POWER IN COLLABORATIVE NETWORKS

by

Alexandra P. Joosse

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Alexandra Joosse, titled Power in Collaborative Networks and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

____ Date: 5/13/2015
H. Brinton Milward

____ Date: 5/13/2015
Joseph Galaskiewicz

____ Date: 5/13/2015
Adam Henry

____ Date: 5/13/2015
Kirk Emerson

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

____ Date: 5/13/2015
Dissertation Director: H. Brinton Milward

STATEMENT BY AUTHOR

SIGNED: Alexandra Joosse

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DEDICATION

First and foremost, this dissertation is dedicated to my faithful and supportive husband Matt, who lived every turn of this process with me. You have encouraged me, listened to me, and cheered me on. We've accommodated one another's dreams from the get go, a true partnership.

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ABSTRACT

The research described herein focuses on understanding the effects of power on the processes and outcomes of collaborative networks. Power is conceptualized from a structural perspective, as the dependence that exists in the relationships that tie network participants together. Using the method of social network analysis, the dissertation first validates a measure of structural power in collaborative networks, betweenness centrality. It then examines the effect of uneven distributions of structural power among participants on an important variable for these networks: cohesion as measured from a behavioral perspective. This effect is examined from the perspective of two levels of analysis: the whole network level and the working group level. Results indicate that structural power has a variable effect on cohesion, depending on the level of analysis. At the whole network level, uneven distributions of power negatively affect the cohesive behavior of participants. At the working group level, on the other hand, the relationship between the variables is curvilinear. Finally, the effect of structural power on three dimensions of participant satisfaction is examined: process satisfaction, human capital satisfaction, and outcome satisfaction. The research finds that being in a power disadvantaged position affects how participants rate their satisfaction with the process of collaboration.

CHAPTER 1: INTRODUCTION

Collaborative networks[1] are an organizational form in which independent actors—individuals or organizations—come together to jointly address a mutual problem. Collaborative networks have increasingly become the go-to method for solving complex public problems that organizations acting in isolation struggle to solve on their own (Boardman 2011; Head 2008; Kettl 2006; Leach et al. 2014; Milward and Provan 2006; Raab, Mannak, and Cambré 2015; Suárez 2011). In their purest form, collaborative network members participate on equal footing as they contribute unique knowledge, skills, and sometimes tangible materials or products with the intention of producing a joint outcome that is greater than the sum of its parts. While this form of organization has led to many positive outcomes, it faces a range of challenges as well.

The scientific consortia facilitated by the nonprofit Critical Path Institute (C-Path) provide an illustration of the benefits and struggles of collaborative networks. C-Path emerged in response to a report published by the Federal Drug Administration (FDA) that described the problems plaguing the development process for innovative pharmaceutical drugs ("Challenge and Opportunity on the Critical Path to New Medical Products" 2004). The report came to the overarching conclusion that the "critical path from laboratory concept to commercial product" is outdated, inefficient, and proprietary. In particular, the technology along the "development process" is not keeping pace with the advances in "discovery process" (p. ii). This mismatch has resulted in sky-rocketing costs as drugs

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[1] Collaborative networks are also known by many names including collaborations, goal-directed networks, and productive exchange networks.

are deemed unsafe for use well into the drug approval process. To ameliorate these sunk costs, pharmaceutical companies are forced to concentrate on developing drugs with anticipated high market returns, rather than on drugs that may be more needed. C-Path acts as a neutral facilitator of several collaborative networks, which they call consortia. Three of C-Path's consortia are the subject of the research described herein, each of which addresses a portion of this larger problem.

Ten years in, C-Path's consortia have succeeded in many ways. They have convened participants from the government, nonprofit, and for-profit sectors around the same table, no small feat given the competitive nature of the pharmaceutical drug industry. They have made tangible progress on several goals including creating standard data formats for drug trial data, sharing of drug trial data in a pre-competitive space, and working with the FDA to qualify disease biomarkers to enable a faster, more efficient drug approval process. They have also made strides in intangible objectives like sharing knowledge and expertise among participants and building relationships between industry experts across organizational and sector lines.

With that said, C-Path's consortia have faced their share of difficulties as well, two of the most persistent of which are discussed here. First and foremost, they have struggled to incentivize active participation from members who participate on behalf of their organizations, but are not compensated monetarily for the time and energy spent on the work of the collaborative network. While some organizations value and support the time their employees spends on consortium-related activities—by, for instance, recognizing their participation in performance reviews—others do not. Especially in recent years as the pharmaceutical market undergoes consolidation, participants' time is increasingly being spread thin.

Second, consortium leadership must manage relationships between participants who not only have different personalities, but hail from different organizational cultures. These cultures arise both from the sector in which participants work, as well as their professional training. Participants from academia, for instance, abide by different professional norms than participants from big pharmaceutical companies. Even within pharmaceutical companies, though, differences exist between toxicologists, for example, and clinicians. These differences can and do lead to difficulties in communication between participants and vision setting for the consortia as a whole.

The experience of the C-Path consortia should not come as a surprise for scholars studying collaborative networks. In his seminal article recognizing networks as a distinct form of organization from markets and hierarchies, Powell (1990) brought together the knowledge that had been gleaned from the early years of network research (c.f., Galaskiewicz 1985; Laumann and Knoke 1987) to outline three main conditions under which a network is a beneficial and even preferable form of governance. First, networks are preferable when the good that is being transmitted is know-how, or tacit knowledge. This form of good is more efficiently and fluidly diffused through the informal, on-going, and reciprocal relationships that compose networks. Second, networks are dynamic and, thus, can adapt relatively quickly to changes in the environment, due in part to their ability to distribute and integrate new information. Finally, networks—particularly those in which members are homogenous—encourage trust to form between members due to their relational nature. Research by Provan and Kenis (2008) expanded the conditions under which networks are preferable by identifying network governance structures that can accommodate conditions that were once thought to be difficult for networks to handle: larger number of participants and technically more complex problems.

Around the same time, Gray (1989) highlighted some of the main challenges of networks as a form of governance. Writing on collaboration, or "the process through which parties who see different aspects of a problem can constructively explore their differences and search for solutions that go beyond their own limited vision of what is possible," she described several obstacles that could hinder the success of collaboration. These obstacles include historical and ideological barriers, uneven distributions of power between participants, differing organizational cultures, and different perceptions of the problem. Gray's research inspired a wealth of work in the collaborative governance literature on managing the process of collaboration in order to avoid these problems[2].

While a lot has been learned about the network form of organization, there remains much that is underexplored, specifically about its challenges. The research presented in this dissertation represents an effort to begin understanding one such challenge that looms large for collaborative networks: uneven distributions of power between participants. The concept of power is one that is omnipresent, but under-conceptualized in the literature dealing with collaboration networks. It is of critical importance to understanding the processes and outcomes of these networks because

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[2] For references on this literature, see the special edition of Public Administrative Review (Supplement 66), as well as the book, Big Ideas in Collaborative Public Management edited by Bingham and O'Leary (2008).

uneven distributions of power among participants are likely to exacerbate the problems that are faced by collaborative networks like the consortia facilitated by C-Path mentioned above.

Specifically, when power is unevenly distributed among participants, those without power or with less power are unlikely to feel that the network is cohesive. In other words, the sentiment of “we are all in this together” begins to deteriorate when power imbalances exist because it becomes clear that not all contributions and opinions are treated equally and that some have more say than others. Uneven distributions of power are also likely to create and intensify conflicts between participants, making the management of these collaborative efforts more difficult. In other words, uneven distributions of power are likely to underlie many of the challenges faced by these networks. Of course, power is rarely completely evenly distributed; however, the more unevenly power is distributed, the more severe the effects are likely to be.

Understanding power, then, is imperative for scholars and practitioners working with collaborative networks. This dissertation attempts to better conceptualize power and examine its effects in this setting by asking the following questions: 1) how should power be best conceptualized and measured in collaborative networks? 2) how does the distribution of power in a collaborative network affect how cohesively participants behave? 3) how does power affect the level of satisfaction participants feel regarding the process and outcomes of a collaborative network? In answering these questions, both conceptually and empirically, only voluntary, problem-solving collaborative networks are considered.

The rest of this chapter is organized as follows. First, in order to underline the necessity of this research, collaborative governance scholars' treatment of power is reviewed. Attention is then turned to the topic of conceptualizing power. Given the complexity of the concept and the wealth of scholarship on it, a brief history of the study of power is first provided. Next, the conceptualization of power that is most suitable for collaborative networks and thus is the focus of this research, structural power or power as dependence is explained. The chapter concludes with an overview of the remaining chapters.

Power in the collaborative governance literature

The collaborative governance literature is the most logical home for this research given its focus on understanding how and why collaboration occurs in the public sphere, its advantages, and its challenges. In particular, collaborative networks in the health policy domain, like the effort led by C-Path, are becoming an increasingly frequent focus of study for scholars. This increase in scholarship mirrors the dramatic rise of partnerships that followed the realization that many health concerns—concerns like infectious and neglected diseases—are now globalized in nature and require solutions that are formed collaboratively between governments and organizations from all sectors of economic life (Buckup 2008; Buse 2003; Buse and Harmer 2004; Ramaiah and Reich 2005; Sorenson 2009).

With that said, collaborative governance is a relatively young field that has room for growth. In particular, it can learn from related disciplines. This dissertation aims to do just that: use methods and theories from two disciplines in particular, organizational networks and social exchange, to inform the study of power in collaborative networks. First, though, it is important to understand how the collaborative governance literature has treated power.

Initially, scholars studying collaborative networks concentrated almost exclusively on cooperation between actors working towards a common goal, a natural early focus because this form of organization lacks the formal, hierarchical structure on which traditional organizations rely to function[3] (Gray 1989; Kickert, Klijn, and Koppenjan 1997). As the following quote from Kickert et. al's (1997) book on managing complex collaborative networks demonstrates, an early assumption in this literature was that the lack of hierarchy meant that power was evenly distributed among the actors:

> The network approach considers public policy making and governance to take place in networks consisting of various actors (individuals, coalitions, bureau, organizations) none of which possesses the power to determine the strategies of the other actors. The government is no longer seen as occupying a superior position to other parties, but as being on equal footing with them (9).

More recently, scholars have begun to create room for the study of uneven power distributions between actors. Two of the most prominent, recent frameworks on the collaborative governance process include power relations or power differences between stakeholders as key variables (Ansell and Gash 2008; Emerson et. al 2012). Many other scholars acknowledge that uneven distributions of power are a regular, if not expected source of potential conflict in collaborative networks (Agranoff 2006; Bryson, Crosby,

[3] Lacking hierarchy is not the same thing as lacking structure. Provan and Kenis (2008) propose three ideal type structures for collaborative networks: shared, lead organization, and network administrative organization structure, the latter two of which are more common. The structure talked about by Provan and Kenis differs from hierarchy, though, in that members are independent and thus do not have to the same lines of authority that are built into hierarchy.

and Stone 2006; Buse 2003; Buse and Harmer 2004; Gazley 2008; Purdy 2012; Sorenson 2009).

Despite the increasing interest in power, most of the research in the collaborative governance field merely describes the presumed negative effects that uneven distributions of power can have on a collaborative effort without studying why or how these effect occur, a trend that led Huxham and Vangen (2005) to describe power as an area in need of more development. For example, an uneven distribution of power is mentioned as a potential source of mistrust (Bryson et. al 2008; Huxham and Vangen 2005) and is presumed to contribute to frustration for those who are not in power (Huxham and Vangen 2005), both of which can reduce the desire to cooperate. It is also linked to a breakdown of communication (Mayer 1987), and can even result in cooptation of the less powerful actor by the more powerful actor (Buse 2003; O'Toole and Meier 2004). Finally, if power is unevenly distributed at the start of the collaborative process, there is potential for these inequities to be reinforced through the collaborative process (Feiock 2008; Koontz and Thomas 2006; Leach 2006). Although these scholars are to be commended for identifying the potential problems associated with uneven power distributions, this research rarely concretely identifies what power is and from where it comes. Moreover, it by and large does not systematically study the effects of power.

A slightly more in-depth treatment of power in collaborative networks can be found in several attempts to develop typologies of power. These studies examine the sources of power in an effort to determine where and how uneven distributions of power arise. In doing so, they treat power as an attribute of an actor. Examples of power sources include authority-based (Purdy 2012), habit-based (Mayer 1987), actor-based (Choi and Kim), and psychologically-based (Gewurz 2001) power. While these studies are important because they are the first to focus exclusively on power, typologies of power sources are plagued by a variety of problems. First, many of the sources of power overlap. Choi and Kim (2007)'s actor-based and cognitive-based sources of power, for example, would be difficult to differentiate in practice. Second, there is an air of arbitrariness surrounding these typologies. Gewurz (2001) lists ten categories of sources of power. What is to stop us from developing more sources and at what point does this exercise become useless? Finally, the typologies imply a hierarchy of power sources, but stop short of filling in the hierarchy or explaining the implications of different power sources.

The most developed conceptualization of power in the collaborative governance literature comes from scholars who focus on conflict resolution networks. While working with the Harvard Negotiation Project in the late 1980s, Roger Fisher and William Ury (1981) advanced the idea that power is directly related to the quality of the alternatives available to each actor, the "Best Alternative to a Negotiated Agreement" (BATNA). The better an actor's BATNA, the more leverage, or power it has over other actors in a negotiation because it is less dependent on reaching an agreement. The conceptualization of power as dependence has been accepted among scholars studying conflict resolution networks (c.f., Lax and Sebenius 2006; O'Leary and Bingham 2007); however, it has not widely gained traction in the larger literature.

In sum, a review of the collaborative governance literature's treatment of power leads to one overarching conclusion: scholars in this field recognize the importance of uneven distributions of power for collaborative processes and outcomes, but have not agreed upon a conceptualization of power itself. The lack of a precise conceptualization is not surprising, given the complexity of the concept. To begin grappling with this complexity, a brief history of power is now in order.

Brief history of power

Power has been a topic of scholarly interest and heated debate for centuries. Scholars to whom many disciplines look as founding fathers, like Karl Marx and Max Weber, wrote extensively about power insofar as it determines who controls the major decisions that shape society. Their writings laid the groundwork for most modern-day conceptualizations of power, but many other prominent scholars over the years have expanded and even challenged their ideas. What has resulted is a rich, yet complex and often confusing understanding of power and how it manifests itself. While the frequency with which power is mentioned in scholarship is still alive and well, the emphasis on understanding power has begun to fade in certain disciplines as it appears that most scholars have metaphorically thrown in the towel on understanding this concept. This dissertation represents an attempt to delve back into understanding what power is and what its ramifications are in a very specific context: collaborative networks. Here, a selection of the major contributions and controversies in the discussion of power are briefly reviewed to illustrate the complexity of the topic. Then, the conceptualization of power most fitting for the collaborative context, structural power, is reviewed in greater detail.

Any conversation on power must begin with Karl Marx, who examined power in the context of class conflict in the mid-1800s. He viewed power as absolute, meaning that a finite amount of power exists in society and is divided among groups of people. In particular, Marx argued that two main groups, or classes, of individuals exist in society: the powerful ruling class, or those who control the means of economic production, and the weak working class, or those who are employed by the ruling class. He views power from an inherently negative stance in which the ruling class uses its power to exploit the working class. Marx' conceptualization of power focuses on power that manifests itself in the economic realm of society (Coser 1977).

Max Weber took up with subject of power in the late 1800s and early 1900s and, like Marx, is one of the most cited scholars on the subject. He gave us perhaps the most well-known definition of power, which he describes as "the probability that one actor within a social relationship will be in a position to carry out his own will despite resistance" (Weber 1947, 152). He agreed with much of what Marx said about power, but argued that power can manifest itself in ways others than economic relations. For example, in addition to power as class in the economic realm of society, it can also manifest itself as status in the social realm, and party in the political realm. Weber's contribution to the conversation is of particular importance to this research because he was the first to recognize that power can also manifest itself in *positions* of authority. In championing bureaucracy as the most technically superior form of governmental organization, he claimed that power manifests itself as authority, not in the individual who occupies the office, but in the office itself. In other words, he recognized that power can exist in structure, a major advancement in the thinking on power.

While Marx and Weber are viewed as the fathers of power, many other scholars have extended their arguments. Lukes (2005) provides a summary of the important contributions in the second edition to his own widely-cited discussion of power, which he wrote in mid-1970s. He also highlights some of the debates that have occurred over the years between scholars of power.

One of the most central debates revolves around how power should be observed and thus, how it is measured. Two main sides exist, but disagreement occurs even among scholars on the same side. On the one side are scholars who argue that power is best studied through its use. Dahl (1957), for example, examined concrete decisions in determining whether one party was able to assert its will on the other. Other scholars within the power use camp assert that the exclusive focus on decisions as the arena to study power omits an equally important arena in which power is used; namely, in the forcing of non-decisions. Bachrach and Baratz (1962) argue that power can be used to create barriers to issues being brought to a decision, and thus, must also be considered in examining power. While the precise unit of observation of power use may differ, these scholars treat power as influence. The more power an actor possesses, the more s/he influences both decisions and non-decisions in society. This view of power is widespread in the contemporary literature (c.f., Brass 1984; Brass and Burkhardt 1993; Provan and Milward 1995).

On the other side of the debate are scholars who argue that power does not need to be used to exist. C. Wright Mills (1956), for example, asserts that power use is not as important as examining potential power; namely, the people who are in positions to make important decisions. He says, "Whether they do or do not make decisions is less important than the fact that they do occupy such pivotal positions" (Mills 1956 (2000), 3–4). Emerson (1972b) and Cook and Emerson (1978) agree, arguing that power exists in the structure of exchange relationships in which an actor in embedded, and thus does not have to be used to exist. To describe this further, imagine two actors, *A* and *B*, who have identical motivations and personal characteristics. Actor *A*, however, is considered more powerful because she can affect outcomes in her favor more than can *B*. This power results from the fact that the people with whom *A* is exchanging resources have no other exchange partners while *B*'s exchange partners do. Therefore, even if *A* is not aware of her position of power, the authors argue that her exchange partners will be more accommodating to his wishes than *B*'s. More recently, Provan (1980) added even more nuance to this conversation by differentiating power even further into perceived, potential, and enacted power, all of which contribute to the overall distribution of power.

The work of these and other scholars have contributed to a rich picture of power, but has also resulted in much confusion about the concept. Lukes captured this confusion, saying (2005, 61):

> We speak and write about power in innumerable situations, and we usually know, or think we know, perfectly well what we mean. In daily life and scholarly works, we discuss its locations and its extent, who has more and who less, how to gain, resist, seize, harness, secure, tame, share, spread, distribute, equalize or maximize it, how to render it more effective and how to limit or avoid its effects. And yet, among those who have reflected on the matter, there is no agreement on how to

> define it, how to conceive it, how to study it and, if it can be measured, how to measure it. There are endless debates about such questions, which show no sign of imminent resolution, and there is not even agreement about whether all this disagreement matters.

The complexity of power has led some scholars to question whether it is a worthwhile focus of study at all. James March (1966), for example, suggests that power may not be real and, thus, scholars should resist the temptation of studying it. Simply leaving power unexamined, however, is not the way forward. Doing so will limit the progress made in understanding how society functions. Rather, the more useful lesson to be drawn from the power scholarship is that scholars need to be specific about the type of power they are studying. As Weber pointed out, power comes in many shapes and forms, depending on context. While understanding a particular type of power does not explain the whole story, it is more likely to provide concrete knowledge about power than either attempting to study it as one unified concept or in not studying it at all. Therefore, the approach of this dissertation is to start with a narrow focus by studying a specific type of power in a specific type of situation. In doing so, it by no means suggests that there is only one type of power or that the type of power studied here is the most important. Rather, building on the foundation of the research presented herein, future research should begin to expand little by little to the study of other types of power and other contexts. This expansion is discussed more in the concluding chapter.

Structural power: power as dependence

With this thought in mind, what type of power is most salient for understanding power in collaborative networks and, thus, is the focus of this research? To answer this question, it is important to understand a bit more about what makes collaborative networks tick. Just because one of the hallmark features of collaborative networks is their lack of formal structure, or hierarchy, does not mean that they lack structure altogether. Rather, this form of organization relies on what is known as informal social structure, or the pattern of stable social relationships between participants in the network, to coordinate and monitor behavior (Scott 1998). Relationships are able to take on this role because through them, norms governing appropriate behavior are created and spread, obligations between participants are created in the name of reciprocity, and trust is developed over time, all of which help with coordination of behavior (Coleman 1988).

Given the importance of relationships for the functioning of collaborative networks, examining the power that derives from these relationships provides an excellent starting point for understanding power in collaborative networks. This relationally-based power, made famous by Emerson (1962; 1972a; 1972b), underlies the idea of structural power, where structure refers to the informal social structure rather than the formal hierarchical structure. The term structural power is used throughout this dissertation as referring to the idea of power that derives from dependence relationships.

Based on the ideas of sociologists Thibaut and Kelley (1959), Emerson argued that the relationships that occur between actors, whether they be material or social in nature, lie at the root of power. While each relationship an actor initiates and maintains with others is assumed to have benefits—for without some kind of benefit, there is no reason to maintain a relationship—it is also assumed to have costs like time, energy, and potentially material costs. Power, then, derives from the amount of cost an actor is willing to bear in order to establish or maintain a particular relationship. Formally, Emerson defines the power between two actors in an exchange relationship as, "the power of *A* over *B* (P_{AB}) is the level of potential cost which *A* can induce for *B*, and *A*'s power advantage = $P_{AB} - P_{BA}$" (Emerson 1972b, 64). In other words, the more dependent *A* is on *B*, or the more *B* has something that *A* needs, the more cost *A* is willing to accept. This type of power, then, is agnostic to the specific type of resource that is being exchanged, as long as the exchange partner needs that resource.

Viewing power from a perspective of structural dependence is distinguished from other views of power by its claim that power should be viewed as an attribute of a relationship not of an actor. An actor's power is therefore determined based on who s/he is connected to and how dependent s/he is on those exchange partners. In contrast to the Marxian view that power is absolute, meaning there is a finite amount of power that is distributed amongst actors, Emerson's view of power is relative in nature. How much power an actor has depends on how much others need what he has. Therefore, one actor's power cannot be determined in isolation. On a related note, power is not necessarily bad; rather, it is a ubiquitous and fundamental part of life. Without some level of dependence, a relationship would not exist. Finally, structural power is characterized as potential power because actor A's dependence on actor B does not necessarily mean that actor B will try to influence actor A's behavior.

This conceptualization of power was developed into what became known as power dependence theory, a theory that not only spurred a huge literature known as the social exchange literature in sociology, but has also become widespread in the organizational networks literature. In fact, it lies at the heart of one of the most common theories in this literature: resource dependence theory (Pfeffer and Salancik 1978). Resource dependence theory assumes that organizations seek to reduce uncertainty by ensuring a stable flow of resources necessary for survival. In order to do this, they attempt to reduce their dependence on other organizations in their environment (DiMaggio and Powell 1983). Many scholars have used resource dependence theory to understand power relationships between organizations (c.f., Malatesta and Smith 2011; Provan 1980; Provan, Beyer, and Kruytbosch 1980).

Despite the overlap in subject between organizational and collaborative governance research, though, structural power has not been widely applied to understanding power in collaborative network settings[4]. The research that follows focuses exclusively on understanding the effect of this type of power in collaborative networks. In doing so, it attempts to bridge two literatures that are complementary, but have not been in enough direct communication.

Overview of dissertation

This dissertation seeks to understand how structural power affects the processes and outcomes of collaborative, problem-solving networks. To do this, the method of social network analysis is used to examine the networks composed of the exchange of a particular type of resource in three scientific consortia: information. Chapter 2 provides an overview of the research setting and the consortia. The data collection methods are

[4] The exception being conflict resolution scholars like Fisher and Ury (1981), Lax and Sebenius (2006), and O'Leary and Bingham (2007).

then explained in detail. In this discussion, the challenges of collecting network data are discussed as well as the methods used to address those difficulties.

Chapter 3 digs deeper into structural power. In particular, it looks to two literatures that operationalize structural power differently: the social exchange literature and the organizational networks literature. Using network data gathered from the three C-Path consortia, it then validates both operationalizations. It is found that the operationalization from the organizational networks literature fits the data while that of the social exchange literature does not.

Building on this, Chapter 4 then examines how the distribution of structural power affects a very important variable for collaborative networks: cohesion. Like power, cohesion is a concept that has been used and interpreted in a multitude of ways, leading to confusion as to what exactly it means. An overview of the concept is thus provided before the conceptualization used in this research is presented. Namely, cohesion is viewed from a behavioral perspective, occurring when actors form tightly connected groups of communication partners. It is proposed that this conceptualization of cohesion most displays true collaboration by participants. The chapter then examines the relationship between structural power and cohesion at two levels of analysis: the whole network level and the working group level. The results indicate that the effect of structural power on cohesion does differ depending on the perspective taken. In particular, the results from the working group level of analysis suggest that structural power is not always negatively associated with cohesion.

With the knowledge that structural power affects the extent to which participants behave cohesively, Chapter 5 examines how structural power affects individuals; namely, the level of satisfaction a participant feels with regards to his/her participation in the collaborative network. Participant satisfaction in collaborative networks is conceptualized as consisting of three dimensions: process satisfaction, human capital satisfaction, and outcome satisfaction. Using survey data from participants of the three consortia, hypotheses from the literature are tested. Results indicate that that structural power has a large effect on a participant's process satisfaction, but not on the human capital or outcome satisfaction dimensions.

Finally, Chapter 6 concludes by recapping the results from the dissertation and discusses their implications for network managers. The limitations of the research presented herein are examined and a future research agenda is proposed.

CHAPTER 2: RESEARCH SETTING AND DATA COLLECTION

This chapter describes the research setting and data on which this dissertation is based. The original data[5] used herein come from three collaborative networks, called consortia, concerned with improving the drug development process for pharmaceutical drugs, an area of public health that has seen a tremendous increase in collaborative efforts over the last decade. Background on the non-profit organization that oversees the three consortia as well as on the consortia themselves is provided first, with similarities and differences between the consortia highlighted. Next, the data collection procedures are detailed and potential challenges are addressed, followed by a description of the main measures and methods that are used throughout the dissertation. Finally, the network diagrams for each consortium are presented and discussed.

Research setting

This research examines three consortia facilitated by the Critical Path Institute (C-Path), a 501(c)(3) nonprofit organization formed in 2005 in response to a report published by the Federal Drug Administration (FDA) that described the problems plaguing the development process for innovative drugs (U.S. Department Health and Human Services 2004). The report came to the overarching conclusion that the "critical path from laboratory concept to commercial product" is outdated, inefficient, and proprietary. In particular, the technology along the "development process" is not keeping pace with the advances in "discovery process" (p. ii). This mismatch has resulted in sky-rocketing

[5] The research project and its data collection described herein was submitted and exempted from human subjects protection by the University of Arizona's Institutional Review Board (IRB). The approved exemption is dated March 19, 2014.

costs as drugs are deemed unsafe for use well into the drug development process. Figure 1 illustrates the increase in drug development costs between 1995 and 2002, just prior to when C-Path was founded.

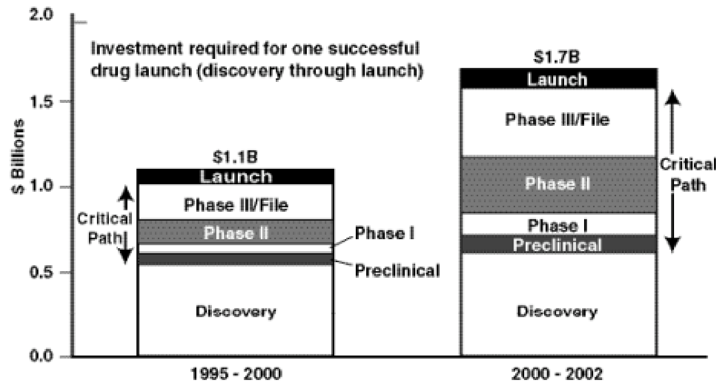

Figure 1: Increase in drug development costs from 1995 through 2002
**Note: Reproduced from FDA report: Figure 3*

The increasing costs associated with moving a drug along the “critical path,” in turn, have far-reaching effects. Most critically for public health, pharmaceutical companies are focusing more on developing drugs with high expected market returns in order to make up for the resources wasted on drugs that do not make it to market. Consequently, fewer drugs are being developed that target diseases that are less common like polycystic kidney disease, or those that are more prevalent in third world countries, like tuberculosis. To address these challenges, the report advocated for a collaborative effort between the pharmaceutical industry, academia, and the FDA to modernize the tools and standards involved in the drug development process (“Challenge and Opportunity on the Critical Path to New Medical Products” 2004).

It was in response to this call to arms that C-Path was formed. While heading the Pharmacology Department at Georgetown University Medical Center in the 1990s, C-

Path founder Ray Woosley worked closely with the FDA, work that exposed him to the issues faced by the pharmaceutical drug development process. For years, he had tried to encourage more open communication between the pharmaceutical industry and the FDA, but, in his words, "It just wasn't working. Things weren't bad enough yet. Firms thought they could do what they wanted without having to collaborate" (Woosley 2014). Several years later, though, the FDA report in effect removed the blinders, making clear that the problems plaguing the drug development process were not ones that could be addressed adequately through the efforts of individual organizations. At the encouragement of his contacts at the FDA, Woosley embarked on the journey to create C-Path.

First researching other collaborative efforts—namely, efforts in the semi-conductor industry and the food safety industry—Woosley recognized that one of the most important elements was to have it be organized by a neutral third party. Any collaboration between a regulatory agency and the organization it regulates is complex. The FDA, in particular, was mindful of developing too close of a relationship with the pharmaceutical companies for fear of giving off the impression of being captured. The industry participants were also initially skeptical. Accustomed to a hyper-competitive environment, they were wary of sharing knowledge with one another. Having a neutral, third party at the helm helped to alleviate these fears. C-Path filled that role (Woosley 2014).

C-Path began with only one consortium but has since expanded to include eight, each of which focuses on a segment of these overall challenges. Some consortia are disease specific, whereas others address broader issues like developing better testing standards. For this research, five of the eight consortia were originally selected because they were similar enough in structure and composition to compare with one another and the consortium leadership was cooperative with the researcher. One of those five was used to pre-test the survey questions and another was dropped from the analysis due to low response rates. The final three consortia included in this study are described in

Table 1 and in the section that follows. Each constitutes one collaborative network.

Table 1: Consortia Descriptions

Consortium Name	Focus	Member Type	Year Founded
Predictive Safety Testing Consortium (PSTC)	Facilitate collaboration between “pharmaceutical companies to share and validate innovative safety testing methods under advisement of the FDA (Food and Drug Administration), its European counterpart, the EMA (European Medicines Agency), and PMDA (Japanese Pharmaceutical and Medical Devices Agency).”	Pharmaceutical companies, academics, and regulatory agencies	2006
Coalition Against Major Diseases (CAMD)	“Increase the efficiency of the development process of new treatments for Alzheimer’s disease (AD) and Parkinson’s disease (PD).”	Pharmaceutical companies, academics, non-profit research organizations, and regulatory agencies	2008
Multiple Sclerosis Outcome Assessments Consortium (MSOAC)	“Collect, standardize, and analyze data about MS with the goal of qualifying a new measure of disability as a primary or secondary endpoint for future trials of MS therapies”	Pharmaceutical companies, academics, patient advocacy organizations, and regulatory agencies	2012

*Source: www.c-path.org

The Predictive Safety Testing Consortium (PSTC), the Coalition Against Major Diseases (CAMD), and the Multiple Scleorosis Outcome Assessments Consortium (MSOAC) share many similarities due to the fact that they exist under the same umbrella organization. These similarities are useful for this research because they act as controls for several variables that are likely to affect levels of cohesion: membership criteria, governance structure, funding, leadership, and overarching goals. To begin with, the consortia all have a membership agreement in place that must be signed by incoming members[6]. This agreement governs issues such as intellectual property protection, conflict resolution, and voting procedures. Members are incentivized to participate in large part by the lure of sharing the costs of developing better regulatory standards and processes and, thus, making progress on the development of needed drugs. While regulatory agencies are part of each of the consortia in an advisory capacity, they are not official members.

All three consortia have a similar formal governance structure, a generalized depiction of which is shown in Figure 2. They each have a consortium director, project manager, and support staff who are employees of C-Path. C-Path staff are not to be thought as supervisors in a hierarchical sense; rather, they serve in an administrative capacity and are charged with easing coordination difficulties in the day-to-day workings of the consortium. The governance structure also includes a coordinating committee[7] that serves as the main strategic decision-making and advisory body of the consortium. It is composed of consortium directors, working group chairs (see below), and one voting member from each of the member organizations. A majority decision rule is used in this decision-making body.

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[6] Members are technically organizations or individuals representing themselves (like academics).
[7] This committee is called the Advisory Committee in PSTC.

Reporting into the coordinating committee are working groups, which are organized around specific milestones and goals. It is in the working groups that operational decisions are made and the day-to-day work is carried out. For the most part, participants select the working group(s) to which they belong, with some participants involved in multiple groups[8]. Each working group is headed by one or two working group chairs who are voted into a limited term by the working group participants and must be confirmed by the coordinating committee. The role of the chair(s) is to represent his/her working group on the coordinating committee and to take a lead on coordinating the activities of the group.

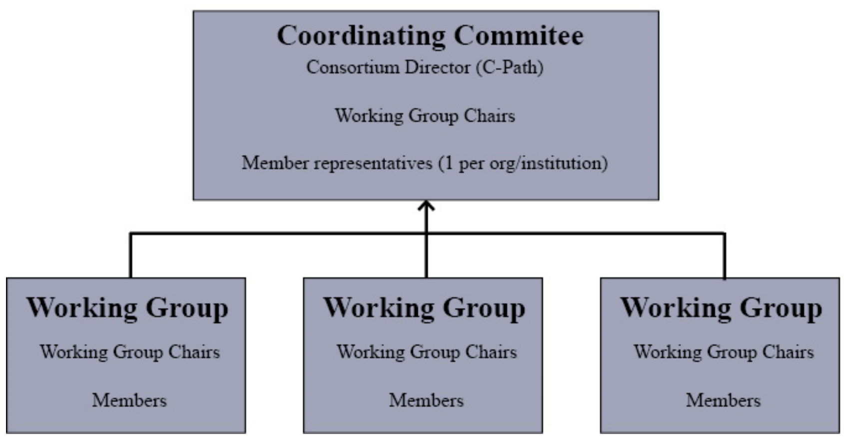

Figure 2: C-Path Consortium Structure

The consortia have a similar funding structure that comes in part by grants and in part by membership fees. For PSTC and CAMD, the grant comes from the FDA while the National MS Society provides grant funding for MSOAC. The only major difference in funding structures occurs because MSOAC's grant funding is the primary funding

[8] A common exception here is the working group focused on statistics. For this working group, the consortia generally ask specific organizations to assign a representative to this group due to a history of lagging participation.

source for the consortium while the other two consortia receive half of their funding from a grant and the other half from membership fees. This difference is not a major concern for this research, given that membership fees are not a significant burden for organizations. In fact, at the time of data collection, PSTC's members had recently voted to increase the membership fees so that they could have more budget to work with. According to consortium director John-Michel Sauer, the membership fee is inexpensive for organizations, so this increase in fees faced no real complaints.

The role and effectiveness of leadership, while inherently individual traits, were deemed similar enough across the three consortia to serve as a control. Each consortium director described their leadership role in a similar way. As the following quotes from the consortium directors of CAMD, MSOAC, and PSTC, respectively, illustrate, they all view their primary role as being the force that keeps the consortium moving in the right direction by facilitating collaboration between members:

> A lot of it [leadership] is aimed at trying to get to know the people, the members. You have to understand where they're coming from so that you can be effective at that fine line between helping them understand that we all have a common goal that's going to help patients, that's why we're doing this…to help patients, but that they also can see that they're going to get something out of it both individually and as an organization. Unless you get to know them as people, you can't do that (Stephenson 2014).

> I think that keeping everything on course is something that is really important…dealing with sometimes difficult personalities is also something that I think the director has to do in a fair way and not pass along anything that you wouldn't want to say right in front of the person… I need to make sure things are moving along even if someone doesn't have enough time to do what they should be doing (Hudson 2014).

> I think it is running a dating service in a lot of ways. We're trying to get people to have the right conversations to work together in the right way (Sauer 2014).

In terms of the effectiveness of leadership across the three consortia, the survey asked respondents to rate how helpful C-Path leadership[9] is in facilitating collaboration in their consortium. Responses from across all three consortia reveal that leadership is widely viewed as helpful: between 90 and 95 percent of respondents rated their leaders as being either “very helpful” or “fairly helpful.”

Finally, while the consortia vary in terms of specific goals, they share similar overarching goals that fall into two main categories: outputs and processes. Outputs of the consortia include regulatory action, like the qualification of biomarkers[10], outcome measures, and models; the creation of disease-specific data standards; and clinical trials databases. The process goals of the consortia include the sharing of expertise and developing relationships with other members and with regulators. According to President and CEO Martha Brumfield, these process goals are just as important as outputs, but are more difficult to measure (2013). As a result, “success” is often described only by the outputs produced by each consortium.

Below, the consortia are described in greater detail, with the most significant differences between them highlighted, differences that primarily revolve around environmental variables like members’ willingness to work together and the degree to

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[9] The question asked about the helpfulness of the consortium’s C-Path leadership in general, not the consortium director in particular.

[10] Biomarkers are defined as “a biological molecule found in blood, other body fluids, or tissues that is a sign of a normal or abnormal process, or of a condition or disease. A biomarker may be used to see how well the body responds to a treatment for a disease or condition.” (http://www.cancer.gov/dictionary?cdrid=45618)

which other collaborative efforts exist with a similar mission. This variation opens the door to examination into these differences.

PSTC

PSTC was the first of C-Path's consortia and is principally concerned with qualifying testing standards and processes by the FDA and its European and Japanese regulatory counterparts. This mission fits into a space that is called "non-competitive" because it involves the sharing of safety data rather than data tied to specific disease areas (Woosley 2014). Being in this space has meant that organizations have shared data relatively willingly with one another. With regards to membership composition, PSTC is the most homogenous of the three consortia, with the vast majority of participants representing organizations from the pharmaceutical industry. In all, 165 individuals participate in the consortium.

As the first of its kind, this consortium had a lot of excitement surrounding it in the early days, excitement that has waned as the following quote from consortium director John-Michel Sauer (2014) illustrates:

> I think that there was a lot of excitement when, 8-9 years ago when things were formed and it looked like it was going to be pretty straightforward to do these qualifications. Everybody was very excited. What's happened over time it's become more difficult to qualify these biomarkers, which has taken its toll on the membership excitement. There's also been a number of other consortia that have started up and so we get into the consortium fatigue idea.

In other words, one of the challenges of this consortium is incentivizing members to actively participate and contribute to the consortium in the face of more competitors and results that have been harder to achieve than originally expected. With that said, PSTC has made progress. Outputs include the qualification of seven drug development tools by the FDA, EMA, and PMDA and the creation of six shared databases ("Metrics of Progress in C-Path Consortia (Internal Document)" 2014).

CAMD

CAMD emerged in response to the failure of several drugs for Alzheimer's Disease and Parkinson's Disease very late in the drug development process. These failures led pharmaceutical companies to take a step away from the relative uncompetitive nature of sharing safety data into the more proprietary and thus competitive area of sharing specific disease data (Woosley 2014). Membership composition in CAMD is mixed. Participants represent pharmaceutical companies, non-regulatory governmental agencies, academia, and other non-profits. In total, 113 individuals participate in CAMD.

The main challenge for this consortium emerges directly from the challenges of collaborating in a fiercely competitive area, as described in the following quote from consortium director Diane Stephenson (2014):

> In these disease areas because it's extremely competitive and there's a huge market and the investments within industry are so great, it's extremely challenging to get sharing of information, pre-competitive alliances, everybody coming together for the sake of the patients…They [the orgs] don't tell you that. But it's clear when you can't make progress that it's because they're choosing not to share.

Like PSTC, CAMD also struggles with making itself unique as more and more collaborative efforts emerge in these disease areas. In response, CAMD leadership is actively trying to communicate the benefit of their consortium to its members in order to increase members' willingness to contribute. For example, in monthly teleconferences and annual meetings, the leadership places great emphasis on highlighting tangible progress as well as the areas in which participants' organizations benefit in intangible way, like informal advice from regulators and access to key opinion leaders.

Despite these challenges, CAMD has made progress towards its goals in spite of the competitive environment in which it exists. Outputs include two drug development tool qualifications, one endorsed method, three database standards, and two shared databases ("Metrics of Progress in C-Path Consortia (Internal Document)" 2014).

MSOAC

The newest consortium included in this study is MSOAC. The impetus for the consortium came from the National Multiple Sclerosis (MS) Society, which approached C-Path to facilitate MSOAC at the suggestion of the FDA. Similar the other two consortia, MSOAC is geared toward the goal of qualifying a better drug development tool for use in clinical trials. The consortium is composed of representative of pharmaceutical companies, non-regulatory governmental agencies, academia, and other non-profits, with a larger presence of academics than in the other two consortia. In total, 59 individuals participate in MSOAC.

The main challenge for MSOAC also revolves around incentivizing active contribution.

Lack of time is often cited as the reason why a member cannot follow through on consortium work. This reason is becoming increasingly common as the pharmaceutical industry undergoes consolidation, meaning that certain disease areas as seeing fewer and fewer organizations contributing to research. At the time of this research, for example, Bristol-Meyers Squibb, a large pharmaceutical company, had just dropped its neuroscience portfolio, which included research on MS. Thus, even though MSOAC does not have any competitor collaborations because it exists in an underserved disease area, it still struggles to find ways to incentivize active contribution from members.

Although it is still young, MSOAC has also shown signs of progress. It has developed one shared database and one data standard, milestones on the way to qualifying drug development tools ("Metrics of Progress in C-Path Consortia (Internal Document)" 2014). These outputs have been firsts of their kind and have allowed for more progress to be made in the MS disease area because the actors are working with each other, rather than in isolation as is most often the case in this industry.

Methods

The main method of analysis used throughout this dissertation is social network analysis. Social network analysis is a method of visualizing and measuring social structure, or regular and persistent relations among individual or collective actors. It does so by examining the relations, or ties, between the set of actors in some bounded network defined by the researcher. One of the assumptions driving the use of social network analysis is that an actor's set of relations affects their attitudes and behaviors. Thus, studying these relations provides insight that attribute variables do not (Knoke and Yang 2008). Several software programs now exist to analyze network data. UCINet, the most widespread software for network analysis, is used here (Borgatti, Everett, and Johnson 2013).

Debate exists as to whether social network analysis is strictly a method or a set of theories (Burt 1980; Galaskiewicz 2007). Here, it is relied upon first and foremost to measure the main variables of interest. With that said, theoretical arguments developed by network scholars are relied upon as well throughout the dissertation. The attempt is made, particularly in Chapter 4, to add more theoretical backbone to network analysis.

In addition to social network analysis, standard regression methods are used to investigate how network measures affect non-network measures of participant satisfaction. It is here, in the overlap of network and non-network measures and methods that some trouble arises. In particular, the dependence of network data becomes an issue when network measures are used in standard analysis, an issue that is discussed below.

Dependence of observations

Standard regression techniques are used in this dissertation to investigate the effect of certain network measures—namely participants' betweenness centrality and clustering coefficients—on non-network measures. Doing so, however, may violate the assumption of standard regression that observations are independent. The inclusion of network variables means that there is a natural dependence built into these observations because they are calculated based on ties connecting two participants. Without correcting for this interdependence, the estimates of the standard errors are could too small and thus, the significance of results may be falsely inflated (Hox 2010).

This issue is most problematic when the unit of analysis is the dyad, meaning when the researcher is examining the effect of some variables on the relationships between two actors. When the unit of analysis is an individual actor, as it is here, the dependence effect is not as problematic. However, dependence is an issue that must be acknowledged and future research can look to ways that better model these data. More detail on the dependence issue is provided here, as well as two potential models that have been proposed to address it.

The dependence of network data is a well-known issue among network scholars. Rather than use statistical methods to remove dependencies from the data as is the prevailing norm in non-network research, network scholars do not wish to rid the data of its dependencies because it is the dependencies themselves that can be used to explain social phenomena and behavior (Robins and Pattison 2005). On that vein, network scholars are developing methods by which the dependencies can be modeled, and thus embraced.

Two models that could be of use in future iterations of this research are discussed here: exponential random graph (p*) models and a particular generalization of p* models proposed by Robins et. al (2001), both of which expressly permit and model the dependence that is inherent in network data. To start, the family of exponential random graph models (ERGM), commonly referred to as p* models, seek to find the stochiastic process that generated the observed network. To do this, it assumes that each tie in a network is random variable that has some level of statistical noise attached to it. Treating the observed network as one possible configuration of these ties that is drawn from a distribution of all possible configuration of those ties, the model then assesses the degree to which hypothesized network configurations exist more in the observed network than expected by random chance (Robins et al. 2007). A simple example of a research question that ERGM models are suited to answer is the degree to which a particular network exhibits more reciprocal ties between participants than can be expected by chance.

Although ERGMs are useful in that they provide a way for network researchers to look at network data from a statistical, rather than just descriptive perspective, they are designed to understand the degree to which certain network structures exist. In other words, the network configurations are, for all intents and purposes, the dependent variable. In this dissertation, on the other hand, the network structures are for the most part treated more as independent variables use to explain other, non-network phenomena.

A generalization of p* models, developed by Robins et. al (2001) presents a potential solution. A type of social influence model, this generalization allows researchers to examine the degree to which shared opinions influence network configurations. It does this by creating a directed network in which ties flow between one set of variables (the parent block) to another (the child block). Network variables can be assigned to the parent block while attribute variables can be assigned to the child block, thereby allowing the researcher to investigate the degree to which some attribute, like common attitudes, affect network configurations, like cohesive subgroups. More investigation into this model is needed, but it does present a potential way to address the dependence issue while still being able to investigate the relationship of interest for this research.

For now, the regression results presented in this dissertation use standard regression techniques with the knowledge that the network variables may violate the independence of observations assumption. As was stated above, the severity of the problem is not likely to be high given that the unit of analysis is the individual participant, not the relationship between participants.

Data collection

Nodes and ties

Social network analysis examines networks composed of nodes, or actors, connected by ties, which represent some relationship or resource exchange that exists between the two nodes. Before the data collection procedures are reviewed in detail, then, it is first important to clarify what the nodes and ties represent in these consortia. To begin, each node could be defined in one of two ways: as an organization or an individual. Technically, the consortia members are the organizations themselves, but most organizations have multiple representatives serving on the consortia. Academics, on the other hand, most often represent themselves rather than their academic institutions. While it has long been argued that organizations shape their employee's behavior by creating an organizational culture with rules and norms, early organizational theorists also recognized that it is impossible to force employees to act solely in the interest of their organization (Barnard 1938; Simon 1945). This complexity makes it difficult to tease out whether an individual action was made on behalf of an organization or the individual themselves.

Further complicating matters, while many of those participating in the consortia are given permission to participate and share information on behalf of their sending organization, the work is accomplished by individuals, not organizations. As a result, the relationships that are established are more accurately captured by studying individuals rather than organizations. For these reasons, individuals are used as the nodes in the networks and are referred to as "participants." Nevertheless, it should be noted that, for the most part, the individual participants represent organizations.

The participants were identified and contacted using information provided by the consortium directors and staff. Namely, the researcher was given a membership roster as well as contact information for all participants. Because membership in the consortium is well defined, defining the network boundary was straightforward.

The only membership issue that had to be settled was whether or not to include C-Path employees as nodes in the network. It was decided that they should be included because they are active participants in the workings of the consortium. In light of the role of the consortium director and project manager, it was expected that these individuals would be central in the communication network and thus their exclusion would potentially result in a more incomplete network. However, given that C-Path employees are unlike other members in that their loyalties are first and foremost to C-Path, their responses were excluded from the data analysis based on evaluative data (e.g., question about satisfaction with the progress, etc.) in order to avoid biasing the results.

The primary resource network of interest is the information sharing network. In other words, ties represent communication between two participants. The selection of information as the resource of interest is based on its importance to problem-solving collaborative networks. In other types of collaborative networks, like service implementation networks, ties based on referrals or service contracts between organizations coordinating service delivery have been deemed to be a particularly important for understanding their performance (c.f., Huang and Provan 2007; Isett and Provan 2005; Provan, Isett, and Milward 2004). Problem-solving networks, however, have a different purpose: to develop innovative solutions to complex problems. For these networks, information is perhaps the single most important resource since good ideas often arise from being able to access diverse knowledge and alternative ways of thinking (Burt 2004). With this in mind, examining the communication networks provides a good starting point for understanding the dependence, and therefore power relationships in the consortia.

Survey administration

The survey was administered online via Qualtrics survey software between May and September of 2014 to most of the participants of the three consortia. The only participants who did not receive the survey were regulators, who occupy an advisory, rather than a voting role. In an attempt to encourage participation, the recruitment of consortia members to participate in the survey employed several tactics that researchers studying online survey design have found to increase response rates. Respondents first received an introduction email from their consortium director alerting them to and endorsing the research as well as encouraging members to respond (Fan and Yan 2010; Cook, Heath, and Thompson 2000).

The survey itself was then distributed via an initial email sent through Qualtrics survey software with an explanation of the research and an assurance that responses would be confidential (see Appendix A for the text of the initial email and Appendix B for the survey questions). Recipients were informed that they would receive follow-up emails from the researcher if they did not participate in the survey (Klofstad, Boulianne, and Basson 2008) and were given an estimate of the expected time it would take to complete the survey (Trouteaud 2004). Finally, three reminder emails were sent to non-respondents one, two, and three weeks after the initial email, respectively (Fan and Yan 2010).

Response rates

Response rates were similar across the three consortia, ranging from 32 to 37 percent[11]. While not ideal, these response rates mirror, if not slightly improve upon average response rates for online surveys (Andrews, Nonnecke, and Preece 2003; Witmer, Colman, and Katzman 1999). Moreover, interviews with C-Path's leadership revealed that they have struggled to get high response rates for internal surveys as well, which suggests that non-respondents are not likely to have purposefully not participated in this particular survey. Instead, the suspected reason for non-response is lack of time. As one consortium director put it, participation in a consortium is not a member's day job and taking a survey about their involvement is even less of a priority for many (Stephenson 2014).

Despite being unsurprising, these lower response rates have the potential to bias the validity of the findings. In particular, if non-respondents would have answered questions differently than respondents, then the inferences drawn from the data may be biased (Singer 2006). Following the advice of Armstrong and Overton (1977) and Provan and Gassenheimer (1994), one way to test for non-response bias is to compare the data

[11] Response rates were as follows: MSOAC=37%, PSTC=35%, CAMD=32%.

from the first 75 percent of respondents to that of the last 25 percent of respondents. The last 25 percent of respondents are considered most similar to non-respondents because they required significant of prodding to answer. The Mann-Whitney nonparametric test[12] was performed to compare the two groups of respondents for each variable in each consortium separately. One of the variables, the likelihood that respondents would invest in an alternative to the consortium in the future, showed significant differences (alpha = .10) in the two populations in all three networks, although the direction of the difference varied. Because the small size of the networks, the data was pooled and the tests were re-run. Using pooled data, none of the variables differed significantly between the two populations. This suggests that non-respondents would not have answered significantly differently than respondents.

Another way to test for non-response bias is to determine whether certain types of respondents were missing at a greater frequency than others by examining "known values" for both respondents and non-respondents (Armstrong and Overton 1977). For instance, if consortium members from non-profit organizations were more likely to not respond to the survey, then the results would likely be biased because the voice of non-profit representatives would be underrepresented.

This method necessitates having the same type of information on both respondents and non-respondents. The information available to the researcher about all consortia members was 1) the organization the member represents (from which the researcher inferred organizational type: nonprofit, for-profit, or governmental agency),

[12] This test was used instead of a t-test because the data are mostly ordinal.

and 2) the working groups within the consortia to which the member belongs. Tables C1 through C6 in Appendix C shows the results of these comparisons. Across the three consortia, respondents were representative of all of the organizational types and working groups. The only exception is with MSOAC, which did not have a respondent from the governmental agency category. This is not especially concerning, though, given that the consortium only includes one governmental agency representative. This analysis provides further confidence that non-response bias is not a significant issue in the data.

Network instrument

The portion of the survey focused on collection of network data asked respondents for information on three types of ties: with whom they communicated, whom they perceived as influential, and on whom they depended to get work done. The latter two ties were used to validate the main measures used herein. Here, the communication network is the focus.

The communication networks were created using two survey questions. The first question asked respondents to list up to 15 consortium participants with whom they communicated via phone, email, or in-person meetings about consortium-related work over the last six months. The time period was restricted in order to guide respondents to think about a similar length of time. Six months, a time period used by other organizational network scholars, is short enough to increase the accuracy of participants' memories, but long enough to allow trends to develop (Provan et. al 2009). Moreover, limiting the number of participants a respondent could report forced respondents to focus on their most important communication partners. Respondents were also instructed to exclude communication via consortium-wide teleconferences unless the respondent “personally communicate(d) in a substantive way" with others in this venue. The exact wording of this and all other survey questions is available in Appendix B.

A follow-up question then asked respondents to provide the frequency of communication with the participants they named. This question was asked in order to provide more nuance in the communication network since the relationship between two participants who communicate frequently is likely to be different than that of participants who only communicate on occasion. Respondents chose between the following frequency options: approximately once per week or more, approximately twice per month, and approximately once per month or less.

The main communication network question employed what is known as the roster method to generate names of communication partners, known as “alters” in network terminology. In other words, respondents were presented with a list of all of the members in the consortium and were asked to list those with whom they communicate (Wasserman and Faust 1994)[13]. While reviewing a roster can be a lengthy and burdensome task when networks are large (Marsden 2011), this method reduces the chance of omission errors that occur when respondents are asked to report alters without a memory aid (Brewer 2000; Henry, Lubell, and McCoy 2012). Networks generated through the roster method have been shown to be more inclusive (albeit with sparser ties between actors) than networks generated through free recall (Henry, Lubell, and McCoy 2012).

[13] The roster included regulatory agency representatives even though they did not receive the survey.

Once collected, a weighted communication matrix was constructed in which the row and column headers consisted of all survey respondents as well as their named communication partners within the consortium (if not respondents themselves). The values in the matrix represented the reported frequency of communication between two consortium members. The weights assigned to the frequency responses were on a ratio scale to ensure that results would reflect ratio-scale intervals between the nominal categories. Weights are as follows: approximately once per week or more=four; approximately twice per month=two; approximately once per month or less=one. A value of zero was entered if no communication is reported between two participants.

The ties were then made symmetric, meaning a tie does not take into account who initiates the communication. Put differently, if respondent A indicated a communication tie to respondent B, it was assumed that respondent B would have also listed respondent A had s/he responded to the survey or had s/he not been limited to 15 communication partners. Specifically, for very active participants who communicate with many others, not reporting a tie does not necessarily mean that a tie does not exist; rather, it means that the participant communicates more frequently with other participants.

Provan et. al (2004) argue that the use of symmetric ties is consistent with the undirected nature of communication. While one actor must initiate the communication (and thus, could be considered the sender of information), the sender and receiver labels that exist when the tie is initially established are unlikely to be remain the same during the course of the communication relationship. Rather, at some point in time, the original receiver is likely to reciprocate and provide different information back to the original sender, thus reversing the original roles.

While the use of symmetric ties is warranted due to the nature of the resource being exchange and the nature by which the data were collected, it runs the risk of producing inaccurate results (Marsden 1990). In particular, this could be an issue because structural power is based on the idea that power is asymmetric. In power imbalanced relationships, one participant's dependence on a communication partner is not equal to the partner's dependence on him/her. Symmetricizing the data, then, runs the risk of removing this dependency relationship from the data.

To ensure that the results attained herein using symmetric data are not merely a product of how the ties were defined, an additional set of tests is run comparing a measure for structural power based on the symmetric communication network data against a measure for power based on the asymmetric communication network data. The first measure is the primary measure for structural power used in this research: betweenness centrality (this measure is describe in greater detail below). The second is the measure that would be used if the ties were asymmetric, the in-degree centrality scores in the communication network. It measures the number of times a participant was nominated as a communication partner by respondents.

The degree of statistical dependence is calculated between each of the two measures and a third measure, a common proxy for power use: perceived influence (c.f., Brass 1984; Brass and Burkhardt 1993; Provan and Milward 1995). Influence data was collected by asking respondents for the first and last name of the top ten participants whom they considered to be influential in the decision-making of the consortia. Since influence in not a shared resource, this data resulted in an asymmetric influence matrix for each of the three consortia.

Results, shown in Table 2, reveal that associations, measured using Spearman's rho, are significant and positive across all of the consortia for both measures. For example, the correlation between a participant's indegree centrality score based on the asymmetric communication matrix and his/her perceived influence is 0.491 while the correlation between a participant's betweenness centrality score based on the symmetric communication matrix and his/her perceived influence in 0.312. This means that both the symmetric and the asymmetric measures of structural power are significant and positive predictors of a participant's influence in the network. In fact, the results attained using the asymmetric data are stronger in magnitude, which suggests that the use of symmetric data waters down the results, rather than spuriously inflates them.

Table 2: Comparison of asymmetric to symmetric communication data

	Asymmetric Communication		*Symmetric Communication*	
Consortium	**Spearman's rho**	**Prob > |t|**	**Spearman's rho**	**Prob > |t|**
CAMD	0.491	0.000	0.312	0.106
MSOAC	0.576	0.000	0.683	0.002
PSTC	0.725	0.000	0.329	0.020
Combined	0.608	0.000	0.382	0.000

Defining the ties as symmetric, then, is warranted given that they are more fitting for the nature of communication networks and because doing so does not appear to produce inaccurate results. With the networks thus defined, Table 3 reports the percentage of network participants included in the three consortia's communication networks.

Table 3: Member Representation in Communication Networks

Consortium	% of Members Represented in Network
CAMD	64
MSOAC	74
PSTC	100

Measures

Two categories of measures, both of which are based on the survey data, are used in this dissertation: network measures that quantify the structural characteristics and trends in the communication networks, and perceptual measures that capture participants' feelings about their experience in the consortia. In this section, a thorough discussion of how the network measures are calculated is provided given that they are used throughout the dissertation. The theoretical explanations for their use and test of their validity and appropriateness are performed in the analytical chapters that follow. The perceptual measures are discussed in this section as well, albeit more broadly. Because the specific perceptual measures only apply to specific chapters, their details are provided in those chapters.

Network measures

The main network measures, betweenness centrality/centralization and the globalized clustering coefficient derive from the weighted communication networks of the three consortia. They are measures for structural power/power distribution and cohesive behavior, respectively. To begin with, one of the main concepts to be measured is structural power distribution among participants of a collaborative network. This idea is measured using a weighted version of the betweenness centralization measure. Betweenness centralization is a group level measure that reveals the degree to which one or a few actors control the flow of communication in the network. Controlling information flow is important for participants of collaborative networks because it affects decision-making. The more information to which one participant has access, the more s/he can affect the decisions driving the actions and direction of the consortium.

To understand what betweenness centralization captures, it is first necessary to understand the measure on which it is based, the individual level measure of a participant's betweenness centrality. A participant's betweenness centrality is calculated by determining the extent to which an actor falls on the shortest path, or geodesic, connecting two other actors (Freeman 1979). It assumes that communication will flow through the shortest path between two participants; thus, participants who sit on the shortest path between two others can control the flow of information between them. The more an actor resides *between* two others, the more s/he can choose which information to pass along and which information to keep. The formula for betweenness centrality is shown in equation 1, where *j* and *k* are participants in the network, g_{jk} is the number of geodesics connecting them, g_{jk}(i) is the number of geodesics between the two participants that include actor *i* (Freeman 1979). This measure can be standardized by dividing the result by $\frac{(g-1)(g-2)}{2}$, where g represents the number of participants in the network. Standardizing the measure enables betweenness centrality scores to be compared across networks of different sizes.

$$C_B(i) = \frac{g_{jk}(i)}{g_{jk}} \qquad [1]$$

Betweenness centralization is based on the betweenness centrality scores of all network participants and reveals the extent to which the network tends towards centralization or decentralization. When it is based on the standardized measure of betweenness centrality, as it is in the research presented here, it varies between zero and one, where a value of zero indicates that power is evenly distributed among all of the members of the consortium, and a value of one indicates that power is centralized around one member. The formula for betweenness centralization is shown in equation 2 (Wasserman and Faust 1994: 192), where $C_B\ (i*)$ is the largest observed standardized actor betweenness score.

$$C_B = \frac{\sum_{i=1}^{g}[C_B(i*) - C_B(i)]}{g-1} \qquad [2]$$

The betweenness centralization measure described above is based on binary ties, meaning either a tie exists between two participants (resulting in a tie of "1") or it does not (resulting in a tie of "0"). The network data collected for this research, however, went a step further in that it asked respondents about the frequency of their communication with each of the participants they named. This additional information creates a weighted network in which all ties are not created equal; rather, some ties are "stronger" than others because the participants are in frequent communication with one another. Research has shown that stronger ties transmit information more quickly and easily than weak ties (Granovetter 1973).

Opsahl et. al (2010) develop a weighted generalization of the betweenness centralization measure that allows the researcher to harness this additional information. In particular, their measure allows the researcher to determine the relative importance of tie weights as compared to the number of ties in how the "shortest path" is calculated through the inclusion of the parameter, α. In selecting a value for α that is most appropriate for the particular research setting, the researcher determines whether the "shortest path" is defined as the fewest number of intermediary participants or the strongest ties between participants. The formula for weighted betweenness centralization is shown in equation 3, where *w* is the weighted adjacency matrix:

$$C_B^{w\alpha}(i) = \frac{g_{jk}^{w\alpha}(i)}{g_{jk}^{w\alpha}} \qquad [3]$$

An α of zero ignores the weights of the ties and thus is equal to un-weighted betweenness centralization, while an α greater than one means that additional ties are relatively unimportant compared to the strength of a participant's existing ties. Here, an α of 0.5 is used, which gives equal attention to both weight and number of intermediary nodes when calculating the geodesic. The selection of α as 0.5 follows the logic that a mix of strong and weak ties is preferred since different tie strengths serve different purposes: weak ties allow for the integration of new perspectives while strong ties are better at creating feelings of unity (Granovetter 1973; Provan and Lemaire 2012).

The second network measure, the global clustering coefficient, is a behavioral measure for cohesion, or the extent to which participants are densely tied to one another in the communication network. It is a subgroup-based measure, meaning that it embraces the fact that clusters of densely-connected participants can achieve high levels of cohesion just as can whole networks in which all participants are densely tied to one another.

Cohesive subgroups are measured using the global clustering coefficient, which is based on the network property of transitivity. It is measured by the degree to which triples, defined as three nodes connected by either two or three ties, are fully connected by three ties. Put differently, the global clustering coefficient "measures the fraction of triples that have their third edge filled in to complete the triangle" (Newman 2003, 183). It varies between zero (no closed triples) and one (all nodes are involved in a closed triple). The formula for the global clustering coefficient is shown in equation 4, where $\sum \tau$ represents the total number of triples and $\sum \tau_{\Delta}$ represents the number of closed triples.

$$C = \frac{\sum \tau_{\Delta}}{\sum \tau} \qquad [4]$$

Again, because the communication ties for this study are weighted according to frequency of communication, a weighted version of the global clustering coefficient is preferable because it captures more nuanced information. When three participants are fully connected by strong ties, for example, information is likely to flow more freely and quickly than when they are only weakly connected. The traditional, non-weighted global clustering coefficient is calculated simply on *whether* ties exist between three actors, not on the strength of those ties. By incorporating weights, closed triples composed of all strong ties contribute most to a high global clustering coefficient, triples composed of all weak of weak ties contribute the least, and triples composed of mixed strong and weak ties contribute in between.

Opsahl and Panzarasa (2009) propose a way to incorporate tie weights into the global clustering coefficient by including a parameter that defines the value assigned to a closed triple, ω. In other words, ω represents the degree to which a triple composed of all strong ties is more valuable than a triple composed of weak ties. They suggest several ways in which ω can be calculated: the arithmetic mean, the geometric mean, the minimum, or the maximum of the tie weights that comprise the closed triple. Here, the arithmetic mean is selected for ω because it is the simplest method and the data do not require anything more complex. The formula for the weighted global clustering coefficient is shown in equation 5[14]:

$$C_{\omega} = \frac{\sum_{\tau_{\Delta}} \omega}{\sum_{\tau} \omega} \qquad [5]$$

Perceptual measures

The second category of measures can be broadly defined as perceptual measures because they are based on consortium participants' feelings about how the consortium is doing, how they feel about their participation, and anticipations about their own futures in the consortium. Perceptual measures are used in three ways in this dissertation. First, they are used to validate the structural measures depicted above. Especially because the structural measures are based on the same set of ties, perceptual data is used to ensure that each measure is truly capturing the essence of its underlying concept. Validation of the measure for structural power, betweenness centrality, is achieved using perceptual network data. Namely, respondents are asked about the participant whom they perceive to

[14] The tnet package in R was used to calculate both weighted betweenness centrality scores and the weighted global clustering coefficients.

be most influential in the decision-making of the consortia. Results for this validation are discussed in Chapter 3. Validation of the measure for cohesion, the global clustering coefficient, are discussed in Chapter 4 using data on the degree to which participants felt that their consortia was cohesive.

Second, perceptual measures are used as an alternative measure for structural power distribution. In contrast to measuring structural power using the communication network structure, this explanation relies on determining how dependent participants are on the consortium itself for achieving their own personal goals. To this end, perceptual data was collected asking participants about the type and attractiveness of their alternatives to participating in the consortia. This measure is contrasted with the structural measure of power in Chapter 3.

The final use of perceptual data is to understand more about how structure of the communication networks affects how participants feel about their participation. To gauge this, respondents were asked to answer a series of questions with Likert-scale answers. For instance, they were asked the extent to which they agreed their contribution to the consortium is valued by other participants. The data that results was converted into ordinal variables for the analysis. More detail on these measures is provided in Chapter 5.

Network diagrams

Using the symmetric weighted communication networks, diagrams for each of the consortium was created using UCINet software. The diagrams for CAMD, MSOAC, and PSTC, are shown below in Figure 3, Figure 4 and Figure 5, respectively. They are included here because they provide descriptive information about the networks; namely, they reveal the types of actors involved and the general structure of the collaborative network.

The nodes represent all of the consortia participants who either responded to the survey or were identified by a respondent as a communication partner. Consequently, the network diagrams are more centralized than is likely the reality because non-respondent nodes are, by the nature of not responding, going to be less connected with others than respondent nodes. Given that the three networks had similar response rates, though, the network diagrams are likely to suffer from a similar magnitude distortion towards centralization.

The nodes are sized proportionally to their betweenness centrality scores, with higher scores represented by bigger nodes. Node color and shape are based on the type of organization the participant represents—with distinctions made between C-Path employees, for-profit, nonprofit, regulatory agency, and non-regulatory government agency—and the width of the ties is based on the frequency of communication reported by the respondents[15]. It should be noted that isolates—nodes that are not tied to any other node—are not included in these diagrams.

The diagrams reveal different patterns of social structure in the three consortia. To begin with, CAMD's communication network, shown in Figure 3, appears to be the most centralized of the three and is dominated first and foremost by a small group of very centralized C-Path employees. Despite this consortium's inclusion of participants from

[15] Because the data were treated as undirected, the highest weight reported by either respondent was used as the tie weight.

the non-profit and governmental sectors, it appears that representatives of for-profit organizations are by far the next most active participants in this network. In particular, four for-profit representatives appear to play critical roles in the communication network—nodes E, AK, AL, and BC. These individuals occupy critical positions, known as gatekeeper positions, because they provide and receive information from otherwise unconnected individuals (Lewin 1947).

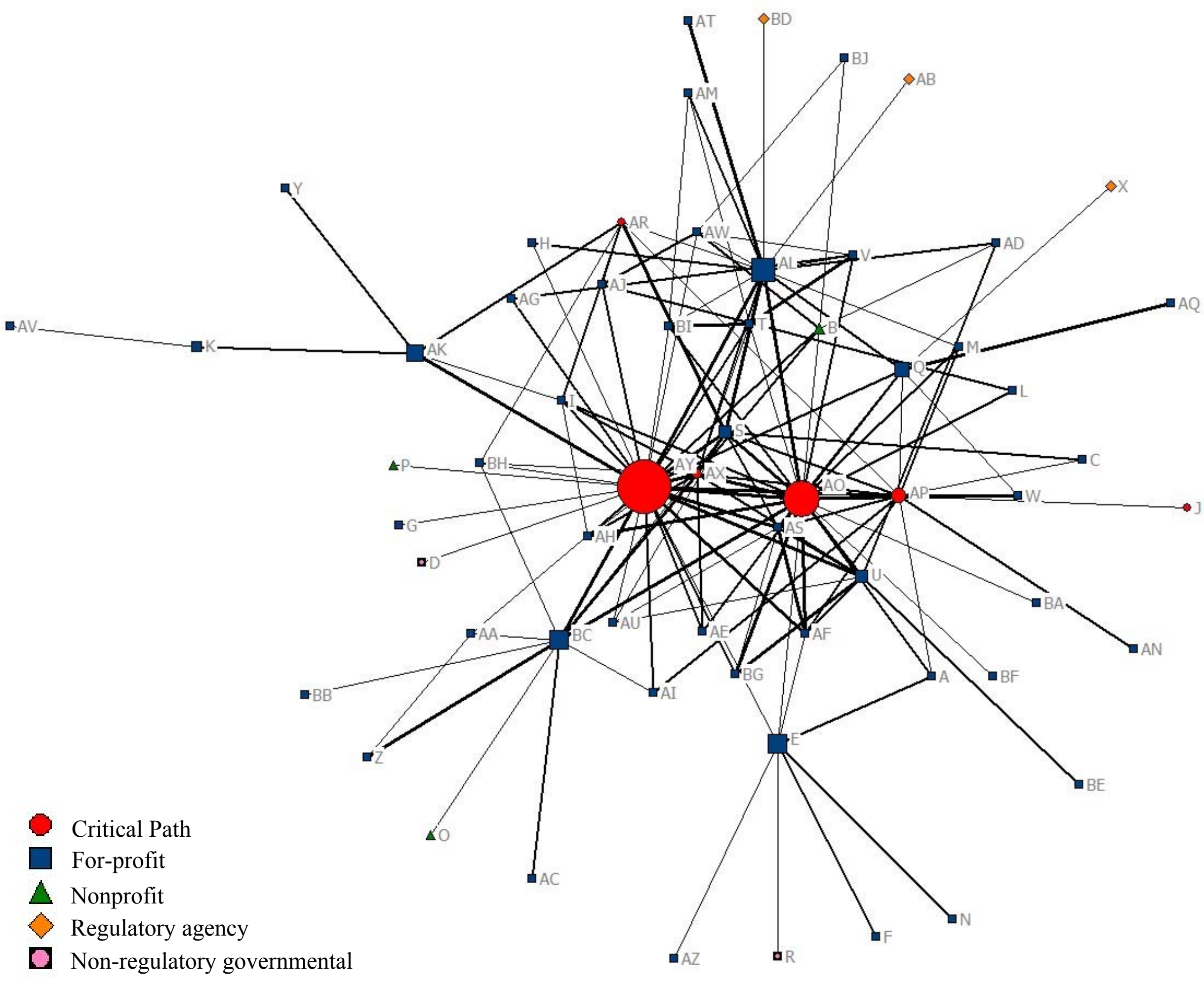

Figure 3: Communication network of CAMD: 62 nodes

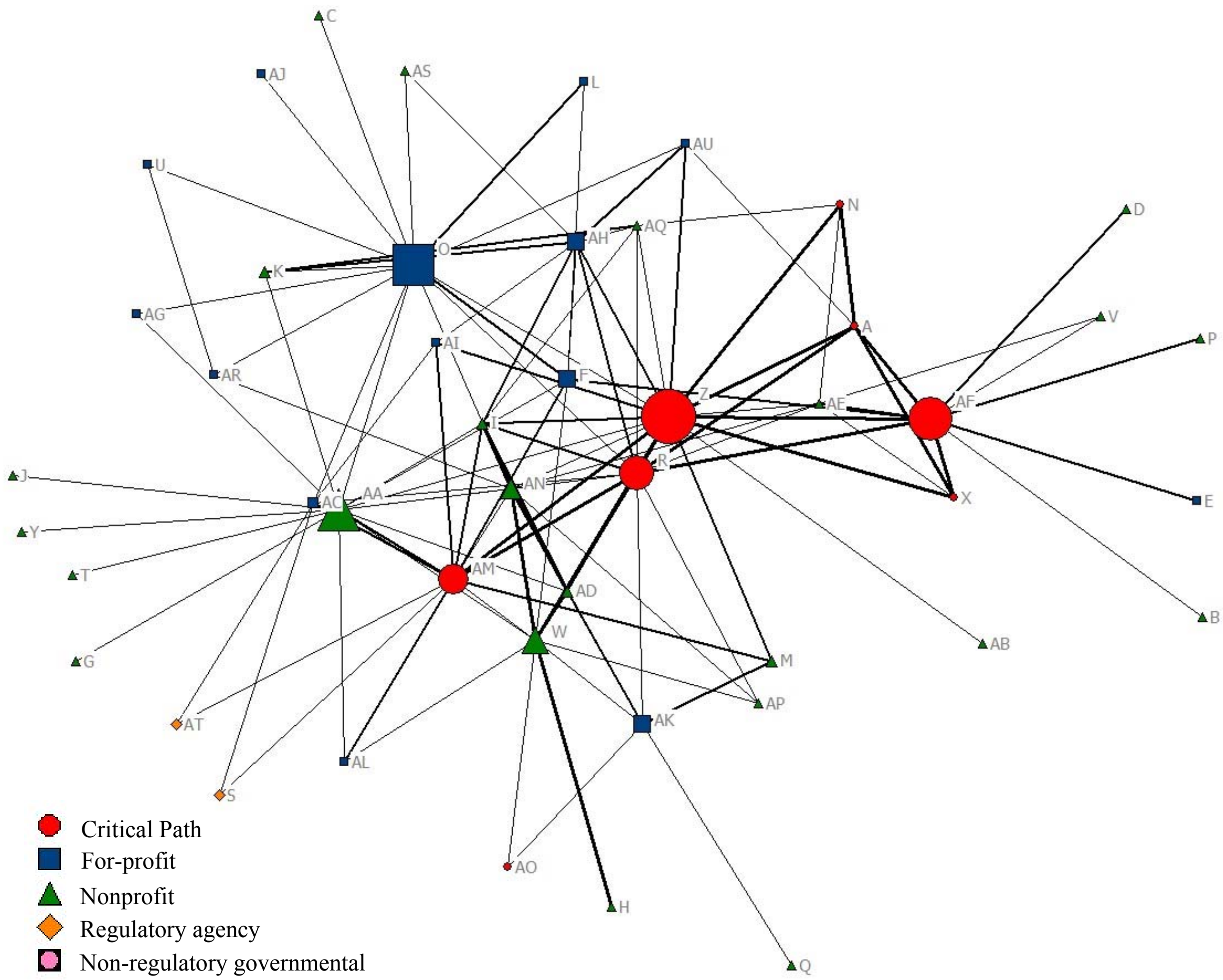

Figure 4: Communication network of MSOAC; 47 Nodes

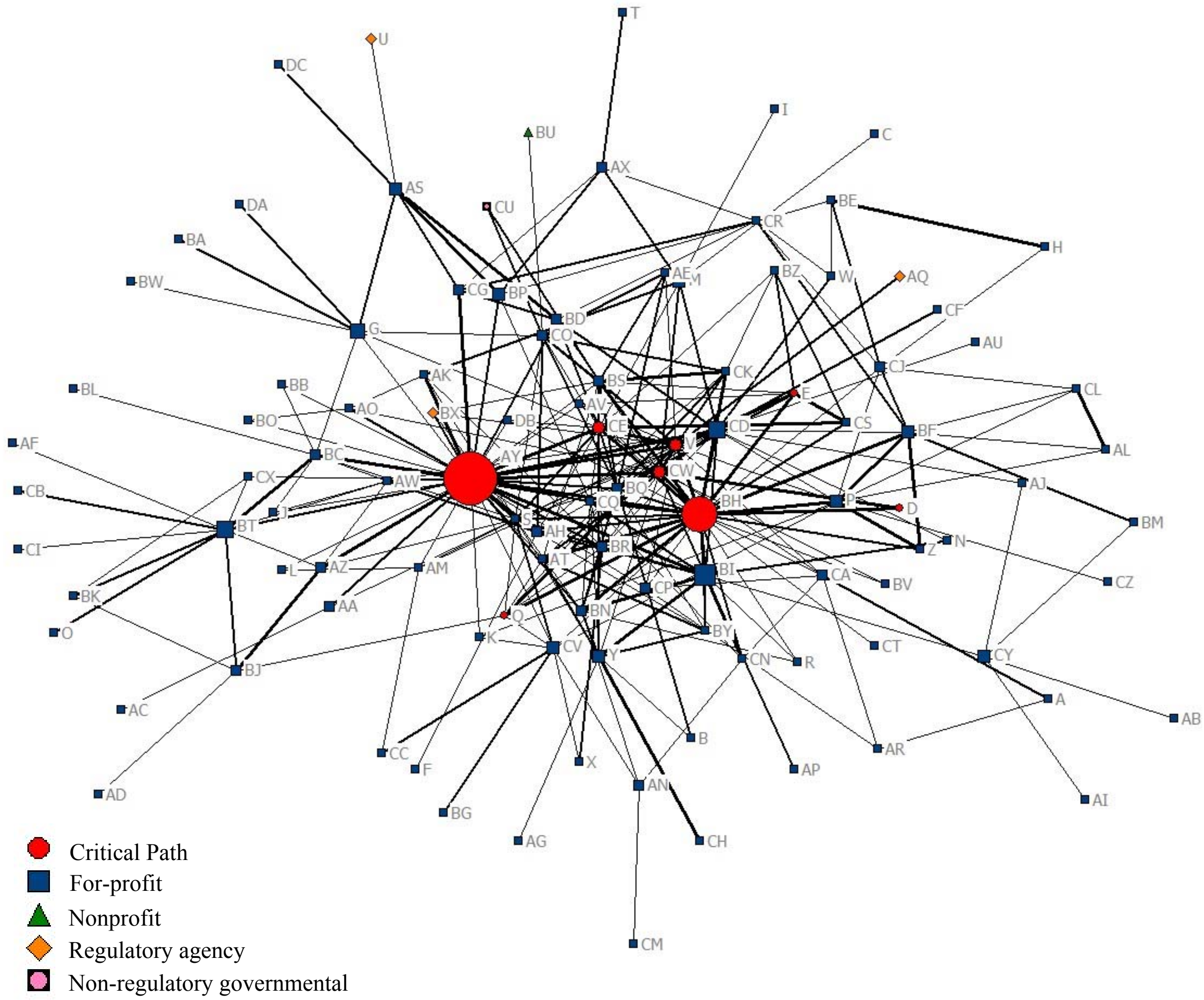

Figure 5: Communication network of PSTC; 107 nodes

The network diagram of MSOAC, shown in Figure 4, reveals a very different communication structure. Although several C-Path employees are highly central like in CAMD, there exists a greater mix of participants, including participants representing both for-profit and nonprofit organizations, who occupy central positions in this network. Moreover, the network does not appear to be very centralized, with many nodes of a similar, high centrality.

Finally, the diagram of PSTC, Figure 5, depicts yet another informal communication structure between participants. Like the other two networks, C-Path employees are the most central nodes in the network. Given that this consortium is composed almost exclusively of participants representing for-profit organizations, not much more can be said about the mix of participants who occupy critical positions. What is interesting, though, is the relative equality of many for-profit representatives. As compared to CAMD in which four nodes clearly occupied critical gatekeeping positions, no such nodes exist in PSTC. Put differently, there appear to be more redundant ties to actors on the periphery, meaning that fewer actors serve as any one participant's sole communication link.

Taken together, the network diagrams suggest structural similarities and differences in the communication network of the consortia. The main similarity is the importance of C-Path employees. In all three networks, they occupy central positions. This is not surprising, given the administrative roles of the C-Path consortia directors and project managers. On the other hand, the networks differ in terms of how centralized they are and the sectors that are most represented in the core of the communication networks.

MSOAC appears to be the least centralized and have the greatest diversity in terms of the sectors represented by the most central participants while CAMD appears to be the most centralized and least representative in terms of which sectors contribute central participants. These visual observations will be tested more rigorously in Chapter 4.

Summary

This chapter describes the original data that was collected for this dissertation. First, the environment in which C-Path was founded was presented, a highly competitive environment in the pharmaceutical drug development domain that was just starting to recognize the need for collaboration amongst its many actors. C-Path filled the needed role of neutral third party to facilitate collaboration between the pharmaceutical industry and its regulator, the FDA, through the creation of disease- or problem-focused consortia.

The three C-Path consortia examined in this dissertation were then described, with special attention being paid to the similarities among them and differences between them. These consortia provide an excellent opportunity to examine structural power in collaborative networks for two main reasons. First, because they exist under a single umbrella organization, C-Path, the consortia share several important characteristics like governance structure, leadership, and funding. These similarities are useful not only because they effectively control for the effects of these potentially confounding variables, but also because they allow the data from the three consortia to be aggregated for individual-level analysis. Second, the consortia function largely independently from one another and exhibit variation on key variables, allowing them to be compared. Being able to compare networks is an improvement over the common single case study design that is prevalent in network research.

The network instrument used to collect data was also described in detail, as well as the limitations with the data that resulted. In particular, the response rates achieved could be problematic due to non-response bias. Tests revealed, however, that the data seem to be missing at random and therefore can be relied upon with a good degree of confidence. Therefore, while the response rates were lower than desired, they meets or exceeds acceptable response rates used in other research of this nature.

A description of the main measures used in the analytical chapters was provided, as were with network diagrams of the three consortia, which provide a visual of the communication network between participants. The chapters that follow include brief descriptions of the data, but the reader should refer back to this chapter for full descriptions of the data.

CHAPTER 3: CONCEPTUALIZING STRUCTURAL POWER IN COLLABORATIVE NETWORKS

In Chapter 1, it was argued that power is a frequently-used but not well understood concept in the literature on collaborative networks, or networks in which independent actors work together to achieve a shared goal. Generally speaking, it is assumed that uneven distributions of power are bad for collaborative networks (c.f., Buse 2003; Bryson et. al 2008; Huxham and Vangen 2005; Mayer 1987). However, without a precise conceptualization and measure for power, it is difficult to examine this assumption with any degree of rigor. This chapter, then, begins the journey of understanding the effects of a specific type of power, structural power, in a specific setting, collaborative networks by exploring what structural power is and from where it comes.

Structural power, or power as dependence, is selected as the focus of this research, not because it is the only or even most important type of power, but because it is a particularly salient type of power for collaborative networks. The very premise behind collaboration is the notion that two heads is better than one (Gray 1989). In order for collaborative networks to function, actors become interdependent as they jointly contribute towards their shared goal or purpose. These dependency relationships are an integral part of collaboration and thus, are a logical place to begin an exploration of power and its effect on collaborative network processes and outcomes.

Narrowing the scope of focus to structural power is a start; however, different operationalizations of structural power exist. In particular, two distinct, but related research traditions view power through a structural lens: the social exchange literature and the organizational networks literature. These literatures diverge in that they focus on different sources of this power. As will be argued below, the social exchange literature focuses on structural power that derives from relationships external to the collaborative network, meaning it focuses more on the environment in which a collaborative network exists. The organizational networks literature, on the other hand, concentrates on structural power that derives from within the boundaries of the collaborative network itself; namely, from the relationships that are established and maintained between the collaborative network's participants.

One of the problems with developing a better understanding of structural power in collaborative networks is that these two traditions began from a similar foundation, but developed under separate academic disciplines. Thus, they use different language to talk about a similar phenomenon and use different methodologies to study it. It is the goal of this chapter to determine whether one of these operationalizations or a combination of them most accurately reflects structural power in collaborative networks. Later chapters will then use the most appropriate operationalization to examine the effects of structural power and its distribution in collaborative networks.

In order to pursue this goal, the two perspectives are first explained and their basic premises are turned into hypotheses. These hypotheses are then tested on original data collected from participants in three collaborative networks. Results, which support the internal operationalization of power, are then reviewed and discussed.

Structural power in the social exchange literature

The conceptualization of structural power originated in the sociological tradition often referred to as social exchange[16]. Given the presumed lack of familiarity with this discipline for collaborative network scholars, the basics of social exchange are provided here. Broadly speaking, the social exchange literature examines the social relationships that form when people or collective entities like organizations—called “actors” in this literature—engage in exchanges of material or social benefits (Molm 2006). In particular, it focuses on the power dynamics that are inherent in these relationships.

Scholars in this tradition predominantly use experiments to tease out causal linkages, which has resulted in a theoretically driven, tested, and precise conceptualization of power. In what follows, what is meant by structural power is first explained and then research that examines it in a collaborative context—one referred to in this literature as productive exchange—is reviewed and turned into a testable hypothesis. To the author’s knowledge, this is the first direct examination of this hypothesis in a real-world setting.

Using concepts originally formulated in Thibaut and Kelley (1959), Emerson (1962) suggested that power is best viewed from a structural perspective as deriving from the dependence of one actor on the other in a dyadic exchange, meaning exchange that occurs between two actors. Formally, Emerson proposed that $P_{AB} = D_{BA}$, or the power of actor A over actor B is equivalent to the dependence of actor B on actor A. Power in an exchange is balanced, or evenly distributed, if both actors are equally dependent on one

[16] This subfield goes by many names including structural social psychology and group processes.

other and imbalanced, or unevenly distributed, if one actor is more dependent on the other (Emerson 1972a; Emerson 1972b).

So power is dependence, but what is dependence? The answer to this question is contingent upon the context in which the exchange occurs. Scholars have long recognized that the context, or form, of exchange determines which factors contribute to dependency relationships (Ekeh 1974). Power as dependence was first examined in the context of dyadic, competitive exchanges (referred to as direct, negatively-connected exchanges). In this context, exchange with one actor *precludes* exchange with another (Cook and Emerson 1978, 725). Imagine, for example, a local government that wishes to contract out its waste management service. All waste management organizations that wish to bid on this proposal must compete against one another for the one contract that the local government will issue. It was for this type of exchange that power dependence theory was developed by Emerson and his colleagues (Emerson 1962; Emerson 1972a; Emerson 1972b; Cook and Emerson 1978; Cook et al. 1983). Power dependence theory states that dependence is jointly derived from two factors: the value of the exchange and the availability of alternatives to the exchange (1962; 1972a; 1972b). As the value of what one actor has to offer in an exchange increases, dependence upon that actor increases. Conversely, as the number of alternatives that produce a similar or better benefit to an actor increases, dependence decreases.

Although power dependence theory was originally formulated to determine power distribution in dyadic exchange, scholars quickly recognized that rarely do exchanges occur between two isolated actors; rather, actors are generally embedded in larger networks of exchange. In fact, Emerson himself devoted a portion of his seminal work on power dependence theory to understanding power relations in exchange networks, or "sets of exchange relations among actors" (1972a, 70). Given the complexity introduced when a number of exchange relations are connected to one another, Cook et. al (1983) argued that in order for power dependence theory to be harnessed to understand power dynamics in networks, it must be applied one relation at a time across the whole network. In other words, power distribution in a network is determined by examining the aggregate of every actor's dependence on their exchange partners. This strategy has been employed by other scholars, like Yamagishi et. al (1988) and Markovsky et al (1988).

The advance of enabling power dependence theory to be applied to networks of actors makes it more useful for understanding power in collaborative network settings; however, the one hurdle still remains. The main work on power dependence theory was developed for and tested on direct, negatively-connected exchanges, a form of exchange that it does not apply to collaborative network settings because actors are not in competition with one another with regards to their exchanges. Rather, they most often contribute unique benefits like information and data to a joint cause. For lack of a better word, relationships are collaborative, rather than competitive in nature.

Luckily, social exchange scholars recognized early on that other forms of exchange exist; among them, a form called productive exchange (Emerson 1972b; Molm 1994). Molm (2006, 27) defines productive exchange as occurring when "two (or more) actors contribute their individual efforts to produce a joint good that benefits both (or all) of them." It is described as "productive" because the joint benefit produced by the collaborative effort is greater than the sum of the individual benefits that result. In other words, something extra is created when actors work together. Productive exchange is theorized to occur between an actor and the group as a collective entity, which is referred to here as a collaborative network. Actors provide a unique resource to the collaborative network—knowledge, expertise, financial support, legitimacy, etc.—and receive in return a share of the joint benefit that is produced.

Lawler et. al (2000)'s work provides the primary reference for exploring what power as dependence means in productive exchange. Unlike in direct, negatively-connected exchanges where power is derived from the value of the exchange and the alternatives to it, the authors conceptualize power in a collaborative setting as being derived solely from alternatives. The omission of the value of the exchange as a factor of dependence is based on the assumption that each actor contributes something unique to the joint product and therefore actors' contribution cannot be compared. While in "real world" collaborative networks, this assumption may not always hold true, it is in line with the fundamental idea that each actor brings something unique to the table in a collaborative endeavor (Gray 1989). It is therefore reasonable to assert that the value of the exchange is less influential for determining dependency relationships in collaborative networks.

Lawler et. al (2000) posit that alternatives, on the other hand, are still relevant for determining power because collaborative networks are embedded in a surrounding environment. Consequently, the participants of these networks are likely to have other opportunities available to them in which they can derive a similar level of benefit. For the collaborative networks in this study, alternatives do not necessarily have to be other collaborative endeavors that are pursuing similar missions. An organization may also have the option to pursue the shared goal on its own or perhaps not pursue it at all. While the benefit gained from one of these alternatives it almost certainly not as high as participating in the collaborative network, the organization will not incur costs of collaboration, like time and energy spent (Head 2008). To the extent that participation in a collaborative network imposes costs on actors like increased decision costs, then, alternatives do not have to produce exactly the same level of benefit as the collaborative network in order to be attractive.

Alternatives can take another form as well. Participants of collaborative networks are likely to have additional goals that they wish to see accomplished through their participation in the consortium that are not directly related its mission, like the desire to use collaborative work to further their business or research or the desire to use participation in a consortium to better their public image. In fact, as Knoke and his colleagues (1996, 7) noted, “No organization acts solely and entirely on behalf of a generalized ‘public interest,’ although some may do so more than others.” The fewer alternatives a participant has to accomplish its additional goals, the more dependent it becomes on the consortium. Furthermore, the more dependent a participant is on the consortium, the more it will be flexible and accommodating to others’ wishes with regards to joint decisions made by the consortia. In contrast, actors who are not very dependent on the collaborative network are likely to take a harder line on getting what they want from the network because they can pursue their goals elsewhere if they are dissatisfied.

Figure 6 depicts how even and uneven distributions of power are conceptualized by Lawler et. al (2000). To make the network diagrams more concrete, consider a setting in which four actors—a mixture of academics and representatives from pharmaceutical and non-profit organizations—all view the development of a vaccine for Ebola to be desirable. Given the time and cost required to produce a vaccine that will likely have a low market return, the actors are not inclined to pursue this goal on their own.

Focusing on the left panel, imagine that a recent epidemic of Ebola has led to increasing pressure from media and politicians to make progress on a vaccine. In response, two collaborative efforts emerge with a similar overarching mission but a slightly different way of achieving that mission. These collaborative networks invite the main actors in the field to participate, including all four of the actors shown below. These actors are likely to have a range of motivations to participate: provide a public health service through the development of a vaccine, increase in the organization's public image, meet and develop relationships with others in the field, etc. In this example, each actor chooses to participate in both networks. If they are dissatisfied with the progress and/or process of collaborative network 1, the actors can choose to leave or simply focus more time and energy on collaborative network 2. This situation depicts external structural power that is evenly distributed because all actors have the same number of viable alternatives, and thus are equally dependent on collaborative network 1.

Shifting focus to the panel on the right, now consider that the Ebola epidemic is under control and thus, pressure on the actors in this field to act immediately has diminished. Actors are still interested in developing a vaccine, but now only one collaborative effort exists that pursues this mission. Actors B, C, and D, all of whose participation in collaborative network 1 is driven first and foremost by a desire to develop a vaccine, are highly dependent on the network and thus are likely to be more committed to it. On the other hand, imagine that Actor A's main incentive for participating in the collaborative network had more to do with increasing its public image than with developing an Ebola vaccine per say. That actor still has another alternative available: participation in another network that is pursuing another admirable public health goal. If actor A is dissatisfied with the progress and/or process of collaborative network 1, it can choose to leave or stop actively participating. Given that it is the only actor in this example with a viable alternative to participation, an uneven distribution of structural power exists between the members. In other words, actor A is likely to have more say in agenda setting and decision-making in order to incentivize more active commitment to collaborative network 1. Moreover A is more likely to push for its own agenda because it has less to lose.

It should be noted here that the diagrams and scenarios described here are simply examples. Even and uneven distributions of structural power can occur in a number of other scenarios.

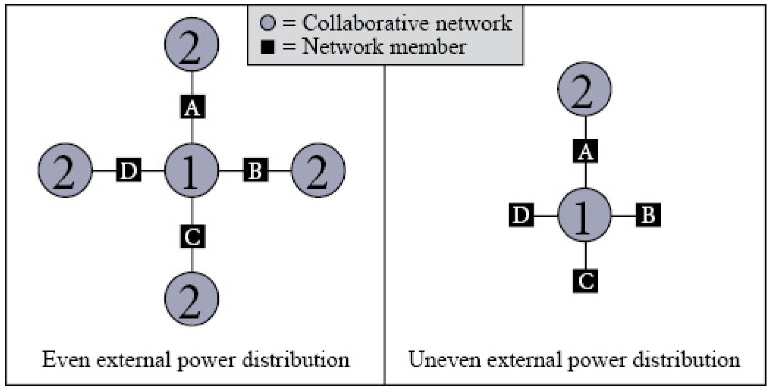

Figure 6: External structural power distribution scenarios

To summarize, the social exchange literature is valuable because it provides the theoretical basis for the conceptualization of structural power, or power as dependence, and offers one way to operationalize it. Structural power is thought to derive from sources external to the network itself; namely, it focuses on the environment in which the network is embedded. The more alternatives to participation in the collaborative network that are available to each actor, the less dependent the actor is on the collaborative network as a collective entity. This operationalization is intuitively appealing, but has not yet been tested outside of the laboratory. The hypothesis that results from the social exchange literature's operationalization, then, reads as follows:

Hypothesis 1: As an actor's alternatives to participation in a collaborative network decrease, his or her structural power in the network decreases.

Structural power in the networks literature

Scholars in the networks literature likewise examine structural power, but offer a different operationalization of it: one that focuses on the dependence relationships that are developed between participants of a collaborative network. As a field, the networks literature revolves around the study of the patterns and structure of relationships between interconnected actors like individuals, organizations, or events. It is built upon the idea that humans are by nature social, interactive beings (Simmel 1964) and, further, that much can be learned by visualizing and quantifying the structure of their interactions (Freeman 2004). Scholars in this tradition have studied a wide range of networks including, to name just a few, the social interaction between monks (Sampson 1969); the diffusion of liberalization policies between countries (Simmons and Elkins 2004); and the collaboration between policy actors for regional planning purposes (Henry, Lubell, and McCoy 2010). Although many of the networks that have been studied are collaborative in nature, collaborative governance network scholars have by and large not integrated the learnings from this tradition into their approach.

The networks literature has been criticized as being largely a theoretical, focusing its attention on developing the set of the methodological tools encompassed under the method of social network analysis (Burt 1980; Galaskiewicz 2007). Though not as driven by theory as the social exchange literature, it is valuable for understanding power from a structural perspective because it provides a clear way to measure it.

Power has consistently been operationalized by scholars in this discipline by measures of centrality, which locate an actor in a strategically advantageous location in the structure of resource flows within a network (Wasserman and Faust 1994). Several measures of centrality exist that differ slightly based on which locations are deemed most advantageous; however, a common finding across all measures of centrality is that highly central actors in a network are also the most powerful (Brass 1984; Brass 1985; Brass and Burkhardt 1992; Burkhardt and Brass 1990; Fernandez and Gould 1994; Fombrun 1983;

Galaskiewicz 1979; Ibarra and Andrews 1993; Krackhardt 1990; Mintz and Schwartz 1985; Milward and Provan 2006; Mizruchi 1982; Padgett and Ansell 1993).

Of the main centrality measures developed by Freeman (1979), betweenness centrality, is particularly appropriate for this research because of its close linkage to the idea of power as dependence (Brass 2012). Betweenness centrality is based on occupying locations in the network that provide control over the flow of resources between actors and is calculated by determining how often an actor falls on the shortest path, or geodesic, connecting two other actors (Freeman 1979). An actor with a high betweenness centrality in a communication network, for example, is considered powerful because s/he receives information from many parts of the network and decides which information is made available to others. Scholars often refer to this role as being the "gatekeeper" (Lewin 1947). In other words, because the highly central actor aggregates information, other actors *depend* on it for access to that information (Brass and Burkhardt 1993). Betweenness centrality forms the basis for betweenness centralization, a whole network statistic that measures the dispersion of the betweenness centrality scores of the actors in the network. The higher a communication network's betweenness centralization, for example, the more one or a few actors control the flow of information.

Figure 7 provides an example of how networks scholars think about power and its distribution across members of a collaborative network; namely, they focus their attention exclusively within the boundaries of the focal network. Going back to the example scenario used above, imagine that five actors participate in a collaborative network whose mission is to develop an Ebola vaccine. In the panel on the left, all member share information directly with one another as they work towards their goal. In other words, because all members receive the same information directly from the original source, no single network member can control the flow of information in the network. Consequently, each actor is likely to have a similar level of say in the decisions made jointly by the collaborative network. This situation results in an even distribution of internal structural power between the members.

In the panel on the right, on the other hand, actor E is the central actor. This means that all of the other actors communicate only with actor E. Consequently, actor E can control the flow of information in the network because it is the only actor that is connected to all others. As a result, actor E is likely to have more influence on the decisions made by the collaborative network because s/he can choose which information to share and which information to withhold. This situation results in internal structural power that is unevenly distributed.

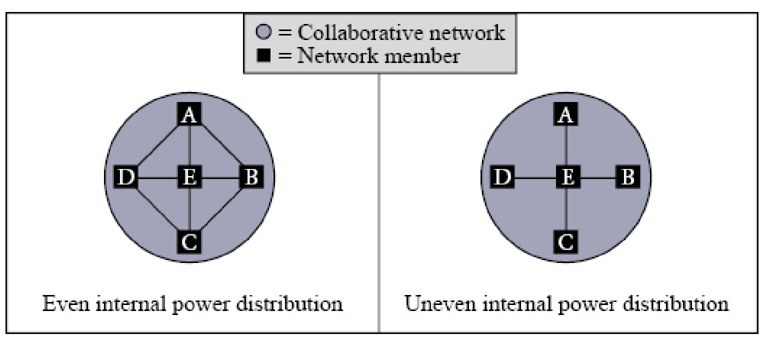

Figure 7: Internal structural power distribution scenarios

These two scenarios, like the external power distribution scenarios described above, are only examples. In fact, they are the extremes of how internal structural power can be distributed. In reality, almost all network structures will exist between these extremes; however, the more centralized the flow of a resource like information in a network, the more uneven the distribution of internal structural power.

In summary, the networks literature provides a way to graphically represent and mathematically calculate structural power that is based on the relationships, or ties, between actors. An actor's power is based on his/her position in the network. In particular, the more an actor can control the flow of resources in the network, the more dependent are others on this actor. On a network level, the more one or a few actors control the flow of resources in a network, the more unevenly this power is distributed. In hypothesis form:

Hypothesis 2: As an actor's betweenness centrality in a collaborative network increases, his or her structural power in the network increases.

Data

The two operationalizations of structural power in collaborative networks focus on different set of relationships as the explanation for dependence. The social exchange literature operationalizes power as alternatives to participation in the collaborative network. This conceptualization provides a way to measure *external* power because power is derived from factors outside of the boundaries of the collaborative network. The networks literature, on the other hand, operationalizes structural power as a position in the network structure that provides control over the flow of resources between actors. This operationalization provides a way to measure *internal* power because betweenness centrality and centralization scores are based solely on the ties between actors in a bounded network.

To examine the appropriateness of these measures for structural power in collaborative network, the hypotheses are tested on data from the three C-Path consortia: the Predictive Safety Testing Consortium (PSTC), the Coalition Against Major Diseases (CAMD), and the Multiple Sclerosis Outcome Assessments Consortium (MSOAC). For detailed descriptions of both C-Path, the three consortia studied here, and the data collection methods, see Chapter 2.

The network measures, described below, are calculated on the whole networks. In other words, each participant's structural power was measured based on his/her position in the communication network of his/her consortium. These measures were then aggregated across the consortia. The unit of analysis is therefore individual participant. In total across the three consortia, 115 out of 337 participants responded, for a response rate of 34 percent, although not all respondents provided answers for all questions. Data on the distribution of those responses is provided in Table 4.

Table 4: Survey respondents

Consortium	# of total members	# of respondents	% response rate
CAMD	113	36	32
MSOAC	59	22	37
PSTC	165	57	35

Measures

The goal of this chapter is to determine which operationalization of structural power (or a combination of them) most accurately reflects an actor's structural power in a collaborative network. To do this, it is first necessary to settle on a way to observe power against which the measures can be compared and validated. The research here follows the line of thinking that the use of power by an actor is observed as the actor's ability to influence others (c.f., Brass 1984; Brass and Burkhardt 1993; Provan and Milward 1995). In a collaborative setting, powerful actors typically have more sway over decisions that are made by the collective, especially when decision-making involves bargaining as it often does in collaborative networks (Fung 2006). Powerful actors can demand more and give less, while less powerful actors are more likely to compromise in order to keep the collaborative network moving forward (Feiock 2008). Using the observation of power use as influence, then, measures for internal and external structural power are examined in relation to how well they explain a collaborative network participant's perceived influence in the decision-making processes of his or her consortium.

To begin, then, a participant's perceived influence is needed. For this, consortia participants were asked to name up to ten consortium participants whom they considered to be influential in the decision-making of their consortium. All participants identified as the recipient of an influence nomination were included in the influence network. An in-degree centrality score, which simply counts the number of times a participant was nominated, was calculated for each participation in the three networks. The measure was standardized to allow for comparison across consortia. It varies between a low value of zero and a high value of one. The higher the in-degree centrality, the more the actor was identified by others as being influential.

Internal power is measured using a participant's betweenness centrality in the communication network of the consortia. A detailed discussion of how this measure is calculated is provided in Chapter 2; here, only a brief discussion is included. Betweenness centrality measures the degree to which the focal participant can control the flow of information between participants. Based on the assumption that information will flow between two participants via the shortest path between them, it is calculated by examining the degree to which the focal participant sits on the shortest path between two other participants (Freeman 1979).

Because the communication network data is weighted based on the frequency of the communication, weighted betweenness centralization was used (Opsahl, Agneessens, and Skvoretz 2010), with a higher weighted tie between participants contributing to a higher betweenness centralization score. The measure was standardized to allow for comparison across consortia. Values thus range from a low value of zero to a high value of one. The higher the score, the more an actor can control information flow in the collaborative network.

External power is conceptualized as dependence and, more specifically, as a perceptual measure of dependence that derives from the alternatives to participation in the focal consortium. To measure this, respondents were first primed with two questions to get them to think about their/their organization's alternatives. Specifically, they were first asked to rank a list of several additional objectives over and above the consortium's stated goals that they/their organization wish to achieve through its participation in the consortium. The list of additional goals was created with the help of C-Path leadership and included relational objectives (such as "build/maintain relationships with other members of the consortium" and "be exposed to expertise from other organizations"), reputational objectives (such as "use participation in consortium to increase public image in industry"), and material objectives (such as "use output or outcome of this consortium to further own research" and "use output or outcome of this consortium to further own business processes or products"). Respondents were also given space to list their/their organization's own additional objectives.

Following this rank-order question, respondents were then told to concentrate on their/their organization's most important additional objective and were asked to select the most appropriate leading alternative to achieving this objective from the following list of options, once again developed with the help of C-Path leadership: other collaborations or partnerships similar to this consortium, addressing the objectives within my organization instead of through a partnership, other (please specify), I/we have no meaningful alternatives, I don't know. Together, these priming questions were intended to put the respondent in a frame of mind to think about different ways that they could achieve their/their organization's goals, ways that could include simply going it alone.

After priming respondents, the question on which the alternatives measure is based was presented. Namely, they were asked to assess their/their organization's likelihood of investing in an alternative to the consortium in the future. The wording of this question was intended to minimize the chance that respondents would include unrealistic or unattractive alternatives in their calculations of dependence. Respondents were asked to choose from Likert scale answer choices ranging from 1 (very likely) to 5 (very unlikely). Thus, the higher values of this variable indicate fewer alternatives, and thus higher dependence on the consortium.

External power was also captured in a different way; namely, a survey question asked respondents directly about how dependent they were on the consortium for achievement of their main additional objective. The answer choices ranged from 1 (not dependent) to 4 (very dependent). While more straightforward, this variable is likely more susceptible to biased responses (Meier and O'Toole 2012), as confessing dependence admits a weak position. Nevertheless, it is useful as a robustness check on the main measure of external power. Table 5 displays the descriptive statistics for these variables.

Table 5: Descriptive Statistics

Variable Name	N	Mean	Standard Deviation	Min	Max
Perceived Influence	96	0.012	0.029	0	0.188
Betweenness Centrality	96	0.023	0.395	0	0.178
Alternatives	88	2.864	0.912	1	5
Dependence	96	1.760	0.750	1	4

Results

Hypothesis 1 tests the social exchange literature's operationalization of power as the existence and attractiveness of alternatives to participation in the collaborative network. If supported, the actors who expressed the least likelihood of investing in an alternative to the consortium in the future (represented by higher values) should be most dependent on the consortium. Following the predictions of power dependence theory as applied to productive exchange networks, then, the most dependent actors should be the least influential within the consortium itself. In other words, hypothesis 1 predicts a negative correlation between alternatives and influence.

Spearman's rho, a non-parametric measure statistical dependence, is calculated between the alternatives variable and the influence variable. It ranges between -1, which represents a perfect negative association, to +1, which represents a perfect positive association. Its use is preferable because it is appropriate for both continuous and ordinal variables. The measure is calculated for respondents in each of the three consortium separately as well as the respondents from all three consortia combined. The number of observations used to test this hypothesis is limited by the number of respondents who provided an answer to the alternatives question. Respondents who did not receive an influence nomination received an in-degree centrality score of zero.

Table 6: Association between perceived influence and external structural power (alternatives)

Consortium	# observations	Spearman's rho	Prob > |t|
CAMD	28	0.089	0.653
MSOAC	15	-0.099	0.727
PSTC	45	0.105	0.492
All Respondents	88	0.045	0.674

The results, shown in Table 6, do not provide support for hypothesis 1. A respondent's likelihood of investing in an alternative to the consortium in the future is not significantly associated with a participant's perceived influence in the consortia. Even combining the participants from the three consortia results in a non-significant relationship that is very close to zero in magnitude. Thus, it is not likely that low number of observations in each individual consortium is at fault for the lack of relationship.

The associations were re-calculated using the dependence variable in place of the alternatives variables to try to see if the lack of relationship had to do with the measure itself. The Spearman's rhos were similar in their direction, magnitude, and lack of significance[17]. In other words, even an alternative measure for external power does not result in a significant relationship. The lack of significance of the external power operationalization is discussed at length below.

The second hypothesis tests the network literature's contention that a participant's ability to control information flow between other participants in a collaborative network confers power. Specifically, the degree centrality scores for influence were associated with the betweenness centrality scores for the participants. Spearman's rho was again calculated for each consortium as well as for all of the respondents combined. The number of observations is slightly higher than the number used to test hypothesis 1 because it includes eight respondents who did not answer the alternatives question but were included in the communication and influence networks. However, the results do not change materially when the sample used to test hypothesis 1 is used to calculate the association between perceived influence and betweenness centrality.

Table 7: Association between perceived influence and internal structural power (betweenness centrality)

Consortium	# observations	Spearman's rho	Prob > |t|
CAMD	28	0.312	0.106
MSOAC	18	0.683	0.002
PSTC	50	0.329	0.020
All Respondents	96	0.382	0.000

The results in Table 7 provide support for the second hypothesis. The association between a participant's perceived influence and his or her position in the network of communication flow is positive and highly significant in two of the three consortia. In the

[17] Spearman's rho (with the prob > |t| reported in parentheses) for the association between perceived influence and dependence as follows. CAMD: rho=0.170 (0.388); MSOAC: rho=-0.089 (0.726); PSTC: rho=0.166 (0.249); All respondents: rho=0.113 (0.273)

third, CAMD, the result is significant at an acceptable level given the number of observations on which it is based. Moreover, the results attained when all of the participants are combined is positive at even higher significance levels than in any of the individual consortia. This is to be expected, given that uncertainty of the resultant association decreases as the number of observations on which result is based increases.

While these results suggest a positive and significant relationship, they say nothing about how much betweenness centrality contributes to the explained variation in perceived influence. For this, an ordinary least squares regression model is used, with a participant's degree centrality score for influence as the dependent variable and his or her betweenness centrality score as the main independent variable. For this regression, all observations were combined across the three consortia. The sample size is reduced by two observations from that used to test hypothesis 2 because of missing observations on a control variable.

Two models were calculated. Model 1 serves as the base model. It includes two attribute-based control variables that are likely to affect a participants' perceived influence—their years of experience in their field of expertise and their years of participation in the consortium—as well as dummy variables for two of the three consortia to control for variation between the consortia. MSOAC is the excluded consortium. Model 2 introduces betweenness centrality as an independent variable in order to see how much additional variation in perceived influence is explained. Results, shown in Table 7, report the beta coefficients for both models so that the magnitude of the variables' effects are more comparable.

Table 7: Regression models for perceived influence

	Model 1		Model 2	
	Coefficient	***P* Score**	**Coefficient**	***P* Score**
Bet. Centrality			0.324	0.001
Participation (years)	0.107	0.380	0.109	0.344
Experience (years)	0.288	0.013	0.231	0.037
CAMD	-0.016	0.909	-0.003	0.984
PSTC	-0.110	0.494	-0.076	0.619
Constant	0.000	0.571	0.000	0.323
N	94		94	
R^2	0.125		0.226	
Prob>F	0.017		0.004	
Note: Ordinary Least Squares model; beta coefficients reported				

In the base model, Model 1, the only significant predictor of a participant's perceived influence is years of experience in his or her field. The beta coefficient can be interpreted to mean that a one unit change in the standard deviation of experience increases a participant's standardized degree influence score by 0.288 standard deviations. The model is a good fit and explains 12.5 percent of the variation in perceived influence.

Model 2 is of more interest because it adds betweenness centrality as an independent variable. This addition almost doubles the amount of explained variation to 22.6 percent. In addition, it reveals that a participant's betweenness centrality is a stronger predictor of perceived influence than a participant's years of experience, with one standard deviation increase resulting in a .324 increase in the standard deviation of perceived influence. The higher an actor's standardized betweenness centrality score, the higher his or her perceived influence in the decision making processes of the consortia. The regression result provides more support for the second hypothesis and suggests that betweenness centrality is an appropriate conceptualization of structural power in collaborative networks. It should be noted here that using network measures in a standard regression model is complicated by the fact that network data violates the independence of observations assumption on which regression is built. See Chapter 2 for a discussion on this topic.

Two reasons are offered for why, even with the inclusion of betweenness centrality, the explained variation in perceived influence is only 22.6 percent. Both reasons stem from a similar foundation, though. Namely, influence measures power use whereas structural power measures potential power. Just because a participant is well placed to control the information flow in a consortium does not necessarily mean that s/he will use this position to influence others by choosing which information to share and which information to keep. Influence, on the other hand, is only observed and thus reported when it is used.

With this mind, the amount of explained variation suggests that structural power is not the only contributor to a participant’s perceived power. Power that derives from a participant’s attributes, in particular, may interact dynamically with structural power to produce differences in a participant’s perceived power. Another explanation, though, is that not all participants use the structural power they have. Both explanations provide interesting venues for further research and is discussed in the summary section.

Discussion

Contrary to the experimental results produced by Lawler et. al (2000), the results attained in this chapter show that the measure of structural power that derives from sources external to the collaborative network is not a suitable measure for power in three real world collaborative networks. Rather, the results suggest that power derives only from internal sources: the participant's position in the flow of communication between participants. The more a participant is able to control that flow of information, the more power s/he possess.

Given Lawler et. al's (2000) experimental results and the logical appeal of the external power explanation, its lack of its significance is puzzling. One potential reason could be with the assumption that internal and external power were independent of one another. It is possible that external and internal power are related; namely, the effect of external power may work *through* internal power. In other words, it could be that a participant's higher dependence on the collaborative network causes him or her to engage more with members of the collaborative network. The more a participant establishes and maintains these communication channels with other participants, the more central that participant will be, a position that was shown above to contribute to perceived influence.

To test this possible explanation, an ordinary least squares regression is run to test whether external power, measured as alternatives, explains any variation in internal power, measured as standardized betweenness centrality. The resulting beta coefficient is negative and insignificant (-0.010, p-value=0.924). A similar result is achieved using dependence as the measure for external power (0.091, p-value=0.377). In other words, based on the data from the three consortia studied here, a participant's position in the communication network is not explained by how dependent s/he is on the consortium. Put differently, a participant's behavior within the consortium is not affected by outside motivators, at least those related to dependence. Rather, it seems that structural power is accrued by those who put forth more effort, a conclusion that would be in line with the more egalitarian ideal of collaboration.

While the external power hypothesis is not supported using this data, it is possible that the measures used here did not accurately capture this concept. One big issue arises because the measures assume a participant's dependence on the consortium must be known to other participants in order for it to affect how much influential s/he is accorded. In other words, if the focal participant does not share information about how dependent s/he is on the consortium with others, then they will not be able to assess the risk of losing his/her participation. Consequently, they will not be more accommodating to the wishes of a participant who is less dependent on the consortium. In the laboratory setting in which Lawler et. al (2000) tested their theory, the authors were able to ensure that all participants knew of one another's alternatives. This may not be the case in the real world. Future research can investigate other ways to capture this external power dimension.

Summary

This chapter examined two different operationalizations of structural power in collaborative networks: one coming from the social exchange literature and the other from the networks literature. Both perspectives broadly speaking agree that structural power derives from the dependence that arises from an actor's relationships; however, they differ in terms of the relationships on which they focus and the methods by which they measure the resultant dependence.

The social exchange literature focuses on the relationships developed by actor to others external to the collaborative network. Dependence on the focal collaborative network decreases as the actor has more alternatives available to him/her. In particular, external dependence can be thought of as the number and quality of alternatives to the focal collaborative network that are available to each participant. The less dependent an actor in on the focal collaborative network, the more power s/he has. The networks perspective, on the hand, concentrates on internal power, power that derives from a collaborative network participant's position in the structure of resource flows within the network. The more a participant is able to control that flow, the more structural power s/he possess.

Both explanations were examined using data from participants in the three C-Path consortia. Results support the network literature's view that structural power is derived from internal sources and do not support the social exchange literature's perspective of externally-derived structural power. Thus, the remaining chapters in this dissertation rely exclusively on the internal power conceptualization.

With that said, the results bring up two main areas of future research. First, validating betweenness centrality as a measure for structural power is a good first step, but it does not speak to the issue of the causes behind why one participant may be more central than others. It was shown here that a participant's lack of alternatives—at least in the way they were measured here—is not associated with his/her internal position of power. Other factors have yet to be explored, though. For instance, a participant's position in their home organization, the sector from which a participant's home organization hails, or a participant's age may influence their position in the internal power structure. Moreover, agency may be involved. It could be the case that any participant, regardless of background, can become central in the communication network if they put in the effort. In sum, more research is needed about the causes of centrality.

The second area for future research brought to light by the findings of this chapter is the issue of potential power versus power use. In particular, it was suggested that a participant's structural power explains only a portion of his/her perceived influence in the consortium. One explanation is likely that structural power is a measure of potential power while perceived influence is a measure of power use. Thus, the question becomes, what causes or limits a participant from using his or her structural power? Norms, for example, are likely to come into play in answering this question.

While the research discussed in this chapter brings up many questions, it nevertheless provides a clearer understanding of how to measure structural power in collaborative networks. Now, attention is turned to understanding its effects.

CHAPTER 4: STRUCTURAL POWER AND COHESION

Collaborative problem-solving networks are distinct from organizations in that they convene a diverse set of independent stakeholders without the formal structure of hierarchy. In place of hierarchical relationships in which a supervisor delegates work to employees and holds them accountable, collaborative networks function on the premise that members are equal partners in the pursuit of a joint mission. The premise of equality is thought to foster an environment in which the sharing of knowledge, skills, and material resources is more likely to occur (Gray 1989). Moreover, it is when participants work together that collaborative networks are at their best, producing innovative solutions that are not likely to emerge when each actor works in isolation (Powell 1990).

Simply convening a collaborative network, however, does not ensure that participants will actually collaborate, or actively engage with one another. Mayer (1987) suggests that one of the causes of lower collaborative behavior, which he observes as a communication between participants, may be uneven distributions of power among participants. Other scholars likewise point to the negative ramifications associated with uneven distributions of power, ramifications that are likely to eventually affect a participant's behavior in a collaborative effort (Bryson and Crosby 2008; Buse 2003; Buse and Harmer 2004; Huxham and Vangen 2005; Sorenson 2009). These scholars do not specify precisely what power is, though, or precisely how it negatively affects participant behavior. It is the desire to better understand this relationship between power and participant behavior—in particular, cohesive behavior—that drives the research presented in this chapter. In particular, it seeks to answer the question, how does the distribution of a particular type of power, structural power, in a collaborative network affect how cohesively participants behave?

To answer this question, a comparative case study of the communication networks in the three C-Path consortia is performed using social network analysis. Why communication ties? Communication between participants is the means by which one of the most important resource in collaborative networks is shared: information or knowledge (Huang and Provan 2007; Reagans and McEvily 2003). Examining the patterns of communication between participants provides a means to study the degree to which one or a few actors are powerful vis-à-vis their ability to control the flow of information through the collaborative network. Moreover, the communication networks provides insight about the extent to which participants engage with one another.

The analysis proceeds at two levels of analysis following Brass' (1981) finding that the effect of structural power may not be uniform. First, each consortium is treated as a single network. This analysis is intended to examine whether the overall distribution of power in a consortium affects how actively participants establish and maintain communication ties. The second level of analysis harnesses the fact that a lack of hierarchy does not mean that the consortia have no governance structure (Provan and Kenis 2008). In fact, in order to organize work, working groups centered around specific issue areas and goals exist in each of the three consortia. The analysis is thus repeated using the working groups as the unit of analysis in order to determine if different dynamics occur in the subgroups where work is actually done.

The chapter is organized as follows. First, cohesion is introduced as a concept, accompanied by a discussion of why it is so desirable in collaborative network settings. This discussion is followed by a review of the relationship between structural power, measured as betweenness centralization, and cohesion from the extant literature. The data and measures are then presented, followed by the results. An explanation of why the different dynamics may be at play at the two levels of analysis is developed in the discussion section, followed by propositions that can be tested on larger numbers of collaborative networks.

Cohesion in collaborative networks

The concept of cohesion is useful because it captures not only the actual behavior of collaborating, but it also provides an explanation for why cohesive relationships tend to be self-perpetuating, and thus, why they are so important for the success of collaborative networks. To begin with, cohesion is generally defined by network scholars in terms of behavior; namely, cohesion results from individuals establishing and maintaining relationships, or ties, with those around them (Blau 1977; Burt 1987; Granovetter 1973; Gargiulo and Benassi 2000; Reagans and McEvily 2003). As more ties are established and maintained, the network is described as becoming more cohesive. From a theoretical standpoint, the benefits of cohesion are most easily understood at its extreme: a condition referred to as network closure that occurs when all actors are tied to one another (Coleman 1988; Gargiulo and Benassi 2000). Coleman argues that a closed network structure causes levels of trust and cooperation to increase through the development of obligations, expectations, and social norms. In other words, the more actors are tied to one another, the more they are affected by group-level conditions and the more pressure towards unity exists. Reagans and McEvily (2003) add that knowledge is transferred and motivational impediments are overcome more easily in closed networks.

Other scholars define cohesion in terms of attitudes. They define cohesion as the positive feelings associated with being part of a group, such as closeness, harmony, and unity (Carron and Brawley 2012; Schaefer and Kornienko 2009; Lawler et. al 2000). In his thorough examination of the what he terms social cohesion, Noah Friedkin (2004) asserts that the behavioral and attitudinal approaches to conceptualizing cohesion are not at odds with one another. Rather, he argues that cohesion manifests itself as reciprocally linked attitudes and behaviors. In other words, behaviors both reflect and reinforce attitudes. This dynamic can occur at both individual level as well as at the group-level, a phenomenon described by Friedkin (2004: 410) as occurring "when group-level conditions are producing positive membership attitudes and behaviors and when groups members' interpersonal interactions are operating to maintain these group-level conditions."

For this research, cohesion is considered from a behavioral perspective for several reasons. First, it more accurately captures the extent to which participants engage with one another. Second, recent research posits that behaviors may actually be *more important* than attitudes with regards to establishing cohesion because behaviors can create path-dependent structures that then change attitudes (Kelman and Hong 2015). Finally, in doing survey research, behavioral measures are less susceptible to bias responses than are attitudinal measures (Meier and O'Toole 2012). With that said, the behavioral measure of cohesion is validated using survey data on cohesive attitudes.

The most common measure of cohesion by network scholars is that of density, or the proportion of possible ties that are present in a network (Festinger, Back, and Schacter 1950; Provan and Milward 1995; Scott 2000; Wasserman and Faust 1994). However, another approach to measuring cohesion acknowledges and harnesses the tendency in larger networks for cohesive subgroups, or "subsets of actors among whom there are relatively strong, direct, intense, frequent, or positive ties" (Wasserman and Faust 1994, 249) to form. Subgroup-based measures are more nuanced because they allow levels of cohesion to vary within a single network. Put differently, a network can be cohesive if there are clusters of actors that are densely tied to one another, but those clusters are only loosely tied together (Festinger 1949; Watts 1999; Luce and Perry 1949). The tendency for subgroups to develop occurs, in part, because maintaining ties with every member of a network is prohibitive in terms of both time and energy constraints (Gazley and Brudney 2007; Head 2008). In addition, it is often unnecessary and indeed inappropriate for every member to work closely with every other member of a network (Provan and Lemaire 2012). Once formed, these subgroups have the ability to produce the same pressure towards unity as do whole networks. Friedkin (1981) argues that detection of subgroups should be the preferred method of operationalizing cohesion when subgroups exist, which is the case for the consortia studied here.

Structural power and cohesion

The organizational networks literature has no shortage of studies on structural power and cohesion. In fact, two of the most frequently-used measures in network studies are centralization and density, measures for the distribution of structural power and cohesion, respectively (Valente, Chou, and Pentz 2007; Huang and Provan 2007; Milward et al. 2010; Morrissey et al. 1994; Provan and Milward 1995; Provan, Isett, and Milward 2004; Provan, Huang, and Milward 2009). Despite the frequency with which centralization and density variables appear together in organizational networks studies, the relationship *between* them is rarely the focus of study. Instead, the measures are treated as two ways to describe network structure. As a result, this is an area of network studies that is lacking in theory.

One potential conclusion from this observation is that the relationship between the two variables is definitional, and thus, theoretically uninteresting. In other words, it could be that cohesive structures only occur when power is decentralized. In a study of community mental health service delivery networks, Morrissey et. al (1994) support this conclusion by finding, "[o]ur quantitative network approach has sensitized us to the fact that density and centralization in service delivery systems cannot both be maximized at the same time; as density increases centralization decreases and vice versa" (76). Below, it is argued that this conclusion is only accurate for a subset of networks and, thus, that the relationship between power and cohesion is in need of closer examination.

Structural power and cohesion at the extremes

For the subset of networks in which either the distribution of power or cohesion is at its extremes, the relationship between the two variables is indeed definitional. To understand this, consider the two hypothetical networks depicted in Figure 8. The network on the left shows a network in which power is maximally centralized, with all nodes connected to a single central node. This network, by definition, cannot have high cohesion, a structure characterized by many ties between the nodes. Now consider the network on the right, a network that is maximally cohesive because all nodes are connected to one another. By definition, this network cannot have high centralization because high centralization necessitates that one or a few nodes are more connected than others.

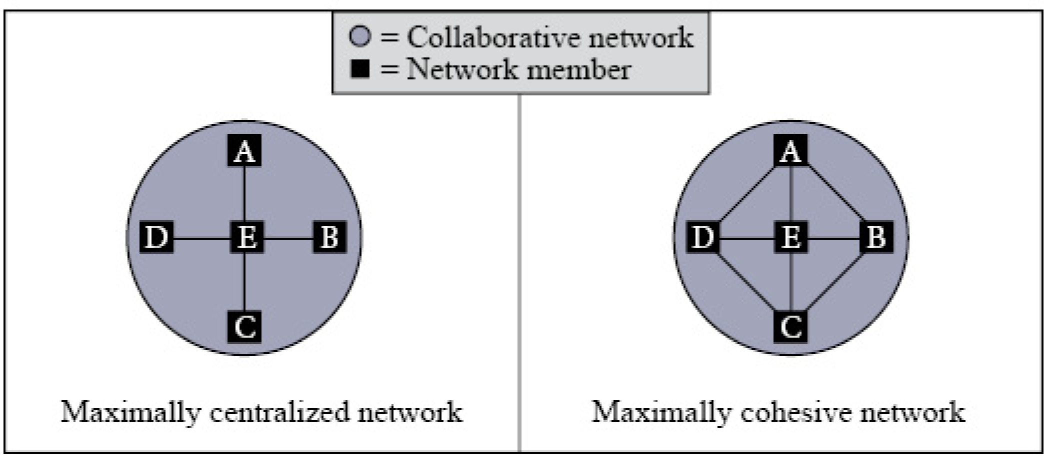

Figure 8: Structural power and cohesion at their extremes

Results from the networks literature supports this conclusion. A group of scholars led by Keith Provan and Brint Milward conducted several whole network studies on service implementation networks delivering services to severely mentally ill patients (Huang and Provan 2007; Milward et al. 2010; Provan and Milward 1995; Provan, Isett, and Milward 2004; Provan, Huang, and Milward 2009). Using a measure of density, the studies show that at the highest levels of centralization, the density of ties between the network participants was lowest. Conversely, the least centralized networks exhibit the highest density of ties between network participants.

The same conclusion is reached when cohesion is measured via subgroups. In his investigation of the small-world phenomenon, Duncan Watts (1999) finds that one particular network structure, called the "connected caveman graph" and displayed in Figure 9 below, approaches the same level of cohesion as a fully closed, or fully cohesive network as the size of the network increases. This network structure, in which cohesion nears its highest levels, occurs when no actor is central. In other words, Watts' work provides more support for the relationship between centralization and cohesion at an extreme: cohesion approaches its highest level when the network is decentralized.

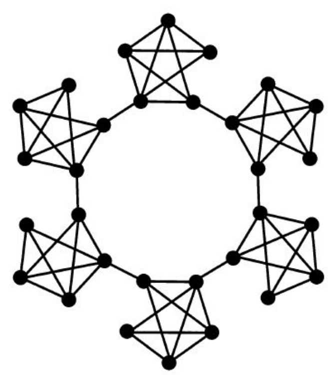

Figure 9: The connected cave-man graph from Watts (1991)

Structural power and cohesion between the extremes

Most networks, however, fall between the extreme values of these variables. As Provan and Kenis' (2008) work suggests, a network characterized by complete decentralization is unlikely to exist because of coordination difficulties. Likewise, a completely centralized structure is also unlikely in a collaborative network because it defeats the purpose of collaboration among participants. A more interesting and practical question, then, is: what is the relationship between structural power and cohesion when these variables have middle-range values?

Results from the networks literature reveal a relationship that is far from definitional. Figure 10 graphs the relationship between structural power, measured as network centralization, and cohesion, measured as network density from the studies of mental health service delivery networks over many years. The networks shown in the figure come from the following studies (with the corresponding network number in Figure 10 in parentheses): Huang and Provan's (2007) study of contract (1), influence (2), information (3), referral (4), and reputation (5) ties in a Maricopa county network in 2000; Provan et. al's (2009) study of information (6) and referral (7) tie in the same Maricopa county network in 2004; and Provan and Milward's (1995) study of organizational links—defined as at least one link of referrals, case coordination, joint programs, or contracts—in service delivery networks in Tucson (8), Akron (9), Albuquerque (10), and Providence (11). A centralization score of one represents a network in which all actors are connected to a single central actor. A density score of one represents a network in which all actors are tied to each other.

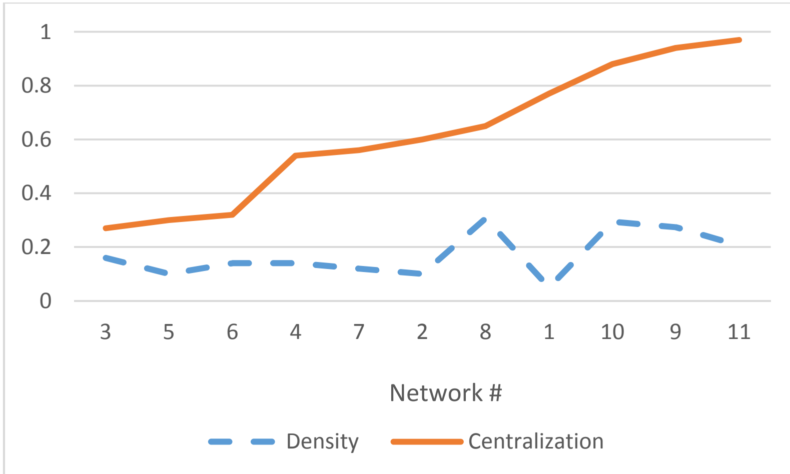

Figure 10: Density and centralization scores from existing studies
**Note: Networks 1-5 from Huang and Provan (2007); networks 6-7 from Provan et. al (2009; and networks 8-11 from Provan and Milward (1995)*

The results reveal a relationship between the two variables that varies. In fact, no obvious relationship exists when structural power and cohesion are in between the extremes. In other words, it would be inaccurate to say that structural power is always negatively related to cohesion. Rather, this relationship is likely to depend on a number of factors.

First and foremost, the relationship may depend on the level of analysis. Brass (1981) studied the relationship between a worker's centrality at three different levels of an organization—the organization as a whole, the department level, and the subunit level—and job characteristics like autonomy, skill variety, and task significance. While he expected to find a positive relationship between all three measures of centrality and job characteristics, he found that the three levels of analysis produced different results. In particular, organizational centrality was negatively associated with job characteristics, while subunit centrality had a positive relationship to job characteristics and department centrality was not significant. While the exact reason for this is not relevant to the current study, Brass' work is important because it points to the conclusion that different levels of analysis within the same entity can produce different results. Applying this idea to collaborative networks, Brass' research suggests that the relationship between structural power and cohesion may differ depending on the perspective of the researcher; namely, whether the researcher focuses on the whole network or the subgroups within a whole network.

Secondly, the relationship may depend on the content of the tie. The results above aggregate many different types of ties, a step that only makes sense if the relationship between centralization and density is so robust that it does not matter what the tie denotes. This is likely not the case, given the differences between more formal ties like contracts and referrals and more informal ties like information exchange, influence, and reputation organizations (Huang and Provan 2007). In order to properly examine the relationship, then, it is important to focus on one type of tie across multiple networks or multiple points in time.

Given the lack of theory on this relationship in the networks literature, a comparative case study design is used here to begin exploring the relationship between structural power and cohesion in greater detail. In particular, the communication ties in three collaborative networks are examined at two levels of analysis: the whole network level and the working group level. Using the results as a guide, the discussion offers ideas about *why* these results occurred and develops propositions that may be used to test these conclusions on more collaborative networks.

Examination of structural power and cohesion in information networks

In order to better understand the relationship between structural power and cohesion, the communication three C-Path consortia are examined: the Predictive Safety Testing Consortium (PSTC), the Coalition Against Major Diseases (CAMD), and the Multiple Sclerosis Outcome Assessments Consortium (MSOAC).

The C-Path consortia are well-suited for a study of the relationship between structural power and cohesion because their common governance structure naturally leads to middle ranges of power distribution, the range about which little is known with regards to its relationship with cohesion. In particular, the consortia have administrative structure that is intended to organize the activities of its participants. This structure, a version of what Provan and Kenis (2008) call a Network Administrative Organization (NAO) structure, places the administrative responsibilities on a consortium director and project manager, both of whom are employees of C-Path. These individuals have no more authority than any other member, but are charged with helping to coordinate behavior. Due to their role, they do cause a certain minimum level of centralization exists in the communication networks of the three consortia.

For detailed descriptions of both C-Path, the three consortia studied here, the data collection methods, and the measures, see Chapter 2. In the next section, the measures for structural power and cohesion are presented. Then, the relationship is examined at two levels of analysis: the whole network level and the working group level.

Measure for structural power

The distribution of structural power is measured using a weighted version of the standardized betweenness centralization measure. A detailed discussion of how this measure is calculated is provided in Chapter 2 and its validation as an appropriate measure of structural power is provided in Chapter 3; here, only a brief discussion is included. Broadly speaking, betweenness centralization is a group level measure that reveals the degree to which one or a few actors control the flow of communication in the network, or the level of network centralization. Controlling information flow, in particular, is important for participants of collaborative networks because it affects decision-making. The more information to which one participant has access, the more s/he can affect the decisions driving the actions and direction of the consortium.

Because the network data on which this measure is based is weighted, meaning some ties have a higher value than others due to higher reported frequency of communication, Opsahl et. al's (2010) weighted version of the betweenness centralization measure is used. This measure allows the researcher to determine the degree to which a higher weighted tie between participants contributes to a higher betweenness centralization score. Here, tie frequency and tie weight are treated as equivalent, meaning a participant can attain high betweenness centrality if s/he sits on the paths made of weak ties between many participants *or* if s/he sits on the path made of strong ties between fewer participants.

The weighted betweenness centralization scores are standardized to allow for comparison across consortia that are of different sizes. Therefore, they vary between zero and one, where a value of zero indicates that power is evenly distributed among all of the members of the consortium, and a value of one indicates that power is centralized around one member.

Measure for cohesion

Cohesion is measured from a behavioral perspective as the presence of cohesive, or densely connected subgroups in a network. A subgroup based measure is chosen over the more common density measure because of the existence of a variety of subgroups to exist in the consortia. First and foremost, the consortia have formal subgroups in the form of working groups that divide the work to be done into specific topic areas. The existence of working groups means that not all participants are equally likely to communicate with one another; rather, those in the same working group have more opportunity and more reason to do so.

However, subgroups may also form outside of the working groups for several reasons. First, participants generally select the working group(s) to which they belong and can belong to as many as they wish, creating the potential for cross-fertilization of communication ties. Second, the coordinating committee, which is largely composed of one representative from every organization that contributes participants to the consortia, provides another venue for communication ties to be established outside of working groups. Finally, communication ties may exist between participants from the same organization or between participants who have a pre-existing relationship with one another. Because subgroup-based measures allow cohesion to be high when these various subgroups are densely connected, this type of measure is more appropriate in this research setting.

Like betweenness centralization, a full discussion describing how this measure is calculated is provided in Chapter 2. Briefly, though, cohesive subgroups are measured using the global clustering coefficient, which determines the degree to which three nodes are fully connected by all three ties.

Again, because the communication ties for this study are weighted according to frequency of communication, Opsahl and Panzarasa (2009)'s weighted version of the global clustering coefficient is used. With regards to clustering, incorporating weights means that each triple has a weight based on the ties that close it. Closed triples composed of all strong ties contribute most to a high global clustering coefficient, triples composed of all weak of weak ties contribute the least, and triples composed of mixed strong and weak ties contribute in between. To calculate the value of each triple, the arithmetic mean of the three ties is calculated.

As was mentioned above, cohesion is best characterized as positive behaviors and attitudes that reinforce each other. Given that the global weighted clustering coefficient is a behavioral measure, it is verified using an attitudinal measure to ensure that it accurately reflects the essence of cohesion. To do this, survey respondents were asked to rate the cohesiveness of their professional relationships with other members in the consortium. At the level of the whole network, the percentage of respondents rating their relationship as either "very cohesive" or "cohesive" was calculated and compared to the global weighted clustering coefficient for each of the three consortia. Results, displayed in Table 8, show that the higher the generalized clustering coefficient, the higher the consensus that the relationships within the consortium are cohesive, as was expected.

Table 8: Validation of cohesion measure: network level

Consortium	Global weighted clustering coefficient	% of "very cohesive" or "cohesive" responses
CAMD	0.288	91%
MSOAC	0.339	100%
PSTC	0.292	96%

Results

The following sections reports the results of the relationship between structural power and cohesion at two levels of analysis: the whole network level and the working group level. A discussion section then follows that examines these results in greater detail and offers propositions about why these results occur.

Whole network level

For the whole network level, each of the three consortia comprise one unit of analysis, resulting in a sample size of three. The results, shown in Figure 11, reveal a negative relationship between structural power and cohesion. Specifically, MSOAC is characterized by the most even distribution of structural power among participants (betweenness centralization=.246) and the highest level of cohesion (global clustering coefficient=.339). PSTC and CAMD have similar levels of both structural power distribution and cohesion, with both experiencing more uneven structural power distribution (betweenness centralizations of .453 and .484, respectively) and lower cohesion (global clustering coefficients of .292 and .288, respectively) than MSOAC. These results suggest that centralized power and high cohesion are unlikely to occur together at this level of analysis.

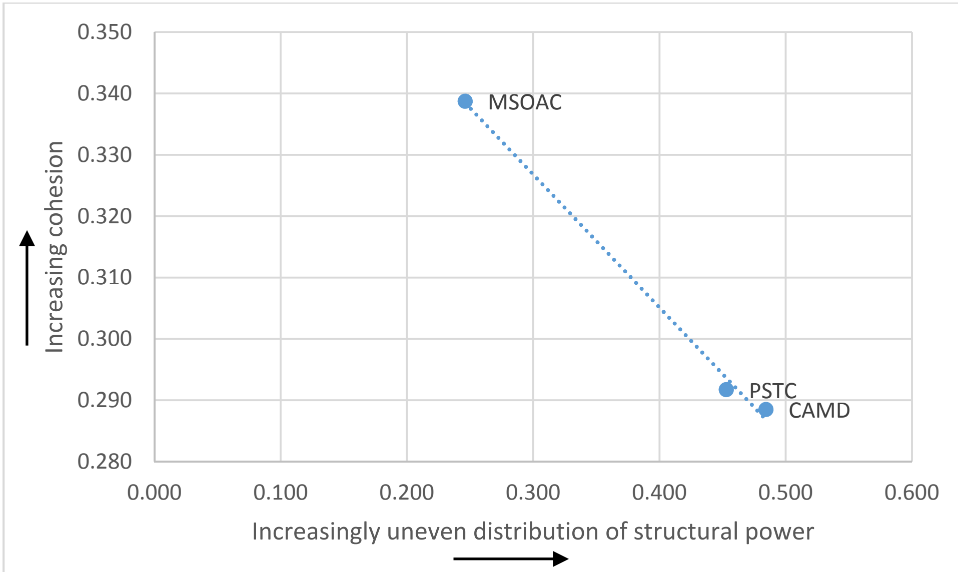

Figure 11: Structural power distribution versus cohesion: network level

Working group level

Information about working group members, provided by the consortium directors and staff, enabled the partitioning of the communication network in each consortium into its constituent working groups. This resulted in a sample size of 18 working groups across the three consortia: six in MSOAC, four in CAMD, and eight in PSTC. The size of the working groups varies from a low of eight participants to a high of 49 participants; however, the average size was relatively similar across the consortia: 18 for MSOAC, 24 for CAMD, and 28 for PSTC. The differences in average size reflect the differences in overall consortium sizes. For this analysis, both the measure for structural power distribution, betweenness centralization, and cohesion, the global clustering coefficient, were recalculated based solely on the communication networks between each of the working groups' participants.

Figure 12 plots the relationship between structural power distribution and cohesion. Each point represents one of the 18 working groups. The first observation to note is that all three consortia have workings groups that range in the value of the two variables, meaning that the consortium itself does not appear to affect either the distribution of power or level of cohesion in their working groups. The second observation is that the relationship between the two variables takes on a different form at this level of analysis; namely, one that appears to be curvilinear in nature.

In other words, the relationship between structural power distribution and cohesion changes. For working groups characterized by relatively even distributions of structural power, the relationship between the two is similar to the whole network level: the more unevenly (relatively speaking) structural power is distributed, the lower the cohesion. There comes a point, however, when this relationship reverses. For working groups characterized by relatively uneven distributions of structural power, increasing levels of centralization are associated with *higher* levels of cohesion. This means that two very different structures are associated with high cohesion: either relatively even structural power distribution or relatively uneven structural power distribution. It is when structural power distribution is in the middle ranges that cohesion is at its lowest.

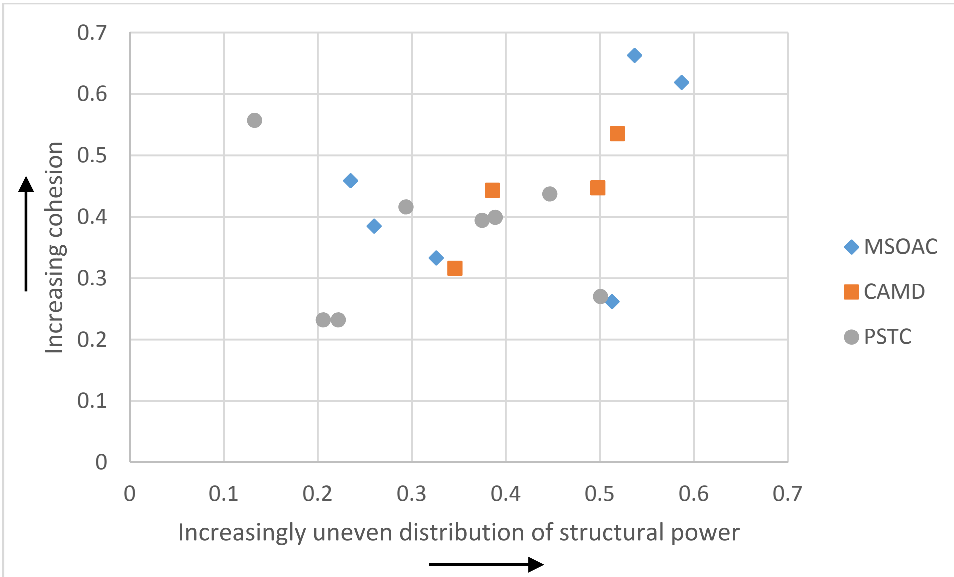

Figure 12: Structural power distribution versus cohesion: working group level

To test whether the visual pattern of curvilinearity is significant, a quadratic term was included in an ordinary least squares regression of betweenness centralization on the global weighted clustering coefficient. As shown in Table 9, the quadratic term is significant using an alpha of 0.10, a result that confirms the curvilinear relationship between structural power and cohesion at the working group level of analysis. It should be noted that this result is based on a sample size of only 18; however, when the scatter plot and regression results are taken together, a consistent picture of a non-linear relationship between structural power and cohesion emerges.

Table 9: Regression results of structural power on cohesion: working group level

	Coefficient	***P* Score**
Betweenness Centrality	-2.247	0.097
Betweenness Centrality^2	3.487	0.058
Constant	0.705	0.005

Note: Ordinary Least Squares regression: N=18; Pr>chi^2=0.064; R^2=0.307

Discussion

The results presented above paint nuanced picture of the effects of structural power on the behavior of collaborative network participants. In particular, they reveal a negative relationship between structural power and cohesion at the whole network level, but a curvilinear relationship at the working group level.

The explanation for these results is suggested to lie in Provan and Kenis' (2008) description of one of the three main network tensions that is inherent in the governance of networks: the tension between efficiency and inclusiveness. The authors state, "In networks, the primary tension regarding efficiency is the need for administrative efficiency in network governance and the need for member involvement, through inclusive decision making" (242). The tension arises because the decision-making process is made less efficient, both in terms of time and cost, as more participants become involved in the process; however, inclusion of a wide variety of opinions and stakeholders is foundational to collaboration (Ansell and Gash 2008; Fung 2006; Gray 1989; Johnston et al. 2011; Lasker and Weiss 2003; Leach 2006). In many ways, this tension boils down to idealism versus pragmatism. While inclusiveness is an ideal to strive for, it comes with an efficiency cost.

The network results from the three consortia not only affirm that the tension between efficiency and inclusiveness is alive and well, but suggest that different dynamics between the two ideals occur depending on the level of analysis. Below, how the tension plays out at both levels of analysis is discussed. Based on this discussion, propositions are offered that may be tested on a larger number of networks in the future.

At the whole network level of analysis, the results indicate that when structural power is more unevenly distributed participants are less likely to actively engage with one another, which implies that the expectation that the decision-making processes be inclusive is more likely to dominate at the whole network level. Survey responses to a free-form question about the pros and cons of participating in their particular consortium confirmed this expectation. One respondent listed as a pro, “leadership appear [sic] to strive for inclusiveness” while another listed as a con, “Be more engaging with all members of the consortium rather than a select few.”

An expectation of inclusiveness does not necessarily mean that participants expect the ideal form of collaboration, in which every participant is involve in every decision, be realized; however, Leach (2006) and Fung (2006) both argue that those who make the decisions should at least be representative of the broader population. Leach (2006, 101) says, “a representative process ensures that the interest of all affected individuals are effectively advocated, either in person or through proxies.” In other words, all participants should feel that their perspective is reflected in the major decisions of the consortium, even if they are not personally involved in that process. It is thus perhaps at this level of analysis that the ideals of collaboration are expected to be upheld.

The results from the three consortia support the idea that participants desire inclusion in the form of being represented by the decision-making body. Of the three consortia, MSOAC was the most inclusive in two ways. First, MSOAC’s decision-making body, the coordinating committee, was more directly inclusive. Sixty percent of its members are members of its decision-making body, as compared to just 25 percent for

CAMD and 17 percent for PSTC's coordinating committees. It should be noted that MSOAC's smaller size allows for more direct inclusion. However, in addition to being more inclusive, MSOAC's coordinating committee is also the most representative of its membership. In examining the top ten most powerful actors in each of the three networks, MSOAC's top ten include actors from both non-profit and for profit sectors. CAMD's top ten, on the other hand, include only representatives from the for profit sector (PSTC is composed only of for-profit organizations, so it cannot be compared to the other two consortia here). Taken together, these statistics suggest that MSOAC participants felt that decision-making power was spread more evenly among actors who are representative of the consortium participants' own interests. Given that MSOAC also has the highest level of cohesion, this suggests that the more individuals feel that strategic decisions are made collectively, the more they are likely to engage with one another in active collaboration. This leads to the second proposition:

Proposition 1: *At the whole network level of analysis, collaborative networks characterized by relatively uneven distributions of structural power are less likely to be cohesive than networks characterized by more even distributions of structural power due to participants' desire for inclusiveness in decision-making.*

Results from the working group level of analysis suggest that a different dynamic, or *set* of dynamics, is at play between structural power and cohesion. In particular, it appears that this is the level of analysis where the tension between efficiency and inclusiveness is most evident. While inclusion of participants is foundational to the idea of collaboration, survey responses revealed that efficiency concerns are a common concern as well. One respondent simply listed as a con of collaboration, "work faster," and another echoed that sentiment, saying, “It takes a tremendous amount of time to make decisions.”

In contrast to the whole network level, it appears that neither inclusiveness nor efficiency always dominates since working groups can be cohesive both when structural power is relatively centralized as well as when it is relatively decentralized. In fact, of the four workings groups with the highest levels of cohesion, three of them had the most centralized communication structure while one had the least centralized communication structure of the 18 working groups examined. Rather, it is when structural power distribution is in the middle ranges of centralization that cohesion is lowest.

These results suggest that this is the level of analysis in which efficiency concerns may sometimes overpower the striving for inclusiveness. At the more even levels of power distribution, enough participants are included in the process of decision-making that small increases in centralization of communication seem to be met with a negative reaction; namely, the exclusion of a few participants may appear to be strategic, a move that is in direct contrast to the nature of collaboration. However, there reaches a point when power is centralized enough that cohesion begins to rebound. It could be that in these types of working groups, participants realize that centralization of work will lead to increased efficiency.

Working groups are where the rubber hits the road. Given that participants are accustomed to hierarchy in their home organizations (Gray 1989), it is reasonable to suggest that the working group level is where some form of hierarchy is more accepted because participants may be more likely to favor efficiency when the goals are more tangible. In fact, it has been shown that complete decentralization can lead to disorganization and frustration (Provan and Milward 1995). If participants feel that the centralization of communication is occurring because of efficiency concerns and not in order to exclude just one or a few participants, then uneven power distributions associated may be more palatable to participants, causing them to communicate with one another more in order to make progress. The second proposition, then, has two parts:

<u>Proposition 2a:</u> *At the working group level of analysis, working groups that are characterized by relatively even distributions of structural power are more likely to be cohesive than working groups that are characterized by less even distributions of structural power due to participants' desire for inclusiveness in decision-making.*

<u>Proposition 2b:</u> *At the working group level of analysis, working groups that are characterized by relatively uneven distributions of structural power are more likely to be cohesive than working groups that are characterized by more even distributions of structural power due to participants' desire for efficiency in decision-making.*

Summary

Networks in which participants are actively engaging, or collaborating, with one another are more cohesive. Cohesion has many positive qualities for collaborative networks. It has been found to improve knowledge transfer (Reagans and McEvily 2003); make individuals more open to changing their views (Gerard 1954); and increase an individual's feelings of trust, solidarity, and even affection for the group and its members (Blau 1964; Emerson 1972b). Taken together, cohesion eases the problems involved with coordinating the actions of multiple independent actors (Lazega 2001). With that said, very little is known about the source of cohesion.

The research conducted in this chapter was aimed at understanding how structural power distribution affects levels of cohesion in the three C-Path consortia. In particular, the relationship was examined at both the whole network level as well as within the working groups that exist within the networks. The results suggest that the relationship between structural power and cohesion may in fact depend on the level of analysis considered. At the level of the whole network, uneven distributions of structural power are associated with lower cohesion. It is suggested that participants' desire for inclusiveness—and displeasure when inclusiveness does not occur—may drive this relationship.

In the working groups, on the other hand, the relationship between power and cohesion is not as clear cut. Working groups with both relatively even and relatively uneven distributions of power can both attain high levels of cohesion. The explanation for the result is suggested to lie with the tension between efficiency and inclusiveness. When participants believe that centralization of power is done for efficiency reasons rather for in order to exclude select participants from the decision-making processes, it may become more palatable. More research is needed to understand the dynamics occurring at this level of analysis.

Overall, the results imply that network managers must be sensitive to how communication flows between participants. Facilitating direct communication between a broad range of participants at the whole network level is likely to increase cohesion; however, complete decentralization of communication is neither practical nor desirable for efficiency reasons (Provan and Milward 1995; Valente, Chou, and Pentz 2007). The results from this research suggest that network managers may be able to address the tension between inclusiveness and efficiency by concentrating their desire for efficiency on the working groups. It is here that that the centralization of power is more acceptable.

While this analysis has provided fresh insight into the relationship between structural power and cohesion, it is limited by small sample sizes. Further research is needed at both levels of analysis to determine whether the trends that emerged from the three consortia studied here are more widespread. If, indeed, the level of analysis does matter, network managers will have a better way to address the efficiency versus inclusiveness tension that is inherent in collaboration as a form of organization. In properly managing this tension, the foundation on which collaboration is built and which causes it to thrive as a form or organization, collaborative behavior between participants, will benefit.

CHAPTER 5: PARTICIPANT SATISFACTION IN COLLABORATIVE NETWORKS

Thus far, it has been argued that structural power, or the power that derives the dependence relationships characteristic of collaborative networks, is a good place to start in the quest to understand more about the effects of the uneven distribution of power in this type of setting. In Chapter 4, its effects on the degree to which participants actively engage with one another were examined at two levels of analysis: the whole network level and the working group level. In this chapter, the examination of structural power is taken down yet another level of analysis to the individual participants of collaborative networks. Specifically, the focus shifts to understanding the effect of structural power on an important dimension of collaborative network effectiveness: how satisfied participants are with their involvement in the network.

Collaborative networks face a dilemma: they struggle with how to measure effectiveness, but realize that being able to measure effectiveness makes them much more attractive to a variety of stakeholders. Participants in collaborative networks want to know if their time and energy is being well-spent. Facilitators and managers of collaborative networks want to know if what they are doing is working or if they need to tweak things. Funders of collaborative networks want to know if their investment is worth it (Provan and Milward 2001).

Measuring effectiveness is easier said than done, not only because collaborative outcomes are often difficult to measure (Conley and Moote 2003; Emerson et al. 2009; Koontz and Thomas 2006; Mitchell and Shortell 2000), but because different stakeholders often care about different kinds of outcomes. Provan and Milward (2001) argue that effectiveness must be viewed from each of three levels of analysis: the network, the community (i.e., those receiving services from the network), and the organization/participant. As a first step in the journey to evaluate collaborative effectiveness, one of these perspectives is examined in greater detail in this chapter, that of the individual participant.

Although participant satisfaction with a collaborative network is not, on its own, an indicator of effectiveness (Coglianese 2002), Susskind and Cruikshank (1989) point out that participants are perhaps the best positioned stakeholders to determine how a collaborative network is faring. Moreover, their participation is one of the most important factors in determining the success of a collaborative network. As Provan and Milward (2001, 420) point out, "…it is important to recognize that individual agencies and their managers are still motivated partly by self-interest. For organizations considering becoming part of a network, the relevant question is, how can network involvement benefit my agency?"

If the answer to that question is unclear, then collaborative networks risk losing members, or losing active engagement of members in the network. Research from the organizations literature finds a strong and significant relationship between worker satisfaction and turnover, meaning less satisfied workers are much more likely to leave (for a review, see Mitra et. al 1992). Besides leaving, another possibility is that dissatisfied participants may remain as members in order to reap the benefits of being associated with the network, but will stop actively contributing, an equally, if not more severe problem. Rusbult et. al (1988: 601) refer to this behavior as neglect, defining it as, "passively allowing conditions to deteriorate through reduced interest or effort, chronic lateness or absences, using company time for personal business, or increased error rate." While those participant who choose to leave the collaborative network can be replaced by others who may be more actively engaged, participants who neglect their roles pose a serious problem for long-term progress and network morale.

A frequent assumption in the collaborative governance literature is that unevenly distributed power between members of a collaborative network is bad. For example, an uneven distribution of power is mentioned as a source of mistrust (Bryson et. al 2008; Huxham and Vangen 2005) and can contribute to frustration for those who are not in power (Huxham and Vangen 2005), both of which can reduce the desire to cooperate. It is also linked to a breakdown of communication (Mayer 1987), and can even result in cooptation of the less powerful actor by the more powerful actor (O'Toole and Meier 2004). This chapter tests this underlying assumption at the individual level of analysis by examining how structural power affects three dimensions of participant satisfaction: outcome, process, and human capital dimensions. The results suggest that structural power affects participant satisfaction through the process satisfaction dimension.

Review of the literature

It would be tempting to conclude that participant satisfaction in collaborative networks can be explained using the results of decades of studies by organizational scholars on worker satisfaction in organizations. While this research certainly contributes to understanding participant satisfaction, collaborative networks are distinct from organizations and thus, participant satisfaction is also distinct from worker satisfaction.

Here, the most relevant findings from the organizational literature are reviewed before the differences between collaborative networks and organizations, and their implications for understanding participant satisfaction are highlighted.

Organizational scholars have long been interested in understanding the factors that contribute to worker satisfaction. Individual characteristics like gender (Glenn et. al 1977; Hodson 1989) and tenure (Pfeffer 1981) as well as job characteristics like skill variety and task significance (Hackman and Oldham 1975) have commonly been included in explanations for why certain workers are more satisfied—usually measured simply as general satisfaction—than others in organizations. These explanations, however, often leave much variance in worker satisfaction unexplained.

Salancik and Pfeffer (1978) argued that attribute-based explanations could only go so far in explaining differences in workers' satisfaction because attitudes and perceptions are socially constructed. Thus, they argued that researchers must look to the relationships in which individuals are embedded to better understand their satisfaction. While scholars studying group processes in experimental settings had recognized the importance of structure on positive outcomes (see Shaw 1964 for a review of this early work), it was Salancik and Pfeffer's theory, called social information processing theory, that spawned research in organizations that took on a more structural tilt to understanding worker satisfaction. Ibarra and Andrews (1993), for example, found that structural variables—namely, a worker's centrality in the advice network and social proximity in the friendship network of an organization—affect individuals' perceptions about their jobs more than the attributes of gender, tenure, prestige, and education.

Conclusions drawn from the study of networks within organizations, however, do not translate directly to collaborative networks. While networks within organizations can certainly be thought of as networks, they differ from collaborative networks as stand-alone entities because they exist in the shadow of the organization's hierarchical structure. This difference has two important implications for understanding participant satisfaction in a collaborative setting.

First, the absence of hierarchy in collaborative networks affects a participant's expectations. The existence of hierarchal structure means that employees in traditional organizations are not likely to have the expectation that their voice be given equal credence as compared to all other employees of the organization. For example, in most organizations, supervisors' opinions are expected to be given more weight than those working under them.

On the other hand, collaboration is built upon the premise of equality and fairness for all members, a notion that comes from the procedural justice literature, which argues that the process by which outcomes are reached is judged independently from the outcomes themselves (Korsgaard, Schweiger, and Sapienza 1995; Molm, Peterson, and Takahashi 2003). This focus means that participants of collaborative networks are likely to have a heightened emphasis on process satisfaction. The importance of this aspect of participant satisfaction is evidenced by the attention it has received from collaborative governance scholars (c.f., Bingham 1986; Bryson et. al 2006; Gray 1989; Thomson and Perry 2006; Thomson et. al 2008). Research on computer-assisted collaboration in the field of information systems has gone a step further by explicitly distinguishing between satisfaction with outcomes and satisfaction with process (Briggs, Reinig, and Vreede 2006; Reinig 2003).

The second implication of a lack of hierarchy in collaborative networks is that relationships between participants are even more important than they are in organizations. Gray (2000) identifies the "generation of social capital," a concept that will be discussed more below but is defined as the capital that comes from relationships, as one of the five ways in which collaborations are assessed. For collaborative networks, so many of the benefits of participation are tied to these relationships (Provan, Huang, and Milward 2009). This point is illustrated by Diane Stephenson, director of one of the consortia, CAMD, studied here. She says:

> In terms of value and in terms of how you measure success and progress around your goals, if your goal is only the one [biomarker] qualification, you're selling yourself short because honestly, if you just look at our day-to-day value of what members get by being members of this consortium, it's informal advice from the regulators…it's access to key opinion leaders (2014).

In fact, it is not uncommon to hear of participants who join collaborative networks *for* the relationships that are built (Bingham 1986; Head 2008).

Relationships matter in organizational networks as well, of course, but in a slightly different way. In organizations, relationships between employees form what is known as the informal network or social structure. While informal networks have been shown to be both instrumental and influential (c.f., Brass 1985; Krackhardt and Stern 1988), they still exist alongside the hierarchical structure. In other words, the formal network to some extent enables and constrains informal networks in a traditional organization. While most collaborative networks are not entirely without structure–many have network administrative organizations and subgroups–this structure is thought to be less rigid than in organizations (Powell 1990). For them, the informal relationships between participants are the main mechanism by which resources flow through the collaboration.

Participants of collaborative networks look to these relationships not only to make progress towards the collaborative network's goals, but also to build human capital, defined by Coleman (1988, S100) as "the skills and capabilities that make them able to act in new ways." He studied high school drop-out rates and found that human capital, operationalized as education, is only transferred from parents to children in the presence of strong relationships. In other words, an important benefit of social capital is the creation of human capital. Leach and his co-authors (2002) agree, citing the development of human capital as one of the dimensions of success in their study of stakeholder partnerships dealing with watershed management. The absence of hierarchy in collaborative networks, thus, leads to emphasis on what is termed here human capital satisfaction.

In sum, participant satisfaction in collaborative networks hinges not only on the obvious dimension of satisfaction with the outcomes of the collaborative network, but also upon participants' satisfaction with process and human capital dimensions. Work done by McKinney and Field (2008) suggests that the latter two dimensions may be *more* important, in fact, than the first. In their examination of over 50 cases of community-based collaborations on federal lands and resources, they find that participants view working relationships and process factors as more important than outcomes. However, participant satisfaction without an outcome dimension would be incomplete. Many scholars discuss the importance of demonstrating progress to participants in order to keep them actively engaged and encouraged (c.f., Ansell and Gash 2008; Huxham and Vangen 2005; Vangen and Huxham 2003).

Development of hypotheses

The amount of structural power a participant holds in a network is likely to affect how they feel about their experience. Here, hypotheses are developed predicting the effect of a collaborative network participant's structural power on the three dimensions of participant satisfaction described above.

Power can be conceptualized and measured in many ways. As was argued in Chapter 3, a specific type of power, structural power, in collaborative networks is best conceptualized and measured using the measure of betweenness centrality in the communication network. The higher an actor's betweenness centrality, the more control s/he has over the flow of information throughout the network (Freeman 1979). Given the lack of research on betweenness centrality and participant satisfaction, though, research is included here that uses other measures of centrality as well. While these other measures—namely, degree and closeness centrality—differ slightly based on which locations are deemed most advantageous, a common finding across all measures of centrality is that highly central actors in a network are also the most powerful (c.f., Brass 1984; Fernandez and Gould 1994; Galaskiewicz 1979; Milward and Provan 2006).

Most of the studies that examine centrality and participant satisfaction rely either on general measures of self-reported satisfaction or create a scale that combines together outcome, process, and human capital dimensions of satisfaction. The use of scales makes it difficult to tease out the specific effects of centrality on the different dimensions of interest for this chapter. Here, the general findings are first discussed, followed by the studies that point more specifically at particular dimensions of participant satisfaction.

Early experimental research found an actor's centrality in communication networks to be positively associated with self-reported participant satisfaction in small, five-person groups (see Shaw 1964 for a review of early studies). These early findings are supported by Mullen et. al's (1991) meta-analysis of studies on the effects of centrality in communications networks. Beyond confirming that centrality impacts satisfaction positively, the authors also found that actors with high betweenness centrality, in particular, are more likely to report being satisfied with their job. They conclude that being in a position to control the flow of information is associated with more positive evaluations.

It should be noted that not all research is in agreement on this relationship. Brass (1981) examined the relationship between worker satisfaction and centrality in three different levels of analysis in an organization: the workgroup, the department, and the organization as a whole. He found no relationship in the first two levels of analysis and a negative one between satisfaction and centrality in the organization as a whole. One possible reason for these contradictory findings is that Brass measured centrality using the closeness measure, which Mullen et. al (1991) also found was not associated with worker satisfaction.

Several studies support the idea, more specifically, that actor centrality is associated with higher satisfaction with the process of collaboration. Actor centrality has been found to be positively related to satisfaction with team-based learning in a graduate school environment (Baldwin, Bedell, and Johnson 1997) and with feelings of acceptance or belonging (Miller 1980). In addition, Korsgaard et. al (1995) conducted experimental research on intact management teams and found that an individual's influence on decision-making, another way of measuring power, had a significant effect on his/her perception of the fairness of the procedures used to arrive at decisions. In particular, subjects in the high influence condition judged the procedures to be fairer. These results suggest the following hypothesis:

<u>*Hypothesis 1:*</u> *Actors with higher structural power will rate their satisfaction with process aspects of collaboration as higher than actors with lower structural power.*

The relationship between structural power and human capital satisfaction is, at first blush, not obvious; however, when structural power is measured as a participant's betweenness centrality in a collaborative network, its relationship to human capital satisfaction becomes clearer. Namely, the most common benefit associated with having a high betweenness centrality is control of resource flow (Freeman 1979). In a communication network, this means that highly central actors have access to the largest amount of human capital in the form of information. Ibarra and Andrews (1993) findings lend support to this idea, finding that centrality is associated with access to information. Therefore,

<u>*Hypothesis 2:*</u> *Actors with higher structural power will rate their satisfaction with human capital aspects of collaboration as higher than actors with lower structural power.*

Finally, to the author's knowledge, the link between structural power, measured as centrality, and satisfaction with outcomes has not been studied at the individual level; rather, this relationship is studied at the network level. Provan and Milward (1995), for example, find that centralized service delivery networks are judged by clients of those networks to be more effective. At the individual level, centrality is studied more in relation to individual performance, rather than satisfaction (c.f., Ahuja, Galletta, and Carley 2003; Sparrowe et al. 2001; Tsai 2001). The lack of research on centrality and participant satisfaction with outcomes is perhaps because no clear relationship exists. While it is possible that highly central actors view the collaborative network's outcomes in a positive light because they have put a lot of effort into their work, it is also possible that they see the flaws more clearly because of their more intense involvement. Therefore,

Hypothesis 3: Actors with higher structural power will rate their satisfaction with outcome aspects of collaboration as the same as actors with lower structural power.

Data

The three hypotheses are using individual-level data from participants of three C-Path consortia. The research setting and data source are covered in greater detail in Chapter 2. Briefly, the data come from an online survey conducted of participants of the Predictive Safety Testing Consortium (PSTC), the Coalition Against Major Diseases (CAMD), and the Multiple Sclerosis Outcome Assessments Consortium (MSOAC). Although members from the regulatory agencies are represented on the consortia, they fulfil a purely advisory role; therefore, they were not included in the survey. Response rates and network size for the consortia can be found in Table 10.

Each of these networks exists under the umbrella organization, the Critical Path Institute (C-Path), whose mission is to improve the process and standards surrounding the pharmaceutical drug development process in the United States. While each consortium addresses either a particular aspect of this problem, they share many similarities like governance structure, leadership roles, funding sources, membership criteria, and overarching goals. Due to these similarities, the individual responses from all three consortia are combined to test the hypotheses, resulting in a total sample size of 93 individuals. Dummy variables are added to the models to control for differences that may be due to the consortia themselves, with MSOAC as the excluded category.

Table 10: Consortium sizes and response rates

Consortium	Size	Response Rate
CAMD	113	32%
MSOAC	65	37%
PSTC	165	35%

Measures

The measures used to examine the relationship between structural power and participant satisfaction are detailed below. Descriptive statistics are provided in Table 11. In addition, the Spearman's rho statistics, a measure of statistical dependence suitable for ordinal data, are presented for the pairwise relationships between all of the variables in Table 12.

Dependent variables

Three categories of dependent variables are examined, one for each of the following three dimensions of participant satisfaction: process satisfaction, human capital satisfaction, and outcome satisfaction. While it is suggested that these three dimensions contribute to participant satisfaction for all problem-solving collaborative networks, the specific measure or measures used to capture each of the dimensions will vary from one collaborative network to another. Consider, for example, the human capital dimension. For the C-Path consortia, one of the main human capital benefits is gaining access to knowledge about the regulatory approval process. This specific measure is likely to an inappropriate measure of this dimension for other collaborative networks.

The measures described below were selected using knowledge about how the three consortia function and how participants benefit. This information was gathered via one-hour interviews with the founder and former CEO, the current CEO, and each of the individual consortium directors. Some of the dimensions were measured using a single survey question while others used two questions.

All of the survey questions on which the three dimensions of participant satisfaction are based had Likert-scale responses, meaning the resultant variables are ordinal in nature. Questions that were negatively stated were reverse-coded for the sake of consistency. The result is that higher values are associated with more positive feelings and perceptions. Many of the dependent variables described below are significantly correlated (see Table 12), which is to be expected given that they all revolve around the bigger concept of participant satisfaction. Several indices of variables with higher correlations were attempted both based on logic and the Spearman’s rho correlations, but

Table 11: Descriptive Statistics

Variable	Variable type	Mean	Min	Max
Betweenness Centrality	IV	0.023	0	0.178
Valued	DV	4.094	2	5
Trust in rules	DV	4.333	3	5
Reg process knowledge	DV	3.990	1	5
Broadened understanding	DV	2.458	1	3
Progress	DV	3.510	1	5
Participation (years)	Control	3.507	.5	9
Experience (years)	Control	18.457	1	42
CAMD	Control	0.292	0	1
PSTC	Control	0.521	0	1

Note: IV=independent variable; DV=dependent variable; Control=control variable

Table 12: Spearman's correlations

	1	2	3	4	5	6	7	8
Betweenness Centrality	1.000							
Valued	0.317**	1.000						
Trust in rules	0.263**	0.176*	1.000					
Reg process knowledge	0.174*	0.340**	0.162	1.000				
Broadened understanding	0.203**	0.288**	0.216**	0.456**	1.000			
Progress	0.190*	0.251**	0.235**	0.233**	0.218**	1.000		
Participation (years)	0.141	0.056	0.173*	0.076	0.213**	-0.067	1.000	
Experience (years)	0.138	0.036	0.214**	0.190*	0.164	-0.161	0.284**	1.000

Note: N= 94; * denotes significant at the .10 level; ** denotes significant at the .05 level none of them attained a Cronbach's alpha above the value generally deemed acceptable, 0.80[18].

Based on the knowledge of the three consortia, two variables were used to measure the process satisfaction dimension. First, consortia participants indicated the degree to which they agreed their contribution to the consortium is *valued* by other participants. They chose from a five-item Likert scale that ranged from strongly disagree to strongly agree. Across the three consortia, the directors agreed that recognizing participants' contributions—and even presenting awards to those who went above and beyond—was very important in order to ensure that participants feel that their investment is appreciated. MSOAC's consortium director put it well, describing one of her roles as "thanker-in-chief" (Hudson 2014).

The second process satisfaction measure was based on a survey question that asked respondents to assess the degree to which they *trust in rules* by rating the degree to which they trust that members of the consortium abide by the rules governing it. Respondents chose from a five-item Likert scale that ranged from not much to a great deal. This variable emerged as being particularly important in the three consortia due to the competitive nature of the pharmaceutical drug domain and the sensitive nature of sharing drug trial data. In fact, founder Ray Woosley (2014) stressed the importance of creating mutually agreed-upon rules for the functioning of consortia efforts in this area. If

[18] The indices attempted are reported here. Variables in the index are displayed in parentheses and the value following the equal sign is Cronbach's alpha: (valued, trust in rules, knowledge, broadened understanding, progress)=0.627; (knowledge, broadened understanding, valued)=0.603; (knowledge, broadened understanding, valued, progress)=0.596; (broadened understanding, knowledge)=0.592; (knowledge, broadened understanding, progress)=0.509; (trust in rules, valued)=0.339.

participants are to feel that they are being treated fairly, they must have confidence that other participants will play by the rules. As the descriptive statistics show, responses across both process satisfaction variables was overwhelmingly, but not uniformly positive.

Human capital satisfaction was also measured using two survey questions, both of which were based on the information benefits that membership in these particular consortia should provide. The first variable, *regulatory process knowledge*, was created by asking respondents the degree to which they agree or disagree that participation in the consortium has increased their knowledge about the regulatory decision process. Respondents selected from a five item Likert-scale that ranged from strongly disagree to strongly agree. One of the main reasons C-Path was founded was to improve the drug development process by bringing in the perspectives of non-governmental actors like pharmaceutical companies and non-profits. Perhaps the biggest carrot dangled in front of these actors was access to information about how the drug development process works. In fact, in describing the day-to-day benefits of consortium participant, CAMD's consortium director stressed as one of the most overlooked, yet important benefits is the access to the informal advice and insight from regulators (Stephenson 2014).

The second measure of human capital satisfaction taps into the gaining of knowledge that is more general in nature. The variable, b*roadened understanding*, was created by asking respondents to report the extent to which their understanding of the issues that brought the consortium together has broadened as a result of their participation. Answer choices were not at all, somewhat, and to a large extent. As compared to the very specific nature of regulatory process knowledge, this variable was intended to capture the broader knowledge that participants of the consortia can expect to gain through their participation. PSTC’s consortium director cited as one of the main benefits of participation the gaining of a much larger amount and variety of information than they would have normally be able to access (Sauer 2014). As with the process satisfaction measures, the descriptive statistics reveal a largely high degree of satisfaction on both of the human capital satisfaction measures.

Finally, the outcome satisfaction dimension was measured via one variable: perceived *progress* towards consortium goals. To measure this dimension, respondents were asked to report the degree to which they were satisfied with the progress the consortium has made toward achieving its goals. In response, they selected from a five item Likert-scale that ranged from strongly disagree to strongly agree. Despite all of the additional benefits of consortium participation, most participants still want to see progress on goals. PSTC consortium director described how lack of progress can affect participant satisfaction:

> I think that there was a lot of excitement when…things were formed and it looked like it was going to be pretty straightforward to do these [biomarker] qualifications. Everybody was excited. What’s happened over time is it’s become more difficult to qualify these biomarkers, which has taken a toll on the membership excitement (Sauer 2014).

The descriptive statistics reflect the sentiments expressed in this quote. Of the three dimensions, participants are least satisfied with this dimension, although the ratings are still generally positive.

Independent variables

The main independent variable is a measure for structural power, which is measured using *betweenness centrality*. It is touched on briefly here, but the reader is referred to Chapter 2 for a full discussion. Betweenness centrality measures the degree to which a participant sits on the shortest path connecting two other participants (Freeman 1979). Because the examination here focuses on the communication networks, or the networks in which information is shared between participants, a high betweenness centrality indicates that a participant is able to control the flow of information in the consortium. The communication networks on which this measure is based are weighted, with tie weights representing the frequency of communication between any two participants. Therefore, a weighted generalization of betwenness centrality is used (Opsahl et. al 2010).

The measure is calculated for each participant using the consortium in which they participate. In other words, only the ties to participants in their own consortium are used in the calculations. The betweenness centrality measures are then standardized so the results can be compared across the differently-sized consortia. The resultant measure can vary between a low score of zero and a high score of one, but the descriptive statistics reveal that betweenness centrality scores are clustered near the low end in the three consortia. In fact, its mean value is 0.023 and its maximum value is a mere 0.178. The lack of high values can be explained by the fact that establishing and maintaining ties to many communication partners is difficult and time-consuming to do (Gazley and Brudney 2007; Head 2008). Given the range of this measure, the analysis presented below refers to a one unit change in a participant's structural power as a .1 increase in his or her standardized, weighted betweenness centrality score.

In addition to the effects of structural power, the models include four control variables that may also contribute to participant satisfaction. Two variables are intended to capture a respondent's experience. *Participation* and *experience* measure, in years, how long a respondent has participated in the consortium and how long the participant has been working in their current area of expertise, respectively. Previous research has shown that an individual's experience level does affect levels of worker satisfaction (c.f., Hunt and Saul 1975; Pfeffer 1981). An individual's tenure has also been shown to affect worker satisfaction (Ibarra and Andrews 1993). In addition two dummy variables, *PSTC* and *CAMD* are included to control for differences between the three consortia, with MSOAC serving as the excluded consortium.

Methods

Given the ordinal nature of the dependent variables, ordinary least-squares regression (OLS) would be inappropriate because it assumes a continuous normal distribution. Instead, an ordered logistic regression, which accommodates ordinal dependent variables. One of the challenges of ordered logistic regression is that the interpretation of the coefficients, which are in log-odds units, is not straightforward. Therefore, in the results that follow, the marginal effects for the highest ordinal category are reported. For example, the results report the likelihood that a respondent will "strongly agree" that their contribution is valued, given a one unit increase in the independent variable. As was noted above, one unit is defined as .1 for betweenness centrality.

One methodological issue that needs to be acknowledges is the models' potential violation of the assumption that observations are independent. The inclusion of a network-based variable—the measure for structural power—means that there is a natural dependence built into these observations because they are calculated based on ties connecting two participants. Without correcting for this interdependence, the estimates of the standard errors may be too small and thus, the significance of results may be falsely inflated (Hox 2010). The violation of the independence assumption, along with some potential solutions, is discussed in further detail in Chapter 2. While solutions to this issue have been developed, it is unclear to the researcher if they are flexible enough to address the particular research questions developed in this chapter. Future iterations of this research will attempt to use these solutions. For now, the regression results presented below are based on standard regression techniques with the knowledge that the network variable may violate the independence of observations assumption. The effects of dependence are not anticipated to be severe for this data because the unit of analysis is the individual participant, not the relationship between participants.

Results

The results of the three model specifications are discussed below. After the results section, a discussion section considers interpretations and conclusions suggested by the results.

Process satisfaction

For the process satisfaction dimension, both the models for *valued* and *trust in rules* as dependent variables were significant.

Table 13 shows the results for *valued* as the dependent variable. Structural power has a large effect on how strongly a respondent reports that his or her contribution is valued by consortium members. In particular, a .10 unit increase in centrality score, the measure for structural power, is associated with being 25 percent more likely to strongly agree that the respondent's contribution to the consortium is valued.

Table 13: Results for valued

	Marginal Effects	***P* Score**
Betweenness Centrality	2.457	0.038
Participation (years)	0.018	0.439
Experience (years)	-0.002	0.728
CAMD	0.057	0.674
PSTC	-0.071	0.598

Note: Marginal effects are for "strongly agree" response; N=93; Pr>chi^2=0.102

How strongly a respondent trusts that the rules of the consortium will be followed by other members is also affected by how much power s/he possesses. The results, displayed in Table 14, show that a .10 unit increase in an actor's standardized betweenness centrality is associated with the respondent being 37 percent more likely to strongly agree that that the rules of the consortium will be followed by members. The only other significant predictor was for CAMD. Participants of CAMD are 31 percent less likely to strongly agree that the rules of the consortium will be followed by members than participants of MSOAC.

Table 14: Results for trust in rules

	Marginal Effects	***P* Score**
Betweenness Centrality	3.680	0.035
Participation (years)	0.034	0.255
Experience (years)	0.009	0.194
CAMD	-0.311	0.058
PSTC	-0.009	0.960

Note: Marginal effects are for "strongly agree" response; N=93; Pr>chi^2=0.002

These results lend some support to hypothesis 1, which states that structural power will positively affect an individual's process satisfaction, is supported for both the *valued* and the *trust in rules* variables. Namely, the more central an individual is in the communication flow of the collaborative network, the more s/he feels valued and the more s/he trust in the rules.

Human capital satisfaction

With regards to the human capital dimension of participant satisfaction, only the model with *regulatory process knowledge* as the dependent variable is significant; however, the effect of structural power is not significant for either of the human capital dimensions. Results for the model using *regulatory decision knowledge* as the dependent variables are displayed in Table 15. The only significant predictor of regulatory process knowledge is the dummy variable for PSTC. PSTC participants are 26 percent less likely to strongly agree with this statement than MSOAC participants. The results for the model using *broadened understanding,* which is not significant, are shown in Table 16.

Hypothesis 2, then, is not supported. In other words, an actor's structural power does not facilitate the transmission of human capital.

Table 15: Results for regulatory decision knowledge

	Marginal Effects	***P*** **Score**
Betweenness Centrality	1.455	0.769
Participation (years)	0.109	0.298
Experience (years)	0.019	0.466
CAMD	-0.645	0.296
PSTC	-1.242	0.057
Note: Marginal effects are for "strongly agree" response; N=93; Pr>chi^2=0.167		

Table 16: Results for broadened understanding

	Marginal Effects	***P*** **Score**
Betweenness Centrality	1.086	0.427
Participation (years)	0.055	0.065
Experience (years)	0.003	0.615
CAMD	0.012	0.940
PSTC	-0.018	0.914
Note: Marginal effects are for "strongly agree" response; N=93; Pr>chi^2=0.229		

Outcome satisfaction

The model using perceived *progress* towards consortium goals as the dependent variable, the results of which are provided in Table 17, is not significant, nor were any of the variables within it significant. From these findings, it appears that an individual's position of structural power has no effect on perceptions of progress, which supports hypothesis 3.

Table 17: Results for progress

	Marginal Effects	***P*** **Score**
Betweenness Centrality	0.520	0.187
Participation (years)	0.001	0.905
Experience (years)	-0.003	0.113
CAMD	0.066	0.183
PSTC	0.036	0.456
Note: Marginal effects are for "strongly agree" response; N=93; Pr>chi^2=0.185		

Discussion

The effects structural power on the three dimensions of participant satisfaction were examined. The results indicate that structural power has a large effect on a participant's process satisfaction, but no significant effect on the other two dimensions. Potential reasons for and implications of findings are discussed here.

To begin, structural power affects a participant's satisfaction with the process of collaboration. Structural power is measured as high betweenness centrality, meaning that a powerful participant is able to control the flow of information in the network and thus is likely to have more say in the decisions of the network. The results indicate that participants in positions of power have increased confidence in how the collaborative process is being undertaken. In particular, powerful individuals are more likely to feel that their contribution is valued and are more likely to trust that the rules developed by the consortium will be followed. Conversely, less powerful participants do not feel as valued by consortium members. Moreover, they are less likely to have had a say in the decisions of the consortium and are therefore less likely to trust that the rules governing the consortium will be followed. These findings are in-line with findings that power affects perceptions of fairness and feelings of belonging (Korsgaard, Schweiger, and Sapienza 1995; Miller 1980).

The lack of a significant effect of structural power on the human capital dimension of participant satisfaction is surprising because it suggests that those participants who acquire the most information do not report being more satisfied with how that information contributes to their knowledge about the regulatory process or the issues that brought the consortium together. The lack of a result here may be due to the measures used for human capital satisfaction. Human capital comes in many forms and it is possible that regulatory process knowledge is not the primary form of knowledge desired by participants.

Likewise, the insignificance of the model using *broadened understanding* as the dependent variable may be due to the fact that not all consortium members join a consortium to increase their knowledge; they may already feel that they know a lot about the problems that the consortium addresses and participate with the intent of sharing that knowledge. These individuals are likely not to expect to gain a broadened understanding, and therefore, do not factor it into their satisfaction with the consortium. Another potential explanation for the lack of a significant effect of structural power on human capital satisfaction is more sociological in nature. It is possible that being central in a communication network makes a participant more aware of the problems of collaboration. In other words, central actors may not necessarily be more satisfied with the amount of knowledge they gain because they are more aware of what is *not* being shared by other participants.

No effect was found for power on the outcome satisfaction dimension. This result is interesting because it suggests that power imbalances between actors in collaborative networks are bad due to how they make participants feel, but not on the more commonly looked to metric: progress towards goals. Evaluators only looking at this last dimension may conclude that unevenly distributed power is not as bad as some assume. This one dimensional evaluation, though, does not give the full picture.

The results discussed above suggest that even in environments in which progress towards goals is difficult to measure, network managers have another way to increase participant satisfaction: namely, by focusing on facilitating communication between participants. It is unrealistic and unnecessary for all participants to communicate; however, the results point to the importance of having a more even distribution of power in the communication network. Participants who are actively engaged via communication with peers feel more valued and trust that the rules that were agreed upon will be followed. These efforts to increase communication, though, are not expected to directly improve performance, per say. The more participants communicate directly with one another, rather than through a central actor, the less efficient the process becomes. How managers can address this tension between inclusiveness and efficiency is addressed at length in Chapter 3. The bottom line from these findings, however, is that concentration on making progress towards goals is likely to result in participants who are not very satisfied and are at a higher risk of leaving the consortium entirely or becoming less actively engaged.

Summary

The working assumption in the collaborative governance literature is that power negatively impacts collaborative networks (Bryson and Crosby 2008; Huxham and Vangen 2005; Mayer 1987; O'Toole and Meier 2004). The results presented above begin to delve into understanding this assumption from the perspective of one critical group of stakeholders: the participants themselves. In particular, participant satisfaction was divided into three dimensions that are particularly important for collaborative networks:

satisfaction with the process, with the creation of human capital, and with the outcomes of the collaborative network. The results suggest why uneven power distributions are bad: they affect participants' satisfaction with the process of collaboration. These results provide more nuanced insight into the effects of power.

The reliance on cross-sectional data from three consortia has obvious limitations. While the consortia do differ in several aspects, the fact that they exist under the same umbrella organization makes it impossible to generalize these findings to other collaborative networks. In addition, the cross-sectional nature of data makes potential reverse causation an issue. It is assumed here that a participant's position of centrality in the communication network, for example, causes them to feel more valued. Without longitudinal data, though, it is impossible to rule out the possibility that participants who feel more valued communicate more with others, thus making them more central. Finally, the use of standard regression models means that the results must be interpreted cautiously given that the inclusion of a network measure violates the independence of observations assumption. Despite these limitations, the results here provide more detail into a topic that is not well understood.

The results from this chapter are insightful, but ultimately they provide information on only one of the three levels of analysis Provan and Milward (2001) suggest are necessary for understanding network effectiveness: the participant level. The other two, the network level and the community level, remain unstudied. To understand the former perspective, the leadership of the consortia could be interviewed while funders and other important external stakeholders could provide the community perspective. All are needed for a more complete picture of a network's effectiveness. Future research can begin to tackle these other two dimensions.

CHAPTER 6: CONCLUSION

Collaborative networks are becoming an increasingly common organizational form of public management (Agranoff 1991; Gray 2000; Head 2008; Jennings and Ewalt 1998; Kettl 2006; Leach et al. 2013; Provan and Milward 2001; Provan et al. 2005; Sabatier 2005). Funders, in particular, are touting collaborative networks as a solution to a broad array of public problems (Suárez 2010; Graddy and Chen 2006; Ostrower 2005). In fact, in a study of 1,192 grantors, the Wallace Foundation found that 69 percent of respondents "actively encouraged" collaboration (Ostrower 2005). As the collaboration between government, non-profit, and for profit sectors becomes more common, the need to understand this form of organization becomes more pressing. In particular, in order to ensure that the increasing use of collaborative networks produces more benefits than risks to society, public management scholars must continue to study the challenges of this form of organization.

In an ideal problem-solving collaborative network, actors participate on equal footing as they contribute knowledge, skills, and resources to some jointly-held and difficult-to-solve public problem. In this ideal network, each actor is valued and their perspective given equal weight as they contribute something unique to the joint cause. Scholars studying collaborative networks have recognized that this ideal is not realistic. In particular, uneven distributions of power with regards to who influences the decisions that are made are prevalent, and these power differentials are thought to have a negative effect on collaboration (Bryson, Crosby, and Stone 2006; Gazley 2008; Gray 1989; Hardy and Phillips 1998; Huxham 2003; McGuire 2006; Ostrower 2005; Purdy 2012).

Despite the recognition that the subject of power is an important avenue of research for scholars of collaborative networks, research on the topic is in its infancy. As a result, many questions regarding power and its effects have not been answered. The research described herein presents a first step in understanding a particular type of power, structural power, and its effect on the process and outcomes of collaborative networks.

Two main purposes drives this final chapter. First, it seeks to summarize the approach taken by this dissertation, the results it produced, its implications for collaborative network managers, and its limitations. Second, it offers a way forward, one that attempts to avoid the pitfalls of the approach taken herein. In doing so, it points to future avenues of research in the quest to better understand power in collaborative networks.

Summarization of results

There exist many types of power that are likely to contribute to a participant's ultimate influence in the decision-making process of a collaborative network; however, power is too complex to study as one, unified concept. This research, therefore, concentrates on a particular type of power that is especially salient for collaborative network settings: structural power. Structural power, or the power that arises from the dependence of one actor on another, lives in the relationships that bind network participants together. While viewing power as dependence is not new, this research breaks new grounds by focusing on understanding the effects of structural power on the processes and outcomes of collaborative networks.

Structural power has been operationalized in different ways. The main motivation behind Chapter 3 was to understand which operationalization is most appropriate for the collaborative network setting. Results from an examination of the three C-Path consortia revealed that only the relationships within the network's boundaries contribute to an actor's influence in decision-making of the collaborative network, a finding that supports the organizational network's conceptualization of structural power. Specifically, the more a participant is able to control the flow of information between other participants, the more dependent those participants are on him/her; in turn, the more power that participant wields in the decision-making of the collaborative network. On the other hand, the social exchange literature's operationalization of power as dependence, in which power derives from a participant's alternatives to participation in the focal collaborative network, does not seem to contribute to a participant's influence. In other words, the laboratory-tested finding that the more dependent an actor is on the collaborative network, the less power s/he will have in the network does not hold true for the consortia examined here.

Chapter 4 examined the effects of the distribution of structural power on cohesion, a behavioral measure that indicates how actively participants are collaborating with one another. The relationship between the two variables was shown to differ depending on the level of analysis used. At the whole network, it was found that the networks in which structural power is unevenly distributed are more likely to exhibit lower levels of cohesion among participants. It was suggested that this result can be explained by participants' desire to be represented by a like-minded participant—be that someone else from their organization or at least someone else from their sector—in the decision-making of the consortium. When they are not, they are less likely to actively engage in collaboration. A different relationship was found to exist between structural power distribution and cohesion at the working group level of analysis. Namely, a curvilinear relationship emerged, indicating that cohesion can be high both when structural power is relatively unevenly distributed as well as when it is relatively evenly distributed. In other words, this is the level of analysis where concerns for efficiency may begin to outweigh concerns for inclusiveness, particularly when an uneven distribution of structural power is created specifically for efficiency gains.

The last analytical chapter, Chapter 5, explored how structural power affects the extent to which participants are satisfied with the consortium. It was anticipated that structural power, would have different effects on three dimensions of participant satisfaction: process satisfaction, human capital satisfaction, and outcome satisfaction. Results indicate that the biggest effect of structural power is on process satisfaction. The more powerful actor, the more s/he is satisfied with the process of collaboration. This also means that the opposite is true. Namely, less powerful actors are less likely to be satisfied with the process of collaboration. In other words, these results substantiate the claims that structural power negatively impacts an actor's sense of value and trust in a collaborative network. Through cohesion, they also affect human capital satisfaction, albeit to a smaller degree. On the other hand, the findings suggest that a participant's human capital and outcome satisfaction are unaffected by their degree of structural power.

Implications for network managers

The research presented here suggests several implications for managers or leaders of collaborative networks. In the introduction, some of the key challenges facing the C-Path consortia were discussed. Chief among them was the challenge of incentivizing active participation and managing conflict between participants. Here, the results are discussed with regards to their implications for managing these key challenges.

One of the main findings of the dissertation is that uneven distributions of structural power are associated with lower levels of cohesion, as measured from a behavioral standpoint, at the whole network level of analysis. Network managers are therefore advised to be as inclusive as possible in strategic decision making and overall vision-setting in order to increase the desire to actively collaborate. With that said, it is not realistic or even desirable to have every participant involved in every decision because it invariably reduces the efficiency of collaborative network. In a decision process that is already characterized as lengthy due to a desire for consensus or near-consensus on decisions, collaborative networks must find a way to recognize and embrace the desire for inclusiveness while also concentrate on efficiency concerns. The results presented herein suggest two ways to address this tension.

First, inclusiveness can be at least simulated at the whole network level by ensuring that similar categories of voices are represented. While each individual participant is different, it is likely that participants representing non-profits, for example, have more similar views than participants from pharmaceutical companies. This similarity has long been documented as arising from norms that arise through influences like similar schooling and training (Provan et. al 2003; Provan et. al 2004). The results support this notion, with the consortium exhibiting the highest level of cohesion also being the most representative of the sectors from which its members come. While sector-based representation is an obvious starting point, future research can look into other factors that may lead participants to hold similar views like size of organization or reason for their participation in the network.

Second, the research suggests that efficiency concerns are best addressed in the working groups. It is here that participants may be more accepting of centralized power structures, particularly if the centralization occurs in order to make progress rather than to specifically exclude certain participants. This result is intuitively appealing. Given the specialization of working groups, it is here that those who hold specific expertise can take charge. It is natural to allow a participant with expertise in statistics, for example, to play more of a central role in the statistics working group. In many ways, it is more likely to be a merit-based centralization of power that occurs at this level of analysis.

Another main finding of the research is that the negative effect of structural power is most felt at the individual level in the form of disillusionment with the process of collaboration. The less structural power a participant holds, the less s/he feels trusts that their participation is valued and that the other participants will play fair. Ultimately, concerns about the process create tensions in the network that are likely to aggravate conflict between participants. Therefore, network managers facing conflict between participants are advised to take a closer look at these factors. By directly addressing feelings of value and trust in rules, managers may be able to ameliorate some sources of conflict.

Limitations

The approach taken in this dissertation followed the traditional path of attempting to discern the effect of one variable on another. In particular, it sought to examine the effect of structural power on cohesion as well as its effect on participant satisfaction. This causal approach is limited by several factors that are discussed below.

The relationship between structural power and attributional power

The research herein focuses on understanding structural power, conceptualizing structural power using an actor's position in the consortium's communication network. The exclusive focus on this type of structural power is a good first step, but it overlooks many interesting interactions that are likely to provide a fruitful path for future research. Here, those potential interactions are preliminarily explored.

To begin, structural power, or power as dependence, was distinguished from attributional power, or the power that comes from an actor having a particular attribute like wealth or status. Structural power stems from the idea that a particular attribute only makes an actor powerful if someone else needs what s/he has to offer. From this perspective, structural power can be said to encompass attributional power.

However, just because attributional power can be integrated into the concept of structural power does not mean that doing so is seamless or straightforward. The analytical tools of social network analysis are most simply and cleanly applied when one type of tie is analyzed and compared across networks. Here, the communication networks created by the exchange of information between participants was deemed most suitable since collaborative networks like the C-Path consortia strive to create innovative solutions through the sharing of participants' unique knowledge. Using the communication networks, it was possible to compare apples to apples when examining power distribution in the three consortia.

Of course, the focus on just one type of tie content, information exchange, is narrow and thus ignores many of the other potential contributors to a participant's structural power in a collaborative network. An actor who is not central in the communication flow may still be perceived as influential because of his/her possession of a different attribute that creates dependence relationships. One way around this relatively narrow focus is to analyze multiple tie contents created by different attributes simultaneously. This approach, known as multiplexity, has become relatively common in the network literature (c.f., Isett and Provan 2005; Provan and Milward 1991; Provan et. al 2004). An analysis, for instance, may treat an actor's structural power as equal to the average of his/her centrality in the communication network, the reputation network, and the funding network created by the amount of monetary resources that are exchanged between participants.

It is theoretically possible, then, for attributional power to be fully encompassed within structural power. For this to occur, though, many different types of relationships—namely all of the attributes that may contribute to an actor's dependence—must be simultaneously examined. This type of analysis would, of course, be difficult to conduct since power can derive from innumerable attributes. Therefore, practically speaking, examinations of structural power can only encompass one or potentially a few sources of attributional power at any time. The researcher is still required to select the attribute(s) that is most salient for the given the context.

This discussion about the interplay between structural power and attributional power leads to some interesting paths for future research. Namely, future research could compare and contrast the effects of structural power when it is based on different attributes. Are certain attributes more conducive to a structural analysis than others? It is suggested here that structural power is particularly fitting for attributes that are related to resources that are transferable, like possession of information or money. These attributes flow through a network and therefore can be given from one actor to another, thus creating situations of dependence. Actors who are powerful because of their possession of one of these attributes can influence behavior, but in a rather subtle way. Those who comply are less likely to think about the powerful person as forcing them to behave in any particular way – the compliance is more willing because the actor has what they need. In other words, structural power analysis is most conducive to attributes that confer soft power (Nye 1990).

On the other hand, a structural perspective may not be as fitting for resources like personality characteristics or status that are not transferrable. These attributes confer power because their owner in many ways can demand power. An actor with status, for example, is more likely to be seen as powerful by others because s/he has the ability to penalize those who do not comply. This type of power is more coercive in nature and thus can be thought of describing attributes that confer hard power (Nye 1990).

While hard power attributes are not as conducive to structural analysis by the nature of the fact that they does not flow from one participant to another, future research can investigate the interaction between attributes that confer soft power and hard power. For example, how does the influence of an actor who is both highly central in the communication network and is situated high in his/his home organization's hierarchy compare to an actor who is highly central in the communication network but is low on the organizational totem pole? More generally, how do the effects of attributes that confer soft power vary depending on an actor's hard power attributes?

Generalizability of the results

Another notable limitation of this study is its reliance on a sample size of three collaborative networks. Given the difficulty of collecting network data, this is a very common issue in network research. In fact, a sample size of three is an improvement on the more common single network case study used in much of the research. While larger N methods like the one used by Meier and O'Toole (2001, 2005), in which a single network actors responds on behalf of an entire network, can be used to compare larger numbers of networks, these methods lack the richness that is provided by surveying all members of a network. Nevertheless, the small sample size limits the generalizability of the results presented herein.

On a related note, the research setting examined is very specific: problem-solving collaborative networks working to improve the pharmaceutical drug development process. The results can be most easily generalized to studies of similar health policy networks (c.f., Buckup 2008; Buse 2003; Buse and Harmer 2004; Ramiah and Reich

2004; Sorenson 2009); however, it is an open question whether the results can be generalized not only to problem-solving collaborative networks in other policy domains, but also to other type of networks. In particular, how generalizable are the results to the three other broad categories of public management networks outlined by Milward and Provan (2006): information diffusion networks, service delivery networks, and community capacity building networks?

Without further research on collaborative networks in other policy domains, it is impossible to answer this question with certainty. With that said, there is reason to believe that the results presented in this dissertation are likely to be applicable to other types of collaborative networks. First, the conceptualization of structural power and its importance to collaborative networks is not likely to be specific to problem-solving networks in the health policy domain. Previous research shows such power to be associated with influence across different types of networks using different types of tie content. Brass (1984), for example, examines three networks—workflow, communication, and friendship—embedded within a newspaper publishing company and finds that centrality in all three is strongly related to perceptions of influence. Provan et. al (2009) also find centrality to be key in explaining an actor's influence. They do so by examining communication, contract, and referral networks among organizations providing services to the severely mentally ill population. These examples suggest that the conceptualization and measurement of structural power is broadly applicable.

Another reason to think that the results of this dissertation may not be limited to problem-solving networks is because all collaborative networks share similar core characteristics. Most importantly, participants hold some degree of expectation that their opinion will be valued and taken into consideration. Moreover, the tension between inclusiveness and efficiency is one under which all networks are likely to suffer (Provan and Kenis 2008) and can only be managed, not solved. Given these characteristics, there is good reason to believe that results of uneven distributions of structural power will be similar across different types of networks; namely, that participants in networks that have uneven distributions of structural power are more likely to become disillusioned with the process and thus engage less with one another.

The application of this research to other contexts will, however, require one major modification that bears mentioning. The researcher must think about the particular tie content(s) that is most appropriate for the given network. In service delivery networks, for example, researchers often use referral networks to examine structural power (c.f., Isett and Provan 2005; Huang and Provan 2007). For community capacity building networks, on the other hand, friendship and joint project ties are likely to be more informative with regards to the distribution of structural power (Milward and Provan 1998). Information diffusion networks, of course, are likely to be similar to problem-solving networks in that information ties are especially salient (Milward and Provan 2006).

In summary, while the analysis may have to change with regards to the ties that are examined, it is suggested that the results presented here are likely to apply to a broader array of collaborative networks. Future research will look to test this assertion by replicating this study not only on different problem-solving networks, but on different types of collaborative, public management networks.

Cross-sectional data

Another limitation of this research revolves around the fact that the data are cross-sectional in nature, meaning they only reveal the distribution of structural power between participants at one point in time. As a result, it is impossible to determine with absolute certainty the direction of the causal relationships examined herein. With regards to the relationship between structural power and the process dimension of participant satisfaction, for example, it is possible that another, unobserved factor caused participants to feel valued. Feeling valued, in turn, could have caused them to become more active in the collaborative network. To rule out this explanation, longitudinal data is needed.

In addition to being able to shed more light on issues of causality, longitudinal analysis embraces the dynamic nature of networks. By nature of the fact that networks are composed first and foremost of relationships between participants, networks are likely to be even more dynamic than organizations that are rooted in a more stable system of hierarchy. A frozen picture in time is unable to provide the dynamism that is seen as one of the biggest benefits of networks. In the future, another round of data collection on the same three C-Path consortia can begin to address these issues.

Context matters

The last major limitation of the approach taken here is that it does not do enough to take each consortium's context into account. In Chapter 3, an attempt was made to integrate a participant's alternatives to the consortium into the determination of his/her structural power. It was shown, at least in the way that this idea of environmental competitiveness was measured herein, not to affect a participant's structural power. With that said, other contextual variables that varied from consortium to consortium were not taken into account in the analysis.

For example, variables like consortium age (also known as its life cycle stage), consortium size, and the extent to which prior relationships existed between participants differed across the three consortia. It could be, for instance, that MSOAC was the most cohesive network because it is the youngest of the three consortia and therefore its participants are still excited about the collaborative process. Alternatively, MSOAC could be the most cohesive because it has the fewest participants and therefore, it is simply more plausible for participants to actively communicate with a larger percentage of participants than in PSTC or CAMD. Finally, because of how close-knit the MS community is, it could be that MSOAC is most cohesive because most of its participants had prior relationships with one another and therefore began from a more cohesive foundation than the participants of the other two consortia.

The analysis here did not consider the effect of these contextual variables on a consortium's cohesion or on its participants' satisfaction. The exclusion of these variables was done out of practical necessity; namely, with only three networks to compare, the number of explanatory variables that could be simultaneously considered had to be limited. However, their exclusion casts a shadow of doubt on the effect of structural power in these collaborative networks.

A new path forward

The approach taken in this dissertation, one that can be described as causal in nature, focused on a narrow conceptualization of structural power and its relationship to both cohesion and participant satisfaction. As was discussed above, this approach produced some overarching patterns that are likely to be generalizable beyond the three consortia studied; however, its narrowness, by definition, ignored other potential contributors to structural power. Namely, it largely disregarded the broader contexts in which the three consortia exist and how those contexts may affect a participant's structural power. The conclusions that can be drawn from this research are therefore limited by the nature of the approach that was taken.

In order to harness the complexity of the different environments in which these consortia exist as well as to avoid the causality problems that arise from cross-sectional data, a new approach is proposed for future research. This approach can use the data already collected, but would cast aside the causal approach in favor of an approach focused more on exploring the various ways in which structural power manifests itself in collaborative networks. In essence, this new approach would turn the focus of the analysis on its head, from one that seeks to explore a hypothesized relationship to one that seeks to explore the structural configurations that exist in real world collaborative networks attempting to deal with uneven power distributions. In doing so, such an approach would recognize that collaborative networks are constantly changing, trying different strategies to improve the experience of collaboration for their participants as they evolve. Furthermore, this approach would acknowledge that there are often multiple strategies that can be used to address a problem and that the “right” strategy is likely to depend on a number of contextual factors.

As an example, this new approach would highlight the result in Chapter 4 that working groups can achieve high levels of cohesion when structural power is both relatively decentralized as well as when it is relatively centralized. It would then proceed by examining not just structural power, but other contextual variables that describe the most cohesive working groups. What is likely to emerge is a set of the different ways in which networks or working groups deal with uneven distributions of power.

This new path forward mirrors the progression of broader theories of structure in the organizational literature, theories that began by trying to find the one best way to do something (a la Taylor [1911] and Weber [1947]), then sought the one best way given certain conditions (a la Lawrence and Lorsch [1967]’s contingency theory), and more recently stressed equifinality, or the idea that no single best way exists (a la the configurational approach described by Meyer et. al [1993]). Whether the result will be more in line with the contingency theory or the configurational approach is impossible to say at this juncture; however, as more collaborative networks and their structural configurations are examined, it is likely that some patterns may begin to emerge. When and if that happens, more informed hypotheses that take the nuanced and complex contexts of these networks into account can be developed.

Future research can use the data collected here and begin to analyze it from this new perspective, one that focuses less on causality and more on the characterization of different structural configurations.

Contributions

Despite its limitations, the research presented in this dissertation contributes to several academic disciplines. In particular, the findings should be of interest for scholars of collaborative governance, organizational networks, nonprofit management, and social exchange.

First and foremost, the research adds to the collaborative governance literature. The frequency with which power is mentioned by scholars in this field indicates that it is a pervasive issue for collaborative networks; however, thus far it has mainly been a side conversation in the literature (for exceptions, see Choi and Kim 2007; Gewurz 2001; Purdy 2012). This dissertation brings power to the forefront and, in doing so, responds to calls by scholars to take power more seriously (Huxham and Vangen 2005; Sorenson 2009). It also demonstrates the utility of using the method of social network analysis to study collaborative networks. This methodology is particularly valuable for scholars who wish to know more about how resources flow between participants, but has not been widely used by collaborative governance scholars.

The organizational networks literature, whose scholars primarily use network analysis to understand inter-organizational phenomena, was one of the main literatures referred to throughout this research. Scholars in this field have focused primarily on the structure of organizational networks, but do not as often connect that structure to the process of what occurs between interconnected actors. This research contributes to the organizational networks literature by exemplifying the utility of using structure to talk about process. In addition, organizational network scholars have tended to focus on one level of analysis. The findings from Chapter 3 suggest that different dynamics may be occurring at different levels of analysis. More research is needed in this area.

Collaborative networks are of great interest to scholars of nonprofit management as well. Nonprofits, which struggle to find enough resources to adequately address problems, turn to alliances, or networks with actors from both the for-profit and nonprofit sectors (Austin 2000; Seitanidi 2010). These networks enable nonprofits to benefit from the expertise and resources of others. However, nonprofits must not be relegated to the bench in these networks. This research provides initial hope that nonprofit actors can indeed be influential in collaborative efforts if they actively participate.

Finally, the findings of this dissertation contribute to the social exchange literature. It was from this literature's conceptualization of productive exchange that the operationalization of dependence as a participant's number and quality of alternatives hails. This study provides the first known field test of Lawler et. al's (2000) theory, a theory that surprisingly did not hold true for the C-Path consortia. The conclusion to be drawn from the results presented herein is either that their laboratory-tested theory does not translate to the field *or* that something about C-Path's consortia or the measures that were used caused the theory to not hold true. More research is needed before their theory is discarded; however, future laboratory research could try to better understand the relationship between structural power and cohesion.

In summary, this dissertation provides an in-depth look at a concept that is known to everyone, but is not understood by many. To fully understand power would likely take many lifetimes, but that does not mean that it is a journey scholars should avoid. This dissertation represents a first step into a complex area of study that can bear much fruit with regards to better understanding power in collaborative networks. Much work remains ahead.

APPENDIX A: TEXT FOR EMAIL INVITATION TO SURVEY

My name is Alexandra Joosse and I am PhD candidate at the School of Government and Public Policy at the University of Arizona. As part of my dissertation research, I would like to request your participation in a study I am conducting on pre-competitive collaboration. The link to the survey is below, as is a brief description of the research and your role in it. **This survey is anticipated to take approximately 10-15 minutes to complete.**

[survey link here]

My main research objective is to understand the factors that make pre-competitive collaboration by organizations effective. I expect that this study will result in practical implications about designing and facilitating successful collaborations. The results will be used to write scholarly articles as well as a case study that may be used by business and public administration/policy schools.

You have been selected for this survey because you represent your organization in the [insert consortium name]. The survey questions that follow will ask for some basic information about your organization, your perceptions about issues related to the process of collaboration in this consortium, as well as information about the members with whom you most frequently communicate regarding consortium-related work.

Your participation is entirely voluntary, but I hope that you will help me by completing this survey. Should you choose to participate, your answers will remain confidential and your answers will only be used in the aggregate to discuss overall trends. **Neither your name nor your organization's name will be used in any publications.**

An Institutional Review Board responsible for human subjects research at The University of Arizona reviewed this research project and found it to be acceptable, according to applicable state and federal regulations and University policies designed to protect the rights and welfare of participants in research. There is no monetary compensation for completion of this survey. If you choose to participate in this survey, you may decline to answer a question at any point, and you may also stop at any time.

If you have any questions about this research study, please feel free to contact me at ajoosse@email.arizona.edu. Thank you in advance for your time and help with this research project.

Sincerely,
Alexandra Joosse, PhD Candidate
University of Arizona

APPENDIX B: SURVEY QUESTIONS

[Note: Depending on the respondent's answer to question 4 regarding whom the respondent most feels s/he represents, slightly different text appeared in some of the questions in order to match this response (either "you" or "your organization" was used, for example). Here, these questions are combined to reduce redundancy.]

Q1 Informed Consent Statement
You have been selected for this survey because you are a member of the [insert name] consortium. The survey questions that follow will ask for some basic background information, information about the members with whom you most frequently communicate regarding consortium-related work, as well as your perceptions about issues related to the process of collaboration in this consortium. Your participation is entirely voluntary, but I hope that you will help me by completing this survey. Should you choose to participate, your answers will remain confidential and your answers will only be used in the aggregate to discuss overall trends. Neither your name nor your organization's name will be used in any publications. An Institutional Review Board responsible for human subjects research at The University of Arizona reviewed this research project and found it to be acceptable, according to applicable state and federal regulations and University policies designed to protect the rights and welfare of participants in research. There is no monetary compensation for completion of this survey. If you choose to participate in this survey, you may decline to answer a question at any point, and you may also stop at any time. If you have any questions about this research study, please feel free to contact me at ajoosse@email.arizona.edu. Thank you in advance for your time and help with this research project.
❍ I have read and understand this informed consent statement

Q2 In years, how long have you participated in this consortium?

Q3 How many years of experience do you have working in your current disease area or area of expertise (e.g., statistician)?

Q4 Who do you feel you MOST represent on this consortium?
❍ Yourself
❍ Your organization

Q5 Are you the only member in this consortium from your organization/institution?
❍ Yes
❍ No
❍ I don't know

Q6 Do you have decision-making authority for your organization with regards to what happens in this consortium?

- ❍ Yes
- ❍ No
- ❍ I don't know
- ❍ Not applicable

Q7 Please select the working group(s)/committees to which you belong (if any):
[Respondents asked to select from a list of working groups pertinent to that consortium]

Q8 The following series of questions revolves around the ties, or relationships, that link consortium members together. Responses will help to reveal how work flows are structured in the consortium. You will be asked three main questions: 1) with whom you communicate about consortium-related work (this question has a follow-up about frequency of communication); 2) on whom you rely to do consortium-related work; and 3) whom you perceive to be most influential in making consortium-related decisions. When answering, please consider all members of the consortium, including C-Path staff and regulatory representatives. As a reminder, your identity, as well as anyone you identify in the following questions will remain anonymous to everyone except the researcher.

Q9 Thinking back to the last six months, please use the text boxes provided below to enter the first and last name of the consortium members with whom you have personally communicated (via email, phone, or in person) about consortium-related work. Individuals who are on the same teleconference or in the same meeting should be excluded unless you personally communicate in a substantive way with them in these venues. Fifteen boxes are provided. Fill in only as many as you need; order does not matter. Please use one box for each person. A list of consortium participants is available below for your convenience. Participants are listed in alphabetical order of their organization:

Q10-Q24
[15 spaces provided for respondents to fill in the first and last name of communication partners]

Q25 Thinking about the last six months, how often do you personally communicate (via email, phone, or in person) with each of the consortium members you identified above about issues related to this consortium?
[Names entered in response to Q10-Q24 appear here. Respondents are asked to check a box for “approximately once per month or less”, “approximately twice per month,” or “approximately once per week or more” for each name]

Q26 Please use the text boxes provided below to enter the first and last name of the consortium members on whom you rely most for accomplishing your own work in this consortium. Ten boxes are provided. Fill in only as many as you need; order does not matter. Please use one box for each person.

Q27-Q36
[10 spaces provided for respondents to fill in the first and last name for participants on whom they depend]

Q37 Finally, please use the text boxes provided below to enter the first and last name of the consortium members who you perceive to be the most influential in the decision-making of this consortium. Ten boxes are provided. Fill in only as many as you need; order does not matter. Please use one box for each person.

Q38-Q47
[10 spaces provided for respondents to fill in the first and last name of participants they regard as being influential]

Q48 On the whole, how would you describe your professional relationships with members of this consortium?
- ❍ Very divisive
- ❍ Divisive
- ❍ Cohesive
- ❍ Very cohesive

Q49 In general, would you say the members of this consortium are more team-oriented or self-oriented?
- ❍ Very self-oriented
- ❍ Somewhat self-oriented
- ❍ Somewhat team-oriented
- ❍ Very team-oriented

Q50 In general, to what degree do you trust the members of this consortium to abide by the rules governing it?
- ❍ Not much
- ❍ A little
- ❍ Somewhat
- ❍ A lot
- ❍ A great deal

Q51 Please select the degree to which you agree or disagree with the following four statements: My participation in this consortium has allowed me to develop and/or strengthen relationships with other individuals and organizations in my field.

- ❍ Strongly Disagree
- ❍ Disagree
- ❍ Neither Agree nor Disagree
- ❍ Agree
- ❍ Strongly Agree

Q52 My participation in this consortium has increased my knowledge about the regulatory decision process.

- ❍ Strongly Disagree
- ❍ Disagree
- ❍ Neither Agree nor Disagree
- ❍ Agree
- ❍ Strongly Agree

Q53 Participants in this consortium are treated as equal partners, regardless of which organization they represent.

- ❍ Strongly Disagree
- ❍ Disagree
- ❍ Neither Agree nor Disagree
- ❍ Agree
- ❍ Strongly Agree

Q54 I feel that my contribution is valued in this consortium.

- ❍ Strongly Disagree
- ❍ Disagree
- ❍ Neither Agree nor Disagree
- ❍ Agree
- ❍ Strongly Agree

Q55 Overall, to what extent has your understanding of the issues that brought this consortium together broadened as a result of your participation in this consortium?

- ❍ Not at all
- ❍ Somewhat
- ❍ To a large extent

Q56 In general, do you feel that some members participate more than others in this consortium?
- ❍ Definitely yes
- ❍ Probably yes
- ❍ Maybe
- ❍ Probably not
- ❍ Definitely not

Q57 How satisfied are you with the progress this consortium has made towards achieving its goals?
- ❍ Very Dissatisfied
- ❍ Dissatisfied
- ❍ Neutral
- ❍ Satisfied
- ❍ Very Satisfied

Q58/Q59 How likely are you/your organization to actively participate in the consortium in the coming year?
- ❍ Very Unlikely
- ❍ Unlikely
- ❍ Undecided
- ❍ Likely
- ❍ Very Likely

Q60 How helpful was any previous experience you've had with collaboration in shaping your participation in this consortium?
- ❍ Very helpful
- ❍ Fairly helpful
- ❍ Slightly helpful
- ❍ No help at all
- ❍ I have no previous experience with collaboration

Q61 How helpful is C-Path leadership in facilitating collaboration in this consortium?
- ❍ Very helpful
- ❍ Fairly helpful
- ❍ Slightly helpful
- ❍ No help at all
- ❍ I prefer not to answer

Q62 To what degree is your participation in this consortium valued in your organization?
- ❍ Not much
- ❍ A little
- ❍ Somewhat
- ❍ A lot
- ❍ A great deal
- ❍ I prefer not to answer

Q63 Which sentence most accurately reflects how work is pursued in this consortium?
- ❍ When a new task emerges, we most often follow pre-set procedures and routines in order to accomplish the task.
- ❍ When a new task emerges, we most often "make it up as we go along," meaning we must create new procedures and routines in order to accomplish the task.
- ❍ I don't know

Q64/Q65 Participants in collaborative endeavors often have objectives in addition to the consortium-wide goals that they wish to accomplish by participating in a collaboration. From the following list, please rank the additional objectives you/your organization hope to achieve by participating in this consortium, with "1" being the highest. Only rank those with which you agree. If you do not feel you can rank the additional objectives, please place an "1" next to all objectives with which you agree.

______ Build/maintain relationships with other members in the consortium (excluding the FDA/EMA)
______ Build/maintain a relationship with the FDA/EMA
______ Publish results in academic or industry publications
______ Use participation in consortium to increase public image in industry
______ Use output or outcome of this consortium to further own research
______ Use output or outcome of this consortium to further own business processes or products
______ Be exposed to expertise from other organizations
______ No additional objectives for this consortium
______ Other (please specify)

Q66/Q67 Focus on the most important additional objective you identified. How dependent are you/your organization on this consortium to achieve this goal?
- ❍ Not dependent
- ❍ Somewhat dependent
- ❍ Very dependent
- ❍ I don't know

Q68/Q69 With regards to the most important additional objective you identified, what is your/your organization's leading alternative to participation in this consortium?

- ❍ Other collaborations or partnerships similar to this consortium
- ❍ Addressing the objectives within my organization instead of through a partnership
- ❍ Other (please specify) ____________________
- ❍ I have no meaningful alternatives
- ❍ I don't know

Q70/Q71 How likely are you/your organization to invest more time and energy in an alternative to this consortium?

- ❍ Very Likely
- ❍ Likely
- ❍ Undecided
- ❍ Unlikely
- ❍ Very Unlikely

Q72 In one or two sentences please describe an area in which you feel the consortium is doing a good job.

Q73 In one or two sentences, please describe an area in which you feel the consortium could be doing a better job.

APPENDIX C: TEST FOR NON-RESPONDENT BIAS

Table C1. MSOAC respondent versus non-respondent comparisons: organizational type

Organizational type	# of total members	% of respondents	% of non-respondents
For-profit	23	39	61
Nonprofit	30	37	63
Governmental Agency	1	0	100

Table C2. MSOAC respondent versus non-respondent comparisons: working group composition

Working Group Acronym	# of total members	% of respondents	% of non-respondents
CC	27	41	59
DSI	8	50	50
CDA	13	46	54
DD	5	60	40

Table C3. PSTC respondent versus non-respondent comparisons: organizational type

Organizational type	# of total members	% of respondents	% of non-respondents
For-profit	157	34	66

Table C4. PSTC respondent versus non-respondent comparisons: working group composition

Working Group Acronym	# of total members	% of respondents	% of non-respondents
AC	25	60	40
CHWG	13	46	54
HWG	40	38	63
VIWG	11	45	55
SKM	8	50	50
NWG	39	46	54
TWG	13	54	46

Table C5. CAMD respondent versus non-respondent comparisons: organizational type

Organizational type	# of total members	% of respondents	% of non-respondents
For-profit	78	35	65
Nonprofit	8	25	75
Governmental Agency	19	21	79

Table C6. CAMD respondent versus non-respondent comparisons: working group composition

Working Group Acronym	**# of total members**	**% of respondents**	**% of non-respondents**
CC	23	43	57
AD	43	44	56
HA	10	20	80
PD	17	53	35

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