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Analyzing the Effectiveness of Networks for Addressing Public Problems: Evidence from a Longitudinal Study

Research Article

Abstract: *While scholars and practitioners frequently laud the potential of networks to address complex policy problems, empirical evidence of the effectiveness of networks is scarce. This study examines how changes in network structure (centralization and transitivity), network composition (sector diversity and geographic range), and tie properties (stability and strength) influence community-level outcomes. Relying on a statutory requirement in the state of Iowa requiring local governments to file all instances of intergovernmental and intersectoral collaboration, we measure collaboration networks in 81 counties over 17 years in the areas of crime and economic development. Using fixed effects models, we examine how changes in the structure and composition of these county-level networks affect substantive policy outcomes. Our findings indicate that network properties matter, but that the specific properties may be context dependent. We find network centralization and stability are stronger predictors of crime while network composition is more strongly associated with economic development.*

Evidence for Practice

- The performance of intergovernmental collaborations is rarely studied, either in terms of the outcomes of individual agreements or from the networks resulting from multiple agreements.
- The properties (structure, composition, stability) of the networks that emerge from the actions of local government officials to address critical public problems are generally not visible to the public, state policy makers, or even the local officials themselves.
- Our research suggests that properties of these networks of agreements affect their impact on improving public problems, suggesting opportunities for policy makers to encourage more effective structures.
- Our finding suggests that county networks effectively designed to improve economic development would differ in meaningful ways from one effectively designed to reduce crime.
- Our findings indicate that network centralization and stability are stronger predictors of crime rates while network composition is more strongly associated with indicators of economic development. Stable networks, as measured by average amount of time the agreements are in place, may reduce violent crime, property crime, and unemployment.

Despite the frequent use of networks and corresponding growth in scholarly attention, little is known about the structural forms of networks most conducive to innovation and performance (Turrini et al. 2010). This paper explores how changes in the structure and composition of county-level networks influence the effectiveness of those networks in addressing public problems. Understanding the relationship between network characteristics and performance is critical as it can help policy makers shape networks in ways most conducive for success (Whetsell et al. 2020).

The success or performance of networks has been measured at three levels: the community/clients served by the network, the network itself, and the individual actors or organizations within the network (Provan and Milward 2001). Much of the literature attempting to link networks to performance has focused on the actor level (i.e., the individuals or organizations which comprise the nodes in the network) (e.g., Meier and O'Toole 2001, 2003; Mewhirter and Berardo 2019). Research examining network level performance emphasizes the network's internal governance, accountability mechanisms, external legitimacy, and the range of services provided (Carr, Blöschl, and Loucks 2012; Emerson and Nabatchi 2015). While the performance of individual actors and of the network itself, as an organizational entity, is important, success at these levels does not necessarily translate into effectively addressing policy problems at the community level (Provan and Milward 2001). Community-level outcomes can be defined as the value provided, such as improved

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access or the reduction in a problematic condition, to the area and clients served by the network (Provan and Milward 2001). Because public networks are used to address policy problems that spill over organizational and jurisdictional boundaries, understanding their implications at the collective or community level is essential for targeting scarce resources toward effective service delivery mechanisms (Provan and Milward 2001).

Unfortunately, little research exists to address how the structure and composition of a network influence outcomes at the community level. A systematic review of the network literature in 40 journals of public administration and policy from 1997 to 2019 found only 21 empirical articles examining network effectiveness at the community level (Medina et al. 2020). A major reason for this lack of research is the significant data challenges facing statistical analyses of network performance at the community level. Here, it is important to make a distinction between studies that use the term network as a form of organization and studies that use networks as a structural phenomenon and collect data on the ties that link actors together. Our interest in the effect of networks on community outcomes is not simply a question about whether collaboration works, but rather how the actual structure and composition of networks that emerge through collaborative arrangements influence collective performance. When measuring performance at the community level, only a single observation of performance is available for each network. In contrast, when looking at actor level performance, you have an observation for every actor in the network. To statistically model how network structures affect community-level performance, data on a large number of networks are therefore required as each network provides only a single observation. However, network data are time-consuming to collect and require high response rates to produce valid measurements (Borgatti, Everett, and Johnson 2013). Consequently, prior empirical work examining the relationship between network characteristics and performance outcomes relies predominately on small sample methods (case studies, qualitative comparative analysis) (Cristofoli, Macciò, and Pedrazzi 2015; Provan and Milward 1995; Raab, Mannak, and Cambré 2015; Sandström and Carlsson 2008; Wang 2016). In the few instances where enough observations of complete networks have been obtained to conduct statistical analysis using community-level outcomes, the data have been cross-sectional (Kelman, Hong, and Turbitt 2013; Nowell 2009; Yi 2018).

These studies, though reliant on small samples and cross-sectional data, have produced important findings for our field. The body of research suggests that community-level outcomes may be affected by a network's structure and composition. However, due to data limitations, prior work has been (i) unable to control for time-invariant unobservable factors that may influence performance outcomes and (ii) unable to explore how, within a given network, changes in structure and composition influence performance over time. For example, the seminal work of Provan and Milward (1995) found that centralized networks tend to perform better, and this finding has been supported by other studies (Raab, Mannak, and Cambré 2015). However, because prior work has relied on case studies and cross-sectional data, it is unable to assess whether increasing centralization leads to improved performance; it has simply found an association between network centralization and performance at a point in time. It could be that networks that are more centralized result from having actors who are more powerful, who possess more resources, and who are more willing to collaborate with others, and it could be those aspects of the network rather than its centralization, which are the drivers of performance.

We address these prior limitations by examining network performance at the community level using a longitudinal dataset of complete networks in the 81 counties in Iowa with populations greater than 10,000. Our data on collaborations consist of complete, whole network data on the agreements formed by local governments in Iowa over a period of 17 years (2000–16). In the forthcoming analysis, we assess how changes in the county-level network structure and composition affect substantive performance outcomes in two critical policy areas of crime and economic development.

This article makes several contributions to our understanding of network performance and local government collaboration. Responding to Isett et al.'s (2011, i163) declaration that "[w]e face significant limitations in our knowledge of how networks perform over time," this study statistically examines longitudinal data linking networks and performance at the community level. Through these longitudinal data, we show that changes in network structure over time significantly influence community-level outcomes. This suggests that while networks may be an effective means to address collective challenges, the structure and evolution of the networks (and not just the fact that actors are collaborating) are determinants of collective outcomes. By exploiting an Iowa statutory requirement that all intergovernmental or intersectoral agreements created by public agencies be filed with the state government, this analysis captures complete networks composed of both public and private actors. In doing so, we are able to identify how the effect of network composition change on performance is dependent on the policy area in which the network operates. Finally, the article demonstrates how emergent properties of networks formed predominantly through a series of bilateral agreements have implications for the performance of the broader policy system. Because the emergent characteristics of networks matter, local, state, and federal government leaders can work to develop incentives and systems that facilitate the formation of networks in ways most amenable for addressing collective problems (Whetsell et al. 2020).

Research Context: Polycentric Systems and Interlocal Agreement Networks

The local government landscape in United States is characterized by large numbers of relatively small governments that are simultaneously interdependent yet substantially autonomous. This "fragmentation" of political authority is seen by many to simultaneously increase the problems facing governments and undercut their ability to confront these challenges (Carr and Siciliano 2019; Goodman 2019). Relying on small population units to produce services creates an environment of service production scale mismatch (Ostrom, Tiebout, and Warren 1961) and exacerbates the problems of the disarticulated state (Frederickson 1999). The fact that cities and counties, as general-purpose governments, are responsible for providing many different services to their residents guarantees that mismatches between political boundaries and optimal production scale will exist. In our study, we look particularly at the provision of services within a county by actors operating at different jurisdictional levels (city, township, special district, county) and sectors (public, private, nonprofit) through collaborative agreements to address public problems.

As a consequence, these agreements represent an important tool available to local government officials to seek efficiencies, enhance effectiveness, and expand access to critical infrastructure and services. The prevalence of polycentric regions in United States makes intergovernmental agreements critical to the performance of local government, yet research examining the effects of networks of agreements is scant (for reviews see Andrew 2009; Carr and Hawkins 2013). In sharp contrast to the highly visible structure of public service delivery responsibilities created by the formal institutions of local government, the networks of intergovernmental agreements are largely opaque. The biggest gap in this literature, and in the broader literature on governance networks, is on the performance of these networks at the community level. Intergovernmental agreements may improve performance by linking local governments together to create networks where local governments function as collaborative partners in information sharing and coordinated policy action. In this study, we connect these agreements to community-level outcomes for two critical public problems: crime and economic development.

Crime and economic development were chosen as the policy contexts for our analysis for several reasons. First, these policy areas are understood to be local problems in the United States. Municipal and county governments play primary roles in addressing criminal activity and in promoting their area's economic development. Thus, focusing on the county (in terms of both the county network structure and county-level outcomes) is an appropriate unit of analysis. Second, both policy areas have clear links to objective outcomes captured in existing administrative data. When cities, counties, and nonprofits work together on police protection and criminal investigations, these collaborative activities are designed to reduce crime. Likewise, collaboration around economic development is motivated by joint interests in improving the economic base and financial welfare of local residents. Third, crime and economic development also differ in important ways. Services directed at public safety are highly regulated by state and federal agencies and are typically comprised of a set of common activities, including police patrol, criminal investigation, and detention/incarceration. These component services often consume a substantial share of local government budgets and involve ongoing commitments of resources. In contrast, economic development activities are more disparate, often project-based, and likely to involve smaller commitments of resources for limited duration. The variation in the nature of the policy areas provides an ability to examine how generalizable findings from one policy area may be to others.

Literature and Hypotheses: Networks and Performance

A primary motivation for the development of interlocal agreements is to improve the effectiveness of service delivery. Chen and Thurmaier (2009) surveyed city and county officials in Iowa and found that over 90 percent indicated service improvement as an important or very important impetus for their use of cooperative agreements. Thurmaier and Wood (2002) analyzed interlocal agreements in Kansas City and concluded that administrators were more focused on improving service effectiveness than operational efficiency. Despite these motivations, the effectiveness of service delivery networks, and in particular, how variation in their structural properties and actor composition matter for effective outcomes at the community level, has not been empirically tested with longitudinal data.

Based on prior research and extant network theory, we consider three categories of network factors. We examine how network structure (centralization and transitivity), composition (sector homophily and geographic range), and tie properties (network stability and strength) influence policy outcomes in the areas of crime and economic development.

Network Structure

Centralization

Centralization refers to the extent to which a network revolves around a focal node or set of nodes. For example, a network where all city governments in a given county partner with a single actor (e.g., the county government) for jail and police services and engage little with one another would be highly centralized. In contrast, a decentralized system would exist if all actors in the network have the same number of ties. More highly centralized networks are posited to improve policy outcomes via several mechanisms. One is through efficiency gains that result from minimizing production costs for a given service. Local governments typically operate in a constrained fiscal environment where slack resources are rare. In the absence of interlocal collaboration, governments may be unable to take advantage of scale economies and be forced to devote scarce resources to higher operational costs or to simply forgo offering the service altogether (Oakerson 1999; Ostrom, Tiebout, and Warren 1961). Performance may suffer in these cases because resources that could have been used elsewhere are consumed or important elements of a function/program are not provided due to insufficient resources. In a highly centralized network, however, a single or few centralized actor(s) could be able to offer services requiring highly skilled employees or investments in assets that are not easily redeployed to other uses.

Similarly, centralization may improve efficiency by shifting redundant activities and collaboration and coordination costs to fewer actors. Redundancy may lead to zero-sum competition, especially in economic development, and increase coordination costs for services or policies with regional impacts, such as public safety. Coordinating a large number of small producers involves costs that are likely reduced by agreements that integrate these activities. Provan and Milward (1995) found that forming relationships with core central agencies (i.e., increasing network centralization) improves performance. These findings have been supported by additional empirical work finding that centralized networks are more efficiently coordinated and capable of obtaining network goals (Raab, Mannak, and Cambré 2015; Sandström and Carlsson 2008).

H1: Network centralization will be positively associated with the performance of the network in addressing public problems.

Cohesion/Transitivity. Network cohesion occurs when groups of three actors (or nodes) are all connected, creating locally dense structures of network activity. Cohesive structures emerge for a variety of reasons, including opportunity (actors are more likely to connect if they share partners; a process known as triadic closure), homophily (actors are more likely to connect with those who are like themselves), and risk avoidance (actors in cohesive networks are less likely to defect). These processes result in networks with high levels of transitivity, though risk mitigation has been the most prominent rationale offered in the literature on intergovernmental agreement networks (Feiock 2009, 2013; Feiock, Lee, Park, and Lee 2010). Building from the risk hypothesis (Berardo and Scholz 2010), transitive structures are presumed to promote bonding social capital (Coleman 1988; Lin, Cook, and Burt 2001), which facilitates the formation of norms and trust. When actors operate in dense clusters of relationships, their actions are more easily observed by others and thus more likely to be rewarded or sanctioned for their behavior (Berardo and Scholz 2010; Lubell 2007). This ability to reward or sanction is viewed as an important facilitator of collaboration that allows for the development of trust, the movement of resources, sharing of tacit knowledge (Carr and Hawkins 2013; Hawkins and Carr 2013; LeRoux, Brandenburger, and Pandey 2010), and ultimately learning (Siciliano 2017). As Argote, McEvily, and Reagans (2003) argue, cohesion affects actor motivations and willingness to transfer information to others and devote resources to assist them.

> **H2:** Network transitivity will be positively associated with the performance of the network in addressing public problems.

Network Composition

Sector Diversity and Geographic Range

Factors related to composition move beyond structural configurations to consider the distribution of actors involved in the network. Conflicting theories and findings exist in the literature concerning the effects of network composition on performance. On the one hand, challenges exist when attempting to work with heterogeneous actors who have varying resources, agendas, and policy beliefs (Huxham, Vangen, Huxham, and Eden 2000; Ospina and Saz-Carranza 2010; Siddiki, Kim, and Leach 2017). Actors often choose to work with others who are similar to them or connected to a common third party as a means to increase trust and reduce risk (Frederickson 1999; LeRoux 2008; LeRoux and Carr 2010). On the other hand, diversity is also an essential component for accessing nonredundant and novel information (Burt 1992) and therefore can be critical for promoting learning (Reagans and McEvily 2003). This creates a tension between more homogenous relations that establish shared norms and values and more heterogeneous ties that may create friction in exchanging resources but ultimately provide needed access to new information and ideas (Siddiki, Kim, and Leach 2017).

Network composition is often measured through its diversity, or range, and is defined as "the extent to which network connections span institutional, organizational, or social boundaries" (Reagans and McEvily 2003, 245). Scholars examining the impact of diversity have operationalized the concept in a variety of ways, including measures based on demographics, clients served, beliefs, sector, and scale. Discussing the importance of access to unique resources, Nohrstedt and Bodin (2020) argue that connections to dissimilar partners are needed to broaden the skills of the network. Similarly, Schrama (2018) argues that information from diverse actors is deemed to be more valuable and a range of perspectives is needed to develop complete information on policy implementation processes.

Collaboration involving partners from different sectors impacts performance through the introduction of innovative practices, greater operational flexibility, and increased responsiveness to market pressures (Bel and Sebő 2021; Hefetz and Warner 2011; LeRoux, Brandenburger, and Pandey 2010). Networks that include actors from other geographic areas, such as those that involve organizations from different counties, may also benefit from more novel information. Actors who operate in different physical environments likely confront variations in the context in which a policy issue operates. This may lead to variation in the types of information available and strategies employed to address policy problems. Based on the theories of structural holes and network heterophily, we argue that diverse service delivery networks (i.e., composed of both public and private sector organizations), and networks with a high range (i.e., marked by the presence of ties that span geographic borders) can enhance performance.

> **H3:** A network's proportion of ties that join public and private organizations (i.e., sector diversity) will be positively associated with the performance of the network in addressing public problems.

> **H4:** A network's proportion of ties that span county borders (i.e., geographic range) will be positively associated with the performance of the network in addressing public problems.

It is important to note that hypotheses 3 and 4 may appear to conflict with hypothesis 2 regarding transitivity. To the extent that transitive ties are driven by homophily and opportunity, it is likely that the actors involved in dense clusters are similar to one another. This highlights the potential pitfall of homogenous networks—while they are effective at building trust and norms, they often consist of redundant information that may limit access to novel ideas and innovation benefits that accrue through collaboration. Similarly, hypothesis 1 and hypothesis 2 potentially advocate for distinct types of network structures. One highly centralized with low density; the other more cohesive and more decentralized. Many have viewed these tensions through the lens of open (bridging) and closed (bonding) networks, often arguing that one is more beneficial than the other (Burt 1992; Coleman 1988). Ultimately, bridging and bonding can be present in networks at the same time. Burt (2005) has argued that networks that have dense structures locally but bridging structures globally might be the best performing. In support of that contention, Reagans and McEvily (2003, 263) argued that "[t]he benefit of network cohesion need not come at the expense of network range…the results reported here are consistent with an emerging line of work emphasizing that the optimal network structure combines elements of cohesion and range." Prior research in public administration also offers support for performance benefits of combining cohesion with diversity. For example, Yi (2018) found that states with higher levels of both bridging and bonding in clean energy governance networks tended to have higher performance. Similarly, Shrestha (2013) found that network performance was enhanced through the development of ties that balance network reach with cohesion. More recently, research by Ter Wal, Alexy, Block, and Sandner (2016) has begun to explore how actor diversity and structure interact to shape outcomes.

Tie Properties

Tie Strength and Stability

The previous hypotheses considered the structure and composition of the network. The structural measures of centralization and transitivity are based on whether or not actors within the network have a tie with one another. In addition to simply being present or absent, a tie connecting two actors can vary in a number of important ways including its strength and stability.

One important indicator of tie strength is the extent to which a tie between two actors serves multiple purposes; a concept known as multiplexity. When actors engage in a variety of relationships, they tend to establish greater levels of agreement and consensus on goals (Erickson 1988). Multiplex ties also provide assurances of commitment as overlapping forms of connectivity ensure that even if one type of tie or form of collaboration dissolves, the connection between the two actors remains (Provan and Milward 2001). Such strong ties are more likely to be of assistance when called upon, provide valued resources, and lead to the establishment of trust (Granovetter 1983; Krackhardt 1992).

> **H5:** The average tie strength within a network will be positively associated with the performance of the network in addressing public problems.

Another important tie property is its duration or stability. Networks that experience significant change through the development of new ties and the dissolution of existing ties undermine effectiveness as actor time and resources are spent on establishing the relationships rather than producing services (Provan and Milward 1995). Instability also hurts the network's ability to maintain consistent access to needed resources, hindering capacity to fulfill its responsibilities and meet obligations (Wang 2016). Recent research has found that system stability is an important predictor of network performance (Raab, Mannak, and Cambré 2015; Wang 2016). As Dahlander and McFarland (2013, 69) note: "[r]epeated collaborations have fewer startup costs than new ones, they entail greater certainty and trust, and the individuals engaged in long-standing ties frequently communicate better."

> **H6:** Network stability will be positively associated with the performance of the network in addressing public problems.

Data and Measures

The challenges of collecting network data have led to several limitations in the network performance literature: a lack of complete network data, emphasis on individual actor rather than collective performance, and a reliance on cross-sectional data. Many of the studies connecting networks to outcomes fail to collect complete or whole network data, often choosing to rely on proxy measures or governance processes rather than identifying the structure and composition of the network itself (Aldag, Warner, and Bel 2020; Kim, Song, and Park 2019; Meier and O'Toole 2001, 2003; Scott 2015). While such research designs permit large-n studies of collaboration, they tend to focus on the individual actor and fail to measure the network's structure or the organization's position within that structure. Existing studies that do collect whole network data to analyze effectiveness at the network or community level, therefore, tend to be small-n case studies (Cristofoli, Macciò, and Pedrazzi 2015; Provan and Milward 1995; Sandström and Carlsson 2008) or rely on qualitative comparative analysis to analyze a moderate number of cases (Raab, Mannak, and Cambré 2015; Wang 2016). Given the time and resources needed to collect complete network data, the few studies with sample sizes large enough to conduct statistical analysis of network performance at the community level are cross-sectional (Kelman, Hong, and Turbitt 2013; Nowell 2009; Yi 2018). This creates concerns for omitted variable bias and does not allow for an assessment of how network change influences network performance. As Kapucu, Hu, and Khosa (2017, 1,111) state, "[t]he application of longitudinal analysis is largely missing in the field."

To examine the relationship between policy network structure and substantive, community-level outcomes over time, we evaluate all interlocal agreements filed in the state of Iowa from 2000 through 2016. The data on intergovernmental agreements were acquired by taking advantage of a state law that requires interlocal and intersector agreements to be filed with the state government prior to being entered into force (Iowa Code, Chapter 28E, Section 8). The law permits "state and local governments in Iowa to make efficient use of their powers by enabling them to provide joint services and facilities with other agencies and to cooperate in other ways of mutual advantage" (Chapter 28E, Section 1).

The Iowa Secretary of State maintains a filing repository that can be accessed online. In addition to archiving photocopies of each agreement, their website allows the public to search for agreements based on metadata provided by each agreement's filer. The search categories include participant name, service type, agreement file date range, organization type, county, state region, and internal filing number. Each agreement has a webpage that lists its filing number, filing date, expiration date, and a one-sentence summary of purpose. To end an agreement prior to its initial expiration date, participants must file a dated termination notice that includes the filing number of the agreement being terminated.

The agreements on file with Iowa's Office of the Secretary of State capture collaborative interactions across multiple scales (cities, townships, counties, special districts, and state agencies) as well as sectors (public, private, and nonprofit organizations). These agreements also cover a range of mechanisms and forms of interactions. These include partnerships, resource and staff sharing, support provision, cooperative purchase agreements, service contracts, and joint operations (Li, Sanchez, Carr, and Siciliano 2021). For more information and access to the full text of all agreements on file visit: https://sos.iowa.gov/search/28ESearch.html.

Researchers from the Networks and Governance Lab (NGL) at the University of Illinois utilized this repository to create the dataset used in this study. Using web scraping scripts tailored to the online agreement repository, all publicly available metadata were extracted from the Secretary of State website. Prior to the analysis, typographical errors (e.g., misspellings of and variance in the use of contractions and acronyms that refer to an organization across agreements) and organization classification mistakes (e.g., categorizing a municipality as a county) were manually corrected. The resulting data consist of approximately 20,000 agreements formed within 33 service areas.[1] In the forthcoming analysis, we focus on two core responsibilities of local governments: crime/ public safety and economic development.

For crime and public safety, we included agreements that were classified as jail and corrections, police protection, and criminal investigation. Jail and correction agreements are frequently used to facilitate the provision of work through public service for offenders, create and operate interagency or intergovernmental detention facilities, and to coordinate prisoner transfers. Police protection agreements include instances when one government is providing police protection and dispatching services for another (e.g., patrol, pursuit, and crowd control) and when an intergovernmental police task force needs to be created. Criminal investigation agreements are usually formed to allow local governments to request aid for investigating criminal cases, obtaining evidence, operating crime labs, and preparing reports. Economic development agreements include collaborative efforts to promote local businesses, tourism, and unemployment services, and are often used to establish economic development commissions and to formalize financial contribution processes that multiple governments use to advance regional economic development projects. In total, 3,227 crime agreements and 248 economic development agreements were formed during the study period.

In line with prior research related to local service delivery and public safety outcomes (e.g., Gazel, Rickman, and Thompson 2001; Huang 2014; Provan, Huang, and Milward 2009), we rely on the county as the unit of analysis. There are 99 counties in Iowa, 81 of which had a population of 10,000 or higher in at least one year between 2000 and 2016. We used a population of 10,000 as a cutoff for inclusion in the following analysis as estimates of crime and other per capita rates become imprecise and can lead to errors in statistical analyses in small populations (Pridemore 2005).

We bound each county network by identifying 28E agreement participants who list a given county as their organization's location or who were signatory to an agreement where at least one of the cosigners operated within that county. To that list of participants, we also include all other municipal governments who reside within the county but, to date, have not yet participated in an intergovernmental agreement. The county government itself was also added as an isolate if it did not participate in any agreement during the years analyzed. Thus, the network is comprised of all possible local governments in a given county and any other private/nonprofit actors who participated in an agreement at any point during our study period. This approach keeps a consistent boundary on the network while allowing actors to move from being isolates to active participants in the network. Since we maintain a consistent set of nodes for each county network for each year, we do not consider network size in our fixed effects models (as it is time invariant and thus captured by the county fixed effects).

Dependent Variables. Performance of the crime network was operationalized via the number of reported violent and property crimes in each county. In general, violent crimes involve another person, and property crimes do not. Examples of violent crimes include murder, forcible rape, robbery, and aggravated assault, while property crimes include burglary, larceny, motor vehicle theft, and arson. Note that robbery is considered a violent crime since it involves the use of force or the threat of force against another person. This is in contrast to larceny (simple theft) and burglary, which refers to entering a building with the intent to commit a crime.

Data for each year was obtained from the Iowa Department of Public Safety. Both violent and property crime rates are calculated per 100,000 residents and then logged (e.g., Gazel, Rickman, and Thompson 2001; Kovandzic and Vieraitis 2006). Economic development outcomes were measured using annual county unemployment rates and median household income, derived from the U.S. Bureau of Labor Statistics and U.S. Census Bureau, respectively. Median household income was standardized to the 2010 dollar and then logged.

Network Structure Variables. County networks were measured for each year for each of the two problem areas (crime and economic development). Ties within the network were determined by co-participation in a specific agreement. For example, on November 29, 2011, the Tama County Sheriff's Office established an agreement with the City of Montour, stating that "[t]he county, through its County Sheriff, agrees to provide police protection within the corporate limits of the City of Montour." Thus, this agreement would establish a tie in Tama County's crime network between Tama County and the City of Montour for 2011. The tie would remain in the crime network in subsequent years until the agreement expiration date was reached or a termination noticed filed. This process of adding links to a given county's network in a given year for a given problem area occurred for every relevant agreement filed between 2000 and 2016.

Once each county-year network was established based on the relationships identified in the agreements, a number of network measures were calculated. Centralization, or the extent to which a network revolves around a single node or set of focal nodes, was determined for each county-year network by the following formula (Wasserman and Faust 1994):

$$\text{Centralization} = \frac{\sum_{i=1}^{n} |c_{\max} - c_i|}{\sum_{i=1}^{n} |x_{\max} - x_i|}$$

Figure 1 demonstrates variation in centrality for two counties in Iowa. The figure on the left is a plot of the network formed in Lyon County in 2016 in the policy area of economic development. The network is completely decentralized, with a centralization score of 0.00. The figure on the right is a plot of the network formed in Madison County in 2016 in the policy area of economic development. The network is more highly centralized in Madison County, with a centralization score of 0.52.

Transitivity, a network's tendency to form closed triads, was calculated as follows:

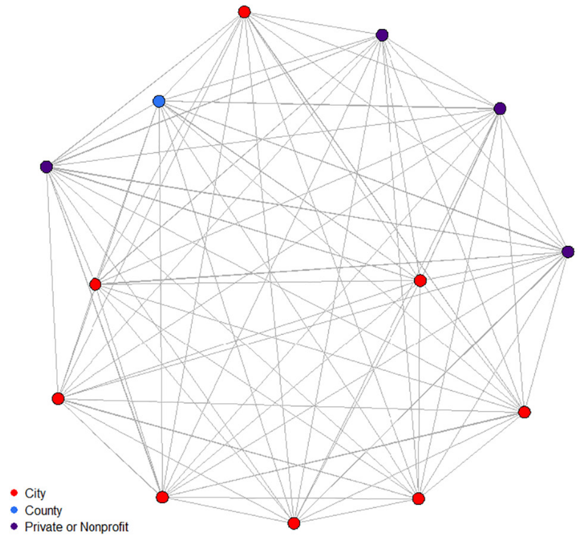

Figure 1 County Networks with Varying Levels of Centralization

$$\text{Transitivity} = \frac{\sum_{i,j,k} x_{ij} x_{jk} x_{ik}}{\sum_{i,j,k} x_{ij} x_{jk}}$$

Transitivity, also referred to as the clustering coefficient in other studies (e.g., Yi 2018), is a common measure for capturing closure in a network. The clustering coefficient was originally measured based on averaging ego-level transitivity (Watts and Strogatz 1998). However, when a weighted average is taken (which accounts for variation in the size of each ego network), the weighted overall clustering coefficient is equal to transitivity (Borgatti, Everett, and Johnson 2013).

Network Composition Variables. Two network composition variables were calculated: sector diversity (the proportion of private sector actors in the county network) and geographic range (the proportion of actors who resided outside of the county). Network diversity and range were measured using Krackhardt's E–I Index (Krackhardt and Stern 1988), which ranges from −1 (complete homophily) to + 1 (complete heterophily):

$$E - I \text{ Index} = \frac{EL - IL}{EL + IL}$$

This formula was used to calculate sector diversity, where *EL* (external links) is the number of county network participants that were from the private sector and *IL* (internal links) is the number of county network participants that were from the public sector. Participants were considered public sector if their organization was categorized as a municipality, township, county, school district, special district, or state agency. Participants were considered private sector if their organization was categorized as private or nonprofit (unfortunately the 28E database does not distinguish between these two types of nongovernmental actors).

The geographic range variable was similarly computed, where *EL* is the number of county network participants that reported their location as being outside of the county and *IL* is the number of county network participants that reported their location as being inside the county. For both measures, participants were only considered if they were currently involved in an active agreement in the given year. For instance, in Wright County, there were 97 organizations active in their crime network in 2015. Of the 97 actors, 92 were public and only 5 were private. Thus, the EI index for sector diversity for Wright County is –0.897.

Tie Properties. We measure two tie properties: strength and stability. Average tie strength is a measure of the average number of agreements a given pair of connected actors in the network (for a given county and year) have with each other. This value was determined by counting, across the entire county's network, the number of agreements each pair of connected actors were signatories to and then dividing that value by the number of total ties. The lowest value this measure can take is one, indicating that each pair of connected actors in the network only have a single collaborative agreement with each other. Network stability was calculated in a similar manner by first summing the duration of each tie in the network (i.e., the number of years each tie has been active) and then dividing the result by the number of ties in the network. The resulting value indicates the average duration for which a pair of connected actors has been collaborating. Higher levels indicate longer-term relationships and thus higher levels of network stability.

Control Variables. Controls include population density as well as county government operating expenditures and capital outlays. Models that did not use unemployment rate or median household income as dependent variables included them as controls. Operating expenditures and capital outlays were adjusted to the 2010 dollars and were logged. Finally, we control for two other network measures associated with ILA usage: average degree and number of active ILAs. Average degree was calculated by dividing the number of ties within a county-year network by the total number of nodes. Active ILAs is simply the total number of active (or "in force") agreements. After accounting for agreement filing, expiration, and termination dates, we totaled the number of active ILAs in each county for each year. The number of active ILAs was logged. Note that average degree is distinct from our measure of average tie strength. Average tie strength is based on the weight of existing ties in the network, where weight is based on the number of different activities two actors engage in with one another. In the calculation of average degree, tie weight is ignored, as average degree is simply the proportion of dyads that are connected regardless of strength.

To clarify, consider two different counties comprised of 20 actors. Each county could have 40 ties among the actors in its network (for an average degree of 2), but the weights of those ties may be significantly different. The ties in one county may have an average weight of 5 and in the other only a weight of 2. Thus, actors in one county are simply doing more with the same actors resulting in a higher average tie strength but the same overall average degree. Furthermore, the number of active ILAs or in-force agreements is not redundant with either average degree or tie strength. The reason is that a single agreement can be formed between two actors, three actors, or twenty or more actors. Thus, the number of in-force agreements controls for how counties structure collaboration; some may prefer to rely on a small number of large agreements, others on many small agreements. Therefore, while the variables of average degree, average tie strength, and active ILAs are related, they capture distinct aspects of network structure and activity.

Data Sources and Summary Statistics. The non-network variables described above are available from 2000 through 2016 and were sourced from the Iowa Department of Public Safety, U.S. Bureau of Economic Analysis, U.S. Census Bureau, and the Small Areas Estimates Branch of the Census Bureau. Table 1 below lists the variable names, sources, and a brief description. Table 2 provides summary statistics for the variables as well as network-level descriptive statistics for both the crime network and the economic development network. Descriptive statistics were generated after calculating, at the county level, the mean for each variable across each year. Values exclude county-year observations where population was less than 10,000.

Empirical Strategy and Results

To test our hypotheses, we estimate panel models with both county and year fixed effects and two-way cluster-robust standard errors. We build four separate models looking at each of our performance outcomes. For crime, we analyze violent and property crime rates, and for economic development, we analyze the unemployment rate and median household income. For each model, the predictor variables have been lagged by one year. The variables were lagged because interlocal agreements are being formed throughout the duration of any given year and, therefore, the structure of the network as it was observed in a specific year is the result of a continuous process of tie formation and dissolution. Thus, we use the structure and composition of the network in the preceding year to predict performance changes in the following year.

Our model, displayed here for violent crime rate, is as follows:

$$\begin{aligned}\log(\text{Violent Crime}_{it}) &= \beta_0 + \beta_1\text{Centralization}_{i,t-1} + \beta_2\text{Transitivity}_{i,t-1}\\ &+\beta_3\text{Sector Diversity}_{i,t-1} + \beta_4\text{Geographic Range}_{i,t-1} + \beta_5\text{Network Stability}_{i,t-1}\\ &+\beta_6 \textit{Avg.Tie}\,\text{Strength}_{i,t-1} + \boldsymbol{X}\delta + \alpha_i + \tau_t + \varepsilon_{it}\end{aligned}$$

where the values on the β coefficients and their significance level provide the tests of our main hypotheses. Additionally, $\boldsymbol{X}$ is a matrix of control variables, δ is a vector of parameters, α_i are the

Table 1 Summary of Variables

	Source	Description
Dependent variables		
Violent/property crime rate	Iowa Department of Public Safety	Number of violent or property crimes reported per 100,000 residents.
Unemployment rate	U.S. Bureau of Economic Analysis	County-level unemployment rate.
Median household income	U.S. Census Bureau	Median household income in 2010 constant dollars, logged.
Network structure		
Centralization	28E Agreements	Centralization measures the extent to which activity in the network centers around a small number of highly connected actors.
Transitivity	28E Agreements	Transitivity is the likelihood that two actors who share a common third party will themselves be connected. For example, in instances where City A and City B have an agreement with City C, transitivity is the probability that City A and City B also have an agreement with one another.
Network composition		
Sector diversity	28E Agreements	Ratio of the difference in private and public sector participants to total participants in each network.
Geographic range	28E Agreements	Ratio of the difference in participants outside and inside the county to total participants in each network.
Tie properties		
Avg. tie strength	28E Agreements	For each pair of connected actors (or edges) in the network, the total number of agreements between them were summed and then divided by the total number of edges in the network. The resulting measure indicates, on average, the number of agreements that exist between two connected actors.
Network stability	28E Agreements	For each pair of connected actors (or edges) in the network, the duration of their relationship was summed. That value was divided by the total number of edges in the network. The resulting measure indicates, on average, the number of years that two connected actors have been collaborating.
Control variables		
Average degree	28E Agreements	The sum of the number of ties present in a network divided by the number of actors or nodes. Note, ties are different from agreements. While agreements are the basis for establishing a tie, a single agreement could produce one, two, or more ties among the actors who are part of that agreement.
In-force agreements	28E Agreements	The total count of the number of agreements in a given county that are currently active.
Population density	U.S. Census Bureau	Total county population divided by a county's area in square miles.
Operating expenses	Iowa Department of Management	Total expenditures minus capital outlays in 2010 constant dollars, logged.
Capital outlays	Iowa Department of Management	Expenditures allocated to capital projects in 2010 constant dollars, logged.

Table 2 Summary Statistics

Dependent Variables	Mean	Std. Dev.	Minimum	Median	Maximum
Violent crime rate	157.821	142.920	7.107	110.041	715.492
Property prime rate	1,436.732	1,129.240	74.038	1,007.803	5,959.305
Unemployment rate	4.523	0.720	2.905	4.517	6.936
Median household income	10.748	0.114	10.443	10.744	11.140
Control variables					
Population density	51.821	85.901	9.557	27.241	707.431
Operating expenses	16.556	0.624	15.693	16.441	19.206
Capital outlays	13.876	0.900	11.859	13.925	16.553
Crime Networks					
Network Structure	Mean	Std. Dev.	Minimum	Median	Maximum
Centralization	0.371	0.122	0.082	0.374	0.668
Transitivity	0.825	0.115	0.063	0.845	0.980
Network composition					
Sector diversity	–0.933	0.076	–1.000	–0.954	–0.544
Geographic range	0.532	0.285	–0.800	0.607	0.915
Tie properties					
Avg. tie strength	2.401	0.760	1.201	2.326	4.092
Network stability	7.938	2.388	4.122	7.098	13.671
Control variables					
Avg. degree	5.045	2.148	0.234	5.000	10.889
In-force agreements	33.545	33.974	5.063	23.938	186.313
Economic Development Networks					
Network Structure	Mean	Std. Dev.	Minimum	Median	Maximum
Centralization	0.247	0.122	0.000	0.263	0.478
Transitivity	0.929	0.125	0.230	0.980	1.000
Network composition					
Sector diversity	–0.826	0.304	–1.000	–1.000	0.167
Geographic range	0.419	0.532	–1.000	0.613	0.941
Tie properties					
Avg. tie strength	2.387	2.039	1.000	1.667	9.000
Network stability	9.378	2.099	1.250	9.828	14.515
Control variables					
Avg. degree	2.578	2.986	0.000	1.556	11.678
In-force agreements	6.199	9.355	0.000	3.875	66.000

fixed effects estimated for each county in order to control for unit-specific time-invariant confounders, and τ_t are the year fixed effects to control for aggregate time trends. The unemployment rate and median household income are controls in the crime models; for the economic development models, median income is used as a control in the unemployment model and vice versa.

As noted above, due to precision concerns and statistical errors that can arise when calculating rates with small populations, our models include only the 81 counties that had populations over 10,000. The number of counties in the analyses conducted below varies slightly from that total, however. One county, Monona, only reaches the threshold of 10,000 residents in the year 2000. Since observations of Monona County after the year 2000 were dropped, independent variables from the year 2000 cannot predict dependent variables from the year 2001. Models including a 1-year lag therefore drop Monona County, reducing the number of counties available to 80 (see Table 3). The economic development models displayed in Table 4 rely on 74 counties, as six counties were excluded due to not having any active interlocal agreements between 2000 and 2016. Network variables can be highly correlated, and so we calculated variance inflation factor (VIF) estimates using a pooled model. No variable in the model had a VIF greater than 4.9 and no network variable had a VIF greater than 2.4. We also tested each of the four models for spatial dependence using the 'slmtest' function in the *splm* package in R and found no indication of spatial correlation.

Estimating Crime Rates. Table 3 presents the results for the crime models. Hypotheses 1 and 2 focused on the network structural effects of centralization and transitivity. For both violent crime and property crime, network centralization had a significant effect. Because centralization is scaled between 0 and 1, we will look at the effect of a .01 unit change in centralization. Specifically, a .01 unit change in centralization leads to a 2.3 percent reduction in the violent crime rate $((\exp(-2.308 \times .01) - 1) \times 100)$. For property crimes, we see a reduction of 1.5 percent for a .01 unit change in centralization. These findings align with prior research, indicating that more centralized networks tend to perform better. For hypothesis 2, we find a negative effect of transitivity on violent crime rate, but no significant effect on property crimes. Like centralization, transitivity ranges from 0 to 1. The results suggest that a .01 unit change in a county's network transitivity is associated with a reduction of 0.6 percent in the violent crime rate $((\exp(-0.605 \times .01) - 1) \times 100)$.

With regard to network composition, the variables of sector diversity and geographic range were not significant. There is no evidence to suggest that network diversity influences either the violent crime rate or the property crime rate. Thus, we find no support for hypotheses 3 and 4 for the crime models.

Two properties of ties were also analyzed; hypothesis 5 concerns tie strength and hypothesis 6 concerns network stability. We find no

Table 3 Crime Models

	Violent Crime Rate (Logged)	Property Crime Rate (Logged)
Network structure		
Centralization (H_1)	–2.308 (1.044) *	–1.518 (0.700) *
Transitivity (H_2)	–0.605 (0.290) *	–0.059 (0.196)
Network composition		
Sector diversity (H_3)	–1.169 (0.799)	–0.373 (0.569) ***
Geographic range (H_4)	0.239 (0.264)	0.036 (0.134)
Tie properties		
Average tie strength (H_5)	–0.061 (0.076)	0.076 (0.062)
Network stability (H_6)	–0.084 (0.028) **	–0.041 (0.024)
Control variables		
Average degree	–0.017 (0.036)	–0.005 (0.036)
In-force agreements	0.454 (0.197) *	0.164 (0.121)
Population density	–0.006 (0.004)	–0.004 (0.002)
Unemployment rate	0.028 (0.040)	0.004 (0.038)
Median household income	0.900 (0.507)	–0.360 (0.561)
Operating expenses	–0.308 (0.484)	0.100 (0.299)
Capital outlays	0.007 (0.019)	0.009 (0.015)
Number of counties	80	80
Sample size	1,218	1,218
Within R^2	0.064	0.021
County fixed effects	Y	Y
Year fixed effects	Y	Y

Notes: Excludes county-year observations where population was less than 10,000. All predictor variables are lagged one year. The reported *R*-squared in the models (both here and in Table 4) is the within *R*-squared. This value indicates the amount of variation within units over time in the dependent variable that is accounted for by the model. As with other panel data, much of the variation in the dependent variable is between-unit variation, and thus explained by the fixed effects. For instance, if a dummy variable approach to panel data is used, the overall r-squared, which includes the impact of the fixed effects, is .72 for the violent crime model.* $p < .05$.
** $p < .01$;
*** $p < .001$.

Table 4 Economic Development Models

	Unemployment Rate	Median Household Income (Logged)
Network structure		
Centralization (H_1)	–0.203 (0.459)	0.035 (0.045)
Transitivity (H_2)	–0.457 (0.205) *	0.027 (0.019)
Network composition		
Sector diversity (H_3)	–1.116 (0.347) **	0.088 (0.020) ***
Geographic range (H_4)	0.116 (0.326)	0.006 (0.013)
Tie properties		
Average tie strength (H_5)	–0.028 (0.050)	–0.004 (0.006)
Network stability (H_6)	–0.039 (0.023)	–0.002 (0.001)
Control variables		
Average degree	–0.019 (0.018)	–0.003 (0.001)
In-force agreements	0.129 (0.168)	–0.027 (0.011) *
Population density	0.004 (0.001) **	–0.000 (0.000)
Unemployment rate		–0.009 (0.003) **
Median household income	–0.737 (0.824)	
Operating expenses	–0.181 (0.226)	0.024 (0.013)
Capital outlays	0.014 (0.014)	0.002 (0.002)
Number of counties	74	74
Sample size	1,093	1,024
Within R^2	0.033	0.085
County fixed effects	Y	Y
Year fixed effects	Y	Y

Excludes county-year observations where population was less than 10,000. All predictor variables are lagged one year.
* $p < .05$;
** $p < .01$;
*** $p < .001$.

support for the effect of tie strength on violent crime or property crime, but we do find a significant effect of network stability on violent crime. Network stability ranged from 4 to almost 14. A one-unit change in network stability, meaning that the average tie between organizations in a county network has existed for one year longer, is associated with an 8 percent reduction in violent crime. Network stability also had a negative effect on property crime (a one-unit change was associated with a 4 percent reduction), but significant at only the .10 level. Together, these results suggest that network stability is associated with reductions in both violent and property crime.

Of the control variables in the crime model, only the log of the number of active agreements was significant. Since both the independent and dependent variables have been logged, the coefficient can be interpreted as elasticity. The results suggest that a 1 percent increase in the number of agreements actively operating in a county is associated with an increase in the violent crime rate of 0.5 percent.

Estimating Economic Outcomes. We found no support for the first structural hypothesis in the economic development models. The level of network centralization did not have a significant effect on either the unemployment rate or median household income. For the second hypothesis, we found a negative and significant effect of transitivity on the unemployment rate. Specifically, a .01-unit change in transitivity resulted in a 0.005-point reduction in the unemployment rate. We found strong support for the effect of network sector diversity, hypothesis 3, for both the unemployment rate and median household income. The sector diversity measure ranges from −1 (all public organizations) to 1 (all private organizations). Given the scale, we interpret the effect based on the standard deviation of the variable. As seen in Table 2, the standard deviation of sector diversity is 0.3. For the unemployment rate, a standard deviation change in sector diversity results in a −0.33 point drop in the unemployment rate. For household income, because the variable is logged, a standard deviation change in sector diversity results in 2.7 percent increase in median household income $((\exp(0.088 \times .3) - 1) \times 100)$. We find no support for hypothesis 4 as geographic diversity did not have a significant effect on either the unemployment rate or median household income. For hypotheses 5 and 6, we find no effect of either tie duration or tie strength on economic development outcomes. However, as with property crime, the effect of network stability was significant at the .10 level for unemployment; suggesting that more stable networks are associated with reductions in the unemployment rate.

Of the control variables in the economic development model, only the log of the number of active agreements was a significant predictor of median household income. As with the crime rates, both the independent and dependent variables have been logged, allowing the coefficient to be interpreted as elasticity. The results suggest that a 1 percent increase in the number of agreements actively operating in a county is associated with a decrease in the median household income rate of 0.03 percent.

As a robustness check, we estimated several additional models. This includes a model with no lag for the predictor variables (Table A1) and models using different population cutoffs for inclusion.

Population cutoffs used were 7,500 (Table A2) and 15,000 (Table A3). The results of these additional models are consistent with the results presented above and are available in the appendix.

Discussion

A compelling rationale for collaborative approaches to policy implementation and service delivery is that local problems often do not stay within political boundaries. These spillovers require researchers to look beyond the municipality or local government agency as the unit of analysis. Thus, rather than focusing on a single agency, our research centered on local governments and private, nongovernmental actors within the geography of a county who may collaborate to address public problems. Whereas prior research has tended to position a single actor in a broader network and examined the implications for that actor, we examine the structure of the entire network emerging through the creation of interlocal agreements and model how network structure and composition affect community-level outcomes.

This study contributes to our understanding of the connection between network properties and performance. Existing research has been limited by data collection challenges resulting in studies that lack complete network data or rely on cross-sectional data. We overcome these challenges and examine networks that emerge from 2000 to 2016 through the development of interlocal and intersector agreements in 81 Iowa counties. We then assess how the resulting county-level network structures, composition, and tie properties relate to county-level improvements in crime and economic development. We find that network properties matter for performance, but that the specific properties appear to be context dependent. Our findings suggest that network structure and tie properties are stronger predictors of crime rates while network composition is more strongly associated with economic development. While there has been some convergence in the literature suggesting that centralized networks are most conducive to performance, our findings suggest that the connection between centralized structures and performance is likely dependent upon the particular policy domain in which the network operates.

Overall, we find that (i) the structural characteristic of centralization is an important determinant of crime rates but not economic conditions, (ii) increasing levels of transitivity were associated with reductions in violent crime and unemployment, but did not have a significant effect on property crime or median household income, (iii) network diversity, with regard to the proportion of private sector actors, is an important predictor of economic performance but not crime rates, and (iv) more stable networks, as measured by average tie duration, reduced violent crime and, at the .10 level, reduced property crime and reduced the unemployment rate. Table 5 summarizes the results.

The interlocal networks we observe in Iowa emerge predominately through bilateral agreements. Within the crime networks, 82.4 percent are bilateral, and for economic development 81.7 percent are bilateral. Because these networks develop and evolve agreement by agreement, the networks and structures we measure are emergent features rather than designed. While the actors comprising the crime and economic development networks are engaged in purposeful collaborative action (to gain resources, information, or reap efficiencies), their decisions to collaborate with a given partner are made without an overarching strategy toward a particular network structure or an overall understanding of the broader network. This is an important consideration. The findings suggest that emergent properties of the network, which no single actor determined, can have important impacts for the collective capacity of those actors to address public problems. The literature on networks has broadly focused on two categories: managed or purpose-oriented networks (Nowell and Kenis 2019) and emergent networks. While managed networks have been the dominant emphasis of study and hold a greater capacity to be consciously structured, emergent networks can be influenced by well-intentioned interventions (Valente 2012). For example, Whetsell et al. (2020) found that the federal government was able to promote the self-organizing property of preferential attachment in a network to increase its overall level of centralization. They write, "[t]his suggests broader implications … in a variety of network governance settings. If decision makers can identify particular network structures best suited to address complex problems, for example, centralized networks tend to enhance service delivery (Milward and Provan 2000; Provan and Milward 1995), then they might also act with minimal interference to accelerate self-organization around emerging hubs of cooperative activity in broader interorganizational networks (p. 2)." More research is needed on the ways in which government can coordinate action or incentivize certain collaborative relations to facilitate the emergence of networks with properties beneficial to the collective group.

Table 5 Summary of Findings

Network Measures	Violent Crime	Property Crime	Unemployment Rate	Median Household Income
Network structure				
Centralization (H_1)	✓	✓	ns	ns
Transitivity (H_2)	✓	ns	✓	ns
Network composition				
Sector diversity (H_3)	ns	ns	✓	✓
Geographic range (H_4)	ns	ns	ns	ns
Tie properties				
Tie strength (H_5)	ns	ns	ns	ns
Network stability (H_6)	✓	✓*	✓*	ns

ns, not significant.
* These effects were significant at the .10 level.

These findings also provide important insights for the literature examining intergovernmental agreement networks. This study offers an initial attempt to link the structure and diversity of intergovernmental agreement networks to county-level outcomes over time. Indeed, extant research rarely studies the performance of individual agreements (Bromberg 2015) let alone the networks created by thousands of these agreements. Furthermore, when analysts do attempt to examine the performance of intergovernmental agreements, the focus is on the effects of the operational performance of an individual government and not the impacts on community outcomes. A few studies (Bel and Sebő 2021; Chen and Thurmaier 2009; Morton, Chen, and Morse 2008; Zeemering 2012) have sought to assess high-performing collaborations, but this is one of the first to examine the performance of entire networks of these agreements.

Our findings provide strong support for Carr and Siciliano's (2019) call for more attention to the networks local public officials create to address public problems. There is a data infrastructure that has been built over decades by the federal and state governments that compile annual information about what local governments raise and spend individually, but we know relatively little about what these governments do together. Our findings underscore the need for states to collect and publish the intergovernmental agreements created by their local governments. Success in confronting public problems arises not just from the actions of individual governments, but from the performance of networks of governments, both managed and emergent, working together on these problems. Absent information on the agreements they have created together—this critical element of the local government system goes unexamined.

Limitations and Conclusion

There are several limitations to this study that should be noted. First, due to the observational nature of our data, we are unable to identify and isolate the causal mechanisms at work. As Burt (2004, p. 354) notes "networks do not act, they are a context for action." Thus, while we can say that changes in certain network properties are associated with changes in community-level outcomes, we cannot provide specific details on the causal mechanism by which a particular structure or feature produces such positive effects. Theory is necessary to connect network features to network outcomes, and we identified several mechanisms that may lead to changes in network performance. These include imitation and learning, efficiency, and innovation. These mechanisms are linked to specific variables. Cohesion is most often seen as a driver of imitation and learning; centralization as a means toward efficient action and information diffusion; and network diversity as an important ingredient for innovation. Taken collectively, our findings suggest that the network properties associated with a community's capacity to address public problems may be determined by the problem type. Thus, while we have demonstrated a link between network properties and community-level outcomes, further research is needed to unpack the mechanisms and settings in which those factors operate. Relatedly, future research should develop frameworks that more fully take into consideration the beliefs and risk assessments of the decision makers. Most of the interorganizational network research relies on organizational attributes as primary factors rather than the human elements associated with partner choice.

Second, while we capitalize on a dataset that consists of agreements filed by local governments in the state of Iowa, we do not know the actual impetus for the agreements. Some may be formed for purposes that are not directly related to the outcomes we measure. As noted above, our selection of problem areas, crime and economic development, were driven by our concerns that the agreements in these policy areas match the outcomes we were measuring. While it is logical that agreements filed around police protection and criminal investigations should be linked to crime, further qualitative investigation into the specific types of activities these agreements establish is needed.

Third, and a challenge for all network research, is the generalizability of the findings and conclusions. "Networks are embedded in a specific policy context, and the behavior of network actors is defined by that context" Isett et al. (2011, i164). Our research spans 81 different counties, but all from within one state, which might limit its generalizability to the networks created in other states. Furthermore, the small population, rural character, and minimal racial diversity of most of Iowa's local governments might make it seem even less generalizable to other states. However, this description of Iowa also fits substantial portions of many states, outside each state's one or two urban regions. The local government landscape in United States is comprised of large numbers of small governments with generally homogeneous populations, and thus our findings likely have insights that apply to settings beyond Iowa. A second issue of generalizability stems from our focus on two specific problem areas and our findings that the important network properties are context dependent. Future research focusing on additional functional activities and problem areas is needed to identify the specific elements of the problem context accounting for the differences in our findings for the crime and economic development networks and perhaps to identify patterns in these differences.

Overall, our findings suggest that the networks that emerge from the purposeful collaborative actions of individual local governments scale to produce network properties that have important implications on community-level outcomes. Our findings also reveal the importance of structural characteristics for the performance of these networks differs by the type of problems addressed or policy context. Our analysis suggests that a county network effectively designed to improve economic development would be different in meaningful ways from one designed to reduce crime. Our findings also reveal the importance of stability in these networks for performance and may suggest a role for state or county governments in promoting stability in collaborative relationships once formed.

Finally, the importance of network centralization and stability, at least for the performance of the crime networks, raises an interesting question about the role and value of networks as a form of organizing. The organizational literature on networks suggests the primary benefit of networks compared to hierarchies is in their flexibility and horizontal relationships (Podolny and Page 1998; Powell 1990). However, these were not the features that were beneficial to the crime networks. Our evidence, also aligned with prior work, suggests that we should seek structures that are stable and centralized, features much more characteristic of a traditional bureaucratic hierarchy. Discussions about local public service delivery are often framed as a choice between intergovernmental networks or governmental consolidation, but it may be that both options can be effective solutions. If so, a key factor is likely the public problems being addressed by the services delivered by the governments involved.

Note

1 The research team at NGL updates this data set annually to capture newly posted agreements and plans to release the data to the public in the future. Further information can be found at https://cuppa.uic.edu/net-gov-lab/.

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Appendix

Table A1 Crime and Economic Development Models, No Variable Lags

	Violent Crime Rate	Property Crime Rate	Unemployment Rate	Median Household Income
Network structure				
Centralization (H_1)	–2.754 (1.097) *	–1.887 (0.768) *	0.107 (0.622)	0.026 (0.051)
Transitivity (H_2)	–0.361 (0.420)	–0.028 (0.308)	–0.365 (0.429)	0.004 (0.022)
Network composition				
Sector diversity (H_3)	–1.019 (0.854)	–0.064 (0.613)	–1.100 (0.450)*	0.100 (0.028) ***
Geographic range (H_4)	0.490 (0.300)	0.205 (0.191)	0.198 (0.366)	0.014 (0.014)
Tie properties				
Average tie strength (H_5)	0.014 (0.074)	0.134 (0.064) *	–0.021 (0.068)	–0.009 (0.007)
Network stability (H_6)	–0.082 (0.030) **	–0.029 (0.034)	–0.036 (0.031)	–0.001 (0.001)
Control variables				
Average degree	–0.050 (0.042)	–0.011 (0.040)	–0.033 (0.020)	–0.004 (0.002) *
In-force agreements	0.303 (0.238)	–0.018 (0.151)	0.069 (0.189)	–0.029 (0.012) *
Population density	–0.007 (0.004)	–0.005 (0.002) *	0.002 (0.002)	–0.000 (0.000)
Unemployment rate	–0.017 (0.054)	–0.005 (0.055)		–0.008 (0.004) *
Median household Income	0.508 (0.596)	0.035 (0.685)	–1.863 (0.788) *	
Operating expenses	0.077 (0.462)	0.083 (0.496)	–0.236 (0.203)	0.019 (0.012)
Capital outlays	0.005 (0.021)	0.017 (0.016)	0.012 (0.023)	0.004 (0.001) **
Number of counties	81	81	75	75
Sample size	1,226	1,226	1,099	1,099
Within R^2	0.052	0.022	0.049	0.101
County fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y

Excludes county-year observations where population was less than 10,000.
* $p < .05$;
** $p < .01$;
*** $p < .001$.

Table A2 Crime and Economic Development Models, Excluding Populations Under 7,500

	Violent Crime Rate	Property Crime Rate	Unemployment Rate	Median Household Income
Network structure				
Centralization (H_1)	–2.108 (0.983) *	–1.174 (0.598) *	–0.163 (0.505)	0.044 (0.038)
Transitivity (H_2)	–0.479 (0.355)	–0.061 (0.329)	–0.267 (0.189)	0.013 (0.020)
Network composition				
Sector diversity (H_3)	–0.925 (0.765)	–0.335 (0.526)	–0.862 (0.299) **	0.067 (0.021) **
Geographic range (H_4)	0.157 (0.250)	0.027 (0.136)	0.105 (0.314)	0.001 (0.012)
Tie properties				
Average tie strength (H_5)	–0.118 (0.072)	0.030 (0.066)	–0.021 (0.055)	–0.002 (0.006)
Network stability (H_6)	–0.048 (0.035)	–0.005 (0.034)	–0.038 (0.024)	–0.002 (0.001)
Control variables				
Average degree	0.020 (0.041)	0.032 (0.053)	–0.019 (0.021)	–0.002 (0.001)
In-force agreements	0.496 (0.178) **	0.175 (0.128)	0.165 (0.165)	–0.023 (0.010) *
Population density	–0.006 (0.004)	–0.004 (0.003)	0.004 (0.001) **	–0.000 (0.000)
Unemployment rate	–0.010 (0.050)	–0.009 (0.046)		–0.009 (0.003) ***
Med. household income	1.075 (0.532) *	0.192 (0.620)	–0.406 (0.717)	
Operating expenses	–0.211 (0.507)	0.133 (0.321)	–0.196 (0.226)	0.027 (0.012) *
Capital outlays	0.016 (0.021)	0.032 (0.020)	–0.013 (0.026)	0.000 (0.002)
Number of counties	93	93	87	87
Sample size	1,438	1,438	1,291	1,210
Within R^2	0.038	0.011	0.028	0.066
County fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y

Excludes county-year observations where population was less than 7,500. All predictor variables are lagged one year.
* $p < .05$;
** $p < .01$;
*** $p < .001$.

Table A3 Crime and Economic Development Models, Excluding Populations Under 15,000

	Violent Crime Rate	Property Crime Rate	Unemployment Rate	Median Household Income
Network structure				
Centralization (H_1)	–2.055 (0.895) *	–1.597 (0.847)	–0.367 (0.582)	0.032 (0.068)
Transitivity (H_2)	–0.438 (0.295)	–0.098 (0.252)	–0.529 (0.269) *	0.033 (0.026)
Network composition				
Sector diversity (H_3)	–0.282 (0.612)	–0.429 (0.447)	–1.309 (0.432) **	0.092 (0.025) ***
Geographic range (H_4)	0.181 (0.234)	0.053 (0.197)	–0.185 (0.227)	–0.032 (0.016)
Tie properties				
Average tie strength (H_5)	0.010 (0.056)	0.013 (0.044)	–0.005 (0.065)	–0.000 (0.006)
Network stability (H_6)	–0.037 (0.019) *	–0.007 (0.018)	–0.051 (0.018) **	–0.003 (0.001) *
Control variables				
Average degree	0.026 (0.034)	0.027 (0.024)	–0.012 (0.023)	–0.001 (0.002)
In-force agreements	0.366 (0.166) *	0.276 (0.181)	0.263 (0.173)	–0.027 (0.012) *
Population density	–0.004 (0.003)	–0.003 (0.002)	0.002 (0.001)	–0.000 (0.000)
Unemployment rate	0.025 (0.034)	0.024 (0.043)		–0.013 (0.004) **
Med. household income	0.822 (0.623)	–0.145 (0.487)	–0.647 (0.811)	
Operating expenses	0.444 (0.325)	0.461 (0.454)	0.078 (0.250)	0.037 (0.016) *
Capital outlays	–0.022 (0.019)	0.000 (0.009)	–0.001 (0.017)	0.003 (0.002)
Number of counties	55	55	52	52
Sample size	839	839	754	706
Within R^2	0.085	0.045	0.042	0.112
County fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y

Excludes county-year observations where population was less than 15,000. All predictor variables are lagged one year.
* $p < .05$;
** $p < .01$;
*** $p < .001$.