Empirical Measures of Collective Capacity: A Social Network Approach

Matthew Anthony Adan

College of William and Mary

Follow this and additional works at: https://scholarworks.wm.edu/honorstheses

Part of the Community-Based Research Commons, Health Communication Commons, Interpersonal and Small Group Communication Commons, and the Quantitative, Qualitative, Comparative, and Historical Methodologies Commons

Recommended Citation

https://scholarworks.wm.edu/honorstheses/1112

This Honors Thesis is brought to you for free and open access by the Theses, Dissertations, & Master Projects at W&M ScholarWorks. It has been accepted for inclusion in Undergraduate Honors Theses by an authorized administrator of W&M ScholarWorks. For more information, please contact scholarworks@wm.edu.
Empirical Measures of Collective Capacity: A Social Network Approach

A thesis submitted in Interdisciplinary Studies at
The College of William & Mary

by

Matthew Anthony Adan

Accepted for ____________________________
(Honors, No Honors)

________________________________________
Dr. David Aday, Director

________________________________________
Dr. Francie Cate-Arries

________________________________________
Dr. Amy Quark

Williamsburg, VA
May 3, 2017
Empirical Measures of Collective Capacity: A Social Network Approach

Abstract

Collective capacity building is often referenced in the development literature as an integral component of development projects, but few attempts to measure capacity empirically are documented. This research examines social network analysis (SNA) as a way to measure changes in network structure that are indicative of collective capacity. By theorizing about network features that may optimize information flow, I have identified promising network parameters for measuring change over time. By manipulating original SNA data sets from two undergraduate community development projects to promote information flow via network structure, I evaluated the robustness of the proposed network measures. Findings include the identification of breadth, component ratio, connectedness and fragmentation as four network measures that may serve as reliable measures of key changes in collective capacity over time.
Chapter 1: Background and Research Questions

Current development literature suggests several specifiable models for community engagement. One model, participatory development, highlights the importance of active involvement of community members in decision-making. It emphasizes the role of locals, residents and community groups as the prime movers and as stakeholders in efforts to mitigate the effects of changes that have marginalized individuals and communities. Adherents recognize methodological, technical, political, and practical challenges that such approaches may create. Jnanabrata Bhattacharyya (2004) articulates a framework for community development that advances this participatory model. Drawing from classical sociological theory on solidarity, Bhattacharyya (2004) invokes the work of Emile Durkheim and argues for the promotion of solidarity in development practices (cf. Simpson 1933).

According to Durkheim, solidarity is a social force that holds societies together (in Simpson, 1933). Bhattacharyya (2004) applies this Durkheimian notion of solidarity to development in a way that is instructive, arguing that social cohesion is a crucial component to creating social change. Solidarity is distinct from closeness facilitated by place and involves shared identity and mutual obligations that enable “people to take collective measures to address shared problems” (Bhattacharyya 2004: 12).

However, it is important to note that Bhattacharyya (2004) accepts Durkheim’s theories rather uncritically, while sociologists such as Robert K. Merton (1934) have pointed to flaws in Durkheim’s arguments, as presented principally in The Division of Labor in Society. According to Merton (1934), Durkheim claims that the division of labor in society is the sole source of modern solidarity, which overlooks community interests and
interpersonal factors that contribute to a society’s connectedness. Among other things, Merton (1934) suggests that it may be more useful to view Durkheim’s descriptions of solidarity as a conceptual scheme that may be valuable in the interpretation of empirical data. He contended that the more rigid linear model of evolving solidarity is more problematic (Merton 1934).

Based on the concept of solidarity and its relevance for viable community organization, Bhattacharyya (2004) argues for the centrality of the following factors: self-help, felt needs and inclusive participation. He asserts that these are crucial to engaging communities in meaningful community development and social change because they promote solidarity and agency. I will contend that solidarity and agency both depend on and promote recognition of shared problems, which is essential to the initiation of collective action (cf. Hilgartner and Bosk, 1988). Simply stated, I theorize that effective development in the face of globalization and its accompanying marginalization requires strategies that restore or promote solidarity and agency rather than dependency. Effective development fosters an environment in which communities can identify and address needs of their own (Jennings 2000). This places communities at the center of development and works to overturn inequalities in distribution of resources and power, aspects of marginalization (Vasas 2005).

According to Bhattacharyya (2004), the pursuit of solidarity and agency can be viewed as an end of community development, allowing for people to influence the realities they face and live according to values defined by themselves and not others. This entails

---

1 Vasas defines marginalization as the "process through which individuals or groups are peripheralized on the basis of their identities, associations, experiences, and environments" (Vasas 2005: 194)
the ability to recognize undesirable conditions and advance strategies to address them (Bhattacharyya 2004). Moreover, solidarity is at least related to and likely depends on recognition of shared social problems as the foundation for collective strategies of change. Solidarity is undermined by many top-down development projects that utilize the label “participatory” or “community based” to reduce costs by utilizing local labor or to garner greater support from donors who wish to see more seemingly equitable practices employed in international development (Chambers 1994). Such practices may ultimately prove unsustainable and fail to recognize local needs (Jennings 2000). As noted by postcolonial scholar Ilan Kapoor (2004), some instances of participatory development projects may foster panopticism, in which involved communities are supervised to an extent that stifles genuine collaboration and problem solving. In these instances, development does not promote the agency and solidarity I theorize to be necessary for effective collection action (Kapoor 2004: 127).

Through my involvement with the Student Organization for Medical Outreach and Sustainability (SOMOS) at the College of William and Mary, which conducts community-based research and development project implementations in Esfuerzo, Dominican Republic, I have grown interested in understanding solidarity and its relationship to community capacity. What are the structural dimensions of solidarity and how do these relate to community capacity? How can these dimensions be measured? I have seen through work with the SOMOS project that many development organizations suggest participatory models in their rhetoric but it is less clear that they are engaged in research or project strategies that reflect or advance key ideas or operational processes that engage issues of solidarity, shared beliefs about social problems, felt needs, self-help, or agency.
Over the past decade, SOMOS team members have aspired to fit their efforts to community needs in ways that reflect carefully identified community concerns and that promote agency rather than dependency. In light of countless examples of development projects that undermine local infrastructure and operate from an outside-in patriarchal stance, members of the team have rooted themselves in a community-based approach that aims to foster sustainable and inclusive social change. Beginning with sensitizing concepts such as respect for local wisdom, good intentions are dangerous things, and every helping act is a political decision, SOMOS has sought to build authentic partnership relationships. Determined to build from the best systematic literatures of theories, research, and practice in international development and public health, the team has developed an approach that reflects the intersection of understandings from ethnographic research and key insights from formal theory and research. These intersections between theory and research exist at the forefront of the SOMOS project and have highlighted the many unanswered questions that exist within the development literature.2

Grounded in the experiences, accumulating research, and the emerging model of SOMOS, I aim to identify empirical ways of understanding solidarity, collective capacity, and strategies for participatory development focused on mitigating problems of health and health care. Specifically, I aim to focus on what I believe is a central structural feature of collective capacity, which I will argue is essential for effective and sustainable social change in support of locally-owned and driven development. For the purpose of this investigation, I begin with a broad definition of collective capacity as structural arrangements and shared

---

2 See Aday, et al., 2015.
resources for solving collective or public problems and for advancing shared prospects
(borrowing from Goodman et al. 1998 and others).

The research questions

Working as part of the SOMOS project, I have theorized, following Bhattacharyya
(2004) and Hilgartner and Bosk (1988), that participatory approaches to development will
disable collective capacity by promoting shared beliefs about shared social problems and
that these shared beliefs can become the foundation for organized collaboration in
identifying solutions, strategies, and resources. Bhattacharyya’s (2004) descriptions of
community development provide a theoretical framework. I seek a more empirically
specified approach to describing communities and collective capacity. Moreover, I hope
that this work will contribute to developing strategies of community-based participatory
development.

My approach is focused by ongoing work in the SOMOS project, including previous
studies of social networks and interpersonal ties as structural arrangements that can be
examined empirically. This structural approach emphasizes examining communities as
networks of socio-spatial relationships that create frameworks for exchange of ideas and
information. In the course of these studies, my colleagues and I have approached social
networks as one dimension of community collaboration and I intend to examine social
networks analysis (SNA) as a tool for measuring changes in collective capacity.

Empirical measures of collective capacity are largely non-existent in social scientific
literature. Many researchers have described relevant phenomena qualitatively and

3 There is interesting parallel research on social capital that uses network analysis concepts and analyses
(see, for example, Borgatti and Jones, 1998). The concept of social capital appears to focus on egocentric
commented on their importance in community development, but valid and reliable measures are still under investigation. This thesis, rooted in sociology and social science generally, will attempt to identify analytical methods suitable for understanding collective capacity and assess the extent to which these tools are useful for detecting meaningful changes in collective capacity over time. The overarching question of this investigation can thus be summarized: “What is collective capacity and how can it be observed with reliability?” This overarching question will be deconstructed into a series of four questions that guide the search for a thorough answer.

The first of these questions is “How is collective capacity defined and what are potential empirical indicators?” Through previous work on the SOMOS project, I have given consideration to definitions of collective capacity, but I will now develop these ideas further by connecting this conceptual understanding to practical measurement tools. My investigation focuses more narrowly on social networks as a promising structural dimension of collective capacity, because I believe that communication and interpersonal exchange are at the heart of this community feature. I will use a mixed methods approach considering both qualitative and quantitative methods to complement one another. Specifically, I will use qualitative data collected through informant interviews and quantitative analyses of these data using social network analysis (SNA).

This leads to the second sub-question of this thesis: “What features of a network of interpersonal relationships facilitate communication and collaboration and how do these networks and how these may aggregate to create community capabilities. My work focuses on collective capacity, which I believe is a structural-level reality, with properties discernible at the community level that cannot be understood at the egocentric level. Thus, social capital will not be further addressed in this investigation.
features vary?” To answer this question, I will examine theoretical and research literatures on social networks to conceptualize the characteristics of a network that may be ideal for promoting collective capacity. These characteristics may include the arrangement of social ties within the network, the strength of these ties and the overlap in ties among nodes (locations of individuals and relationships within community networks). I will attempt to identify characteristics of an ideal network and examine variations in those characteristics.

The third sub-question focuses on specific measures of network characteristics: “What metrics of networks best describe structural features of this dimension of collective capacity?” I will use the computer software package UCINET, which is intended for analysis of social network data through visual modeling and statistical measures. UCINET offers diverse statistical calculations that describe different aspects of social networks, such as the density of social ties, the average ties per individual, and how clustered communication is around specific individuals. I expect that only some of these measures will prove relevant to quantitatively describing the traits that reflect and support collective capacity. By connecting the theoretical investigation of ideal networks with statistical calculations that may reflect these understandings, empirical measures of collective capacity can be specified.

Lastly, the final sub-question of this thesis investigates the question “Is it possible to measure changes in network characteristics that reflect important differences in the network’s ability to support and advance collective capacity?” This consideration is particularly important because in order for measures of social network properties to be useful for understanding this dimension of collective capacity, they must be able to detect differences or changes that bear on capacity. Communities may experience changes in
network arrangements in response to community development projects, important political events or other factors that alter interpersonal contacts and relationships. Because such changes are theorized to be important to collective capacity, successful measures must be able to identify and describe the differences. For this portion of the thesis, I will use data collected from the SOMOS project and its sister project, MANOS. I will use illustrative data sets to describe and examine changes that I believe will reflect and support collective capacity.

Ultimately, I intend to propose social network metrics that can be used to describe, measure, and assess social network characteristics that I believe are reflective of and supportive of collaboration and collective capacity.

Chapter 2: Conceptualizing and Measuring Collective Capacity

Theoretical Foundations

As previously stated, the work of Bhattacharyya (2004) serves as a theoretical foundation for this thesis. Bhattacharyya’s (2004) theory aligns with the emergent model developed by generations of SOMOS students and Professor David Aday (project faculty advisor) through grounded theoretical and ethnographic research in Esfuerzo, Dominican Republic. To keep this project manageable, I have framed the research through the core concepts offered by Bhattacharyya (2004) and I hope to operationalize one dimension of the derived concept of collective capacity as that concept is reflected in Bhattacharyya’s work. Specifically, I will focus on Bhattacharyya’s (2004) characterization of the

---

4 Note that we see this as a form of convergence. The research was oriented by sensitizing concepts and while the research continued, we read from literatures in the field of development, moving first to critical theories and then to theories of participatory development. We connected with Bhattacharyya’s theory and publications by Kapoor (2004) and others about six years into the project’s efforts.

5 Recall the orienting conception of collective capacity as structural arrangements and shared resources for solving collective or public problems and for advancing shared prospects.
importance of interpersonal networks for achieving and advancing solidarity through collective capacity.

I conducted a literature search of all scholarly articles citing Jnanabrata Bhattacharyya’s (2004) publication, “Theorizing Community Development,” and identified 215 articles from Swem Library databases and Google Scholar. Because I am interested in previous studies that have attempted to operationalize Bhattacharyya’s (2004) theories or measure collective capacity, I found a subset of articles largely irrelevant to my investigation, for they merely used the author’s ideas to bolster a theoretical claim. However, the majority of the articles were not purely theoretical in nature. Most involved some form of case study on community development or commented on ways to better define, analyze and understand communities. It is clear that Bhattacharyya’s (2004) piece is well respected in this field, for among the papers that cite him, he is most often cited in discussions of foundational definitions and theories. Nevertheless, almost none of the articles go beyond this point. Bhattacharyya (2004) serves as a fixture in the development literature, he is cited at the outset, almost as if obligatorily, but his work does not pervade the arguments and studies that ensue. None of the publications I found directly attempted to operationalize Bhattacharyya’s (2004) core concept of collective capacity or the component concepts of solidarity, agency, self-help, felt needs and participation within the context of capacity building, although some did take steps in promising directions.

More specifically, Bhattacharyya’s (2004) work is important theoretically because it links mid-range theories about development to classical grand theory about social change via Durkheim’s (in Simpson, 1933) concept of solidarity. Durkheim (in Simpson, 1933) describes social solidarity as the cohesive factor that holds societies together, either
through homogeneity of roles (mechanical solidarity) or through specialized social roles that create mutual interdependence (organic solidarity). Durkheim’s (in Simpson, 1933) conceptualization of solidarity presents a theoretical basis for understanding social change and collective action, arguing that societies require a certain degree of cohesiveness to survive and to navigate change. By applying Durkheim's theory (in Simpson, 1933), Bhattacharyya (2004) characterizes communities in terms of solidarity, rather than in terms of locality, and recognizes the importance of a focus on shared identity in community development. Bhattacharyya (2004) argues for the relevance of social cohesiveness, communication and recognition of shared issues as critical for the promotion of collective action at the community level.

More specifically, Bhattacharyya considers solidarity a “shared identity (derived from place, ideology, or interest) and a code for conduct or norms” (2004:12). Bhattacharyya (2004) views solidarity as a crucially important characteristic of communities or other social units. Solidarity is important to effective community development because it is a foundation of shared norms and connections that ties members together and facilitates collaboration. Collective capacity entails structural arrangements for solving collective or public problems including shared beliefs about what the problems are.

Recall, “solidarity” refers to shared identity and a code of conduct (or norms) about how people are to be related and how they cooperate. One significant study that I identified in my effort to locate empirical indicators of collective capacity and the related concepts is Jaclyn Redekop’s (2013) master’s thesis for the University of Manitoba. The author attempts to define the concept of community and subsequently evaluate a particular
Redekop (2013) cites Bhattacharyya (2004) throughout her thesis (38 times to be exact), and uses his theory to describe the intricate connections between community development, solidarity and agency. For example, Redekop (2013) describes the evolution of the concept of community, which has evolved from definitions based on geographical location to definitions that emphasize structural properties such as solidarity, such as that of Bhattacharyya (2004), that identify social connections, shared values and social support. Solidarity can encourage collective action, according to Redekop (2013), through common interests and greater social cohesion. Agency, the ability to enact self-defined goals or influence a process, is also crucial to social change, and requires ownership of events or processes by community members (Redekop 2013). Redekop (2013) asserts that Bhattacharyya’s definition of community development, “the fostering of social relations that are increasingly characterized by solidarity and agency,” establishes distinct components of development that can be measured, tested and compared (2004: 14). The author goes on to consider self-help, felt needs and participation within the context of community development and uses these as sensitizing concepts for her critical analysis. Redekop (2013) summarizes the ways in which community development can empower communities, foster ownership and promote solidarity and agency in the table shown below (see Table 1).
However, Redekop’s (2013) analysis is descriptive, with no identifiable coding scheme or tests of validity and reliability. This highlights the most salient obstacle in the literature surrounding Bhattacharyya’s (2004) suggestive theory: a lack of empirical measures. Theoretically grounded observation and description as evidenced in Redekop’s (2013) research, are powerful tools, but this study does not take the next steps in testing for reliability and validity. Redekop’s (2013) analysis is conceptually compelling in its consideration of self-help, felt needs and participation, but her observations are not verifiable or easily replicated.

Kate Hall (2010) comes closest to operationalizing Bhattacharyya’s (2004) theory of community development in her thesis for the University of Guelph. In this investigation, Hall (2010) uses theories of community development to consider the potential for municipal organizations to participate in community development planning. Hall’s (2010)
work introduces a conceptual framework for her analysis, using Bhattacharyya’s (2004) theory to elucidate the notions of shared meaning, participation, power and agency. These four factors serve as the analytical lens for the study, with indicators of each clearly laid out by the author. For example, for shared meaning, Hall lists “common language” and “formal and informal communication” as two of the potential indicators (2010: 35).

Bhattacharyya’s (2004) conception sits at the heart of this piece, for the author ties solidarity and agency to conceptualizations of power and asserts the links between participation, self-help and felt-needs. Hall (2010) attempts to operationalize Bhattacharyya’s (2004) core concepts both directly and indirectly. Through focus groups and semi-structured interviews, Hall (2010) gathers data, used to reconstruct stories of past development projects. These transcripts are then coded using the theoretical framework (shared meaning, participation, power and agency) and their respective enumerated indicators, followed by a subsequent round of sub-coding. Several rounds of coding support the consistency of the coding scheme. The product of this analysis is a series of descriptive paragraphs. A complete layout of Hall’s (2010) research design is shown in Table 2, with particular focus on the “data analysis” row of this figure.
This is a step towards more specified empirical measurement, for a clear coding scheme was developed; nevertheless, the analysis does not yield a replicable method for measuring the key concepts. Hall (2010) codes the transcripts herself, searching for instances of shared meaning, power, participation and agency, but without assigning values to these instances. The analysis is descriptive and she does not use a coding scheme that can be replicated or tested for inter-rater reliability. Although the scheme appears well

---

Table 2: Kate Hall Research Design (Hall 2010: 50)
formulated, without testing for consistency or reliability, the value of the author’s conclusions remain uncertain and replication of her work would be difficult.

At the conclusion of the study, Hall (2010) discusses each of the four key concepts from her theoretical framework and ranks their explanatory power for understanding community development planning. Explanatory power refers to the relevance of each factor for describing important roles and practices of communities and municipalities, and their ability to conduct community development planning. These rankings are shown below in Table 3. These rankings consist of describing the concepts as high, moderate or low in terms of explanatory power. Again, the delineations are not tested for reliability or consistency. While factors with high explanatory power may be more important to consider in future investigations, this form of output does not provide a means of measurement that is broadly applicable or verifiable by replication. Moreover, the author mentions collective capacity, but does not draw sufficiently strong ties between Bhattacharyya’s (2004) theory and the measurement of collective capacity. Hall (2010) does not attempt to measure capacity in this study and does not propose any ways in which the measured factors translate to gauge a community’s collective capacity. Hall suggests that “Social networks lead to reciprocity; reciprocity builds trust; trust builds solidarity and solidarity increases the capacity for collective action” (2010: 24) Thus, Hall (2010) asserts the role of solidarity in collective action, but does not return to this concept in her conclusion or use the data to explore this claim.
Important to note as well, is the work of Jackson et al. (2003) in attempting to develop indicators of community capacity through interviews with residents of Toronto neighborhoods. Jackson and her colleagues (2003) sought to understand community experiences and socioenvironmental conditions in four community sites. They asked residents about activities their communities had done together and about factors that assisted or impeded the community from working together. They inquired about skills, talents, strengths and weaknesses of these communities through focus groups. Using a coding framework and content analysis software, the researchers arrived at a set of indicators of collective capacity, shown below in Table 4.

<table>
<thead>
<tr>
<th>Concepts</th>
<th>ROLES</th>
<th>PRACTICES</th>
<th>CAPACITIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHARED MEANING</td>
<td>High</td>
<td>High</td>
<td>Moderate</td>
</tr>
<tr>
<td>PARTICIPATION</td>
<td>Moderate</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>POWER</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>AGENCY</td>
<td>Low</td>
<td>Moderate</td>
<td>High</td>
</tr>
</tbody>
</table>

Table 3: Explanatory Power of Four Concepts in Hall’s Study (Hall 2010: 160)
Examples of indicators from the table include, “residents celebrate together”, “community is welcoming and supportive to diversity” and “people from all parts of the community are involved in community activities” (Jackson et al. 2003: 345). These indicators are instructive in describing collective capacity, but once again, are difficult to compare across time or test for reliability and validity. Such measures and qualitative description surely are important for understanding collective capacity from a multidimensional perspective, but I assert that more precise and replicable indicators and measures can be developed.

I will build upon the works of Redekop (2013), Hall (2010) and Jackson (2003). By utilizing qualitative methods such as those described above, in conjunction with more
quantitative approaches such as social network analysis, I intend to use a mixed methods approach to facilitate measurements that are replicable and can be tested more directly for reliability. I seek to measure a key element of collective capacity, but with greater potential for replicability and the potential to test for reliability. Moreover, by explicitly linking Bhattacharyya’s (2004) claims with collective capacity and using the analysis as a way to operationalize collective capacity, a more empirical approach to describing communities will result.

Defining Key Concepts

Social Networks and Social Networks Analysis

With this theoretical foundation rooted in Bhattacharyya (2004), I will now consider social network analysis (SNA) and foundational definitions for use of SNA methodology. I aim to test the usefulness of network measures as empirical indicators of capacity. I will provide an overview of SNA metrics relevant to understanding collective capacity.

Since its conceptualization in 1932, the study of social networks has developed into a complex field with a wide array of analytical tools for understanding the structures of social interactions (Borgatti et al. 2009). One such tool is SNA. SNA seeks to model interpersonal connections within a community or group of actors by tracking how individuals are connected with each other, creating ties that link actors (Borgatti et al. 2009). As explained by Mitchell et al., the SNA model views a social network as “a specific set of linkages among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behavior of the persons involved” (1969: 2). Interviews and questionnaires, using name-generating
questions, are utilized to create lists of names or entities with whom actors within a network interact, resulting in data that describe interpersonal relationships.

Because clearly defined interview questions are essential for generating network data, research applications can be replicated and observations can be tested for consistency. Social networks can be described quantitatively and qualitatively, with reproducible and broadly applicable methods (Tichy et al. 1979). Moreover, these methods can be utilized to assess change in networks and network characteristics over time. Computer programs such as UCINET have been developed to assist in this process.

Community

Because networks are examined in the context of community here, I require a definition of community. Communities exist both as groups of geographically co-located individuals within delineated boundaries and also as clusters of interpersonal relationships. The interpersonal relationships can be characterized in terms of structural properties. For example, they may be more or less hierarchical, more or less dispersed or aggregated, and more or less durable or transient. One form of interpersonal ties is communication: the sharing of information and expectations.

It would be efficient for current purposes to define community as Bhattacharyya (2004) does. However, he offers a conception only for the purpose of advancing his theoretical point: “We can say that any social configuration that possesses shared identity and norms is a community” (Bhattacharyya, 2004: 12). Because this research is focused on variable rather than categorical distinctions, it will be necessary to refine the definition of community.
Drawing from Aday (2008), I regard communities as clusters of interpersonal ties that have geographic location and identity and that may have socio-political, historical, economic and other shared characteristics. Communities may have more or less fixed, permanent, and permeable boundaries. Those who share community co-location very likely participate also in shared and contested cultures and histories. “Communities cannot be reduced to the individuals that comprise them” because they are distinct from any of the specific individuals and the groups of individuals that exist at any given moment in time (Aday 2008: paragraph 4).

This broad definition of community aligns with that suggested by Minkler, Wallerstein and Wilson (in Glanz et al. 2008). They focus on understanding communities for the purpose of promoting social change and describe ways in which the concept of community has been defined: “functional spatial units, units of social interaction, units of collective identity and social units where people unite to make political changes” (in Glanz et al. 2008: 290). Communities may possess to a greater or lesser degree shared ideals, values, needs (economic and otherwise) and history. Their constituents may face common problems and obstacles and participants may be more or less aware of their commonalities. Sources and origins of collective action have not been described in any empirically systematic way. Therefore, even if participants are aware of common obstacles or share common goals, no common plan of action for overcoming obstacles may follow because coordinated, collective action may require more than common problems.

Communities vary in access to resources, the cohesion among residents, the socio-demography of residents, the extent and nature of interpersonal relationships, the extent of place identification, the extent of shared identity and understandings, and on many other
dimensions. Overall, they are dynamic structural arrangements that change over time in response to a host of both endogenous and exogenous variables.

Collective Capacity

I proposed a broad definition of collective capacity earlier in the thesis: structural arrangements and shared resources for solving collective or public problems and for advancing shared prospects. Goodman et al. (1998) defined collective capacity as a “potential state” that may result in collaboration and collective action within a community. Others have defined capacity as “the set of assets or strengths that residents individually and collectively bring to the cause of improving local quality of life” (Easterling et al. 1998: 12). Diclemente and co-authors note that interpersonal networks are the “foundation for collaboration and coalition building,” and this suggests the link between collective capacity and social networks (2009: 209). The definition proposed and elaborated here points to structural arrangements of patterned social positions and interactions and ordered processes that facilitate conjoined action.

Interactions of diverse kinds affect the ability of people to work together. For the purposes of this research, I will focus on the flow of information and ideas within a community as parts of persisting social networks. Actors within a social network may fulfill roles that involve diverse activities and require knowledge and skills. These activities and social roles associated with them contribute differentially to a community’s collective capacity. Examples might include leadership, technical knowledge, or access to and use of resources. Moreover, such activities may be parts of larger arrangements, such as commerce, banking, education, or politics. And, they may be wholly oriented internally or
they may be linked in important ways to external agents that place communities within a larger context of social interaction (Chaskin et al 2001).

With respect to collective capacity, social networks can be thought of as arrangements that support or promote interaction. For purposes of this thesis, I will focus on a basic form of interaction: communication. More specifically, I will focus on network properties that facilitate or inhibit the flow of information. I assume that communication is necessary to allow the identification and promotion of shared beliefs and collective agreements concerning social problems. Goodman and colleagues (1998) note that building connectedness among individuals and organizations within a community may allow them to better organize and more efficiently address social and health concerns. Consequently, properties of social networks observable through SNA can serve as indicators of the potential for collective action within a community.

This idea is further supported by the work of Hilgartner and Bosk (1988), who offer a social constructionist conception of social problems. Social problems exist as “collective sentiments,” which can only be recognized as such if there is sufficient communication, feedback and synergy amongst members in a community (Hilgartner and Bosk 1988: 53). A condition or situation can only be constructed as a problem if it is framed as such through shared understandings, which are facilitated by interpersonal connections. Different issues within a society compete for recognition, and only some will gain sufficient attention to become social problems (Hilgartner and Bosk 1988). 6

6 The authors also discuss the idea of “carrying capacity,” which is the “limit on the number of social problems that [a society] can entertain at any one time” (Hilgartner and Bosk 1988). This concept is not discussed at length in the thesis, but is mentioned in brief here for completeness. A society’s carrying capacity is too small to accommodate all possible social problems, and thus the public must deem which are worthy of attention.
Network Properties and Collective Capacity

My reading of relevant studies using social networks analysis and some experimentation with those measures with existing data sets led me to identify some promising ways to characterize social networks structures for the purpose of understanding collective capacity. These measures include network density, centralization and average distance.

**Density**

Density is defined as the sum of all dyadic ties present in a community divided by the total number of ties possible (Hanneman & Riddle 2005). This measure thus results in a proportion ranging from 0 to 1 that provides a general sense of interconnectedness within a community. The more ties among individuals, the more likely it is that communications necessary for collaboration and collective action can occur or are occurring, but additional information is needed to draw conclusions with greater specificity. Figure 1 below provides an example of two networks containing the same actors, but differing densities. Figure 1a is denser than figure 1b, because it contains more ties, evident in the gaps seen in figure 1b when compared to 1a.

Here it is important to note the convention of displaying directionality in social network diagrams, for it will be used consistently starting with figure 1. If a social tie is one directional, meaning, for example, that a node shares information with another node but this communication is not reciprocal, this is indicated with an arrowhead at the end of the
tie, showing its direction. This arrow suggests the “flow” of information. If a tie is reciprocal (bidirectional), then an arrowhead is placed at both ends of the social tie. However, if all ties in a network are bidirectional, then no arrowheads are used and it is implicit that all ties are bidirectional. This convention is standard in UCINET. For this reason, some figures (2, 3, 4, 5 and 6) contain no arrowheads and consist of bidirectional ties.

![Network Diagram](image)

(a) Density = 0.767

(b) Density = 0.333

Figure 1: Network Density

Centralization

Centralization helps to elucidate understanding of density, because this measure indicates the extent to which these social ties are organized around particular focal points (Scott 2012). The least centralized network exists when all actors have equal numbers and
types (e.g., bi-directional) of connections to other actors, while a maximally centralized network exists when a single actor is connected to all others, each of whom is not connected to others ("star-shaped network"). Examples of a minimally centralized and maximally centralized network are shown in figure 2. Figure 2a is as decentralized as possible (score of zero) while 2b is as centralized as possible (score of 1). Comparisons of centralization and scoring of centralization will be revisited later in this investigation.

This helps to describe the dispersion of information flow and how inclusive a network is to its members (Kim et al. 2011). This figure also illustrates the network approach taken in this thesis. Centralization of the network as a whole is examined; the perspective of individuals within the network is not the focus in this investigation. Taken together, density and centralization can be used to infer the potential for communications across and throughout a community and the extent to which all members of the community are implicated in this communication. In this regard, density and centralization offer one view of collective capacity of a community. For the current analysis, then, I propose that a
dense social network with minimal centralization indicates greater potential for collective capacity than a highly centralized and sparsely connected network.

**Average Geodesic Distance**

Another potentially useful measure of collective capacity as seen in networks is average geodesic distance, or average distance. The distance between two nodes in a network is the number of vertices or edges (ties), contained in the path that connects the two. Counting the number of vertices between two nodes is synonymous with counting the number of ties between them. The geodesic distance is the shortest possible path to connect two actors, meaning it contains the least number of vertices possible. Geodesic distance is illustrated by figure 3. Consider the distance between nodes A and D. It is possible to connect these two nodes via nodes B and C, which results in a path length of three, because this path traverses three vertices. However, it is also possible for node A to reach node D with a path length of two, via node E. Thus, the geodesic distance between nodes A and D is two, because this is the shortest possible path, even though alternative paths exist. The geodesic distance between A and C is two, by comparison.

![Figure 3: Geodesic Distance](image)
By generalizing this measure to an entire social network, the average distance can be defined as the average path length required by any actor in a network to reach any other connected actor. Average distance is an instructive measure because actors separated by greater amounts of social distance have less direct ties and information flow is thus dependent on more actors or nodes. When distances are large, communications may be inhibited by time and the number of connections needed to complete linkages. There also likely will be issues of information reliability as it is transmitted across multiple connections. (The old party game of “telephone” illustrates this point.) As discussed above, information sharing is essential for recognition of shared problems and thus a lower average distance may indicate greater potential for organizing inclusively around community concerns. There is a relationship between network density and average distance: In more dense social networks, average distance tends to decline, because such networks are better connected as a whole (Hanneman & Riddle 2005).

Betweenness Centrality

It is also important to consider clusters of communication in a social network, as well as the links across clusters. An isolated but tightly connected group of individuals would not contribute to collective capacity if these individuals were not in communication with the rest of the community. Thus, individuals who act as “bridgers” by connecting different cliques in a social network play essential roles in facilitating the flow of

---

7 Note that I am considering only information flow here and not other aspects of interpersonal connections or communications. The reference to “reliability” is used here only for brief illustration. This point will be discussed more fully later in the thesis.
8 The term “clique” is used here to refer to regions of communication in a social network that are more highly connected in comparison to other regions of the network. Cliques can be thought of as clusters of communication. This is a less stringent definition of a clique than used by most social network analysis programs (i.e. groups with maximal connectivity).
information. These “bridgers” can be identified using visual outputs of SNA maps or calculating the betweenness centrality of each individual in the community, which measures how often an actor in a network is likely to be a point of connection between two other members in the network. With regard to information, this suggests that some individuals within a community and network arrangement might serve as “relay points”. In general, betweenness centrality is an egocentric measure (focused on single individuals rather than on network properties) and thus would not prove useful as a direct measure of collective capacity. However, application of this tool in conjunction with visual outputs allows for a descriptive understanding of how dependent a social network is on specific nodes (or, individuals) for information flow. Figure 4 below shows examples of two networks in which node C has differing amounts of betweenness centrality. In figure 4a, node C serves as a relay point for communication across the network and thus has high betweenness (value of 6). In contrast, in figure 4b, node C is no longer a key relay point and thus its betweenness score decreases to 1.33.
The above discussion suggests the outline of network characteristics that would promote and support collective action. The analyses that follow reflect the methodology of important network parameters included other measures that proved to not be as instructive as anticipated in measuring collective capacity. One such measure was analysis of cliques within social networks. A clique is defined as “a sub-set of points in which every possible pair of points is directly connected” by a social tie (Scott 2012). Clique analysis seemed worthwhile, because as stated by Hanneman and Riddle (2005), “differences in the ways that individuals are embedded in the structure of groups within a network can have profound consequences for the ways that these actors see their ‘society,’ and the behaviors that they are likely to practice” (ch. 11, paragraph 4). I proposed that because a clique cannot be contained within another clique (this is part of the definition), the number of cliques that exist indicates a meaningful measure of clusters of communication and that an

Figure 4: Betweenness Examples

Social Networks and Collective Capacity as Communications Flow: An Ideal Type

(a) Node C Betweenness = 6

(b) Node C Betweenness = 1.33
an “ideal type” as described by Max Weber (1949). Weber’s ideal type envisions a “conceptual” model that is not a “true” reality, but rather synthesizes relevant phenomena to create a “unified analytical construct” (1949: 112). The ideal type is not intended to describe an existing reality, but is rather a methodological tool for creating a conceptually clear model that can be used to understand real situations (Segady 2014). The ideal type is used to “increasingly clarify the changes that occur” in the phenomena of interest (Segady 2014: 358). Ideal types themselves are not predictive of change and are not intended to be reified as reality, but rather must identify “empirical referents” that it can assist in explaining (Segady 2014: 359).

In the following analysis, I will describe the structure of a social network I propose to be optimal for promoting collective capacity based on the potential for information flow, an ideal type of sorts. It is unlikely that such an elegant and carefully organized social network exists in a real community, but rather this ideal type serves as a referent that I will be able to apply to real data. With this ideal type, I will manipulate data from a real social network to illustrate these ideal characteristics and observe measurable differences produced by these manipulations.

As noted, for the purposes of exploring enabling social network structure, I will focus on information sharing. It is likely that the content of information shared via social networks matters. However, for current purposes, I will focus only on who is connected with whom and, thus, who can share information. Drawing from Hilgartner and Bosk
I argued that shared beliefs about a problem and shared beliefs about the ability to address the problem are necessary preconditions for constructing social problems. Theoretically, if members of a community cannot or do not share information then collective action cannot occur.

I begin this more detailed analyses of social networks with an idea put forth by Marwell et al. (1988), who after using hypothetical social network data and mathematical modeling, arrive at a keen discernment about ties in social networks:

We may draw out some of the implications of our analysis by considering its relation to Granovetter’s (1973) important and frequently cited analysis of the effects of strong and weak ties. Granovetter argues that strong ties tend to form cliques, while weak ties tend to bridge cliques and bring everyone into the same network, so that weak ties are a better basis for collective action. The imagery of this argument suggests that decentralized nets and centralized wheels of weak ties would be equally effective network structures for collective action. Our results imply that it is not weak ties, per se, that are useful but their tendency to be centralized. Residents who are all bridged by the same weak tie-to a parish priest, for example-are more likely to be mobilized than those linked by the same number of weak ties distributed more widely through cross-cutting associational memberships (Marwell et al. 1988: 531).

Assuming Granovetter (1973) and Marwell et al. (1988) are correct, groups connected through centralized weak ties would be successful in organizing collective action because this arrangement promotes attainment of the critical mass of support needed to initiate a community project. On the other hand, more decentralized networks may facilitate wider information sharing, because information is not consolidated at single individuals who broker the sharing of information to others. In this way, more two-directional exchanges may occur, which allow for greater flow of information than one-directional communication. Such arrangements would tend to promote collective action.

Weak ties involve less time investment, intensity, trust or reciprocity (this list is not exhaustive) than strong ties. Tie strength is discussed in greater detail below.
and thus may be a factor that is sufficient for collective capacity, but not necessary to it. It is likely that other possible network arrangements function to promote capacity in different ways.

Assuming equal densities, the more decentralized a network, the more widely dispersed are ties in the network. Recall that density is defined as the sum of all dyadic ties present in a community divided by the total number of ties possible (Hanneman & Riddle 2005). A decentralized network does not rely on ties to a single node and thus information is shared through more ties to different actors – as noted, given equal densities. Fewer nodes center their communication on any one other node and thus information travels in a more dispersed manner. It is likely that upper and lower thresholds exist for the benefit of centralized weak ties. A completely decentralized arrangement of weak ties would scatter information across a network in a manner that may not promote information flow productive for consensus or traversing greater distances in the network. Conversely, a completely centralized arrangement of weak ties may focus communication too heavily on specific individuals to allow for information to reach a sufficient number of individuals in the network for collective action to be achieved. Thus, a balance between the characteristics of centralized networks and decentralized networks has advantages for both information sharing and mobilization (i.e., through the organizational power of a network).

Centralization is calculated by comparing a given network to the most centrally organized network possible, a star shaped network, expressed as a percentage. This is represented by the following equation: \( C_D = \frac{\sum_{i=1}^{n} [C_D(n^*) - C_D(i)]}{[(N-1)(N-2)]} \), in which \( n^* \) represents the largest degree found in the network (degree is the number of ties one node has to another
node), \( N \) represents the number of nodes in the network, \( i \) represents the degree of any given node and \( C_D \) represents degree centralization, also simply referred to as centralization. The denominator of this equation models the ties present in a star shaped network while the numerator represents the ties in the network of interest. Thus a ratio of these two values produces a percentage value of how centralized a network is compared to a star-shaped network. Centralization is scored from zero to one (or 0% to 100%), with one being the most centralized network possible and zero being least centralized. To illustrate this, figure 5 exemplifies four potential arrangements for five actors in a network. These different arrangements reflect varying amounts of centralization, specifically showing maximum, minimum and intermediate levels of centralization. These networks have different implications for information flow, for some depend on central actors more than others to mediate information flow to other nodes in the network.

Figure 5a models a network that is the least centralized possible and thus receives a score of zero. In this ring-shaped network, there is no central actor and all nodes are equally tied to other nodes. It is useful to note that the ring-shaped network contains one more tie than the other three networks shown, and is used here only to demonstrate a completely non-centralized network. Its density is not meant to be compared to the other arrangements. Figure 5b is as centralized as possible, with a centralization score of one. It is known as a star-shaped network. In this scenario, all actors are tied to a central node and to no other nodes. Lastly, figures 5b and 5c show networks that are intermediate in centralization. One actor is or more actors are more central than the others, but the maximum centralization is not realized. These networks have centralization scores of 0.583 and 0.083, respectively. Across figures 5b, 5c and 5d, density is held constant, because each
of these networks contain five nodes and four ties, but centralization is altered by rearranging the positioning of these four ties.

![Network diagrams](image)

(a) centralization = 0 (0%)
Density = 0.50

(b) centralization = 1.0 (100%)
Density = 0.40

(c) centralization = 0.583 (58.3%)
Density = 0.40

(d) centralization = 0.083 (8.3%)
Density = 0.40

**Figure 5: Network Centralization Comparison**

Marwell et al. (1988) also highlight the distinction between strong and weak ties. Granovetter (1973) posits that the strength of a tie is determined by a “combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie” (Granovetter 1973). Granovetter’s (1973) description of tie strength is theoretically interesting but it may not be an exhaustive cataloguing of relevant tie properties. It serves as a basis for further development. Examples of other factors that may require consideration are trust, familial relation, personal compatibility and past interactions (Burt 2000, McPherson et al. 2001, Popielarz & McPherson 1995). It
may not be possible to combine these factors in the way that Granovetter (1973) proposes, but these factors do seem relevant to tie strength to some extent. Granovetter (1973) notes that while strong ties indicate more frequent communication between two individuals, the individuals within a clique tend to share the same strong ties amongst each other, creating relatively closed loops of communication. 11

Strong ties do not tend to bridge different social circles. Weaker ties appear to make connections among individuals outside of close social circles. Such relationships may include acquaintances, co-workers or individuals who communicate with less regularity or intensity compared to strong ties (Granovetter 1973). Initial analyses suggest that geodesic distance may be a useful structural measure for describing variations of interest in Granovetter's (1973) work. Geodesic distance is the shortest possible path between two actors, in terms of number of nodes between them (Hanneman & Riddle 2005). Weak ties often bridge actors who otherwise are separated by many social ties, represented by greater path length (number of vertices or edges) in a social network diagram. This is exemplified by figure 6. Consider nodes B and F, indicated by red circles. These two nodes are separated by a distance of one, for they are directly connected to one another. The tie between them can be considered a weak tie, because it bridges the social cluster that node B belongs to (with A, C, D and E) and the cluster that node F belongs to (with G and H). If it were to be removed, a path length of eight would separate B and F. Granovetter describes the relevance of weak ties as “local bridges” that create “more and shorter paths” between actors in a network (1973: 1365). We can see how this is described using geodesic distance

11 Recall that the subtleties of strength of ties is not considered directly in this thesis, which focuses exclusively on the potential for information flow.
in figure 6. The removal of a weak tie would thus result in reduced transmission of information between actors who are distant in terms of geodesic distance without the existence of the bridging, weak tie. A community without weak ties that bridge its cliques exists as a “fragmented” structure, with little potential for community-wide collective action. Thus, an ideal

---

12 It is important to note that geographic distance is not implicit within the definition of geodesic distance. Some social ties may traverse greater physical distance than others, but strong or weak ties do not necessarily span different physical distances. In some settings physical distance may not matter, because of technology and social media, while it may be more important in others. This thesis focuses on geodesic distance, meaning distance within networks and social space and does not examine physical parameters of distance.

13 This discussion will continue to focus on the role that weak ties play in serving as bridges. Other aspects of strong and weak ties that Granovetter (1973) suggests, such as intimacy and intensity, will not be further
network has advantages in including arrangements of bridging weak ties to promote the flow of information across all areas of the community (Granovetter 1973). As suggested by Granovetter (1973), weak ties are important for this thesis because they serve as bridges. As shown below in figure 7, bridging ties, or weak ties, link four different social clusters (weak ties indicated by red arrows numbered 1-4). If one of these weak ties were removed, the geodesic distance between many actors in the network would drastically increase and information flow would be impeded. The average path length between an arbitrary pair of points is lowered through weak ties, making communication possible across this social network. Strong ties can also reduce distance in a network, but average distance is more greatly impacted by the presence of weak ties. To illustrate this, in the example provided, the average geodesic distance between any two actors is 2.912. With the removal of weak tie one, the average distance increases to 3.640. Similarly, the removal of tie two from the original network increases the average distance to 3.331. The removal of tie three increases average distance to 3.904 and the removal of tie four increases the distance to 3.588. Hence each of these four ties is essential in information flow across this imagined community, because removal of any of these ties increases distance between members in the network significantly. For reference, the removal of a tie that is not a weak tie, such as tie number five (indicated by the black arrow), increases average distance from to 2.912 to 2.919. Such a change is marginal compared to the aforementioned weak ties.

pursued, for it is unclear how they should be defined or measured and how they may be as relevant for collective action.
Combining these insights from Granovetter (1973) and Marwell (1988), it seems that strong ties within cliques promote flow of information, and thus, communication. As noted earlier, a clique refers to a cluster of individuals with greater interconnectedness amongst themselves than with others outside the group. Cliques with strong ties promote within-clique communications. Such connections are relevant for facilitating information flow, and thus, collective capacity. But by themselves, strong ties would not necessarily facilitate collective action at the community level because they might not enable dispersion of information across cliques. As mentioned above, ties that act as bridgers are considered weak ties, and thus centralized arrangements with weak ties that bridge cliques better enable communications across the community. Flow of information across cliques enables

---

14 According to Granovetter, “all bridges are weak ties” (Granovetter 1973: 1364).
collaborations among cliques. Thus, each clique would include strong internal ties and also include weak ties that bridge it to other cliques.

Following the logic of Marwell et al. (1988), weak ties should be centralized by ties to strong tie networks with specific focal points, such as a neighborhood organizer or pastor. These individuals linked by weak ties need not bear formal roles, such as the example of a pastor, but could function in arrangements at the organizing level. For instance, a social arrangement in which weak ties across strong-tie cliques are to nodes that have average or above-average number of ties within the strong-tie cliques would facilitate information dispersion. This structure does not imply intention or deliberate organizing. It is a theoretical description of what seems implied by the concept of collective capacity.

Figure 8 below is an example of such an arrangement, in which overlapping social ties bridge two cliques. In this way, the centralized weak ties allow the “bridger” from a different clique to effectively share information with members of the first clique and potentially spark collective action. Similarly, this “bridger” can utilize strong ties within his/her clique to share new information received via these weak ties. In summary, weak ties create bridges across tightly knit social clusters in a network while strong ties enable more frequent dissemination of information to co-members of a strong-tie clique or social cluster. This suggests the image of interlocking cliques, with links across cliques consisting of centralized weak ties to key nodes or representatives in each clique, and strong decentralized ties internally amongst the members of each clique.
Experimental Manipulation of Network Properties

I will now manipulate the parameters of density and centralization in figure 8 and examine the consequences, to better illustrate their significance. I begin by arbitrarily reducing the number of ties in the network by removing links between eight nodes, thus decreasing network density and creating a sparser network. This network is shown below in figure 9. Note that while density has decreased, centralization is not drastically changed and actually has decreased slightly. Thus density and centralization are not dependent necessarily upon one another. The average distance in this network also has increased, because many pathways for communication no longer exist. Next, I have reduced again the number of ties in the original network by eight, but removed specific ties to create both a highly centralized and sparse (not dense) network. This is shown in figure 10. In this scenario, density is again reduced to 0.200, but centralization has greatly increased due to the focused arrangement of the ties. It is also important to consider that figure 10 possesses a smaller average distance than figure 9, because the centralized arrangement creates more efficient (shorter) paths between all actors in the network. Efficiency will be discussed in greater detail below.
This concept of strong internal ties within a clique and strategic weak ties across a community is supported also by literature concerning organizational dynamics. Individuals who leave a clique (whether of strong ties or mixed strong and weak ties) and thus vacate their role within that group, either by joining a different one or by leaving the community altogether, create small disruptions in social networks. Such events may eliminate paths of communication among individuals who were not linked any other way. This role must be filled in order for the existing organizational arrangement to continue to function. It is essential to note that it is not the identities of the specific individuals that are important
here, but rather the roles that they fill at an organizational and structural level. The individuals in a social network may change while roles remain constant. Thus, group turnover (loss of members and arrival of new ones) potentially can be disruptive of information flow if new individuals do not fill vacated roles. In the most sustainable social network for promoting collective action, established roles remain filled and are quickly refilled when group turnover occurs\textsuperscript{15,16}.

Moreover, the parameter of network density should also be considered more extensively. As previously discussed, density is defined as the sum of all dyadic ties (ties between two nodes) present in a community divided by the total number of ties possible (Hanneman & Riddle 2005). The maximum number of potential connections is calculated by the formula $PC = \frac{n(n-1)}{2}$, where $n$ is the number of actors in the network. To illustrate this numerically, consider a network of six individuals, with three ties. The maximum number of potential connections would be $\frac{6(6-1)}{2} = 15$. Thus, the ratio of actual ties to potential ties produces a ratio of $\frac{3}{15}$ and a density of 0.2. A dense social network thus has a large number of social ties and more paths for potential communication than less dense networks. Because I theorize that communication is essential for recognition of shared

\textsuperscript{15} A more lengthy discussion of group turnover is omitted from this discussion to maintain clarity of the argument. It is assumed that network characteristics will be compared while holding constant relative mobility/transience. Generally, more ties within a group reduce group turnover while ties to external actors may increase turnover. For greater detail, I defer to the work of McPherson et al. (1992) and Popielarz & McPherson (1995).

\textsuperscript{16} Duration or persistence of a social cluster is another variable that will not be investigated in this thesis but is important to consider. McPherson et al. (1992) note that because strong ties bind two individuals more tightly, they should increase the probability of group participation and ultimately prolong group membership. Ties that are strong in reciprocity and foster frequent communication are most relevant to this investigation. Merging notions of collective capacity with organizational dynamics, it seems reasonable that all other network characteristics being equal, a clique of ties with greater frequency and reciprocity in communication will persist longer than groups that are similar but in which, participants don't communicate regularly. This assertion is one of interest, but is not given greater consideration for this study.
problems and social issues (following Hilgartner & Bosk, 1988), density facilitates collective capacity. Although density ranges from zero to one computationally, it is reasonable to assume that communities of any size would not reach a density of one. Consider an example of 90 households with two adult members per household. The total possible ties among adults is \((180 \times 179)/2 = 16,110\). What is the realistic possibility of more than 16,000 ties given the limits of time and resources for investing in and maintaining social connections, as suggested by sociologist John Scott (2013)? Thus, in actuality the maximum density of a social network is theorized to be near 0.5 (Mayhew & Levinger 1976). There seem to be no intrinsic downsides to a dense social network, and thus, realistically, a social network with a density of or approaching 0.5 would be optimal for collective capacity.

To synthesize each of these components into one description, a model social network for enabling and advancing collective capacity would be dense, contain decentralized strong social ties within cliques and centralized weak ties to “organizers” in other cliques, and exhibit limited membership turnover. This arrangement would facilitate inclusive communication that is capable of achieving sufficient support for collective action, while acknowledging that individuals have limited time for maintaining strong social ties and cannot be strongly tied to every community member.

There are limitations to assessing the described model. For example, consider the distinction between efficiency and effectiveness. I use “efficiency” in this context to refer to the ease with which information can flow through a network. There are many other structural properties that are assessed in the literature, such as reliability or predictability, but for the time being this study will focus on how likely information is to flow through a
network. An efficient network is direct, in that information travels throughout the network via cliques and bridgers. In such arrangements, there are fewer “isolates” (individuals left out of the communications). In addition, information is communicated through fewer “middlemen” or roundabout paths of social ties to link specific actors, meaning geodesic distance between actors is small. Efficient networks optimize the ease of information flow, but is it possible that some arrangements of efficient networks may not promote collective action? Based on the network measures described above, it appears that this would be the case, that efficiency must be considered in conjunction with the “effectiveness” of these networks in fostering collective action.

I use the term “effectiveness” to refer to factors that promote collective action, such as how inclusive information flow is to network members and how well information reflects and promotes shared beliefs of all community members. It is possible that the ideal network parameters I have described above are indicators of such factors, although this will not be explored in this thesis. The described ideal network balances efficiency and effectiveness, because it considers elements such as communication across cliques and network density, which promote inclusivity and sustainability. Other networks exist that may be more efficient. For example, a highly centralized network in which all individuals communicate with a central actor could be a more efficient manner for accomplishing a task, because all information is consolidated at one point. This individual could then allocate resources and tasks among others and serve as the leader of the proposed projects.

17 In this realm, there are unanswered questions, such as how information changes as it travels from person to person or if different types of information are more likely to travel faster than others. The existing literature does not provide answers to these questions, so such ambiguities must be kept in mind as this investigation seeks empirical answers.
or endeavors. However, this network arrangement might exclude marginalized members of the community or favor majority opinions while excluding community members from processes that promote and sustain solidarity. Recall that Bhattacharyya emphasized inclusive participation as a key element of development centered on solidarity. The proposed ideal network is centered on optimizing the potential for inclusive collective action, while other more efficiently arranged networks may diminish inclusiveness in preferring efficiency.

**Analysis of SOMOS and MANOS Data**

The SOMOS Data

In transitioning to analysis of data sets from existing social networks, I must make a concession to the theoretical outline described above. As previously described, my analysis focuses on the flow of information and social arrangements that promote collective capacity through sharing of information. For this reason, it will not be feasible to simultaneously examine strength of social ties in addition to the structural features of the networks. Thus, I will focus on relatively raw and crude data sets that lack information on tie strength – in part because the communities that were studied displayed little evidence of developed interpersonal networks. Accordingly, this analysis will not make assertions about the strengths of social ties within these networks. Granovetter (1973) and Marwell (1988) make interesting and important propositions about the role of tie strength in interpersonal communication, but further consideration of these factors would complicate my investigation because the analyses of tie strength are incomplete and suggestive rather than definitive.
During the summer of 2009, the SOMOS team conducted SNA interviews in a small, marginalized community in the Dominican Republic. The team attempted to interview as many people as possible, to attain a population for this community. At least one representative from each household was interviewed, and accordingly, this may be regarded as a population of households. However, it was not clear then and is still not clear what the relevant population should be for this analysis: a population of adults, of men, of women, or of households with single respondents? During these interviews, the “name-generating” question that was asked is translated from Spanish as “With whom in your community would you want to work on a project to improve the health of your community?” This question was followed by “Which of these people do you trust?” Interviews were conducted with 99 individuals. In total, those interviewed plus those named produced a list of 125 individuals.

For this analysis, I have chosen to work with the SNA matrix produced by the follow up question listed above “Which of these people do you trust?” I have chosen this data set because the question asks about trust, which is an essential component of interpersonal relationships that promotes the flow of information. It seems reasonable that community members are more likely to communicate with those whom they trust relative to those whom they do not trust, thus allowing for information flow to trusted co-members in the network (Granovetter 1973). This question is preferable to the previous one, inquiring with whom community members would like to work, because desire to work with fellow residents does not imply information flow to the same extent that trust does. Still, it is fair

---

18 This is the effective phrasing of the question. On the survey given to community members, this question was preceded by a question asking about interest in working on projects to improve community health, which impacted the specific phrasing of the following question.
to note that the name generating question and the “population” are not ideal for network analysis. The SOMOS team was focused more on finding ways to partner effectively than on the rigor of the method. For the following analyses, I have converted the names of individuals to numbers to ensure anonymity of those who participated in the study.

I began first with a visualization of the raw data set, shown below in figure 11. Note the large number of isolates along the left side of the figure as well as the three clusters of individuals that are not connected to the main portion of the graph. It is also evident that certain nodes within the network are more central than others and thus, may exhibit greater betweenness centrality.

Figure 11: Original Social Network Graph
Upon examining the graph visually and seeing the key nodes that were focal points of communication, I decided to run a betweenness centrality analysis on the network, to identify the nodes that exhibited the greatest levels. Six nodes emerged as those with the highest scores, which can be predicted by the graphic representation. Further examination revealed that these six nodes were not connected completely to one another and thus I made my first experimental manipulation by connecting these six central nodes to one another via reciprocal social ties (14 new ties, if each direction counts as one tie). By connecting those actors with the highest betweenness scores, it is likely that overall average geodesic distance will be reduced, which is one theorized ideal characteristic for collective capacity. This first iteration of a manipulated data set with a more idealized structure is shown below in figure 12. This network looks almost identical to the original because so few changes were made, but structurally it differs in important ways that will be considered further below.
Next, I created a network that built upon the previous. In this second iteration, in addition to connecting the 6 main actors in the network bi-directionally I also connected one actor from each isolated social cluster (called a component) to one of the six main actors, in order to integrate these components into the flow of information in the network. Namely, nodes 35, 61 and 110 were connected to main actor 71 (addition of six new ties from the first manipulation). Node 71 was chosen as the actor to connect with these

---

It is important to note that the description of the analysis provided here may present a more linear process than occurred. Several other iterations of the original network were created before arriving at the second and third networks discussed in the thesis, but are omitted because they did not yield results different from those included or did not provide additional insight into the characteristics of interest.

As defined by Hanneman and Riddle (2005), components of a network graph are "sub-graphs that are connected within, but disconnected between subgraphs" (ch. 11, para. 49)
components because it has the smallest degree (number of ties to other nodes) of the six main actors and thus does not reinforce further centralization of communication on the nodes with the greatest number of connections. This network arrangement increases inclusive communication that may foster consensus for collective action, by seeking to reduce distance between actors and include isolated components into the main component of the network. This second iteration of the ideal network is shown below in figure 13.

Figure 13: Connecting Components to Central Nodes to Increase Inclusiveness

As is evident in figure 13, although the main component of the network is well connected, there are many nodes on the left side of the network that are not connected to
any other actors. To fully optimize information flow in the network, these isolates must also be connected. To do so, I created a third iteration of this idealized social network. In this iteration I began by connecting the six main actors bi-directionally (as in the first iteration) and connecting one actor from each isolated component to one of the six key actors in the main component, as done before. I then divided the isolates into six equal groups (36 isolates results in 6 groups of 6) and connected the actors in each group to one of the six central nodes. All ties made were bidirectional, because two-directional ties allow for greater flow of information than one-directional ties (57 new ties compared to second manipulation). Connecting all of the isolates to actors in the network eliminates complete isolation of any node from the network and thus results in the most inclusive of the three network iterations. This network may be most appropriate structurally of the three for promoting collective capacity, for it attempts to reduce average distance, reduce disconnectedness among components/isolates, increase density by increasing number of ties and does not centralize new social ties to only one or two individuals. This network is shown below in figure 14.
After constructing these three iterations of the original network, I ran statistical analyses in UCINET to determine if the changes made to the original network could be detected computationally with reasonable clarity. These statistics included those previously discussed (density, average distance and centralization), as well as others that I did not discover until experimentally manipulating the networks and being dissatisfied with the three original measures to accurately reflect changes in the networks. These
additional network measures will be discussed below, with descriptions of the insight they add to this investigation. All of the discussed measures were applied to the original network and then to each of the three iterations. The results of these calculations are shown below in table 5, with a focus on the first three measures shown at this point.

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Original Network</th>
<th>Manipulation 1</th>
<th>Manipulation 2</th>
<th>Manipulation 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>0.011</td>
<td>0.012</td>
<td>0.013</td>
<td>0.017</td>
</tr>
<tr>
<td>Centralization</td>
<td>0.154</td>
<td>0.153</td>
<td>0.152</td>
<td>0.212</td>
</tr>
<tr>
<td>Average Distance</td>
<td>3.103</td>
<td>2.822</td>
<td>2.991</td>
<td>3.266</td>
</tr>
<tr>
<td>Breadth</td>
<td>0.961</td>
<td>0.956</td>
<td>0.941</td>
<td>0.841</td>
</tr>
<tr>
<td>Connectedness</td>
<td>0.095</td>
<td>0.1</td>
<td>0.147</td>
<td>0.449</td>
</tr>
<tr>
<td>Fragmentation</td>
<td>0.905</td>
<td>0.900</td>
<td>0.853</td>
<td>0.551</td>
</tr>
<tr>
<td>Component Ratio</td>
<td>0.892</td>
<td>0.883</td>
<td>0.856</td>
<td>0.55</td>
</tr>
</tbody>
</table>

Table 5: Network Calculations

It is clear that density does not change substantially across the iterations, even though social clusters are being connected and important actors are being tied to one another. This is because relative to the number of possible social ties in the network, the number of new connections is small. For this reason, the proportion of existing ties to possible ties does not change substantially. Even with the addition of 36 bidirectional ties to all of the isolates in the third iteration, density only increases by 0.006 compared to the original network. Thus, density proves to be a relatively insensitive measure of change over time, although at a single time point it is helpful in understanding how well connected a network is.
Centralization remains fairly constant across the networks. Comparing the original network, the first iteration and the second iteration, the centralization score fluctuates only by 0.002. Such a small change does not suggest a meaningful shift in centralization with the given network manipulations. In the third iteration, centralization increases by 0.058 compared to the original network. While this change is more substantial, it occurs only with the addition of a significant number of new ties. This increased centralization suggests more connections to the six main actors in the network, which facilitates greater interconnectedness in the network. But, overall, centralization is not a measure sensitive to change over time.

Next, average distance displays an inconsistent trend in the manipulations. From the original network to the first iteration, average distance decreases by 0.281. This change is predictable, because by connecting the six actors with high betweenness centrality, all those who are connected to these main actors may now have shorter communication paths to other network members (smaller distance is understood as beneficial for communication). However, the average distance calculation does not account for nodes that have no connections to one another. Thus, in the second network iteration, which ties in the three isolated components on the periphery of the network, average distance increases by 0.169 compared to the first iteration. Even though the network has become more inclusive, the addition of the new components to the average distance calculation drives the value up. Similarly, in the third iteration, average distance increases by 0.163 compared to the original network. The average distance calculation thus proves to be misleading, because changes beneficial for information flow in the network are not accurately reflected in changes in average distance. As the network becomes more inclusive
(connection to components and isolates), average distance increases, thus not capturing this beneficial change in network structure. The concept behind average distance is useful, but this particular method of calculating distance must be resolved with an alternative that can account for changes in isolates and isolated components.

Although these measures were selected with sound reasoning and theory, density, centralization and average distance considered individually did not exhibit clear trends that show the desired ability to measure changes in capacity over time. For this reason, I next examined additional measures to enhance and detect network differences with greater sensitivity. It was not until conducting the analysis of these three original measures that it became apparent that new measures would be necessary to track changes in capacity that are suggested by the orienting theory. The three measures of density, centralization and average distance proved helpful but incomplete in characterizing an ideal social network, for my analysis of the SOMOS data set revealed that they are limited in detecting changes in network structure. Thus, I returned to the statistical measures available in UCINET and sought to locate measures that build upon the initial three, but detect more subtle variations overcome limitations of the original measure. The selection of these additional measures was done using the same theoretical basis as discussed above, with the aim of characterizing information flow in a social network.

I next considered an alternative or complement to measuring average distance called breadth. The measurement of average distance is useful for understanding the ease with which information may flow in a social network. However, average distance is limited by the fact that this calculation does not include those who are not connected to nodes in the network (isolates and isolated components). For this reason, it is possible for a network
to contain many isolates but still have a low average distance score even though a network of this sort would not be effective at fostering inclusive and collaborative communication. Moreover, average distance is limited in its ability to detect change over time. This is because if isolates in the original network at time 1 become connected to other nodes in time 2, these connections may actually increase average distance in the time 2 network, even though the network has become more inclusive. Thus, a comparison of average distance in these two networks would not reflect beneficial changes that have occurred.

Breadth is an alternative measure to average distance that allows for the inclusion of isolates and those who are at the end of one-directional ties and thus do not communicate with anyone else in the network. Breadth is calculated by taking the reciprocal of valid distances between nodes in a social network and assigning zeroes to invalid distances (isolates and those not connected to any other nodes). Breadth is an inverse measure of social cohesion, meaning that smaller values indicate greater social connectedness. Breadth offers a more nuanced measure than average distance because all nodes in a network, whether isolated or not, are included in the calculation. It measures the same network characteristic as average distance, but in a way that will more accurately detect changes over time, particularly if a network becomes more inclusive to isolates.

Next, I examined a measure that offers additional insight compared to a simple calculation of network density, called the component ratio. The measurement of network density is useful for obtaining a snapshot of how well connected a social network is, in terms of existing social ties compared to the number of ties possible. However, a weakness

---

21 Breadth is calculated by $B = 1 - \frac{\sum_{i,j} d_{ij}^{-1}}{n(n-1)}$, where $d_{ij}$ is the geodesic distance from $i$ to $j$ and $n$ is the number of nodes in the network.
of the density calculation is that it does not account for the broader structure of a social network. For example, if a social network exists as two distinct parts that are densely connected, but these parts are not well connected, density will be high but information flow is likely not occurring across the network. Another limitation of density is that it is relatively insensitive to even relatively large increases in ties. Because the number of possible social ties in a network is large, the ratio of existing to possible ties (density) is insensitive to change over time.

The component ratio utilizes the number and size of components (distinct regions of a network that are not connected to one another) to produce a measurement of social cohesion. By taking a ratio of the number of components over the number of nodes, it measures the extent to which connections exist across social clusters in a network. This normalized measure ranges from zero to one, with a score of one indicating that every node is an isolate and a score of zero indicating that there is just one component in the network. This is an inverse measure, because lower scores suggest greater social cohesion and connectedness. Component ratio adds greater nuance to the measurement of density because this number changes more perceptibly as the number of components decreases in network and as the number of ties increases. Component ratio still provides a gauge on potential for information flow in the way similar to density, but incorporates measurement of information flow across components and is more sensitive to change over time.

Thirdly, the network measures previously discussed do not fully capture changes in the number of isolates and changes in the number of nodes able to communicate with one

---

22 Component ratio is calculated by the equation $CR = \frac{c-1}{n-1}$, where $c$ is the number of components and $n$ is the number of nodes in the graph.
The measures of fragmentation and connectedness allow this to be done with greater clarity. Fragmentation is the proportion of pairs of nodes in a social network that cannot reach each other. Fragmentation ranges from zero to one. Conversely, connectedness is the proportion of pairs of nodes that can reach each other and thus also ranges from zero to one. A high connectedness score and a low fragmentation score suggest greater social cohesion. These two measurements indicate the same aspect of a social network, just in opposite terms.23

Fragmentation/connectedness are useful measures for detecting changes in social networks over time because these measures are sensitive to changes in the inclusiveness of a network, which may foster collaborative dialogue. While other measures such as average distance may change in ways perceived as negative for collective capacity when isolates are included into a network or components become connected, fragmentation/connectedness will accurately detect these changes and thus add a more nuanced understanding to change over time.

These four new measures (component ratio, breadth, connectedness and fragmentation) will now be applied to the experimental manipulations of the SOMOS-generated network. Recall that these values are shown in table 5. In comparison to density, centralization and average distance, these measures show greater sensitivity in detecting change in collective capacity.

\[ F = 1 - \frac{\sum_{i,j} r_{ij}}{n (n-1)} \]

where \( r_{ij} \) is 1 if nodes i and j are in the same component and zero if they are not. Also, \( \text{fragmentation} = 1 - \text{connectedness} \). Thus a network with a fragmentation score of 0.9 has a connectedness score of 0.1.
While density did not change greatly across the iterations, the component ratio (alternative measure to density) does exhibit significant changes across the network iterations. The component ratio decreases by 0.009, 0.036 and 0.342 across the three network iterations respectively, when compared to the original network. Even after only the first network iteration, the component ratio changes more than density did across any of the networks. Because component ratio is an inverse measure, this trend in decreasing component ratio implies greater interconnectedness among regions of the social network and thus, greater potential for information flow to all network members. Component ratio is more sensitive to change over time than density and is more indicative of changes in collective capacity because of this.

Nevertheless, the calculation for breadth, an alternative to average distance, does demonstrate a more consistent trend that may help to elucidate changes in collective capacity. Breadth is also an inverse measure, so decreases in breadth indicate shorter communication paths between nodes. Breadth consistently decreases across the network iterations compared to the original network, by 0.005, 0.02 and 0.12 respectively. With each inclusion of more actors into the main component of the network and greater interconnectedness among the main actors, breadth steadily declines and thus accurately captures network changes indicative of enhanced collective capacity. The steady decline is not drastic, but the consistent trend makes breadth a promising measure.

Fragmentation and connectedness also exhibit consistent trends across the network manipulations that may indicate increases in collective capacity. Connectedness increases across the iterations relative to the original network by 0.005, 0.052, and 0.354 respectively. Conversely, fragmentation decreases across the network iterations by 0.005,
0.052 and 0.354 respectively (values are the same as for connectedness). These increases in connectedness and decreases in fragmentation indicate that more actors are connected to one another (by paths of any length) and thus have potential to share information. While other measures such as average distance may be obscured when isolated nodes or components are brought into the network, connectedness and fragmentation accurately capture these beneficial changes for promoting collective action.

The MANOS Data

After conducting the analysis of the SOMOS data and finding clear trends in the measures of breadth, fragmentation, connectedness and component ratio, I have applied the same series of network manipulations to a data set from the sister project of SOMOS called MANOS (Medical Aid Nicaragua: Outreach Scholarship). The MANOS team constructed this data set after conducting SNA interviews with a marginalized community in Cuje, Nicaragua in 2010. The question asked to generate these data was “Is there someone who works for the good of your community? If so, who?” As with the SOMOS data, this is not an ideal name generator for this analysis because it does not ask specifically about communications between and among individuals in the community. For purposes of analysis, I assume that respondents identified people with whom they would share information in order to collaborate on a community project.

The original data set contains 56 nodes and 83 ties. There is one main component and seven isolates in the network. This data set is thus significantly smaller than the SOMOS data set and contains many fewer isolates. For this reason, it is useful to examine because its characteristics are different from the previous data in theoretically interesting ways. For example, the experimental manipulations of a smaller network may produce
different changes in breadth and average distance because there are fewer nodes in the network that an actor could potentially reach. Smaller network size also reduces number of potential ties substantially, and this directly affects network density calculations. Also fewer isolates impact component ratio and breadth. Thus, reduced size and the smaller number of isolates likely will influence information flow and the manifestation of information flow in UCINET measures. If analyses of the effects of the experimental manipulations continue to prove instructive in describing and tracking differences, this will further affirm the usefulness of these measures for project efforts to describe a dimension of collective capacity. As noted, although the question asked to generate these data does not ask directly about information sharing flow, the manipulation of these data can illustrate variable characteristics of networks and SNA measures for analyzing them. The original MANOS social network is shown below in figure 15. Notice the isolates along the left side of the network graph and the relatively small size of the network compared to the SOMOS network.
Next, just as with the SOMOS data, I began the network manipulations by conducting a test of betweenness centrality. This identified four nodes that had between centrality scores (all other nodes had zero betweenness). I then connected these four individuals to one another with bidirectional ties to produce the first network manipulation. This required the addition of nine social ties, with a bidirectional tie counted as two ties, one for each direction. This network is shown below in figure 16. Only four nodes were connected to one another, so this network does not look much different from the original.

Figure 15: Original MANOS Network
To build upon this first manipulated network, I then added ties in order to include the isolates. Thus, I connected each of the four main nodes to isolates with bidirectional ties. Because there are seven isolates in the network, three of the main nodes were tied to two isolates each, and one of the main nodes was only connected to one isolate (addition of 14 ties, meaning 7 bidirectional ties). This second network manipulation is shown below in figure 17. Notice that now the network is one large component, with no isolates. Because the MANOS data contained fewer components and isolated social clusters, only two manipulations were needed to reach the same final ideal social network as with the three manipulations done to the SOMOS data.
After constructing these idealized networks, I ran the statistical analyses of interest on the networks. The results are shown below in table 6.

![Figure 17: Connecting Isolates to Central Nodes to Increase Inclusiveness](image)

<table>
<thead>
<tr>
<th>Network Measures</th>
<th>Original Network</th>
<th>Manipulation 1</th>
<th>Manipulation 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>0.027</td>
<td>0.030</td>
<td>0.034</td>
</tr>
<tr>
<td>Centralization</td>
<td>0.066</td>
<td>0.063</td>
<td>0.077</td>
</tr>
<tr>
<td>Average Distance</td>
<td>1.313</td>
<td>1.523</td>
<td>2.113</td>
</tr>
<tr>
<td>Breadth</td>
<td>0.968</td>
<td>0.957</td>
<td>0.922</td>
</tr>
<tr>
<td>Connectedness</td>
<td>0.037</td>
<td>0.056</td>
<td>0.138</td>
</tr>
<tr>
<td>Fragmentation</td>
<td>0.963</td>
<td>0.944</td>
<td>0.862</td>
</tr>
<tr>
<td>Component Ratio</td>
<td>0.982</td>
<td>0.945</td>
<td>0.818</td>
</tr>
</tbody>
</table>

Table 6: MANOS Network Calculations
The same trends are found with this data set as with the previous one. With each network manipulation there is a consistent decrease in breadth and component ratio, as well as a steady increase in connectedness that corresponds to a parallel decrease in fragmentation. As before, these changes suggest decreasing distance between nodes in the network, greater communication across regions of the network and increased ability for a node to reach other nodes in the graph. Similarly, average distance once again does not exhibit a constant trend, for it decreases with the first network manipulation and then increases with the second. The inclusion of isolates in the second manipulation increases average distance even though the network is becoming better connected. This confirms that average distance calculations may be misleading when attempting to track change over time.

One interesting difference between the MANOS networks and the SOMOS networks is that in this case, network density also exhibits a more distinct upward trend. Because the number of nodes is significantly smaller than those in the SOMOS one, each addition of a new social tie has a greater effect on density (number of existing social ties divided by number of possible ties). Thus, density increases from 0.027 in the original network, to 0.034 in the second network manipulation. This is an increase of 0.007. This change is still not drastic, but it is possible that in relatively small social networks, density scores may be able to detect changes in collective capacity, although with limited sensitivity.

Chapter 3: Conclusions and Implications

I have investigated empirical measures of collective capacity, by first considering the theoretical origins and explications of the concept. After contextualizing my investigation in the work of Durkheim (in Simpson, 1933) and Bhattacharyya (2004), I
defined collective capacity and examined what the existing literature offers for measuring and describing capacity. I then advanced to an approach aimed at identifying more replicable and reliable measures. I have focused on one key dimension from the theoretical and empirical literatures: interpersonal networks, especially as necessary to communication and the sharing of beliefs about common problems. I examined properties of networks, imagining that the central issue is the network capability for sharing information. Using theoretical and research literatures, I described network arrangements that may be ideal for promoting information flow and collective capacity.

Next, I examined descriptive and analytical strategies for representing network characteristics and variations in those characteristics. I drew upon statistical measures and terminology available through the software package UCINET in this process of theorizing about ideal networks and selecting relevant network measures. Through these analytical processes, I have identified statistical tools that appear to be strong candidates for describing variations and, ideally, for measuring change over time, for this dimension of community or collective capacity. The tools help to describe structural features of social networks that suggest changes in the potential for collective action.

After having identified these measures, I applied them to real data sets from the SOMOS and MANOS projects. These data were gathered through one-on-one interviews and then converted to SNA matrices, which were analyzed statistically, thus combining qualitative and quantitative approaches. By experimentally manipulating the original data sets to optimize theoretically important network characteristics, I produced several iterations of these networks. By applying the identified measures to these network manipulations, I confirmed the usefulness of several of them for detecting change over time.
and demonstrated the limitations of others. While this thesis investigated the reliability of social network measures in detecting changes in network structure indicative of changes in capacity, the issue of validity was not taken up directly. This study marks only the beginning stages of identifying and measuring dimensions of what is a very complex, multidimensional issue. How could the identified insights be applied in development strategies, and particularly in those strategies that purport to respect local wisdom, individual and collective agency, and community ownership? Can these data-based strategies inform efforts in participatory development guided by critical assessments by Kapoor (2004) and others?

As previously discussed, Bhattacharyya (2004) proposes that promoting solidarity and agency are the goals of community development, for development must address the erosion of these factors that has occurred historically. According to this theory of social change, communities must overcome the effects of marginalization that accompany globalization, including the loss of solidarity in order to become viable in the modernizing world. To do that requires collective efforts that allow residents to address their own felt-needs, mobilize self-help efforts, and engage in inclusive participation to find and act with the necessary resources. As described by Bhattacharyya, practices of community development “must regard people as agents from the beginning” and remain “respectful of the will of the people” (2004: 21). Thus, the methods utilized to engage with communities throughout development projects must acknowledge these goals as valuable and prioritize partnership with community members.

---

24 Ilan Kapoor, drawing from Foucault (1984) offers critical assessments of western-centric development efforts that emphasize the problematic nature of top-down efforts that undermine local solidarity and are disrespectful of local cultures and realities.
There is a strategy of community development known as participatory development that is apt to facilitate this form of community partnership. Moreover, there is a method of research (community-based participatory research, or CBPR) that appears appropriate for grounding participatory development strategies.

According to Viswanathan and colleagues (2004), CBPR is effective in sustaining long-term partnerships between communities and other groups (such as universities). It facilitates the use of culturally appropriate research methods and creates a basis of knowledge about the locality and a framework for applying development practices to the specific needs of a community (Viswanathan et al. 2004). In CBPR endeavors, community residents are invited into the research process and participate in the formulation of research questions. They are invited to engage where possible in data collection, data analysis and application of this information to address identified problems. Most importantly, they are invited into the identification and formulation of the research questions and purposes. This process of inviting communities into the investigative work undertaken by many development projects may not only lead to more successful projects, but also promote collaborative dialogue that builds capacity.

As described by Meredith Minkler and colleagues (1998), there are many models of community development, some of which operate under the principles described above and others that do not. Minkler and her colleagues (1998) offer a helpful summary of these models, which is shown in figure 18 below. Community-based participatory research is most clearly described in the lower left quadrant of this figure, under “community building and capacity building,” for the theory emphasizes consensus, collaboration and respectfully working with communities to reach common goals (Minkler et al. 1998: 293). This
approach is “strengths-based” in terms of Minkler’s vocabulary, because it acknowledges skills and wisdom that community members bring to a partnership and establish them as equal stakeholders in the decisions made (1998: 293).

FIGURE 18: COMMUNITY ORGANIZING CATEGORIZATIONS (Minkler et al. 1998: 293)

I have been guided by the principles of participatory development throughout the thesis research and I am sensitive to the risks of crude social engineering that may be inferred from the approach described here. The application of social network analysis and its implications by outsiders would be contrary to the central premises of critical and participatory development theories. A participatory strategy grounded in CBPR would
begin by inviting residents into discussions about the potential for collective action when, individually, residents have meager resources and when descriptive research reveals that residents believe that they might be able to improve their circumstances if they worked together. It would proceed through research on and discussions of shared beliefs about the nature of shared problems. Such research and dialogues might identify resources, such as time, energy, talents, materials, and government support. This early work also might reveal the lack of needed resources. A participatory strategy would then foster planning, including identifying agreements about priorities, goals, and objectives. For example, early research may reveal that community members identify specific concerns, but that they do not recognize that these concerns are shared among others. Findings such as these could serve as a starting place for building awareness of a community's felt needs using social network analysis to help guide action based upon these felt needs.

The SOMOS project serves as an example of implementation of this process. Note however, that the project was not guided by an explicit model of participatory development and had not embraced CBPR at the outset. Rather, this novice team was searching empirically and “on the ground” for ways to partner respectfully with a community, taking seriously that communities are more than aggregations of individuals. Beginning with basic ethnographic research, SOMOS members learned that residents of Esfuerzo believed that the local government should do something to help mitigate the effects of flooding in the community but most likely government officials would not. Through interviews, community meetings and informal conversations, SOMOS members learned that residents believed they could accomplish small-scale improvements if they could more effectively work together. Interviews also revealed that community members individually expressed
concerns about health, such as pollution and mosquito-borne illness, but they were not aware that these concerns were shared with others. Thus, SOMOS team members began actively to foster exchange of information about health concerns among neighbors and across the community. Still working with traditional notions about leadership and community organization, SOMOS team members used SNA to identify local leaders and, in the process, identified organic clusters of residents who talk together on a regular basis. The SOMOS team thought that these clusters might serve as the starting place for more regularized conversations that might increase participation in community meetings and facilitate the identification of agreements about priorities and goals.

At the outset of a network approach to building collective capacity, conversations with community members could include questions aimed at understanding different features of shared concerns and information flow. To begin, conversations may seek to better define health priorities, such as the list of sample questions below:

1. What do you consider to be the most significant health concerns faced by residents in this community?
2. Do you think that others in the community identify these as significant problems?

---

25 SOMOS team members were frustrated in finding ways to partner effectively by the apparent lack of local leaders or government arrangements. There was a “junta de vecinos” (JDV; neighborhood association) that was recognized by the municipal government, but it recently had been discredited with allegations of misappropriation of funds collected for setting utility posts. Ethnographic research revealed that the JDV did not have or require community-level support because such associations can be constituted by the collection of no more than a handful of signatures and agreement that some of those who sign will serve as officers. The SOMOS team observed as JDV organizations emerged and disbanded and, throughout the 10 years of ongoing research, only the most recent JDV has support beyond a small percentage of the households in the community.
3. What health concerns have most impacted members of your household in the past year?

After obtaining a sense of what specific concerns a community faces, CBPR practitioners could then seek to understand how flow of information might inform shared beliefs and shared definitions of social problems. Questions of this nature that a researcher could ask are shown below:

1. With whom in this community have you discussed health concerns?
2. How do you hear about health issues?
3. Who in this community has told you about a health risk?

In addition, questions specifically about collaboration could be asked as a follow-up to questions about information flow. The intent of such questions is to understand and share understanding with residents about the role of communication in community organizing and potentially draw attention to ways in which community endeavors could be enhanced if people were more effectively communicating with one another. A list of collaboration-based questions is provided below:

1. With whom would you work to try to improve the health issue that you identified?
2. Do you participate in community meetings?
3. Have you participated in discussions of health risks at community meetings?

The goal is to work with community members to understand how residents might collaborate by sharing information, form consensus, plan, identify resources that can be shared, and take ownership of a change process. If residents implement measures to
promote wider information sharing through methods congruous with their cultural and social practices, an organic respectful and inclusive dialogue could result.

To construct social network diagrams such as those shown throughout this thesis, name-generating questions must be utilized, particularly those that focus on information flow. The first question in the second list above, “With whom in this community have you discussed health concerns?” is an example of a question of this nature. Such name-generating questions would elicit responses that include the names of specific others in a community. Thus, knowing those interviewed and those who were named by each interviewee, social network matrices and diagrams could be constructed using UCINET or other similar software packages. The information gleaned from these social network diagrams should be shared with community members and members should be invited to discuss the relevance and implications of the findings to create a vision for social changes based in inclusive participation.

By sharing the results of a social network analysis investigation with the community, residents may become more aware of who is excluded from communication or recognize regions of the community that do not exchange information with one another. In this way, residents may begin to encourage new paths of information flow and conceptualize the role of communication in collective action with greater clarity.

Ultimately, a CBPR approach to social networks aims to allow members of a community to

---

26 In the current thesis, I am not considering issues of conflict and competition that may fundamentally undermine efforts to promote inclusive and consensus-based strategies. I recognize that these are important and real and I have observed them first-hand in work with the SOMOS project. For now, these issues are assigned to consideration under a separate conceptual category identified here summarized as “complex reciprocity.”
enact changes in network structure through their own agency and to promote an intentional network structure that facilitates information flow optimal for collective action.
References


Easterling, Doug, Kaia Gallagher and Jodi Drisko. 1998. Promoting Health by Building
Community Capacity: Evidence and Implications for Grant Makers. Denver, The Colorado Trust


Position, Niche Overlap, and the Duration of Voluntary Association Memberships."

*American Journal of Sociology* 101 (3): 698-720


Appendix

Examples of Cliques