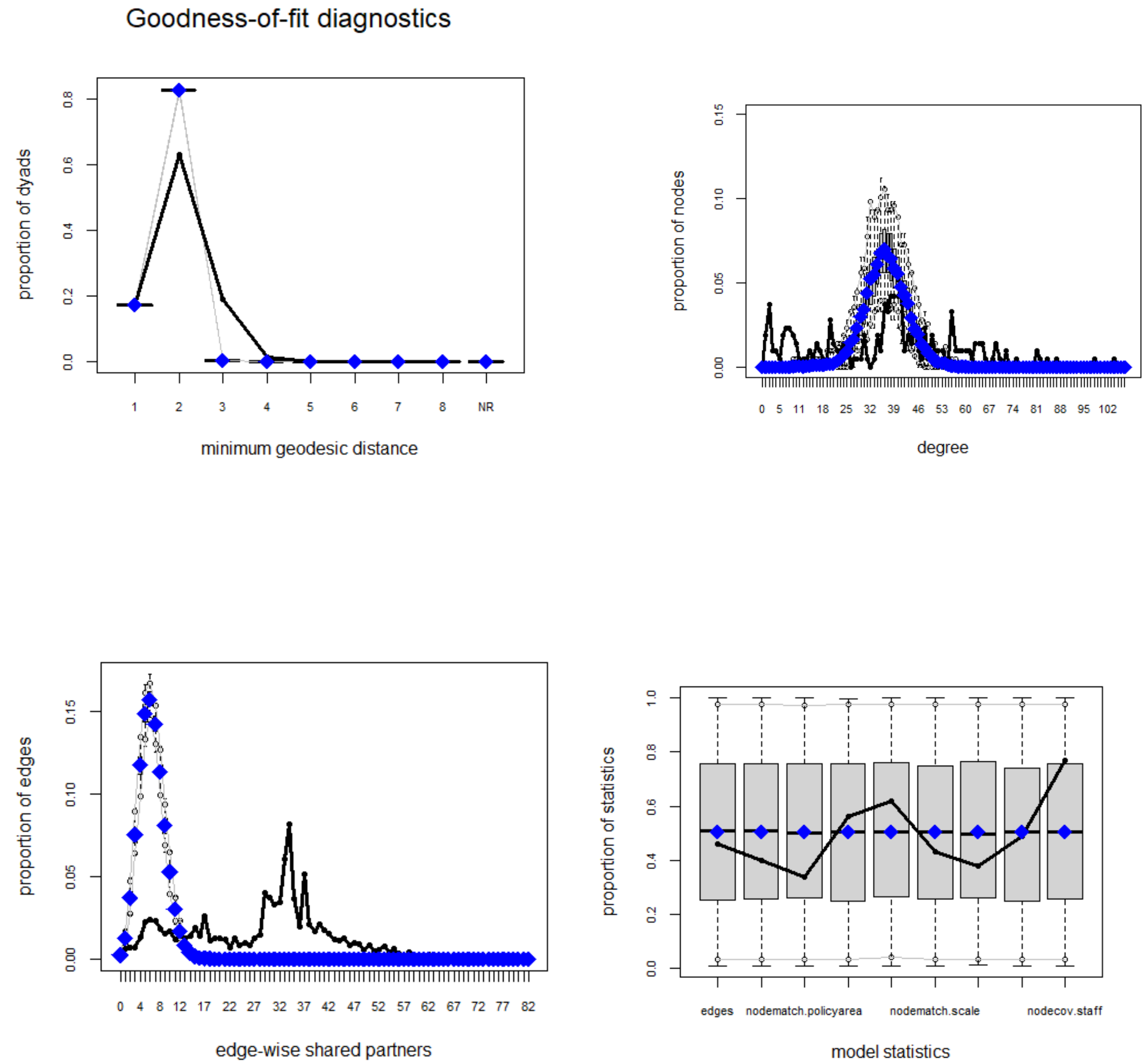
Table 1. The 70 CGRs with Highest K-Core Index Score

Alsea Stewardship Group
Ashland Forest All-Lands Restoration
Ashland Forest Resiliency Project and All-Lands Restoration
Baker County LPSCC
Benton County Willamette Criminal Justice Council
Better Together Central Oregon
Blue Mountains Forest Partners
Clackamas River Basin Council
Clackamas Stewardship Partners
Crooked River Watershed Council
East Cascades Oaks Partnership
Eastern Oregon Workforce Board
Gilliam County LPSCC
Greater Oregon STEM Hub
Harney County Restoration Collaborative
Harney-Malheur Lake Basins Community Based Water Planning
Health Share of Oregon
Hebo Stewardship Group
Hood River Forest Collaborative

Hood River Partnership
Hood River Watershed Group
Illinois Valley Watershed Council
John Day Basin Partnership
Josephine County LPSCC
Klamath County LPSCC
Klamath Promise Initiative
Klamath Siskiyou Oak Network
Lakeview Stewardship Group
Lane Workforce Partnership
Lincoln County LPSCC
Marion & Polk Early Learning Hub
Marys Peak Stewardship Group
Master Stewardship Agreement on the Fremont-Winema
McKenzie River Watershed Council
McKenzie Watershed Stewardship Group
Mid John Day Bridge Creek Watershed Council
Mid-Coast Water Planning Partnership
MidCoast Watershed Council
Mid-Columbia Health Equity Advocates
Middle Deschutes Watershed Council
Middle Fork Willamette Watershed Council
Oregon Health Equity Alliance
Partnership for the Umpqua Rivers
Regional Solutions: South Central Advisory Committee
Regional Solutions: South Coast Region Advisory Committee
Regional Solutions: South Valley/Mid Coast Region Advisory Committee
Sandy River Basin Watershed Council
Siuslaw Coho Partnership
Siuslaw Stewardship Group
Smith-Umpqua-Dunes Stewardship Group
South Coast Connect For Success
South Santiam All Lands Collaborative
South Santiam Watershed Council
Southern Willamette Forest Collaborative
Tenmile Lakes Basin Partnership
Umatilla Forest Collaborative Group
Umpqua Basin Partnership
Umpqua Forestry Coalition
Umpqua Valley STEAM Hub

Upper Grand Ronde Initiative
Upper Grande Ronde River Watershed Partnership
Upper Nehalem Watershed Council
Wallowa County LPSCC
Wallowa Fish Habitat Restoration Partnership
Wasco County & Mid John Day Bridge Creek Watershed Council
Wasco County Forest Collaborative
Wild Rivers Coast Forest Collaborative
Willamette Valley Community Health CCO
Williams Creek Watershed Council
Worksystems

Appendix 2: Goodness-of-Fit Plots



I assess the goodness-of-fit of the model to determine how “as-expected” the model is behaving. The goodness-of-fit procedure simulates many networks using the estimated coefficients. In every one of the graphs, the bold lines represent the values from the observed OAC data, while the other plots are the values from the simulated networks. Ideally, the mean of the simulated networks should overlap with the observed value. ERGM goodness-of-fit tests produce plots on minimum geodesic distance, degree, edge-wise shared partners, and model statistics.

Appendix 2 shows that the model adequately finds the geodesic path, meaning the shortest past with the minimum sum of edge weights, between two CGR nodes in the collaborative system. Edge-wise shard partners measures how many common neighbors two *connected* vertices have, meaning that the models generally do a poor job of representing the local clustering (edgewise shared partner distribution) in the collaborative system (i.e., the friends of friends). Network scholars refer to this as k-triangles. Although estimating k-triangles is a high-order estimation that is beyond the scope of this analysis, this does suggest there may be endogenous network terms missing. Future research should revisit theory to uncover what omitted endogenous network terms drive k-cliques in the Oregon collaborative system, which may improve overall model fit and improve the accuracy of the results.

The model does an adequate job at simulating degree, meaning the simulated graphs have similar CGR nodal degrees as the observed collaborative system. A degree is the number of membership overlaps a CGR node has with the other CGR nodes. The goodness-of-fit test for model statistics shows the simulated networks are on par with the observed collaborative system, and overall, the lowered BIC after adding my model statistics to the null and the good fit for model statistics, degree, and average path length demonstrate my chosen model’s ability to generate many networks like the collaborative system in Oregon and the output can be interpreted for my purposes.

Appendix 3: CGR 1 Interview Protocol – COVID Emergence

Thank you for your time and willingness to do this interview. The main focus of today's interview is to gain an idea of how your network is operating in the COVID-19 pandemic.

Now, I'd like to ask you a few questions about your experience operating your network and using the UniteUS system during this pandemic.

General/Background Questions

- How has COVID-19 changed the way that CGR 1 operates?
- How did CGR 1 leadership respond to COVID-19?
    - From your knowledge, how have partner organizations responded to COVID-19?
- Can you describe any significant leadership or staff changes that have occurred during the pandemic? If any, both in the coordination center and across the network.
- I am interested in knowing about communication both within the coordination center and across the network of providers.
    - Have communication protocols or channels changed as a result of the COVID-19 pandemic?
        - What methods of communication are used for outreach to providers?
        - Can you describe any changes in outreach strategies for clients?
- Has COVID highlighted any shortcomings of the Unite Us platform?
- Have there been any features of the Unite Us platform that have made dealing with the pandemic easier?
- Sometimes when people don't like how a technology system is structured, or they think there's a better way to do something, they find a workaround. Has the COVID-19 pandemic given rise to any workarounds for the Unite Us system?
- Decision rules are statements that guide what actions to take under certain circumstances. Has your coordination center implemented any new decision rules or procedures because of COVID-19?
- What has your network learned about your network as a result of the COVID-19 pandemic?

Thank you for describing how your network and coordination center are responding to the pandemic. We are interested in learning more about how your providers adapted in the face of the COVID-19 pandemic.

Capacity Questions

- How did COVID-19 impact the providers in your network?
    - Did any providers change the services they offered? If so, which ones?
    - Did any providers reduce or increase the number of clients that they served? If so, which ones?
    - Have any new organizations joined your network? If so, what motivated their participation?

- Did the pandemic change the reasons why providers might reject a referral? If so, please explain.
    - In my view, what have been common reasons for rejecting a referral during the COVID-19 pandemic?
- Did the pandemic change the reasons why you might recall a referral from a provider? If so, please explain.
    - In your view, what have been the common reasons for recalling a referral during the COVID-19 pandemic?
- In the last interview, I asked how you know when a provider does not have the capacity to take on additional service requests.
    - How has the pandemic affected your ability to make this assessment?
    - How is provider capacity captured and managed? Has this changed since the COVID-19 pandemic began?

- As the pandemic continues, does the coordination center often honor client preferences for specific providers?
    - If so, how do you execute these requests in the referral platform?
    - If not, what do you tell clients when they ask for particular providers?

Use a peg from the previous section and segue to the next, in this last section, I would like to talk about what I found from my analysis regarding referral activity in your network during the COVID-19 pandemic.

Questions for Quantitative Observations:

General quantitative

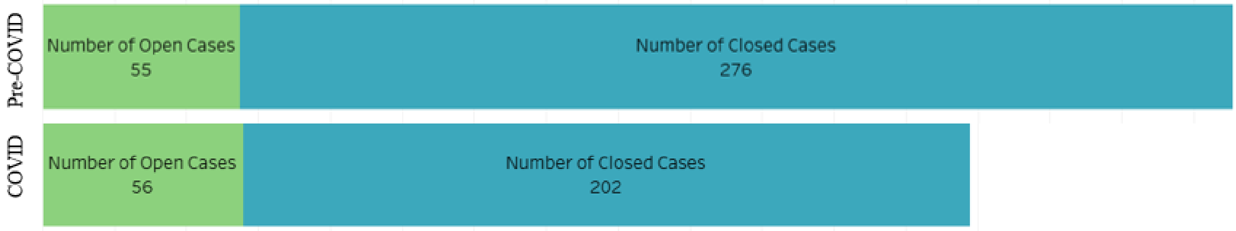
- I collected this data between 04/01/2020 and 05/01/2020. Was there anything unusual that happened immediately before or during that time period, other than the onset of the COVID-19 pandemic, that might make these patterns unusual?

COVID

Number of Cases

- Please refer to Figure 1. Figure 1 shows the number of open and closed cases in pre-COVID on the top, compared to COVID on the bottom.
    - In general, I observe a decrease in the total number of cases during COVID. Why might this be?
    - The number of open cases was similar in both time periods. However, there was a large decrease in the number of closed cases during the COVID time period. Why might this be?

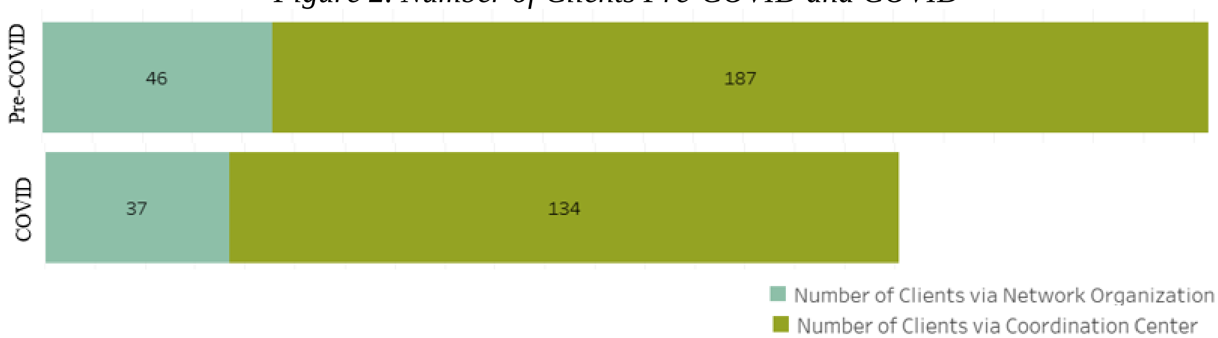
Figure 1. Number of Open versus Closed Cases Pre-COVID and COVID



Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

- Please refer to Figure 2. This figure shows the number of clients, with the Pre-COVID data on top and COVID data on the bottom.
    - Why is there a decrease in the total number of clients during COVID?

Figure 2. Number of Clients Pre-COVID and COVID

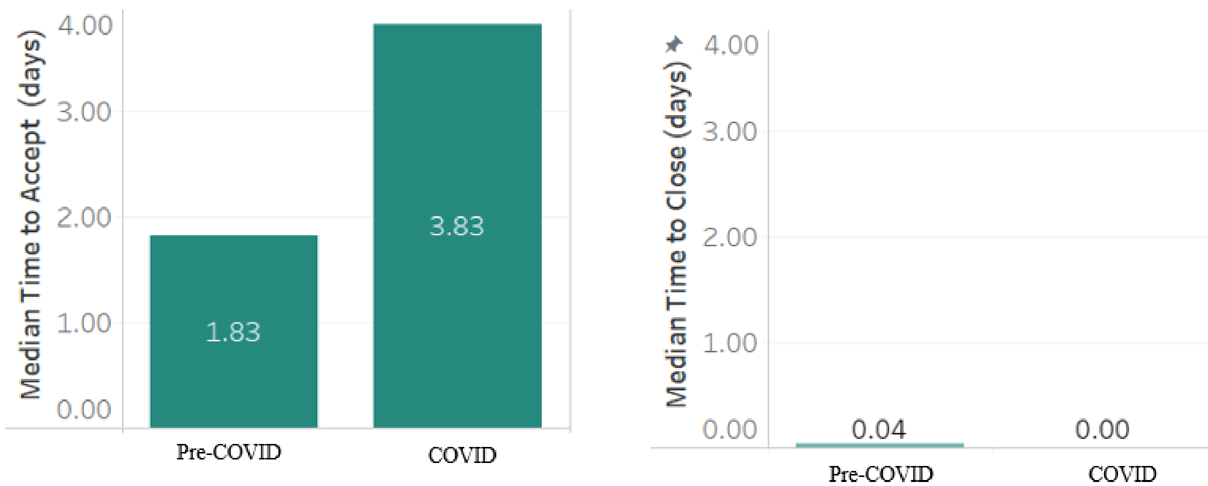


Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

Time-to-Care

- Please refer to Figure 3. The left side shows the median time to accept, and the right side shows the median times to close from both time periods.
    - Looking at the same figure, I observe a 110% increase in the median time to accept during COVID. Why do you think referrals took more to accept during the COVID time period?
    - Why do I see a 100% decrease in the median days to close after a referral was accepted? Why do you think referrals closed more quickly during the COVID time period?

Figure 3. Time to Care in CGR 1 Pre-COVID and COVID



Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

- During COVID, the median time to accept decreased by 63% across all of the AmericaServes network. The median time to accept increased by 110% for *CGR 1* during COVID. Why do you think that is?

- Now, I would like to ask you about specific service areas.
    - I saw a decrease in the total time to care for the Employment requests. Can you explain why this occurred?
    - I saw an increase in the total time to care for the Benefit Navigation requests. Can you explain why this occurred?
    - I see an important decrease in the total number of Social Enrichment service episodes during the COVID period. Why is this?

Number of Active Organizations

- Please refer to Table 1. Table 1 shows a list of provider organizations that had the largest percent increase in referrals from the pre-COVID data compared to the COVID data.
    - Can you help us understand this finding?
    - Did any providers start receiving or accepting more referrals in the network as a result of or in response to the onset of COVID-19?

Table 1. Organizations with Largest Percent Increase in Referral Receipt during COVID

Organization
Asheville Buncombe Community Christian Ministry
Veterans Bridge Home
Catholic Charities Diocese of Charlotte (Charlotte Regional O
A Place for Heroes
Alliance Credit Counseling
Charlotte Center for Legal Advocacy
Express Employment Professionals
NCServes - Central Carolina Coordination Center
ABCCM - SSVF/HVRP
Gaston County Family YMCA Resource Connection Gateway
NCServes - Western Coordination Center
Patriots Path
Union County Veterans Services Office

- Please refer to Table 2. Table 2 lists provider organizations that had three or more referrals in the pre-COVID data but did not have any referrals during the COVID data study period.
    - Did any providers stop receiving or accepting referrals in the network as a result of or in response to the onset of COVID-19?

Table 2. Organizations with No Referrals in COVID

Organization
American Red Cross - Carolina Piedmont Region
American Red Cross - Western North Carolina
Catholic Charities Diocese of Charlotte (Western Regional Office)
Creative Management Staffing Services (Inactive)
Family Preservation Services of North Carolina
Habitat for Humanity of Charlotte
Hope For The Warriors
IVMF Enrollment Services
Lone Survivor Foundation (Inactive)
NCWorks Career Center - WNC
Northern Virginia Community College
University Of North Carolina at Charlotte
Urban Ministry Center
Volunteers of America of the Carolinas
Wingate University
Wounded Warrior Project - North Carolina

Changes in the Flow of Referrals

- In the pre-COVID period, referrals that originated at *Catholic Charities Diocese of Charlotte* ended up being accepted by two providers:
    - *Mecklenburg County Veteran Services*
    - *Charlotte Center for Legal Advocacy*

  *In COVID, r*eferrals that originated at the *Catholic Charities Diocese of Charlotte* ended up being accepted by three providers:

    - *Express Employment Professionals*
    - *Stop Soldier Suicide*
    - *Central Piedmont Community College*

  Why did referrals that originated from *Catholic Charities Diocese of Charlotte* end up with a more diverse set of providers in the COVID period?

- Referrals that originated from *Veterans Bridge Home* ended up being accepted by a more diverse set of providers in the pre-COVID period, including:
    - *Catholic Charities Diocese of Charlotte*
    - *Team Red White and Blue Charlotte*

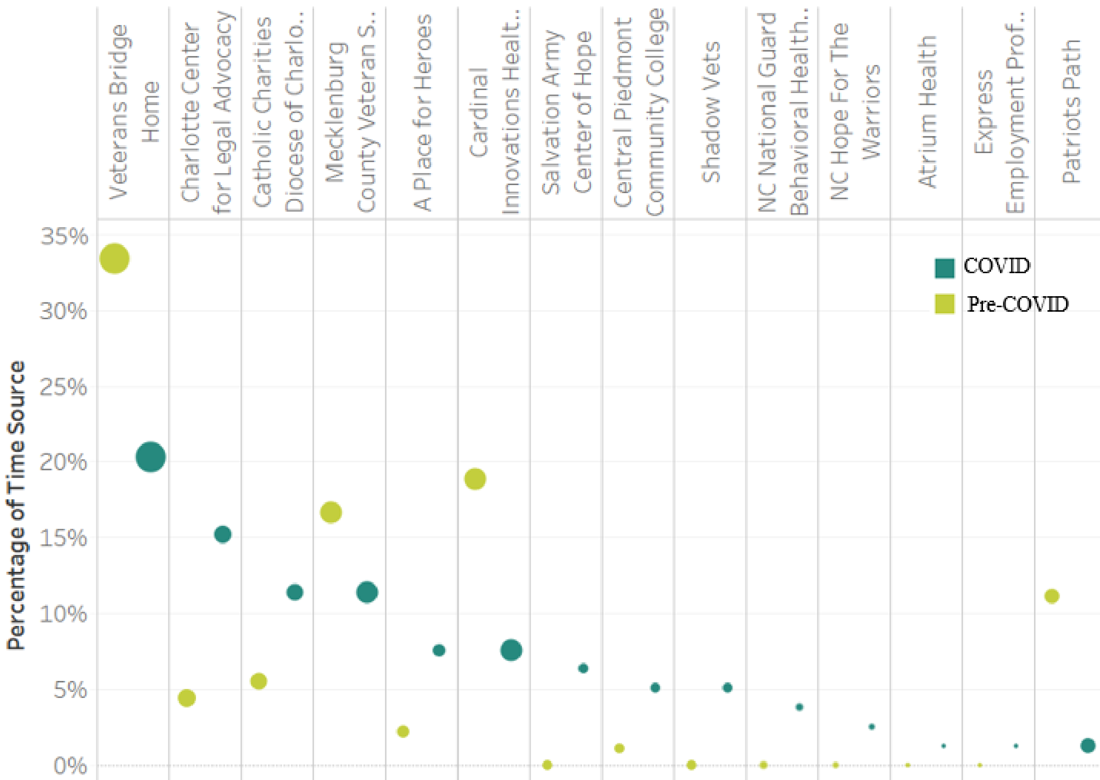
  In the COVID period, referrals that originated at *Veterans Bridge Home* *w*ere only accepted by
    - *Catholic Charities Diocese of Charlotte,*
    - *Team Red White and Blue Charlotte,* and
    - *Shadow Vets.*

Why did referrals that originated from *Veterans Bridge Home* end up at a more diverse set of providers during COVID?

Please refer to Figure 4. This figure shows the percentage of times an organization was the originating source of referrals Pre-COVID and COVID.

- Fewer referrals originated from the *Veterans Bridge Home* and *Cardinal Innovations Health* during COVID. Why might this be?
- I can see an increase in the percentage of times an organization was the originating source of referrals for *Charlotte Center for Legal Advocacy* and *Catholic Charities Diocese of Charlotte.* Why might this be?
- *Salvation Army Center of Hope* moved from not being the originating source for any referrals in my pre-COVID data to being an originating source for at least 5% of referrals in the COVID data. Why might this be?

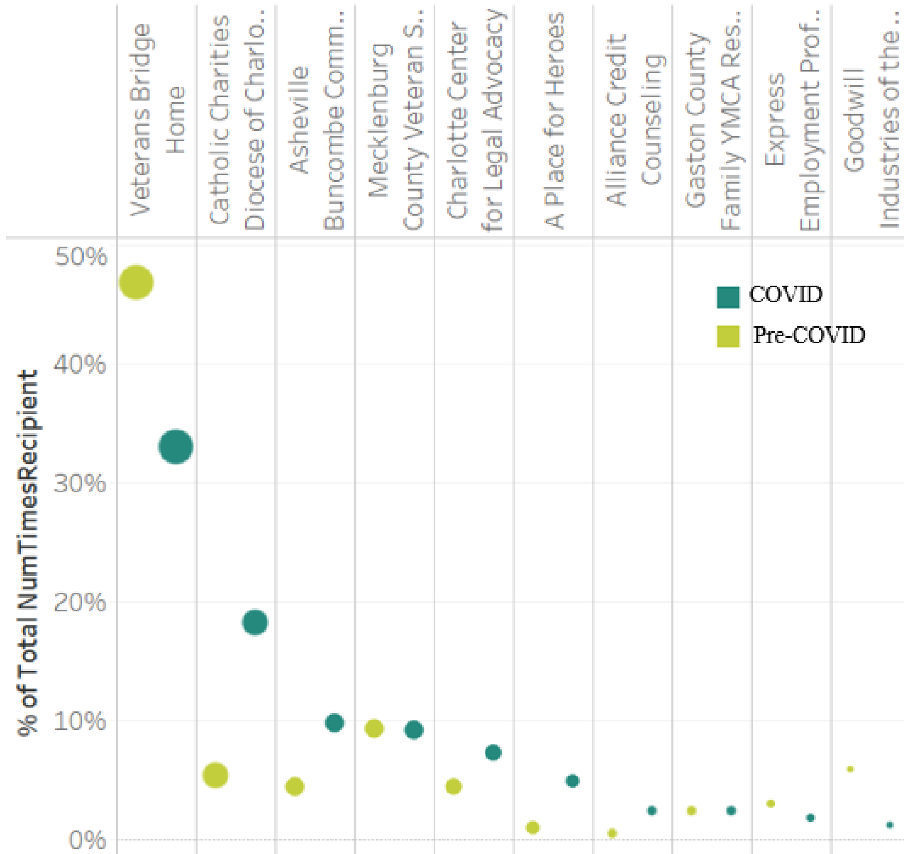
Figure 4. Change in Organizations Where Cases Originated Pre-COVID and COVID



Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

- Please refer to Figure 5. This figure compares how often organizations received referrals in CGR 1 Pre-COVID and COVID.
    - My COVID data shows an increase in the percentage of referrals received by *Catholic Charities Diocese of Charlotte* compared to the Pre-COVID study period. Can you explain this finding?
    - My COVID data shows a decrease in the percentage of referrals received by *Veterans Bridge Home* compared to the Pre-COVID study period. Can you explain this finding?

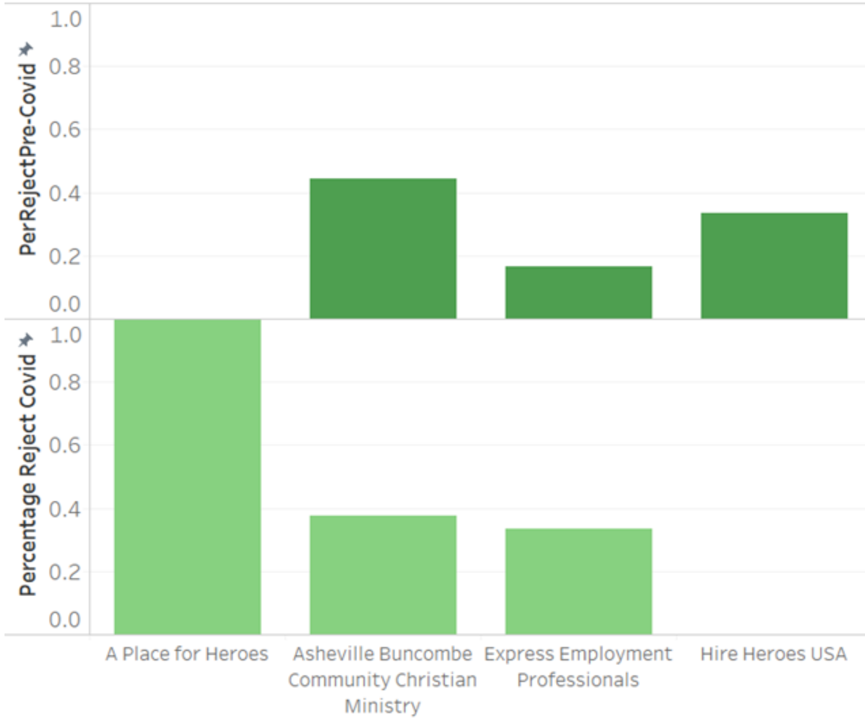
Figure 5. Change in Organizations Where Referrals Were Received in CGR 1 Pre-COVID and COVID



Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

- Please refer to Figure 6. This figure shows the percentage of referrals rejected by providers. Pre-COVID data is on the top, and COVID data is on the bottom.
- It appears that overall, there was a higher percentage of referrals rejected during COVID. Can you explain why this may be?

Figure 6. Number of Referrals Rejected in CGR 1 -Pre-COVID and COVID

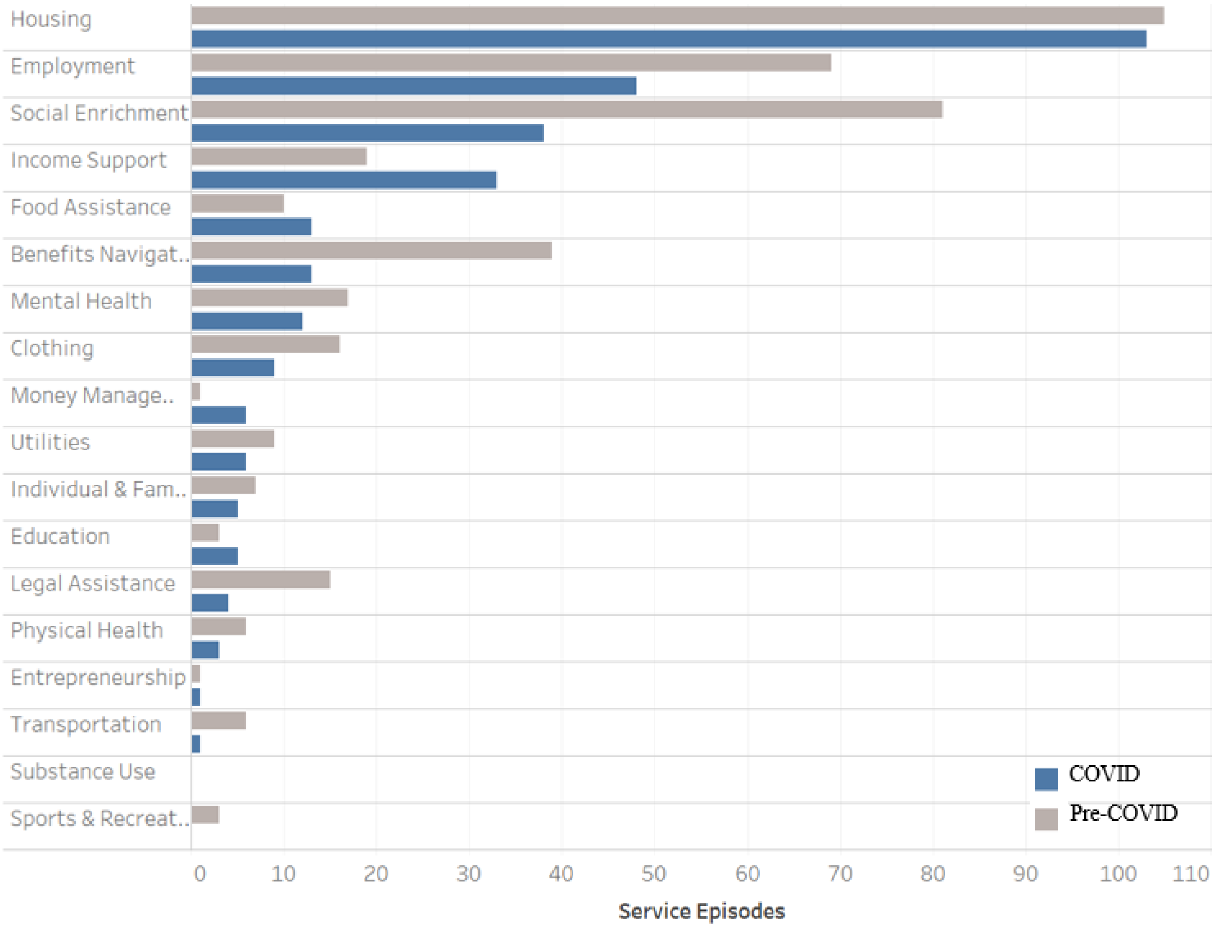


Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

Service Area Related

- Please refer to Figure 7. This figure shows the number of service episodes by service type, with pre-COVID data in grey and COVID data in blue.
- Earlier in the interview, I asked about the decrease in social enrichment service episodes during the COVID time period. Now looking at the graph, is there anything else that comes to mind that may explain this finding?
  - I see that benefit navigation has more service requests in the pre-COVID period than in the COVID period. Can you explain this finding?
  - I see that income support has fewer service requests in the pre-COVID period than in the COVID period. Can you explain this finding?
  - Can you describe any other contextual factors that explain the results in this graph?

Figure 7. Comparison of Service Episodes -Pre-COVID and COVID



Pre-COVID dates 1/11/2020-2/11/2020 and COVID dates 04/01/2020-05/01/2020

Concluding remarks

That is all of the questions that I have today.
Are there any other things that you think would help us to know as I continue this research?
Do you have any questions for us?

Thank you very much for your time.

Appendix 4: Codebook – Parent and Child Codes

Covid-19 changes (COVID emergence interview transcripts only)

a) Changes in processes
b) Leadership responses
c) Provider responses
d) Staffing changes
    a. Staffing changes in coordination center
    b. Staffing changes in the network
e) Changes in communication protocols or channels
    a. Communication changes in coordination center
    b. Communication changes in the network
f) Outreach to clients during COVID-19

Isolates – Names of organizations that they don’t work with anymore <Select Each Name Separately that is mentioned>

a) Because they are inactive
b) Because they don’t provide quality service in view of the coordination center
c) Not usually an isolate
d) New Organization

Rules about timing

a) Amount of time in review
b) Number of days to recall
c) When a provider might be contacted outside of the system because they haven’t responded

Time to care factors

a) Type of service
b) Need for additional documentation for some services
c) Only one organization offers the service
d) The way that the end of the referral is seen
e) Some organizations only review cases periodically
f) Infrequent use of the referral technology system

Effectiveness of the coordination center

a) Coordination center capacity
    b) Coordination center understaffed
    c) Competing organizational priorities
    d) Coordination center is part of public institutions

e) Surge of clients
f) Organizational changes

Decision Referral Rules

a) Documentation for decision rules about referrals
b) Client-based factors
    a. Income Eligibility
    b. Urgency of Need
    c. Where they Live
    d. Discharge Status
    e. Era of service
    f. Military affiliation
    g. DD214 on file
    h. Client preference
c) Organization-based factors
    a. Perceived quality of care
    b. Niche services - specific program for a specific population
    c. Broad array of services
    d. Relationship coordination center has with particular providers
    e. Only provider
    f. Capacity issues
    g. Staff change
    h. Geographic catchment area
    i. The provider is an information hub - talks about a special service
d) System-based factors
    a) The decision to refer out to multiple organizations
    b) The organization requires all referrals to go through the coordination center
    c) Norms about when to use the referral technology system versus directly referring from organization to organization using other technologies
    d) Natural matches between the types of services that two providers offer

Role of the coordination center

a) Broker of cases
b) Manager of data
c) Intake of clients to identify co-occurring needs
d) Case management
e) Gathering provider information

Technology codes

a) Presence of different technology systems for the same task

b) Use of e-mail and phone instead of referral technology system
c) Other workarounds
d) What the referral technology system doesn't capture
e) Features or functions used within the referral technology system
f) Technology likes and dislikes

Typical needs that co-occur

Unresolved cases

Appendix 5. Medicare Populations who Pay for Prescriptions

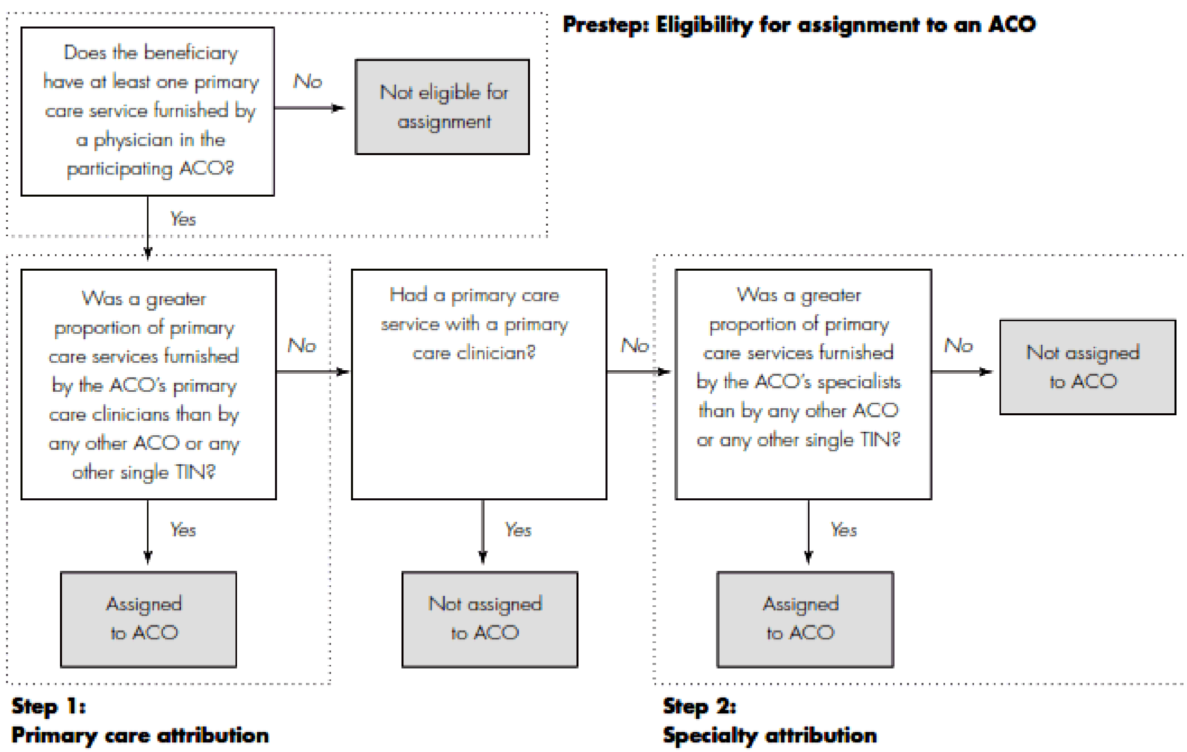
I provide a discussion of differences in drug coverage amongst Medicare programs. Medicare covers prescription medications in different ways depending on the Medicare plan. Medicare Parts A and B mainly cover drugs supplied in the inpatient setting or directly by a patient's physician, and therefore outside of the retail pharmaceutical setting. Medicare Part A covers the drugs a patient needs during an inpatient hospital stay, skilled nursing facility stay, and Medicare hospice beneficiaries. Those covered by Medicare Part B covers most drugs that are administered by a patient's physician. The physician or the facility must buy and supply the pharmaceuticals. Medicare Part B also covers a select few types of outpatient prescription drugs (mainly oral cancer drugs for chemotherapy). Anyone who has Medicare Part A or Part B (or both) can get Part D coverage regardless of income or health (American Association of Retired Persons, n.d.).

Medicare has an optional program called Medicare Part D that provides insurance to help individuals pay for prescription drugs. To get Medicare drug coverage, individuals must join a private plan that is regulated by Medicare but run by an insurance company. Individuals who select to have the coverage pay a monthly premium. ACO beneficiaries are those enrolled in Original Medicare programs and therefore can choose from multiple stand-alone Part D plans, at least 18 in each state (Medicare, n.d). No Medicare Part D plan puts a cap on out-of-pocket spending by the consumer unless the consumer is enrolled in the Extra Help program discussed further below.

Medicare Parts A and B mainly cover drugs supplied in the inpatient setting or directly by a patient's physician, and therefore outside of the retail pharmaceutical setting. Every Medicare Part D plan categorizes its covered drugs independently and Medicare Part D drug plans often place drugs into payment tiers. Higher tiers usually mean higher copayment and coinsurance costs (Baum, 2022). The ACO beneficiary's actual drug coverage costs will vary depending on whether their prescriptions are on the plan's list of covered drugs (formulary), what tier the medication is in, which drug benefit phase they're in (i.e., whether that patient has met their deductible), and their pharmacy (Medicare, n.d). ACO beneficiaries always have the option of paying out-of-pocket costs for brand name or generic drugs, which are sometimes cheaper than what the drug would cost by going through their insurance plan. ACO and other Medicare beneficiaries who are less likely to be impacted by cost-related barriers to medication adherence are beneficiaries who are enrolled in the Extra Help program. The Extra Help program helps low-income beneficiaries afford their Medicare Drug coverage, including out-of-pocket costs when they fill their prescriptions (copays and coinsurances). In 2022, beneficiaries in this program will pay no more than $3.95 for generic drugs or $9.85 for brand-name drugs (Medicare, n.d.).

Appendix 6. ACO Assignment in the Medicare Shared Savings Program

FIGURE 6–1 **ACO assignment in the Medicare Shared Savings Program**



Note: ACO (accountable care organization), TIN (taxpayer identification number). According to regulations found in 42 CFR §425.20, an ACO is identified by a Medicare-enrolled TIN that alone or together with one or more other ACO participants constitutes the ACO. The proportion of primary care services is measured by Medicare-allowed charges. Specialty attribution occurs only for beneficiaries who did not have a primary care service with a primary care clinician but did have a service with an ACO specialist.

Source: Centers for Medicare & Medicaid Services. Financial and beneficiary assignment specifications Versions 3–6. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/program-guidance-and-specifications.html.

Source: (MedPac, 2019)

There are two ways Medicare assigns a beneficiary to an ACO. First, an eligible beneficiary is assigned to an ACO if they received a higher proportion of their primary care from the ACO's primary care clinicians than from any other ACO or provider. Step 2 details specialty attribution, where Medicare assigns a beneficiary to an ACO if the ACO's specialists furnished a higher proportion of their care services than any other ACO or provider.

Appendix 7. Matched Sample Comparisons

Table 1: Matched Sample Comparisons

	N_1	% Change	N_0	% Change
Patient did not get Rx	5919	-6%	24675	-25%
Skipped doses to make Rx last	5907	-6%	24687	-25%
Did not fill Rx due to cost	5919	-6%	25167	-23%
Stroke	5919	-6%	30139	-8%
Osteoporosis	4626	-26%	29497	-10%
Myocardial Infarction	5582	-19%	28853	-12%
Depression	5582	-19%	30850	-19%
High Cholesterol	5084	-27%	26118	-23%

N_1= Number of treated. N_0= Number of comparisons. The MSSP included data on 6,293 MSSP ACO beneficiaries and 32,794 non-ACO beneficiaries.

In Chapter Three Analysis 3, I use a matched sample design to compare the groups (Table 14). After matching, I lost 6% of the sample size of the original data for the ACO group and an average of 24% of the comparison group for variables related to medication nonadherence. I lost between 6%-27% for variables related to health diagnoses for the treatment group and 8%-23% in the comparison group.

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Teaching Assistant, Public Administration PAI 755: Public Administration and Democracy, Maxwell School of Citizenship and Public Affairs, Syracuse University, Summer 2020

Teaching Assistant, Public Administration PAI 895: Managerial Leadership, Maxwell School of Citizenship and Public Affairs, Syracuse University, Fall 2019

Teaching Assistant, International Affairs INR 5936r: Theories of Global Engagement, College of Social Sciences, Florida State University, Summer 2013

PEER-REVIEWED JOURNAL ARTICLES

1. Tang, T., Hou, J. (Jove), Fay, D. L., & **Annis, C**. (2021). Revisit the drivers and barriers to e-governance in the mobile age: A case study on the adoption of city management mobile apps for smart urban governance. *Journal of Urban Affairs*, *43*(4), 563–585. https://doi.org/10.1080/07352166.2019.1572455

2. **Annis, C**., Hou, J. (Jove), & Tang, T. (2021). Perceptions, motivators and barriers of using city management applications among citizens: A focus group approach. *Information Technology & People*, *ahead-of-print* (ahead-of-print). https://doi.org/10.1108/ITP-03-2020-0148

ARTICLES UNDER REVIEW

1. **Annis, C**., Gibson, Z., Carboni, J.L., Shumate, M. Version 1. System Data for Network Analysis in Public Administration: An Overview and Application.

2. Shi, J., Canuelas-Torres, L., **Annis, C**. Version 2. How Do You Feel: News Attentions, Emotions, and Perceived Partisan Ambivalence in the Era of Trump.

POLICY BRIEFS

1. Carboni, J. L., **Annis, C.**, & Sontheimer, T. (2022). *Landscape Assessment of Veteran Care in New York State*. Institute for Veteran and Military Families.

2. Staley, S. R., **Annis, C**., & Boodry, T. (2019). *Cost Overruns and Public Infrastructure: The Case of Tallahassee's Cascades Park & Trail*. The DeVoe Moore Center.

3. Staley, S. R., **Annis, C**., & Matthew, K. (2018). *Regulatory Overdrive- Taxi Regulations, Market Concentration and Service Availability*. Institute for Justice.

WORKING PAPERS

1. **Annis, C**., Carboni, J.L., Nabatchi, T. Version 2. Collaborative Governance System Structures: Mapping Collaborative Networks in Oregon. *Under revisions.*

2. **Annis, C**., Barthuly, B., Cochran, B., Nabatchi, T. Version 2. The Role of Collaborative Platforms in Supporting Collaborative Governance. *In preparation to be submitted to Public Administration Review.*

3. **Annis, C**. Version 1. Institutional Layering: Understanding the Relationship between State Policy and Accountable Care Organization Performance.

4. Gibson, Z.M., Escallon-Barrios, M., Miles, J.P., **Annis**, **C**., Carboni, J.L., Smilowitz, K., Cantor, G., Armstrong, N., Shumate, N. Version 1. Beyond Network Effectiveness: The Value of

Operational Metrics in Evaluation. Northwestern Institute for Policy Research. https://www.ipr.northwestern.edu/our-work/working-papers/2022/wp-22-17.html

5. **Annis, C**. Version 1. Measuring the Contribution of Structural Factors in the Collaborative System.

6. **Annis, C**. Version 1. Referral Network Adaptation During COVID-19.

CONFERENCE PRESENTATIONS

1. **Catherine Annis**, Zachary M. Gibson, Julia L. Carboni, Michelle Shumate. "System Data for Network Analysis in Public Administration: An Overview and Application". *Public Management Research Conference*. Phoenix, AZ. May 2022.

2. **Catherine Annis**. "Referral Network Adaptation During COVID-19". *American Society of Public Administration Conference.* Jacksonville, FL. March 2022.

3. Zachary M. Gibson, Mariana Escallon-Barrios, Joshua-Paul Miles, **Catherine Annis**, Julia L. Carboni, Karen Smilowitz, Gilly Cantor, Nicholas Armstrong, Michelle Shumate. "Beyond Network Effectiveness: The Value of Operational Metrics in Evaluation." Online. *Canadian Institute for Military and Veteran Research Forum*. August 2021.

4. **Catherine Annis**, Bryce Bathuly, Bobby Cochran, Tina Nabatchi. "The Role of Collaborative Platforms in Supporting Collaborative Governance." Online. *Public Management Research Conference*. June 2021.

5. Jian Shi, Laura Canuelas-Torres, **Catherine Annis**. "Emotions and Ambivalence Matter: Examining A Parallel-Serial Mediation Model between Media Exposure and Civic Engagement." Online. *ICA 71st Annual International Communication Association Conference*. May 2021.

6. **Catherine Annis**. "Institutional Layering: Understanding the Relationship between State Policy and Accountable Care Organization Performance." *American Society of Public Administration Conference.* Online. April 2021.

7. Jian Shi, Laura Canuelas-Torres, **Catherine Annis**, Zanira Ghulamhussain. "Partisan Ambivalence, Emotions, and Civic Engagement: Hierarchy Regression Analyses on Online and Offline Civic Engagement." *Association for Education in Journalism and Mass Communication*. Online. August 2020. *AEJMC Third place student paper.

8. **Catherine Annis**, Julia Carboni. "Mapping Collaborative Networks in Oregon." *American Society of Public Administration Conference.* Online. June 2020.

9. Tian Tang, Jinghui Hou, Daniel Fay, **Catherine Annis**. "From Customers to Partners: Revisiting Barriers and Strategies for E-governance through Smart City Mobile Applications." *Association for Public Policy Analysis and Management International Conference*. Mexico City, Mexico. July 2018.

10. **Catherine Annis**. "Community Health and Waste Management in Rural Nepal." *South Asian Media and Cultural Studies Conference*. Tallahassee, Florida. January 2015.

INVITED TALKS

1. **Catherine Annis,** Jonathan Beagles, Julia L. Carboni, Kirk Emerson. Program for the Advancement of Research on Conflict and Collaboration's Collaborative Governance Initiatives. Syracuse University Maxwell School of Citizenship and Public Affairs. Conversations in Conflict Studies. March 20222.
2. **Catherine Annis**, Jinghui Hou, Tian Tang. The Road toward Smart Cities: A Study on Citizens' Perceptions and Use of Mobile Applications for City Management. The University of Georgia New Voices Series. April 2021

OP-EDS

Annis, C. (2019, May 11). Technology-focused approach to community feedback needed | Opinion. Tallahassee Democrat.

Hass, M., & **Annis, C**. (2018, February 1). Opinion: Airbnb, Homestay, strengthen tourism and hospitality industry. Tallahassee Democrat.

PRESS RELEASES

Carboni report on collaborative networks published by IBM center for the business of government. (2022, July 1). Syracuse University Maxwell School of Citizenship and Public Affairs. https://www.maxwell.syr.edu/research/article/carboni-report-on-collaborative-networks-published-by-ibm-center-for-the-business-of-government

Waters, T. (2019, April 29). Study: Cascades Park, infrastructure projects cost taxpayers millions more than expected. Tallahassee Democrat. https://www.tallahassee.com/story/news/money/2019/04/29/study-cascades-park-projects-cost-tax-payers-millions-more-than-expected/3576024002/

SERVICE TO DISCIPLINE

Graduate Student Advisory Board (GSAB), International Public Management Journal (4)

Reviewer for Nonprofit Management & Leadership (1)

SERVICE TO COMMUNITY

Young Professional Member, Zonta International Foundation. 2016-2017.

Nepal Project Director, Global Peace Exchange. 2013-2015.

PROFESSIONAL ORGANIZATION MEMBERSHIPS

American Society of Public Administration

Association for Public Policy Analysis and Management

Association for Research on Nonprofit Organizations and Voluntary Action

Public Management Research Association

GRANTS

PI. Roscoe Martin Fund for Dissertation and Thesis Research (01/2022) "Leveraging System Context to Understand the Processes, Structures, and Outcomes of Collaborative Systems in Modern Public Management." Maxwell School of Citizenship and Public Affairs at Syracuse University. Amount: $1,000. Status: Funded

Co-Investigator. **Community Research for Health Equity Grant (09/2021)** Robert Wood Johnson Foundation and AcademyHealth. Status: Not Funded

Collaborator. **2021 IBM Research Report Stipend Syracuse, NY (07/2021)** "Management Insights on the Design and Implementation of Interorganizational Referral Networks." Institute for the Business of Government. Amount: $20,000. Status: Funded

PI. **Spencer D. Parratt Summer Research Award Syracuse, NY (05/2020)** Awarded $1,600 from the Department of Public Administration and International Affairs at Syracuse University to perform research on utilizing veteran and military service networks to leverage community outcomes during COVID-19.

CO-PI. **Public Service Research Fellowship Tallahassee, FL (02/2015)** Awarded $2,000 to do research on women's menstrual health in Nepal. Status: Funded

Collaborator. **Diehl Family Social Enterprise Competition, Tallahassee, FL (01/2015)** Co-authored a $50,000 grant for Clinic Nepal that led to the building of the Meghauli Marketplace, a marketplace and storm shelter in Chitwan, Nepal. Status: Funded

FELLOWSHIPS AND AWARDS

Maxwell Student Fellow, Public Affairs Diversity Alliance Syracuse, NY (09/2021-present) Alliance providing professional development and networking platforms for diverse candidates in public affairs

Co-author. **Third Place Top Student Paper Award Online (08/2020)** 2020 Political Communication division Association for Journalism Education and Mass Communication annual conference

2018 NASPAA-Batten Competition Regional Winner Orlando, FL (02/2018)
Honor issuer: Network of Schools of Public Policy, Affairs, and Administration
Topic: Stopping the spread of a global flu epidemic

ASSISTED WORKS

1. Carboni, J. L., & Eikenberry, A. (2018). *Giving Circle Membership: How Collective Giving Impacts Donors*. Collective Giving Research Group. https://scholarworks.iupui.edu/bitstream/handle/1805/17743/giving-circle-membership18.pdf