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The Evolution of a Collaborative Network: Understanding Partnerships in a Policy Mandated Collaboration Through Social Network Analysis

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THE EVOLUTION OF A COLLABORATION NETWORK:
UNDERSTANDING PARTNERSHIPS IN A POLICY-MANDATED
ENVIRONMENT THROUGH SOCIAL NETWORK ANALYSIS

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
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requirements for the degree of
Doctor of Philosophy

in

The School of Leadership &
Human Resource Development

by

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Dedicated to my parents, Usha Sharma and Shyam Bihari Roy

who gave me the gifts of personal resiliency, a love of learning, and a generous spirit.
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ABSTRACT

Federal funding agencies that administer financial support in the form of program grants to non-profit organizations (NPOs) that provide child and family services increasingly require NPOs to formalize inter-organizational partnerships in order to receive this vital source of funding. That is, by mandate NPOs must participate in inter-organizational collaboration networks to receive these essential federal funds. Therefore, there is a need to understand the collaboration behavior of NPOs in a policy-mandated environment. This study considers collaboration behavior as information sharing and advice-seeking between the organizations who are part of a collaboration network as a result of a policy mandate.

Drawing on collaboration theory, social capital theory, and social network theory, this study examines the evolution of a collaboration network by assessing how NPOs in a policy-mandated context chose to engage in information-sharing behaviors and how these behaviors changed over time as NPOs developed a working history together. This research examined the production and distribution of social capital as the primary mechanism for motivating collaboration (i.e., information exchange) as the network evolved. Using Louisiana’s Project Linking Actions for Unmet Needs in Children’s Health (LAUNCH) as a case study, this study analyzed five years of self-reported organization-level data on collaboration behaviors and information exchanged among NPOs within the LAUNCH network.

A social network approach was used to analyze the evolution of collaboration practices and found that existing ties play a pivotal role in facilitating information exchange behaviors among the NPOs in the study. That is, organizations are more likely to create information-sharing partnerships with other organizations that have been endorsed and vouched for by an existing partner, or they share information with organizations that have already shared
information with them in the past. This showed a tendency towards bonding social capital wherein organizations are provided security against the high levels of risk within a policy-mandated collaboration by the convenience and accessibility offered by maintaining existing relationships. Results of this study were consistent throughout the different model specifications employed in the analysis, and reveal key implications for organizations engaged in policy-mandated partnerships, as well as for funders who require collaboration.
CHAPTER 1. INTRODUCTION

1.1. Background

Policy makers, administrators, and the general public vigorously promote collaboration among the non-profit organizations (NPOs) that provide services to children and families in the United States (Sandfort, 1999). Requirements to engage in collaboration are mandated either through legislation or as a condition of receiving federal funding and dictate that NPOs collaborate with other child and family service providers (Congressional Research Service, 2017; Khosla, Martsteller & Holtgrave, 2013; National Head Start Association, 2013; US Department of Health and Human Services, 2009, 2010).

Government funding is a critical source of revenue for NPOs that provide child and family services, accounting for approximately 65 percent of their annual budgets, according to one report by the Urban Institute (2013). Further, much of this funding serves as the “life blood” for the survival of the organizations, compelling these organizations to collaborate (Chambre & Fatt, 2002; Jang & Feiock, 2007). For example, in a National Survey of Nonprofit-Government Contracts and Grants by the Urban Institute (2013), it was found that non-profits reported a decrease in organizational activities, including decreased hours of operation or closing of program sites, if the government funding was taken away or reduced. It has become increasingly clear that in order to secure funding, these organizations need to invest in inter-organizational collaborations (Heinrich, Lynn, & Milward, 2010; Milward & Provan, 2000).

Inter-organizational collaboration can be defined as “a process in which organizations information sharing, alter activities, share resources and enhance each other’s capacity for a common purpose” (p.3; Himmelman, 2004). The desire to enhance capacity drives organizations to share their information, knowledge, or expertise (Guo & Acar, 2005). However, traditional
modes of encouraging collaboration such as mandates, legislation, and contracting mechanisms may be perceived as means by which funders can exercise control over NPOs functions (Bunger, McBeath, Chuang, & Collins-Camargo, 2016) which might discourage organizations from engaging in collaboration.

In a policy-mandated context, collaboration is motivated by beliefs that engaging in the collaboration will lead to rewards and that not engaging will lead to punishment, whereas voluntary collaboration is not directly linked to either rewards or punishment (Holland, 2007; Shumate, Fulk, & Monge, 2005; Stephens, Fulk, & Monge, 2009; Tyler, 2011). Issues regarding lack of autonomy, communication problems, and mistrust can emerge during collaboration. Furthermore, organizations that engage in mandatory collaborations may have more at stake as failure does not just affect the parties involved in the collaboration, it also affects their relationships with funders and organizational partners (Ada & Lionel, 2014; Bierly & Gallagher, 2007). As a result, NPOs must navigate these complex challenges while still adhering to their own unique missions and continuing to provide services.

This suggests a re-centering of research around the challenges of fostering collaboration in a policy-mandated environment, where the NPOs operate as an independent, autonomous entity with their own organizational features, while still controlled by mandates. Given this, it is clear that more research is needed to empirically evaluate the rationale behind how NPOs engage in collaboration in a policy-mandated context. This research addressed this need by drawing on collaboration theory, social capital theory, and social network theory to examine how NPOs in a policy-mandated context engage in information sharing behaviors and how these behaviors change over time.
1.1.1. Collaboration in Louisiana Project LAUNCH

Personal and social issues that challenge the well-being of children and families cannot be solved by any individual agency alone. Collaboration is needed among government agencies, non-governmental organizations, and community-based child and family service-providing organizations. These inter-agency partnerships are considered critical for comprehensive, integrated, effective, and accessible services (Sowa, 2009). Therefore, policy makers require that evidence of existing or planned collaboration be a criterion for determining whether child and family service providers receive federal funding to support or expand their programming services.

This study uses the Louisiana Project LAUNCH (Linking Actions for Unmet Needs in Children’s Health) as a case study. One goal of Project LAUNCH is integrated service delivery through improved coordination and collaboration across organizations that serve young children and their families. Numerous organizations are charged with this task, including but not limited to primary care providers, community-based agencies, government agencies, school districts, and not-for-profit private organizations that provide a variety of services such as mental and medical health consultations. LAUNCH was created to engage a range of organizations across these entities; these are the NPOs being examined in this study. Due to the diversity of organizations participating in the LAUNCH network, attributes of organizational size, geographical locations and roles are also included in this study to examine the information exchange behaviors.

In the context of this study, information exchange within the collaboration is operationalized as advice-seeking behavior wherein an organization seeks information and guidance from another organization within the LAUNCH network. Organizational partnerships that result in information exchange can lead to the production and distribution of social capital.
based on a self-interested maximization of access to resources (i.e., benefits to the organization seeking information) and a network enriched with resource-sharing (i.e., benefit to the LAUNCH network as a whole) (Lin, 2001; Kadushin, 2004). Thus, information-sharing in the context of collaboration allows organizations to access, maintain, or manage key resources that can help balance the needs of organizational goals and collective systems-level goals.

1.2. Inter-Organizational Collaboration and NPOs Leadership

The study of inter-organizational collaboration in a policy-mandated context provides evidence-based guidance to leaders of NPOs to develop better inter-organizational collaboration networks for serving their missions and securing the vital funding needed to do so. The leaders in NPOs seek collaborative arrangements in order to help their organizations acquire a pool of resources, skills (Hamel, 1991; Williamson, 1991; Gulati, Nohria, & Zaheer, 2000), and new knowledge (Anand & Khanna, 2000; Kale, Singh, & Perlmutter, 2000) that allows for synergistic solutions to complex problems (Weiss, Anderson, & Lasker, 2002). The results of this study can potentially guide NPO leadership to evaluate their rationale for engaging in a collaboration that is mainly guided by a mechanism to secure rewards (funds) and avoid punishment (lack of funds). Information sharing behavior in collaboration leads to the access of new information that has implications for the transfer and application of innovative practices into everyday community settings (Schoenwald & Hoagwood, 2001; Simpson, 2002). However, if organizations do not fully collaborate and are not exchanging new or innovative knowledge through information exchange behaviors, the members of their communities ultimately suffer the consequences. NPO leaders that are operating within a policy-mandated collaboration environment need to revisit the collaboration strategies they adopted so that they are able to meet both funder requirements as well as community needs.
1.3. Purpose of Study and Research Questions

The purpose of this study is to examine the evolution of collaboration (i.e., information sharing) behaviors within a systems network. This study explores how organizations choose to engage partner organizations in information exchange within a policy-mandated context, and seeks to understand how those organizational partnerships change over time. In doing so, this study also examines the role of social capital as a mechanism for motivating organizations to engage in collaboration behavior within the LAUNCH network.

The following research questions are proposed for this study:

1. How do non-profit organization select their collaboration partners?
2. How do partnerships change over time?
3. What role do organizational attributes play in selecting partners?
4. How does partner selection affect the production and distribution of social capital as the collaboration evolved?

1.4. Context of Study

Due to increased pressure to collaborate in order to obtain funding or meet funding expectations and requirements, this study focused on NPOs providing child and family services. Currently, at the local, state, or national levels, there is increasing emphasis on organizational partnerships and collaboration across early care and education sectors to provide consistent, high-quality services to better meet the needs of families with young children.

The U.S. government has allocated $31.5 billion in funding to over 40 programs focused on child and family services (National Institute for Early Education Research, 2014). Additionally, the federal government has also appropriated $8 billion for child welfare programs (Congressional Research Service, 2017). Both funding sources require collaboration among
organizations to improving services for children and families. In particular, there is at least $600 million allocated from child welfare grants specifically for the purpose of building partnerships among organizational stakeholders (Congressional Research Service, 2017). Programs such as Head Start and state Pre-K account for 50 percent of the funds concentrated on providing children and family services, and these organizations are required to work together to improve families’ well-being through improved access to a system of coordinated and effective services (National Head Start Association, 2013).

Furthermore, there are other federal programs that demand collaboration be one of the strategies for successful implementation of child and family services programs. In their funding guidelines, the U.S. Department of Health and Human Services suggests that “the proliferation of early childhood programs from diverse and unconnected service systems left significant gaps between the service systems that needed to be addressed” through collaboration (USDHHS, 2009, p. 1). As one of the largest sources of federal funding for children and family services, these guidelines make it clear that USDHHS prioritizes collaboration as being critical in successful program implementation. Similarly, the funding opportunity announcement for the Affordable Care Act-supported Maternal, Infant, and Early Childhood Home Visiting (MIECHV) program states that organizational collaboration will be the mechanism to “improve the health and well-being of vulnerable populations by envisioning child development within the framework of life course development and a socio-ecological framework” (USDHHS, 2010, p. 4). Additionally, the Council on Accreditation (2016), the largest accrediting institution in the human service sector, sets partnership standards according to the rationale that children are best served by providers that are strongly engaged with communities and institutions.
With the pressure on child and family services NPOs to collaborate with other organizations serving the same populations to meet the expectations of these funding agencies, it is imperative that researchers generate information that is both theoretically sound and useful to practitioners working in the field of children and family services in order to ensure efficient use of resources. With this goal in mind, the current study examines the evolution of a collaboration network of NPOs in a policy-mandated context to understand how these organizations choose which partner organizations to share information with, how these partnerships change over time, and the extent to which organizational attributes such as the organization’s size role, geographical location, and role affect this evolutionary process within the network.

1.5. Theory Framing

The main theories framing this study are collaboration theory, social capital theory, and social network theory. Collaboration theory identifies collaboration as a complex process requiring a number of factors, or antecedents, for it to occur and for the desired outcomes to be achieved (Gray & Wood, 1991; Wood & Gray, 1991). Collaboration theory fails, however, to explain how the processes inherent in collaboration are operationalized, particularly within a policy-mandated collaboration. As such, it is not clear how governmental policy affects the readiness of organizations to engage in collaboration behavior such as information exchange. The traditional methods used by funders for requiring collaboration such as mandates, legislation, and contracting mechanisms may be perceived by organizations as being a means to exercise control over the NPOs’ functioning (Bunger, McBeath, Chuang, & Collins-Camargo, 2016). The risk associated with a failed collaboration is a substantial as it also affects the NPO’s relationships with funders and organizational partners (Ada & Lionel, 2014; Bierly & Gallagher,
2007). Collaboration theory fails to explain how much organizations are willing to sacrifice to assure the funders that NPOs are participating in the collaboration as required.

This lack of specificity indicates that collaboration theory has some gaps, particularly in terms of explaining the deeper dynamics influencing the actions or behaviors of those involved in collaboration. To understand collaboration more thoroughly, this study applies theoretical principles of social capital theory and social network theory. The use of social capital and social network theories allow for an improved understanding and identification of how social capital relates to an organization’s preference for forming collaborative ties with other organizations.

![Theoretical Framework](image)

**Figure 1.1. Theoretical Framework**

### 1.5.1. Collaboration Theory

For the purposes of this study, collaboration theory is a framework used to better understand collaboration in the context of a policy-mandated environment. This theory identifies collaboration as a complex process requiring a number of factors, or antecedents, for it to occur and for the desired outcomes to be achieved (Gray & Wood, 1991; Wood & Gray, 1991). Collaboration theory comprehensively describes the principles required for successful collaboration, with Thomson and Perry (2006) asserting that the principles or elements of
collaboration include governance, administration, agency and organizational autonomy, mutuality, and norms of trust and reciprocity.

Governance involves having the appropriate organizational and network structures and processes in place that allow participants to jointly make decisions and rules for governing their behavior, relationships, decision-making processes, as well as what information needs to be provided, and how costs and benefits are distributed (Huxhan & Vangen, 2005; McGuire, 2002; Scott, Ruef, Mendal, & Caronna, 2000; Thomson & Perry, 2006). Governance requires trust and reciprocity (Thomson & Perry, 2006; Zhang & Huxham, 2009) to come to consensus.

The administration dimension of the collaboration process involves clarifying roles and responsibilities; Thomson, Perry, and Miller (2009) argue that more structured processes are required when collaboration is less voluntary. By examining how organizations select partner organizations to exchange information with and learning how partnerships change over time, this research examines how collaboration is enacted within a mandatory collaboration.

Organizational autonomy is a defining process of collaboration that involves understanding the managerial dilemma of achieving individual organizational goals compared to goals of the collective. The literature commonly assumes individual and organizational goal matching is required for successful collaboration (Dietrich, Eskerod, Dalcher, & Sandhawalia, 2010). Here, autonomy means that organizations in a collaboration have a distinct organizational identity separate from that of the collaboration network as a whole. However, the literature is less clear on how an agency is impacted in situations of mandated collaboration (i.e., when evidence of inter-organization collaboration is required for funding to be allocated) or when collaboration is promoted by policy (i.e. collaboration is encouraged but not required for
funding). This research addresses this knowledge gap by examining how organizations choose their collaborators and how they maintain their relationships.

The mutuality dimension of collaboration involves the creation of mutually beneficial relationships between organizations (Thomson & Perry, 2006). In other words, mutuality relates to the notion of gaining or sacrificing, or even winning or losing, as parties “agree to forego the right to pursue their own interests at the expense of others” (Powell, 1990, p. 303). However, the literature is not clear on how this is achieved in a government-mandated collaboration. This begs the question: what are organizations doing to achieve mutuality? Further research is required to understand the deeper dynamics of collaboration to better understand how organizations engage in information sharing behaviors. This study addresses this gap by examining how NPOs select their collaborators and how these relationships change to be mutually beneficial.

The final principle of collaboration is norms of trust and reciprocity, which involves creating a climate in which participants are willing to fulfill reciprocal obligations to other participants (Bin, 2008; Thomson & Perry, 2006; Vangen & Huxham, 2003; Zhang & Huxham, 2009). Ostrom (1998) claims that norms of reciprocity are related to trust, or at least reputations of trustworthiness, to fulfill or deliver on commitments between participants.

As evident from the discussion above, collaboration theory alone does not explain how the processes inherent in collaboration are operationalized, especially in policy-mandated collaboration, nor does it explain the readiness of the key organizational players when the risks are high. To better explain how collaboration occurs in a policy-mandated environment, this research expands upon this framework and incorporates theoretical principles associated with social capital and social network theory.
1.5.2. Social Capital Theory

Social capital theory is used to frame this research because of the inherently relational nature of collaboration (Daley, 2008; Gaboury, Bujold, Boon, & Moher, 2009; Thomson & Perry, 2006; Thomson, Perry, & Miller, 2009; Zhang & Huxham, 2009). Social capital is commonly referred to as a resource (Adler & Know, 2002; Portes, 1998) and definitions of social capital vary in terms of being focused at the individual (Burt, 1997) or collective level (Fukuyama, 1995; Nahapiet & Ghoshal, 1998; Putnam, 1993; Tsai & Ghoshal, 1998). Individually-focused definitions of social capital conceptualize it as an asset accessible to those involved in social relations within a network (Burt, 1997). On the other hand, collectively-focused definitions of social capital propose that social capital is inherent within a network structure (Fukuyama, 1995; Nahapiet & Ghoshal, 1998; Putnam, 1993; Tsai & Ghoshal, 1998; Putnam, 1993) and is available to all members regardless of levels of involvement in social relations (Fukuyama, 1995).

This research adopts the conceptualization that social capital is an accrued resource that is embedded in the relationships between two or more individuals or organizations. This definition is adopted for this study because of its emphasis on relationships, which is congruent with collaboration theory (Huxham & Vangen, 2005; Thomson & Perry, 2006). There is an overlap between collaboration theory and social capital theory as scholars commonly argue that trust and reciprocity are essential to successful collaboration (Huxham & Vangen, 2005; Thomson & Perry, 2006), which shows the relevance and usefulness of social capital theory in examining collaboration, particularly in regards to the inter-relational processes between those involved.
In addition, social capital theory allows the researcher to consider the social, relational, and communicative nature of the organizations involved in collaboration as well as the impact of a variety of factors, such as organizational characteristics (Adler & Kwon, 2002). This is important in the context of this study because measuring social capital also allows inequalities of influence to be examined within a collaboration network in terms of who has more or less social capital when collaborating and why this discrepancy may exist. Therefore, the researcher is able to examine the process of social connectedness and cohesiveness between organizations to attain actions, or more effective action, through a social capital lens.

Social capital theory also allows the researcher to understand how collaboration may be influenced by those who have more or less access to social capital in a collaboration. Hence, social capital allows for the identification of those organizations who are more or less important and further allows the willingness of participating organizations to collaborate to be examined. Therefore, applying the concept of social capital allows the researcher to conceptualize the non-monetary benefits that result in information transfer, influence, and solidarity (i.e., collaboration behaviors) between organizational members within the structure of a systems-level network (Cots, 2011).

In this study, social capital is segmented into two different components: bridging social capital and bonding social capital. Putnam’s (2000) work in distinguishing bridging and bonding forms of social capital is an extension of Granovetter’s (1973) concept of strong and weak ties, which is well recognized by many researchers (Agnitsch, Flora, & Ryan, 2006; Cheung & Kam, 2010; Westlund & Gawell, 2012; Newman & Dale, 2007; Sekhar, 2007; Woolcock, 1998).
1.5.2.1. Engaging in Collaboration Behavior through Bridging and Bonding Social Capital

Bridging social capital is concerned with linkages across similar, but different, groups or social networks, with linkages often being much weaker between heterogeneous groups than within a relatively homogeneous group. These ‘weak ties’ (Granovetter, 1973) however, can be very important as they provide a critical mechanism for the diffusion of knowledge and innovation (Grafton, 2004). In the context of collaboration, bridging social capital may also play a crucial role in meeting the goals of providing better services by generating regional cooperation across early childhood NPOs and in conflict resolution across competing needs such as funding, clients, etc. Bridging describes social relationships of exchange, often of associations between people with shared interests or goals but with contrasting social identity (Pelling, Mark, & High, 2005).

Bonding social capital involves linkages or ‘strong ties’ within groups of like-minded individuals (e.g., families) that often correspond to denser and more localized networks. Strong ties are particularly useful in the context of collaboration because they are associated with trust and cooperation that in turn encourage individual organizations to adhere to norms and sustainably collaborate with other organizations. Manifestations of collaboration have emerged with a specific intent of fostering coordination among people and organizations from a variety of sectors to engender trust among stakeholders and provide a platform for resource exchange and ultimately to achieve the purpose of collaboration (Himmelman, 1992).

Social capital can be seen as the structure and quality of social networks, and as such, the core dimensions of social capital are seen to be networks of social relations (structure). Structural proponents of social capital (Granovetter, 1973; Grootaert, 2001; Uphoff, 2000; Lin, 2001; Sabitini, 2006; Uzzi, 1997) point to the actual relationships held between individuals that
increase a shared level of social capital in a network. For example, if a group of twenty people are part of a community, we could take a measure of each person’s level of social capital and make claims about how these levels affect the group as a whole. On the other hand, if a certain person in the group has an enormous amount of social capital, but chooses not to interact with the other people in the group, then there is really no increase in social capital for the group. It is not until that person makes connections with the others in the group that the community level of social capital as a whole increases. For this reason, the structural aspects of social capital (that is, the way that people interact) are a necessary part of getting an accurate measure of social capital. This study emphasizes the structural aspects of social networks and their relationship to the concept of social capital. This network-based approach to measure social capital with a theoretical approach is applied based on the works of leading network theorists (Borgatti, Jones, & Everett, 1998; Burt, 1980; Granovetter, 1982) and social capital authors (Bourdieu, 1986; Coleman, 1988; Putnam, 1995).

The fundamental elements of social capital are social structures and social networks (Bourdieu, 1986; Coleman, 1988; Lin, 1999; Pretty & Ward, 2001; Putnam, 1993; Uphoff & Wijayaratna, 2000). Therefore, social network theory is being invoked to define and measure social capital. Social networks act as a platform for the interaction and activation of relationships with other members in the network to positively influence the collaboration process. Therefore, the ways in which the individual organizations are themselves positioned in the network, as well as the characteristics of the network, determines the extent of social capital accrued (Greve & Salaff, 2003; Ulhoi, 2005). The next section expands on this discussion of social network theory and how it draws on the concept of social capital in the current study and further informs collaboration theory.
1.5.3. Social Network Theory

The social network phenomenon is an abstract concept which is made up of nodes and edges that tie these nodes together (Degenne & Forse, 1999). In the narrowest sense, the social network approach and analysis thereof is a method of numerically and or graphically mapping the type, direction, and intensity of relationships between groups of actors (Oztas & Acar, 2004).

According to Gulati (1998), the basic assumption of social network theory is that an organization’s actions are influenced by the social context in which they are situated, and similarly, that actions are influenced by the positional characteristics of the organizations that make up the social network. According to Wasserman and Faust (1994), the four main foundations of social network analysis are mutual loyalty, connections between the actors, the influence of the network structure, and the continuity of the relationships between the actors. Social networks are created through all social relationship clusters that are possible within a certain context (collaboration, communication, power, or exchange relationships) and connect the actors with each other (Borgatti & Foster, 2003; Emirbayer & Goodwin, 1994; Hanneman & Riddle, 2005).

Social network theory gained popularity through its role in the explanation of the creation of social capital. Social network theory stipulates that the relationships (or ties) between actors (i.e. organizations) in a network and the network structure (the position of the organizations within the network) have consequences for the actors in the network (Borgatti, Mehra, Brass, & Labianca, 2009). In network theory, members of a collaboration have a determinate set of opportunities to connect, exchange, and practice that can be measured against the actual occurrence thereof. Actors are interdependent and their relational ties are routes for ideas,
information, and resources to travel (Wasserman & Faust, 1994). These ties can also reflect features of interpersonal relationships, such as advice-seeking.

Since collaboration in this study is characterized as information exchange, which includes aspects of advice-seeking, social network theory is being employed as the theoretical framework that guides the operationalization of variables in the present study. Social network theory is the study of how individuals, organizations, or groups form connections with others inside their network. Additionally, social network theory provides the methodology by which to measure social capital, thereby increasing the usage of social network theory in this study twofold.

Two different approaches of understanding the creation of social capital have existed within social network theory. The first approach is that of an open network, which was first coined by Granovetter (1973) and further extended by Burt (1992), while the second approach is a closed network concept popularized by authors such as Bourdieu (1986) and Coleman (1988). Proponents of the open network concept are of the belief that open networks offer diversity of information and opportunities to members of its network. This diversity of information leads to greater social capital benefits such as finding new partners and generating new information. In contrast, Coleman’s (1988) concept of social capital is based on that of a closed network, in which the network ties are shared between the same members over and over again. This kind of social capital allows for deployment of new information and establishment of new partners for an organization’s own benefit. For example, after locating new useful collaborators, the organizations can work together to implement ideas (Jansen, van den Bosch, & Volberda, 2006; Rowley, Behrens, & Krackhardt, 2000). In addition, stronger ties between groups tend to exist in closed structures and promote cohesion, whereas weak ties are more likely to exist in open structures and are more conducive to group fragmentation (Smylie & Hart, 1999).
Putnam’s (2001) distinction between bridging and bonding social capital relates directly to particular network structures – bridging social capital constitutes weak ties and open network structures, while bonding social capital constitutes strong ties and dense or closed network structures. Burt (1992, 2000, 2004) introduced the concept of network closure and structural holes, which extends the theoretical understanding of bonding and bridging social capital, respectively.

The present study builds on Burt’s conceptualization of social capital where network closure can be viewed as a closed and densely connected network which controls access to information, while facilitating sanctions that make it less risky for people in the network to trust one another (Coleman, 1988, 1990; Burt, 2000). In contrast, structural holes are the gaps formed between non-redundant contacts or groups (Burt, 1992; Uzzi & Schwartz, 1993). Both network closure and structural holes are important concepts in analyzing group relationships and dynamics. High network closure is associated with strong bonding social capital, whereas a more open network structure indicates higher bridging social capital.

1.5.3.1. The Similarity Effect: Homophily

Social network theory describes how actors in a network are attracted to one another based on certain attributes (or behaviors) they possess. In general, similarity is seen as the main basis for getting attracted to others (McPherson, Smith-Lovin, & Cook, 2001). The similarity effect on forming collaborative ties is termed in the literature as homophily (McPherson et al., 2001) and is defined as the social situation of actors preferring to form social ties with others who are similar to themselves (Blau, 1977; McPherson et al., 2001). Homophily is consistently identified as an important determinant of network structure, and actors contribute to network stability by binding to similar actors (McPherson et al., 2001). Shared traits or characteristics are potentially
important facilitators of social interaction because individuals equate similarity with trust and congruent expectations (Brass, 1995). Similarity, therefore, may reduce the transaction costs associated with interaction or collaboration (Feiock & Scholz, 2010; McPherson et al., 2001) and strengthen existing social bonds between individuals (Cantner & Graf, 2006; McPherson et al., 2001; Reagans, 2011; Tallman & Phene, 2007). Therefore, the concept of homophily gives this study insight into how organizational attributes affect partner selection in a policy-mandated collaboration.

1.6. Study Contribution and Significance

This research makes a theoretical contribution to the scientific understanding and practical application of NPOs inter-organizational collaboration. It integrates three theoretical frameworks of behavioral inter-organizational collaboration to examine the choice of organizational partners and the strengthening of information exchange within a network of NPOs that specialize in early childhood and family services in a policy-mandated context. Through analysis of the influence of social capital on partnership formation within a network, this study examines the evolution of collaboration behavior to understand how NPOs select their partners and how those partnerships change over time within a policy-mandated environment.

By applying the principles of collaboration theory, social capital theory, and social network theory, this research seeks to broaden the theoretical perspective by which collaboration is analyzed and measured to advance knowledge about partnership formation within a systems-level setting. As discussed earlier, collaboration theory does not explain the willingness of organizations to collaborate, especially in the context of policy-mandated collaboration, and particularly within the field of early childhood and family services. Social capital theory allows the researcher to examine the willingness of participants to collaborate and allows social capital to be conceptualized as a resource that gives benefits to those with higher levels of social capital.
Social network theory allows for an examination of the dynamic nature of collaboration by providing the opportunity to operationalize changes in the relationships that occur over time. Social network theory further allows the researcher to identify which players are more relevant or important in a collaboration.

In grounding collaboration within a theoretical context, the key principles of collaboration were discussed, namely, governance, administration, organizational autonomy, mutuality, and norms of trust and reciprocity. However, the above discussion suggests that additional processes are required to address and resolve these principles. The literature reviewed reveals that these principles are inadequate in explaining how collaboration occurs within the context of policy-mandated collaboration. Understanding this requires further investigation to empirically determine whether collaboration is actually occurring, or whether collaboration theory represents the activities being undertaken by the participants involved in collaboration. The specific activity under investigation in this study is the choosing of organizational partners. If the policy-mandated collaboration showed incongruence or inconsistencies with the existing collaboration theory, it is argued that collaboration theory may need to be revised in the case of policy-mandated collaborations. Consequently, this research provides an opportunity to reveal the process of organizational partner selection that may extend and expand on collaboration theory. By using social capital theory and social network theory to answer the proposed research questions, the current study advances collaboration theory particularly in terms of the key principle that addresses processes of collaboration.

From a practitioner perspective, understanding whether and how NPOs adjust their partnerships in response to mandatory collaboration has implications for policy and funding strategies aimed at integrating programs across the entirety of the human services system. NPOs
may choose to consider revisiting their collaboration strategies by testing a collaborative partner prior to developing more intensive partnerships by investing earlier in relationships that are not too demanding. This may help in reinforcing trustworthiness, potentially leading to stronger and more valuable partnerships (Impink, 2004; Snavely & Tracey, 2002).

1.7. Definition of Terms

The following terms are listed and defined for the purpose of this study:

**Collaboration:** “a process in which organizations exchange information, alter activities, share resources and enhance each other’s capacity for mutual benefit and a common purpose by sharing risks, responsibilities, and rewards” (Himmelman, 2004, p. 3).

**Non-profit organizations:** not-for profit, task-oriented, concerned voluntary group organized on a local, national, or international level to address issues in support of the public good and humanitarian functions (DeMars, 2005; Sharfeddin, 2008; Stephenson, 2005). The terms organizations and NPOs are used interchangeably throughout this document.

**Network:** a set of self-organizing working relationships among actors such that any relationship has the potential both to elicit action and to communicate information in an efficient manner.

**Collaboration network:** “a collection of loosely connected or closely knit organizations that share resources” (Arya & Lin, 2007).

**Social capital:** “a resource that actors derive from specific social structures and then use to pursue their interests; it is created by changes in the relationship among actors” (Baker, 1990, p. 619).
**Bridging social capital**: When organizations in a group create ties and connect to other organizations with whom they had little or no contact up to that point, granting access to new resources (Berardo, 2014; Granovetter, 1973; Putnam, 2001).

**Bonding social capital**: Organizations in a group create relationships that bring them closer together, improving the quality of resources available to each of them (Berardo, 2014; Putnam, 2001).

**Network structure**: “Patterns of relationships that are created by the flow of resources among the individuals or organization through time and space” (Monge & Contractor, 2003, p. 3).

**Homophily**: the propensity of an actor in a network to form relationships with actors who are similar to themselves (McPherson & Smith-Lovin, 1987).

**Network cohesiveness**: Network cohesiveness refers to a network structure where the ties are widely distributed across network and members are closer to each other as a result the resources and information is available to all network members (Moody & White, 2003; Friedkin, 2004).

**Network centralization**: Network centralization refers to a network structure where a few network members dominate the resources and information flow in a network (Borgatti, 2005).

**Social network analysis**: An analysis of the relationships and links that foster exchange of resources and collaboration (Cross, Borgatti, & Parker, 2001).

**1.8. Summary and Organization of the Document**

Chapter 1 introduced the background of the study along with the context in which the study was completed, study contributions, theoretical frameworks employed, significance of the study, and defined key terms that are used throughout the paper. Chapter 2 provides the literature review section of this dissertation to further explain the existing research surrounding non-profit collaboration, social capital, and network structure of non-profit collaboration that anchors and provides support to the proposed hypotheses. Chapter 3 describes how the study was planned and
conducted, including the sample population, data collection procedures, measures, and data analysis strategy. Chapter 4 discusses the data preparation steps required for this study followed by sample characteristics. Then descriptive hypothesis results are discussed followed by longitudinal analysis of the network from year 1 (2014) to year 4 (2017) as well as the exploratory prediction for the year 5 network (2018). Chapter 5 discusses the summary of findings arranged in order by each of the four research questions. This dissertation concludes by addressing the research and practice implications of this study along with limitations and directions for future research.
CHAPTER 2. LITERATURE REVIEW AND STATEMENT OF HYPOTHESES

The overall aim of this study was to examine the production and distribution of social capital as the primary mechanism for motivating collaboration in a policy-mandated environment. Specifically, the research studied how NPOs in this context selected their partners over time. This was done by examining the structure of the collaboration network and changes to that network over time – in other words, how NPOs selected partners to exchange information when collaboration was mandatory. Additionally, this longitudinal study also tested whether organizational attributes such as organization’s size, geographical proximity, and role similarity had an effect on the evolution of the network.

Using Louisiana’s Project Linking Actions for Unmet Needs in Children’s Health (LAUNCH) as a case study, this study aimed to empirically examine the proposed research questions. With this objective in mind, the present study explored two network dimensions – network cohesiveness and network centralization – to understand how these dimensions might influence NPOs’ selection of partners in the LAUNCH network, and how the partnerships changed over time.

This chapter reviews literature that provides support to the proposed hypotheses. The literature reviewed comprises aspects of inter-organizational collaboration, non-profit organizational collaboration, and social network analysis.

2.1. Collaboration in the Current Study

For the purpose of this study, collaboration was considered to be advice-seeking from other organizations who were part of Louisiana Project LAUNCH and included the belief that partnering with another actor offered a unique perspective or form of expertise that was valuable to understand and/or address a shared problem or concern. The legitimacy of each stakeholder’s
expertise in the eyes of others has been found to have important implications for the willingness of a collaboration group to make full use of the diverse perspectives and forms of expertise represented at the table (Bond & Keys, 2000; Clark, Baker, Chawla, & Maru, 1993). Scholars of inter-organizational collaboration have made similar observations, noting that legitimacy of a member in the eyes of a group makes it more likely that the knowledge, perspectives, and resources available to that member will become a resource available to the group (Alter & Hage, 1993). As such, member relationships characterized by perceptions of a high degree of recognized expertise can become a collective resource to the entire network and therefore represent an important form of social capital.

The next section describes the hypothesis related to the first network dimension – network cohesiveness – followed by the second network dimension, network centralization. This is followed by the research hypothesis that relates to organizational attributes. The chapter also discusses the proposed conceptual model. Finally, the chapter ends with the exploratory prediction discussion.

2.2. Network Cohesiveness

Network cohesiveness refers to a network structure where the ties are distributed widely across the network and network members are familiar with each other (Moody & White, 2003; Friedkin, 2004). A cohesive LAUNCH network means that organizations are well acquainted with each other, and that the information is widely available to the majority (if not all) of the organizations. In terms of seeking advice it means that organizations tend to seek advice from the organizations with whom they already have an existing relationship, either directly or through a mutual organization. Network cohesiveness indicates an excess of bonding social capital. A network with an excess of bonding social capital might reflect a lack of new information as new
relationships are built on existing relationships, leading to redundancy of information (Granovetter, 1973). In this study, network cohesiveness was operationalized as density, reciprocity, and transitivity.

2.2.1. Density

The concept of network cohesiveness has commonly been defined as density (Kilduff & Brass, 2010). Density is expressed as a percentage and describes the actual ties between actors that are present compared to the total number of possible ties (Hanneman & Riddle, 2005; Prell, 2012). An increase in density in an advice-seeking network like LAUNCH means that organizations trust the expertise of other organizations and are seeking advice from a large number of organizations. In contrast, low density suggests that organizations are limiting themselves in seeking advice from only a select few other organizations.

Haines, Godley, and Hawe (2010) conducted a longitudinal study of the scholarly relationships between members of an interdisciplinary collaboration group working on improving population health. The findings of this study indicated that over time, there were statistically significant gains in density as members worked more closely together, increasing the frequency of their scholarly interactions. Another study collected social network data three times over the course of a year to study the growth of an interdisciplinary center (Aboelela, Merill, Carley, & Larson, 2007). Findings from that study indicated growth in connections between group members and the development of a more interconnected organizational structure within the course of a year, and point toward more heterogeneous membership over time.

Poole (2008) used social network analysis to examine collaboration among 21 non-profit healthcare providers before and after implementation of a Community Awareness and Relocation Services (CARS) project. This collaboration was based on implementation of a state-promoted
effort to move individuals with physical disabilities from nursing facilities to community-based living facilities. The study compared the density of the network of five sites before and after implementation of CARS, and found that the networks varied before and after CARS implementation. It makes sense that the more ties with other actors, the more likely there will be a chance for information to be shared by at least one of the actors with another. Poole (2008) found that the collaboration among the non-profits affected the outcome of the project – the more networked, the better the outcome.

Hemphala and Magnusson (2012) examined innovation in open and closed network structures and focused more on the network itself than on collaboration. The authors explain that “innovation is a social and interactive process in which collaboration and exchange of knowledge and information play crucial roles” (Hemphala & Magnusson, 2012, p. 3). This study tested structural hole and density hypotheses using social network analysis and regressions in 22 pharmacies and found that the type of innovation measured (structural holes or density) altered the outcomes of the study. Hemphala and Magnusson (2012) also supported the previous argument by Obstfeld (2005) that collaboration is fostered in dense networks.

Networks with higher density appear more integrated and interactive, meaning that actors are taking available opportunities to connect with one another, such as participating in weekly meetings or reciprocated interaction between each group member. Evidence suggests that higher density results in more opportunities for collaboration, innovation implementation, and sharing of resources (Balkundi & Harrison, 2006; Kilduff & Brass, 2010). Higher network density has also been associated with clearer, more firmly held and more easily monitored and sanctioned behavioral norms because the individuals in a dense network are more connected with one another and share more common contacts (Berardo, 2009; Granovetter, 2005). These findings
suggest that higher density may have a positive influence on the sustainability of an inter-organizational collaboration network.

While higher density scores indicate a greater degree of cohesiveness and are generally associated with greater social capital (Lee, Robertson, Lewis, Sloanne, et al., 2012), it should be noted that the ideal density of a network depends on the context and goal of each collaboration. Greater density within a network such as a LAUNCH collaboration means that there are more and stronger ties among actors in the network. For example, in the context of the present study, it would indicate that more members are more trusting of one another’s expertise, communicate more frequently, perceive one another to be legitimate contributors to the group, and are more willing to go out of their way to help each other. This can be further understood in that a dense network indicates that actors are actively engaged with one another, and dense networks of expressive ties indicate a high level of emotional closeness between actors (Reagans & Zuckerman, 2001). Theorists argue that groups with high network density have greater access to the full range of resources available within the network, and therefore have an increased capacity to leverage these resources toward achieving their collective goals (Coleman, 1988). As such, network density across stakeholder dyads is suggested to be indicative of social capital due to its potential for facilitating the achievement of common goals within groups like those in the LAUNCH network (Aldrich & Zimmer, 1986; Coleman, 1988; Portes, 1998). Therefore, the following hypothesis was proposed:

Hypothesis 1: The density of the collaboration network will increase from Time 1 to Time 4.

2.2.2. Reciprocity

In a collaboration network, organizations depend on reciprocal ties as they foster mutuality (Innes & Booher, 1999). Reciprocity, expressed as a percentage, refers to mutuality of
ties in a relationship (Wasserman & Faust, 1994). Reciprocity in an information sharing network such as LAUNCH suggests that organizations tend to strengthen their existing partnerships with other organizations by seeking advice from those who have sought advice from them in past. Reciprocated relationships represent mutual cooperation and are therefore stronger than one-way relationships.

Reciprocity is the tendency to develop mutual relationships, whereby agencies share resources with partner agencies that share resources with them (Bunger, Doogan, & Cao, 2014). Agencies that share their expertise expect their partners to share their expertise in turn, and therefore, these agencies are likely to develop partnerships in reciprocity with existing partners (Lee & Feiock, 2012). Without mutuality among all network members, support will be lacking and the members may face resistance from those left out of the process (Mancini & Marek, 2004). Reciprocity facilitates a dialectic process among actors that leads to legitimacy (Kouzes & Posner, 2007). The legitimacy of a member in the eyes of group makes it more likely that the knowledge, perspectives, and resources available to that member will become a resource available to the group (Alter & Hage, 1993).

Reciprocity is one of the key structural aspects of bonding social capital (Coleman, 1990), and refers to the case in which two actors mutually choose each other in a network (Moolenaar, 2012). In the literature, reciprocal ties in a network have been treated as strong evidence of bonding relationships at the dyadic level (Gouldner, 1960; Granovetter, 1973). Higher reciprocity indicates more one-to-one (dyadic) relationships between actors, indicating cohesiveness within the network (Moolenaar & Sleegers, 2010). As Granovetter (1973) posits, the strength of a tie is a function of the frequency and duration of interaction, the level of emotional intensity and intimacy, and the reciprocal services found within the tie. On a
continuum, strong ties involve more frequent interaction, emotional intensity and intimacy, and feelings of reciprocity. This cultivates feelings of social solidarity and overall social cohesion (Rademacher & Wang, 2014). Ostrom (1998) argues that when reciprocity prevails, network members are motivated to acquire a reputation for keeping promises and performing actions with short-term costs but long-term net benefits. Strong ties have been shown to lead to higher reciprocity in inter-organizational alliances (Uzzi, 1997).

Individuals or organizations may voluntarily exchange knowledge or expertise with those who benefit from information exchange and are likely to consult each other if they cannot resolve issues on their own. According to the social capital perspective on collaboration, organizations tend to be actively engaged in searching or obtaining the necessary resources to meet their goals (Inkpen & Tsang, 2005; Sparrowe, Liden, Wayne, & Kraimer, 2001; Wasko & Faraj, 2005). Network theory posits that individuals make an advisory selection decision by assessing trade-offs between expected value of the advice and the anticipated cost (Nebus, 2006).

Berardo and Scholz (2010) studied the evolution of a collaboration network of 28 estuaries in the National Estuary Program and measured bonding social capital in terms of reciprocity. In their study, they found that organizations seek popular partners (that is the organizations who are sought after for advice by the majority of organizations in a network) first and reciprocal relationships second. They further explained how actors create informal policy coordinators by seeking advice from the same source that others seek advice from, and speculate that informal policy coordinators are sought because they provide the most effective means for enhancing policy outcomes.

Mitchell, Klinck, and Burger (2004) state that any collaboration or partnership will test the members’ values, vision, and capacity to work together. Success depends on reciprocity and
a common purpose. In the context of this study, an increase in reciprocity over time means that organizations in the LAUNCH network exchange information with other network organizations who have already sought advice from them in the past. That is, new relationships are built on existing relationships. Reciprocal ties are regarded as a salient characteristic of networks with high levels of social capital.

Based on the literature discussed above, the following hypotheses were proposed:

*Hypothesis 2a: Reciprocity will increase from Time 1 to Time 4.*

*Hypothesis 2b: An organization will seek to reciprocate the ties with other organizations in the collaboration network over time.*

![Figure 2.1. Reciprocity](image)

2.2.3. Transitivity

Transitivity measures the network closure (Hanneman & Riddle, 2005). The term transitivity, coined by Granovetter (1973), refers to the tendency that actors have to choose others that their close connections have already chosen. This leads to network closure because individuals tend to introduce their network partners to each other, or because they tend to operate in cohesive team-like structures, (Lubell, Robins, & Wang, 2011). In a policy-mandated context such as that of the LAUNCH network, this means that NPOs use their existing relationships to learn about prospective advisors in the network and therefore are likely to seek advice from an organization that already works with one of their existing partners.
Network closure is an important structural effect that frequently occurs in social network data. Granovetter (1973) argues that transitive relationships occur in bonding networks consisting of strong ties through which people frequently interact and share trust and emotional supports. In social terms, a transitive relationship is one where ‘a friend of my friend is also my friend’. Some studies on social networks have discovered empirically that strong bonds between actors are more likely to be observed in closed networks and that this tends to be manifested in transitive triads in directed networks (Granovetter, 1973; Louch, 2000).

Past studies on the formation of inter-organizational alliances found that closely located firms within the network of past alliances are more inclined to form cooperative ties among them (Gulati, 1995; Gulati & Gargiulo, 1999). Two underlying reasons for closure include the desire to gain access to new resourceful partners, and to cope with the risk of opportunistic behavior (Lee, 2012). Further, the tendency to share rather than compete for scarce resources, including information, has been empirically proved in diverse settings, including venture capital investment (Batjargal, 2007), political communication (Carpenter, Esterling, & Lazer, 2004), and research and development collaboration (Newman, 2001). Among them, Newman’s (2001) research on the patterns in collaboration networks among scientists in the fields of biomedicine, physics, and computer science found that scientists who have published one or more papers with a common third scientist are at least 30% more likely to coauthor a paper together later. This means that transitivity had occurred in the networks of scientists that Newman (2001) studied.

Thus, if academic knowledge is shared and coproduced among faculty in universities under the influence of bonding social capital, transitive triads are more likely to appear in directed (research and teaching) knowledge-sharing networks than by random chance alone.
In a study conducted by Senga (2016) to understand the dynamic of trust relationships in a Village Conservation and Development Committee (VCDC) network consisting of 23 organizations, he found that some of the VCDC members tended to form and extend their ties with the collaborators of already collaborating organizations (similar to the idea of ‘a friend of a friend’). In another study by Gerber, Henry, and Lubell (2013) that explored a local government’s decision to participate in an important form of intergovernmental collaboration, a regional planning network, found that the planning network exhibited a strong tendency towards transitivity.

Berardo (2014) conducted a longitudinal study on the network of communication among 44 organizations whose goal was to reduce the levels of environmental stress on the river in a small Argentina river basin. Berardo’s (2014) study aimed to test whether more bonding structures tended to form in the collaboration network and found that organizations engaged in the building of more transitive triads. In fact, Berardo (2014) found that the stakeholders favored the creation of transitive relationships over the simpler bonding structure of reciprocal dyads, suggesting that actors generally value the greater reassurance against multi-actor defection that transitivity provides and which reciprocity cannot offer.

In the context of a collaboration network such as LAUNCH, an increase in transitivity indicates that organizations tend to seek advice from the organizations who have been vouched for or endorsed by an existing advisor. Based on the literature above, the following hypotheses were proposed:

Hypothesis 3a: Network cohesiveness will increase from Time 1 to Time 4.

Hypothesis 3b: The formation of a collaboration network entails closure behavior in which Organization A seeks to collaborate with Organization B, while Organization B seeks to
collaborate with Organization C, and in turn, Organization A and Organization C will ultimately collaborate over time.

2.3. Network Centralization

Centralization represents the variability in the importance of individuals in a network. A network with high centralization is characterized by one or a few highly central organization(s) and many other more peripheral organizations (Wasserman & Faust, 1994). A centralized network indicates an excess of bridging social capital. This is measured in terms of degree centrality (Freeman, 1979). Degree centrality describes an actor’s activity level within the network, indicating someone who is a strong conduit for information (Freeman, 1979; Prell, 2012).

Social capital theory suggests that the network of relations possessed by an individual (capital) constitutes a valuable resource for social action (Adler & Kwon, 2002; Baker, 1990; Bourdieu, 1986; Burt, 1992; Coleman, 1990; Jacobs, 1965; Putnam, 2000). Putnam (2000) argues that social capital embedded with networks of mutual recognition not only provides potential access to opportunities and to useful resources, but also further facilitates cooperation and coordination for mutual benefit. Bridging structures are measured in terms of preference for popular partners and powerful partners (Crowe, 2007; Ramirez-Sanchez & Pinkerton, 2009). In
social network analysis, the popularity and powerfulness of partners can be measured using in-degree centrality and betweenness centrality respectively. (Freeman, 1979; Hanneman & Riddle, 2005).

In-degree centrality measures the number of ties given by an actor (Freeman, 1979; Scott, 1991), and indicates the popularity of an actor within a network. Betweenness centrality is often a more powerful measure of connectivity and measures the organizations between other connected actors. If an actor sits between members, they serve as intermediaries and can often have vital control over access to information dissemination (Kircher, 2004; Prell, 2012; Wasserman & Faust, 1994). They are also the influential members and have brokerage advantage in the network, that is, if these actors are removed from the network the whole network falls apart (Hanneman & Riddle, 2005).

In a study to test the impact of network structure on performance, Scholz, Berardo, and Kile (2008) found that collaboration responds instead to bridging relationships as measured by the number of network partners (degree centrality) and the brokerage position of the actor in the network (betweenness centrality). This led the authors to conclude well-connected policy actors playing central roles in policy networks collaborate at higher levels, and the most motivated stakeholders seek more contacts and centralized positions. They also concluded based on their analysis that information about potential partners appears to pose the greatest constraint to the success of collaboration, at least at the initial stage in the development of the estuary policy arena.

Berardo and Scholz (2010) building on previous research found similar results. Berardo and Scholz (2010) utilized in-degree and betweenness centrality to understand the propensity of
22 estuary organizations in a network to find partners and found that organizations preferred to partner with others that have high in-degree and betweenness centrality.

In a study conducted by Lee (2012) on the evolution of advice networking and knowledge contribution in the context of virtual financial communities (VFCs) in which people voluntarily participate in exchanging investing-related information, the author found that the popularity of the actor was one of the influential factors driving network dynamics. This implies that actors with high inbound advice network links (i.e. high in-degree centrality) have greater access to relevant resources. Thus, when entering the networked community of VFCs, new members tend to establish advice ties with a large number of existing incoming advice ties or those with so-called high social capital (Giuliani, 2010).

In addition, a network may be more centralized around a few influential, informal leaders in the collaboration than around another organization. For instance, a study of Dutch schools by Moolenaar, Daly, and Sleegers (2010) found considerable variation in the extent to which principals occupy a central position in their school’s advice network, resulting in differences in the influence they have on the system through direct advice relationships with teachers. Other studies have shown that the more central an organization is in the collaboration network, the more opportunities it has to access resources, information, or support from the collaboration network (Balkundi & Kilduff, 2005; Krackhardt, 1996), as well as to guide, control, and even broker the flow of information and resources (Burt, 2005).

These studies taken together suggest that bridging rather than bonding social capital may provide both more effective and more sought-after relationships in policy-mandated collaboration network than would be expected from the extant social capital literature. However, in a review of 24 articles about the role of bridgers, brokers, and boundary spanners in
collaboration networks, Long, Cunningham, and Braithwaite (2013) concluded that the costs of brokerage are that bottlenecks in information flow may form at the level of the broker, who risks being overloaded and stressed by others’ reliance on them. There may also be a decrease in productivity as the “vision advantage” of a team high in brokerage is tempered by the cost of a dispersed focus. In addition, individuals/organizations must also bear the costs involved in maintaining bridging ties. Furthermore, “actors outside your cluster are likely to be different to you: involved in different work, located somewhere geographically distant or from a different profession” (Long, Cunningham, & Braithwaite, 2013, p. 158). As such, since similar actors find it easier to communicate and predict one another’s behavior, trusting ties are easier to form and maintain (Brass, Galaskiewicz, Greve, & Tsai, 2004) and bridging ties require more work. Bridging ties are also harder to keep viable over time and were shown by Burt (2002) to decay faster than ties to actors within one’s own cluster. Moreover, bridging ties have a short shelf life with time rendering many bridging ties and the information they broker as obsolete. Additionally, Soda, Usau, and Zaheer (2004) in a study on the Italian television production industry showed that old bridging ties are not effective for generating innovative ideas since their usefulness is so dependent on the ever-changing context of the industry.

Negative network outcomes arising from bridging or brokering ties include the potential to hoard or distort information, bottlenecks in the flow of information and individual role overload, all resulting in a decline in overall network efficiency (Stasser & Titus, 1985). For example, if Organization A in the LAUNCH network has the ability to introduce Organization B to Organizations C, D, and E, Organization A can put unreasonable demands on Organization B due to its power in mediating the connection to the other organizations. Similarly, Organization A can experience overload because it has been receiving a large number of requests for advice;
due to high overload, the organization may choose to ignore requests for advice from other organizations. As such, these factors might discourage other organizations in the network from seeking advice from Organization A, even though it is a popular advisor due to the high number of advice-seeking requests. Maintaining ties with a powerful and popular organization can be demanding on other organizations. Based on the literature above, the following hypotheses were proposed:

Hypothesis 4a: The overall network centralization as measured through in-degree centrality will decrease from Time 1 to Time 4.

Hypothesis 4b: The overall network centralization as measured through betweenness centrality will decrease from Time 1 to Time 4.

Hypothesis 4c: The organizations will reduce seeking collaborative ties from popular (measured using in-degree centrality) organizations from Time 1 to Time 4.

Hypothesis 4d: The organizations will reduce seeking collaborative ties from powerful (measured using betweenness centrality) organizations from Time 1 to Time 4.

Figure 2.3. In-degree Centrality

Figure 2.4. Betweenness Centrality
2.4. Organizational Attributes

In an inter-organization collaboration network, organizations create new ties or dissolve existing ones, thus leading to change in the network structure. New tie formation is influenced by both characteristics of the actors and of their existing ties (Ahuja, Soda, & Zaheer, 2012; Contractors, Wasserman, & Faust, 2006; Provan, Fish, & Sydow, 2007). Ibarra and Andrews (1993) and Lazega, Mounier, Snijders, and Tubaro (2012) suggest that the search for advice is socially driven. This means that certain actors in a network rapidly gain reputation because of the information about them that diffuses in a network. The selection of an actor may be influenced by quality judgements based on the actor’s attributes (Giuliani & Matta, 2013). In the current study, three organizational attributes are expected to influence the formation of inter-organizational collaboration: the organization’s size, geographical proximity, and role of organization. The following discussion outlines how these attributes have been studied in the literature on collaboration networks. The similarity effect these attributes have on forming collaborative ties is termed “homophily” in the literature (McPherson, Smith-Lovin, & Cook, 2001).

2.4.1. Homophily

Building on a large body of theoretical and empirical work on social networks, one of the leading hypotheses is that actors with similar characteristics will be more likely to form network ties than actors with different characteristics (Bidwell & Yasumoto, 1999; Coburn, Choi, & Mata, 2010; Daly, Moolenaar, Bolivar, & Burke, 2010; Heyl, 1996; Kochan & Teddlie, 2005; Moolenaar, 2010; Penuel, Riel, Krause, & Frank, 2009; Spillane, 2005; Yasumoto, Uekawa, & Bidwell, 2001). This phenomenon, known as homophily, is consistently identified as an important determinant of network structure (McPherson, Smith-Lovin, & Cook, 2001).
Organizations also contribute to network stability by binding to similar actors (McPherson et al., 2001). Forming collaborative ties based on homophily or similarity is an indicator of bonding social capital (Amin, 2000; Asheim, 1996; Malmberg, 1997).

2.4.2. Organization Size

It has been argued that large organizations, with their greater financial and human assets, have more resources to offer, whereas smaller organizations have a greater need for resources provided by the collaboration network (Graddy, 2008). Large organizations are better able to absorb the considerable costs of sustaining inter-organizational relationships. Small organizations, however, have a greater need for the resources provided by the network and will look to collaboration to access more resources (Magnusson & Nilsson, 2006; Graddy, 2008; Sulej, Stewart, & Keogh, 2001). Collaborating with large players may be beneficial for small organizations in that their association with well-known and reputable organizations can signal legitimacy to key stakeholders (Podolny, 1993).

Giuliani, Balland, and Matta (2018) conducted a longitudinal investigation of advice networks among 47 small-scale industries in Argentina and found that larger firms (measured using staff size) received more advice requests. Kim et al. (2016) conducted research on inter-firm collaboration and found that organizations similar in size, when measured in terms of total number of staff, have a positive propensity for forming collaborative ties. In the same study, when organizational size was taken into account, the large organization was found to be more likely to receive requests to form collaborative ties.

In line with existing research, organizational size reflects staff size (Camisón-Zornoza, Lapiedra-Alcamí, Segarra-Ciprés, & Boronat-Navarro, 2004; Josefy et al., 2015). Berardo and Scholz (2010) found that large organizations are endowed with greater organizational resources
that can explain a higher level of activity in a network, and further found that organizational size will have a positive effect on the formation of collaborative ties; organizations similar in size show a propensity to interact with each other more. Based on this literature, the following hypotheses were proposed:

_Hypothesis 5a: Organizations similar in size will show a propensity to collaborate with each other._

_Hypothesis 5b: Large organizations are more likely to be sought as an advisor than small organizations._

2.4.3. Geographical Proximity

Geographical proximity increases the benefits and reduces the costs for NPOs who are located physically near to one another as they often share geographic features that pose common challenges or opportunities for development (Diestre & Rajagopalan, 2012; Gerber et al., 2013; Kim, Howard, Cox Pahnke, & Boeker, 2016; Kono, Palmer, Friedland, & Zafonte, 1998; Rothaermel & Boeker, 2008). In Giuliani et al.’s (2018) longitudinal investigation of advice networks among 47 small-scale industries in Argentina, they found that firms located in close geographical proximity (measured by distance in kilometers) were forming more advice ties compared to firms who were located more than two kilometers apart. In a study by Juhász and Lengyel (2017) on inter-organizational knowledge networks among 38 organizations in the printing and paper industry, the authors found that geographical proximity was a significant factor in the evolution of the advice network. These findings underline the importance of geographical proximity and suggests that geographical proximity provides added opportunities for establishing collaborative ties.
In the context of this study, advice seekers in the LAUNCH network can learn and model behavior from similarly situated actors and engage in repeated interaction. Additionally, shorter distances makes it easier to meet, discuss common issues and interests, and generally facilitate cooperation (Gerber et al., 2013). This proximity may lead to greater ease of forming network ties and may increase the likelihood that two organizations will collaborate within the LAUNCH network. Based on the literature it follows:

**Hypothesis 6:** Organizations in close geographical proximity will show a propensity to collaborate with each other.

### 2.4.4. Organization Role

NPOs’ decisions to maintain or develop partnerships can be driven by fixed characteristics of prospective partners. One of the goals of Project LAUNCH is to provide integrated services to their clients, wherein an organization’s role within the LAUNCH network can influence information sharing behavior. Organizations often tend to partner with other organizations that serve the same population in the same sector of care (Bolland & Wilson, 1994; Rivard & Morrissey, 2003), and overlapping services have been linked to improved performance (Arya & Lin, 2007). Bunger, McBeath, Chuang, and Collins-Camargo (2016) found that non-profit organizational collaboration occurs around the core service delivery functions, where the organizations required to collaborate under institutional pressure partnered with agencies that provided similar services to the population. In another study on transfer of knowledge and expertise among mental health clinicians, it was found that participants formed or maintained relationships with those who have similar disciplinary training (Bunger, Doogan, Hanson, & Birken, 2018). In a study about advice seeking, Lazega and Van Duijan (1997) concluded that the organizations will seek advice from organizations offering similar service to reduce the
transaction costs. Further, the organizations with similar roles will collaborate together because they face similar kinds of challenges and will seek advice from other organizations who they think have the same role. Having the same role can offer highly applicable knowledge (Frenken, Van Oort, & Verburg, 2007; Juhász & Lengyel, 2017). Based on the above studies, NPOs offering similar types of services or serving similar populations, like those in the LAUNCH network, are more likely to seek advice from other organizations who are like them. This led to the development of the following hypothesis:

_Hypothesis 7:_ Organizations with similar roles in the LAUNCH collaboration network are more likely to form collaborative ties with each other.

A summary of the proposed hypotheses and related research questions is presented in Table 2.1.

Table 2.1. Summary of Hypotheses and Research Questions

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Related Research Question</th>
<th>Expectation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 1: The density of the collaboration network will increase from Time 1 to Time 4.</td>
<td>1,2,4</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 2a: Reciprocity will increase from Time 1 to Time 4.</td>
<td>1,2,4</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 2b: An organization will seek to reciprocate the ties with other organizations in the collaboration network over time.</td>
<td>1,2,4</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 3a: Network cohesiveness will increase from Time 1 to Time 4.</td>
<td>1,2,4</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 3b: The formation of a collaboration network entails closure behavior in which Organization A seeks to collaborate with Organization B, while Organization B seeks to collaborate with Organization C, and in turn, Organization A and Organization C will ultimately collaborate over time.</td>
<td>1,2,4</td>
<td>+</td>
</tr>
</tbody>
</table>

(Table 2.1 cont’d.)
**Hypothesis**

- **Hypothesis 4a**: The overall network centralization as measured through in-degree centrality and decrease from Time 1 to Time 4.
- **Hypothesis 4b**: The overall network centralization as measured through betweenness centrality will decrease from Time 1 to Time 4.
- **Hypothesis 4c**: The organizations will reduce seeking collaborative ties from popular (measured using in-degree centrality) organizations from Time 1 to Time 4.
- **Hypothesis 4d**: The organizations will reduce seeking collaborative ties from powerful (measured using betweenness centrality) organizations from Time 1 to Time 4.
- **Hypothesis 5a**: Organizations similar in size will show a propensity to collaborate with each other.
- **Hypothesis 5b**: Large organizations are more likely to be sought as an advisor than small organizations.
- **Hypothesis 6**: Organizations in close geographical proximity will show a propensity to collaborate with each other.
- **Hypothesis 7**: Organizations with similar roles in the LAUNCH collaboration network are more likely to form collaborative ties with each other.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Related Research Question</th>
<th>Expectation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 4a</td>
<td>1,2,4</td>
<td>-</td>
</tr>
<tr>
<td>Hypothesis 4b</td>
<td>1,2,4</td>
<td>-</td>
</tr>
<tr>
<td>Hypothesis 4c</td>
<td>1,2,4</td>
<td>-</td>
</tr>
<tr>
<td>Hypothesis 4d</td>
<td>1,2,4</td>
<td>-</td>
</tr>
<tr>
<td>Hypothesis 5a</td>
<td>3,4</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 5b</td>
<td>3</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 6</td>
<td>3,4</td>
<td>+</td>
</tr>
<tr>
<td>Hypothesis 7</td>
<td>3</td>
<td>+</td>
</tr>
</tbody>
</table>

**2.5. Conceptual Model**

This study was informed by collaboration theory (Thomson & Perry, 2006), social capital theory (Coleman, 1988; Putnam, 1995), and social network theory (Granovetter, 1973; Wasserman & Faust, 1994). Collaboration theory informed this study by revealing the dimension of the collaboration process: governance, administration, autonomy, mutuality, norms of trust, and reciprocity. However, recognizing the identified dimension of collaboration theory does not provide information about the readiness of the organization to collaborate. For this, we turned to social capital theory, which provided the needed information about the willingness of organizations to collaborate by operationalizing willingness in terms of bridging and bonding.
social capital. Bridging social capital reveals the preference of organizations to form weak collaboration ties with other organizations in the network. This can also mean that the organization is forming weak ties because they are still in the initial phases of collaborating and are searching for partners. Bonding social capital, on the other hand, shows the preference to form strong collaborative ties with other organizations in the collaboration network, including the preference of the organization to continue collaborating with organizations with similar organizational attributes. Social network theory provided the mechanism to operationalize bridging and bonding social capital in terms of network structure. As discussed earlier, this study used network analysis to study the social capital in inter-organizational collaboration because it provided an objective measure of social capital compared to other methods.

With respect to the aforementioned theoretical framework and information presented regarding bridging and bonding social capital, network structure, and network measures, the following proposed conceptual model in Figure 2.5 explains how these concepts relate to one another.

![Figure 2.5. Proposed Conceptual Model](image-url)
2.6. The Final Network - Exploratory Prediction

This study examined the evolution of a collaboration network to determine how organizations selected their partners in a policy-mandated environment and examine how these partnerships changed over time. This time-dependent perspective on network evolution employs a longitudinal design, which is scarcely applied to the investigation of this phenomenon in the literature due to rigid data requirements associated with this type of research design. However, not only does the richness of this type of research design allow researchers to assess the degree of change that can be sustained in collaboration partnerships within a policy-mandated environment, as hypothesized above from baseline (year 1; 2014) and assessed annually (year 4; 2017), this design also allows for predictive determinations for how the network might evolve over time. Based on the analysis for all the hypotheses, the network structure at time 5 (year 5; 2018) was proposed to be analyzed separately and applying the trends that emerge across years 1 to 4 in order to predict projected patterns that will emerge in the year 5. This trend analysis is strictly exploratory given the lack of existing literature demarcating network trends in the evolution of networks in this research context, therefore predictive hypotheses were not proposed for year 5, but findings will be discussed.
CHAPTER 3: METHOD

3.1. Research Design

The aim of this study was to examine the evolution of a collaboration (i.e. information sharing) network. This study used a longitudinal quantitative approach that applied a network analysis methodology. The network design employed in this study was ‘whole-network’ design where the researcher studied information sharing among all pairs of organizations in the LAUNCH network (Borgatti, Everett, & Johnson, 2013). The whole-network design enabled the researcher to employ full sets of network concepts and techniques (Borgatti et al., 2013). The network analysis methodology further allowed the researcher to take into account the interdependence that exists in a network, that is, network ties cannot be assumed to be independent from each other (Desmarais & Cranmer, 2012), thus limiting the use of other statistical techniques.

3.2. Population Sample

The target population for the study were NPO child and family service providers who received federal funding to engage in policy-mandated network collaboration. The sample population was NPOs working in the southwest region of Louisiana who participated in Louisiana Project LAUNCH. This sample was selected as the grant funding for five years ensured retention of the organizations needed for this study, thereby ensuring the availability of data to measure the evolution of the collaboration network. The population was recruited due to their involvement with a federal grant, and was further selected as they were collaborating with other organizations to improve families’ access to a system of coordinated and effective services. These organizations had been collaborating with the network members for over four years. As a result, this population provided an opportunity to study collaboration over a period of time. Finally, state-level support for the project also ensured the data were available throughout the
grant duration, making it an ideal sample for answering the proposed research questions. In year 1 (2014) there were a total of 28 organizations as part of the collaboration network, year 2 (2015) had 28 organizations, year 3 (2016) had 31 organizations, year 4 (2017) had 33 organizations, and year 5 (2018) had 31 organizations.

The sample included all of the NPOs identified to deliver LAUNCH services that reported annual evaluation data about their organization’s involvements with LAUNCH as part of the federal grant requirement. This dissertation is a case study of a single whole-network system that was analyzed at the organizational level. The data were gathered from one representative from each organization who was asked to report on the information sharing behavior between their organization and other LAUNCH network organizations as a whole. That resulted in a map of all network connections in the LAUNCH network (Borgatti, & Everett, 1998).

3.2.1. Power Analysis in Network Studies

Power analysis is a process that allows the researcher to estimate the sample size in order to confidently observe an anticipated effect to achieve desired statistical power (Cohen, 1977). Sample size is a concept originating from statistical models constructed of independent observations, and is not directly applicable to network studies (Stadtfeld, Snijders, Steglich, & Marijtje, 2018). The sample size of the network is determined by the context, where the researcher needs to make sure all of the network members are present, such that no one should be excluded if they are part of the network nor should anyone be included if they are not part of the network.

Researchers conducting network analysis have the option to define the study design, for example, the researcher may be able to reduce non-response. In the current study, the researcher
was able to include all organizations who were part of the network, while accounting for the composition change, which occurs due to actors joining or leaving the network. (Ripley, Snijders, Boda, Voros, & Paulina, 2018).

There are several longitudinal network study in wide range areas, which have utilized the similar data analysis strategy focused on collaboration as this study and with comparable sample sizes. For example, Berardo, (2014), Berardo & Scholz, (2012), Bunger et al. (2014), Bunger et al. (2016), Bunger et al. (2018), Gerber, Henry & Lubell (2013), Haines et al.,( 2010); Hemphala & Magnusson (2012) Lee, (2012), Lubell, Robins & Wang, (2011), Poole, (2008), Senga, (2016) Scholz, Berardo & Kile (2008). The supporting literature has been discussed throughout chapter 2. It is possible that some of the studies were underpowered, however, there has been no method to perform power analyses for study designs in longitudinal network research (Stadtfeld et al., 2018). One of the possible reasons could be the fact that longitudinal social network analysis is fairly new area of inquiry and continues to expand.

3.3. Procedure

This study was based on the data gathered for a federal initiative funded by the Substance Abuse and Mental Health Services Administration (SAMHSA). One of the aims of this federal initiative was to improve coordination and collaboration across disciplines at the local, state, territorial, and federal levels. Two different types of data were collected for the study: social network data (i.e., information sharing), and demographic data related to the organizations. The responses were gathered from employees of the NPOs that were part of the LAUNCH collaboration and were the appointed representatives of their organizations for the purposes of this grant. This current study utilized social network data collected primarily for evaluating the coordination and collaboration across the NPOs involved in this federal grant. The collaboration data was collected annually each fall from 2014 to 2017; the 2018 data was collected in July
2018 and will not be included in the hypothesis testing, but was rather used for exploratory purposes only.

The survey used in this study was created on a Microsoft Word document and distributed personally by the Principal Investigator during the first wave (Fall 2014). For all of the later waves, the survey items were entered into the Qualtrics online survey platform, and Qualtrics generated a link that could be distributed to each organization’s representative. As the representatives completed the survey, their information was recorded into a Qualtrics database, and responses were downloaded and added to a larger spreadsheet for data analysis purposes.

All of the primary data for this study was collected following protocol approval through the Louisiana State University Institutional Review Board #3295.

3.4. Instrumentation

Using a roster method, social network information was gathered about prospective and actual advice networks (respectively, “From whom would you seek advice?” and “From whom have you sought advice in the past month?”). For this study, the data from the second question was included in the analysis since the current research was interested in measuring the collaboration behavior of information exchange and advice-seeking over time. A roster refers to a list of all members in the network (Prell, 2003; Wasserman & Faust, 1994) and this method was chosen to provide a clear network boundary. Sociometric (or whole, complete, or global) network design was used to study collaboration in the current study. Sociometric designs are appropriate when all of the members of a network (actors) can be identified before the data collection begins.

The survey also included demographic questions about the organizations and the representatives responding on behalf of each organization (e.g., organizational size, geographical location, organization role, etc.).
3.5. Variables and Measures

For an organization to be included in the network analysis, it had to either send or receive ties or both. Table 3.1 provides the summarized information about the sample size of the study and the average change in the number of ties for each observed wave from 2014 through 2018.

Table 3.1. Study Sample Summary

<table>
<thead>
<tr>
<th>Year</th>
<th>Sample size</th>
<th>Average number of ties</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>28</td>
<td>2.371</td>
</tr>
<tr>
<td>2015</td>
<td>28</td>
<td>3.029</td>
</tr>
<tr>
<td>2016</td>
<td>31</td>
<td>5.886</td>
</tr>
<tr>
<td>2017</td>
<td>33</td>
<td>7.629</td>
</tr>
<tr>
<td>2018</td>
<td>31</td>
<td>5.6</td>
</tr>
</tbody>
</table>

The number of organizations in the collaboration network fluctuated over the course of the study. In 2014 and 2015 there were 28 organizations, and in 2015, two organizations joined the network while two others left. In 2016, two organizations left and five organizations joined, for a total of 31 organizations. In the fourth year (2017), one additional organization left, while one other re-joined the network and two new organizations joined, for a total of 33 organizations. Finally, in 2018, four organizations left and two other organizations rejoined the network for a final total of 31 organizations.

The average number of ties increased over the course of four years, for 2014 (year 1) the average number of ties was 2.371 – that is, there were an average of two requests per organization for advice across the system. In year 2 (2015), the average number of ties increased to 3.029 – that is, there was a slight increase in advice-seeking to three requests in the network. Year 3 (2016) followed this increasing trend, and 5.886 average ties were detected across the system. The average number of ties in 2017 (year 4) was 7.629, that is, an average of almost
eight requests per organization for advice across the system. In the final year (2018), the average number of ties was 5.600, or an average of almost six requests for advice per organization.

### 3.5.1. Network Cohesiveness Variables

Network cohesiveness reflects bonding social capital. The network structure is comprised of redundant, overlapping, cohesive, “strong-tie” relationships that can promote the development of trust, common knowledge, credibility of commitments, and maintenance of cooperative norms (Burt, 2005; Coleman, 1988; Putnam, 1993). Network cohesiveness in this study was operationalized as density, reciprocity, and transitivity. Table 3.2 provides summary statistics for some of the network cohesiveness variables in this study.

Table 3.2. Summary of Network Variables Descriptives

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>0.069</td>
<td>0.35</td>
<td>0.089</td>
<td>0.34</td>
<td>0.173</td>
<td>0.41</td>
<td>0.224</td>
<td>0.43</td>
<td>0.164</td>
<td>0.40</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.203</td>
<td>0.23</td>
<td>0.14</td>
<td>0.25</td>
<td>0.241</td>
<td>0.22</td>
<td>0.254</td>
<td>0.27</td>
<td>0.146</td>
<td>0.15</td>
</tr>
<tr>
<td>Transitivity</td>
<td>0.313</td>
<td>--</td>
<td>0.549</td>
<td>--</td>
<td>0.621</td>
<td>--</td>
<td>0.619</td>
<td>--</td>
<td>0.623</td>
<td>--</td>
</tr>
<tr>
<td>In-degree centrality</td>
<td>0.015</td>
<td>0.02</td>
<td>0.238</td>
<td>0.11</td>
<td>0.218</td>
<td>0.12</td>
<td>0.222</td>
<td>0.11</td>
<td>0.21</td>
<td>0.08</td>
</tr>
<tr>
<td>Betweenness centrality</td>
<td>1.928</td>
<td>4.29</td>
<td>1.114</td>
<td>2.13</td>
<td>1.62</td>
<td>2.42</td>
<td>1.048</td>
<td>2.00</td>
<td>1.37</td>
<td>3.07</td>
</tr>
</tbody>
</table>

Density reflects the overall connectedness within a network by relating the number of existing ties to the number of theoretically possible ties between all network members. An increasing density score indicates a greater degree of cohesiveness meaning the members of the network are well connected with each other and is associated with high social capital (Lee et al., 2012), while a decreasing density suggests a decrease in cohesiveness and the network member
are sparsely connected. The highest density possible in any network is 1, where all network members are connected to every other member.

Reciprocity specifies the number of mutual relationships by measuring the extent of bidirectional connections. Reciprocity captures the tendency of an actor to form a connecting tie with those who seek collaboration from it, and is reflected in the objective function by the number of mutual ties of each given actor. In this study, reciprocity indicated whether the organization sought advice from an organization who sought advice from them. High reciprocity indicates more one-to-one (dyadic) relationships between actors, thereby indicating cohesiveness within the network (Moolenaar & Sleegers, 2010).

Transitivity refers to the propensity to seek collaboration from one’s collaborator’s collaborator, and is defined by the number of transitive patterns in Actor I’s relations, i.e. ordered pairs of actors (J, H) of whom Actor I is tied to both, while Actor J is also tied to Actor H. In this study, the transitivity scores indicated that organizations preferred to seek advice from the organizations who have been vouched for by an existing advisor. Transitivity leads to network cohesiveness as the network members tend to introduce their network partners to each other, or because they tend to operate in collaborative team-like structures, (Lubell, Robins, & Wang, 2011).

3.5.2. Network Centralization Variables

Network centrality refers to a network structure where a few network members dominate the resources and information flow in a network. Network centralization reflects bridging social capital in the LAUNCH collaboration network. In the current study, network centralization was operationalized as in-degree centrality and betweenness centrality. Summary statistics of network centralization for the study sample are found in Table 3.2.
In-degree centrality is defined as the total number of ties received by an actor in a network (Hanneman & Riddle, 2005), and reflected the popularity of an actor in the LAUNCH collaborative network. Any organization that is highly sought for advice indicates that organization has a higher level of expertise compared to other organizations and is therefore considered to be popular among all other organizations. An increase in in-degree centrality indicates organizations are receiving more advice requests, and that the information is situated among a few select organizations, instead of being widely distributed.

Betweenness centrality is defined as the extent to which an actor sits on the shortest pathway between other actors in a network (Hanneman & Riddle, 2005). Betweenness centrality reflected the power of an actor in the LAUNCH collaboration network. An organization with high betweenness centrality reflects a majority of information flowing through that particular organization, making it powerful in terms of information control. An increase in betweenness centrality means that the advice seekers have to go through some key organizations as these organizations offer the shortest possible path to build a connection.

3.5.3. Organizational Attributes

Based on the literature review, three organizational attributes were chosen for the proposed study: organization’s size, geographical proximity, and role of the organization in the collaboration. An organization’s size was operationalized as the number of staff working in the organization. Geographical proximity was operationalized as the ZIP code of the organization as identified by the survey respondents. The role of the organization was operationalized as the service delivery type and had seven categories: local or regional administrative council, state administrative council, state management team, mental health clinician, medical health clinician, child and adolescent psychiatric consultant, and other.
3.6. Data Analysis Strategy

The survey responses collected from the organizations were used to create a corresponding matrix for each time. The network matrix was subsequently used to create both a graphical representation of the network as well as a statistical analysis. All of the attributes data were transformed into binary code and an adjacency matrix was created for each corresponding organizational attribute. The network was composed of the organizations who sent and/or received advice requests. An additional file was created for the composition change in the network over time as the actors joined and left the network between observations; this file is a requirement to analyze longitudinal data in the Simulation Investigation for Empirical Network Analysis (SIENA) package of R program (Ripley et al., 2018). The details about SIENA are discussed later in this chapter.

The researcher applied two analysis techniques to answer the proposed hypotheses: descriptive social network analysis and longitudinal social network analysis. The descriptive social network analysis was calculated using UCINET 6.0 (Borgatti, Everett, & Freeman, 2002) for each year. The network diagram was plotted using Netdraw (Borgatti, 2002), an embedded feature of UCINET 6.0 (Borgatti et al., 2002), and diagrams were produced for four years of inter-organizational collaboration. Each actor is represented by a node, and the lines represent whether they are tied to one another.

To explain the change observed in the network from year 2014 to year 2017, a stochastic actor-oriented model (SAOM) of network dynamics (Snijders, 2001) was fitted to the network data. SAOM is a recently developed model approach for longitudinally observed social networks that captures the forces underlying individual tie changes that contribute to the total network changes observed between two or more time points. Statistical analysis of network data is
complicated by the fact that network ties cannot be assumed to be independent from each other (Desmarais & Cranmer, 2012). SAOMs explicitly take this dependency into account and model network dynamics in part endogenously, as a function of the current network structure (Snijders, 2001). The behavior of actors results in constantly changing network configurations, and SAOMs for network dynamics give evidence about the evolution of social networks over time (Bunt, Duijin, & Snijder, 1999). They model network evolution based on the individual, rational choices made by actors over time. Strong tendencies, as formulated in the hypotheses, represent significant effects in the model, i.e. prevalence of motifs in the network that cannot be due to random processes of tie formation.

SAOMs assume that a changing network can be interpreted as the outcome of a Markov process, that is, the current state of the network determines probabilistically its further evolution. This means that all relevant information is assumed to be included in the current state of the network (Snijders, van de Bunt, & Steglich, 2010). This type of model further assumes that while we observe networks at discrete moments in time, network changes are continually occurring (Snijders et al., 2010). These changes in the network are made by the actors who send ties, on the basis of their and others’ attributes, their position in the network, and their perceptions about the rest of the network. SAOM models are implemented in an add-on package for the R statistical computing environment called SIENA (Ripley, Boitmanis, & Snijders, 2014).

Stochastic actor-oriented models (SAOMs) were applied to test the proposed hypotheses. These models will be estimated with the SIENA package in R (Ripley et al., 2013; Ripley et al., 2011). Results were accepted if the overall maximum convergence ratio was less than 0.25 and the convergence t-value for each individual parameter was smaller than 0.1.
Three models were tested: Model 1 only included network variables – density (hypothesis 1), reciprocity (hypothesis 2b), transitivity (hypothesis 3b), in-degree centrality (hypothesis 4c), and betweenness centrality (hypothesis 4d). Model 2 expanded on Model 1 by including organizational attributes to measure homophily in terms of the organization’s size (hypothesis 5a), geographical proximity (hypothesis 6), and role (hypothesis 7). Model 3 included organizational attributes related to the organization’s size (Hypothesis 5b). An additional model 4 was also tested for exploratory analysis purposes (without hypothesis) and included relational data at time 5. A summary of the proposed hypotheses and analyses for each variable is included in Table 3.3.

Table 3.3. Summary of Hypotheses and Analyses

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hypothesis</th>
<th>Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network variables</td>
<td>1, 2a, 3a, 4a, 4b</td>
<td>Descriptive</td>
</tr>
<tr>
<td>Network variables</td>
<td>2b, 3b, 4c, 4d</td>
<td>SAOM - Model 1</td>
</tr>
<tr>
<td>Organizational attribute - homophily</td>
<td>5a, 6, 7</td>
<td>SAOM - Model 2</td>
</tr>
<tr>
<td>Organizational attribute</td>
<td>5b</td>
<td>SAOM - Model 3</td>
</tr>
<tr>
<td>Exploratory prediction</td>
<td>None</td>
<td>SAOM - Model 4</td>
</tr>
</tbody>
</table>
CHAPTER 4. RESULTS

The purpose of this study was to examine the evolution of a collaboration network and explore how organizations selected their partners in a policy-mandated environment while discovering how the partnerships changed over time. In doing so, this study also examined the production and distribution of social capital in the collaboration network. Data analysis included two components. First, social network analysis using UCINET was used to assess overall network density, reciprocity, transitivity, and centrality scores for each organization from year 1 (2014) to year 4 (2017). Then, a longitudinal analysis using stochastic actor-oriented models (SAOM) in SIENA was conducted to examine the proposed hypotheses from year 1 through year 4. Exploratory analyses were conducted using year 5 (2018) data to predict network analytics based on trends that emerged from the first four years of data.

4.1. Data Transformation

To prepare data for social network analysis, an adjacency matrix was created for every year’s network. The organization’s names were removed to remove identifying information. All of the attributes data were transformed into binary code and an adjacency matrix was created for each corresponding organizational attribute. The network included all of the organizations who sent and/or received the advice requests. In other words, an organization was included in the dataset if it was connected to the network via one incoming or outgoing tie.

Finally, the researcher also used structural zeros to account for the network composition changes over time (i.e. organizations joining and leaving the network). Structural zeros were specified for all ties to and from organizations who were absent at a given observation. This would allow the researcher to run longitudinal analysis with change in composition. This was used to create a file for composition change in the network over time (Ripley et al., 2018).
4.2. Characteristics of the Sample

All members of the sample for this study were the organizations who were connected to the network via at least one incoming or outgoing tie. Table 4.1 presents the demographic characteristics of the network from 2014 through 2018. The demographic characteristics include organizational size, the organization’s role in the LAUNCH network, and finally the ZIP code distribution.

Table 4.1. Demographic Characteristics

<table>
<thead>
<tr>
<th>Organization size</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 25</td>
<td>46%</td>
<td>50%</td>
<td>52%</td>
<td>48%</td>
<td>48%</td>
</tr>
<tr>
<td>25 - 200 employees</td>
<td>25%</td>
<td>25%</td>
<td>23%</td>
<td>27%</td>
<td>26%</td>
</tr>
<tr>
<td>201 - 500 employees</td>
<td>7%</td>
<td>7%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>More than 500 employees</td>
<td>21%</td>
<td>18%</td>
<td>19%</td>
<td>18%</td>
<td>19%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Role in Project LAUNCH</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local or Regional Administrative Council</td>
<td>43%</td>
<td>43%</td>
<td>42%</td>
<td>39%</td>
<td>45%</td>
</tr>
<tr>
<td>State Administrative Council</td>
<td>7%</td>
<td>4%</td>
<td>6%</td>
<td>6%</td>
<td>3%</td>
</tr>
<tr>
<td>State Management Team</td>
<td>11%</td>
<td>7%</td>
<td>10%</td>
<td>12%</td>
<td>10%</td>
</tr>
<tr>
<td>Mental Health Clinician</td>
<td>4%</td>
<td>7%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>Medical Health Clinician</td>
<td>0%</td>
<td>4%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>Child and Adolescent Psychiatric Consultant</td>
<td>25%</td>
<td>25%</td>
<td>19%</td>
<td>21%</td>
<td>23%</td>
</tr>
<tr>
<td>Others</td>
<td>11%</td>
<td>11%</td>
<td>10%</td>
<td>9%</td>
<td>6%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ZIP Code</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>70037</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>70112</td>
<td>11%</td>
<td>7%</td>
<td>10%</td>
<td>9%</td>
<td>10%</td>
</tr>
<tr>
<td>70501</td>
<td>18%</td>
<td>18%</td>
<td>16%</td>
<td>18%</td>
<td>19%</td>
</tr>
<tr>
<td>70502</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>70503</td>
<td>7%</td>
<td>7%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>70504</td>
<td>7%</td>
<td>7%</td>
<td>6%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>70506</td>
<td>14%</td>
<td>18%</td>
<td>13%</td>
<td>12%</td>
<td>16%</td>
</tr>
<tr>
<td>70508</td>
<td>7%</td>
<td>11%</td>
<td>10%</td>
<td>9%</td>
<td>10%</td>
</tr>
<tr>
<td>70510</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
</tbody>
</table>

(Table 4.1 cont’d.)
### Yearly Distribution of ZIP Codes

<table>
<thead>
<tr>
<th>ZIP Code</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>70526</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>70560</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>70802</td>
<td>7%</td>
<td>7%</td>
<td>3%</td>
<td>12%</td>
<td>10%</td>
</tr>
<tr>
<td>70806</td>
<td>4%</td>
<td>4%</td>
<td>13%</td>
<td>3%</td>
<td>0%</td>
</tr>
<tr>
<td>70809</td>
<td>4%</td>
<td>4%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>70896</td>
<td>4%</td>
<td>0%</td>
<td>3%</td>
<td>3%</td>
<td>0%</td>
</tr>
<tr>
<td>70520</td>
<td>0%</td>
<td>0%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>71201</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>3%</td>
<td>3%</td>
</tr>
</tbody>
</table>

About 50% of the organizations had staff sizes of less than 25 employees, followed by 25 to 200 employees. When it came to individual organization’s role in the Louisiana LAUNCH collaborative, an average of 40% of the organizations had the role of local or administrative council for all 5 years, followed by child and adolescent psychiatric consultant. In the Louisiana LAUNCH collaborative, organizations were distributed amongst 17 ZIP codes, where one ZIP code (70501) represented 18% of the organizations, which is the geographic heart of the southwest Louisiana region targeted for the LAUNCH initiative. All of the demographic characteristics were included as covariates in the longitudinal analysis of the LAUNCH collaborative network (discussed later in this chapter).

### 4.3. Hypothesis Testing

The hypothesis testing was done in two phases; the first phase analyzed the relational data descriptively and the second phase analyzed the data longitudinally to understand the evolution of the LAUNCH collaboration network.

#### 4.3.1. Descriptive Analysis Results

The researcher conducted descriptive social network analyses for five hypotheses to examine the aggregate changes in the collaboration network over time. The hypotheses are listed
in Appendix A. Results related to each hypothesis are discussed in the following section of this chapter.

4.3.1.1. Density (Hypothesis 1)

Hypothesis 1 proposed that the density of the collaboration network will increase from Time 1 to Time 4. Density describes the actual ties between actors that are present in comparison to the total number of possible ties (Hanneman & Riddle, 2005; Prell, 2012). As outlined in Table 4.2, the density in the LAUNCH collaboration network in 2014 (Time 1) was 0.069 meaning that of all possible ties, 7% of the possible ties were present in the network. In 2015, the density score was 0.089, i.e., 9% of all possible ties were present in the network. In 2016, the density score increased to 0.173 suggesting that 17% of all possible ties were formed in the network. In 2017, the density score increased to 0.224 such that 22% of all possible ties were present in the network. In 2018, the density score decreased to 0.164 suggesting 16% of the possible ties were found in the network. In sum, the ties found in the LAUNCH collaboration network, as represented by density change, increased from 2014 (Time 1) to 2017 (Time 4): by 29% from 2014 to 2015, by 94% from 2015 to 2016, and by 29% from 2016 to 2017.

Table 4.2. Density Score from Time 1 (2014) to Time 4 (2018): Hypothesis 1

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>0.069</td>
<td>0.089</td>
<td>0.173</td>
<td>0.224</td>
</tr>
<tr>
<td>Total ties</td>
<td>87</td>
<td>106</td>
<td>206</td>
<td>267</td>
</tr>
<tr>
<td>Density change</td>
<td>--</td>
<td>29%</td>
<td>94%</td>
<td>29%</td>
</tr>
</tbody>
</table>

The network size increased as the collaboration progressed. Large networks do have a greater potential for more ties (Prell, 2006). However, it also makes sense for large networks to have high densities. However, the density in current study increased in spite of the fact that the network size increased. This increase in density score indicates the growth in connections.
between organizations and the development of a more interconnected network. The maximum possible density score is 1, where higher density scores indicate a greater degree of cohesiveness and are generally associated with higher social capital (Lee et al., 2012). Greater density within the LAUNCH collaboration network suggests that there are stronger ties among the organizations within the network. Based on the results discussed above, the density of the collaboration network increased from Time 1 to Time 4, thereby supporting Hypothesis 1.

4.3.1.2. Reciprocity (Hypothesis 2a)

Hypothesis 2a proposed that reciprocity will increase from Time 1 (2014) to Time 4 (2017). Reciprocity is the tendency to develop mutual relationships, whereby agencies share resources with partner agencies that share resources with them (Bunger et al., 2014). Mathematically, reciprocity is the ratio of reciprocal relationships in the network to the total number of dyads with any kind of relationship (reciprocal or otherwise). In the case of the LAUNCH collaboration network, the reciprocity indicated whether an organization sought advice from the organizations who sought advice from them. As summarized in Table 4.3, the reciprocity score in 2014 was 0.20, meaning that of all pairs of actors that have any connection, 20% of the pairs have a reciprocated connection. In 2015, the reciprocity score decreased by 31% to 0.14, that is, the network in 2015 had 14% reciprocated connections. The reciprocity then increased from 0.14 to 0.24 from 2015 to 2016, an increase of 72%. Finally, there was a 5% increase in reciprocity from 0.241 to 0.254 from 2016 to 2017.

One probable explanation for the decreased reciprocity score observed from 2014 to 2015 is that when the network was in its infancy, the organizations collaborated with organizations they already knew, and that in 2015, the organizations may have concentrated on forming new network ties versus reciprocating the existing ties. This is further supported by the fact that the
density increased from 2014 to 2015, suggesting an increase in connectedness but a decrease in reciprocal ties. Based on these results, Hypothesis 2a was not supported.

Table 4.3. Reciprocity Score from Time 1 (2014) to Time 4 (2017): Hypothesis 2a

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reciprocity</td>
<td>0.203</td>
<td>0.140</td>
<td>0.241</td>
<td>0.254</td>
</tr>
<tr>
<td>Reciprocity change</td>
<td>--</td>
<td>-31%</td>
<td>72%</td>
<td>5%</td>
</tr>
</tbody>
</table>

4.3.1.3. Transitivity (Hypothesis 3a)

Hypothesis 3a proposed that network cohesiveness, as measured by transitivity, will increase from Time 1 (2014) to Time 4 (2017). Transitivity refers to the tendency of actors to prefer to consult with other network members who have experience dealing with the existing partner(s). As shown in Table 4.4, transitivity increased from 0.313 to 0.549 from 2014 to 2015, an increase of 75%. There was a 13% increase in transitivity from 2015 to 2016, and no increase from 2016 to 2017.

Table 4.4. Transitivity Score from Time 1 (2014) to Time 4 (2017): Hypothesis 3a

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transitivity</td>
<td>0.313</td>
<td>0.549</td>
<td>0.621</td>
<td>0.619</td>
</tr>
<tr>
<td>Transitivity change</td>
<td>--</td>
<td>73%</td>
<td>13%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Transitivity is an important characteristic of network closure and suggests that organizations prefer to form collaborative ties with a common organization. Berardo (2014) suggests that the stakeholders favor the creation of a transitive relationship over a reciprocal relationship, suggesting that actors generally value the greater reassurance against multi-actor defection that transitivity provides and which reciprocity cannot offer. In the case of the
LAUNCH network, the change in transitivity over time suggests that organizations formed ties with other organizations that shared a common bond. Based on the results discussed above, Hypothesis 3a was accepted.

4.3.1.4. Network Centralization (Hypothesis 4a and 4b)

Degree centrality describes an actor’s activity level within the network, with higher centrality scores indicating someone who is a strong conduit for information (Freeman, 1979; Prell, 2012). In directed networks such as in the LAUNCH collaboration, actors have both outdegree and in-degree centrality. Outdegree centrality reflects how an actor reaches out to other actors, or expands their network (Hanneman & Riddle, 2005; Prell, 2015); in-degree reflects who other actors seek out. The current study concentrated on the measure of in-degree centrality, which was calculated for all LAUNCH network organizations from Time 1 (2014) to Time 4 (2017). Hypothesis 4a proposed that the overall network centralization as measured through in-degree centrality will decrease from Time 1 to Time 4.

Figures 4.1 to 4.4 represent the network structure from Time 1 (2014) to Time 4 (2017). The nodes represent the organization, and the size of the node represents the in-degree centrality, i.e., the number of requests reach organization received. Larger node sizes represent a greater number of requests. For all four years (2014-2017), the organization with the highest in-degree centrality was Organization #17. While Organization #20 was found to have low in-degree centrality in 2014, it was the second most popular organization from 2015 to 2017. Organization #7 received increased advice-seeking requests from 2014 to 2017: in 2014 it had no requests for advice, whereas in 2017 it was the second most-sought advisor. This suggests that organizations in the LAUNCH collaboration network seek advice from new organizations and also maintain ties with popular organizations.
Figure 4.1. In-degree Centrality Network Diagram for Time 1 (2014)

Figure 4.2. In-degree Centrality Network Diagram for Time 2 (2015)
Table 4.5 below shows the changes in in-degree centrality from Time 1 (2014) to Time 4 (2017). The in-degree centrality of the LAUNCH collaboration increased from 2014 to 2015 by
over 500% (0.022 to 0.144), and increased by 58% from 2015 to 2016, followed by a 14% increase from 2016 to 2017.

Table 4.5. In-degree Centrality Score from Time 1 (2014) to Time 4 (2017): Hypothesis 4a

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-degree centrality</td>
<td>0.015</td>
<td>0.238</td>
<td>0.218</td>
<td>0.222</td>
</tr>
<tr>
<td>In-degree centrality change</td>
<td>--</td>
<td>538%</td>
<td>58%</td>
<td>14%</td>
</tr>
</tbody>
</table>

This increase in in-degree centrality is due to the fact that the total number of ties kept increasing from Time 1 (2014) to Time 4 (2017), suggesting that the organizations in the LAUNCH network started seeing other organizations as offering a unique perspective or form of expertise that is valuable to understanding and addressing the shared problem. However, the existence of a large number of ties does not necessarily mean that the network is centralized (Provan & Milford, 2015), and the researcher tested this in the longitudinal inferential analysis later in this chapter. Based on the above results, there was no support found for Hypothesis 4a that the overall network centralization as measured through in-degree centrality decreased from Time 1 to Time 4.

Betweenness centrality is the position of one actor between two others actors in a network (Wasserman & Faust, 1994). Actors with the highest betweenness centrality may be more powerful in the network and may be an important link between unconnected actors (Hanneman & Riddle, 2005). Betweenness centralization for the entire network can be calculated based on actors’ individual betweenness scores and indicates how concentrated the overall network is around particular actors (Hawe & Ghali, 2008). This study proposed in Hypothesis 4a
that the overall network centralization as measured through betweenness centrality will decrease from Time 1 (2014) to Time 4 (2017).

Figures 4.5 to 4.8 represent the network structure from Time 1 (2014) to Time 4 (2017). The nodes represent the organization, and the size of the node represents the betweenness centrality, i.e. the number of requests each organization received. Larger node sizes indicate a higher number of requests. In 2014, the organization with the highest betweenness centrality was Organization #17, followed by Organization #4 and Organization #2. In 2015, the actors with the highest betweenness centrality were Organization #2, Organization #24, and Organization #17. In 2016, the highest betweenness centrality scores were observed among Organization #13, Organization #6, and Organization #17. None of these organizations were in the top three for betweenness centrality in 2014 or 2015. Further, Organization #17, who had the highest betweenness centrality for 2014 and 2015, did not have any betweenness centrality in 2016, suggesting declining power of Organization #17. Finally, in 2017, there were new organizations that had the top three highest measures of betweenness centrality: Organization #20, Organization #23, and Organization #14, respectively. This suggests the formation of new ties and the change in the position of the organization (in terms of power) in the LAUNCH network.
Figure 4.5. Betweenness Centrality Network Diagram for Time 1 (2014)

Figure 4.6. Betweenness Centrality Network Diagram for Time 2 (2015)
Figure 4.7. Betweenness Centrality Network Diagram for Time 3 (2016)

Figure 4.8. Betweenness Centrality Network Diagram for Time 4 (2017)
Table 4.6 shows the change in betweenness centrality of the LAUNCH collaboration network from Time 1 (2014) to Time 4 (2017). The network’s betweenness centrality decreased from 1.92 to 1.14 from 2014 to 2015, suggesting a decrease of 42% in the overall betweenness score. However, there was an increase of 45% (1.62) in the overall betweenness centrality score from 2015 to 2016. There was a 35% (1.048) decrease in betweenness centrality from 2016 to 2017.

Table 4.6. Betweenness Centrality Score from Time 1 (2014) to Time 4 (2017): Hypothesis 4b

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
<th>Time 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Betweenness centrality score</td>
<td>1.928</td>
<td>1.114</td>
<td>1.62</td>
<td>1.048</td>
</tr>
<tr>
<td>Betweenness centrality change</td>
<td>--</td>
<td>-42%</td>
<td>45%</td>
<td>-35%</td>
</tr>
</tbody>
</table>

One of the possible explanations for this oscillation seen in the LAUNCH network could be that as the network evolved and organizations joined or left the network, organizations are left trying to reach a balance between organizational status and overload on one hand, and consensus around the approach to the address the situation on the other (Lageza, Sapulete, & Mounier, 2009). Based on the analysis above, Hypothesis 4b, that the overall network centralization as measured through betweenness centrality will decrease from Time 1 to Time 4, was not found to be supported.

4.3.2. Longitudinal Model Results

The descriptive techniques described above are widely used to investigate distinguishable network structural configurations and to examine the enabling and constraining structural dimensions in social relationships. Even though the techniques serve a valuable purpose in
investigating structural network features, they do not allow inferences to be made about the process that might lead to the network structure.

Recent years have witnessed several powerful statistical methodological developments for a well-fitting model of observed social networks (Robbins et al. 2007). Dynamic network models concentrate on explaining how the potential social mechanisms govern changes in the network over time. Advice networks are dynamic by nature: advice network ties are established over time, perhaps evolving into mutual relationships, or suddenly dissolving. These relational changes may be attributed to the results of the structural position of the focal actors within the network (Snijders et al., 2010). A longitudinal perspective and analysis of advice networks offers opportunities to capture the dynamic evolution of advice networks and to understand the underlying social process mechanisms.

To perform a longitudinal analysis on advice networks, the researcher specified a stochastic actor-based model (SAOM), which allows for examining how a variety of actor-driven micro-mechanisms (i.e., individual choices) induces advice network formation over time. In a social network context, the actor-driven micro-mechanism includes three types of decisions on tie formation: they can create new advice network ties with others, terminate existing ties, or make no changes to their network configuration.

Table 4.7 reports the tie changes within the LAUNCH network during three time periods between subsequent observations. The Hamming distance measures network change, which is the sum of the number of ties changing, both ties dissolved (1→0) and ties emerged (0→1). The Jaccard index measures network stability between consecutive time points (within a range from 0 to 1, where 1 means no change). Ripley et al. (2014) pointed out that based on past experiences with SAOM, there can be estimation difficulties when the Jaccard index is less than 0.1. In this
study, there are no such estimation problems. From Time 1 (2014) to Time 2 (2015), 7% of new ties emerged (0→1). From Time 2 (2015) to Time 3 (2016), 12% of new ties emerged (0→1). Between Time 3 (2016) and Time 4 (2017), 16% of new ties emerged. Between Time 1 and Time 2, 5% of total ties dissolved (1→0). From Time 2 to Time 3, 4% of ties dissolved. Lastly, 11% of ties dissolved from Time 3 to Time 4. Similarly, ties that were maintained for the duration of the network evolution were 2% for Time 1 to Time 2, 5% from Time 2 to Time 3, and 7% from Time 3 to Time 4.


<table>
<thead>
<tr>
<th>Time Period</th>
<th>Ties Unexplored (0→0)</th>
<th>Ties Emerged (0→1)</th>
<th>Ties Dissolved (1→0)</th>
<th>Ties Maintained (1→1)</th>
<th>Hamming Distance</th>
<th>Jaccard Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time 1 (2014) to Time 2 (2015)</td>
<td>1022 (86%)</td>
<td>85 (7%)</td>
<td>62 (5%)</td>
<td>21 (2%)</td>
<td>147</td>
<td>0.125</td>
</tr>
<tr>
<td>Time 2 (2015) to Time 3 (2016)</td>
<td>936 (79%)</td>
<td>148 (12%)</td>
<td>48 (4%)</td>
<td>58 (5%)</td>
<td>196</td>
<td>0.228</td>
</tr>
<tr>
<td>Time 3 (2016) to Time 4 (2017)</td>
<td>795 (70%)</td>
<td>189 (16%)</td>
<td>128 (11%)</td>
<td>78 (7%)</td>
<td>317</td>
<td>0.197</td>
</tr>
</tbody>
</table>

4.3.2.1. Model Estimation

The models were estimated with the SIENA package in R (Ripley & Boitmanis, 2010; Ripley et al., 2011). Results can be accepted if the overall maximum convergence ratio is less than 0.25 and the convergent t-value for each individual parameter is smaller than 0.10.

The first model (Model 1) included only the network parameters. The network parameters included in this study were reciprocity, transitivity, in-degree centrality, and
betweenness centrality. The second model (Model 2) expands on the first model and includes organizational attributes (termed as covariates in SAOM) to measure homophily in terms of the organization’s size, geographical proximity, and role of the organization in the LAUNCH collaboration network. The third model (Model 3) further expands Model 2 and includes organizational attributes of organizational size - larger, that is organizations in LAUNCH network tend to collaborate with larger organizations. Table 4.8 shows all of the parameters and their estimates along with levels of significance. The maximum convergence ratio for Model 1, Model 2, and Model 3 is 0.1517, 0.2423, and 0.1217 respectively. A maximum convergence ratio of less than 0.25 is desirable, and less than 0.35 is acceptable (RSIENA Manual, 2018). This suggests that all three model estimations in this study converged. The results obtained from non-converged models are considered misleading, which is not a problem in this study (Ripley, 2018).

Table 4.8. SAOM Model Results: Time 1 (2014) to Time 4 (2017) – Hypotheses 5a, 5b, 6, 7

<table>
<thead>
<tr>
<th></th>
<th>Model 1 Estimate (SD)</th>
<th>Model 2 Estimate (SD)</th>
<th>Model 3 Estimate (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Network Rate</td>
<td>8.8662** (1.2827)</td>
<td>8.8552** (1.3223)</td>
<td>9.1815** (1.1574)</td>
</tr>
<tr>
<td>(Period 1, 2014-2015)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant Network Rate</td>
<td>10.9891** (1.4704)</td>
<td>10.8926** (1.5231)</td>
<td>11.3549** (1.6525)</td>
</tr>
<tr>
<td>(Period 2, 2015-2016)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant Network Rate</td>
<td>19.9124** (2.3508)</td>
<td>20.0198** (2.6417)</td>
<td>21.8310** (3.2272)</td>
</tr>
<tr>
<td>(Period 3, 2016-2017)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdegree (density)</td>
<td>-1.1077** (0.3836)</td>
<td>-1.1077** (0.5695)</td>
<td>-0.8495** (0.5320)</td>
</tr>
</tbody>
</table>

(Table 4.8. cont’d).
<table>
<thead>
<tr>
<th></th>
<th>Model 1 Estimate (SD)</th>
<th>Model 2 Estimate (SD)</th>
<th>Model 3 Estimate (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reciprocity</strong></td>
<td>0.9974** (0.2011)</td>
<td>0.9609** (0.186)</td>
<td>0.9917** (0.1826)</td>
</tr>
<tr>
<td><strong>Transitivity</strong></td>
<td>3.6856** (1.0637)</td>
<td>3.6412** (0.945)</td>
<td>3.6223** (0.1038)</td>
</tr>
<tr>
<td><strong>In-degree Centrality</strong></td>
<td>-0.5603** (0.2447)</td>
<td>-0.5603** (0.1878)</td>
<td>-0.533** (0.2317)</td>
</tr>
<tr>
<td><strong>Betweenness</strong></td>
<td>-0.4385** (0.0886)</td>
<td>-0.4385** (.0927)</td>
<td>-0.4162** (0.0675)</td>
</tr>
<tr>
<td><strong>Organizational Size</strong></td>
<td>-0.124* (0.114)</td>
<td>-0.2863** (0.1277)</td>
<td></td>
</tr>
<tr>
<td><strong>Geographical Location</strong></td>
<td>0.7093** (0.181)</td>
<td>0.6952** (0.1761)</td>
<td></td>
</tr>
<tr>
<td><strong>Role Similarity</strong></td>
<td>-0.2326* (0.1357)</td>
<td>-0.2215* (0.1301)</td>
<td></td>
</tr>
<tr>
<td><strong>Organizational Size - Larger</strong></td>
<td>-0.4378* (0.1572)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. *p < 0.10. **p < .05

**4.3.2.2. Network Rate**

For each model, the rate parameter or network rate represents the expected average number of opportunities for tie changes per actor between subsequent times. The network rate parameter is generated by default in SIENA model and there was no hypothesis proposed related to network rate. The rate parameter for each observation is significant and positive for all three models, indicating that there is change occurring between the two time points in the networks. As presented in Table 4.8, the rate parameter in Model 1 for Period 1 (2014 to 2015) was 8.8662 ($SD = 1.2827, p < 0.05$), which means that each actor made on average 8.86 changes in the advice relationship during the period (i.e., changed one of their outgoing ties). The rate parameter for Period 2 (2015 to 2016) was 10.9891 ($SD = 1.47, p < 0.05$) and was larger than the
rate parameter for Period 1, which indicates that there were more changes in advice tie creation and dissolution between 2015 to 2016 than between 2014 to 2015. Similarly, the rate parameter for Period 3 (2016-2017) was 19.9124 (SD = 2.35, \( p < .05 \)), which was higher than in Period 2 and indicates there were more changes in advice tie creation and dissolution. The significance in rate parameters across all models indicate that there was an increase in information sharing behavior as the collaboration progressed from Time 1 (2014) to Time 4 (2017). The change in information sharing found in Period 2 (2015-2016) was less than that of Period 3 (2016-2017).

### 4.3.2.3. Density Parameter

The out-degree centrality (density) parameter is a basic control variable in the dynamic network variable (Ripley et al., 2018). The negative out-degree parameter in Models 1, 2, and 3 suggests that the actors in the advice network are unlikely to create ties with others at random (Chanheon, 2012; Ripley et al., 2018; Robbins, 2018; Steglich, Snijders, & West, 2006). This might happen due to the establishment of advice ties being a costly action since each organization allocates their limited resources, such as time, to create such ties.

### 4.3.2.4. Reciprocity (Hypothesis 2b)

The estimation results for reciprocity in all three models was positive and significant. Each model showed positive parameter estimates for reciprocity (Model 1: \( \beta = 0.9974, p < .05 \); Model 2: \( \beta = 0.9609, p < .05 \); and Model 3: \( \beta = 0.9917, p < .05 \)). This indicates that the reciprocity effect had a positive and significant impact on the formation of advice ties, such that there exists a strong tendency for organizations to seek advice from those who sought advice from them. The results above suggests that Hypothesis 2b, an organization will seek to reciprocate the ties with other organizations in the collaboration network over time, was supported.
4.3.2.5. Transitivity (Hypothesis 3b)

The estimation results for transitivity in Models 1, 2, and 3 were positive and significant. Positive parameter estimates for transitivity (Model 1: $\beta = 3.6856, p < .05$; Model 2: $\beta = 3.6412, p < .05$; and Model 3: $\beta = 3.6223, p < .05$) implies that organizations sought advice from organizations with whom they shared a common advisor. This reflects the phenomenon of ‘a friend of a friend is a friend.’ Based on the above results, Hypothesis 3b that the formation of a collaboration network entails closure behavior in which Organization A seeks to collaborate with Organization B, while Organization B seeks to collaborate with Organization C, and in turn, Organization A and Organization C will ultimately collaborate overtime as supported.

4.3.2.6. In-degree Centrality (Hypothesis 4c)

In-degree centrality (popularity effect) is measured as the number of incoming advice ties, and the parameter estimates were negative and statistically significant across all three models (Model 1: $\beta = -0.5603, p < .05$; Model 2: $\beta = -0.5603, p < .05$; and Model 3: $\beta = -0.5333, p < .05$). Individuals with high popularity at a given point in time are less likely to be sought by advice seekers as an information exchange partner or advisor. This implies that network members did not seek advice from already sought-after (or popular) network members, and that the network members who were highly popular had a low probability of being nominated or sought by others over time. Based on these results, Hypothesis 4c, that the organizations will reduce seeking advice from popular organizations from Time 1 to Time 4, was accepted.

4.3.2.7. Betweenness Centrality (Hypothesis 4d)

Betweenness centrality is measured as the number of times an organization falls between the shortest path of two other organizations, where high betweenness centrality gives a position of power to the organization. The parameter estimates for betweenness centrality were negative
and statistically significant across all three models (Model 1: $\beta = -0.4385$, SD = 0.0886, p < .05; Model 2: $\beta = -0.4385$, p < .05; and Model 3: $\beta = -0.4162$, p < .05). This indicates that LAUNCH organizations did not form information sharing ties with powerful organizations as the network evolved, and that the powerful organizations have a lesser probability of being sought by others over time. Based on the results above, Hypothesis 4d that the organizations will reduce information sharing from powerful organizations from Time 1 to Time 4 was supported.

4.3.3. Organizational Attributes

The organizational attributes function as covariates in SAOM. Four attributes were included in the models to check for a homophily effect where organizations selected partners based on the similarity of the following organizational attributes: size, geographical location, and role in the LAUNCH network. The homophily effect was included in Model 2. Model 3 expanded on Model 2 and included one additional covariate – larger organizational size (than the organization seeking advice). The next section will discuss the role of each organizational attribute as it relates to homophily and other effects.

4.3.3.1. Organizational Size (Hypothesis 5a and 5b)

Organizational size was defined as the total number of staff in the organization. Model 2 included the homophily effect of the organization size, i.e., whether or not organizations similar in size chose the same organizations as partners. The estimation results for organizational size in Model 2 was negative and not significant ($\beta = -0.124$, p < .10). This suggests that similar organizational size did not influence the advice-seeking behavior of the organizations in the LAUNCH collaboration.

Model 3 expanded on Model 2, and included the larger organizational size, that is, organizations will seek advice from the organizations who are larger in size than themselves. The
parameter estimates for this attribute were negative and not significant ($\beta = -0.4378, p < .10$). This suggests that organizations who were larger in size did not necessarily get nominated as an advisor. Based on the results above, Hypothesis 5a (organizations similar in size will show a propensity to collaborate with each other) and Hypothesis 5b (large organizations are more likely to be sought as an advisor) were not supported.

4.3.3.2. Geographical Proximity (Hypothesis 6)

In this study, geographical proximity was measured by the ZIP code in which an organization was based. There were a total of 17 ZIP codes represented in the LAUNCH network (Table 4.1). The estimation results for geographical proximity in Model 2 (Table 4.8) showed parameter estimates that were positive and significant ($\beta = 0.7093, p < .05$) and estimations results for Model 3 were also significant ($\beta = 0.6952, p < .05$). This suggests that organizations sought advice from other organizations located in the same ZIP code. Based on these results, Hypothesis 6, that organizations in close geographical proximity will show a propensity to collaborate with each other, was supported.

4.3.3.4. Role Similarity (Hypothesis 7)

The roles of organizations in the LAUNCH network were divided into seven categories: local or regional administrative council, state administrative council, state management team, mental health clinician, medical health clinician, child and adolescent psychiatric consultant, and others. The parameter estimation results (Table 4.8) for role similarity of Models 2 and 3 were negative and not significant (Model 2: $\beta = -0.2326, p < .10$; Model 3: $\beta = -0.2215, p < .10$), indicating that similarity in organizational role did not play any part in the process of network formation. Based on the results above, Hypothesis 7 that organizations with similar roles in the LAUNCH collaboration network are more likely to share information and form collaboration ties
with each other was not supported. Table 4.9 presents an overview of the proposed hypotheses and associated findings.

Table 4.9. Synopsis of Hypotheses and Findings

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 1: The density of the collaboration network will increase from Time 1 to Time 4</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 2a: Reciprocity will increase from Time 1 to Time 4.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 2b: An organization will seek to reciprocate the ties with other organizations in the collaboration network over time.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 3a: Network cohesiveness will increase from Time 1 to time 4.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 3b: The formation of a collaboration network entails closure behavior in which Organization A seeks to collaborate with Organization B, while Organization B seeks to collaborate with Organization C, and in turn, Organization A and Organization C will ultimately collaborate over time.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 4a: The overall network centralization as measured through in-degree centrality and decrease from Time 1 to Time 4.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 4b: The overall network centralization as measured through betweenness centrality will decrease from Time 1 to Time 4.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 4c: The organizations will reduce seeking collaborative ties from popular (measured using in-degree centrality) organizations from Time 1 to Time 4.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 4d: The organizations will reduce seeking collaborative ties from powerful (measured using betweenness centrality) organizations from Time 1 to Time 4.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 5a: Organizations similar in size will show a propensity to collaborate with each other.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 5b: Large organizations are more likely to be sought as an advisor than small organizations.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 6: Organizations in close geographical proximity will show a propensity to collaborate with each other.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 7: Organizations with similar role in the LAUNCH collaboration network are more likely to form collaborative ties with each other.</td>
<td>Not supported</td>
</tr>
</tbody>
</table>
4.3.4. Exploratory Analysis for Year 5 (2018)

A separate analysis was run to explore the structure of the final year’s (Time 5, 2018) network. To do so, a descriptive analysis was run on the 2018 network data, followed by a longitudinal analysis by adding the final year to the model. Table 4.10 shows the results from this analysis for Time 4 (2017) to Time 5 (2018).

While density increased from 2014 to 2017 (Table 4.2), density decreased by 27% from Time 4 (2017) to Time 5 (2018). Similarly, reciprocity showed an increasing trend from 2014 to 2017 (Table 4.3) but showed a 43% decrease from 2017 to 2018 (Table 4.10). The transitivity score increased by 1% from 2017 to 2018 (Table 4.10). In-degree centrality also showed an increasing trend from 2014 to 2017 (Table 4.5), however, it decreased by 17% in 2018 (Table 4.10). In contrast, the betweenness centrality continued to show the same oscillating trend, with an increase of 31% from 2017 to 2018 (Table 4.10). One probable explanation for this decrease in the network activity could be the fact that the network members knew that the LAUNCH grant was coming to an end and did not seek advice as much as they would have in the past.


<table>
<thead>
<tr>
<th></th>
<th>Density</th>
<th>Reciprocity</th>
<th>Transitivity</th>
<th>In-degree centrality</th>
<th>Betweenness centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Score</td>
<td>0.164</td>
<td>0.146</td>
<td>0.623</td>
<td>0.21</td>
<td>1.37</td>
</tr>
<tr>
<td>Change</td>
<td>-27%</td>
<td>-43%</td>
<td>1%</td>
<td>-17%</td>
<td>31%</td>
</tr>
</tbody>
</table>

Finally, to explore whether including the 2018 network in the longitudinal analysis indicated a difference in the way organizations sought collaborative partners in LAUNCH network, the researcher ran an additional model that included the 2018 network and organizational attributes. The results are presented in Tables 4.11 and 4.12.

<table>
<thead>
<tr>
<th></th>
<th>Ties Unexplored (0→0)</th>
<th>Ties Emerged (0→1)</th>
<th>Ties Dissolved (1→0)</th>
<th>Ties Maintained (1→1)</th>
<th>Hamming Distance</th>
<th>Jaccard Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 4 (Time 4 – Time 5)</td>
<td>830 (70%)</td>
<td>93 (8%)</td>
<td>164 (14%)</td>
<td>103 (9%)</td>
<td>257</td>
<td>0.286</td>
</tr>
</tbody>
</table>

The unexplored ties from Time 1 (2014) to Time 4 (2017) showed a decreasing trend (Table 4.7), however from Time 4 (2017) to Time 5 (2018), the number of unexplored ties increased from 795 to 830. Similarly, the number of ties that emerged showed an increasing trend from Time 1 to Time 4 (Table 4.7) but decreased from Time 4 to Time 5 (Table 4.11). As observed from Time 1 to Time 4 (Table 4.7), the number of dissolved ties showed a continued increase from Time 4 to Time 5 (Table 4.11). Finally, the number of ties maintained also followed the increasing trend, with a 9% increase from Time 4 to Time 5 (Table 4.11).

Next, the researcher discusses whether including year 5 (2018) in the SAOM model changed the parameter performance in network evolution. Table 4.12 presents the SAOM model results that include Time 5 (2018) in the longitudinal analysis to examine the evolution of the collaboration network.

Table 4.12. SAOM Model Results: Time 1 (2014) to Time 5 (2018)

<table>
<thead>
<tr>
<th>Model Parameters</th>
<th>Model 4</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Network Rate (Period 1)</td>
<td>9.5205**</td>
<td>1.2084</td>
</tr>
<tr>
<td>Constant Network Rate (Period 2)</td>
<td>12.1837**</td>
<td>2.0019</td>
</tr>
<tr>
<td>Constant Network Rate (Period 3)</td>
<td>19.8857**</td>
<td>2.5448</td>
</tr>
<tr>
<td>Constant Network Rate (Period 4)</td>
<td>14.0938**</td>
<td>1.5149</td>
</tr>
<tr>
<td>Outdegree (density)</td>
<td>-0.6298**</td>
<td>0.7284</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.7855**</td>
<td>0.1786</td>
</tr>
</tbody>
</table>

(Table 4.12. cont’d.)
This exploratory analysis that included Time 5 (2018) data shows that all network parameters had the same effect as found in earlier models. The organizational attributes or covariates also had similar effects on the evolution of the network. One significant difference noticed after inclusion of Time 5 in the SAOM model was the change in significance level of the covariates or the organizational attributes. These covariates are organizational role similarity and larger organizational size. Role similarity in earlier models was negative and not significant in earlier models, and after Time 5 was included in the model, parameter estimates continued to be negative but significant for role similarity ($\beta = -0.3687, p < .05$) and larger organization size ($\beta = -0.2509, p < .05$) but the significance level increased.

These findings suggest that although network members chose their collaborating partners in the same way for the first four years, the activity within the network from 2017 to 2018 decreased as compared to earlier times. The probable explanation could be that while the earlier data (2014-2017) was collected after a gap of 12 months, the 2018 data was collected after a gap of only six months and network members may not have had as much opportunity to collaborate as they had previously. Another possible explanation for the decreased network activity could be that the organizations who were part of the LAUNCH network knew that the end of the grant period was approaching and did not continue to collaborate with other LAUNCH organizations.
CHAPTER 5. DISCUSSION

The overall aim of this study was to examine the production and distribution of social capital as the primary mechanism for motivating collaboration in a policy-mandated environment. Specifically, the research studied how NPOs selected their partners over time in the context of the Louisiana Project LAUNCH collaboration network. This was done by examining the structure of the collaboration network and changes to that network over time – in other words, how NPOs selected partners to exchange information when collaboration was mandatory. Additionally, this longitudinal study also tested if organizational attributes such as the organization’s size, geographical proximity, and role similarity had an effect on the evolution of the network.

5.1. Summary of the Study

This study examined the evolution of a collaboration network and explored how organizations selected their partners in a policy-mandated collaboration while discovering how partnerships changed over time. Using LAUNCH as a case study, this study also examined the levels of social capital within the collaboration network. Data analysis methods included social network analysis to describe the structure of the network. For the longitudinal analysis, the research employed a stochastic actor-oriented model (SAOM) that works in the SIENA package (Ripley, Boitmanis, & Snijders, 2018; Ripley et al., 2018) of the R program to examine the evolution of the network by estimating how the network configuration and organizational attributes are more or less attractive in terms of network choices. The next section discusses the summary of findings.
5.2. Summary of Findings

This study’s results led to interesting, yet encouraging, findings and implications for mandatory collaborations among NPOs. The study finds overall support for many of the hypotheses; Appendix A summarizes the results from the hypothesis testing. This section discusses and deliberates the results described in detail in Chapter 4. This section is arranged by the order of the four research questions that directed this study:

1. How do non-profit organizations select their collaborative partners?
2. How do partnerships change over time?
3. What role do organizational attributes play in selecting collaborative partners?
4. How does partner selection affect the production and distribution of social capital as the collaboration evolved?

5.2.1. Research Question 1

A stochastic actor-oriented model (SAOM) was used to estimate how NPOs selected their collaborative partners. Four network configurations were proposed to answer Research Question 1: reciprocity (Hypothesis 2b), transitivity (Hypothesis 3b), in-degree centrality (Hypothesis 4c), and betweenness centrality (Hypothesis 4d). The analysis and results discussed in Chapter 4 found support for all of the hypotheses.

Reciprocity is the tendency to develop mutual relationships, whereby agencies share resources with partner agencies that share resources with them (Bunger et al., 2014). In this study it was found that organizations preferred to form mutual ties by seeking advice from organizations that have sought advice from them. This is consistent with research that has studied inter-organizational collaboration networks (Berardo & Scholz, 2010; Goldenberg, 2010; Gulati & Gargiulo, 1999; Leifeld & Schneider, 2012; Robbins, 2018). A probable reason for forming reciprocal ties can be the desire to seek legitimacy (Kouzes & Posner, 2007). Agencies
that share their expertise expect their partners to in turn share their expertise, and therefore, these agencies develop partnerships in reciprocity with existing partners (Lee & Feiock, 2012).

Mitchell, Klinck, and Burger (2004) state that any collaboration or partnership will test the members’ values, vision, and capacity to work together. Success depends on reciprocity and a common purpose; over time, the partnerships may change focus to adapt to new context and potential.

Transitivity refers to a tendency for actors in a network to choose others whom their close connections have already chosen. Organizations in the LAUNCH network showed a tendency to form transitive relations with other organizations, i.e., they preferred to collaborate with the organization(s) who their current collaboration partners had existing ties with. This phenomenon is popularly known as ‘a friend of a friend is a friend.’ This finding is also in alignment with the studies on inter-organizational collaboration (Carpenter, Esterling, & Lazer, 2004; Gulati, 1995; Gulati & Gargiulo, 1999; Lee, 2012; Senga, 2016). Additionally, the longitudinal analysis of the network suggests that organizations in the LAUNCH collaborative preferred to form transitive relationships over reciprocal relationships. This phenomenon has also been found in other inter-organization studies (Berardo, 2014; Scholz & Berardo, 2010; Bunger et al., 2014). The reason to form transitive relationships can be due to transitivity offering network closure. That is agencies collaborate with those which they are familiar and those who have a known reputation due to a mutual collaboration partner (Castro, Casanueva, & Galan, 2014). The underlying reasons for the inclination towards network closure may include the desire to gain access to new resourceful partners, and to cope with the risk of opportunistic behavior (Lee, 2012).

The study also measured two centrality parameters to answer this research question: in-degree centrality and betweenness centrality. In-degree centrality measures the number of ties
received by an actor (Freeman, 1979; Scott, 1991) and indicates the popularity of an actor within the collaborative. Betweenness centrality measures the power of an organization and measures the organizations between other connected actors. If an actor sits between members, they serve as intermediaries and can often have vital control over access to information dissemination (Kircher, 2004; Prell, 2012; Wasserman & Faust, 1994).

The longitudinal data analysis of the LAUNCH collaboration network showed that the organizations did not prefer to form ties with the organizations that were popular (measured through the in-degree centrality) or powerful (measured through the betweenness centrality). One possible explanation for not forming collaboration ties with popular and powerful organizations could be that the cost of forming and maintaining ties with highly popular organizations is high and therefore not ideal (Long, Cunningham, & Braithwaite, 2013). Another possible reason is the decay of the ties with popular and powerful organizations due to high costs associated with forming and maintaining the ties (Burt, 2002). This cost could be the amount of time and effort required as well as the loss of autonomy from entering into collaboration relationships.

Large networks have a great potential for more ties (Prell, 2006), which makes it difficult for large network to have high densities. However, in this study, the density increased as the network size increased. This suggests information exchange by the process of retaining existing ties, and the formation of new ties along with the loss of old ties, suggesting development of social capital as a result of tie retention and formation (Sasovovan, Mehra, Borgatti & Schippers, 2010, Shah, 2006). Further, for the model estimation, this study takes into account the change in network size as the collaboration progresses. The SAOM model accounts for the network size by controlling for density since all of the parameters in this study (reciprocity, transitivity, indegree and betweenness centrality) are correlated with density (RSIENA Manual, 2018). Density of a
network is dependent on the network size and as the network size increases the density decreases (Wasserman & Faust, 1994). Finally, in order to check whether or not different network sizes produced different estimates across different models i.e., if the model estimates were similar, the different models estimates were similar in this study, thus indicating that social capital formation was not dependent on network size.

5.2.2. Research Question 2

To get a better understanding of how the partnerships changed, the researcher analyzed the aggregated changes in the advice network over time. A summary of the major network-level characteristics at each observed point in time can be found in Appendix B. First, to explore the evolution in the overall tendency of the LAUNCH organizations to collaborate, the density of the advice network was calculated at each time point. Density is calculated as the number of ties present divided by the total number of possible ties in a network. The density of the network kept increasing from Time 1 (2014) to Time 4 (2017), suggesting that the organizations were forming new ties.

This increase in density score indicated growth in the connections between organizations and the development of a more interconnected network. High density scores indicated a greater degree of cohesiveness and are generally associated with higher social capital (Lee et al., 2012). Greater density within the LAUNCH network suggests that there was greater cohesiveness among the organizations in the network. This research confirms past research on inter-organizational collaboration where the density increases as the collaboration progresses (Aboelala et al., 2007; Haines et al., 2010). An increase in density indicates that actors are actively engaged with one another. Networks with higher density appear more integrated and interactive, meaning that actors are taking available opportunities to connect with one another.
Evidence suggests that higher density results in more opportunities for collaboration, innovation, implementation, and sharing of resources (Balkundi & Harrison, 2006; Kilduff & Brass, 2010).

Reciprocity refers to the mutuality of ties in a relationship (Wasserman & Faust, 1994). Reciprocity decreased from Time 1 (2014) to Time 2 (2015) by 31%, but showed increases from Time 2 (2015) through Time 4 (2017). One probable explanation for the decrease in reciprocity from 2014 to 2015 is that when the network was in its infancy, the organizations collaborated with organizations that they already knew. Once the organizations had a chance to know and learn about other organizations, the organizations concentrated on forming new collaborative ties versus reciprocating the ties. Additionally, reciprocity facilitates an interaction process among actors that leads to legitimacy (Kouzes & Posner, 2007). The legitimacy of a member in the eyes of the group makes it more likely that the knowledge, perspectives, and resources available to that member will become a resource available to the group (Alter & Hage, 1993). Ostrom (1998) argues that when reciprocity prevails, network members are motivated to acquire a reputation for keeping promises and performing actions with short-term costs but long-term net benefits.

Transitivity reflects the tendency of an actor or organization to form a tie with another actor that shares a tie with a common third party. The transitivity of the network increased from Time 1 (2014) to Time 4 (2017), suggesting that organizations in the LAUNCH network formed ties with the collaborators of their current partners. This phenomenon is in agreement with the existing research where other scholars (Gulati & Gargiulo, 2001; Carpenter, Esterling, & Lazer, 2004) found that the probability of a new alliance between specific organizations increases along with their common third parties. Two underlying reasons for the increase in transitivity scores includes the desire to access new resourceful partners and, at the same time, cope with the risk of
opportunistic behavior (Agneessens & Wittek, 2012; Berardo, 2014; Gerber et al., 2013; Senga, 2016).

The network centralization was measured using in-degree centrality and betweenness centrality. In-degree centrality measures the number of ties received by an actor (Freeman, 1979; Scott, 1991), and indicates the popularity of an actor within a network. Betweenness centrality measures the power of an organization and measures the number of organizations between other connected actors (Kircher, 2004; Prell, 2012; Wasserman & Faust, 1994). The proposed hypothesis that network centralization measured through in-degree centrality and betweenness centrality will decrease from Time 1 (2014) to Time 4 (2017) was not supported.

Despite this, the longitudinal analysis found that network members in the current study did not prefer to form ties with popular or powerful organizations when measured in terms of in-degree and betweenness centrality, respectively. It was therefore essential to assess the logic of the proposed hypotheses. The original hypotheses were written in such a way that in-degree centrality and betweenness centrality would decrease because the popular organizations would not be selected by others to collaborate, and not in respect to the overall network activity. One possible explanation could be the fact that the network members started exploring and forming new collaborative ties with new organizations as the collaboration evolved. Additionally, this is also evident in that network organizations who were central (high in-degree centrality and high betweenness centrality) kept changing throughout the years. This further supports that the same organization was not receiving advice requests throughout the duration of the collaboration.

5.2.3. Research Question 3

Three organizational attributes were expected to influence the formation of inter-organizational collaboration: the organization’s size, geographical proximity, and role of the
organization in the LAUNCH network. It was proposed that organizations would show a phenomenon of homophily based on organizational attributes, that is, organizations will collaborate with the organizations who are similar to them. None of the hypotheses related to organizational attributes were supported, with the exception of geographical proximity (Appendix A summarizes the results from the hypothesis testing).

Geographical proximity was measured using the ZIP code in which the organizations were located. It was found that organizations sought advice from organizations located within the same ZIP code. This result confirms the findings of earlier research on inter-organizational collaboration such that organizations in close geographical proximity prefer to collaborate. The reasons for such behavior could be that organizations are facing the same challenges or provide services to similar clients (Diestre & Rajagopalan, 2012; Gerber et al., 2013; Kim et al., 2016; Kono et al., 1998; Rothaermel & Boeker, 2008). Additionally, shorter distances make it easier to meet, discuss common issues and interests, and generally facilitates cooperation (Gerber et al., 2013).

The hypothesis related to organizational size that proposed organizations similar in size (as measured by staff size) would show a propensity to collaborate with each other, and that large organizations are more likely to be sought as an advisor than small organizations, was not found to be supported. One possible explanation could be that organizations of similar size did not offer each other any unique resources. This is in agreement with earlier studies by Boje and Whetten (1981) where they found that organizations with similar staff size tend not to collaborate with each other. Another plausible reason in the literature for why organizations with similar staff size do not prefer to collaborate is that they are competing for the same resources. For example, Aldrich and Pfeffer (1976) found that organizations with similar staff sizes are
essentially searching for the same resources. Similarly, Bunger (2013) found that organizations with similar organization size enhances the benefits but increases the conflict. The reason as to why smaller organizations don’t collaborate with larger organizations could be that doing so poses unique challenges such as the power and reputation of large organizations. This may put smaller organizations in a compromising situation where they may fear losing autonomy in the collaboration (Katila, Rosenberger, & Eisenhardt, 2008; Podolny, 1993). A recent review by Lumineau & Oliveira, 2018 discussing promising research opportunities in the area of inter-organizational relationships makes the observation that “differences between a small firm and a large firm influence the way in which each firm perceives dependence, uncertainty, and risk” (p.447).

The hypothesis related to organizational role similarity such that organizations with similar roles in the LAUNCH collaboration network would be more likely to form information exchange ties with each other was not found to be supported. The role of the organization in this study was measured as the service delivery role each organization played in the LAUNCH network. One possible reason for organizations not seeking advice from organizations with similar roles could the grant requirement itself. It is typically desirable in this grant that organizations collaborate with organizations with different roles for integrated service delivery (National Resource Center for Mental Health Promotion & Youth Violence Prevention, 2016). Further, in her research about inter-organizational collaboration among mental health agencies, Bunger (2013) found that partners working in the same domain (role) tend to have increased conflict and therefore collaborated less. This was also supported in earlier research by Das and Teng (2002), where organizations tend to collaborate with organizations offering complementary services thus providing a win-win situation for the involved parties.
One of the potential reasons for the unsupported organizational attributes of organization’s role and organization’s size could be that the same type of organizations have similar roles and similar sizes. Future research should control for the interaction effect between these two variables. The changing network composition could also be a contributing factor in determining the role of organizational attributes and the network structure. The organizations in this network joined or left the network, making organizations choose the organizations with whom they have preexisting ties. The research on longitudinal NPO collaboration is scarce and the research with added features of composition change is extremely rare. Future research should address how composition change affects the network.

5.2.4. Research Question 4

The final research question examined how partner selection affected the production and distribution of social capital as the collaboration evolved. This study segmented social capital into two different components: bridging and bonding social capital. Bonding social capital was measured through network cohesiveness while bridging social capital was measured using network centralization. Therefore, a network showing centralization properties is indicative of bridging social capital while network cohesiveness indicates bonding social capital. This research adopts the conceptualization that social capital is an accrued resource that is embedded in the relationships between two or more individuals or organizations (Adler & Know, 2002; Portes, 1998). Bonding social capital indicates that LAUNCH network organizations accrued social capital through existing relationships with the members of the collaboration, and not through the forming of new relationships.

Network cohesiveness in this study was operationalized as density, reciprocity, and transitivity. The density in this study increased as the LAUNCH collaboration progressed.
indicating a more inter-connected structure where the organizations were working more closely together. Evidence suggests that higher density results in more opportunities for collaboration, innovation, implementation, and sharing of resources (Balkundi & Harrison, 2006; Kilduff & Brass, 2010).

These findings suggest that higher density may have a positive influence on the sustainability of an advice-seeking organizational network. Higher density scores indicate a greater degree of cohesiveness and are generally associated with greater social capital (Lee et al., 2012). Theorists argue that groups with high network density have greater access to the full resources represented within the network, and therefore have an increased capacity to leverage these resources toward achieving their collective goals (Coleman, 1988). Hemphala and Magnusson (2012) also supported the previous argument by Obstfeld (2005) that collaboration is fostered in dense networks. This can be valuable information to an inter-organizational network wanting to increase collaboration.

Reciprocity is the tendency to develop mutual relationships (Bunger et al., 2014), and was found to increase in this study as the LAUNCH collaboration progressed. Additionally, in the longitudinal analysis it was found that members tended to reciprocate ties. Reciprocity is one of the key structural aspects of bonding social capital (Coleman, 1990) and refers to the case in which two actors mutually choose each other in a network (Moolenaar, 2012). In the literature, reciprocal ties in a network have been treated as strong evidence of bonding relationships at the dyadic level (Gouldner, 1960; Granovetter, 1973). Higher reciprocity indicates more one-to-one (dyadic) relationships between actors, indicating cohesiveness within the network (Moolenaar & Sleegers, 2010). Ostrom (1998) argues that when reciprocity prevails, network members are
motivated to acquire a reputation for keeping promises and performing actions. Reciprocal ties, therefore, are regarded as a salient characteristic of networks with high levels of social capital.

Transitivity refers to the tendency that actors in a network choose others that their close connections have already chosen (Granovetter, 1973; Hanneman & Riddle, 2005). Transitivity in the LAUNCH collaboration increased as the collaboration progressed, and in the longitudinal analysis of the network it was found that network members preferred to form transitive relationships. The transitivity leads to network closure because organizations tend to operate in a collaborative team-like structure (Lubell, Robins, & Wang, 2011). Granovetter (1973) argues that transitive relationships occur in bonding networks consisting of strong ties. In the current study, the network members preferred to form transitive ties over reciprocal ties, suggesting that actors in the LAUNCH collaboration network valued the greater reassurance against multi-actor defection that transitivity provides and which reciprocity cannot offer (Berardo, 2014).

The second component of social capital in this study was bridging social capital, which was measured through network centralization. Network centralization represents the variability in the importance of individuals in a network. A centralized network indicates an excess of bridging social capital. Bridging social capital is measured in terms of preference for popular partners and powerful partners (Crowe, 2007; Ramirez-Sanchez & Pinkerton, 2009). Network centralization in the current study was operationalized as in-degree centrality and betweenness centrality. In-degree centrality describes an actor’s activity level within the network, while betweenness centrality describes the power of an organization as this actor connects two otherwise disconnected actors.

In the current study, the in-degree centralization as well as the betweenness centralization of the network increased as the collaboration progressed while the longitudinal analysis of the
network suggested that LAUNCH organizations did not tend to form collaboration ties with either popular or powerful organizations. The increase in the in-degree and betweenness centrality was due to increased advice-seeking activities and not because the network members were collaborating with popular or powerful organizations. This is further confirmed through the longitudinal analysis of the network as well as by the fact that the organizations with higher in-degree and betweenness centrality kept changing as the collaboration progressed.

Based on the social network analysis of the social capital, the current study found that organizations preferred to form bonding social capital over bridging social capital. The advice seeking and information sharing were driven by the NPOs building on and strengthening their existing relationships with the members of the network. Bonding social capital is based on the concept of a closed network and was measured using density, reciprocity, and transitivity. In a closed network, the ties are shared between the same members repeatedly and continuously, which was confirmed by the propensity of organizations to form reciprocal and transitive ties. This kind of social capital allows for the deployment of available information and partners for an organization’s own benefit. This network unwillingness to form bridging ties can be due to the cost associated in forming and maintaining ties with popular and influential members of the network, as organizations may fear losing autonomy. Further, this may be explained by bottlenecks in information flow that can happen due to overloading the popular and powerful actors in a network. Moreover, bridging ties have a short shelf-life with time rendering many bridging ties and the information they broker as obsolete (Soda et al., 2004; Stasser & Titus, 1985).
5.3. Academic Implications

This researcher set out to conduct a study in a context not abundantly available in the literature: the evolution of a collaboration network in a policy-mandated environment. This study attempts to address this gap. This study contributes to the academic literature and extends existing research on NPO collaboration by integrating three theoretical frameworks of inter-organizational exchange as a means to examine the selection and strengthening of partnerships in a policy-mandated collaboration. By applying the principles of collaboration theory, social capital theory, and social network theory, this research broadens the theoretical perspective by which collaboration is analyzed and advances knowledge within collaboration theory. This study expands on collaboration theory (Thomson & Perry, 2006) by adding on to the mutuality element of the theory (To remind the reader: Collaboration theory has five elements: governance, administration, autonomy, mutuality and trust, and reciprocity). As discussed earlier, collaboration theory does not explain the willingness of organizations to collaborate, especially in the context of policy-mandated collaboration. Social capital theory allowed the researcher to examine how organizations collaborated, formed ties, and maintained ties in a policy-mandated context. The mutuality element of collaboration theory has its roots in interdependence. Such interdependent relationships are well documented in inter-organizational relations as organizations need resources to support their operations (Levine and White 1961; Pfeffer & Salancik, 1978; Van de Ven, Emmett, & Koeing Jr., 1975). As long as collaboration partners can satisfy one another’s differing interests without hurting themselves, collaboration can occur (Wood & Gray, 1991). Mutuality dimensions contain hints of generosity with its emphasis on willingness to share information that will strengthen partner organizations’ operations and programs. In the current study, it was found that organizations preferred to collaborate by
reciprocating ties as well as by seeking advice from the existing collaborator’s collaborator when it came to partner selection. This is due to the fact that bonding social capital provides security and assurance which is needed in a collaboration that has been mandated, where the participating organizations have too much stake as failure affects all parties involved in the collaboration. It also affects relationships with funders (Ada & Lionel, 2014; Bierly & Gallagher, 2007). Organizations preferred to form bonding ties as they likely believed that it would provide assurance against the risks associated with entering a collaboration in a policy-mandated context. Further, this study found that organizations did not prefer bridging social capital as measured through in-degree centrality (popular organization) and betweenness centrality (powerful organization). The reasons that organizations did not prefer to form bridging ties could be to maintain their organizational autonomy as well as to avoid the bottlenecks that happens due to overload on the popular and/or powerful organization (Fine, 1995; Gazley & Brudney, 2007).

When collaboration occurs within a policy-mandated environment, a shift seems to appear in the focus of service providers towards collaboration to avoid punishments. The collaboration behavior of the organizations in a policy-mandated context suggest that organizations collaborate in order to secure funding and minimize the risk of failure by collaborating with exiting partners. Collaboration is complicated because although altruistic notions to deliver services to children and families can create a common cause that brings NPOs together, within this context the common need to attain funding also brings NPOs together, thus diminishing the opportunities to build social capital between organizations. Therefore, in the mandatory context under study, for the majority (if not all) of the organizations, the collaboration is about accessing resources or funding rather than synergy. Therefore, although the existing literature acknowledges that mutuality and interdependency between stakeholders is a key driver
of collaboration (Wood & Gray, 1991; Thomson & Perry, 2006), this research indicates that funding and resources, in addition to common altruistic goals, drives organizations to collaborate. Therefore, there is a need to expand on the mutuality element of collaboration based on the funding (and resource) needs of organizations.

One benefit of this research is the longitudinal perspective adopted by the stochastic actor-oriented model. Comparable data for the same process at multiple points in time are rare (Fischer, Manuel, Ingold, Sciarini, & Varone. 2012) and invaluable when it comes to drawing significant and meaningful conclusions about network evolution from a conceptual as well as empirical and methodological point of view. The researcher is aware that these results need confirmation by future research and through a comparative case study design, and that ultimately, an important next step is to ground theory on the evolution of collaboration networks to social outcomes.

5.4. Practice Implications

From a practitioner perspective, understanding whether and how NPOs adjust their partnerships in response to mandatory collaboration has implications for policy strategies aimed at integrating human service systems. In the current study, it was shown that in a policy-mandated context, the organizations formed collaborative ties based on reciprocity and/or transitivity, meaning they collaborated with organizations who have either sought collaboration with them in the past, or who they knew through a common organization within this network suggesting bonding social capital formation in the network.

The NPOs leadership can use the new funding as an opportunity to expand their network of partners. However, reluctance to form ties with popular and/or powerful organization comes with its own disadvantage. It has been established in the literature that popular and/or powerful
organizations have high levels of social capital (Adler & Kwon, 2002; Baker, 1990; Bourdieu, 1986; Burt, 1992; Coleman, 1990; Jacobs, 1965; Moolenaar, Daly, & Sleegers, 2010; Putnam, 2000). As a result of not collaborating with those organizations, the LAUNCH organizations probably missed the opportunity to capture a newer and wider range of resources. These organizations should revisit their collaboration strategy to form bridging ties with popular and powerful organizations. Forming bridging ties comes with its own set of advantages, for example, getting new perspectives on similar or shared challenges, which may not be possible in a bonding relationship as it leads to the same information (Granovetter, 1973). NPOs may consider revisiting their collaboration strategies by testing potential collaborative partners prior to developing more intensive partnerships by investing in relationships that are not too demanding. This will help in reinforcing trustworthiness, potentially leading to stronger and more valuable partnerships (Impink, 2004; Snively & Tracey, 2002).

Funders can harness their influence on inter-organizational collaboration in family and children services by explicitly discussing the advice-seeking behavior with the key stakeholders. Doing this can help with what Penuel and Riel (2007) call a “matrixed” approach, where stakeholders hear about the advice seeking behavior in multiple contexts. Funders can use their position and power to act as an influencer, where they can help build bridging social capital by connecting new organizations and going beyond the use of existing ties. Funders can use the existing relationships between organizations to create buy-in for further collaboration. In this way, funders can utilize bonding social capital as a stepping stone to the development of bridging social capital by investing in organizations who can influence other members faster and more effectively to spread information. Funders can still help in the creation of bridging structures that increase the likelihood of implementing better-designed responses to problems. Designing and
implementing shared-costs programs may be a preeminent way to achieve that goal, since partners seeking to strengthen their collaborative efforts are likely to build ties that in the end favor the transmission of novel information throughout the system.

5.5. Study Limitation and Future Research

A key limitation of this research is the study sample. The researcher used data collected from NPOs located in the southwest region of Louisiana who were part of the LAUNCH collaboration network. The social networks and social capital functions are more likely to be contextual (Ramirez-Sanchez & Pinkerton, 2009) and, therefore, not highly generalizable. However, collaboration among NPOs has been encouraged or required by policymakers and funders to access a broader range of ideas, information, and resources. Therefore, findings from this study can be used to design similar studies elsewhere despite the lack of generalizability.

Alternate sampling methods may lead to a different network sample with different typological characteristics. This study utilized a roster method for sampling, however, if a recall method or snowball sampling would have been used to collect the data, the network structure might appear differently. Future studies should explore these sampling issues and may require multiple sampling approaches and generalization.

Another limitation of this study was that the organizations did not tend to form ties in the last observation when compared to earlier observations. The researcher offered two plausible explanations: first, that organizations knew that the grant period was coming to an end and organizations reduced their advice seeking behavior, and second, that the organizations did not have much time to explore the ties since the time-lapse for the final observation was significantly shorter (six months) than earlier time periods (1 year). Future research should take into
consideration whether the time-lapse between observations and the end of the grant period affects the collaboration behavior in a mandatory context.

This research study is an exploratory study that used organizational attributes and the composition change in the network. Composition change means that the organizations in this collaboration joined or left the network as the collaboration progressed. The composition change has its advantage in the sense that it measures the network change as it happens versus not considering organizations who were present for the entire five years. However, the researcher cannot know the reasons behind the composition change. The research on longitudinal NPO collaboration is scarce and research with the added feature of composition change is extremely rare. Further, due to the composition change the attributes of the network changed as well; future research should take into consideration how composition change affects collaboration behavior.

This study explored how the network evolved and how organizations selected their partners in a policy-mandated environment while discovering how the partnerships changed over time. An important next step could be conducting a multi-level analysis for multiple groups all having the same number of waves and using the same model specification to examine whether effects differ between groups.

5.6. Conclusion

Using Louisiana’s Project Linking Actions Unmet Needs in Children’s Health (LAUNCH) as a case study, this study examined the evolution of a collaboration network and explored how organizations select their partners in a policy-mandated environment. In doing so, this study also examined the levels of social capital in the collaboration network. The study results revealed that organizations formed reciprocal and transitive ties over forming ties with organizations with high in-degree centrality (measuring popularity of the organization) or
betweenness centrality (measuring power of the organization), suggesting that the evolution of the collaboration network was largely determined by preexisting ties and network structures.

The propensity towards bonding social capital provides security against the high levels of risk associated with collaboration in a policy-mandated context due to the convenience and accessibility offered by existing ties and network structures (Berardo & Scholz, 2010; Bunger et al., 2014). The results were consistent throughout the different model specifications employed in this analysis, indicating robustness of the findings. Out of the three organizational attributes included in the model, only geographical proximity had a positive and significant effect in partner selection. Longitudinal studies on network analysis in general are sparse largely due to data requirements. It is further less explored in the case of collaboration occurring in a policy-mandated environment and this study is a step in providing an avenue for additional future research. A large demand for NPO collaboration from funders requires more studies like these to inform funders of the ways organizations select partners in policy-mandated environment to meet the collaboration requirements.
REFERENCES


Kilduff, M., & Brass, D. J. (2010). Organizational social network research: Core ideas and key debates. *The academy of management annals, 4*(1), 317-357.


<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 1: The density of the collaboration network will increase from Time 1 to Time 4</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 2a: Reciprocity will increase from Time 1 to Time 4.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 2b: An organization will seek to reciprocate the ties with other organizations in the collaboration network over time.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 3a: Network cohesiveness will increase from Time 1 to time 4.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 3b: The formation of a collaboration network entails closure behavior in which Organization A seeks to collaborate with Organization B, while Organization B seeks to collaborate with Organization C, and in turn, Organization A and Organization C will ultimately collaborate over time.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 4a: The overall network centralization as measured through in-degree centrality and decrease from Time 1 to Time 4.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 4b: The overall network centralization as measured through betweenness centrality will decrease from Time 1 to Time 4.</td>
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<tr>
<td>Hypothesis 4c: The organizations will reduce seeking collaborative ties from popular (measured using in-degree centrality) organizations from Time 1 to Time 4.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 4d: The organizations will reduce seeking collaborative ties from powerful (measured using betweenness centrality) organizations from Time 1 to Time 4.</td>
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</tr>
<tr>
<td>Hypothesis 5a: Organizations similar in size will show a propensity to collaborate with each other.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 5b: Large organizations are more likely to be sought as an advisor than small organizations.</td>
<td>Not supported</td>
</tr>
<tr>
<td>Hypothesis 6: Organizations in close geographical proximity will show a propensity to collaborate with each other.</td>
<td>Supported</td>
</tr>
<tr>
<td>Hypothesis 7: Organizations with similar role in the LAUNCH collaboration network are more likely to form collaborative ties with each other.</td>
<td>Not supported</td>
</tr>
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</table>
APPENDIX B. NETWORK-LEVEL DESCRIPTIVE STATISTICS

<table>
<thead>
<tr>
<th>Network Parameters</th>
<th>2014</th>
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<th>2016</th>
<th>2017</th>
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<td>Density</td>
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<td>0.221</td>
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<tr>
<td>Betweenness centrality</td>
<td>1.928</td>
<td>1.114</td>
<td>1.62</td>
<td>1.048</td>
<td>1.37</td>
</tr>
</tbody>
</table>
APPENDIX C. IRB APPROVAL

ACTION ON EXEMPTION APPROVAL REQUEST

TO: Pallavi Singh  
School of Leadership and HR Development

FROM: Dennis Landin  
Chair, Institutional Review Board

DATE: August 23, 2018

RE: IRB# E11156


Review Date: 8/22/2018

Approved X Disapproved

Approval Date: 8/23/2018 Approval Expiration Date: 8/22/2021

Exemption Category/Paragraph: 4a

Signed Consent Waived?: N/A

Re-review frequency: (three years unless otherwise stated)

LSU Proposal Number (if applicable): ________________________________

By: Dennis Landin, Chairman

PRINCIPAL INVESTIGATOR: PLEASE READ THE FOLLOWING –

Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU's Assurance of Compliance with DHHS regulations for the protection of human subjects*
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the study ends.
5. Continuing attention to the physical and psychological well-being and informed consent of the individual participants, including notification of new information that might affect consent.
6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
8. SPECIAL NOTE: When emailing more than one recipient, make sure you use bcc. Approvals will automatically be closed by the IRB on the expiration date unless the PI requests a continuation.

*All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/irb
VITA

Pallavi Singh is a native of Varanasi, India, and received her Bachelor’s degree in Psychology from Banaras Hindu University in 2006. Upon completion, she decided to apply her study in work place and started MBA at ITM Business School, Mumbai, India. She spent time working in Insurance and Hospitality industry for five years in India. In 2011, she decided to further her education at Rochester Institute of Technology where she received a Master’s degree in Human Resource Development. She spent time working in non-profit organization focused on youth health before starting her Ph.D. at Louisiana State University. It was here that she completed the necessary requirements to fulfill her lifelong dream of receiving a Ph.D. in Human Resource Education. Currently, Pallavi works as Associate Researcher at the University of Kansas where she provides research and evaluation support for the programs focused on children, youth, and families.