INSIDE THE LINES:
Essays on the Performance of Whole Organizational Networks

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To my family –
for your love, support, and sacrifice.

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There are two things that I heard when I began the PhD program that resonate very strongly as I write these acknowledgments. The first is that research is personal and autobiographical. The second is that if you do not feel like quitting along the way, then you are doing it wrong. The former is a bit more self-explanatory, especially given my seemingly haphazard path to Carlson—undergraduate years working at a microscope, a transition into the business of healthcare, and a failed bid to attend medical school. There is a lot of personal history reflected in this dissertation. The second matter regarding quitting, however, is something different altogether. I never quit at anything “academic,” though in hindsight maybe I should have now and then. But it was nothing about the academics of this endeavor that made me want to quit. Instead, it was the, at times, agonizing realization that my success or failure at this *first* step would depend heavily on my ability to discover my identity as an academic and as an individual. As cliché a sentiment as it may be, I confronted many personal fears and weaknesses throughout the six years I lived in Minnesota. Of course, I did not solve all of them but, as we academics like to say, I now know what questions to ask. I credit my growth and persistence to the various people that I brought with me to Minnesota, and the people I will leave behind.

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ABSTRACT

This dissertation is focused on the study of heterogeneous *network* performance. For decades, most strategy and organizational research has focused on understanding how networks influence a single "node," typically an organization or individual. In contrast, I shift my perspective to view a whole network as the unit of analysis. This approach is designed to deepen scholarly understanding of strategic outcomes and collective performance that only exist at the higher level – the *whole* network level. The motivation for this dissertation is the realization many of society's most complex problems and Grand Challenges require the concerted efforts of organizations towards shared goals, which may not always coincide with local (organization level) incentives. As such, I use the context of healthcare reform in the United States to examine how analyzing the complex patterns of interorganizational patient care may help us better understand the determinants of emergent outcomes at the whole network level. Specifically, the Affordable Care Act of 2010 led to the formation of hundreds of new interorganizational networks, called Accountable Care Organizations, within the Medicare system. Using patient treatment networks based on claims data, I examine two research questions. First, what are the relationships among various network level properties and collective performance? Second, how did the formation of Accountable Care Organizations alter existing patient care patterns and outcomes, if at all? In sum, this dissertation makes theoretical contributions to the study of organizational networks, particularly with regards to network level outcomes. Moreover, this research offers insights into how network studies may inform policy and practice in healthcare.

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I. INTRODUCTION

The history of the modern United States (US) healthcare system tells the story of how a multi-trillion-dollar industry emerged from relatively humble origins—a medical occupation struggling to legitimize itself as a full-fledged profession (Starr, 1982; Stevens, 1998). Today, the problems of healthcare—grown from seeds sown during a relatively short period of time in the mid-1900s—rank among the most important social, economic, and political issues that I face in the US. In particular, the seemingly quantum leaps in technology and specialization contributed to a fragmented, yet interdependent, model of healthcare delivery; one in which individual organizations may be world-class while the system around them fails to meet the basic needs of many of its customers—the patients. While I will reserve a more detailed discussion of the US healthcare industry for the second chapter, this context provides the overarching motivation for this dissertation. Namely, what is the role of strategic management and organizational research when the maximization of firm/organizational performance – the typical focus of our field – may be contributing to systemic shortcomings and failings within a critically important sector of our economy?

More and more, the products and services that are delivered by independent organizations represent only pieces of a solution that must be cohesively integrated to address larger problems. Consequently, while it is important for those organizations to be good at what they do, in some arenas it may be even more important for a group of organizations to be *collectively* high-performing. For example, in the case of health, most people would agree that it would be better to have a system of healthcare organizations that can support health maintenance, as opposed to developing heart disease but having access to the best cardiovascular center in the world. Yet, while the US healthcare system has no trouble diagnosing new cases of heart disease (National Research Council and Institute of Medicine, 2013) and creating new organizations to treat its myriad symptoms, it is *not* well-equipped to prevent it (Centers for Disease Control and

Prevention, 2019).

Further extending this hypothetical case, in such a context, the traditional focus of strategy scholars would likely be on the heterogeneous performance of individual healthcare organizations (e.g., Porter, 1980) that are in the business of treating cardiovascular diseases, such as physicians' practices, hospitals, and diagnostic labs. However, as previously alluded to, the individual excellence of firms and organizations does not always produce outcomes that are desirable for consumers or society, at large. Instead, some of the most important performance outcomes in healthcare delivery exist beyond the level of a single organization.

Although the broader field of management has recently taken a greater interest in tackling complex social issues, or so-called Grand Challenges (George et al., 2014), perhaps the most notable *network* studies in this vein were Keith Provan and colleagues' studies in the late 1990s (Provan & Milward, 1995; Provan & Sebastian, 1998). In contrast to the ego or firm-centric focus of most other network scholars, Provan and colleagues specifically examined the effectiveness of interorganizational networks in the administration and delivery of public services, arguing, as I do in this dissertation, that "not all problems can be solved by the actions of individual organizations" (Provan & Milward, 1995: 2). This truth about society, ever truer today, turns the key outcome of interest for strategy organizational researchers to "the overall well-being of clients [which] depends on the integrated and coordinated actions of many different agencies" (Provan & Milward, 1995: 2). And the activities that lead to improved social welfare are, undoubtedly, strategic phenomena worth further examination.

Thus, in this dissertation, I propose that strategy and organizational research can (and should) engage with socially and economically important performance outcomes above the level of a single organization. Notwithstanding some empirical challenges associated with collecting data at a super-organizational level, performance heterogeneity at a slightly higher level of abstraction not only enables us to study important strategic questions, it also provides new opportunities for theory development. As I will describe further in subsequent chapters, collective outcomes that result from collaboration across organizational boundaries may be more complex than simply the sum of each member's performance. Such complexity may manifest in positive or negative spillovers such that the best performing groups may comprise average individually-performing organizations, whereas a collection of the best organizations may fail as a whole. As the need for effective interorganizational work grows throughout the global economy, scholarship must follow suit to update and extend our theories of firms and organizations to the next frontier or risk an even greater gap between research and practice (Simsek et al., 2018).

As a way forward, I conceptualize the groups of interconnected or interdependent organizations as *whole organizational networks*,[1] and, by extension, collective performance as *whole network performance*. The use of the network-level perspective enables me to not only define specific collective entities for study (whole networks), but also provides a language and set of analytical tools to characterize particular types of interactions among members of these groups that are meaningful for their effectiveness as whole networks.

1.1 Background

Network approaches to studying firm and organizational performance have led to important insights into the consequences of "where" you are within the network (Burt, 1992; Ahuja, 2000), "who" you are connected to (Lin et al., 2001; Fonti et al., 2015), and "how" strongly you are connected to them (Granovetter, 1973; Levin and Cross, 2004; Tortoriello, Reagans, & McEvily, 2012). However, such scholarly inquiry, while invaluable for understanding the strategic implications of networks of intra and interorganizational relationships, has come

[1] Henceforth, I will primarily use the terms "whole network" to reference whole organizational networks at the network-level of analysis. I will contrast with the lower levels of analysis, which include "ego networks," "ego-level network," and "node-level." I also note that Kenis & Knoke (2001) used the term "organizational field network" (or field-net) to refer to the whole network within a specific organizational field. The term field-net is not broadly used—in part, because few others have studied whole networks—but I interpret a field-net to be broader than a whole network. Put differently, I assume that many whole networks, defined by different types of boundaries (Laumann et al., 1983), may exist within a given field.

almost exclusively from the perspective of *focal* firms (c.f., Zaheer, Gozubuyuk, & Milanov, 2010). Notwithstanding the central importance of this viewpoint for management research, the ego-centric or ego network view restricts focus to how interorganizational interactions are internalized to affect the local, or individual, outcomes of a single actor. More specifically, an ego-centric view is considerably narrow and may distort our understanding of full picture. Consider, the ego networks relative to the whole network in Figure 1.1. Note that the two focal nodes (circled) are more central in their ego networks but on the periphery in the whole network. Moreover, consider how different the structure of the whole network appears relative to that of the ego networks. How the ego network affects the performance of a focal node may provide little insight into how the whole network performs collectively.

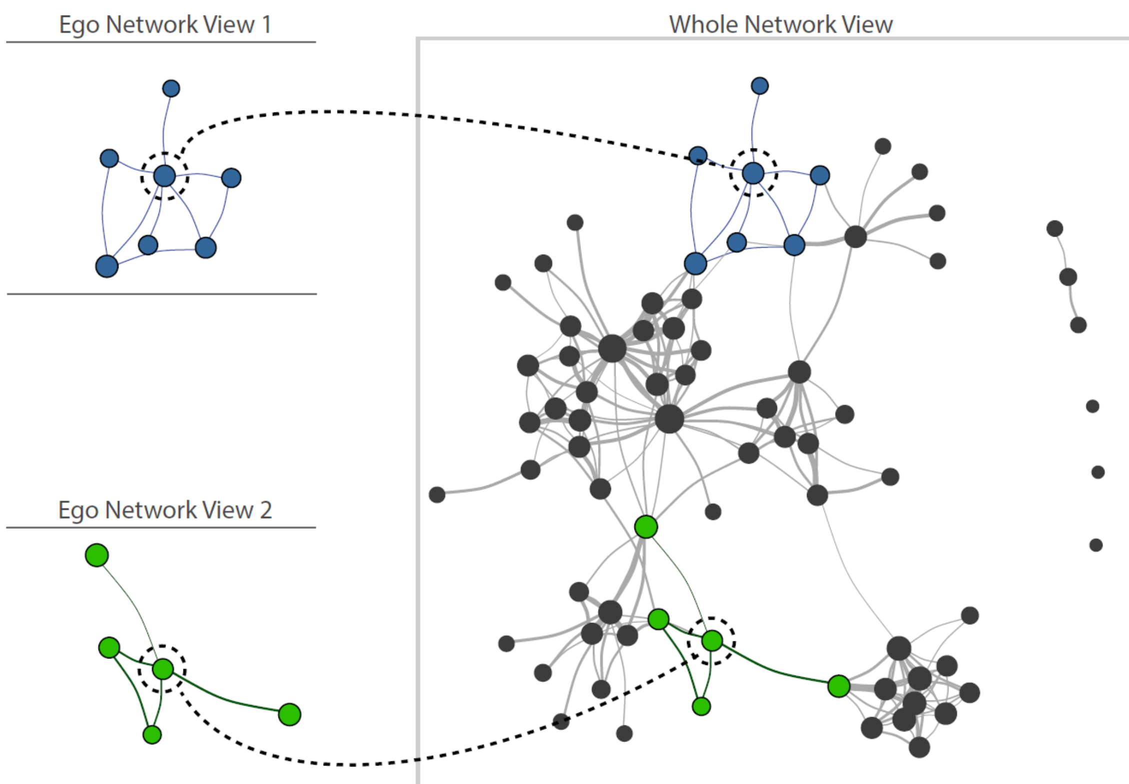

Figure 1.1. Two ego networks and the whole network from which they are derived.

However, as previously discussed, node-level performance is not always strategic outcome that is of greatest interest. Sometimes it is most important to maximize the performance of the *whole* network. While strategy and organizational research have investigated numerous contexts where collective outcomes would be of great importance—such as, open source communities (Zahra & Nambisan, 2012), civil initiatives (Walker & Rea, 2014), R&D consortia (Doz et al., 2000), and social movements (Diani & McAdam, 2003)— "whole network" approaches to understanding collaboration or collective effectiveness are very limited. Consequently, much of the prior literature on whole network performance, particularly those studies published more than twenty years ago, comes from other fields.

What follows is a brief overview of the theoretical and empirical foundations of the study of whole network performance that this dissertation draws on. Importantly, I try to illustrate the separation, both in chronology and in dialogue, between relevant sociological theories and empirical examinations of this topic. This gap represents a key opportunity—one that I take full advantage of in this dissertation—to demonstrate how classic sociological theories may be integrated with networks research to provide new and deeper insights into empirical puzzles.

1.1.1 Simmel, Blau, and Macrosociological Roots

The theoretical foundations for understanding the antecedents of whole network performance can be traced from the classical works of the German scholar Georg Simmel (1858-1918) to the Austrian-American sociologist Peter Blau (1918-2002), who was influenced by Simmel's writings. Both scholars were broadly interested in understanding society, or more precisely the structures or stratifications that comprised society. However, both were also uniquely interested in understanding the emergence of larger social groups and structures from the micro-level interactions among individuals. Although both are often excluded from the citations lists of empirical studies of networks, I argue that their works inform much of how we study organizational networks and are central to the ideas developed in this dissertation.

Simmel's influence on networks research is perhaps most widely through theories of structural holes (Burt, 1992) and Simmelian ties (Krackhardt, 1999). Simmel's writings (1950) on the relational dynamics found in triads are at the core of these important network theories, which are widely used in research on organizational and strategic networks. Yet, Simmel's work on triads was only one part of a broader examination of the nature of human interactions within society. In fact, Simmel highlighted the *dyad* as being a particularly exceptional[2] type of social unit (e.g., marriages) that fundamentally changes in the presence of at least one other (the *tertius*). This dynamic aspect of triads (which he considered to be the elemental unit of society) and larger groups serves as the basis for his attempts to understand the changes in his society. In his view, one of the most prominent changes he observed in the "modernization"[3] of social life was the increasing affiliation of individuals into very large groups, or social circles, such as church, state, organization, or other interest groups. He wrote extensively on the influence of such affiliations on individuals and freedom,[4] and in doing so made important observations about the relationship between social groups and their constituent members.

A key idea from Simmel's work runs throughout this dissertation: the notion that groups can take on a unique *super-individual* existence with regards to its members. That is, a group

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[2] This view of dyads as being exceptional cases contrasts, in some ways, research on strategic and organizational networks in which dyadic interactions between a focal firm and a partner (or an ego-network comprising an individual or firm's direct relationships) are the most commonly studied the unit of analysis.
[3] It is noteworthy that Simmel was not alone in making such observations, though his imprint on network research and the study of groups makes him a central figure in the background of this dissertation. Simmel's contemporary, Ferdinand Tonnies (1855-1936), also wrote extensively about the changes in society spurred by modernization and the move from countrysides to cities. Tonnies framed this change as the rise of *Gesellschaft* (society)—exemplified by industrialized cities—and the gradual demise of *Gemeinschaft* (community)—exemplified by rural communities defined by strong familial and interpersonal bonds.
[4] A structuralist perspective is evident in many of Simmel's works, in which he considers the constraints on individuality and freedom in the context of a larger social structure. Another of Simmel's contemporaries, Emile Durkheim (1858-1917), who is a more prominent figure in structural sociology, also wrote extensively about the role of social structure in influencing human behavior and interactions. Not only credited as a forefather of modern Western sociology, Durkheim also described the study of social structures as "structural morphology," which serves as an inspiration for ideas developed in Chapter 3 of this dissertation.

member can simultaneously feel both a part of the whole but also distance themselves from the group, effectively delegating responsibilities or attributing agency to the larger social entity. This powerful observation is perhaps even more acutely felt today; when we do not immediately respond to a mass e-mail or group text, for example, we are effectively delegating that responsibility to the rest of the group. This relationship between the individual and the group is important because it allows the former freedom to pursue other activities, such as affiliating with additional groups. However, such transient disengagement and superficial affiliation—for example, one might self-identify as Buddhist without practicing any of the customs of the religion—can also create problems for the group, such as conflict, shirking, and free-riding, particularly when group objects necessitate collective engagement and collaboration.[5] Thus, to the extent that collective outcomes depend on engagement and collaboration among members of the network (group), then the presence, or absence, of these group dynamics may be an important determinant of whole network performance. As later chapters will illustrate, these ideas establish the basic theoretical assumptions for why networks (groups) may experience considerable variability in whole network performance. The advantage of integrating these ideas with network methods is the ability to more precisely measure the network properties (e.g., structure, relationship strength) that may be help, or hurt, collective outcomes.

In contrast to Simmel, Blau's influence on networks research is less obvious, though his imprint on modern sociology is vast. Consequently, I hope that the research presented in this dissertation—Chapter 3 in particular—may serve as a bridge between Blau's theories and empirical studies of whole network performance. Blau devoted a significant part of his career to developing a macrostructural theory of social structure (c.f., Blau, 1964; Blau, 1994). Like many

[5] Though these ideas are very similar to problems of collective action (Olson, 1965) or managing common pool resources (Ostrom, 1990), this dissertation does not speak directly to research in those streams, which largely developed in political science and economics and focused on specific issues of sociopolitical change and management of natural resources.

network scholars, Blau was also deeply interested in the implications of "social positions." However, Blau's conceptualization of social positions differed from that of network scholars because he was mainly interested in higher order stratifications in society, such as lines demarcated by race, gender, and socioeconomic status (1994). The connection between his work and networks research, then, is not in his definition of structure but in his curiosity about how such things could emerge from the basic relationships among individuals in society. It is in these research endeavors where Simmel's aforementioned influence on Blau is most evident, and where the connections to studies of whole networks are strongest.

Much like Simmel, Blau also carefully examined interactions between individuals to better understand social dynamics at the level of larger groups. Also like Simmel, Blau believed that even the most basic interaction between two individuals is "of course, strongly influenced by the context in which it occurs [and that even] the analysis of dyads, therefore, must not treat these pairs as if they existed in isolation from other social relations" (Blau, 1964: 31). However, Blau was also significantly more methodical and systematic in unraveling how micro-level interactions aggregated to form higher-order structures that could, reflexively, influence the individuals that comprised them. For example, in an early work (1960), Blau examined how individual preferences and characteristics, when aggregated across all members of social work organizations, could explain why individuals acted in ways that were at odds with their individual orientations. Though perhaps a rudimentary analysis by today's standards, this study empirically demonstrated a basic form of emergence at the level of an organization—the aggregate characteristics of a group, simply measured by averaging individual characteristics, could help explain deviations from expected behavior of group members.

Blau further developed these theories through a series of works spanning multiple decades. Two works, in particular, heavily influenced in the ideas in this dissertation. The first, *Power and Exchange in Social Life* (1964), documented many of Blau's early ideas on the microfoundations of macrostructure—that is, how stratifications in society might emerge from the patterns of relationships among individuals. Blau elaborated on the basic idea of the 1960 study to further elaborate the importance of different types of relationships and institutional or cultural forces in the emergence and resilience of macrostructure. An extensive summary of these ideas can be found in Chapter 3, in which I draw on this aspect of Blau's work to develop a framework for understanding whole network performance. The second work, *The Structural Contexts of Opportunities* (1994), represents the development of Blau's macrostructural theory first published in 1977, and a deliberate shift from microfoundations to a broader focus on understanding social phenomenon by examining the dynamics of, and interactions among, large social groups. Thus, this phase of Blau's work is decidedly more similar to Simmel's ideas on overlapping social circles. The key aspects of Blau's macrostructural theory are described in Chapter 3, but can be loosely summarized as an attempt to quantitatively analyze the propensity for people to interact within and across large social groups or strata—which together comprise the structure of society. His propositions on in-group and out-group relationships are central to the idea of "network bounding" presented later in this dissertation.

Before proceeding, it is worth noting that Blau, in his writing, explicitly placed network analysis in the arena of microfoundations—that is, the study of individual-level interactions. Thus, this research, as well as the research of some contemporary sociologists and network scholars (e.g., Centola, 2015; Bapna & Funk, 2018) influenced by Blau's works, represents a bit of an evolution by using network analysis to study interactions at intergroup and interorganizational levels. Though it is unclear how he would regard this cross-pollination of ideas and tools across levels, I am hopeful that Blau—ever the empiricist and "quant"—would be receptive to these efforts to apply advances in network studies to his decades-long effort to link the micro and macro levels of social structure.

1.1.2 Classic Studies of Whole Network Performance

In addition to classic theoretical roots in sociology, there is another parallel stream of research that serves as a foundation for this dissertation: experimental studies of whole network performance. While the corpus of literature on whole network performance in organizational contexts (i.e., intraorganizational and interorganizational) is significantly smaller than the vast literature on egocentric network effects at the level of focal actors, there was an early period of intense activity on this subject dating back to the 1950s. Notably, scholars from MIT (Bavelas, 1948; 1950; Christie et al., 1952; Macy et al., 1953) and other institutions (Leavitt, 1949; Heise & Miller, 1952; Shaw, 1954a; 1954b; Mulder, 1960), including the Carnegie School (Guetzkow & Simon, 1955), experimentally examined the relationship between network structures and group performance.

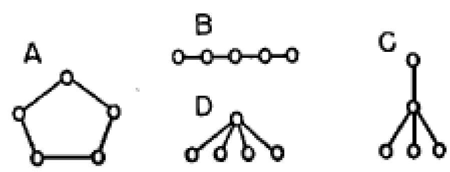


Figure 1.2: Examples of experimental network structures from Bavelas (1950)

The key premise and motivation for this field of research could be summarized as follows: "When the nature of a task is such that it must be performed by a group rather than by a single individual, the problem of working relationships arises … On what principles may a pattern of communication be determined that will in fact be a fit one for effective and efficient human effort?" (Bavelas, 1950: 725). Of particular interest to these multidisciplinary researchers[6]

[6] While most of the researchers cited here are psychologists, or at least have been categorized as psychologists, they also explored many diverse research interests spanning social psychology, mathematics, and computer science. Their diverse affiliations and outlets for publication also indicate the innovativeness of their work and the potentially broad appeal of the basic problem of optimizing group performance. Alex Bavelas, Lee Christie, R. Duncan Luce, and Josiah Macy, Jr. were part of an electronics laboratory at MIT. Harold Leavitt was a psychologist who worked with Alex Bavelas at MIT, Marvin Shaw was at Johns Hopkins, and Mauk Mulder was part of the Netherlands Institute for Preventative Medicine at Utretcht. Harold Guetzkow and Herbert Simon were Carnegie organization researchers with diverse backgrounds, though their connection to this research is perhaps most related to their interests in computer science.

was the flow of information through direct and indirect communication. As such, experimental manipulations often involved constraining and altering the allowed patterns of information exchange among experimental subjects. For example, the classical “Bavelas-Leavitt” experiment involved a group of subjects that were physically isolated by cubicle walls. Each was given a set of symbols and their *collective* task was the correctly identify the symbol that all members held in common. The structure of communication was fixed by allowing only notes to be passed in a particular pattern (i.e., a network structure). Figure 1.1 reproduces a figure from Bavelas (1950) illustrating some five-member structures. Figure 1.2 reproduces a photograph of an experimental setup from Guetzkow & Simon (1955).

Figure 1.3: "Bavelas-Leavitt" type experimental setup, from Guetzkow & Simon (1955)

These experiments on communication networks and group problem-solving did not, ultimately, uncover an optimal structural arrangement that was universally superior in generating whole network performance. However, the experimental evidence and the debates regarding the theoretical explanations for what they were observing led to two important takeaways that, as I

Bavelas’ oft-cited 1950 piece was published in the Journal of the Acoustical Society of America, and his earlier work describing basic network structures of groups was published in Applied Anthropology.

will describe in the subsequent section, continue to pique the interest of scholars. First, the scholars clearly established that *structure matters* for group performance—altering the arrangement of interactions within a network seemed to significantly impact whole network outcomes in these group problem-solving tasks. Second, they found relationships between network structure and performance were *inconsistent* (Guetzkow & Simon, 1955; Mulder, 1960). For example, some studies found that "wheel" structures were associated with worse performance, while others found that they were associated with better performance (Mulder, 1960). Scholars proposed different ideas as to why they were observing such variability across similar studies, including differences in task complexity (Shaw, 1954b), the ability of a group mobilize itself or organize towards the task at hand (Guetzkow & Simon, 1955), and the way in which group members enacted a particular structure (Mulder, 1960). In sum, experimental evidence and interpretation of findings led pointed towards the conclusion that "topological structure does not determine what really happens, but only what is possible" (Mulder, 1960: 2).

1.1.3 Contemporary Studies of Whole Network Performance

More recent research on collective performance of whole organizational networks can organized into two broad categories as they pertain to this dissertation. The first group are observational studies of team or organizational performance in which the unit of analysis is conceptualized as a network—for example, similar to the classic studies, a team of individuals will be studied as a network so the collective performance of the team can be thought of as whole network performance. Studies within this first category are generally from sociology, organizational, and strategy research, and have largely focused on trying to explain a team or organizational outcome, such as innovation, learning, or coordination, through a network-level structural measure, such as centralization (Davis, 2016; Mahmood et al., 2017), density (Sparrowe et al., 2001; Reagans et al., 2004; McFadyen et al., 2009; Davis, 2016), closure (Soda et al., 2004), or path length (Funk, 2014). One notable exception is Provan & Milward (1995) which explicitly focused on interorganizational network effectiveness and the relationship between centralization and whole network performance. Taken together, findings from these study—much like the classic experiments—reveal different relationships between whole network structure and whole network performance, and efforts to aggregate lessons across studies are made challenging due to different contexts and levels of analysis.

The second group of studies come from more multidisciplinary sources and, in many ways, carry on the tradition of the classic studies of whole network performance. Thus, participants in this research stream, including organizational researchers, sociologists, anthropologists, computer scientists, and political scientists, use variations of old experiments (Kearns et al., 2006; McCubbins et al., 2009; Enemark et al., 2011; Mason & Watts, 2012; Shore et al., 2015; Derex & Boyd, 2016; Shirado & Christakis, 2017) and simulations (Lazer & Friedman, 2007; Fang et al., 2010) to, once again, examine the relationship between whole network structures and performance. While knowledge and methods have advanced considerably from the 1950s (e.g., scholars now experiment with much larger networks, using online platforms), the fundamental question remains largely the same: what types of network structures are best for collective performance? Interestingly, recent studies do not only share similar research methodologies with classic studies. Despite reinvigorated efforts to understand the antecedents of whole network performance, findings are still inconsistent. Moreover, current efforts to reconcile incongruities parallel those from decades ago, with explanations such as differences in the type of task (Shore et al., 2015) or variation in how network members enact network structures towards collective outcomes (Mason & Watts, 2012).

1.1.4 Limitations and Opportunities

Integrating theoretical foundations of collective performance with findings from empirical studies of experimental networks, computer simulations, and, to a lesser extent, organizational networks, highlights important gaps and opportunities for contributions. First, the sociological contributions of Simmel and Blau have not been deeply integrated into studies of whole network performance.[7] Thus, I argue that there is an opportunity to draw on these classic works to make advances in empirical work. Indeed, this is one of the intended contributions of Chapters 3 and 4.

Related to the first point, the second potential opportunity is associated with the near singular focus on previous empirical research on network *structure*. This stands in stark contrast to the reviewed theoretical works, which take a more holistic approach to examining different dimensions of collectives and networks. Importantly, whereas structure is clearly viewed as an emergent property in theoretical discussions, it is somewhat taken for granted in experiments and simulations where structures can be easily imposed and manipulated. Consequently, there is foremost an opportunity to both take a more holistic view of whole networks that goes beyond structure (the focus of Chapter 3). Further, there is an equally important opportunity to study variations in network structure *in situ*, where variation is not artificially induced by a researcher but is instead an emergent process reflecting social dynamics within a collective (the focus of Chapter 4).

The third potential gap identified from the literature is that whole network outcomes have been relatively understudied in organizational and strategy research. Instead, much of corpus on whole network outcomes comprises the work of psychologists, computational social scientists, and computer scientists. Consequently, the constituent nodes in the networks being studied are predominantly *individuals* in *experimental* settings. Though it is not my objective to theorize the differences in networks of individuals versus networks of organizations, I do want to draw attention to the striking dearth of evidence from actual organizational contexts. While network performance is undoubtedly a fascinating puzzle in terms of complexity and system optimization, it is also a crucially important matter for real societal issues. The importance of better

[7] Though, as previously discussed, Simmel's work is the foundation for much research on ego networks.

understanding the complexities of collective performance throughout society is not only evidenced by the multidisciplinary contributions to this discussion, but it has also been explicitly noted in the field of management (George et al., 2016). That said, when it comes to studies of networks and performance, management theory and research has primarily focused on outcomes of individual organizations. Though organization or firm-centric theories may provide important insights into collective performance, it would be erroneous to assume that they can simply be extrapolated to the higher level (Lazarsfeld, 1993).

1.2 Outline of Chapters

Given this background, the remainder of this dissertation seeks to address make contributions to research on whole network performance in the opportunity areas outlined above.

The next chapter, Chapter 2, provides a deeper dive into the specific research context—the formation of formal networks called Medicare Shared Savings Program Accountable Care Organizations (ACOs). These networks were created as a result of the *Patient Protection and Affordable Care Act* of 2010, a landmark legislation and the most recent nationwide effort towards reforming healthcare delivery.

Then, through two essays (Chapters 3 and 4), this dissertation looks "inside the lines" of interorganizational networks—that is, within the connecting ties, and the boundaries—to examine the characteristics, dynamics, and performance of whole organization networks in the US healthcare industry, a setting in which network-level outcomes are especially important for patient outcomes and the sustainability of the healthcare system.

Finally, Chapter 5 discusses scholarly contributions, lessons for practice, and potential policy implications. Below is a brief description of the two major studies.

1.2.1 Network Morphology

The first study seeks to understand the relationships between whole network performance and other network-level characteristics. As highlighted above, nearly all studies of whole network performance focused on the relationship between network *structure* and network performance. More importantly, there are conflicting findings as to the whether certain structural properties (e.g., connectedness, centralization) are beneficial or harmful for collective outcomes. The former issue is relatively unsurprising as network methods are primarily used to study structure. However, this structure-centric view ignores other properties of organizational networks, such as the nature of relationships and the prevalent cultural forces, which are essential for the formation, persistence, and evolution of network structures. I argue that this oversight may be intrinsically linked to the latter issue—contradictory findings on the whole network structure-performance relationship—since other network-level properties may lead to different interpretations of the same structure. For example, a fully connected triad may reflect a well-functioning trio, but may also represent a conflict in which two members oppose the other. Therefore, I examine whether the structure-performance relationship can be clarified by taking a closer look at other emergent properties of networks.

The primary contribution of this study is the *network morphology* framework which outlines the theoretical bases for the network structure-performance relationship to be contingent upon the *relational* and *cultural* dimensions of whole networks. Grounded in Peter Blau's theories about the connections between micro and macrosociology (1964), a morphological view of whole network structures mirrors how many scholars of biological morphology view the relationship between physical structures, such as wings or hairs, and survival. For example, while many organisms possess biological structures that are associated with flying or gliding, each organism's resultant fitness or flight performance may depend on the "context"—the other attributes of the organism and how they work together—within which those structures are found (Koehl, 1996). Similarly, I argue that the *inherent* interdependence between the structural, relational, and cultural dimensions of whole networks may explain why similar whole network structures may be associated with a wide range of potential performance outcomes, even within the same industry.

In order to demonstrate how the network morphology framework may generate testable predictions, I apply it to examine the performance of accountable care organizations (ACOs) in the US healthcare system. ACOs are interorganizational networks of healthcare providers formed as part of the *Affordable Care Act*. These networks, which today number in the hundreds, arose across the United States beginning in 2012 with the shared goal of reducing the costs of healthcare through better coordination. At a high level, adopting a morphological view of ACO performance reveals that whole networks may achieve very different performance outcomes, despite having similar structural properties. More specifically, the same level of disconnectedness in the structural dimension may be associated with a wide range of performance outcomes, contingent upon the relational strength and cultural orientation of each network.

1.2.2 Network Bounding

In the second essay, I approach the performance of interorganizational networks from a different perspective. Many interorganizational networks, such as the ACOs studied in the first essay, are formal groups which have clear boundaries and well-defined membership. Similar to the benefits that may arise with establishing organizational boundaries and structure (c.f., Zenger, Felin, and Bigelow, 2011), this strategy—securing and investing in a partnership through a formal agreement—may enhance collective trust, efficiency, and performance. However, while past research has examined the consequences of formalizing a single relationship (e.g., via a contract between two parties), considerably less is known about the consequences of formalizing a *whole network* of relationships.

Therefore, in this essay, I examine the consequences of creating a formal network, with particularly interest in how it changes the relationships among members and the potential implications for performance of the new, whole network. More specifically, I investigate whether the use of contracts to define a new formal group (network) among a specific set of actors can effectively alter underlying, *informal* relationships among members and enhance whole network performance. I first conceptualize this phenomenon as the introduction of a network boundary in a previously informal system of relationships—or "network bounding." I then develop my theory and hypotheses by drawing on Simmel and Blau's works, as well as network theory and recent research on informal versus formal network relationships, arguing that network bounding should be most effective when the group already possesses informal whole network structures that may be beneficial for whole network performance, as these may be activated and strengthened by adding a new formal network boundary.

I study this interaction by examining the 90-day post-operative mortality[8] of Medicare beneficiaries who receive coronary artery bypass graft (CABG) treatment within one of approximately 1,000 health system networks—of which approximately 20% experience network bounding (i.e., join an ACO). I find evidence that network bounding, via joining a new ACO, is associated with a significant increase in structural integration across the whole network—the degree to which there are diverse, or cross-specialty, network ties among physicians of different specialties. However, I also find that network bounding is *not* consistently associated with better whole network performance in terms of CABG mortality at the health system level. Instead, the results suggest that those whole networks with higher levels of structural integration (i.e., have more cross-specialty ties) may be associated with greater benefit from network bounding, whereas network bounding in whole networks with lower levels of structural integration may be associated with no benefit, or may even be hurt.

[8] The use of this outcome is consistent with clinical research that suggests that surgical outcomes are not just a reflection of the success of the procedures, but also significantly affected by both pre-operative and post-operative patient management (e.g., den Harder et al. 2016; Kehlet and Wilmore, 2002).

II. RESEARCH SETTING

> If physicians and hospitals can and will respond to demands for adequate and efficient health services without government controls or incentives, then only health insurance is necessary … If, on the other hand, the health care providers seem unable to respond with more effective services, even to the increased demand generated through more generous insurance benefits, then more direct government action may prove socially desirable and politically necessary.
>
> \- Stevens, 1998

At one point in the history of modern medicine in the United States, the single physician was the purveyor of medicine and health services (Starr, 1982). Yet, in the recent century, rapid advances in science, technology, and medical education gave rise to increasing specialization, which in turn led to a greater need for organization and coordination (Stevens, 1998). This has also led to healthcare becoming one of the most critical drivers of the US economy, with estimated national health expenditures growing from $27 billion in 1960 to $3.5 *trillion* in 2017 (National Health Expenditure Accounts, 2017). However, because the "product" being traded was for all intents and purposes *health*, the delivery of medical care in the United States (US) soon became, and today remains, a matter of great political and public interest.

2.1 The Problem of Fragmentation

The US healthcare system is, by all accounts, a *complex* system, both in the sense that it comprises multiple entities with diverse goals and missions, but also in that these entities are interdependent and co-evolve (McKelvey, 1999). It is also accurate to describe the current state of the system as one that was not particularly well-designed or planned; rather, what we have is the result of decades of a tug-of-war of various professional, political, technical, and economic interests (Starr, 1982). Most often, we describe the system as being "fragmented," referring to any number of misalignments between the demands of the consumers of healthcare (i.e., patients, communities, employers) and the providers of healthcare (i.e., physicians, nurses, hospitals, health insurance providers, pharmacies, clinics, laboratories… etc.). Fragmentation, however, is an emergent symptom of the system as whole, and has a complex etiology. That said, when comparing the US system to other developed nations, such as the United Kingdom, Canada, and Germany, perhaps the most obvious macroscopic differences are the lack of universal health coverage and/or a single payer system—typically the national government. Instead, most Americans receive private insurance through an employer until retirement age (65 years) when the government insurance plan, Medicare, kicks in. Even then, many retirees opt for supplemental or alternative insurance through a private payer (e.g., Medicare Advantage) due to poor coverage or high deductibles associated with Medicare in their communities. Though it is not my intention to imply that universal coverage and a single-payer model would reverse, or further prevent, fragmentation in the US,[9] the absence of these formal institution is often held up as part of the problem.

Of course, fragmented does not necessarily mean poor-performing; indeed, no system is perfect and sometimes systems function better as a whole when it can be organized into smaller sub-systems (e.g., Provan & Sebastian, 1998). Unfortunately, the US healthcare system is, by objective metrics, a mediocre performer compared to other nations. Critically, the US fails to deliver sufficient *value* in most areas of healthcare—the quality or efficacy that we achieve per dollar spent. A 1997 study (Anderson, 1997) using data from the Organization for Economic Co-operation and Development (OECD) found that:

> "the United States spent the most resources on health care of all twenty-nine industrialized countries in 1996 by a wide margin … [but] among the twenty-nine industrialized countries, the United States had the lowest percentage of its population eligible for publicly mandated insurance … [and] on outcomes indicators such as life expectancy and infant mortality, the United States is frequently in the bottom quartile … and its relative ranking has been declining since 1960."

Recent OECD figures illustrate that the story has not changed much in the last two decades. The US is below average in life expectancy, insurance coverage, obesity prevention, and physicians per capita, but is by far the world-leader in spending (OECD, 2017). Put differently, the US

[9] Indeed, even in countries with universal coverage via the government, private insurance and private healthcare organizations play a role in filling in the gaps. Therefore, perhaps the key distinction is that there is not a reliable and accessible public option for a significant proportion of Americans in the United States.

healthcare system is extremely effective at drawing in capital and economic resources but fails to consistently translate those dollars into better health outcomes. Consequently, the reason why fragmentation is linked to poor performance is the assumption that both are related to problems of payment.

Though efforts to “bend the cost curve” (Cutler et al., 2009), or make healthcare more efficient and cost-effective, have been on-going for decades, a watershed moment in contemporary dialogue about the quality and sustainability of the United States healthcare system came in 2001. The Institute of Medicine published an influential report, *Crossing the Quality Chasm: A New Health System for the 21st Century*, which called for a major strategic shift in the delivery of healthcare. The authors called out many of the aforementioned issues of fragmentation and ballooning costs coupled with suboptimal quality, but the key emphasis was on re-imaging the way healthcare was organized—to redesign delivery pathways to maximize safety and efficiency, and to build around patients’ needs rather than medical specialties. This shift also called for greater cooperation among clinicians, a move away from the organization and physician-centric model that took hold during the last few decades (Obama, 2016). It required viewing patients’ long-term health as the complex problem that a community of organizations, physicians, and other service providers would jointly try to solve. Calling patient-centered care the “true north” for a better health care system, there was hope that putting patient needs above all else would also, by extension, reduce fragmentation by promoting more collaboration among clinicians and organizations.

However, implementing this redesigned vision of medicine has proven exceedingly difficult in the United States, where high-quality healthcare has been often been synonymous with *more* healthcare. As Donald Berwick, a noted scholar of healthcare improvement, recently noted, “it’s hard to find a hospital or a clinic, certainly in the United States, where people aren’t aware of problems … but the payment system still supports thinking in fragmented terms” (Caffrey, 2017).

Manifestations of this payment challenge can be observed at both the payer and provider levels. For example, when insurance plans try to prevent beneficiaries from going outside of a specified "network"[10] of physicians, the primer driver is the need to keep costs down. Moreover, insurance companies have little incentive to influence *how* the work gets done—and how the patient experiences that work—unless doing so would improve their financial performance.[11] Similarly, on the provider side, if organizations and clinicians are only paid based on the amount of work they do (as most are), then the system is designed to encourage them to do more. Without enough recompense for activities that generate positive externalities—both for the patients and for other healthcare providers—the most effective levers to move the industry away from fragmented thinking are ethics and a sense of professional duty.[12] Consequently, there is a counter-intuitive relationship between healthcare costs and quality: higher spending may lead to better quality (Porter & Teisberg, 2006). In fact, research shows that in some cases higher spending is associated with worse quality (Fisher et al., 2009). Moreover, the lack of incentives for providers to coordinate with one another increases the risks of overtreatment, redundant work, and medical errors.

2.2 Medicare and the Affordable Care Act of 2010

The founding of Medicare through the Social Security Act of 1965 was, according to some historians, the first major push by the federal government to play a role in protecting the health of Americans (Stevens, 1998). Since its inception, in 1965, Medicare has become the single largest payer (insurer) in the country, covering more than 50 million people. All Americans aged 65

[10] The term "network" here refers to the more abstract concept of network in the health insurance industry. It simply defines a group of physicians and organizations that the payer has contracted with for a specific insurance product, but does not necessarily imply any coordination or group goals. This use is different

[11] This is not to accuse insurance companies from being immoral businesses. Revenue/profit and patient health can move in lock-step, but maximizing the former is the goal of the business.

[12] Unfortunately, this is not a very effective lever. "You know, when we fall on the sword for God and country, that's tough. When you ask the guy to fall on the sword for health care reform, I would say—you know the answer." (Kreindler et al., 2012: 469)

years or older are eligible for Medicare, as well as some younger Americans who are eligible through disability or end-stage kidney disease. Given these eligibility criteria, Medicare beneficiaries[13] (i.e., patients who are covered by Medicare) tend to have more complex health care needs, requiring multiple types of providers spread across different organizational settings. This complexity requires effective communication and cooperation among different healthcare professionals and organizations to make sure the right care is provided in the right place at the right time. However, there are no incentives for such collaboration due to fee-for-service reimbursement being the dominant method of payment for physicians and organizations. This means that healthcare providers primarily receive payment based on the *quantity* of work performed rather than quality or system-level impact. Thus, if the key driver of financial performance for individuals and organizations is to do more work, the system, as a whole, will do more work. Consequently, such financial incentives lead to overuse and waste. Reining in overuse and ballooning healthcare spending is therefore a central concern for the Centers for Medicare and Medicaid Services (CMS), the federal agency that administers Medicare.

Within the context, the *Patient Protection and Affordable Care Act* (ACA) of 2010 marked a pivotal moment in US healthcare reform, one that "could fundamentally affect the future of health care in the United States" (Blumenthal et al., 2015). The ACA was an expansive piece of legislation, perhaps most acutely felt by Americans in the expansion of health insurance and the individual mandate—the requirement for every American to have uninterrupted health insurance coverage. However, the ACA also included numerous provisions for innovative programs—many of which are most accurately described as policy experiments—designed to change the manner in which healthcare is delivered. This was perhaps best symbolized by the

[13] The term "beneficiary" is used to refer to an individual patient who has insurance coverage through a particular health insurance plan. For example, a Medicare beneficiary refers to an individual who is insured by Medicare. For the remainder of this dissertation, I primarily use the term beneficiary to describe patients.

creation of the Center for Medicare and Medicaid Innovation (CMMI) within CMS, which was given substantial resources to fund healthcare reform efforts across the country.

2.3 Medicare Shared Savings Program Accountable Care Organizations

Among the largest of these reform efforts, was the Medicare Shared Savings Program (MSSP) Accountable Care Organization (ACO) model,[14] which launched in 2012 and is on-going at the time of writing. The goal of the MSSP ACO model is to promote greater integration among healthcare providers and reduce fragmentation, or what Donald Berwick (2002) described as healthcare's fatal flaw: "every discipline for itself, every guild for itself … [the assumption] that either we will preserve quality or cut costs."

At the heart of the MSSP ACO model are two changes in the delivery of healthcare. First, each ACO is voluntarily formed by group of healthcare providers, such as physicians' practices, hospitals, and clinics, which agree to collectively be *accountable* for the costs and quality of care of a specific population of Medicare beneficiaries. This grouping, the specific implications of which are a key focus of Chapter 4, essentially superimposes a new organizational arrangement on top of existing organizational boundaries and other affiliations. Each ACO must also designate a board, with clinical and administrative leaders, create a public-facing website, and publicly report its annual performance scores. The mechanisms through which ACOs select their membership and leadership vary. However, research suggests that some key mechanisms include partnerships among private physicians' practices, forming around a central hospital, forming around an integrated health system, or utilizing third-party non-provider partners to help determine membership (Shortell et al., 2014; Lewis et al., 2018).

Second, the ACO model tries to shift the financial incentives for healthcare providers through a subtle tweak. Although physicians and organizations will still be paid the same way by

[14] For more information, refer to the Medicare Shared Savings Program website and FAQ at CMS.gov. https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/about.html

Medicare (i.e., primarily fee-for-service[15]), each ACO is given an annual spending benchmark based on historical per capita medical expenditures for their assigned Medicare beneficiaries (CMS, 2015). If an ACO can achieve lower spending in a year relative to its benchmark, it is eligible to receive up to 50 percent of the savings they generate (hence, *shared* savings).

Healthcare providers can only belong to one Medicare ACO at a time and each patient can only be assigned to one Medicare ACO (though patients are free to seek treatment from non-ACO providers if they wish). Therefore, since ACOs care for unique patient populations and are often localized by geography, in principle, there is no direct competition between ACOs with regards to their cost-savings or quality outcomes—one ACO's high performance does not negatively affect the performance of another ACO. That said, because of patients' freedom of choice, ACOs and ACO members may still compete for patients, overall, since revenue generation is still largely tied to the volume of services provided. Therefore, ACOs may also have incentives to prevent "leakage" and keep the patients within their network in order to better coordinate care and identify opportunities to eliminate unnecessary spending, while also capturing the associated revenue.

Until 2018,[16] MSSP ACOs were able to choose either one-sided or two-sided risk in their agreement with Medicare, with only the latter involving *downside* risk in which ACOs would have to pay a penalty if they exceeded the benchmark by more than two percent. In the one-sided model, ACOs would not be penalized for overages, but they would have to save at least three percent relative to the annual benchmark in order to qualify for shared savings payment.

Finally, in order to ensure acceptable quality, the shared savings payments are weighted by a composite, 34-metric quality score. In 2013, the first year of performance reporting, ACOs were not penalized on quality performance. However, in subsequent years, quality scores have

[15] Though, this is changing to increasingly include more "bundled payments"
[16] Changes to the MSSP ACO program introduced in 2018 will force ACOs to transition more quickly to a two-sided, risk-bearing model.

been factored in to the shared savings calculation.

Beyond these rules, MSSP ACOs are given significant freedom to achieve their goals in whatever ways they feel will be most effective. Although ACOs have a formal contractual basis, experts see them as "a peculiarly social intervention, using social levers—shared accountability and collective incentives—to encourage new relationships among groups" (Kreindler et al., 2012). Thus, attainment of their economic goals is expected to be dependent on ACO members' ability to collaborate. Promisingly, thousands of providers have come together to form ACO networks, with each group sharing responsibility for at least 5,000 Medicare patients who rely on network members for their primary care services.

2.4 Early Medicare ACO Experiences

Still, despite broad interest in the Medicare ACO model, even those involved in promoting the vision of shared accountability among autonomous partners were cautious and realistic about the likely challenges ahead. As Fisher and colleagues (2009) noted, "Clinical transformation is the linchpin of ACOs' success, and it does not happen automatically by simply changing payment arrangements and measuring performance." Early case studies of the experiences of Medicare Pioneer ACOs—a predecessor model to the Shared Savings Program—similarly reveal mixed opinions and interpretations of what an ACO is. Optimists noted that the shared goals were unifying, while still preserving the autonomy and more private practice of medicine that physicians value. According to one ACO physician, "I think it's essential that ... an independent practice organization shows the world that this whole ACO concept can be done well. My previous group sold to [a hospital] ... and these people have basically sold their souls." (Kreindler et al., 2012: 465) In contrast, another ACO physician—a specialist—remarked that the balance between who does the works and who stands to benefit will be difficult to strike: "If [specialists] feel that someone else is benefitting from their work, they're gonna be resentful and it's not gonna work well ... You need ... team spirit like you might have on a college football team." (Kreindler et al., 2012: 467)

Despite the social hurdles that ACOs must overcome to generate buy-in among members, early performance measures for Shared Savings Program ACOs indicated that they were, on average, moderately effective at reducing costs. However, more recent research has questioned whether those overall savings may be offset by incentive payments (McWilliams et al., 2016, McWilliams, 2016a). Other evidence demonstrates that a subset of early ACOs may be learning, based on analysis of improvements in year-to-year performance by start date (Muhlestein, Saunders, & McClellan, 2016). However, the distribution of performance results for ACOs during the first three years of the MSSP indicates that nearly half of the participating networks are unable to achieve cost savings.[17] Thus, despite some promising signs, questions remain as to whether ACO networks will be a sustainable way to improve the delivery of healthcare for Medicare patients, while also ensuring the financial sustainability of the system (McWilliams, 2016a; 2016b; Colla & Fisher, 2017).

The emergence of MSSP ACOs across the US provides the research context for the essays that comprise the core of this dissertation. Chapter 3 will explore the cost-savings performance heterogeneity among ACOs from 2012-2015, conceptualized as interorganizational networks. Chapter 4, then examines how the actual formation of ACOs may have altered patterns in how healthcare is delivered, as well as the subsequent implications for patient outcomes.

[17] Based on Medicare Shared Savings Program ACO Public Use Files, 2013-2016.

III. STRUCTURE IN CONTEXT: A MORPHOLOGICAL VIEW OF WHOLE NETWORK PERFORMANCE

3.1 Introduction

Research on organizational networks has focused on understanding how the embeddedness of actors within networks (i.e., "ego" level networks) shapes their outcomes (Burt, 1992; Gargiulo & Benassi, 2000; Paruchuri, 2010). Against this backdrop, however, a growing group of scholars have adopted a fundamental perspective shift, moving the lens away from nodal outcomes towards a focus on *whole network* performance (Rosenkopf & Schilling, 2007; Fang et al., 2010; Guler & Nerkar, 2012). Rather than considering how a node's embeddedness shapes its performance (Uzzi, 1997; Rowley et al., 2000; Paruchuri & Awate, 2017), this work examines how the *overall* pattern of ties among a group of actors shapes their *collective outcomes*. Put differently, unlike ego network research, this literature uses whole network structure to predict whole network performance, a contrast I showed in Figure 1.1. Taken together, studies in this stream offer evidence that the best-performing whole network structures are not those that maximize individual network members' performance (Mason & Watts, 2012; Shore et al., 2015) but instead those that enable network members to function effectively as a whole (e.g., McCubbins et al., 2009). Thus, initial findings from the whole network literature suggest that the mechanisms and theoretical logic of whole networks are systematically different from those of ego networks, potentially with different performance consequences.

Notwithstanding this progress, the literature on whole network performance has produced conflicting findings, which makes it difficult to cumulate insights across studies. Notably, scholars disagree over the relationship between whole network structure—in particular, "connectedness," i.e., the extent to which network members can reach one another through direct or indirect paths (Lazer & Friedman, 2007; Centola, 2010; Funk, 2014)—and whole network outcomes. One stream of literature argues that the most effective whole networks are those that achieve coordination through *disconnected* structures, where individual members interact with only a few others (Lazer & Friedman, 2007; Derex & Boyd, 2016). Although disconnectedness may reduce the speed at which information flows through a network, it is also theorized to promote greater diversity of ideas (Fang et al., 2010; Derex and Boyd, 2016), reduced noise (Christie et al., 1952), and fewer redundancies (Enemark et al., 2011). Other studies have argued the opposite, instead suggesting that greater *connectedness* is preferable (Fleming et al., 2007). This work finds that more connected structures facilitate communication (Kearns et al., 2006), expose actors to a greater variety of peers (Mason and Watts, 2012; Enemark et al., 2014), and may also help with conflict management (McCubbins et al., 2009). To date, scholars have attempted to address these conflicting findings by examining whether the relationship between whole network structure and whole network performance is contingent on the *task* being undertaken by network members. However, studies have also observed networks with radically different structures producing similar outcomes when conducting the *same* tasks (Lazer & Friedman, 2007; Fang et al., 2010; Mason & Watts, 2012). Collectively, then, this discussion suggests that scholarly understanding of the relationship between whole network structure and whole network performance remains limited.

In this study, I address this gap in understanding by proposing a novel theoretical framework, supported by an empirical application. Drawing on macrostructural sociology—a literature that has developed in isolation from work on whole networks—I expand research on whole networks beyond its focus on structure to include other network dimensions. I build on Peter Blau's (1960, 1964) work, which theorized the emergence of larger, macrosocial structures from individual (microsocial) interactions. Blau argued that structure should not be considered in isolation nor as constant. Instead, because structure is an emergent feature of social activity, its topology depends on the overall norms and values that influence interacting actors and the nature of the relationships they form. I extend this logic to argue that while the same structural pattern may be observed in different networks (Milo et al., 2002), each instance tells a different story depending the context within which it emerged and functions. These insights suggest that theories of whole networks must go beyond structure to also consider the *context* within which a structure is found. Furthermore, I theorize that those very contextual factors may be inherent to networks themselves, reflecting specific instantiations of network "primitives" (Ahuja et al., 2012; Nahapiet & Ghoshal, 1998)—nodes and ties.

Based on this assertion—i.e., that the structure of a whole network does not uniquely determine its function or performance—I propose a framework of *whole network morphology*,[18] inspired by the study of relationships among biological structures. I draw particular inspiration from biomechanical morphology, which posits that "single traits should not be studied in isolation…[because] the performance consequences of a particular morphological change can depend on other aspects of an [organism]" (Koehl, 1996: 515). As an example, Koehl (1996: 515) highlights that the coincidence of multiple "flyer traits" in flying frogs "improved turning performance significantly more than expected from the sum of their individual effects." The network morphology framework argues similarly on the relationship between whole network structure and whole network performance—the same whole network structures, when viewed together with other dimensions, may be associated with different behaviors, functions, and, thus, outcomes. I argue that a morphological view helps reconcile equivocal findings on whole network performance and, more broadly, serves as a platform for theorizing a more contextualized view of whole network structure.

I build the theoretical core of the network morphology framework by extending Blau's theories of macrostructure. Specifically, I examine the interdependencies among the *structural*,

[18] The name of my framework is also a nod to Durkheim's—often considered one of the forefathers of macrostructural sociology—*social morphology* (Durkheim, 1965). However, the similarities between Durkheim's approach and my network morphology framework are limited to the name and broad focus on whole structures.

relational, and *cultural* dimensions of whole networks, revealing insights into the origins of whole network performance. The resultant theoretical model views whole networks much like a chemist would view a molecule. First, each unit of analysis (network) comprises atoms (nodes) that are bound together (ties) in a stable pattern (structure). The aggregate instantiations of each describe different aspects of the whole and how it may function—a type of structural arrangement (e.g., bent, trigonal planar), the nature of the chemical bonds (e.g., weak, strong), or the type of molecule (e.g., organic vs. inorganic compounds). Although each descriptor provides information about the whole, in isolation they are incomplete; I gain more insight into the form and function of the whole when I consider the intersections between these dimensions. Similarly, the topology of network connections as a whole (*structural dimension*) may affect whole network performance differently depending on the character of social relationships (*relational dimension*) and the emergent group norms and values (*cultural dimension*).

I argue that a novel framework is necessary because, as stated earlier, whole networks operate according to a theoretical logic that is fundamentally distinct from ego networks. Moreover, the application of ego level network frameworks to the whole network level may obscure important differences, thereby leading to erroneous predictions and masking interesting questions.[19] Consider the concept of embeddedness (Granovetter, 1985), in which the behavior (and outcomes) of *individual* actors is shaped by their social ties (Rowley et al., 2000; Seibert et al., 2001; Moran, 2005).[20] Scholars in this tradition have developed the notion of positional

[19] Macrostructural sociologists have long cautioned against applying concepts developed at one level to phenomenon at a different level. Paralleling my arguments, for example, Blau (1986: vii, vx) writes, "Macrosociological and microsociological analysis involve different theoretical approaches and employ different concepts...the distinctive problems of nations or cities cannot be clarified by dissecting…interpersonal relations but only by analyzing the implications for social life of major structural features." Similarly, I argue that whole networks cannot be understood using frameworks developed to understand ego networks.

[20] This view of embeddedness as a tool for explaining the outcomes of individuals (rather than whole networks) is evident in Granovetter (1985: 487, emphasis added), who writes, "*Actors* do not behave or decide as atoms outside a social context…Their attempts at purposive action are instead embedded in…social relations."

embeddedness, which refers to the “extent to which [actors] occupy a central position in a network structure” (Polidoro et al., 2011). A common finding is that actors with greater centrality (i.e., better positional embeddedness) experience better outcomes. Extrapolation of these findings to the whole network level may therefore suggest that whole network performance will be greatest in networks where all members tend to have higher centrality. However, contrary to this prediction, in an early study of whole network performance, Leavitt (1949) found that collective outcomes were greatest in *centralized* networks—i.e., networks in which one member had high centrality while others did not (c.f. Provan & Milward, 1995). In short, when applied to whole networks, inferences from ego network theories may lead to misleading predictions. Consequently, there is a need for a novel, whole network framework and theoretical vocabulary.

I complement my theoretical development with an empirical application of the whole network morphology framework, specifically to the performance of 250 interorganizational whole networks in the United States healthcare industry. These whole network structures, known as accountable care organizations (ACOs), were formed as part of the Affordable Care Act with the goal of improving healthcare for specific patient populations.

This work makes several theoretical contributions. Most generally, I introduce a new framework—grounded in macrostructural sociology—for the study of whole network performance. The morphology framework introduces a conceptual vocabulary that helps distinguish whole network from ego network research and provides a platform for future work on whole networks. In addition, I draw on the framework to develop a new approach for reconciling conflicting findings in the emerging whole networks literature on the relationship between structure and performance. Rather than focusing on task moderators—which have not proven a robust strategy for resolving conflicting findings—I theorize that the structure-performance relationship can only be understood by recognizing that structure does not exist in isolation, but rather coexists with two other—relational, cultural—whole network dimensions.

3.2 Theory Development

3.2.1 Structure in Context: Insights from Macrostructural Sociology

Efforts to understand whole network performance can be traced to the 1950s, when researchers used laboratory experiments to determine whether some network structures were better than others for group problem solving (Bavelas, 1950; Guetzkow & Simon, 1955). For instance, one study gave network members (i.e., subjects) colored marbles. The experimenters then tasked groups with identifying the single color that all members had in common (Macy et al., 1953). Subjects were allowed to communicate by passing notes, but the researchers would modify the structural connectedness of the network—i.e. the extent to which network members could directly or indirectly reach one another. That is, experimental network configurations resembling stars or lines would constrain with whom notes could be shared.[21] This literature provided early evidence that certain whole network structures may be superior to others.

Recent attempts to address conflicting findings on whole network performance harken back to these studies. Both classic and contemporary research has focused on the task being undertaken by network members to elucidate how structure may shape collective outcomes (Bavelas, 1950; Mulder, 1960). For example, Shore and colleagues (2015) found that highly connected whole networks excelled at *finding* diverse information; however, when required to *use* diverse information, such configurations tended to converge on fewer (potentially valuable) interpretations. Other studies have tried to disentangle these effects by altering the complexity of the problem or the options (e.g., explore, imitate) available to individual decision makers (Lazer & Freidman, 2007; Mason et al., 2008; Barkoczi & Galesic, 2016; Shirado & Christakis, 2017).

Although this task-focus has led to valuable insights, studies within this stream of literature have generally been conducted using laboratory experiments or simulations. These

[21] A common method of illustrating connectedness is to see if it is possible to trace a path from one node to any other node in the network without lifting your finger or pencil. Connectedness is greater when more pairs of nodes are mutually reachable in such a manner, with fewer intermediary nodes.

approaches afford researchers greater control over network structures and behavior, but they are limited in that the work of organizational networks *in situ* may be too complex to decompose into discrete tasks. For example, interorganizational whole networks in public administration collectively perform a broad range of interdependent tasks (Provan & Sebastian, 1998), each of which may be best served by a different structure.

Alternatively, evidence from the R&D literature suggests that differently configured whole networks pursuing the same task—innovation—may produce similar outcomes. For example, increased innovation output has been associated with connected structures (Fleming et al., 2007), disconnected structures (Guler & Nerkar, 2012), or *both*, contingent upon environmental factors (Funk, 2014). Similarly, for problem-solving tasks, some research suggests that disconnected structures enhance performance by generating more novel solutions (Derex & Boyd, 2016), while other studies find that more connected structures enhance performance because they enable members to better reconcile misaligned incentives (McCubbins et al., 2009), and facilitate more efficient error detection and imitation (Mason & Watts, 2012).

Within this context, I propose an alternative approach to reconciling observations on the whole network structure-performance relationship. My theory development centers on the idea that structure is an incomplete representation of network activity. Structure is not the only driver of whole network outcomes because structure itself is inextricably tied to other (emergent) properties of the elemental units that comprise it—nodes and ties.

My framework is grounded in the work of Peter Blau (1964), who argued that the emergence of macro social structures ("macrostructure")—defined as the stratification of society into different groups that share common features—can be traced to the patterns of recurring interactions ("microstructure") that characterize social life. Macrostructures "have emergent properties [such as value consensus or enduring institutions] which are independent of the properties of individuals…in the sense that no individual can have equivalent properties" (Blau &

Schwartz, 1997: x), but are themselves derived “from the simpler processes that pervade the daily intercourse among individuals” (Blau, 1964: 2). The primary driver for this aggregation was theorized by Blau to be the value that actors derive from social exchange and approval.

Although Blau argues that dyadic interactions between two individuals are fundamental to more complex social structures, even dyads are, “of course, strongly influenced by the social context in which [they occur]. [Consequently] the analysis of social interaction in dyads, therefore, must not treat these pairs as if they existed in isolation from other social relations” (1964: 31). Here, “context” encompasses the broader network of relationships outside the dyad, both in the presence of the ties and in the nature or character of those ties, which may in turn be dependent on other factors, like specialization, power, or trust. Put differently, even the most basic unit of social structure—a single relationship—should not be viewed as a constant, but rather a totem whose meaning or function is imbued by other dimensions of the interaction. This view of the plasticity of a relationship is similar to biological morphology, in which similar structures can perform differently based on other “contextual” factors, such as its dependence on other structures, the size of the organism, and the external environment.

Thus, at a baseline, the nature of interpersonal relations among group members is important for understanding the characteristics of more complex, emergent group structure. To illustrate, Blau suggests that a higher-level construct like group cohesion emerges from individuals' collective efforts to gain approval from others (Blau, 1964). Yet, without knowledge of this lower-level property of social interactions or the norms and values that support and propagate this behavior, one might be led to believe that cohesiveness is simply a byproduct of the structure of relationships. Instead, the key insight from Blau is that the structure of relationships may only reflect one dimension of cohesiveness; what looks to be well-connected group from the outside may actually be one of conflict and tumult.

As lower-level interactions coalesce into larger groups, a dilemma arises in Blau's efforts to link dyadic relationships with social structure. Because "there is no direct social interaction among most members of a larger community or entire society, some other mechanism must mediate the structure of social relations among them" (1964: 253). Here, Blau suggests that prevailing social norms and values serve this mediating role. As social groups become larger, direct social interaction cannot be the only mechanism to maintain the greater social structure. “The legitimation of patterns of social conduct and social relations requires that common values and norms…reinforce and perpetuate them” (1964: 220). This set of norms and values, which Blau referred to as a group’s culture or subculture, compensates for the lack of stabilizing qualities intrinsic to each interaction (e.g., interdependence) by providing guidelines for the types of behaviors expected and valued by the collective. Contemporary macrostructural scholars have embraced this interdependence in theories of social networks, demonstrating that structure emerges from the confluence of individuals and prevailing norms and values, and that, reflexively, the outcomes of network structure are contingent on these factors (Centola, 2015).

3.2.2 Whole Network Morphology

I borrow from macrostructural theory the notion that the effects of whole network structure may be contingent on two other fundamental dimensions of social interaction—relations and culture—which, collectively, I refer to as the whole network morphology framework. This broader view of the structure-performance relationship may clarify why similar whole network structures appear to have different consequences. In what follows, I organize my discussion of the interactions between the structural dimension and the relational and cultural dimensions around Table 1, which provides an overview of each.

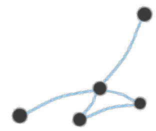
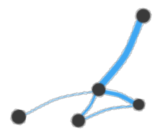
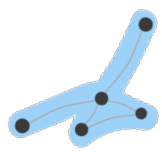
Structural dimension. First, the structural dimension (Table 1, first row) describes the structure of a whole network in terms of how its constituent relationships are arranged. Similar to the way different types of molecules may adopt similar shapes, different types of whole networks may share similar structures. Research on whole network effectiveness has focused on the structural dimension. For example, classic experiments in social psychology cited above utilized fixed structural configurations that varied in centralization (i.e., variance in whole network members' numbers of connections) (e.g., Guetzkow & Simon, 1955). Other studies have focused on measures including density (e.g., Provan & Sebastian, 1998), cohesion (e.g., Moody & White, 2003; Buhr & Owen-Smith, 2010) and connectedness (e.g., Fang et al., 2010).

Relational dimension. The relational dimension (Table 1, second row) captures the nature or character of ties within a whole network, representing qualities like strength or duration. Studies of alliance (Dyer & Nobeoka, 2000) and team (Reagans et al., 2005) performance often find that stronger ties benefit performance through the mechanism of familiarity, which enables group members to work together more effectively.

Past evidence hints that there may be an interaction between the structural and relational dimensions. Studying regional whole networks of law and venture capital firms, Buhr and Owen-Smith find evidence that in addition to strong ties, greater connectedness within institution-spanning whole networks has a positive relationship with performance. Dyer and Nobeoka (2000) similarly noted that Toyota's effective alliance network was characterized by many strong ties among members, but also a high level of connectedness. Alternatively, McFadyen and colleagues (2009) found that tie strength and density may interact negatively in the context of biomedical invention, where access to diverse information is important for performance.

The theoretical underpinnings of this interdependence between the structural and relational dimensions may be traced to Simmel's (1950) insights into how dyadic relationships change in the presence of a third actor. This theme of interdependence is also present in theories of structural balance (Davis, 1967), where consistency in the nature of one's relationships with others is viewed as a determinant of observed structures. In the well-known "forbidden triad" (Granovetter, 1973), if A is connected to both B and C, then the likelihood of a relationship between B and C forming is dependent on the strength of A's relationships with B and C. The

Table 3.1: Dimension of the Whole Network Morphology Framework

Dimension	Description	Example measures
Structural 	Topology of network connections as a whole	Connectedness, density, centralization
Relational 	Character of social relationships	Strength, frequency, age
Cultural 	Emergent group norms and values	Academic, corporatist, professional

stronger the A-B and A-C ties, the more likely B and C are to be connected. Although these simpler theories of dyadic interactions may be better suited to studying ego networks, they highlight how variations in the relational dimension (e.g., the strength of ties) can lead even a simple structure (triads) to function differently. Integrating these ideas, a whole network's relational dimension becomes a crucial lens through which to interpret its structural dimension.

Cultural dimension. Lastly, whereas the relational dimension focuses on the nature or strength of connections among whole network participants, the cultural dimension (Table 1, third row) is concerned with the norms or values prevalent in the whole network (Blau, 1964). Building on Durkheim's insights from *Suicide* that macrosocial forces (e.g., social and economic change) could influence individual behavior, Blau theorized that the values or orientations held by a majority could be important determinants of how a group, overall, behaved. He asserted that the confluence of shared values could also become an identifying trait of a group and influence members to act in accordance with the group's norms, even if it went against their individual orientations (Blau, 1960). Thus, the cultural dimension describes a defining quality of the group that is influenced by members but is also distinct from the identity of any one individual.

Although the cultural dimension cannot be readily displayed using standard visualization techniques for whole network graphs, it is no less important. As Blau (1964) suggests, the cultural dimension becomes increasingly important as groups grow; the whole can no longer be stabilized by direct interactions, and the context within which relationships take place is essential to maintaining—and expanding—the social structure. Regarding whole network performance, the cultural dimension may therefore influence the types of behaviors that are valued within the group. For example, a culture that rewards competition may incentivize members to think more locally, in contrast to one which celebrates individual sacrifice for the greater good.

I distinguish the cultural dimension from the *external* institutional context within which a whole network may exist (Vasudeva et al., 2013; McFarland & Moody, 2014). In defining the cultural dimension as an emergent characteristic of whole networks, I consider those external forces to represent the group culture insofar as members espouse them within the boundaries of the network. Put differently, the whole network's cultural dimension may differ from the prevailing culture in the external environment if network members promote and propagate an alternate value system. In this way, the identities of the members are crucial ingredients that go into creating the cultural dimension of each whole network, and different whole network cultures may enact similar structures in various ways.

3.3 Empirical Application: Whole Networks in Healthcare

I evaluate the ability of the morphology framework to generate novel predictions on the relationship between whole network structure and whole network performance when applied to specific empirical contexts. I focus on the performance of a particular kind of whole network in the healthcare industry, known as Accountable Care Organizations (ACOs).

As previously described in Chapter 2, provisions of the 2010 Affordable Care Act gave rise to the Medicare Shared Savings Program ACOs, a large-scale effort to address fragmentation within the healthcare system. In this empirical application, I conceptualize each ACO as a network of healthcare organizations. Thus, I focus on the whole network performance of ACOs as it pertains to their primary objective: to reduce healthcare expenditures for a specific population of Medicare beneficiaries.

3.4 Hypotheses

Before moving forward, I first lay some additional theoretical groundwork to connect the whole network morphology framework to my empirical context.

3.4.1 Whole Network Morphology and ACO Performance

First, my theorizing requires that I link whole network morphology to outcomes. ACOs are "goal-directed" whole networks (Provan & Kenis, 2008) in which performance is dependent on collaboration. Therefore, I connect ACOs whole network morphology to performance by building on Gulati and colleagues' (2012: 533) insights on the "two indispensable facets of inter-organizational collaboration": *coordination* and *cooperation*. Although I do not explicitly differentiate between cooperation and coordination in my empirical models, I suggest that Gulati and colleagues' framework is a useful organizing device for hypothesis development.

Coordination is defined as the collective pursuit of a group-level goal through the synchronization and alignment of collaborating organizations' work and activities. Under this view, coordination is behavioral or operational in nature, centered on implementation. Accordingly, coordination manifests in good communication, operational efficiency, effectiveness in accomplishing work, and adaptability.

Cooperation is defined as the collective pursuit of a group-level goal based on a jointly agreed upon set of expectations pertaining to members' anticipated level of commitment, responsibilities, risks and rewards. Under this view, cooperation is sociocultural in nature, and centers on generating "buy-in" or shared perspective among the parties to a collaboration (Okhuysen & Bechky, 2009). Accordingly, cooperation manifests in greater stability and satisfaction among parties regarding their partnership and its terms.

Second, although the structural dimension of whole network morphology can be characterized according to many properties, I focus on *connectedness*—defined as the extent to which members of a whole network are mutually reachable through direct or indirect relationships (Lazer & Friedman, 2007). As discussed previously, connectedness has received substantial attention in prior research on whole networks (Kearns et al., 2006; McCubbins et al., 2009; Fang et al., 2010; Mason & Watts, 2012; Shore et al., 2015; Derex & Boyd, 2016).

Finally, I need to unpack the relationship between whole network connectedness and performance in my setting. Starting with coordination, connectedness may be beneficial in ACOs. As connectedness increases, whole network members become more proximate via direct and indirect relationships. Consequently, with greater connectedness, information (e.g., about patients) likely flows more quickly and accurately (Lazer & Friedman, 2007; Mason & Watts, 2012). Because synchronization and alignment of work around patients requires information sharing, connectedness may therefore facilitate coordination and consequently ACO outcomes.

However, consistent with my arguments on the ambiguity of structure, connectedness may also hinder coordination. The greater information sharing that accompanies connectedness likely places heavier demands on network members for information processing (Lazer & Friedman, 2007; Funk, 2014). An ACO in which twenty different primary care practices share patients with ten specialty groups will face more challenging information flows than an ACO in which the same number of practices share a similar number of patients with two. Similarly, previous work finds that connectedness is associated with greater demands to honor requests and favors (Portes & Sensenbrenner, 1993). These considerations suggest that by limiting coordination, structural connectedness may be associated with worse ACO performance.

Turning next to cooperation, the relationship between structural connectedness and ACO outcomes remains unclear. Like coordination, cooperation may benefit from connectedness. Research on social influence, for example, observes that in networks with greater connectedness, actors tend to have more homogeneous behavior and views (Granovetter, 1973; Burt, 1992). Therefore, greater connectedness may be associated with shared perspective, which should facilitate cooperation and therefore ACO outcomes.

However, connectedness may also hinder cooperation. As connectedness among ACO members increases, so does relational complexity. Connectedness may promote shared perspective, but with greater connectedness, remaining differences among whole network members are likely more visible, and efforts to address these differences likely require input from more parties. Similarly, connectedness is also likely to minimize the ability for mediators to find common ground (Simmel, 1950). Together then, these considerations suggest that increasing connectedness may be associated with lower cooperation, thereby hindering performance.

3.4.2 Structural Dimension × Relational Dimension

In this section, I consider how the relational dimension of whole network morphology may moderate the structure-performance association in ACOs. Like the structural dimension, the relational dimension encompasses multiple whole network properties. Below, I focus on relational *strength*, understood as the overall frequency of interactions within a network (Reagans et al., 2005), which has been important in health care research (Everson et al., 2017).

Coordination. I begin with coordination. Following my previous arguments, connectedness is likely to benefit coordination through better information flow, but with greater connectedness, whole network members may also face heavier information processing demands. Prior work finds that relational strength is associated with mutual learning and better knowledge transfer (Uzzi, 1997; Hansen, 1999; Zollo et al., 2002; Levin & Cross, 2004; Reagans et al., 2005). As relational strength increases then, the information processing demands associated with connectedness are likely to lessen, thereby improving coordination. Put differently, the harmful aspects of connectedness may be mitigated by relational strength. Further, there is little reason to expect that relational strength will hinder the information flow benefits of connectedness. Thus, from a coordination standpoint, relational strength will likely positively moderate the association between a connected whole network structure and performance.

Now consider relational strength and coordination when connectedness is *decreasing*. Unlike when connectedness is increasing, relational strength does not offer a clear mechanism for mitigating the challenges of decreasing connectedness. Relational strength cannot increase information sharing across relationships that do not exist; therefore it is unlikely to attenuate the depressed information flows associated with lower connectedness. Relational strength may help information processing; however, with decreasing connectedness, processing demands are likely lower. Thus, focusing on coordination, there are few reasons to anticipate that relational strength will be associated with better or worse performance as connectedness decreases.

Cooperation. I turn next to cooperation. Recall that structural connectedness may benefit cooperation by facilitating shared perspective; however, as connectedness increases, so does relational complexity. Considering this trade-off, relational strength may tip the scales towards better cooperation by mitigating this latter, challenging aspect of connectedness. Prior work suggests that relational strength will likely make it easier to resolve or prevent conflicts, specifically because with greater relational strength, partners have deeper knowledge of their counterparts and their interests (Tortoriello et al., 2011). For similar reasons, relational strength should also work primarily to further the development of a shared perspective.

As with coordination, relational strength is helpful for understanding the conflicting implications of *decreasing* connectedness for cooperation. Following my previous discussion, decreasing connectedness will likely be a hindrance to shared perspective, and greater relational strength is likely to exacerbate this challenge. Because whole network members are at a greater average distance from one another as connectedness decreases, relational strength seems likely push network members towards more parochial orientations, with a heightened focus on those with whom they have strong relationships, rather than the whole network (Lau & Murnighan, 1998; Heidl et al., 2014; Hollingsworth et al., 2015a; Ghomrawi et al., 2018). Consequently, instead of shared perspective, as connectedness decreases, relational strength seems likely to facilitate the emergence of heterogeneous views, thereby inhibiting cooperation. At the same time, when connectedness is decreasing, I also anticipate fewer benefits of relational strength for mitigating the relational complexity associated with connectedness.

In sum, relational strength likely attenuates the information processing demands and relational complexity associated with connectedness, while accentuating the challenges of shared perspective that likely emerge as connectedness decreases. Thus, I propose a first hypothesis.

> ***Hypothesis 1 (H1):*** *As structural connectedness (disconnectedness) increases, greater strength in the relational dimension of whole network morphology will be associated with better (worse) ACO cost performance.*

3.4.3 Structural Dimension × Cultural Dimension

Turning to the cultural dimension, I first describe a common culture in health care that emphasizes physician autonomy. Subsequently, I consider how the presence of this cultural orientation in ACOs may alter the whole network structure-performance relationship.

In the United States, the medical profession has historically exercised great power over health care delivery (Starr, 2008; Stevens, 1998); consequently, the culture of health care delivery has tended to reflect physician values. Among those values, perhaps none has been as important as autonomy (Freidson, 1988), what Pont (2000: 99) has called, “the highest ethic of the medical profession.” Professional autonomy refers to the ability for an individual to practice his or her work according to his or her discretion. For physicians, autonomy manifests in freedom over patient therapies, whether and when to refer patients for consultations, and with respect to organizing and managing patient records. Underscoring this culture of physician autonomy, in the United States, decisions made by physicians are often treated with deference, particularly relative to other professionals (e.g., nurse practitioners, physician’s assistants). Similarly, although physicians are the most powerful professional figures in hospitals, in many health systems, they are not hospital employees, but rather independent contractors, with admitting privileges at multiple institutions (Scott et al., 2000).

Cultures of health care delivery are not, however, universally oriented towards physicians. Historical (Stevens, 1998) and sociological (Freidson, 1994; Ritzer and Walczak, 1988; Starr, 2008) accounts have documented a decline in physician autonomy over time. Reinforcing this trend, health care reform advocates have become vocal in pushing away from the physician-centric model (e.g., Rickert, 2012; Okie, 2012). Many observers note that organizational values (e.g., efficiency, financial performance) have become prevalent, a trend attributed to the corporatization of medicine (Starr, 2008). The growth of professional groups like nurses and pharmacists has also been accompanied by an emerging cultural orientation towards interprofessional collaboration (Horn & Jacobi, 2006). Finally, with growing concerns about cost and quality in the United States, population health and patient-centered care have become important culture orientations (Berwick et al., 2008). Today, health care delivery encompasses a multiplicity of cultural orientations, alongside those that emphasize physician autonomy.

Research suggests that different cultural orientations are likely to have implications for physician behavior. These implications become apparent when examining the tensions between different orientations. Consider the traditional physician orientation alongside more the recent orientation towards organizational values. In part due to the proliferation of expensive drugs and treatments, physicians are almost always restricted in what they may offer patients, either due to insurance or organizational controls. For example, although surgeons may have preferences regarding the products they use intraoperatively or the brands of implants they offer patients, hospitals' cost containment measures (e.g., efforts to achieve economies of scale in negotiations with distributors) often limit choices with respect to these preferences.

The culture that emerges within each ACO network may be influenced by a number of internal and external factors. As Blau (1960; 1964) suggests, group culture may emerge from within both from the characteristics of members but may also reflect the value systems or policies that they establish, such as in an organizational setting. Alternatively, group culture may also reflect some of the prevalent norms or beliefs of the environment(s) that the network is embedded within (Vasudeva et al., 2013). Regardless of the origins, however, the more important matter is that whole networks may vary in their cultural dimensions and this may, in turn, influence how each ACO defines itself and its mission. Although I reserve more extensive discussion for my methods section, I argue that markers reflecting an ACO's cultural orientation may be visible in the names that ACOs give themselves. For example, ACOs like the "Lahey Clinical Performance Accountable Care Organization" and "Cedars-Sinai Accountable Care" are clearly centered around large medical centers—the Lahey Clinic and Cedars-Sinai Medical Center, respectively. Other ACOs, like the "Independent Physicians' ACO of Chicago" unambiguously aligned their identities with the central role of physicians. Paralleling my hypothesis development on relational strength, I argue below that the presence of a physician cultural orientation may differentially accentuate or attenuate the competing implications of connectedness for ACO outcomes.

Coordination. From a coordination standpoint, a physician cultural orientation may ameliorate some information processing demands of connectedness. With its emphasis on autonomy, this cultural orientation is likely to afford whole network members greater discretion in attending to information from the network, thereby allowing them to focus on what is most important. For similar reasons, a physician orientation may help whole network members feel more comfortable declining favors and requests, which tend to increase with connectedness (Portes & Sensenbrenner, 1993). As connectedness *decreases*, by contrast, the implications of a physician cultural orientation appear less beneficial. Most significantly, a cultural emphasis on autonomy does not present a clear mechanism for overcoming the principal coordination challenge—slower and less accurate information flow—of decreasing connectedness.

Cooperation. I previously suggested that connectedness may benefit cooperation by facilitating shared perspective; however, as connectedness increases, so does relational complexity. With respect to shared perspective, the implications of a physician cultural orientation are somewhat unclear. Although, a cultural emphasis on autonomy may limit shared perspective, autonomy and shared perspective are not inherently opposed (Tocqueville, 2000). Thus, with an alternative basis—like increasing connectedness—shared-perspective emergence may occur even in ACOs with a physician cultural orientation. Turning to relational complexity, the benefits of a physician orientation are clearer. An emphasis on autonomy seems likely to impart greater respect among whole network members for differences in views and practices (Kelly & Kelly, 1994; Tocqueville, 2000), thereby potentially mitigating conflict and improving coordination, as connectedness increases.

When a whole network structure becomes *less* connected, however, a physician cultural orientation may have negative implications for the structure-performance relationship. Lower connectedness likely makes shared perspective emergence more challenging, because network members hold on to their diverse opinions, views, and information rather than being able to reconcile them through connectedness. A physician cultural orientation, with its emphasis on autonomy, seems likely to exacerbate this challenge because the autonomy orientation further encourages physicians to behave independently. Thus, paralleling my arguments on relational strength, a physician cultural orientation in a whole network with decreasing connectedness seems likely to promote heterogeneous views and actions among whole network members, thereby diminishing cooperation.

In sum, a physician orientation likely attenuates the information processing demands and relational complexity associated with connectedness, while accentuating the challenges of decreasing connectedness for shared perspective. Thus, I propose a second hypothesis.

> ***Hypothesis 2 (H2):*** *As structural connectedness (disconnectedness) increases, the presence of a physician cultural orientation in the cultural dimension of whole network morphology will be associated with better (worse) ACO cost performance.*

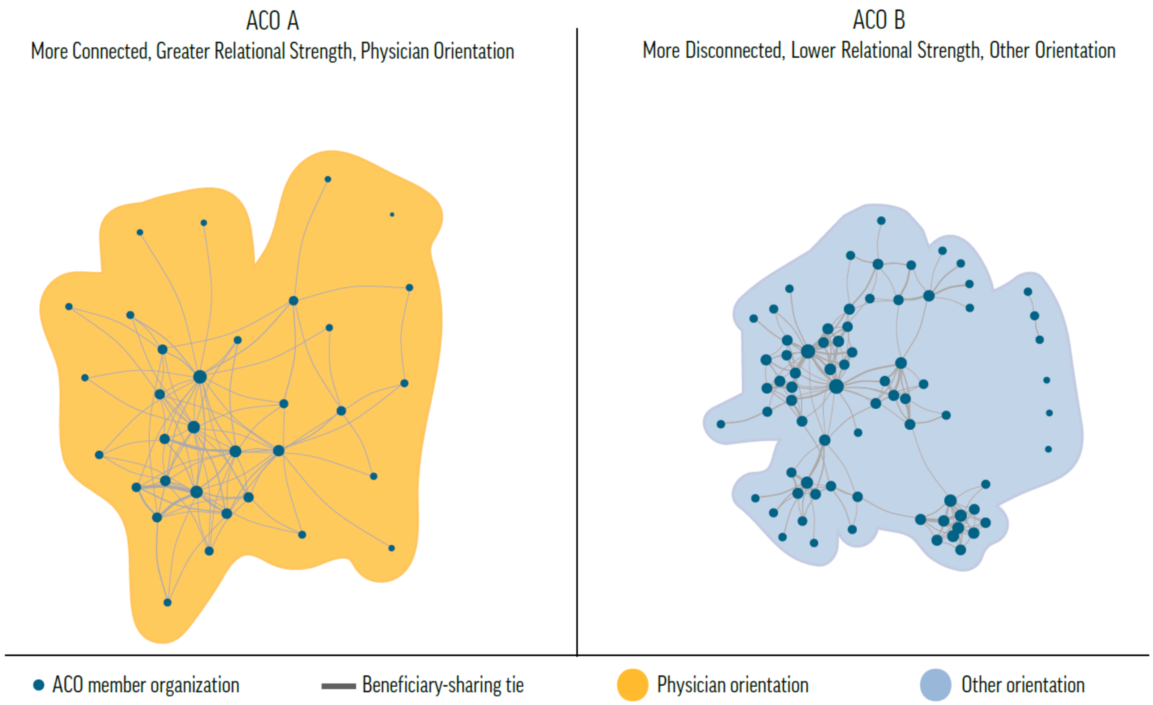


Figure 3.4: Illustration of whole network dimensions for two ACOs. Pictured are two ACOs, exhibiting different degrees of structural disconnectedness and relational strength, and different cultural orientations. Node size reflects relative prominence of the organization in the network based on the number of connections to other network members, line thickness reflects relational strength. ACO A, which was coded as having a physician cultural orientation, is more structurally connected and has greater relational strength than ACO B, which did not have a physician orientation.

Figure 3.1 illustrates the hypotheses by visualizing the whole network morphology of two ACOs. These ACOs are similar in some respects. For example, both are relatively large, with ACO A comprising 41 organizations and ACO B 75 (the mean is 26). Both are also based in large metropolitan areas with a geographic range that spans neighboring states. However, morphologically, ACOs A and B are radically different. ACO A has greater connectedness than ACO B, which has multiple sparsely connected clusters and several isolates. Relative to ACO B, ACO A also has greater relational strength, as evidence by a greater number of thicker ties. Finally, differences in cultural orientation are shown using the yellow and blue backgrounds for the presence and absence of a physician orientation in ACO A and ACO B, respectively. By representing each cultural orientation as a background context, I illustrate that the cultural dimension of whole network morphology affects all nodes and relationships.

3.4 Data and Methods

The first MSSP ACOs began on April 1, 2012, with additional starts on July 1, 2012 and January 1, 2013. Subsequently, new ACOs joined the program on the first of each year. I focus on the 392 ACOs founded between April 2012 and January 2015 and track their performance—measured by CMS on an annual basis—from 2013, the first performance year, through 2016, the last year available at the time of data collection. After excluding observations from Puerto Rico and cases with missing data, my final sample includes 250 ACOs for which I have at least two years of complete records.

3.4.1. Mapping Whole Network Structure in Healthcare

Beneficiary sharing relationships: Conceptual and contextual background. My analysis focuses on the whole network structure-performance relationship in ACOs. To examine this association, I first need to identify and measure relevant relationships (i.e., ties) among ACOs' organizational members. My theoretical development suggests that these relationships should meet several requirements. First, they should be consistent in nature so that whole network properties can be interpreted similarly for all ACOs in my sample. Second, they should be closely linked to shared work (requiring coordination and cooperation) among ACO member organizations. Third, considering my focus on whole network performance, shared work should represent activities that can be theoretically linked to an important collective outcome. Since my primary endpoint is the ability of ACOs to reduce healthcare spending, the relationships should be conceptually relevant for understanding costs.

Beneficiary-sharing relationships meet these requirements and have additional characteristics that make them attractive.[22] Beneficiary-sharing relationships have been used

[22] "Beneficiary" refers to patients who are covered under a particular insurance plan, such as Medicare.

extensively in health services research as a proxy for physician-to-physician interactions (Barnett et al., 2011; Landon et al., 2012; 2013; Hollingsworth et al., 2015b). Beneficiary sharing occurs when healthcare providers treat and subsequently file an insurance claim for the same patient. Unsurprisingly, one of the most common reasons for beneficiary-sharing is patient referral (i.e., when a physician instructs the patient to consult another doctor, usually of a different specialty). However, beneficiary-sharing is also initiated by patients (i.e., when an individual, perhaps with complex medical issues, seeks care from multiple providers) (Bourgeois et al., 2010). In both instances, care requirements generally demand that patients' medical records be communicated from one provider to the next (e.g., Vogus et al., 2010). Due to these communication needs, beneficiary-sharing ties often coincide with professional relationships among physicians. Primary care medicine offers a useful illustration of how beneficiary-sharing relationships form. Primary care providers (PCPs) are typically the first point of contact between a patient and the healthcare system (Friedberg et al., 2010). When a beneficiary has complex needs, a PCP may refer her to a specialist physician for treatment (Wagner et al., 1996). The beneficiary may then follow up with the referring PCP. As this process repeats with additional beneficiaries, the PCP and specialist are likely to develop a deeper professional relationship.

Beneficiary-sharing relationships also form when a patient is transferred from one organization to another. Hospitals vary in their capabilities. For complex cases, beneficiaries may be directed to facilities with more experience (Iwashyna et al., 2012). For instance, a cancer patient may see an oncologist at a community hospital and a cancer psychiatrist at a cancer center. Transfers also occur without patient agency, particularly in emergency situations.

Beyond their conceptual attractiveness, beneficiary-sharing relationships are valuable for data considerations. For administrative purposes, the provision of health care services creates robust records of patient-physician and patient-organization interactions (Barnett et al., 2011). In order for a physician or organization to be paid for services, a claim for reimbursement must be submitted to the patient's insurance company (Beck & Margolin, 2010). As these claims are submitted and processed, they create administrative "breadcrumbs" that trace a beneficiary's journey among providers. Moreover, because reimbursements are on the line—i.e., because providers can only be paid if they submit a claim—these data represent a very complete record of work that is done for Medicare beneficiaries, which represent some 98 percent of all Americans over age 65 and 99 percent of all deaths within that age group (Funk et al., 2017).

Using multiple methods and approaches, studies have validated the use of beneficiary-sharing relationships as proxies for physician networks. Most convincingly, research has shown that shared beneficiaries correlate with physicians' self-reported professional relationships. Barnett and colleagues (2011) surveyed 616 physicians about their referral and advice-seeking relationships with other geographically proximate physicians. The authors compared these survey results to patterns of shared beneficiaries observed in Medicare claims. They found that if the threshold for recording a tie based on Medicare claims was set to nine or more common beneficiaries (over a year), there was an 82 percent overlap with ties found using surveys.

Another study (Landon et al., 2013) used network community-detection algorithms on beneficiary-sharing patterns to inductively determine meaningful groups of physicians serving 4.5 million Medicare beneficiaries. The authors found that this approach—a purely network analytic method—mapped more meaningfully onto patient care patterns than groups based on the hospital to which each physician made the most referrals. Thus, defining regional healthcare systems as the constellation of physicians around hospitals was less predictive of actual patterns of patient-physician visits than clusters that emerged from more complex beneficiary-sharing networks (i.e., that included direct and indirect relationships). Such research provides strong support that beneficiary-sharing ties are a good proxy for physician relationships.

Finally, studies have helped to validate the use of beneficiary-sharing relationships as proxies by examining cost and quality outcomes, finding strong associations between network properties and important endpoints in areas where social factors would be expected to matter, but not where more technical or infrastructural factors would likely predominate (Funk et al., 2017).

Beneficiary sharing relationships: Data and measurement. To map whole beneficiary-sharing networks among ACO member organizations, I began with physician-level data derived from Medicare claims, made publicly available through a Freedom of Information Act request.[23] These data record the number of shared beneficiaries between all pairs of Medicare physicians, identified by unique National Provider Identifier (NPI) numbers. Physician pairs enter the data if, within a 60-day window, both physicians bill for services provided to the same Medicare beneficiary. Due to privacy regulations, dyads are only reported for providers who shared at least 11 beneficiaries over a calendar year. For my study, however, this restriction is fortuitous, because as described above, previous research has found that physician dyads with fewer shared beneficiaries less likely reflect meaningful relationships (Barnett et al., 2011).

For each year in my study window, the full network data capture more than 70 million unique beneficiary-sharing relationships. From this universe of ties, I use Medicare Research Identifiable Files (RIFs)—obtained through special request to CMS—to isolate participating physicians and organizations in each ACO, in each year of the MSSP program.[24] These files provide participant information for ACOs, including the organizations, identified by tax identification numbers (TINs), and the associated physicians, identified by NPI numbers. Physicians are listed individually and nested within the organizational TINs, which, according to the initial ACO rules, can only be assigned to one ACO.[25] I use this nested association between NPIs and TINs to assign providers to organizations. Using physicians' organizational affiliations

[23] CMS provides more detailed information on the beneficiary-sharing (referral) data (accessed Feb 28, 2018): https://questions.cms.gov/faq.php?faqId=7977.
[24] The key files for this step are the Medicare Shared Savings Program ACO Provider RIFs, 2012-2015.
[25] According to the November 15, 2017 Federal Register (https://www.gpo.gov/fdsys/pkg/FR-2017-11-15/pdf/2017-23953.pdf), however, it appears that overlap in TINs across ACOs may be increasingly common and CMS intends to make accommodations to try to account for these.

within ACOs, I then aggregate physician-level ties to the interorganizational level using a three-year window. For example, networks for 2013 are constructed using data from 2011-2013. My use of a rolling window is consistent with prior research on interorganizational networks (e.g., Gulati et al., 2012). More importantly, my rolling window approach aligns with CMS' methodology for assigning patients to ACOs and determining ACO benchmarks, which are based costs incurred for patients treated by ACO members during the prior three years (CMS, 2017).

Although there is generally 1:1:1 assignment between physicians, organizations, and ACOs, respectively, I found that approximately 5% of physicians were associated with more than one ACO, and approximately 17% of physicians were associated with more than one TIN in the 2012-2015 Provider RIFs. I attributed these overlapping physicians to the first organization and/or ACO with which they were affiliated in the Provider RIF (randomly sorted).

Additionally, each year approximately 11% of the TINs (from 670 in 2012, to 2,577 in 2015) were not associated with any physicians. Investigating these TINs, I found that many represented legal businesses for individual physicians that were associated with other ACO member organizations. Others included other healthcare organizations, such as diagnostic labs or home care organizations, which would not be expected to have patient sharing ties. There were also several TINs that were not identifiable based on the legal business name of the entity.

Finally, a small number (~2%) of such TINs were associated with hospitals or clinics. The lack of associated NPIs may indicate that these organizations, or some part of them, were participating in a similar capacity to non-referring organizations (e.g., ancillary services, non-billable capabilities) that would not require specific physician NPIs to be listed. Since the network data that I use requires NPI-to-NPI interactions, such organizations represented by "NPI-less" TINs cannot be included in the ACO beneficiary-sharing networks. Consequently, I control for their presence in the analyses by including a variable for disconnected organizations.

My final sample of 250 ACOs comprises approximately 250,000 physicians working in

44,231 organizations.

3.4.2 Dependent Variable

Cost performance. My outcome is the extent to which an ACO achieves cost savings relative to the benchmark set by CMS. I compute this variable by calculating the ratio of total savings (or losses) to the benchmark, multiplied by 100, for each ACO × year observation. Because losses (expenditures exceeding the benchmark) are also captured, the outcome variable can be negative. My outcome is the *same measure CMS uses to evaluate ACO performance* and therefore is the exact performance metric that ACOs are financially incentivized to maximize. If ACOs fail to save at least 3% of their benchmark, they receive no incentive payment (shared savings) *regardless of their quality*. Therefore, while quality is important—indeed, incentive payments may be reduced for low quality—it is not the primary ACO performance metric. Following related work, I measure performance at t+1; other variables are measured at t (Reagans et al., 2005).

3.4.3. Independent Variables

Structural disconnectedness (S^D). To evaluate whole network structure-performance relationship in ACOs, I operationalize the structural dimension of whole network morphology as structural connectedness. In reviewing the literature, I found that relative to other whole network properties (e.g. centralization) there is less consensus among scholars on how to best quantitatively evaluate connectedness, with most prior work relying heavily on context to guide measurement choice (Lazer & Freidman, 2007; Mason & Watts, 2012; Fang et al., 2010; Shore et al., 2015; Derex & Boyd, 2016). For my study, I capture structural connectedness using a measure developed by Borgatti (2006) to quantify *fragmentation* in whole network structures. Thus, my empirical proxy for whole network structure is properly understood as a measure of *disconnectedness*, such that lower values correspond to more connected networks. Given my purposes, this measure, which I refer to as S^D, is especially attractive because it integrates, into a single summary index, several different aspects of whole network connectedness, including the number of components (i.e., sets of nodes that are mutually reachable through direct or indirect ties) within the network, the relative size of each component, and the relative connectivity (i.e., path length) within each component. Formally, S^D is defined as

$$S^D = 1 - \frac{2\sum_{i>j}\frac{1}{d_{ij}}}{n(n-1)}$$

where $\frac{1}{d_{ij}}$ represents the connectivity between pairs of nodes based on shortest paths. S^D ranges from 0 to 1; the measure takes on a maximum of 1 when the whole network structure consists of only isolates and a minimum value of 0 when the network is completely interconnected.

Relational strength (R^S). The relational dimension of whole network morphology may alter the association between whole network structure and performance. Within the ACO context, I used my morphology framework to predict that greater strength in the relational dimension will be associated with worse performance as structural connectedness increases (Hypothesis 1). To evaluate this prediction, I operationalize relational strength as the average number of shared beneficiaries in each ACO (Berman et al., 2002).[26] Formally,

$$R^S = \frac{\sum_e w_e}{n_c},$$

where w_e is the weight (i.e., shared beneficiaries) of edge e in the network and n_c is the number of connected (non-isolate) nodes. To facilitate interpretation, I divide this value by 10,000.

Cultural orientation (C^O). Finally, the framework I propose suggests that the structure-performance relationship may be altered by the cultural dimension of whole network morphology. In ACOs, I predicted that this relationship differ systematically depending on the presence or absence of a physician cultural orientation (Hypothesis 2). Investigating this

[26] Reagans and colleagues (2005) define an alternative measure that adjusts for *possible* ties. Although attractive, this adjustment is inappropriate for my study because it would introduce structure into the measure of relational strength.

hypothesis poses an empirical challenge—although prior work has discussed a role for cultural orientation in whole networks (Provan & Milward, 1995; Nahopiet & Ghoshal, 1998; Owen-Smith & Powell, 2007), and specifically within ACOs (e.g., Kreindler et al., 2014), no definitive taxonomy of cultural markers has been established.

To address this challenge, I turned to research on organizational culture and identity. While culture and identity are not equivalent constructs, previous literature has shown a strong link between the two (e.g., Hatch & Schultz, 2002), typically viewing identity as a manifestation of culture, "to which individuals can commit their emotions and energies" (Pettigrew, 1979: 578). Borrowing from anthropology, organizational scholars have also noted that organizations create cultural symbols that "evoke emotions and impel men to action" (Cohen, 1974: 23).

Names are a particularly salient symbols of organizational identity construction that provide a window into culture and have "significant functional consequences" (Pettigrew, 1979: 574). Scholars have theorized that organization names "encode central features of meaning and organizational identity" (Glynn & Abzug, 2002: 267). Researchers also note that the creation of a name is one of the first things that confers meaning and a collective sense of existence to individuals, organizations, or even social movements (Cerulo, 1997). For example, the name chosen by the founders of an organization not only makes a fledging collective something "real," but also help communicate cultural values to members. To the extent that names help communicate organizational values, they are likely an important conduit through which individuals relate to an organization as it grows. This identification is a key part of socialization and is thought to be necessary for communication among members, who may otherwise have little in common as a basis for interaction (Kogut & Zander, 1996).

Empirically, I observe wide variation in ACO names, which implies heterogeneity in cultural orientations. Some names reflect little identity building work, particularly those consisting of administrative sounding acronyms, such as "AzPCP-ACO, a Medical Corporation" or “APCN-ACO, a Medical Professional Corporation.” Other ACOs clearly derive their name from and thus identify with a large, central member, like the previously mentioned “Lahey Clinical Performance ACO” or “Cedars-Sinai Accountable Care.” Such ACOs also exhibit other traits that suggest a clear organizational anchoring (e.g., their websites are a subsidiary page of the central organization, rather than a unique domain).

Many ACO names, however, show greater distinctiveness, often through language that relates to values, like the central role of physicians or primary care. For example, “Georgia Physicians for Accountable Care” evokes a sense that this is a group of physicians who support the aim of providing accountable care for their patients. Consistent with this interpretation, the ACO describes, on the landing page of its website (which has an independent domain name), that “[its] goal is to make a fundamental change in the way healthcare is delivered through ensuring high quality and effective care while enhancing the patient experience” (www.gpaco.org, 2019). The name “Independent Physicians’ ACO of Chicago” evokes similar values. The website additionally highlights that the ACO is “100% physician owned…formed entirely by practicing physicians” and “aims to increase the quality of care while reducing overall health expenditures for patients” (www.aco-chicago.com, 2019).

Further supporting my contention that ACO names are consequential, I noticed that during my study window, several ACOs changed their names. For example, one ACO was called the “Accountable Care Network of New Jersey” from 2013-2014, but changed its name to “Advocare Well Network” in 2015. Similarly, “Baptist Integrated Physician Partners” network was originally called “BHS Accountable Care” and briefly changed to “South Texas Care Connect” before settling on its current name. While CMS requires that every ACO has a name, it does not dictate any naming requirements (e.g., needing to contain terms like “accountable care”). Thus, changes to ACO names are likely being driven internally, presumably in the service of crafting or revising a group identity, both for their members and their patients. Consequently, I argue that the name selected by each ACO is a reasonable indicator of its cultural dimension.

My primary method for analyzing ACO names was to hand-code their constituent terms. Guided by my theoretical development, I focused my coding on determining whether a given name was indicative of a physician cultural orientation. I began by cleaning and standardizing the names (based on MSSP ACO Participant files) of all ACOs that were active between 2012-2016. I removed punctuation, collapsed common terms (e.g., state names) into standard abbreviations, and stemmed words using Porter's (1980) algorithm. For example, "collaborative," "collaboratives," and "collaboration" are all converted to "collabor." Then, two of the authors individually categorized whether each of the resulting 697 unique terms evoked the image of physicians or the central role of physicians in patient care. The third author resolved any discrepancies between the two initial coders. Key terms included "physician," "doctor," "md," "med," "clinic," "practice," and "primary." Finally, for each ACO, I counted the number of physician-oriented terms to determine the cultural orientation. The terms "physician," "doctor," and "md" were considered to unambiguously indicate a physician cultural orientation, whereas the others were weighted against the presence of other culturally distinctive terms. Using this methodology, I created a variable for the cultural orientation of each ACO, C^O, where $C^O=1$ if the ACO has a physician cultural orientation.[27]

3.4.4 Control Variables

I adjust my regression models for several covariates, particularly those that may influence both *Cost performance* and the whole network dimensions.

Patient and provider characteristics. I control for the *Total providers* in each ACO,[28] which includes PCPs, specialist physicians, nurse practitioners (NPs), clinical nurse specialists (CNSs), and physician assistants (PAs). Primary care physicians are often seen as critical for care

[27] Additional methodological notes are in Appendix A. Coded names are available on request.
[28] In a prior draft, I controlled for each provider group separately, but these breakdowns did not contribute any explanatory power to my models and produced substantively similar results.

coordination. Specialists generally provide a higher level of care than PCPs, and therefore are more expensive. NPs, CNSs, and PAs perform primary and specialty care roles and therefore contribute to ACO capacity. I also control for the *Total beneficiaries* assigned to each ACO.

Finally, I account for the demographic composition of ACO beneficiaries by including variables for *% Female beneficiaries*, % *Black & Hispanic beneficiaries*, % *Elderly beneficiaries (age 85+), % Disabled beneficiaries,* and *% End-stage renal disease (ESRD) beneficiaries*. Each of these categories represents a patient subpopulation that has previously been associated with increased spending (Lassman et al., 2014) or more complex health and socioeconomic statuses (Kaiser Family Foundation, 2016). The latter two, % *Disabled beneficiaries* and % *ESRD beneficiaries*, also reflect individuals who qualify for Medicare based on factors other than age and that therefore may differ from the typical Medicare beneficiary (Cubanski et al., 2016).

General ACO characteristics. I adjust for characteristics of ACOs that are not directly related to patients or physicians. First, to differentiate ACOs that were provided with up-front financial support from CMS to jump-start their transformation efforts, I include a dummy variable, *ACO Advance Payment*, set to 1 in years where an ACO received such support. Next, I control for each ACO's *Quality score*, measured at $t+1$. CMS reports a composite quality score (out of 100) for ACOs based on 33 metrics, covering patient/caregiver experience, care coordination/patient safety, preventative health, and factors related to at-risk populations, such as diabetes and heart disease (CMS, 2017). Quality is an important control because it helps account for latent variation in organizational capabilities (e.g., leadership, resources). I also include an indicator for *ACO spans noncontiguous states*. While relatively uncommon, the morphology of ACOs with noncontiguous service areas may manifest differently due to greater geographic distance or different strategies for achieving *Cost performance*.

In addition to these factors, I also adjust for whole network characteristics of ACOs. First, I control for *Network size*, defined as the number of member organizations that comprise each ACO. Next, I control for *Network isolates*, defined as the number of organizations in each ACO with no interorganizational ties. Physicians in these organizations share beneficiaries internally, but not with physicians in *other* organizations. Isolates are likely to be associated with both the whole network dimensions and *Cost performance* (e.g., potentially due to the slower diffusion of practices). Additionally, I include a control for *% Non-referring* to account for differences in the proportion of nodes within each ACO that share or do not share beneficiaries with other member organizations. The numerator of this variable includes self-referring *Network isolates* but also adds organizations that are not associated with *any* beneficiary sharing activity at all. These latter organizations account for a minority of ACO members (N=1,598; 11% in 2014); I describe these organizations in the Supplementary Appendix. Finally, I also control for *Network turnover* in each ACO, which reflects changes in organizational membership and may influence both whole network morphology (e.g., through the addition or removal of ties) and whole network performance (e.g., due to new benchmarks, different patients).

3.4.5 Model Estimation

My dependent variable is continuous with an approximately normal distribution (Figure S1) and I have annual observations for each ACO. Therefore, I model ACO *Cost performance* using fixed-effects linear regressions, of the form

$$y_{it+1} = \mu_t + x_{it}{\cdot}\beta + c_i + \epsilon_{it},\ i = 1, ..., \mathrm{N}, \mathrm{t} = 1, 2, 3.$$

These models assume that the performance of ACO i at time t+1 is a function of four components. First, μ_t, captures time-varying factors that affect all ACOs equally. Second x_{it} captures time-varying factors that differ for each ACO, including the independent variables, interactions, and controls. Third, c_i captures all unobserved time *invariant* heterogeneity among ACOs. Finally, ϵ_{it} is an idiosyncratic, time-varying error term for each ACO-year.

As is common when interaction terms are included, the variance inflation factors (VIFs) are increased for some variables, particularly *Relational strength* variable (VIF = 20.77) and its interaction with *Structural disconnectedness* (VIF = 18.35). The remaining VIFs are well under 10, with a mean VIF of 5.41

3.5 Results

Table 3.2 provides descriptive statistics and correlations for the all variables. There are 736 whole network × year observations in my sample, comprising 250 ACOs.

3.5.1 Fixed-effects Regression Results

Table 3.3 displays the fixed-effects regression results of *Cost performance* on *Structural disconnectedness* and the interactions of *Structural disconnectedness* with *Relational strength* and *Cultural orientation*. Robust standard errors are in parentheses. Independent variables (with the exception of *Cultural orientation*) are mean-centered. Model 1 includes only control variables. Model 2 includes just the key independent variables for the structural, relational, and cultural dimensions of whole network morphology. Model 3 adds the control variables. Model 4 introduces the first interaction term between *Structural disconnectedness* and *Relational strength*. Model 5 presents results for the interaction between the *Cultural orientation* variable and structure. Model 6 shows only the key independent variables and interactions. Finally, Model 7 presents the full model, to which I will primarily refer in my discussion of the results.

Whole network structure and performance. Before turning to my hypotheses, I consider the relationship between whole network structure and performance. Recall that in my theory development, I drew on findings from prior work to observe that *Structural disconnectedness* may be either positively or negatively associated with *Cost performance*. These observations led me to theorize that understanding the relationship between whole network structure and performance requires concomitantly attending to other network dimensions. Consistent with this view, I do not find robust evidence of an association between *Structural disconnectedness* and *Cost performance* (Table 3.3, Model 7: $\beta = -0.31$, p=0.918).

Table 3.2: Descriptive Statistics and Pairwise Correlations

Variable	N	Mean	S.D.	1	2	3	4	5	6	7
1. Cost performance	736	1.17	5.89							
2. Structural disconnectedness	736	-0.01	0.27	0.18*						
3. Relational strength	736	0.71	23.87	-0.14*	-0.40*					
4. Cultural orientation (1=Physician)	736	0.10	0.29	0.06	0.15*	-0.10*				
5. Total providers	736	563.24	753.32	-0.13*	-0.21*	0.31*	0.03			
6. Total beneficiaries	736	1.71	1.7	-0.08*	-0.07*	0.21*	0.07	0.73*		
7. % Female beneficiaries	736	0.48	0.17	0.01	0.06	-0.04	-0.01	-0.01	0.17*	
8. % Black & Hispanic beneficiaries	736	0.39	0.49	0.05	-0.02	0.02	-0.00	0.00	-0.20*	-0.94*
9. % Beneficiaries aged 85+	736	0.19	0.12	0.02	-0.04	0.02	0.02	-0.04	-0.17*	-0.92*
10. % Disabled beneficiaries	736	0.11	0.08	-0.01	0.08*	-0.04	-0.06	0.04	0.02	0.64*
11. % Beneficiaries with ESRD	736	0.34	0.59	0.01	-0.05	0.03	0.00	0.00	-0.18*	-0.99*
12. ACO advance payment	736	0.09	0.29	0.14*	0.24*	-0.11*	0.12*	-0.21*	-0.17*	-0.09*
13. Quality score (t+1)	736	90.79	8.39	0.07	-0.13*	0.06	0.02	0.12*	0.19*	0.32*
14. ACO spans noncontiguous states (1 = Yes)	736	0.05	0.21	0.02	0.23*	-0.06	0.08*	0.06	0.10*	0.03
15. Network size	736	44.41	55.7	0.04	0.25*	-0.12*	0.18*	0.40*	0.47*	0.03
16. Network isolates	736	1.50	2.66	0.13*	0.71*	-0.21*	0.18*	-0.05	0.08*	0.05
17. % Non-referring	736	0.38	0.22	0.12*	0.42*	-0.15*	-0.01	-0.04	-0.02	0.14*
18. Network turnover	736	-0.20	10.73	-0.03	-0.02	0.01	-0.01	0.06	0.09*	0.13*
	8	9	10	11	12	13	14	15	16	17
9. % Beneficiaries aged 85+	0.91*									
10. % Disabled beneficiaries	-0.57*	-0.72*								
11. % Beneficiaries with end-stage renal disease	0.96*	0.95*	-0.66*							
12. ACO advance payment	0.09*	0.09*	-0.07	0.08*						
13. Quality score (t+1)	-0.30*	-0.31*	0.20*	-0.32*	-0.04					
14. ACO spans noncontiguous states (1 = Yes)	-0.03	-0.02	0.09*	-0.03	0.08*	0.01				
15. Network size	-0.03	0.03	-0.04	-0.02	-0.13*	-0.08*	0.10*			
16. Network isolates	-0.02	-0.06	0.10*	-0.05	0.16*	-0.07	0.27*	0.27*		
17. % Non-referring	-0.14*	-0.07	0.00	-0.13*	0.03	-0.14*	0.09*	0.30*	0.31*	
18. Network turnover	-0.12*	-0.12*	0.07	-0.14*	-0.01	0.07	0.06	0.08*	0.01	-0.02

Assessments of the hypotheses. I find, however, that when I introduce a moderator for *Relational strength*, the association between whole network structure and performance is clearer. In Model 7 of Table 3.3, the coefficient for the interaction between *Structural disconnectedness* and *Relational strength* is negative and statistically significant (β = -0.30, p=0.005), offering support for H1's prediction that as structural connectedness decreases, greater *Relational strength* will be negatively associated with *Cost performance*. This result is consistent with the possibility that as relational strength goes up, subgroups of actors become more siloed, making it difficult for network members to collaborate in pursuit of collective goals.

Next, I turn to models in which the structure-performance relationship is examined under different cultural orientations. Using my hand-coded measure—where C^O=1 if the name of the ACO reflected a physician orientation, and 0 otherwise—the coefficient for the interaction between *Structural disconnectedness* and physician *Cultural orientation* (Table 3.3, Model 7: β = -21.86, p=0.012) suggests a different structure-performance relationship depending on the presence or absence of a physician *Cultural orientation*. Increasing *Structural disconnectedness* is *negatively* associated with whole network performance in the presence of a physician *Cultural orientation*. This finding supports H2's prediction that the *Structural disconnectedness-Cost performance* relationship would be negative in ACOs with a physician *Cultural orientation*.

3.5.2 Interpreting the Regression Results

Structural disconnectedness* × *Relational strength. The left panel of Figure 3.2 shows predicted values of *Cost performance* at different levels of *Structural disconnectedness* and *Relational strength*. I visualize these values using bar graphs to illustrate how the relationship between whole network structure and performance may be contingent on the relational dimension of whole network morphology. The first set of bars on the left-hand side show *Cost performance* for ACOs with low *Structural disconnectedness* (10^{th} percentile) at low (10^{th} percentile), moderate (median), and high (90^{th} percentile) *Relational strength*. I see that there is not a large

Table 3.3: OLS Regression Models of Cost Performance

Variable	1	2	3	4	5	6	7
Patient and provider characteristics							
Total providers	-0.00		-0.00	-0.00	-0.00		-0.00
	(0.00)		(0.00)	(0.00)	(0.00)		(0.00)
Total beneficiaries	0.10		0.18	0.29	0.16		0.28
	(0.29)		(0.33)	(0.34)	(0.32)		(0.32)
% Female beneficiaries	-12.60		-12.86	-12.62	-9.76		-9.44
	(19.69)		(19.96)	(19.95)	(20.40)		(20.39)
% Black & Hispanic beneficiaries	4.53*		4.52*	4.41*	4.37*		4.25*
	(2.01)		(2.04)	(2.04)	(2.05)		(2.05)
% Beneficiaries aged 85+	-10.20		-11.05	-11.41	-12.38		-12.80
	(14.05)		(14.43)	(14.42)	(14.45)		(14.43)
% Disabled beneficiaries	-5.76		-4.79	-4.06	-2.64		-1.80
	(8.74)		(8.84)	(8.87)	(8.97)		(9.00)
% Beneficiaries with ESRD	5.56		5.79	6.34	8.75		9.40
	(9.07)		(9.23)	(9.20)	(9.41)		(9.38)
General ACO (network) characteristics							
ACO advance payment	1.73		1.77	1.86	0.91		0.98
	(1.70)		(1.69)	(1.66)	(1.67)		(1.64)
Quality score (t+1)	0.03		0.04	0.04	0.03		0.04
	(0.04)		(0.04)	(0.04)	(0.04)		(0.04)
ACO spans noncontiguous states (1 = Yes)	1.58		1.38	0.76	1.82		1.17
	(1.54)		(1.58)	(1.67)	(1.58)		(1.66)
Network size	-0.01		-0.01	-0.01	-0.01		-0.01
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)
Network isolates	-0.14		-0.20	-0.24	-0.15		-0.19
	(0.17)		(0.17)	(0.17)	(0.17)		(0.17)
% Non-referring	2.44		2.33	2.33	2.49		2.49
	(3.64)		(3.64)	(3.62)	(3.62)		(3.60)
Network turnover	-0.00		-0.00	-0.00	-0.01		-0.01
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)
Network dimensions and interactions							
Structural disconnectedness		-0.34	0.64	-1.19	1.61	-1.28	-0.31
		(2.79)	(2.96)	(2.94)	(3.03)	(2.81)	(3.00)
Relational strength		0.01	0.00	-0.13*	0.00	-0.15***	-0.13**
		(0.01)	(0.01)	(0.05)	(0.01)	(0.05)	(0.05)
Cultural orientation (1=Physician)		3.38	3.07	3.12	6.89*	6.85***	7.03*
		(3.53)	(4.14)	(4.06)	(2.99)	(2.31)	(2.77)
Structural × Relational				-0.28**		-0.33***	-0.30***
				(0.11)		(0.10)	(0.10)
Structural × Cultural (1=Physician)					-21.36***	-20.66***	-21.86***
					(7.38)	(6.32)	(7.15)
Constant	-8.16	0.49	-8.55	-10.04	-12.40	-0.30	-14.07
	(11.87)	(0.47)	(12.14)	(12.16)	(12.46)	(0.41)	(12.48)
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.05	0.01	0.05	0.05	0.06	0.03	0.07
N	736	736	736	736	736	736	736

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests); Robust standard errors in parentheses; ESRD: End-stage renal disease

difference in terms of expected *Cost performance* based on *Relational strength*; there is a slight negative trend as *Relational strength* increases, but the differences are not significant. However, at moderate or high levels of *Structural disconnectedness*, there is a more dramatic difference in *Cost performance* as *Relational strength* changes. When *Relational strength* is low, *Cost performance* does not change much with *Structural disconnectedness* (in fact, it increases slightly as disconnectedness goes up). At moderate *Relational strength*, however, *Cost performance* is significantly lower at moderate *Structural disconnectedness* than what it was at low *Structural disconnectedness* (0.9 percent savings vs. 1.7 percent savings, respectively), and even worse at high *Structural disconnectedness* (0.3 percent *overspend*). At high *Relational strength*, the difference is even greater, with *negative Cost performance* in ACOs at moderate and high levels of *Structural disconnectedness* (a 0.2 percent *overspend* for moderate *Structural disconnectedness* and 2.5 percent *overspend* for high *Structural disconnectedness*, compared to 1.6 percent savings for low *Structural disconnectedness*).

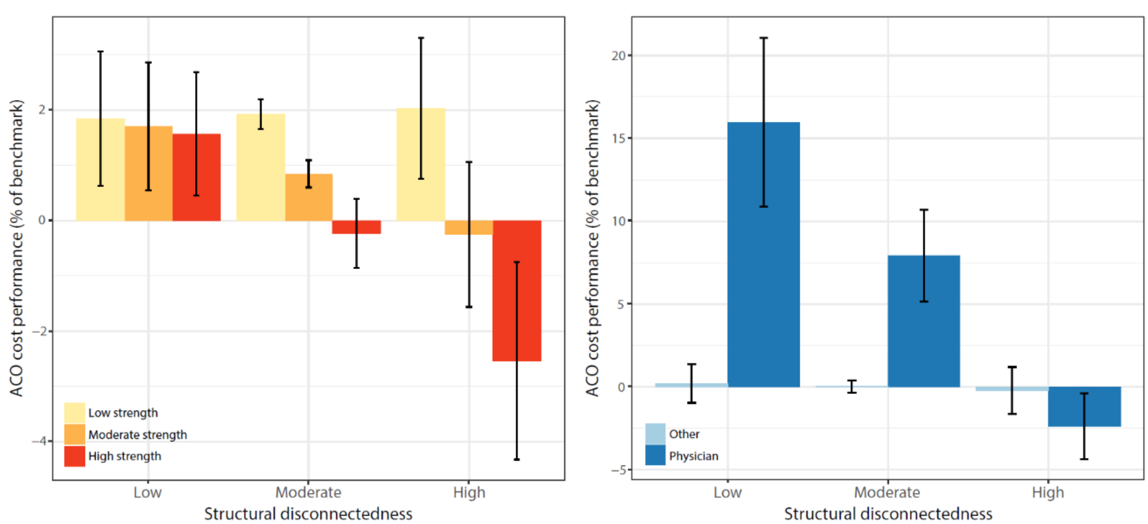


Figure 3.5: Predicted values of cost performance at different levels of structural disconnectedness and relational strength, and structural disconnectedness and cultural orientation. Performance measured in terms of the percentage savings relative to the benchmark. Low, moderate, and high levels of disconnectedness and relational strength represent the 10th percentile, 50th percentile, and 90th percentile values of each variable, respectively. Standard error bars are shown.

These differences can be contextualized using the (2016) average ACO benchmark of $205 million. At low *Structural disconnectedness*, an ACO with low *Relational strength* would be expected to save about 1.8 percent, or approximately $3.7 million. At high *Structural disconnectedness* and low *Relational strength*, an ACO would still be expected to generate approximately 2.0 percent savings, or $4.1 million. Now, if the ACO had high *Relational strength*, it would still perform relatively well at low *Structural disconnectedness*—approximately 1.6 percent savings, or $3.3 million. However, if *both Structural disconnectedness* and *Relational strength* are high, the expected performance changes dramatically to a projected *overspend* of 2.5 percent, essentially resulting in a $5.1 million loss for Medicare.

Structural disconnectedness* × *Cultural orientation. The right panel of Figure 3.2 plots predicted values for the interaction of *Structural disconnectedness* (10^{th}, 50^{th}, and 90^{th} percentiles) and *Cultural orientation*. Recall that I found support for my prediction that the whole network structure-performance relationship would be contingent on the presence or absence of a physician *Cultural orientation*. Figure 3 unpacks this relationship. Consistent with H2, when *Structural disconnectedness* is low, a physician *Cultural orientation* is associated with better performance. However, as *Structural disconnectedness* increases, a physician *Cultural orientation* is associated with worse performance, while performance without this orientation is more stable. At low *Structural disconnectedness*, physician *Cultural orientation* is associated with high *Cost performance*, a savings of 16.0 percent, about $32.8 million based on the average benchmark. In contrast, the absence of physician *Cultural orientation* is associated with savings of nearly zero, or 0.2 percent ($410,000). This surprising result suggests that holding other factors constant, at low *Structural disconnectedness*, the performance differential associated with the presence or absence of a physician *Cultural orientation* could be more than $30 million.

Now, consider how this relationship changes as *Structural disconnectedness* increases. At moderate *Structural disconnectedness*, the gap between the presence and absence of a physician

Cultural orientation shrinks to about a 7.9 percentage points. At high *Structural disconnectedness*, physician *Cultural orientation* is associated with lower performance, with a predicted overspend of 2.4 percent, whereas in the absence of a physician *Cultural orientation* performance is closer to neutral (-0.2 percent), a differential of only 2.2 percent between the presence and absence of a physician *Cultural orientation*. This suggests that with a physician *Cultural orientation*, more connected whole network structures are associated with much better performance than more disconnected ones. However, in the absence of a physician *Cultural orientation*, the structure-performance relationship is relatively more stable.

3.5.3 Additional Analyses

To evaluate the robustness of my findings, I conducted several additional analyses, shown in Table 3.4

Alternative proxy for structural disconnectedness. I began by evaluating the robustness of my results to alternative proxies for the whole network dimensions. As an alternative for the structural dimension, Model 8 measures disconnectedness using average path length (e.g., Lazer & Friedman, 2007). The results are consistent with my main findings.

Alternative proxy for relational strength. I also considered an alternative measure of the relational dimension. Model 9 replicates my main model, but proxies for relational strength using the average number of shared beneficiaries weighted by the total number of organizations, including isolates and disconnected organizations that are not associated with any beneficiary-sharing activity. Findings using this approach are consistent with my main results.

Alternative proxy for cultural orientation (machine learning). Model 10 replicates my main models using an alternative approach for identifying the cultural dimension. Specifically, to complement the hand coding approach used for my main analyses, I also used machine learning methods. These methods detected clusters of similar ACO names based on the co-occurrence of terms (see Appendix). Informed by contextual knowledge and prior work on ACOs, I identified three clusters. The first, like my hand-coded variable, comprised names that evoked the physician profession, using terms like “physician,” “doctor,” or “primary care.” The second comprised names that were community or geography-focused, indicating a clear identification with a service area (e.g., “Accountable Care Coalition of Southeast Wisconsin”). The third cluster comprised names that reflected the organizational or corporate form of the ACO, using terms like “network,” “alliance,” or “coalition.”

Because the results of this approach yielded three distinct clusters, I coded a new variable, C^{O^*}, where $C^{O^*}=1$ for the physician cluster (like my primary variable), $C^{O^*}=2$ for the organizational cluster, and the reference category, $C^{O^*}=0$, represented the community-focused cluster. Results using this alternative variable are substantively similar to those of my main models. I still observe a negative interaction between *Structural disconnectedness* and physician orientation. However, the interpretation is slightly different because the reference category is more specific (community orientation).

Quality outcome measure. In Model 11, I run my main model using a dependent variable adjusted for quality. As previously discussed, although quality is not the primary outcome used by CMS, CMS does use quality scores to calculate a “multiplier,” which determines the proportion of shared savings that ACOs are eligible to receive if they achieve 2 or 3 percent cost savings. Therefore, I multiplied each ACO’s *Cost performance* by the quality multiplier to create a quality-adjusted outcome. This measure is arguably closer to how ACOs perceive their performance because it is more directly related to their shared savings. The results are similar to those in my main regression results. A different specification (available on request) excluding the quality score control variable produced nearly identical results.

Dynamic panel. In Model 12, I replicate my main results using a dynamic panel model (Arellano-Bond GMM). This approach uses historic performance as a covariate, which is important if ACOs respond to past success or failure. Thus, including lagged performance as a regressor may offer insight into whether early ACO performance is driven by "low hanging fruit," which may be negatively related to ACOs' ability to achieve savings relative to benchmarks in subsequent years (McWilliams, 2016). I find that lagged *Cost performance* is positively associated with the outcome (Table 3.4, Model 12: $\beta = 0.48$, $p = 0.045$), which suggests good performance in one year may be a predictor of good performance in the next. Coefficients for the interactions are similar to my main results; the interaction between *Structural disconnectedness* and *Relational strength* is negative (Table 3.4, Model 12: $\beta = -0.29$, $p = 0.006$) and the interaction between *Structural disconnectedness* and physician *Cultural orientation* is also similar to the main model (Table 3.4, Model 12: $\beta = -16.92$, $p = 0.009$).

Selection model. In Model 13, I estimate a Heckman selection model to account for ACOs' potentially "selecting into" using a network approach. My assumption is that all ACOs use networks in some way, and that beneficiary-sharing relationships are a good proxy for their structure. However, not all collaborative work among ACO members is captured by beneficiary-sharing. My main analysis only includes ACOs with at least two members and one tie. 37 ACOs did not fit this criterion. Therefore, in the first stage, I predict "using a beneficiary-sharing network," with an exclusion restriction indicating whether the ACO spans multiple states. Because patient mobility is typically geographically localized, multi-state ACOs may be less likely to use networks, and may instead coordinate in other ways, such as sharing process improvement strategies or administrative resources. In the second stage, I predict *Cost performance* using my independent variables and their interactions, the results of which are shown in Model 16.[29] The results are very similar to those of the main model. I report the first stage estimates in the Appendix C (Table A3).

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[29] The inverse Mills ratio in my second stage is not statistically significant, failing to reject the null. Therefore, the second stage results are the unadjusted output of the GLS regression, following Heckman (1979).

Table 3.4: Robustness Tests

Variable	8 Alt. Structural	9 Alt. Relational	10 Alt. Cultural	11 Quality Outcome
Patient and provider characteristics				
Total providers	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Total beneficiaries	0.15	0.26	0.18	0.09
	(0.31)	(0.32)	(0.30)	(0.15)
% Female beneficiaries	-12.11	-9.77	-11.99	-3.51
	(19.93)	(20.57)	(19.46)	(9.30)
% Black & Hispanic beneficiaries	4.45*	4.33*	3.95*	2.02*
	(2.08)	(2.06)	(1.86)	(0.91)
% Beneficiaries aged 85+	-9.74	-12.74	-16.58	-7.14
	(14.25)	(14.50)	(13.67)	(6.59)
% Disabled beneficiaries	-5.63	-2.08	1.42	-0.39
	(9.05)	(9.04)	(8.30)	(4.15)
% Beneficiaries with ESRD	5.48	9.29	11.80	4.47
	(9.15)	(9.43)	(8.79)	(4.29)
General ACO (network) characteristics				
ACO advance payment	1.80	0.95	0.73	0.31
	(1.63)	(1.65)	(1.47)	(0.76)
Quality score (t+1)	0.04	0.04	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.02)
ACO spans noncontiguous states (1 = Yes)	1.30	1.33	2.14	0.40
	(1.60)	(1.62)	(1.57)	(0.73)
Network size	-0.00	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Network isolates	-0.30	-0.19	-0.23	-0.08
	(0.22)	(0.17)	(0.17)	(0.08)
% Non-referring	2.06	2.06	2.16	1.14
	(3.66)	(3.68)	(3.67)	(1.62)
Network turnover	-0.01	-0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Network dimensions and interactions				
Structural disconnectedness	-0.05	-0.07	5.69†	-0.07
	(0.09)	(3.02)	(3.21)	(1.38)
Relational strength	-0.09*	-0.00*	-0.20***	-0.06**
	(0.04)	(0.00)	(0.06)	(0.02)
Cultural orientation (1=Physician)	5.43†	7.04*	2.03	3.22*
	(2.87)	(2.84)	(1.41)	(1.30)
Cultural orientation (2=Organizational)			3.04*	
			(1.37)	
Structural × Relational	-0.02*	-0.00*	-0.44***	-0.14***
	(0.01)	(0.00)	(0.12)	(0.05)
Structural × Cultural (1=Physician)	-0.43***	-21.95***	-14.29***	-10.38***
	(0.13)	(7.19)	(4.63)	(3.37)
Structural × Cultural (2=Organizational)			-13.76***	
			(4.54)	
Constant	-10.15	-13.72	-15.19	-6.33
	(12.09)	(12.64)	(11.87)	(5.74)
Network fixed effects	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.10	0.08
N	736	736	736	736

Table 3.4 (continued): Robustness Tests

Variable	12 Dynamic Panel	13 Selection Model	14 Exclude Outlier	15 Exclude 2015	16 Exclude Noncontiguous
Patient and provider characteristics					
Total providers	-0.00	-0.00†	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total beneficiaries	0.30	0.29	0.28	0.15	0.24
	(0.36)	(0.24)	(0.32)	(0.49)	(0.33)
% Female beneficiaries	-16.70	-9.48	-8.01	5.96	-10.20
	(34.51)	(15.39)	(20.93)	(14.31)	(21.16)
% Black & Hispanic beneficiaries	3.97	4.24*	4.20*	2.10	4.19†
	(2.86)	(1.89)	(2.07)	(1.78)	(2.15)
% Beneficiaries aged 85+	-6.04	-13.01	-13.08	-11.33	-15.00
	(15.53)	(10.99)	(14.43)	(15.49)	(15.31)
% Disabled beneficiaries	-14.88	-1.76	-2.09	-0.73	-0.97
	(10.49)	(7.19)	(8.98)	(9.61)	(9.45)
% Beneficiaries with ESRD	-7.78	9.47	9.18	12.48	10.29
	(12.10)	(7.60)	(9.38)	(9.84)	(9.73)
General ACO (network) characteristics					
ACO advance payment	-1.95	0.98	1.04		0.98
	(2.78)	(1.26)	(1.66)		(1.66)
Quality score (t+1)	0.04	0.04	0.04	0.02	0.03
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
ACO spans noncontiguous states (1 = Yes)	-2.94		1.15		
	(2.63)		(1.65)		
Network size	-0.00	-0.01	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Network isolates	-0.23	-0.20	-0.19	-0.09	-0.18
	(0.19)	(0.13)	(0.17)	(0.26)	(0.20)
% Non-referring	0.60	2.50	2.45	0.02	2.34
	(4.61)	(2.61)	(3.61)	(2.47)	(3.77)
Network turnover	-0.00	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Network dimensions and interactions					
Structural disconnectedness	-2.97	-0.33	-0.45	-0.20	-0.58
	(3.69)	(2.24)	(3.01)	(3.31)	(3.10)
Relational strength	-0.13**	-0.14***	-0.13**	-0.04	-0.13*
	(0.05)	(0.04)	(0.05)	(0.08)	(0.05)
Cultural orientation (1=Physician)	7.70†	7.04***	7.04*	6.49	6.86*
	(4.48)	(2.11)	(2.77)	(5.11)	(2.92)
Structural × Relational	-0.29**	-0.30***	-0.29***	-0.19	-0.30**
	(0.10)	(0.08)	(0.10)	(0.13)	(0.11)
Structural × Cultural (1=Physician)	-16.92†	-21.77***	-21.73***	-22.78*	-20.09**
	(10.06)	(5.53)	(7.12)	(11.28)	(7.56)
Past performance (t)	0.48*				
	(0.24)				
ρ		-0.01			
		(0.08)			
Constant	8.32	-13.74	-13.87	-16.03	-14.36
	(20.03)	(14.94)	(12.51)	(11.22)	(12.76)
ACO fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes
R^2 or pseudo-R^2	0.18	0.77	0.07	0.11	0.07
N	374	839	734	439	702

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests); Robust standard errors in parentheses; ESRD: End-stage renal disease

Exclude outlier. In Model 14, I exclude an outlier ACO that reported negative performance of -44.25 percent relative to the benchmark in the first year of operation. This level of performance was considerably worse than the next lowest observed, -15.76 percent relative to the benchmark. Excluding this ACO did not affect my results.

Exclude 2015. In Model 15, I exclude the last year of data from my panel (2015). The beneficiary-sharing data that I utilized was truncated in 2015 by CMS to about 80 percent of the full timeframe (one year plus a sixty-day window). To account for the potential impact of this missing data, I exclude all ACO × year observations from 2015. Although the statistical significance of the interaction terms are slightly diminished (as may be expected after dropping a full year of data), the results are substantively supportive of my main findings.

Exclude noncontiguous states. Finally, in Model 16, I perform an additional analysis that excludes ACOs that span noncontiguous states (rather than simply controlling for them). This test is meant to assess whether my results are driven by ACOs which, because they span noncontiguous states, may not actually be trying to coordinate patient care among their members. Excluding these ACOs does not change my results.

3.6 Discussion

I began by observing that over the past few decades, network perspectives have become increasingly important in organizational research. Although scholarship in this area has been productive, research has tended to adopt a fairly limited lens, focusing mostly on how the embeddedness of actors within networks shape their individual outcomes. Against this backdrop, a growing number of organizational researchers have undertaken a fundamental perspective shift, viewing networks more broadly, and concerning themselves with understanding whole network performance rather than that of the individual network actor. Initial findings from the literature on whole network performance suggest that the mechanisms and theoretical logic of whole networks may be systematically different from those of individual node (i.e., ego networks). Consequently, there is excitement that further development of the whole network lens may bring fresh perspective to broader, persistent questions in research on networks and organizations.

Drawing on classic work in macrostructural sociology, I developed a novel theoretical framework for understanding whole network performance that expands research on whole networks beyond a focus on structure to include two other fundamental—relational and cultural—properties or dimensions of whole networks. Inspired by research in biology, my whole network morphology framework suggests that the same whole network structures, when viewed together with different cultural and relational dimensions, may be associated with different behaviors, functions, and thus performance. Consequently, I suggested that the morphology framework may be helpful for reconciling conflicting findings from whole network research on the relationship between whole network structure and performance.

3.6.1 Applying the Morphology Framework

Empirical application of my framework to 250 interorganizational whole networks in the United States healthcare industry illustrates how the morphological perspective—specifically the interactions between structure and other whole network dimensions—can be operationalized in organizational settings. In addition, my analysis responds directly to calls for research on whole network performance *in situ*, where the complexity such structures can be better appreciated (Fang & Schilling, 2010; Shore et al., 2015). Finally, by developing theory about the contingent relationships among whole networks' structural, relational, and cultural dimensions, I begin to reconcile conflicting findings about the structure-performance relationship.

My findings from the ACO context supported a contingent view of the relationship between whole network structure and whole network performance that accounts for the relational and cultural dimensions. In keeping with existing research, I did not find a clear association between structural connectedness and whole network performance. However, I did find robust evidence that the relationship between structure and performance is dependent upon the relational strength and cultural orientation of the whole network. Specifically, I observed that structural disconnectedness is *negatively* associated with whole network performance at higher levels of relational strength, supporting my prediction that stronger ties among fragmented network partners may contribute to siloing that, in turn, likely hinders coordination. I also found a negative relationship between structural disconnectedness and whole network performance in ACOs that espoused a physician cultural orientation; however, this relationship flipped and was *positive* when disconnectedness was low (connectedness was high).

The finding that disconnectedness is associated with worse performance under a physician cultural orientation is interesting. One interpretation is that a physician orientation emphasizes autonomy over the sacrificing for the collective, which likely detracts from the collaborative ethos of ACOs. Since physicians are still reimbursed based on the work they perform locally, they may be resistant to changing their practices in a way that benefits collective outcomes, particularly when the cultural orientation of the whole network gives them license to be autonomous. As connectedness increases, and opportunities for contact and exposure among network members grow, it may be easier for an ACO to establish the buy-in necessary to generate a shared physician perspective. In contrast, the combination of low structural connectedness and a cultural orientation that predisposes members towards autonomy may create a siloing effect and therefore undermine the collaboration necessary for success.

3.6.2 Implications and Future Work

By switching to a whole network lens, I am afforded an opportunity to think beyond dyadic relationships between ego and alter to a larger canvas of social interaction. Specifically, my framework connects to observations Simmel made on social interaction in larger groups, where "a [member] can…hold the group responsible for what he has failed to do" (Simmel, [1950]: 134). Put differently, in large groups (i.e., three or more members) the relationship between each member and others in the collective can be more ambiguous. Consequently, social distance between members may be greater and accountability more diffuse.

In my study of ACOs, I theorized that this distance may manifest in reduced cooperation and coordination, in ways that may be connected to each of the three whole network dimensions. Thus, members of strongly tied, but disconnected, whole networks may identify less with the collective and more with their local subgroup. Similarly, as alluded to earlier, a physician cultural orientation that values the professional autonomy of doctors over contributions to a collective goal may exacerbate the challenges of broader cooperation and coordination. Reducing the distance between members and the group by increasing connectedness may enable providers that emphasize professional autonomy to develop a stronger sense of their collective membership. In sum, by studying whole network performance, the social dynamic of non-dyadic groups becomes substantially more important relative to a focus on ego networks and the outcomes of individual nodes.

Of importance to practitioners is that the potential upside of whole networks may never be realized if member organizations fail to identify the potential pitfalls when entering into partnerships. Nevertheless, it may be difficult for participants, or even architects, of organizational partnerships to take a whole network view of the structure, relations, or culture of a group partly because of complexity but also partly because of the contingent and emergent nature of outcomes. This difficulty may explain why many of the whole networks I studied exhibited considerable disconnectedness or possessed other curious features, such as being geographically distributed across noncontiguous states. Perhaps such ACOs identified other opportunities to collaborate or reduce costs locally, or assumed that participants could more easily adapt to the new model of work despite challenges of distance or limited collaborative experience. Delving deeper into structurally disconnected ACOs may be informative for understanding their approach to achieving shared savings. Similarly, instances where members were able to achieve savings locally but the network performed poorly as a whole could provide a useful context to study externalities that may exist within collaboration networks.

Future work that attempts to unpack the interplay between formal and informal structures may also be valuable (McEvily et al., 2014). Certain variations in the whole network dimensions are "below the tip of iceberg" (Rosenkopf & Schleicher, 2008), in the form of informal relationships. Informal interactions have featured prominently in alliance and network research, such as in the context of organizational functioning (Podolny & Baron, 1997). In my context, the formal network was defined by ACO membership, although informal relationships between entities that eventually formed the ACO existed prior to formalization. However, my study finds that these interactions may also be important for whole network performance *after* formalization. Thus, rather than being merely a means to a (formal) end, it may be important to consider whether informal ties not only predict formal ones, but are also shaped by them (Gulati & Puranam, 2009). Indeed, considering that many collaborative efforts are created only to fail (Greve et al., 2010), there may be opportunities to develop new theories about how network formalization affects the underlying relationships and subsequent outcomes.

Finally, my research also connects to some recent work on whole networks, such as Mahmood et al. (2016), which showed that the centralization of equity ties within business groups was associated with better performance of individual members. This relationship, however, was moderated by an external contingency—environmental turbulence. In contrast, my study proposes that such contingencies may be inherent to each network, in the relational and cultural dimensions. Future work on whole networks may benefit from closer examination of the link between internal network dimensions and the external environment to develop deeper understandings of the dynamics and adaptability of whole networks.

3.6.3 Limitations

My empirical findings should be viewed in the context of several limitations. Although I studied the population of Medicare ACOs, the newness of the setting means that my longitudinal data are relatively limited. My use of observational data limits my ability to make causal inferences. Additionally, healthcare is a unique, highly institutionalized context and the ACO is a new organizational form, and therefore my data describe the characteristics of networks in their infancy. Thus, it is unclear if and to what extent the relationships I observe during these early stages will stabilize or change as they mature. Finally, further work is needed to assess the utility of the morphology framework when applied to contexts where the desired network outcome is not collaboration.

Notwithstanding the idiosyncrasies of my context, I suggest that the interactions among structure and the relational and cultural dimensions of whole network morphology are fundamental features of all organizational networks. Although my empirical analysis was primarily meant to illustrate an application of my theoretical framework, my principal finding that the performance implications of structure are contingent upon other whole network dimensions is unlikely limited to healthcare.

IV. BETTER OFF FRIENDS? THE IMPLICATIONS OF NETWORK BOUNDING FOR STRUCTURE AND PERFORMANCE

4.1 Introduction

An important distinction is often made between informal and formal interactions that exist within and across organizations. Formality connotes directive or planning, perhaps manifested through a written contract, common name or group identity, or restricting the flows of certain information or resources to specific partners. Indeed, some studies of formal interactions, or ties, even invoke an intendedly rational architect (e.g., Gulati & Puranam, 2009), or designer "who devises courses of action aimed at changing existing situations into preferred ones." (Simon, 1969: 111). In contrast, informal interactions—such as friendship (e.g., Westphal, 1999) or advice-seeking ties (e.g., Brennecke & Rank, 2016)—are thought to arise more organically or naturally, and are often defined by their *lack* of formal basis. Consequently, informal ties may be considered inadequate for work of a certain level of import. However, owing to their more emergent and flexible nature, informal ties may also be important conduits of novelty and diversity that can skirt around the constraints of formal structure and boundaries (e.g., Hansen, 1999). Consequently, informal ties may better facilitate adaptation (Srivastava, 2015), innovation (Funk, 2014), and change (Battilana & Casciaro, 2012). In fact, recent research in organizational networks has highlighted the importance of complementarity between informal and formal relationships; the right alignment between informal and formal network structures may be particularly beneficial for firm and organizational performance (Rosenkopf & Schleicher, 2008; Soda & Zaheer, 2012; McEvily, Soda, & Tortoriello, 2014; Clement & Puranam, 2017).

Much of this work on the interplay between informal and formal networks focuses on intraorganizational networks (Soda & Zaheer, 2012; Carnabuci & Operti, 2013), where both informal (e.g., social networks) and formal relationships (e.g., organizational charts) already co-exist and co-evolve. Yet, such interactions are not confined within the boundaries of a single organization, neither do they necessarily naturally occur. Inside organizations, some formality (e.g., organizational charts, roles, chain of command) is often expected, if not necessary. However, across organizations, at the interorganizational level, formality is not a given and less commonplace. Indeed, the introduction of formality (e.g., contracts, formal governance) is seen as a defining characteristics of so-called "goal-directed" whole networks (Provan & Kenis, 2007)—groups of autonomous organizations or individuals distributed across multiple organizations that collaborate towards a collective, or network-level outcome.[30] In other words, within the context of myriad informal network interactions, the act of "making it official" by introducing a formal modality of interaction may be an important turning point. Yet, it remains unclear whether the establishment of formal ties to supplement existing informal relationships will help or hurt at the *network level*. Despite evidence that consistency between informal and formal network structures can benefit individual actors (e.g., Soda & Zaheer, 2012), it is also known that maximizing local performance does not necessarily improve collective performance (e.g., Mason & Watts, 2012; Shore et al., 2015). This raises theoretical and practical questions about a different type of interplay between informal and formal relationships within whole networks. First, how does formalizing a new whole network affect the existing structure of existing informal network connections? Second, is such formalization an effective strategy to enhance collective outcomes? That is, does the introduction of a formal basis of interaction improve whole network performance compared to a network in which the extra layer of formality does not exist?

Thus, the primary objective of this study is to examine the consequences of a particular type of interorganizational, strategic decision in which a group of *informally* interacting partners add a layer of formal association in order to better achieve a collective task.[31] I argue that the

[30] The founding of a new firm or organization may be another scenario where formal relationships—in this case, to define the organizational boundary and/or organizational structure—are established in a context where they previously did not exist.

[31] To illustrate, consider a group of five individuals who have frequently played 5-on-5 pickup basketball games as a team because they all had similar work schedules, which meant they were often at the gym at

introduction of formality (i.e., adding a contract) to create a new whole, goal-directed network is an example of an overlooked, but strategically important, type of network change or network design. In the pursuit of more effective partnerships or strategic outcomes, a group of organizational actors may establish new formal ties on top of existing informal relationships, consequently creating a new network boundary. I refer to this boundary creation as "network bounding," and specifically examine the case when bounding occurs through the formalization of a network—and therefore the creation of a formal and "realist" network boundary (Laumann et al., 1983). In particular, I am interested in understanding how the introduction of a new formal network boundary may influence the *informal* networks among members of the newly formalized group. Specifically, I assume that bounding via formalization and the recognition that one belongs to a group to which others do not belong (Simmel, 1950) may enhance social identification among network members (Tajfel & Turner, 1984) and increase the opportunities for those in the in-group to interact with one another (Blau, 1977). This, in turn, may spur network dynamics in the informal relationships that are more supportive of collective or collaborative outcomes at the whole network level. Furthermore, I want to examine whether or not these changes (if any) are associated with any variation in whole network performance.

Examining the dynamics associated with network bounding through formalization may also provide new insights into why formal collaboration among many partners does not always produce the intended results. As previously stated, the introduction of formality connotes some intentional design, whether it be to directly alter how network members interact, to influence subsequent outcomes, or both. Specifically, because network bounding selects certain actors, and

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the same time. However, because this is just an informal arrangement, sometimes some of players end up with other teammates, or sometimes they do not show up at the usual time. The phenomenon being studies would be akin to this group of five individuals suddenly deciding to formalize their basketball partnership in order to improve as a collective and win more games, perhaps at an up-coming tournament. The formalization could manifest in changes such as all five members reliably showing up to the gym at a scheduled time, or additional interactions off of the basketball court. The basic idea of this study is that such arrangements are frequently made among organizations – the question is what happens to the interactions among those members, and what it means for collective performance.

excludes others, this has consequences for the *informal* ties that are captured within the new boundary. The idiosyncratic arrangement of social interactions among newly minted partners may act as a network imprint (Marquis, 2003), or a set of initial opportunities and constraints. These starting conditions, I hypothesize, may be associated with the effectiveness of the network as a whole. In other words, whether or not formalization enables networks to achieve their intended goals may depend on the interplay between the unique configuration of informal ties and the new formal boundary.

I test my hypotheses in the context of U.S. physician networks that are involved in the continuum of care (pre-operative to post-operative care) for coronary artery bypass graft (CABG) procedures, or heart bypass surgery. CABG procedures are performed by a surgical team within a single medical center, but there are a series of multidisciplinary and interdependent steps in medical care required before, during, and after a patient's hospital stay, requiring the work of multiple physicians in different organizational settings which comprises the health system. Post-surgical patient outcomes, a major indicator of health system effectiveness, can therefore be linked to the quality of the entire continuum of care. Thus, I study the extent to which patient mortality, or death, in the post-operative period is influenced by network bounding, as indicated by a health system's membership in a formal network. Specifically, I focus on network bounding caused by the emergence of Medicare Accountable Care Organizations (ACOs), a type of formal network partnership among healthcare providers, designed to promote greater coordination and integration among physicians and healthcare providers.

This study contributes to research on networks and interorganizational interactions in a few areas. First, differing from previous studies of informal and formal network ties which primarily focused on focal actors or dyadic interactions (Rosenkopf & Schleicher, 2008; Soda & Zaheer, 2012), I study the introduction of formality at the network level, addressing an established gap in the literature on organizational networks and network dynamics: the origins of informal and formal interactions (McEvily, Soda, & Tortoriello, 2014). Second, conceptualize the establishment of a new formal network boundary as the superimposition of a formal network on top of an (existing) informal one, enabling me to develop theoretical predictions about how the formal boundary may alter informal relationships within in the newly "bound" network. By characterizing the implications of the strategic decision to formalize as network as a type of network bounding, this study sheds light on a different type of interplay between informal and formal structures: how a formal network may be imprinted with a pattern of informal relationships. The imagery of a boundary also highlights that network bounding may not only have implications for the bound network, but may also potentially affect those actors that are left out. My findings from the timely and socially important context of US healthcare reform suggest that network bounding of healthcare providers into new formal networks may generate desirable network dynamics in the *informal* relationships among physicians, but this may not always be associated with better whole network performance. Instead, the findings suggest that bounding via formalization may not, itself, be enough for some networks to achieve better outcomes and, sometimes, may even harm whole network performance.

4.2 Theory & Hypotheses

Early foundations for my understanding of how networks of social interaction evolve can be traced back to Simmel's theories about humanity's ever-increasing embeddedness within overlapping social circles (Simmel, 1950). Simmel theorized that as "modern" society affords individuals with greater opportunities to engage in different social circles, "he is deprived of many supports and advantages associated with the tightly-knit, primary group," such as a family unit (Simmel, 1955: 163). That is, although each social circle offers new, and possibly distinct, opportunities for social interaction and the exploration of different interests or preferences, the increasing connectivity of the "modern" person (around the turn of the 20^{th} century) may ironically also lead to greater isolation in the sense that she lacks a "home base." Tönnies (1963) also theorized extensively about this distinction in social life, which he termed *Gemeinschaft* (community) and *Gesellschaft* (society). The former is akin to the "primary group" that Simmel described, and was rooted in a more natural tendency (will) of humans to develop close relationships with those around them, such as family members, friends, and partners. The latter encompassed more instrumental or arbitrary will in which humans developed relationships to further their own ambitions or achieve certain goals. Both Simmel and Tönnies recognized that, as society and industry modernized and became more complex, the salience of the more natural or instinctual forms of human association were being subsumed by more artificial relationships that were designed to facilitate the pursuit of some goal.

In this light, the importance of collaboration across organizational boundaries today suggests that this trend has continued and intensified to the extent that such artificial associations now bring together multiple firms or organizations. Moreover, despite the well-documented risks and challenges of such collaboration (Park & Ungson, 2001; Greve et al., 2010; Gulati, Wohlgezogen, & Zhelyazkov, 2012), organizations continue to formalize partnerships using contracts or investments. To apply Simmel and Tönnies' insights to the context of interorganizational relationships, formalization may represent the second type of association—that is, more artificial or instrumental—but at a higher level of analysis. Then, in contrast to such formal relationships, the more organic types of interorganizational interaction may be captured by informal ties between organizations that reflect some exchange or contract, but do not have a formal basis.

Neither Simmel nor Tönnies clearly states which type of association is better—though perhaps there is an implied lamentation of the increasing prevalence of artificial interactions in modern life—nor is it an objective of this study to try to do so. Instead, I draw on these classic theories to ground my main assumption: that the more agentic and artificial form of association that exemplified by the entry of an individual into a formal organization, or the formalization of relationships among firms, is different from more natural interactions in its *intention*. Namely, formalization implies the existence of some common objective that is shared by all members either morally or to the extent that participation in the collective aligns with individual interests. This also implies that there is some belief that, without the formalization of a dedicated group, the pursuit of the common goal would be impeded in some way. Indeed, the conceptualization of formal groups or organization as artificial closely relates to the notion of design (Simon, 1996), in which a man-made creation serves as a designer's solution to a problem in her external environment.

The contrast between informal and formal interactions is also at the heart of many theories of the boundaries of organizations and firms. For instance, transaction costs may lead previously informal, arms-length exchanges to shift into formal, contractual arrangements or even the integration of one, or more, firms into a single boundary (Williamson, 1980). Alternatively, the boundary of a formal organization may extend so far as individuals are willing to identify as organizational members and preferentially interact with one another (Kogut & Zander, 1996). In the context of common pool resources, delineating a formal boundary is considered to be the first step to governing collective use and preventing the deleterious effects of free-ridership (Ostrom, 1990).

This duality is especially prominent in networks research, where the study of informal and formal interactions has largely fallen into one of two categories. Earlier research focused on the emergence of formal ties, such as strategic alliances, using informal or historical interactions to explain how networks emerge and evolve over time (e.g., Gulati & Gargiulo, 1999). More recent research has focused more specifically on the interplay between informal and formal networks and the implications for performance. For example, in some contexts, informal ties may be just as important as formal relationships and the complementarity between them may determine how actors perform within organizational networks (Soda and Zaheer, 2012). Alternatively, the presence of both informal and formal structures may guide the evolution of each in beneficial ways, with the former's flexibility and range being corralled by the constraints or rules of the latter (Gulati and Puranam, 2009; Clement and Puranam, 2017).

Yet, at the interface of both of these streams—the former leading up to formalization, and the latter situated after informal and formal have both been established—remains an unanswered question. What happens when formality is *introduced* into a previously informal network? More precisely, what are the theoretical implications of adding a formal modality of network interactions to an existing field of organizations,[32] and what effects might this have on the collective performance of the newly formal group?

4.2.1 Formalization and Network Bounding

Prior to developing my theoretical arguments, it is necessary to establish some assumptions and definitions because terminology such as "formal" and "network" can be interpreted differently within different research traditions. My starting assumption is that, similar to the distinction between informal and formal relationships, there is also a distinction between informal and formal networks. Specifically, whereas informal networks may form organically and evolve incrementally over time, formal networks may reflect greater agency or strategic action on the part of the actors, or nodes. That is to say, because formal relationships often require greater costs in terms of negotiating, coordinating, and contracting, they reflect a different type of connection than an informal tie that, for example, forms when two employees attended the same university. For this reason, my definition of what distinguishes a "formal" network from an informal network comprises two key prerequisites. First, a formal network is "goal-directed"

[32] Here, and for the remainder of the chapter, I assume that all organizations are embedded in networks of informal relationships. While there may exist a scenario in which a highly secretive organization does not have any informal ties with other organizations, I am specifically interested in studying organizations that are "at risk" of collaborating with others and, thus, this is not the focus of this study.

(Provan & Kenis, 2008), meaning the members share a *raison d'être* which unites them. Second, a formal network is connected through formal ties which possess some legal or contractual basis, such that all members must decide and commit to join the formal network. In other words, the network, as a whole, also possesses a form of governance (Jones et al., 1997). Given these conditions, I also assume that an established formal network does not replace or transform existing informal ties, but rather is superimposed on the existing informal network (see Figure 1).

Based on these boundary conditions, a formal network exists when three or more actors (nodes) forge formal relationships (ties) with one another. The configuration or topology of ties defines the formal network structure. In the most straightforward case, and the focus of this study, a formal network represents a new formal group within which all participants are fully interconnected by membership. For example, when the North Atlantic Treaty Organization was first established in 1949, the twelve founding countries entered into a formal partnership simultaneously. Therefore, in view of formal NATO ties, those member organizations were fully interconnected with a network density of one. In other words, I consider the simplest case in which there is no variation in individual members' structural position within the formal network (i.e., node-level network measures for the formal network are all equivalent).

From this starting point, I conceptualize the introduction of formal relationships as the establishment of a new network boundary, and therefore as a method of *network bounding*. Specifically, the establishment of formal relationships defines membership and, by extension, non-membership in the new formal network. Put differently, those that possess a formal network tie are members; those that do not are non-members. This delineation serves as the basis of the new network boundary. Before moving forward, it is important to clarify, however, that network formalization or the introduction of formal relationships is not the only way a network may become bound/ For example, informal networks may become bound through the establishment of an informal social hierarchy or limitations on access to certain actors via geographical changes or other barriers. Network bounding, and the boundary creation it implies, refers to the broader phenomenon of introducing a new in-group/out-group distinction in an environment where it did not previously exist. Bounding through formalization refers to a narrower instance in which that boundary creation is based on the introduction of a formal network to which actors may be members or non-members. This special case where network bounding and network formalization coincide is focus of this study and, I argue, a particularly relevant cases for strategy research. Consequently, I will use the terms network bounding and bounding to refer to this special case where it coincides with formalization for the remainder of the study,.

To further develop the theoretical implications associated with this new social ordering based on bounding, I draw on other literatures in which the importance of boundaries is well-established. For example, the boundary is a central part of the theoretical solution to a classic problem of collective action around common pool resources, or activities which have externalities that are difficult to exclude (Olson, 1956; Ostrom, 1990). According to Ostrom (1990), a clear boundary is the first design principle that many successful collectives form to manage access to common pool resources. Because of its role in defining membership to a private collective, the boundary helps specify who is participating and who should benefit from collective activities, thus providing assurances to members that there will be returns on their good behavior, while also limiting access to potential free-riders.

In classic organization theory, the formal boundary of a bureaucratic organization is both a means of control and facilitation (e.g., Weber, 1922). Formal relationships, such as those dictated by organizational charts, not only direct and order important interdependent activities, but also restrict communication patterns where they might be problematic or lubricate the gears where interaction may otherwise be difficult. More modern conceptualizations similarly see the imposition of formality as a boundedly-rational attempt to direct interactions in a particular manner, but also often portray it as more of a recommendation than a rigid rule (Argyres &

Zenger, 2013). That said, formal structure is nearly ubiquitous within modern organizations and recent research provides strong evidence for its benefit, even when it is not strictly adhered to (Clement & Puranam, 2018).

Within the study of networks, the importance of boundaries is both theoretical and empirical (Laumann, Marsden, and Prensky, 1983). Theory and research objective shape a researcher's determination of which nodes to include and what types of ties to consider, and this, in turn, can significantly alter the observed network structure and analysis. Much as a researcher, adopting a nominalist approach, may define the boundary of a network such that it is "analytically relative to the purposes of the investigator" (Laumann et al., 1983: 21), formal relationships and boundaries can also be drawn in such a way to serve the purposes of the network "designers" who are trying to achieve some collective goal.

Yet, whereas the analyst may simply exclude those ties that are outside of her purview, the bounding of network ties, *in situ*, cannot ignore its social context. Prior literature strongly suggests that the establishment of a formal relationship, and by extension the formal boundary, generally occurs in the context of *de alio* systems of informal interactions (e.g., Gulati & Gargiulo, 1999). Consequently, the imposition of a formal boundary may significantly alter the existing informal networks.

To illustrate, I may first envision a field of actors interconnected in a network of informal social interactions (Figure 1, left side). Then, within this context, assume that certain nodes (dark nodes), and not others (light nodes), decide to establish formal relationships (Figure 1, top path). After network bounding, each of the nodes within the formal network is fully connected to other members. However, bounding also encompasses the informal ties among these selected nodes. These informal ties, viewed within the formal boundary, may affect the starting conditions, or imprint, the formal network (Marquis, 2003). This consequence of network bounding, I argue, endows even fully interconnected formal networks with structural heterogeneity that may have implications for network performance.

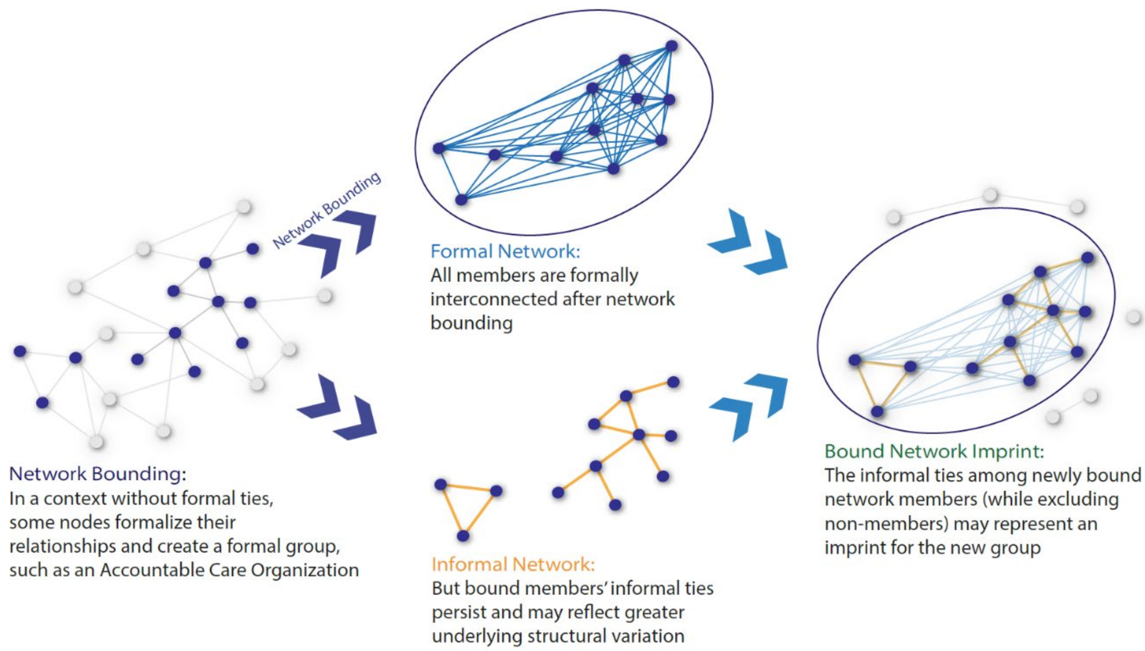

Figure 4.1: Network bounding refers to the establishment of a new network boundary. In the illustration above, bounding via formalization is depicted among a group of nodes that were previously only informally connected (left). Bounding is conceptualized as the establishment of a new network boundary and assumes that there is a clear distinction between members and non-members, as depicted on the left side, where members (darker nodes) are clearly distinguished from non-members (lighter nodes). Members of the new bound network are fully (formally) interconnected (top-middle), but underlying this new association is the configuration of existing informal network relationships (bottom-middle). This configuration of informal relationships among members may act as an imprint (right), providing a set of initial opportunities or constraints for the new group and affecting collective behavior or performance.

4.2.2 Group Identification and Bounding Ties

The previous discussion specifies that network bounding may demarcate a specific context in which informal networks are studied (e.g., Rosenkopf & Nerkar, 2001; McEvily et al., 2014), but such formal lines also provide bases for theoretical constructs such as boundary-spanning (Aldrich & Herker, 1977). Following this example, boundary-spanning is theoretically and practically important because it is difficult, and it is difficult because there are costs associated with traversing boundaries. This implies that for "bound" actors there is a lower cost, or barrier, to interacting within the boundary than across it. This, of course, is also similar to the idea that actors are more likely to form ties based on homophily (McPherson, Smith-Lovin & Cook, 2001), and common membership in an organization or formal group may be an important source of such familiarity (Dahlander & McFarland, 2013). Of course, the underlying mechanism for this type of social gravity does not necessarily require that there is a *formal* basis for interaction. For example, informal boundaries and homophily were especially strong in US immigrant enclaves (Portes & Sensenbrenner, 1998). The key similarity, however, is that there is a social, economic, or cognitive cost associated with crossing the dividing line. Therefore, considering the commitments that go into establishing a formal relationship, it is reasonable to expect that a similar sort of introversion may result from the establishment of a formal boundary. Moreover, this introversion may be exactly what was desired by the architects of the formal network and critical to the theoretical benefits of this form of association; without it, key mechanisms known to be important for collaborative activities, such as communication, monitoring, trust, and identification, may be substantially weakened.

Consequently, network bounding and the exclusivity of formal partnership may engender an internal group identity based even on the simple distinction between "us," inside the boundary, and "them" on the outside. In this way, network bounding may also have important behavioral effects on members by influencing the internal institutions or value systems that may be present within a group (Blau, 1964). For example, newly bound members may gradually perceive it to be more "appropriate" to interact with other members as opposed to outsiders and adjust their interactions accordingly. Alternatively, within-group interactions may simply be easier or less risky if formal bonds increase trust or improve monitoring. Similar mechanisms were central to Kogut and Zander's (1996) ideas about the role that common organizational identity plays in reducing the barriers to communication and knowledge-sharing among organizational members.

While a formal boundary does not necessarily mean that all members will preferentially interact with one another, it should generally increase the incentives for such collaboration. Perhaps more importantly, it should increase the probability of interaction among members who would *not* have connected otherwise—in other words, overcome the tendency of assortative mixing in social systems (Newman, 2003).

Although there has not been a systematic test of this proposition in studies of multiple networks, prior literature offers some supporting evidence that new formal contexts for social interaction may influence network dynamics in ways that are potentially beneficial for collective outcomes. For example, the development of the Nairobi Securities Exchange illustrated how the emergence of new institutional arrangements may have enabled previously segregated investors to overcome ethnic schisms and help grow participation in the new market (Yenkey, 2015). McFarland and colleagues' (2014) study of adolescents also supports the notion that more formal, distinctive institutional contexts may change the attachment preferences students, leading to more diverse friendship groups in environments characterized greater social control and the exclusion of externalities. A key insight was that "as contexts become more marked by external identity exclusion … they have more random and egalitarian mixing" (2014: 1111). Together, past work suggests that insofar as network bounding effectively changes the rules of engagement for a set of actors, informal ties may also evolve in kind to be more cohesive or integrated within the newly established boundary. These changes may suggest that the new group is better equipped to function or collaborate as a collective. Therefore, with regards to the effects of network bounding on the informal ties among members, I predict the following:

> *Hypothesis 1 (H1): Network bounding will be associated with changes in informal network structure that support greater collective action or collaboration.*

4.2.3 Network Bounding and Performance

While network bounding may alter the configuration of ties within the boundary, it does not provide direct insight into whether these dynamics will have a positive or negative impact on the performance of the bound network. In other words, does network bounding facilitate formal networks' pursuit of collective outcomes? Despite the fact that most bounding decisions are likely designed to improve collective performance, or to achieve some desired outcome, existing research strongly hints that the relationship between bounding and performance may be complex.

On one hand, the value of boundaries and formality are well-established in various research streams. In public goods or common pool resource contexts where externalities are not easily excludable, the establishment of a boundary may be critical to effective management of a resource system (Ostrom, 1990). Moreover, scholars have argued that the establishment of a boundary coupled with strong ties among group members may improve the performance of private collectives (Ostrom, 2010; Dorobantu et al., 2017; Kaul and Luo, 2017). In the study of strategic alliances, theory and empirical evidence suggest that the performance of interorganizational activity may benefit from repeated interactions or stabilizing ties through intermediaries (Granovetter, 1973; Krackhardt, 1999). To the extent that these frequent or durable interactions mimic an exclusive or formal relationship, this may suggest that formalization can be beneficial. Studies of network effectiveness also provide evidence that certain types of fixed communication structures may offer performance advantages for group problem-solving tasks (Bavelas, 1950; Guetzkow & Simon, 1955). More recent research on formal and informal networks within organizations also provides some new insights into how formalization may positively affect performance. Specifically, consistency between informal and formal network structure may contribute to better performance for individuals, which may translate to better overall performance of the network (Soda & Zaheer, 2012). Additionally, formal relationships may enable actors to "regenerate" informal relationships that might otherwise have dissolved (Clement and Puranam, 2017). In this way, formal structure may serve as a kind of scaffold or guide that prevents against network failure (Schrank & Whitford, 2011).

These findings suggest that the stability or order introduced by formalization may have beneficial effects for networks, in potentially unanticipated ways.

On the other hand, research on multiparty alliances suggests formal partnerships among organizations may also be susceptible to problems arising from structural and relational heterogeneity that characterize network members' experience and interactions. For example, asymmetry in prior relational experience among network members may lead to the presence of destabilizing fault lines that increase the risk of alliance failure (Heidl, Steensma, and Phelps, 2014). Similarly, cohesive subgroups within larger groups may also threaten group stability by breaking away from an otherwise weakly tied collective (Greve et al., 2010). Alternatively, lack of consensus on how to best execute collaborative work may also be a source of conflict or inefficiency (Davis, 2016). Thus, group performance may vary widely across formal partnerships, and the informal relationships among member organizations may play an important role in shaping the group dynamics that underlay both stability and effectiveness. Furthermore, despite evidence the finding that consistency between informal and formal networks may benefit individual nodes within a network, this does not necessarily translate to the network level. That is, maximizing local performance may not always support the greater good.

These insights from prior research indicate that a critical factor in determining whether formalization or bounding is beneficial may be having the *right kinds* of informal ties. Put differently, bounding alone may not always be sufficient to improve collaboration or collective performance; such outcomes may also depend on having a supportive internal structure. This, in turn, may be significantly impacted by the formal group's starting point, or the arrangement of ties among members at the time of formalization. Since bounding effectively isolates a particular configurations of informal relationships from the larger social context, the omission of a crucial intermediary from the formal network may result in a weaker, or even harmful, set of relationships within the boundary. For instance, in bound network illustrated in Figure 1 (bottom path), the fragmentation in the informal network among members may represent a barrier to effective collaboration.

The previous hypothesis predicted that network bounding may influence members to interact more frequently within the boundary and alter informal networks to benefit collective action and collaboration. These changes in the informal network (within the boundary) may, therefore, be associated with better whole network performance since the network is better able to organize as a whole. At the same time, since bound networks may vary in their informal network structures (i.e., their imprints may be different), it is likely that some bound networks start from a more “favorable” base than others when it comes to whole network performance. Therefore, some networks may be better equipped to benefit from the establishment of a network boundary (and formal relationships, in this case) because there are fewer obstacles in terms of implementing the associated changes (Van de Ven, 1986). Consequently, I make two related predictions about the relationship between network bounding and network performance:

> *Hypothesis 2 (H2): Network bounding will be associated with better whole network performance if informal networks are better suited for collective action or collaboration.*

4.3 Research Context: CABG Surgery in the Time of the ACA

I study the effect of network bounding in the context of coronary artery bypass graft (CABG) surgery within the US healthcare system from 2008-2014, a period which saw the introduction of the *Affordable Care Act*, a major legislative change that made provisions for numerous healthcare reform efforts (see Chapter 2 for a detailed summary). CABG is a major surgical procedure (Figure 2) that is often scheduled electively, meaning that patients and their treating physicians agree to have the surgery in advance, usually in order to prevent a more serious emergency. Thus, the continuum of care for the typical CABG case typically begins well before surgery and extends beyond discharge from the hospital. The entire “episode,” as it is referred to in medicine, can be very complex, requiring the services of multiple physicians and organizations. In addition to the quality of care during the operation and the associated hospital stay, patient outcomes may be affected by the quality of pre-operative care involving multiple physicians, such as primary care physicians (PCPs, also referred to as general practitioners outside of the US), surgeons, and anesthesiologists, as this preparatory work can be important to successful surgery. Moreover, post-operative care during the critical recovery phase can be just as important for patient outcomes, if not more so, and also depends on effective coordination between multiple physicians and caregivers. Consequently, the overall success of a CABG procedure depends on the coordinated and collective efforts of multiple healthcare providers in different organizations, working together through every part of the process. Additionally, since Medicare beneficiaries mostly comprise patients aged 65 years and older, CABG is relatively more common in this patient demographic and is an important driver of healthcare expenditures.

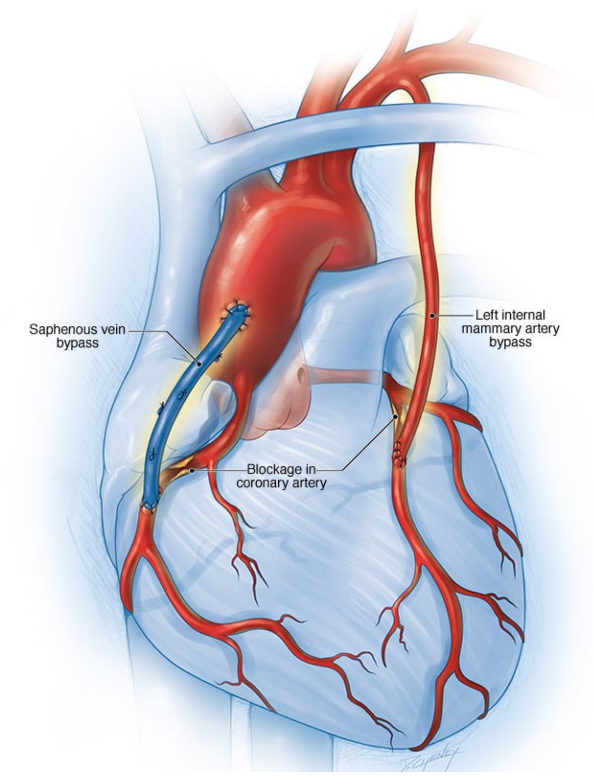

Figure 4.2: Coronary artery bypass graft surgery (CABG, pronounced "cabbage") is a major procedure in which vein is grafted to literally bypass a blockage in a coronary artery. Above, a saphenous vein graft is used to bypass a blockage. This procedure is a treatment modality for heart disease. (Image credit: Mayo Clinic)

Optimal coordination is unfortunately difficult to achieve within the US healthcare system, where multiple providers are often sub-optimally incentivized to work towards a collective outcome. Instead, many providers—both individuals and organizations—work on a fee-for-service basis, meaning that they are primarily compensated for the volume of work they perform. In an effort to ameliorate some of these adverse incentives, and realign providers' financial stakes towards collective, patient and system-level outcomes, the *Affordable Care Act* gave rise to formal networks: Medicare Accountable Care Organizations[33] (ACOs). Administered by the Centers for Medicare and Medicaid Services (CMS), the government bureau for federally funded health insurance, Medicare ACOs are formal networks of healthcare providers that contract with Medicare to care for a well-defined patient population of at least 5,000 elderly and disabled Americans. Thus, the formal tie that forms each ACO is a contractual relationship. Importantly, since ACOs are created as single entities, all members of an ACO enter into the contract simultaneously and, within the view of a formal ACO ties, all members are connected to one another.

The key strategic objective of ACOs is to improve coordination among physicians and organizations and increase the *value*, or cost-effectiveness, of the care that they deliver to patients. As described in Chapter 2, part of the contractual mechanism that formally defines ACO membership for each network, also establishes a shared financial incentive—if an ACO network can reduce healthcare expenditures for their designated patient population, while maintaining high quality, then that network will receive a portion of the savings. In contrast, for non-ACO Medicare providers, there is little incentive—except, perhaps, moral or ethical reasons—for providers to try to reduce expenditures. If anything, due to the relatively low reimbursement rates for Medicare, compared to private insurers, providers may have more

[33] For more information, refer to the CMS.gov website: https://innovation.cms.gov/initiatives/aco/

incentive to more towards higher margin services and procedures for Medicare beneficiaries.

There is also a focus on PCPs as the lynchpin of ACO network success. PCPs are viewed as both patient managers and “gatekeepers” within the healthcare system as PCPs may often be the entry point for patients. PCPs also play an important role in helping patients find the pathway to access more specialized (and expensive) healthcare services, such as those provided by a surgeon or cardiologist. This is not to say that specialists and surgeons do not also have an important role in achieving cost savings—they certainly do, and based on some conversations with ACO leaders, the role of non-PCP physicians may increase. However, because of PCPs’ accessibility and role in communities, the PCP-patient relationship is thought to be critical to achieving the changes that ACOs are designed to produce (Shortell et al., 2014).

I use the emergence of ACOs, and variation in health system participation in these formal networks, to examine the effects of this network formalization on the patterns and outcomes of CABG care. Specifically, I compare the network structures and performance of health systems that join ACOs with those of health systems that do not. As the continuum of care for CABG treatment is inherently multidisciplinary, requiring the services of different types of medical specialists and organizations as a patient prepares for surgery, undergoes the procedure, and then recovers, I focus on the degree to which physicians of different specialties share in the treatment of CABG patients. With increasing recognition that cross-specialty teamwork is a crucial success factor for patient-centered care (Hollingsworth et al., 2017), I expect that the propensity for physicians to work across specialties may be an important factor in whether ACO participation can promote beneficial changes to health systems.

4.3 Data & Methods

My sample is derived from a 20% random sample of all Medicare patients from 2008-2014. Within this initial sample, I first identify all patients who underwent a CABG procedure and then limit the focal cases to the first such procedure that each patient received. Thus, each patient only appears once in my sample. Each patient is then assigned to a particular health system, defined by the tertiary care hospital or medical center within which the surgical procedure was performed. Since not all hospitals are capable of performing such a complex procedure, I anchor subsequent network construction (see below) on these institutions. A key element of my analytical approach is the separation between the networks I study and level at which the network bounding (ACO membership) decision is made. In my sample, hospitals or medical centers are assigned to formal ACO networks at the organizational level. In contrast, I examine the consequences of network bounding at the level of physician networks for a specific surgical procedure. I describe below how I construct the physician networks for each health system and how I operationalize the bounding "treatment" within my sample.

4.3.1 Network Construction

For each CABG case, I first identify all of the physicians involved during the surgery and associated hospital stay, as well as those involved in treatment both 90 days prior to and 90 days after the date of surgery. I then identify the "core providers," the primary care physicians (PCPs), including geriatricians, medical specialists, and surgeons who are most critical to CABG care. I aggregate this information to first create bipartite networks of physicians and patients. I then project this network to a single mode physician-to-physician network, by year and at the level of the health system, defined as the network of providers that are involved in all CABG procedures performed in a specific tertiary care medical center. In this way, individual physicians are connected to one another as part of a health system if they have been involved in the treatment of the same patient within a given year. These network construction steps result in the building blocks of a panel of physician networks for each health system where a health system is observed in each year that it treated at least one CABG patient.

The physician networks constructed here are very similar to the raw data used in Chapter 3, with the exception that the patients which underlay the physician-to-physician relationships are specifically those who received a CABG procedure. In addition to the more general evidence supporting the use of these kinds of administrative data for network analysis, additional research in this patient population has also demonstrated a link between relationships based on shared patients and self-reported perceptions of teamwork from physicians along the care continuum (Everson et al., 2017). While they do not, as in the analysis presented in Chapter 3, directly proxy for direct interactions, because of the narrower scope of the data (CABG patients only), as well as the more limited time frame (within 90 days before and after surgery), these data are more likely to be correlated with real relationships among physicians.

Next, a critical component to my network construction and analytical strategy is the identification of physician specialty. Following previous work in health services that uses similar Medicare claims data to build networks (Funk et al., 2017), I group the physicians into three categories: PCPs, surgeons, and other medical specialists, which includes non-surgical specialists such as cardiologists or pulmonologists. These groups are subsequently used in the measurement of key network measures for each health system.

The full claims data yielded 80,782 unique CABG patients performed within 1,196 unique health systems across the US, from 2008-2014. However, because the degree of structural variation within physician networks is partially dependent upon the number of patients that are treated, I include only networks that perform at least three CABG procedures in a year. This exclusion criterion also has additional benefits. First, it excludes health systems that perform very few CABG procedures (the average number of CABG per health system-year is 10 in the full sample, with 3 being the 25th percentile). Second, this restriction also reduces the impact of missing control variable data which affected several networks with only one or two patients per year. The resulting final sample for analysis includes 4,904 health system-year observations, comprising 1,009 unique health systems with an average of more than 4 observations per health system. I also perform additional sensitivity tests to examine the effects of network size.

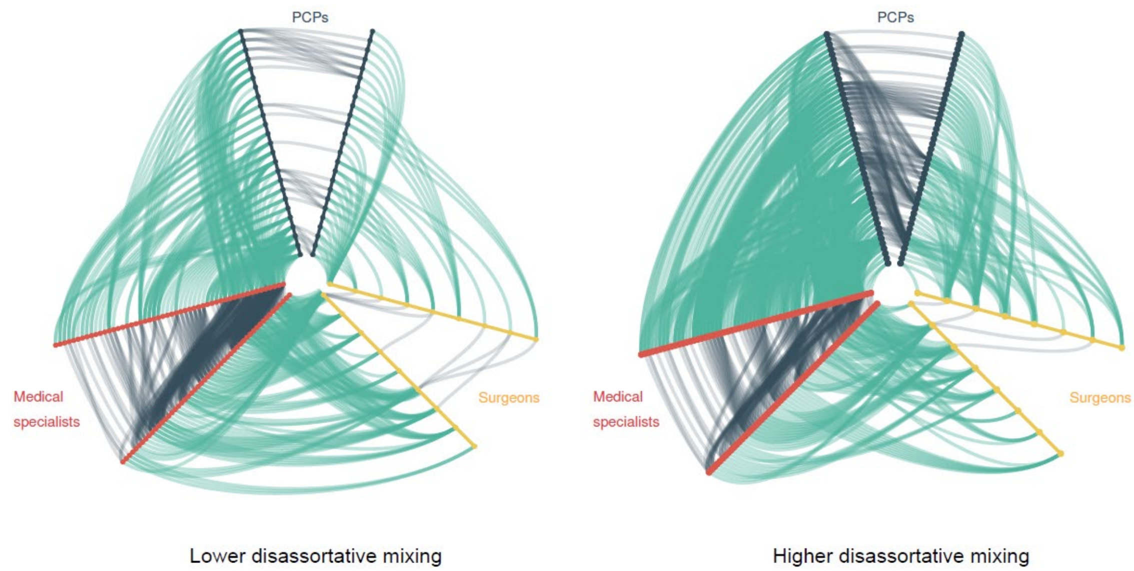

Figure 4.3: Disassortative mixing in CABG treatment networks. Two hive plots represent between-specialty connections within the informal networks of two health systems: one with low disassortative mixing (left) and the other with high disassortative mixing (right). Each "V-shaped" axis represents a specialty (blue = PCP, yellow = surgeons, red = medical specialists) and each node represents an individual physician (note that nodes are duplicated on each arm of the "V"). Lines within each "V" represent ties among physicians of the same specialty. Lines between different "V"s represent cross-specialty ties among physicians. The network on the left comprises 86 physicians and 13 CABG patients; 391 of 793 (49%) total ties are cross-specialty. The network on the right comprises 117 physicians and 19 CABG patients; 641 of 1039 (62%) total ties are cross-specialty.

4.3.2 Dependent and Independent Variables

Disassortative mixing (cross-specialty ties). For H1, I examine the effect of network bounding on the disassortative mixing of informal ties within the CABG network. I defined disassortative mixing as the inverse of assortative mixing, or a property of a whole network that measures how much more likely it is for nodes of *different types* to be connected to one another compared to nodes of the *same type*. This is an ideal measure because I am interested in examining the effects of network bounding on the rates of cross-specialty patient-sharing ties among physicians. I measure disassortative mixing using physician specialty groups (PCP, surgeon, or medical specialist) to categorize the individual nodes in each network. For ease of interpretation in regression models, I multiply the coefficient of disassortative mixing—which typically varies from -1 to 1—by 100 such that it takes on a minimum of -100 (no cross-specialty ties) and 100 (no within-specialty ties). This measure is consistent with previous research in health services (Funk et al., 2017; Kim et al., 2019) and is conceptually similar to structural fragmentation based on within-group segregation (Yenkey, 2015; McFarland et al., 2014). This same measure is used as an independent variable for the H2 test. Figure 2 illustrates how the clinical integration may be depicted in terms of between-group versus within-group ties.

Patient deaths (90 days post-operative). The key dependent variable of interest in H2 measures the overall effectiveness of each collective in terms of CABG patient outcomes. Thus, my performance outcome is the number of patients who died within 90 days of surgery for each network-year. Supplementary analyses looking at alternative measures of patient outcomes, such as the incidence of complications, are currently in progress.

Network bounding (ACO membership). My key "treatment" variable for both H1 and H2 is network bounding. Each health system that joins an ACO has a specific ACO start date. My variable for network bounding takes on the value of 1 if the ACO start date was *before* the start of year for that network-year observation. Thus, if a health system joined an ACO with a start date of April 1, 2012, network bounding is set at 0 in 2012, and 1 in 2013. The data for ACO participation was derived primarily from the Leavitt Partners' ACO Database and cross-referenced with CMS' Shared Savings Program Provider-level Research Identifiable File.

4.3.3 Control Variables

Due to the complexity of comparing many health system networks across the US, I include a number of control variables to try to account for important factors at the patient, health system and community levels.

First, at the patient level, I control for patient health status and co-morbidity—or the severity of their concomitant ailments—using the Charlson comorbidity index, a standard for health services research (Charlson et al., 1994). I also control for patient gender, age at admission, and whether or not the patient is Black, as these factors have been associated with patient outcomes (e.g., Lassman et al., 2013). These variables are constructed using the claims data. Next, I also capture whether or not the patient, based on her home zip code, is from a rural area. Similarly using home zip code, I measure the percent of residents in that geographic area that are below the federal poverty line. The rurality and poverty data are collected from the US Census Bureau's American Community Survey[34] database. Finally, I indicate whether the patient lives in the same core-based statistical area (CBSA) as the treating medical center where she was admitted for surgery. All patient-level controls are first measured for each patient and then averaged at the health system (network)-year level based on the date of the patient's CABG procedure.

At the network level, I control for the total number of CABG patients, the number of physicians per patient, the total number of edges between physicians in the network, and the proportions of medical specialists and surgeons. Additionally, because physicians may work in multiple organizational settings, they may not necessarily be *legally* part of an ACO despite being involved in patient care for a health system that joins an ACO. Therefore, I control for the specific number of physicians who are legally (i.e., by contract) affiliated with an ACO. I also control for the institutional form of the treating medical center (e.g., government, for-profit), and whether the system uses electronic health records.

Finally, since each network may also be influenced by external context, I also control for community-level characteristics to try to capture differences in population and healthcare access. Thus, I control for total population, the population of Black residents, and the population of Hispanic residents, all logged. I additionally control for the number of hospital beds and PCPs per 1,000 residents. All community-level variables were measured at the health service area

[34] https://www.census.gov/programs-surveys/acs

level using data from the Dartmouth Atlas[35] and the American Community Survey.

4.3.4 Model Estimation

In this study, I am primarily interested in examining variance in two outcome variables: disassortative mixing of networks and patient mortality. For both outcomes, the key "treatment" is network bounding, defined as whether or not the focal health system network joins an ACO. In my main linear regressions, I use panel data with network-year observations, with the treatment variable taking on the value of 1 in the years *post-treatment* for treated networks and 0 otherwise. However, because ACOs are *voluntarily* formed by groups of healthcare providers joining together, there is an obvious issue of endogeneity with respect to which networks are treated. The key issue is whether the networks that select into ACOs are different from those that do not join ACOs in ways that would (a) bias the likelihood of changing level of integration among providers, or (b) alter CABG patient outcomes. I try to account for this selection problem through a few strategies.

First, as previously alluded to, my data is structured such that I try to separate the decision-makers from the observed networks. In my context, the decision to join an ACO is made at the level of the treating medical center. However, the specific networks I study are physician networks, for a specific surgical procedure, that are centered on the deciding organization. Therefore, the decision-makers determining ACO membership are not members of the networks I study to examine the consequences of network bounding. Put differently, my study analyzes how a network of doctors that are associated with a particular organization changes when that organization decides to join a formal network. I assume that most doctors that are associated with that organization are at least aware of this new affiliation, even if they do not

[35] Health service areas, or HSAs, are defined by the Dartmouth Atlas as "local health care markets for hospital care." http://www.dartmouthatlas.org/

have direct say in the decision to participate (Schur & Sutton, 2016). Thus, they may alter their behaviors to the extent that they are detectable through changes in network measures, such as integration.

Next, because I have panel data I used network-level fixed effects in all analyses, enabling me to account for time invariant heterogeneity among networks in my sample. Generally, this specification is represented by the following equation:

$$y_{it} = \beta_0 + \beta_1 \cdot bounding + \beta_2 \cdot \mathrm{X} + c_i + \epsilon_{it},\ i = 1, ..., \mathrm{N}, \mathrm{t} = 1, ..., 7$$

where y_{it} is the dependent variable (disassortative mixing or patient mortality), X is a matrix of covariates and c_i captures the time invariant heterogeneity across health system networks. Additionally, I use a unique feature of my sample to further refine my analyses. Because not all health systems that will *eventually* join an ACO do so within my sample, I am able to perform my analyses on a restricted sample of health systems that will, at some point in the near future, join an ACO. This may provide better control for the selection issue since all health systems in the restricted sample will eventually join an ACO. That said, using only the restricted sample greatly limits the power of my study, and would also further limit the potential generalizability of my results. Therefore, for my main analyses I show results for both the full and restricted samples. I also show results for the restricted sample for sensitivity tests where space allows.

4.4 Results

Descriptive statistics and pair-wise correlations for variables are shown in Table 4.1. The main results of the fixed effects linear regression for disassortative mixing (H1) are shown in Table 4.2. Again, disassortative mixing measures the extent to which members of a network, in this case physicians, exhibit more interaction across subgroups (specialty). Greater disassortative mixing suggests that physician networks are more interdisciplinary. Model 1 shows the results for only the control variables. Model 2 shows the results for the full model, including the bounding (treatment) variable. Model 3 shows the results for bounding alone. The results from Model 2 suggest that in the full sample, network bounding is significantly associated with an increase in disassortative mixing, though the magnitude to the effect is relatively small (β=0.58). The result in Model 3 suggests that within a diverse set of networks, this relationship is not as robust without controlling for other potential factors that may affect disassortative mixing. Models 4 and 5 show the same results using the restricted sample of only networks that eventually join an ACO. In these analyses, network bounding is again significantly associated with an increase in integration and the magnitude of the coefficient is larger, though still relatively small (β=0.75). The fact that the relationship is robust without controls in Model 5, suggests that the relative change in integration before and after network bounding is more pronounced when only comparing health system that are known to eventually join a formal ACO network. Therefore, I find support for H1 that network bounding is associated with greater disassortative mixing.

The results for H2 are shown in Table 4.3. For these analyses, I am specifically interested in the interaction between network bounding and disassortative mixing. First, in Models 6 and 7, I use the full sample to assess how the relationship between network bounding and network performance (patient deaths) changes when I introduce disassortative mixing into the model. The results suggest that network bounding, on its own, has no statistically significant association with network performance (Model 6). Moreover, this result does not change when disassortative mixing is introduced into the model—though disassortative mixing, itself, is significantly and negatively associated with patient deaths, as I would expect (Model 7). These results are consistent even in the restricted sample tests, Models 9 and 10. Thus, I find that H2a is not supported because network bounding, itself, does not appear to significantly improve network performance on average.

Next, I look at the interaction between bounding and disassortative mixing in Models 8 (full sample) and Model 11 (restricted sample). Here, I find evidence supporting H2 in Model 8;

the interaction term between network bounding and disassortative mixing is negative and statistically significant, suggesting that for “treated” networks there is greater benefit in terms of patient outcomes at higher levels of disassortative mixing (Figure 4.4). Although the interaction term is not statistically significant at the 5 percent level in the restricted sample (Model 11), the coefficient is consistent with that in Model 8 and the associated p-value is approximately 0.11.

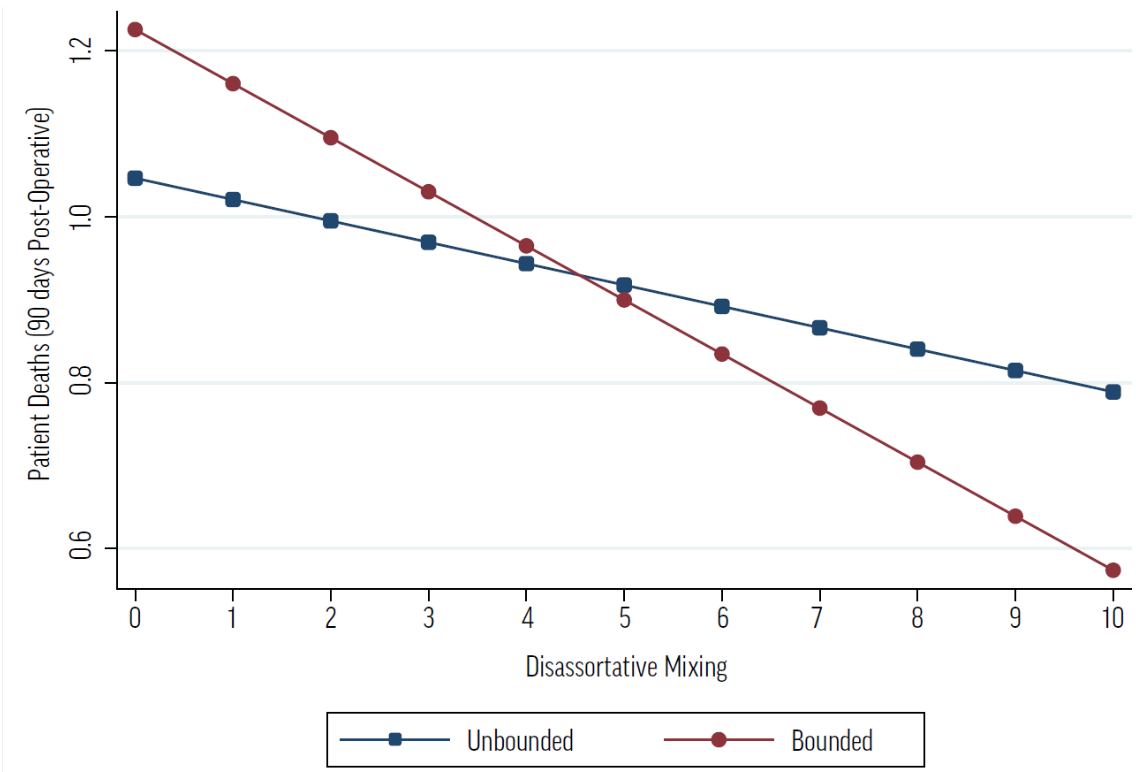

Figure 4.4: Predicted values for CABG patient deaths (90 days post-operative) for bounded (joins ACO) and unbounded (does not join ACO) health systems, 2008-2014.

The result in Model 8 is also robust to various alternate specifications, including OLS with network dummy variables, network random effects, Poisson with fixed effects, zero-inflated logistic regressions, and a dynamic panel specification with a lagged DV (results available upon request). Figure 4 graphically depicts the predicted values from the full sample linear model (Model 8), showing that bounded networks are expected to perform worse than unbound networks at low levels of integration, but expected to perform *better* at high levels of integration.

Additionally, since my predictions are structured such that the DV of H1 (disassortative mixing) is an IV in the analysis for H2, I conducted an additional test for conditional indirect effects—or moderated mediation (Preacher et al., 2007)—in Model 12. I estimate the models for disassortative mixing (H1) and patient death (H2) simultaneously using a structural equation approach, specifically using the gsem command in Stata 14.2. The first equation models H1, with network bounding predicting the level of disassortative mixing. The second equation is a negative binomial regression for patient deaths for H2 using the residuals from the first stage linear regression. The results of this regression suggest that bounding may be associated with fewer patient deaths in networks with greater disassortative mixing. However, the main coefficient on network bounding (β=0.20) suggests that disassortative mixing may need to be relatively high in order for the combined effects of integration and network bounding to yield improved patient outcomes, on average. These results do not change even when I account for the number of patients within each network-year who were emergency surgeries—thus, more likely to experience poor outcomes. Taken together, these results suggest that H2 is supported but also that the story may be slightly more complicated than predicted.

In order to further examine what is driving my results, I adopted a segmented regression approach as recommended by Shaver (2019) in situations where interaction terms are present in linear fixed effects models, as is my case. The rationale for segmentation, or conducting regressions at different ranges of the variables being interacted, is that the inclusion of an interaction term may result in the fixed effects model no longer producing within-unit estimates. In this case, the inclusion of an interaction term between network bounding and disassortative mixing may mean that the statistically significant interaction in Models 8, 11, and 12 are not purely driven by within-network variation. Thus, following the recommendations in this study, I perform individual fixed effects regressions (without interactions) for my DV (patient deaths) at quartiles of disassortative mixing and for bound and unbound networks. The results from this analysis (available upon request) suggest that the statistically significant interaction is being driven by (1) a statistically significant relationship between *within-network* variation in disassortative mixing at different levels of bounding (0 or 1), but also (2) *between-network* variation in the effects of network bounding at different levels of disassortative mixing. In other words, the results provide evidence that increasing disassortative mixing has a greater relationship with network performance in bound networks, but they do not conclusively demonstrate that network bounding will be more effective in network with high disassortative mixing. The practical implications of this distinction will be discussed further in subsequent sections of the chapter.

4.4.1 Supplementary Analyses

In order to more closely examine the results from my main analyses I conducted series of supplementary analyses.

Multi-org physicians. It is not uncommon for physicians to appear in multiple health systems' networks. This is not an artifact of network construction, but rather reflects the nature of the US healthcare system. Physicians may often refer to, and receive referrals from, outside of their most common partners for a variety of reasons, including, but not limited to, patient convenience, patient needs, appointment availability, or simply patient choice. Approximately 10 percent of the more than 420,000 physicians identified in my claims data were associated with more than one health system, 2.5 percent were associated with more than two systems.

I theorized that network bounding would have an integrative effect on members through group identification and the exclusion of non-members. However, physicians that are affiliated with multiple health systems, either through referrals or by seeing patients in multiple locations, may not identify as strongly with a single health system. Thus, these network-spanning physicians may not feel the effects of bounding to the same extent as their colleagues who only

Table 4.1: Descriptive Statistics and Correlations

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Disassortative mixing	4.44	4.08										
2. Bounded (0 = No, 1 = Yes)	0.06	0.23	-0.03									
3. Patient Morbidity	1.9	0.71	-0.20*	0.05*								
4. Gender (0 = Male, 1 = Female)	1.3	0.17	-0.04*	-0.02	0.06*							
5. Age at Admission	74.78	2.2	-0.07*	-0.00	0.10*	0.06*						
6. Black (0 = No, 1 = Yes)	0.04	0.09	-0.06*	0.02	0.13*	0.08*	-0.06*					
7. % Patients from Rural Area	0.01	0.03	0.01	-0.04*	-0.04*	-0.03*	-0.03*	0.03*				
8. % Patients from Impoverished Area	14.67	4.2	0.08*	-0.00	0.01	-0.03	-0.08*	0.08*	0.05*			
9. % Patients from Same CBSA	0.61	0.26	-0.01	0.02	0.01	0.02	0.05*	0.09*	-0.09*	-0.16*		
10. Total CABG Patients	13.21	10.78	-0.20*	0.01	0.03*	0.00	0.06*	-0.03	-0.00	-0.11*	-0.12*	
11. Total MDs per Patient	6.93	2.82	-0.35*	0.09*	0.35*	0.09*	0.12*	0.15*	-0.03	-0.11*	-0.25*	0.16*
12. ACO-affiliated MDs	5.05	15.21	-0.10*	0.48*	0.12*	-0.01	0.04*	-0.01	-0.05*	-0.03*	0.21*	0.02
13. Total Edges	1,096.36	1,491.33	-0.28*	0.07*	0.18*	0.03*	0.12*	0.03	-0.02	-0.18*	0.78*	-0.01
14. Academic Hospital (0 = No, 1 = Yes)	0.63	0.48	-0.11*	0.07*	0.07*	0.01	0.05*	0.09*	-0.05*	-0.04*	0.12*	-0.04*
15. Government Hospital (0 = No, 1 = Yes)	0.08	0.27	0.03*	-0.06*	0.02	-0.04*	-0.03*	0.02	0.02	0.02	-0.05*	-0.05*
16. For-profit Hospital (0 = No, 1 = Yes)	0.13	0.33	0.05*	-0.06*	-0.02	0.02	-0.06*	0.01	0.04*	0.17*	-0.08*	0.01
17. Uses EHR (0 = No, 1 = Yes)	0.96	0.19	-0.02	0.04*	0.03	-0.06*	0.01	0.01	-0.04*	0.03	0.02	-0.01
18. Total Population (log)	5.7	0.98	-0.19*	0.06*	0.09*	0.00	-0.01	0.15*	-0.00	0.02	0.11*	0.10*
19. Black Population (log)	3.32	1.77	-0.20*	0.00	0.10*	0.04*	-0.01	0.28*	0.01	0.02	0.15*	0.15*
20. Hispanic Population (log)	2.97	1.61	-0.16*	0.06*	0.11*	-0.01	-0.00	0.12*	0.01	0.08*	0.06*	0.13*
21. Beds per 1,000 Residents	2.04	0.51	0.07*	-0.04*	0.05*	0.08*	-0.06*	0.18*	0.01	0.26*	-0.10*	0.01
22. PCPs per 1,000 Residents	68.62	16.03	-0.12*	0.08*	0.09*	0.01	0.12*	0.09*	-0.07*	-0.26*	0.07*	0.13*

Variable	11	12	13	14	15	16	17	18	19	20	21
12. ACO-affiliated MDs	0.08*										
13. Total Edges	0.17*	0.29*									
14. Academic Hospital (0 = No, 1 = Yes)	0.15*	0.10*	0.18*								
15. Government Hospital (0 = No, 1 = Yes)	-0.02	-0.05*	-0.06*	0.01							
16. For-profit Hospital (0 = No, 1 = Yes)	-0.04*	-0.06*	-0.11*	-0.22*	-0.11*						
17. Uses EHR (0 = No, 1 = Yes)	0.01	0.06*	0.01	0.13*	0.03*	-0.12*					
18. Total Population (log)	0.27*	0.05*	0.17*	0.19*	-0.08*	0.03	0.06*				
19. Black Population (log)	0.26*	0.00	0.21*	0.17*	-0.01	0.01	0.01	0.80*			
20. Hispanic Population (log)	0.29*	0.06*	0.15*	0.11*	-0.04*	0.15*	0.03*	0.84*	0.65*		
21. Beds per 1,000 Residents	-0.01	-0.07*	-0.07*	-0.04*	0.01	0.07*	-0.07*	-0.01	0.18*	-0.08*	
22. PCPs per 1,000 Residents	0.27*	0.10*	0.19*	0.28*	-0.10*	-0.20*	-0.00	0.27*	0.25*	0.15*	0.01

* $p < 0.05$

Table 4.2: OLS Regression Models for Disassortative Mixing

Variable	(1)	(2)	(3)	(4)	(5)
Bounded (0 = No, 1 = Yes)		0.58*	0.41	0.77*	0.72*
		(0.26)	(0.25)	(0.32)	(0.32)
Patient Characteristics					
Patient Morbidity	-0.25***	-0.25***		-0.00	
	(0.09)	(0.09)		(0.15)	
Gender (0 = Male, 1 = Female)	-0.43	-0.42		-0.31	
	(0.33)	(0.33)		(0.59)	
Age at Admission	0.01	0.01		0.03	
	(0.03)	(0.03)		(0.05)	
Black (0 = No, 1 = Yes)	-0.58	-0.59		-0.48	
	(0.93)	(0.93)		(1.25)	
% Patients from Rural Area	0.48	0.48		-0.96	
	(1.87)	(1.87)		(3.39)	
% Patients from Impoverished Area	-0.01	-0.01		-0.01	
	(0.03)	(0.03)		(0.05)	
% Patients from Same CBSA	0.73*	0.74*		0.63	
	(0.36)	(0.36)		(0.67)	
Health System Characteristics					
Total CABG Patients	-0.11***	-0.11***		-0.12***	
	(0.02)	(0.02)		(0.03)	
Total MDs per Patient	-0.57***	-0.57***		-0.59***	
	(0.05)	(0.05)		(0.07)	
ACO-affiliated MDs	-0.00	-0.01*		-0.01	
	(0.00)	(0.00)		(0.00)	
% of MDs, Surgeons	4.13	4.01		3.66	
	(2.64)	(2.64)		(3.70)	
% of MDs, Medical Specialists	-6.46***	-6.49***		-5.85***	
	(1.11)	(1.11)		(1.86)	
Total Edges	-0.00	-0.00		0.00	
	(0.00)	(0.00)		(0.00)	
Academic Hospital (0 = No, 1 = Yes)	0.04	0.06		0.74	
	(0.27)	(0.27)		(0.48)	
Government Hospital (0 = No, 1 = Yes)	0.58	0.62		0.23	
	(0.83)	(0.82)		(0.91)	
For-profit Hospital (0 = No, 1 = Yes)	-0.20	-0.18		0.40	
	(0.75)	(0.74)		(1.15)	
Uses EHR (0 = No, 1 = Yes)	0.30	0.31		0.09	
	(0.37)	(0.37)		(0.81)	
Community-level Characteristics					
Total Population (log)	-0.01	-0.03		-0.53	
	(0.28)	(0.28)		(0.42)	
Black Population (log)	0.01	0.02		0.15	
	(0.12)	(0.12)		(0.19)	
Hispanic Population (log)	0.15	0.15		0.43†	
	(0.12)	(0.12)		(0.22)	
Beds per 1,000 Residents	-1.99†	-1.71		34.56***	
	(1.11)	(1.17)		(6.70)	
PCPs per 1,000 Residents	-0.01	-0.01		-0.07***	
	(0.01)	(0.01)		(0.02)	
Constant	17.19***	16.53***	4.55***	-50.67***	3.80***
	(4.02)	(4.14)	(0.11)	(14.78)	(0.19)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes	Yes	Yes
R2	0.14	0.14	0.00	0.16	0.01
N	4904	4904	5047	1423	1447

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Table 4.3: OLS Regression Results for Whole Network Patient Deaths (90 days Post-Operative)

Variable	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bounded (0 = No, 1 = Yes)	0.03	0.04	0.19	-0.16	-0.13	-0.02	0.20*
	(0.09)	(0.09)	(0.12)	(0.11)	(0.11)	(0.14)	(0.09)
Disassortative mixing (DM)		-0.02***	-0.02***		-0.03***	-0.03***	-0.05***
		(0.00)	(0.00)		(0.01)	(0.01)	(0.00)
Bounded * DM			-0.03*			-0.03	-0.04*
			(0.02)			(0.02)	(0.02)
Patient Characteristics							
Patient Morbidity	0.10***	0.09***	0.09***	0.09*	0.09*	0.09*	0.19***
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.02)
Gender (0 = Male, 1 = Female)	0.09	0.08	0.08	0.02	0.01	0.01	0.20†
	(0.08)	(0.08)	(0.08)	(0.14)	(0.14)	(0.14)	(0.10)
Age at Admission	0.04***	0.04***	0.04***	0.05***	0.05***	0.05***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black (0 = No, 1 = Yes)	0.13	0.12	0.12	0.00	-0.01	0.00	-0.11
	(0.18)	(0.18)	(0.18)	(0.39)	(0.39)	(0.39)	(0.21)
% Patients from Rural Area	0.11	0.12	0.12	0.74	0.71	0.71	0.20
	(0.40)	(0.40)	(0.40)	(1.12)	(1.08)	(1.08)	(0.47)
% Patients from Impoverished Area	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01	0.01†
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
% Patients from Same CBSA	-0.02	0.00	0.00	-0.15	-0.13	-0.13	-0.13
	(0.08)	(0.08)	(0.08)	(0.16)	(0.16)	(0.16)	(0.08)
Health System Characteristics							
Total CABG Patients	0.05***	0.05***	0.05***	0.07***	0.06***	0.06***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Total MDs per Patient	0.00	-0.01	-0.01	0.02	0.01	0.00	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
ACO-affiliated MDs	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% of MDs, Surgeons	0.40	0.49	0.50	1.91*	2.03*	2.03*	-1.73***
	(0.40)	(0.41)	(0.41)	(0.93)	(0.93)	(0.93)	(0.50)
% of MDs, Medical Specialists	1.18***	1.03***	1.04***	1.14*	0.94*	0.98*	-0.09
	(0.22)	(0.22)	(0.22)	(0.44)	(0.45)	(0.45)	(0.22)
Total Edges	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Academic Hospital (0 = No, 1 = Yes)	-0.05	-0.05	-0.05	-0.20	-0.17	-0.19	0.10*
	(0.08)	(0.08)	(0.08)	(0.13)	(0.13)	(0.13)	(0.04)
Government Hospital (0 = No, 1 = Yes)	0.12	0.13	0.13	-0.28	-0.27	-0.29	-0.00
	(0.22)	(0.22)	(0.22)	(0.48)	(0.47)	(0.46)	(0.06)
For-profit Hospital (0 = No, 1 = Yes)	0.16	0.16	0.16	0.23	0.24	0.24	0.08
	(0.20)	(0.20)	(0.20)	(0.83)	(0.81)	(0.81)	(0.05)
Uses EHR (0 = No, 1 = Yes)	-0.06	-0.05	-0.05	-0.31	-0.30	-0.30	0.13
	(0.08)	(0.08)	(0.08)	(0.26)	(0.26)	(0.26)	(0.13)
Community-level Characteristics							
Total Population (log)	-0.09	-0.09	-0.09	-0.19	-0.21	-0.20	0.13*
	(0.10)	(0.10)	(0.10)	(0.19)	(0.19)	(0.19)	(0.06)
Black Population (log)	0.02	0.02	0.02	-0.00	0.00	-0.00	-0.01
	(0.04)	(0.04)	(0.04)	(0.08)	(0.08)	(0.08)	(0.02)
Hispanic Population (log)	-0.02	-0.02	-0.02	0.08	0.09	0.08	-0.06**
	(0.04)	(0.04)	(0.04)	(0.09)	(0.09)	(0.09)	(0.02)
Beds per 1,000 Residents	0.29	0.25	0.29	-2.26	-1.12	-1.32	0.09*
	(0.62)	(0.60)	(0.59)	(2.14)	(2.13)	(2.15)	(0.04)
PCPs per 1,000 Residents	0.01	0.01	0.01	0.00	-0.00	-0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-4.71**	-4.30*	-4.44**	0.81	-0.86	-0.59	-5.82***
	(1.74)	(1.69)	(1.67)	(4.52)	(4.47)	(4.49)	(0.62)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.19	0.19	0.19	0.21	0.22	0.22	0.10
N	4,904	4,904	4,904	1,423	1,423	1,423	4,904

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

work with one health system. In Table 4.4, I examine the relationship between network bounding and disassortative mixing with the number of multi-org physicians in the network as a moderator. Models S1 (full sample) and S2 (restricted sample) show that the interaction term between network bounding and multi-org physicians is *negative*, suggesting that the presence of more of these physicians within the network slightly attenuates the relationship between bounding and disassortative mixing.

ACO type. ACOs are also quite heterogeneous in terms of their composition. Efforts to classify ACOs based on the types of providers that comprise membership have resulted in three major categories: physician-led, hospital-led, or hybrid/integrated systems (Shortell et al., 2014; Lewis et al., 2017; Leavitt Partners Database). I classified ACOs to be either physician/hospital-led or integrated/hybrid systems with the assumption that the former may experience the effects of network bounding *more* since health systems falling into the latter category presumably already have a high level of integration.

I found that while there was not a statistically significant difference (through t-test) in the average disassortative mixing level between integrated/hybrid ACOs and physician/hospital-led ACOs (4.01 vs. 3.80, p=0.14), the results of fixed effects regression shown in Table 4.5 suggest that bounding may be more consistently associated with greater disassortative mixing for health systems joining physician/hospital-led ACOs (Model S3, β=1.08). In contrast, the coefficient for network bounding in health systems joining integrated/hybrid ACOs (Model S4) is smaller in magnitude and not statistically significant (β=0.33).

Extending this a step further, given the results of the analyses for H2, I also examine how the interaction between network bounding and disassortative mixing is associated with patient outcomes in these different types of ACO networks (Models S5 and S6). Although the relationship between disassortative mixing and patient outcomes is in the expected direction and consistent between the two groups, I find that network bounding appears to have a slightly more robust effect in the group of integrated/hybrid ACOs.

PCP census. The role of PCPs is critical to ACOs' ability to achieve the desired changes in healthcare delivery. As such, despite evidence that network bounding was associated with changes in networks' structure, I wanted to examine whether or not network bounding would noticeably change PCPs' role in health system networks. Table 4.6 shows the results of four regression models in which I examine the number of PCP-to-PCP ties (Model S7), PCP-to-surgeon ties (Model S8), PCP-to-medical specialist ties (Model S9) and the total number of PCPs (Model S10) as outcome variables. The results of these analyses suggest several important changes underlying the observed relationship between bounding and disassortative mixing.

First, bounding is associated with a significant reduction in the number of within-specialty PCP-PCP ties. Since PCP-PCP ties would only arise if multiple PCPs were involved in the care of the same patient, this result is suggestive of better continuity of care with fewer PCPs being involved in the care of a particular patient. Second, bounding is also associated with a significant reduction in the number of between-specialty PCP-surgeon and PCP-medical specialist ties. Again, this result suggests that the set of PCPs, and possibly surgeons, that are involved in CABG care is narrowing for each bound health system. Finally, bounding is associated with a significant decrease in the number of PCPs present within each health system network, further supporting the interpretation that network bounding is effectively reducing variance in who cares for the patient on the primary care side. Similar analyses for the number of surgeons and PCPs, as well as the number of CABG patients, show no statistically significant association with network bounding. Relatedly, similar analyses for other within- and between-specialty ties resulted in no statistically significant association, except an increase in medical specialist-to-medical specialist ties, suggesting greater involvement of medical specialists within their respective health systems. These interesting results provide some evidence that the network changes being elicited by ACO membership are having the intended effects.

Table 4.4: Results for Disassortative Mixing – Multi-org Physicians

Variable	(S1) Full Sample	(S2) Joins ACO Only
Bounded (0 = No, 1 = Yes)	0.77**	1.03***
	(0.28)	(0.35)
Multi-org MDs	0.00***	0.00
	(0.00)	(0.00)
Bounded * Multi-org MDs	-0.00*	-0.01*
	(0.00)	(0.00)
Patient Characteristics		
Patient Morbidity	-0.25***	0.01
	(0.09)	(0.15)
Gender (0 = Male, 1 = Female)	-0.41	-0.29
	(0.33)	(0.59)
Age at Admission	0.01	0.03
	(0.03)	(0.05)
Black (0 = No, 1 = Yes)	-0.63	-0.56
	(0.93)	(1.24)
% Patients from Rural Area	0.47	-1.00
	(1.87)	(3.40)
% Patients from Impoverished Area	-0.01	-0.01
	(0.03)	(0.05)
% Patients from Same CBSA	0.73*	0.61
	(0.36)	(0.67)
Health System Characteristics		
Total CABG Patients	-0.13***	-0.13***
	(0.02)	(0.03)
Total MDs per Patient	-0.57***	-0.59***
	(0.05)	(0.07)
ACO-affiliated MDs	-0.01	-0.00
	(0.00)	(0.00)
% of MDs, Surgeons	3.85	3.54
	(2.64)	(3.70)
% of MDs, Medical Specialists	-6.63***	-6.04***
	(1.11)	(1.87)
Total Edges	-0.00	0.00
	(0.00)	(0.00)
Academic Hospital (0 = No, 1 = Yes)	0.05	0.73
	(0.27)	(0.48)
Government Hospital (0 = No, 1 = Yes)	0.57	0.11
	(0.83)	(0.99)
For-profit Hospital (0 = No, 1 = Yes)	-0.16	0.40
	(0.74)	(1.16)
Uses EHR (0 = No, 1 = Yes)	0.31	0.09
	(0.36)	(0.81)
Community-level Characteristics		
Total Population (log)	-0.03	-0.55
	(0.28)	(0.42)
Black Population (log)	0.03	0.16
	(0.12)	(0.19)
Hispanic Population (log)	0.15	0.44*
	(0.12)	(0.22)
Beds per 1,000 Residents	-1.67	34.18***
	(1.16)	(6.68)
PCPs per 1,000 Residents	-0.01	-0.07***
	(0.01)	(0.02)
Constant	16.62***	-49.65***
	(4.12)	(14.78)
Year Fixed Effects	Yes	Yes
Health System Fixed Effects	Yes	Yes
R^2	0.14	0.16
N	4,904	1,423

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Table 4.5: Results for Disassortative Mixing & Patient Deaths – ACO Type

	Disassortative mixing		**Patient Deaths**	
Variable	(S3) MD group or Hospital	(S4) Integrated system	(S5) MD group or Hospital	(S6) Integrated system
Bounded (0 = No, 1 = Yes)	1.08*	0.33	-0.14	0.26†
	(0.46)	(0.33)	(0.31)	(0.14)
Disassortative mixing (DM)			-0.04*	-0.02***
			(0.02)	(0.00)
Bounded * DM			-0.02	-0.03†
			(0.04)	(0.02)
Patient Characteristics				
Patient Morbidity	0.11	-0.29***	0.13†	0.08***
	(0.21)	(0.09)	(0.07)	(0.02)
Gender (0 = Male, 1 = Female)	0.35	-0.50	-0.08	0.10
	(0.73)	(0.36)	(0.23)	(0.08)
Age at Admission	-0.07	0.01	0.06***	0.04***
	(0.08)	(0.03)	(0.02)	(0.01)
Black (0 = No, 1 = Yes)	-0.79	-0.53	-0.82	0.26
	(1.40)	(1.01)	(0.70)	(0.18)
% Patients from Rural Area	-3.79	0.99	1.30	-0.00
	(6.28)	(1.98)	(1.43)	(0.41)
% Patients from Impoverished Area	0.02	-0.01	-0.02	-0.00
	(0.07)	(0.03)	(0.02)	(0.01)
% Patients from Same CBSA	0.45	0.75†	-0.10	0.02
	(1.01)	(0.39)	(0.23)	(0.08)
Health System Characteristics				
Total CABG Patients	-0.19***	-0.10***	0.06***	0.04***
	(0.04)	(0.02)	(0.02)	(0.01)
Total MDs per Patient	-0.72***	-0.55***	-0.01	-0.01
	(0.12)	(0.05)	(0.04)	(0.01)
ACO-affiliated MDs	-0.02†	-0.01	0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)
% of MDs, Surgeons	4.02	3.94	1.31	0.35
	(5.45)	(2.89)	(1.48)	(0.42)
% of MDs, Medical Specialists	-6.80*	-6.46***	0.69	1.08***
	(2.66)	(1.21)	(0.81)	(0.23)
Total Edges	0.00	-0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Academic Hospital (0 = No, 1 = Yes)	0.38	-0.03	-0.24	-0.02
	(0.76)	(0.28)	(0.20)	(0.08)
Government Hospital (0 = No, 1 = Yes)	0.80	0.87	-0.96***	0.33†
	(0.73)	(1.10)	(0.28)	(0.17)
For-profit Hospital (0 = No, 1 = Yes)	1.04	-0.25	-1.81***	0.28
	(0.87)	(0.77)	(0.34)	(0.21)
Uses EHR (0 = No, 1 = Yes)	0.85	0.29	-0.57	-0.00
	(1.02)	(0.39)	(0.44)	(0.08)
Community-level Characteristics				
Total Population (log)	0.26	-0.03	-0.80***	0.03
	(0.60)	(0.32)	(0.26)	(0.11)
Black Population (log)	0.11	-0.00	0.13	-0.01
	(0.33)	(0.13)	(0.10)	(0.04)
Hispanic Population (log)	0.02	0.15	0.18	-0.05
	(0.35)	(0.13)	(0.13)	(0.05)
Beds per 1,000 Residents	57.27***	-1.83	-0.78	0.43
	(13.65)	(1.15)	(4.07)	(0.55)
PCPs per 1,000 Residents	0.00	-0.01	0.00	0.01†
	(.)	(0.01)	(.)	(0.00)
Constant	-93.76***	16.53***	1.20	-5.27***
	(29.69)	(4.23)	(8.34)	(1.61)
Year Fixed Effects	Yes	Yes	Yes	Yes
Health System Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.22	0.13	0.24	0.20
N	611	4293	611	4293

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests)

Network size. Lastly, I more carefully examined the role that network size might play in my results. For both empirical and theoretical reasons, I use the number of CABG patients to investigate network size effects. Empirically, because my physician networks are projections of the bipartite patient-physician networks, the observed networks naturally grow as the number of patients increase. Indeed, a regression of the total number of physicians per network on the number of patients shows that every additional patient, on average, increases the number of *unique* physicians by about 4 ($p < 0.001$).

Perhaps more importantly, this empirical feature is also closely to Blau's macrosociological theory of structure. First, Blau specifies an important assumption about how social structures emerge: "social associations depend on opportunities for social contacts." (1977: 42) In this context, every new CABG patient within a health system represents opportunities for physicians to associate based on their involvement during the episode of care. However, Blau also theorizes that "the probability of extensive intergroup relations increases with decreasing size" (1977: 36). To the extent that Blau's conception of different groups with society can be applied to different specialty groups within a health system, this would suggest that increasing opportunities for interaction (i.e., the number of patients) is important to the emergence of a stable structure, but if they number too many, the increasing size of the group, or network, may decrease the ability to achieve integration.

In order to both test the empirical sensitivity of my results to network size, as well as to delve deeper into the theoretical implications, I present a final set of regression results in Table 4.7. For each of the key outcomes I examined in my study—disassortative mixing and patient mortality—I run three regressions. The first of each set (Models S11 and S14) are the same as my main results, using the full sample of networks with at least three CABG patients. The next set (Models S12 and S15) increase the minimum threshold to at least five CABG patients, and the last set (Models S13 and S16) further increase the threshold to ten patients.

Beginning with the models for disassortative mixing, I see that the magnitude of the association between network bounding and disassortative mixing increases at five or more CABG patients (Model S12) but decreases sharply, and is no longer statistically significant, at ten or more CABG patients (Model S13). This surprising result may indicate that bounding may be most effective at a moderate network size (the median number of patients per network is 7). On the lower end of network size, this finding may be due to the fact that there is greater room for variability in networks of moderate size compared to very small networks. Recall that even one additional patient may be associated with several new physician nodes. However, as the networks become very large, the effect of bounding may become more diffuse and less salient for network members. Reflecting on Simmel's ideas about group affiliation, it would become more difficult to coordinate activities and align interests across very large groups; physicians in a larger network may not be as engaged in the activities of the whole. Indeed, further increasing the threshold beyond ten patients only serves to reduce the magnitude of the coefficient further (results available upon request).

On the other hand, when I examine the results for patient mortality, I see a different trend. Here, as I gradually increase the thresholds in Models S14-S16, I see that not only is the original result stable, but the magnitude of the interaction term actually increases. Taken together, I interpret these trends to suggest that (1) while network bounding may be associated with greater increase in integration in moderately sized networks, and (2) the marginal returns to disassortative mixing may be amplified both in larger, bound networks. Lastly, I note that these results are almost identical when restricting the sample to only networks that eventually join ACOs, with one notable difference being that the interaction term is more statistically significant in the patient death models at larger network sizes.

Table 4.6: Results for Changes in PCP Census

Variable	(S7) PCP-PCP Ties	(S8) PCP-Surgeon Ties	(S9) PCP-Med Spec Ties	(S10) Number PCPs
Bounded (0 = No, 1 = Yes)	-15.41***	-5.05*	-16.58*	-1.66***
	(4.42)	(2.34)	(6.64)	(0.55)
Patient Characteristics				
Patient Morbidity	2.75***	0.50	3.73***	0.47***
	(0.77)	(0.37)	(1.17)	(0.10)
Gender (0 = Male, 1 = Female)	-1.06	-2.20	-1.33	-0.33
	(2.64)	(1.42)	(3.92)	(0.36)
Age at Admission	0.32	0.10	0.22	0.07*
	(0.22)	(0.12)	(0.34)	(0.03)
Black (0 = No, 1 = Yes)	-4.73	-1.65	-8.37	-0.63
	(6.69)	(3.54)	(9.64)	(0.86)
% Patients from Rural Area	-22.22	-5.94	-49.72*	-1.55
	(15.62)	(6.41)	(23.82)	(1.65)
% Patients from Impoverished Area	0.28	-0.05	0.70†	0.09***
	(0.26)	(0.13)	(0.41)	(0.03)
% Patients from Same CBSA	-4.68	-5.03***	0.97	-1.09***
	(2.99)	(1.51)	(3.87)	(0.36)
Health System Characteristics				
Total CABG Patients	-0.14	1.65***	0.07	1.30***
	(0.39)	(0.18)	(0.61)	(0.05)
Total MDs per Patient	2.82***	1.73***	2.09*	0.98***
	(0.55)	(0.27)	(0.90)	(0.09)
ACO-affiliated MDs	0.25*	0.10	0.32	0.05***
	(0.11)	(0.07)	(0.26)	(0.01)
% of MDs, Surgeons	-246.82***	105.00***	-482.39***	-58.62***
	(18.47)	(10.08)	(30.81)	(2.44)
% of MDs, Medical Specialists	-300.13***	-124.48***	-340.40***	-59.62***
	(12.39)	(5.97)	(18.68)	(1.63)
Total Edges	0.07***	0.04***	0.33***	0.01***
	(0.00)	(0.00)	(0.01)	(0.00)
Academic Hospital (0 = No, 1 = Yes)	2.31	-0.77	6.47	-0.08
	(2.70)	(1.47)	(4.67)	(0.39)
Government Hospital (0 = No, 1 = Yes)	-8.85	0.60	-16.23	0.55
	(7.48)	(3.61)	(14.43)	(1.32)
For-profit Hospital (0 = No, 1 = Yes)	-5.16	0.87	-11.61	0.27
	(6.16)	(3.14)	(10.59)	(0.79)
Uses EHR (0 = No, 1 = Yes)	2.21	-1.26	7.99	0.50
	(5.66)	(1.77)	(10.40)	(0.61)
Community-level Characteristics				
Total Population (log)	-4.05	-0.54	-7.72	-0.44
	(3.45)	(1.65)	(5.65)	(0.44)
Black Population (log)	2.12	0.64	4.58*	0.11
	(1.41)	(0.73)	(2.18)	(0.19)
Hispanic Population (log)	-0.08	0.16	2.15	0.13
	(1.40)	(0.78)	(2.29)	(0.17)
Beds per 1,000 Residents	-60.72***	-15.04*	-84.09***	-6.09†
	(11.79)	(6.23)	(13.85)	(3.42)
PCPs per 1,000 Residents	0.09	-0.21***	0.09	-0.02
	(0.12)	(0.05)	(0.13)	(0.03)
Constant	270.95***	91.91***	354.39***	44.64***
	(39.17)	(21.44)	(53.30)	(9.36)
Year Fixed Effects	Yes	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.65	0.76	0.94	0.88
N	4,904	4,904	4,904	4,904

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests)

Table 4.7: Results for Disassortative mixing & Patient Deaths – Network Size

Variable	Disassortative mixing			Patient Deaths		
	(S11) ≥3 CABG	(S12) ≥5 CABG	(S13) ≥10 CABG	(S14) ≥3 CABG	(S15) ≥5 CABG	(S16) ≥10 CABG
Bounded (0 = No, 1 = Yes)	0.58*	0.84***	0.38	0.19	0.28*	0.26
	(0.26)	(0.29)	(0.34)	(0.12)	(0.14)	(0.18)
Disassortative mixing				-0.02***	-0.03***	-0.04***
				(0.00)	(0.01)	(0.01)
Bounded * Integration				-0.03*	-0.05***	-0.06*
				(0.02)	(0.02)	(0.03)
Patient Characteristics						
Patient Morbidity	-0.25***	-0.13	-0.10	0.09***	0.10***	0.20***
	(0.09)	(0.10)	(0.14)	(0.02)	(0.03)	(0.05)
Gender (0 = Male, 1 = Female)	-0.42	-0.28	0.49	0.08	0.14	0.09
	(0.33)	(0.39)	(0.55)	(0.08)	(0.11)	(0.20)
Age at Admission	0.01	0.02	-0.06	0.04***	0.06***	0.09***
	(0.03)	(0.03)	(0.05)	(0.01)	(0.01)	(0.02)
Black (0 = No, 1 = Yes)	-0.59	0.15	0.86	0.12	0.06	0.33
	(0.93)	(1.09)	(1.61)	(0.18)	(0.30)	(0.61)
% Patients from Rural Area	0.48	-0.79	1.72	0.12	0.22	1.41
	(1.87)	(2.28)	(3.41)	(0.40)	(0.59)	(1.25)
% Patients from Impoverished Area	-0.01	0.01	0.02	-0.00	-0.01	0.00
	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)
% Patients from Same CBSA	0.74*	0.43	-0.14	0.00	0.06	0.09
	(0.36)	(0.39)	(0.54)	(0.08)	(0.11)	(0.19)
Health System Characteristics						
Total CABG Patients	-0.11***	-0.13***	-0.14***	0.05***	0.05***	0.05***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Total MDs per Patient	-0.57***	-0.71***	-1.03***	-0.01	-0.00	0.01
	(0.05)	(0.05)	(0.08)	(0.01)	(0.02)	(0.03)
ACO-affiliated MDs	-0.01*	-0.01	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% of MDs, Surgeons	4.01	-2.02	-8.39***	0.50	1.34*	2.09†
	(2.64)	(2.23)	(2.94)	(0.41)	(0.58)	(1.16)
% of MDs, Medical Specialists	-6.49***	-8.64***	-12.86***	1.04***	1.29***	1.56**
	(1.11)	(1.16)	(1.45)	(0.22)	(0.29)	(0.58)
Total Edges	-0.00	0.00	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Academic Hospital (0 = No, 1 = Yes)	0.06	-0.18	-0.15	-0.05	-0.10	0.06
	(0.27)	(0.30)	(0.38)	(0.08)	(0.09)	(0.16)
Government Hospital (0 = No, 1 = Yes)	0.62	0.75	-0.03	0.13	0.16	0.39
	(0.82)	(0.86)	(1.01)	(0.22)	(0.25)	(0.29)
For-profit Hospital (0 = No, 1 = Yes)	-0.18	-0.18	-1.00	0.16	0.17	0.37
	(0.74)	(0.83)	(0.98)	(0.20)	(0.28)	(0.52)
Uses EHR (0 = No, 1 = Yes)	0.31	0.39	0.27	-0.05	-0.07	-0.22
	(0.37)	(0.36)	(0.52)	(0.08)	(0.10)	(0.21)
Community-level Characteristics						
Total Population (log)	-0.03	0.05	-0.00	-0.09	-0.03	-0.02
	(0.28)	(0.27)	(0.31)	(0.10)	(0.13)	(0.19)
Black Population (log)	0.02	0.04	0.05	0.02	-0.01	-0.03
	(0.12)	(0.12)	(0.13)	(0.04)	(0.05)	(0.06)
Hispanic Population (log)	0.15	0.08	0.15	-0.02	-0.04	-0.02
	(0.12)	(0.13)	(0.15)	(0.04)	(0.05)	(0.08)
Beds per 1,000 Residents	-1.71	-3.22***	-0.63	0.29	0.20	-1.35***
	(1.17)	(0.99)	(0.88)	(0.59)	(0.69)	(0.44)
PCPs per 1,000 Residents	-0.01	-0.03***	-0.01	0.01	0.00	-0.01*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Constant	16.53***	21.15***	24.47***	-4.44**	-5.86***	-4.29†
	(4.14)	(4.03)	(5.04)	(1.67)	(2.04)	(2.21)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.14	0.14	0.18	0.19	0.19	0.21
N	4,904	4,134	2,532	4,904	4,134	2,532

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests)

4.5 Discussion

In this study, I examined the structural and performance implications of establishing formal network relationships in the context of healthcare delivery networks. Importantly, I study a phenomenon that may be considered a precursor to the oft-studied interplay between informal and formal networks (McEvily et al., 2014). Moreover, rather than focusing on the performance implications for focal actors or dyads, I examine performance of a large sample of "whole" networks of physicians which comprise the delivery of healthcare for heart bypass surgery patients across 1,009 health systems across the US. In my theoretical development, I introduce the idea of network bounding, in which the establishment of a formal network is conceptualized as the establishment of a new network boundary. I found support for my initial hypothesis (H1) that this formal boundary would be associated with increased disassortative mixing in the *informal* ties among network members—that is, greater interactions among network members of different subgroups, in my case physician specialties. Surprisingly, I found that, despite the association between network bounding and disassortative mixing, as well as the association between disassortative mixing and patient outcomes, network bounding alone was not significantly associated with lower patient mortality following heart bypass surgery (H2a). Instead, the results of my interaction models testing H2, as well as several additional analyses, suggest that while network bounding was associated with a change in network structure, the magnitude of this change was not enough to improve patient outcomes. Instead, improved network performance was driven by changes in disassortative mixing, with greater marginal gains in bound networks (networks that join ACOs) compared to unbound networks. Taken together, the practical implications of these results suggest that, at least within the narrow context of heart bypass surgery, network bounding may stimulate network change but it, alone, is *insufficient* to improve network performance.

Through a series of supplementary analyses, I also found evidence that the network dynamic and performance implications of network bounding may also depend on network composition and size. Within the specific context of healthcare reform, I also found evidence suggesting that network bounding (ACO membership) is associated with at least some of the desired changes in patient care, exemplified by reduced variance in PCP (primary care) responsibilities within each health system.

4.5.1 Contributions to Theory

My study contributes to research on network dynamics and network performance, particularly with regards to the interplay between informal and formal ties or structure. As initially noted in the introduction, I address a gap in organizational networks research by focusing on the introduction of formality into an informal context, as opposed to studying a context where both informal and formal already co-exist and co-evolve. At the most basic level, my findings provide additional support for existing research by demonstrating that the performance implications of informal-formal network interplay are not limited to contexts in which both have already existed and are relatively stable. However, my findings may also foreshadow important directions for future for research in this area. Building on the well-established notion that formal structures, such as organizational charts, may influence the way in which informal relationships, such as friendship or advice-seeking ties, I provide initial evidence that manipulating formal structure may have different results depending on the configuration of informal ties. That is, my finding that the relationship between network bounding and disassortative mixing may vary depending on things like the network type, size, and composition, suggests that there is opportunity to advance research in different types of strategic network intervention or network design. For example, for hybrid ACOs, where bounding did not appear to be associated with a change in disassortative mixing, are there other approaches, instead of formalization, that administrators might use to encourage greater cross-specialty work?

More broadly, my study may also contribute to research on the role of formality in organizational relationships. Drawing the connection between formalization and boundary-formation may help advance theories in other related streams where formalization may be relevant. In particular, I specifically note the potential for theoretical extensions in entrepreneurship where the introduction of formality, such as in business start-up or founding team formation, is an especially salient event. Likewise, the theoretical mechanisms elaborated in this study may also be relevant for the study of mergers and acquisitions where new formal relationships may suddenly be introduced in contexts where acquirer and target firms were only linked through informal ties. Moreover, the network perspective used in this study may provide additional insights into formalization among multiple parties, not just at the dyadic level.

With regards to network performance, this study also questions whether the creation of a formal, goal-directed network indeed has the benefits that managers or decision-makers anticipate when they decide to begin such a partnership. To date, studies of network performance have not examined whether or not it is beneficial to formalize partnerships for collective outcomes. While there may be some parallels to age-old strategy questions of "make-or-buy," the proposition is different for networks of organizations. Network bounding may represent a sort of middle ground between informal interactions and integration, such as through acquisition or merger. The viability of such a grey area may be of great importance as it may encourage more organizations to attempt to formally organize and tackle larger, more complex problems. Beyond the reality that certain strategic or social outcomes, such as improving population health, education, or reducing crime, require the concerted efforts of multiple organizations, formalization may also represent an important way for organizations and their members to introduce a sense of order or stability within increasingly complex environments. Theories from various research streams in strategic management and organization studies support the notion that establishing formal relationships—even to the extent of expanding the formal boundary of an organization—can be an important way to combat uncertainty (Jones et al., 1997). On the other hand, the expectation of enhanced stability or performance may also lure organizations into pursuing collaborations that are doomed to fail, wasting precious private and public resources in the process. Consequently, a better understanding of the factors that underlay successful formal partnership may enable the creation of more effective networks.

Finally, the notion of network bounding—and by extension "unbounding"—may represent interesting areas for future research in network dynamics. From a theoretical perspective, this study has primarily focused on the effects of bounding for those actors (nodes) *within* the boundary. Yet, the theorized manner in which bounding alters member interactions and outcomes is based on exclusion. That is, the identity and special significance of the formal group stem, in large part, from differentiation between member and non-member. Consequently, it follows that the effects of network bounding may also extend to those nodes that are left out. As Blau notes, "[d]ense networks of ingroup relations integrate individuals in their groups, but they threaten to fragment society" (1977: 33).

The potential negative externalities of network bounding may be most impactful for non-members that are closest to the boundary. Actors that are deeply embedded in informal relationships with organizations that become a part of a formal network may be negatively impacted if network bounding causes former partners to divert attention or resources from cross-boundary relationships, instead prioritizing in-group ties. Moreover, just as network bounding may produce unanticipated changes to network structure through the exclusion of certain key actors, it may likewise reduce access for non-members if important nodes within previously informal networks join a formal group. In a set of preliminary descriptive analyses, I investigated whether or not an effect for "unbound" health systems could be detected, the logic being that non-ACO health systems may experience performance penalties if they have high "exposure" to physicians that are part of a bound network. The results of this analysis, shown in Appendix C (Table A4), seem to suggest the *opposite*—unbound whole networks with greater exposure to bound whole networks are associated with slightly better performance. At the very least, this suggests that such externalities may exist and warrant further study.

As a final thought, if previously informal actors can be bound to create formal whole networks, this process can also be reversed. Occasional bounding and dissolution of relationships may be to social systems what fires or sudden flooding are to ecosystems. Yet, unlike evolutionary network change, bounding events are agentic decisions designed to engineer or reengineer networks towards specific ends. In this sense, even a localized event, such as network bounding around a few actors, may reshape characteristics of the broader the environment, forcing adaptation and altering the trajectory of larger whole. Just as our own lives change when casual relationships become more formal, or when formal bonds fall apart, the coming and going of boundaries within a social system may be an important engine for change.

4.5.2 Implications for Policy and Practice

As described in a companion study that looked, more descriptively, at the relationships between health system integration, ACO participation, and the patient-level outcomes of CABG patients (Kim et al., 2019), there may be some important lessons for health systems and policy makers. First, although it appears that network bounding (i.e., forming an ACO) significantly changed network integration, the implications of such a change are potentially of greater importance. That is, do changes in network measures actually correlate with substantial improvements in patient outcomes? The results from both this study and the companion piece suggest that the network dynamics associated with bounding may not also be meaningful. This highlights the dual importance of understanding whether network bounding is likely to have the desired effect by examining the "starting point," and properly setting expectations. In this particular case, the result that the best patient outcomes appear to be associated with health systems that *already* had high integration and *also* join an ACO seems to suggest heterogeneous treatment effects in the extent to which network bounding may "unlock" some of the benefits of formalizing previously informal relationships. Similarly, for policy makers and program administrators these findings suggest that overall program success could be improved if it were possible to more accurately predict which applicants were likely to easily succeed, as opposed to those that might require more time to learn or improve. Rather than excluding ACOs that may not perform well right away, funneling different groups to different risk-sharing tracks based on their expected performance may better overall outcomes for the whole program.

4.5.3 Limitations

Despite drawing from broad, macrosociological theories of integration, this study is potentially limited in its generalizability as healthcare delivery is a unique context. Moreover, within healthcare I have focused on a specific procedure which may add additional idiosyncrasies to my empirical analyses. Still, there are some reasons to believe that the findings may not simply be an artifact of this particular procedure. First, the network dynamics associated with bounding, specifically the changes in integration and the PCP census, involve physicians that are not particularly geared towards CABG care. In fact, reduction in the overall number of PCPs in bound networks, in conjunction with the fact that the total number of cases did not change significantly, is a desirable outcome from a policy perspective. That is, this change indicates greater continuity of care between a beneficiary and their PCP. Second, by using somewhat coarser groupings (PCP, medical specialist, surgeon) I trade off specificity for some greater generalizability, at least to other types of healthcare delivery networks. That is, the same groupings would likely be relevant for any type of surgical procedure, whereas a more fine-grained approach that differentiated cardiologists, vascular surgeons, and cardiothoracic surgeons may have yielded findings too idiosyncratic to be extended beyond CABG, or other similar cardiovascular procedures.

While I attempt to minimize selection bias related to which health systems join ACOs, I cannot completely identify the effect of network bounding or the interaction with disassortative mixing. Moreover, the results of my segmented regressions reveal that, despite my use of network fixed effects, some of my results are being driven by between-network variation (Shaver, 2018). Therefore, I do not claim identification nor can I claim causality. Nevertheless, given the practical importance of the phenomenon, timeliness of the context, and the dearth of research examining the consequences of using formal networks as a strategy to enhance collective performance, I argue that this study makes an important contribution theory of organizational networks and may have relevance for practice, and policy.

V. CONCLUSION

5.1 Motivation and Purpose of Dissertation

Society's grand challenges demand complex solutions that often must be achieved through the combined efforts of multiple organizations. Goals as such building healthy communities, improving the quality of education, reducing crime, slowing climate change, preserving natural resources, and revitalizing regional industries often require collaboration and are difficult to achieve without coordinated efforts among multiple organizations. Whereas existing research provides plentiful evidence that it is difficult to coordinate complex work across the boundaries—lines that demarcate different cultures, missions, incentives, and capabilities—of multiple organizations (e.g., Park and Ungson, 2001; Greve et al., 2010; Heidl, Steensma, and Phelps 2014; Davis, 2016), it offers relatively less insight to why some perform better than others. Thus, the overarching motivation of this dissertation was to better understand why some networks of organizations perform better—as a whole—than others.

With the above motivation as the "true north," this dissertation represents a milestone along an on-going journey which, thus far, has been colored by my immersion in the science and practice of medicine during the last decade of my life. Within the life sciences, I found particularly fascinating the prospect that macroscopic problems at the level of the human body (e.g., infectious disease, cancer, mental illness) could be solved by examining mechanisms at the *cellular* level. Reflecting on this, I see many similarities between this search across levels of analysis, and the examination of competitive dynamics within industries through the study of firms, or the examination of organizational issues through investigation of organizational behavior and psychology.

Yet, I also know that a cellular biologist would not proclaim to be a physician based on an understanding of cellular signaling, nor would I seek medical care from a lab scientist. There is a clear difference in the level of analysis at which each operates.

In a similar vein, the purpose of this dissertation is thoroughly engage with a different level of analysis in the study of organizational networks. Understanding *whole networks of organizations* is of critical importance for business and society, and we should not presume to know how to assess and treat the problems of complex systems at this level based solely on the study of embedded firms, ego networks, dyadic relationships, or even intraorganizational networks. Of course, research in these related areas provide important insights to build on, as I have demonstrated throughout Chapters 3 and 4. However, I argue that if something is important to study, then we should—to the best of our collective ability as a field—study it directly.

5.2 Summary of Findings

Through two essays, with empirical evidence from the US healthcare industry, I examine the antecedents of whole network performance by first examining the *morphology* of networks, and the inherent contingencies that influence collective outcomes, and then by examining the dynamics and performance implications associated with the strategy of formalizing whole networks through *bounding.*

In the first study (*network morphology*), the key puzzle that is being addressed is the decades-long ambiguity in the relationship between whole network structure and whole network performance. Specifically, why do scholars find contradictory relationships between whole network characteristics and whole network performance? By drawing on sociology theories that have not previously been linked to whole network performance, I develop the network morphology framework which argues that the structure-performance relationship is *necessarily* a contingent one. A contingency perspective on network structure is not, itself, novel—many scholars have examined the contingent relationships between *egocentric* network structure (and network positions) and node-level performance (e.g., Nahapiet & Ghoshal, 1997; Phelps, 2010; Vasudeva et al., 2013). Nevertheless, the two-fold argument put forth in this essay is that (1) the relationship between *whole* network structure and *whole* network performance is contingent, and, most importantly, (2) those contingencies are *intrinsic* properties of the network being studied. In just the same way that a single measure of health, for example body-mass index (BMI), may be a misleading indicator of physical fitness unless we consider other dimensions of an individual (e.g., lifestyle, muscle mass) network structure represents only one dimension of the full story.

Applying the morphological perspective to interorganizational networks in the US healthcare industry, I demonstrate how the relational and cultural properties of whole networks can help explain why similarly structured networks, in the same industry and pursuing the same objective, might perform very differently. In doing so, I contribute an important empirical study of real-world whole organizational networks to complement and challenge past experimental and simulation-based studies. As many scholars in this stream have noted (e.g., Christie et al., 1952; Shore et al., 2015), structures in society cannot exist in a vacuum so it is important that we also consider the performance implications of whole network structure in the context of the other emergent forces.

In the latter essay (*network bounding*), I examine whole network performance from a more strategic perspective—focusing on the implications of a decision to formalize whole networks to support attainment of a collective outcome. This study is characterized by two important differences, both compared to the first essay and the broader research on whole network performance. First, unlike other studies that examine the performance of whole networks that already exist, I study the consequences of forming a *new* network in an environment where it did not previously exist. This relates to the second difference—the change or "intervention" being studied is essentially the addition, or more accurately the *superimposition,* of a new set of relationships (defined by formal network boundary) on a set of existing (informal) interactions. This interplay—how the new formal element affects the structure and collective outcomes associated with a complex of informal ties—is one that has been absent from experimental and simulation work in which there is only one type of tie being studied at a time. Indeed, in this way the second essay integrates studies of whole network performance with more traditional aspects of studying network relationships in organizations (Soda & Zaheer, 2012; McEvily et al., 2014; Kleinbaum & Stuart, 2014).

I find that the decision to formalize whole networks—network bounding—is associated with significant changes in *informal* network structure in the intended direction (greater structural integration, represented by more cross-specialty interactions among doctors). However, I also find network bounding is only associated with improved whole network performance in a subset of networks where the informal structural integration is already high. This points to the potential for heterogeneous treatment effects—the effectiveness of network bounding as a strategy to improve whole network performance may depend on the pre-existing patterns of informal relationships among the selected network members. Consequently, this study offers new empirical evidence regarding the efficacy, or lack thereof, of using a social lever—formalizing a whole network—to stimulate structural changes and performance improvement at the whole network level.

5.3 Implications for Theory

The theoretical developments presented in Chapters 3 and 4 have a number of implications for broader research on organizations and networks. Foremost, the *network morphology* framework presented in Chapter 3 makes two crucial contributions to research on whole network performance in organizational contexts. First, it offers a theoretical explanation for conflicting findings from past experimental and simulation-based research, supported by an empirical example using observational data of *real* networks. Specifically, by integrating research on whole network performance with theories from macrostructural sociology (Blau, 1964, 1977), I propose that the whole network structure-performance relationship may be highly variable in actual networks due to the relational and cultural dimensions of networks—other emergent properties of organizational networks that would not necessarily emerge in computational or experimental research.

Second, the morphological view of whole networks reintroduces the importance of studying other emergent properties of networks together with structure (e.g., Nahapiet & Ghoshal, 1997; Rowley et al., 2000). This is not a new idea, but research on organizational networks has been dominated by a singular focus on the performance implications of structure, overcorrecting, perhaps, from Harold Leavitt's (1962: 91) admonishment that we have "thrown out some useful parts of the baby with the bath water" in placing too much emphasis on the *human* aspect of organization. The morphological view demonstrates a way to take a more integrative perspective of whole networks while not sacrificing the computational and analytical opportunities afforded by network analysis.

The framework and empirical application presented in Chapter 3, thus, complement and advance the aforementioned research on whole network performance (Leavitt, 1949; Bavelas, 1948; 1950; Christie et al., 1952; Guetzkow & Simon, 1955; Mulder, 1960; Kearns et al., 2006; Lazer & Friedman, 2007; Fang et al., 2010; Enemark et al., 2011; Mason & Watts, 2012; Shore et al., 2015; Shirado & Christakis, 2017) by proposing a way to resolve conflicting findings and elucidating new avenues for further work. Indeed, it would be fascinating to see how simulation and experimental results change when we begin to consider multidimensional whole networks. as well as to the broader corpus of work on network performance that comprises scholars from multiple disciplines and spans decades.

The idea of *network bounding* presented in Chapter 4, offers a different view of whole network performance. Rather than taking the passive view that complex networks among organizations exist (which they do), this study begins from the perspective that human decision-makers, in case empowered by policy, also have considerable agency to *create* whole networks with the intention of attaining specific goals. In other words, it relaxes the assumption that complex networks naturally evolve over time and asks what happens when a sudden change is imposed within a system of interactions. More precisely, what happens to the existing structure of relationships, and whole network performance, when a new, *formal*, basis of interaction—the network boundary—is introduced? In contrast to other studies of network dynamics in which changes are more incremental or focus more narrowly on specific nodes (e.g., Sytch & Tatarynowicz, 2014; Hernandez & Shaver, 2018; Kumar & Zaheer, forthcoming), the phenomenon evaluated in this study is a wholesale change affecting (creating) a whole network. Importantly, this highlights the important role that policy and organizational leaders may play in the design and evolution of complex systems of interorganizational interactions. ’

The theory developed in Chapter 4 also contributes to existing research streams on organizational design (e.g., Gulati & Puranam, 2009) and the interplay between formal and informal structure (Rosenkopf & Schleicher, 2008; Soda & Zaheer, 2012; McEvily et al., 2014). In my study, the introduction, or perhaps more accurately the superimposition, of a formal network boundary onto set of actors had differential association with whole network performance, contingent upon both the existing *informal* network structure and the extent to which bounding was able to change that network structure in a beneficial direction (i.e., more integration across different types of nodes). This may provide new insights into organizational founding or mergers and acquisitions, settings in which formal structure or new formal boundaries must be effectively layered upon informal relationships to ensure collective stability and effectiveness.

As a whole, the theoretical contributions of this dissertation are oriented towards developing a more holistic perspective of the emergent properties and outcomes of whole organizational networks. Drawing on the classic sociological theory, as well as research from many disciplines, I propose alternatives modalities of thinking about the collective activities of organizations, arguably the most powerful vehicles for positive social change and social welfare today. As such, perhaps it is no surprise that the classical sociological works that I draw upon

(Simmel, 1950; Blau, 1964) were, at their core, directed at understanding most complex emergent phenomena of the times—large organizations and society. Yet, to go beyond simply understanding how these complex social systems emerge and evolve, I propose that there are also solid theoretical grounds upon which to conceptualize whole organizational networks as complex *strategic* units that can be shaped by policy and the deliberate actions of managers—whether they realize it or not. The two studies in this dissertation demonstrate the opportunities for theory development at the whole network level and provide empirical evidence that whole network phenomena are real and harnessing their potential for large-scale change may be a new frontier for strategy and organizational research.

5.4 Implications for Practice and Policy

The US healthcare industry provides an excellent context to study whole networks, not least of all because it is relatively easy to see why the welfare of the consumer—patients—depends upon the collective effectiveness of many organizations (Provan & Milward, 1995). Moreover, the timeliness of the specific phenomenon being study—the formation of Medicare ACOs from 2012-2015—presents me with a unique opportunity to speak to an on-going experiment in healthcare delivery. While I reiterate that I cannot make any causal claims from the studies in this dissertation, even the descriptive analyses provide important insights into the Medicare ACO program.

Existing studies of Medicare ACO performance have, thus far, not uncovered any systematic properties of ACO networks that seem to be linked with more cost-savings (Herbold et al., 2017). Instead, associations have been found between better performance and ACO experience (Office of Inspector General, 2017), and physician-leadership (Lewis et al., 2017). In contrast, the study of ACO whole network dimensions focuses more on the relationships between *emergent* properties that may not be apparent to key stakeholders when they design their respective ACOs. Admittedly, it is not a trivial exercise to map the beneficiary-sharing networks among a set of potential ACO members; even then, it is not necessarily clear how best to go about selecting the "right" partners to include. However, it may be possible to draw some heuristics about some network "ingredients" that may contribute to a successful ACO.

First, the application of the morphology framework demonstrated that the structure of beneficiary-sharing among ACO members, alone, cannot reliably predict an ACO's performance. This is an important outcome if only in that it likely confirms what policymakers and administrators already suspect—there is no one-size-fits-all approach to designing a cost-effective and efficient healthcare delivery system. As the literature on whole network performance suggests, it is likely that certain structures emerge within—and are better suited to serve—certain types of geographic communities or patient populations. Yet, the interactions between whole network structure and the relational and cultural dimensions suggest that, given a particular network structure, there may also be some actionable takeaways for ACO leaders. For instance, the findings suggest that, all else equal, the more disconnected the beneficiary-sharing network, the more challenging it will be to generate shared savings.

While this may be somewhat intuitive from a theoretical standpoint, the reality is that many ACOs comprise disparate localized networks that are difficult, if not impossible, to bridge between. The interactions between structure and the relational and cultural dimensions suggest that an ACO leadership may be able to shift the scales in their favor by engendering a culture of collaboration or institutionalizing practices, at the level of the network, to bridge network gaps. For example, in one conversation with a physician executive of a large, Midwestern ACO, I learned that ACO leadership plays an important role in communicating and supporting the culture and strategic goals of their ACO to network members. It does so through regular board meetings with representatives of the members organizations, providing constant feedback to members about their performance, and by ensuring buy-in to a shared identity—delivering value-based care. This ACO happens to be on the higher end of disconnectedness but is one of the most successful in the country.

This, then, relates to another possible implication of the findings is related to ACO membership, or *who* to select to include in a network. Lessons from the data, previous studies, and conversations with healthcare leaders across the country suggest that one of the most challenging aspects of implementing changes in the delivery system is overcoming resistance from physicians and administrators at all levels. While this, in and of itself, is not new, the network perspective provides some additional guidance with regards to the factors that may be important when deciding who to partner with. For example, it may not be prudent for an ACO to comprise multiple, disconnected clusters in different geographies and *also* promote values of physician autonomy or independence in decision-making. The evidence suggests that a more disconnected network is better paired with a network culture that is more oriented towards a collective mindset. Additionally, and perhaps more realistically, it is reasonable to draw the conclusion that a more disconnected network would also likely benefit from structural bridges constructed to other types of interactions; if not through beneficiary-sharing, then through regular meetings or administrative rotations, such as described in the above example of the Midwestern ACO.

Similarly, the study of network bounding also speaks to the design of ACO networks but perhaps emphasizes the importance of the "gate-keeper," in this case the administrators at CMS who will approve, or deny, an ACO application. That is, they will determine whether or not a proposed group of healthcare providers will be allowed to participate in the Medicare ACO program. Considering that nearly half of ACOs failed to reduce expenditures relative to their targets, and that ACO quality is "good but not great" (Muhlestein & Hall, 2014), it is worth asking whether or not there should be a higher bar, or perhaps a different set of criteria, when it comes to determining which groups get to "play the game."

While it is not entirely surprising that forming an ACO increases integration among physicians of different specialties—indeed, cost-savings through greater integration is the core assumption of the ACO model—it is somewhat unexpected that this is not consistently associated with better outcomes, all else equal. Perhaps even more surprising is the finding that joining an ACO appears to be associated with better outcomes for health systems that *already* have relatively high levels of disassortative mixing. In order words, rather than stimulating improvements among underperforming health systems, ACO participation may unlock more benefits to well-integrated groups and may be associated with *worse* outcomes for less integrated networks. For CMS administrators and potential ACO leaders, it will be important to weigh the risks associated with forming an ACO against the evidence that some ACOs get better over time. Furthermore, if the program is simply helping the "rich get richer," in a sense, then perhaps there is an additional need to figure out how less-integrated groups of providers can achieve early successes that they can build on.

There may also be the simple takeaway that network analyses of ACOs can be an important analytical tool for both CMS and ACO leaders. Most healthcare leaders I spoke to had never seen a network graph of their physicians' beneficiary-sharing patterns and, perhaps even more importantly, would not necessarily know what to take away from one. This research demonstrates that the data is available, accessible, and potentially a powerful input for decision-making. The further development of network analytics to drive process and performance metrics for key stakeholders may be a way to translate research into practice.

Finally, at the time of this writing, the MSSP ACO program is in the midst of a rule change that will rapidly shift existing and new ACOs into a two-sided risk model—that is, a model in which an ACO may be penalized for overspending. Without discussing the potential political reasons for this decision, previous research combined with the research presented in this dissertation suggest a few insights into what this heightened pressure will be for the MSSP ACO program and its impact on healthcare reform efforts in the US.

First, it is expected that the MSSP ACO program will become more conservative—there will likely be slower growth in the number of ACOs, as well as some attrition, ACOs will probably prune member organizations, and ACOs will undoubtedly be more cautious about the number and types of patients they are assigned. Second, and relatedly, the ACOs that do participate are going to be more likely to *expect* that they can generate shared savings. Therefore, I would expect that the distribution of ACO performance will shift to the right, towards greater shared savings. This, from a bureaucratic perspective, may appear like a success for CMS. However, considering the results from Chapter 4, it may just reflect the fact that the participating ACOs are those comprising member organizations that are better prepared to "act like" ACOs.

If this is the consequence of the rule change, then I fear that the only ones benefitting from the MSSP ACO program will be the systems that would have changed anyway. The one-sided risk model, in effect, provides a safer, less risky, platform for provider organizations to test the waters and potentially learn how to improve at delivering value-based care. It was always expected that ACOs would gradually transition into two-sided risk—indeed, the financial upside is greater so high performers have an incentive—but this rule change suddenly expedited the timelines. Now, only about five years into the MSSP ACO program, the rule change may significantly limit the organizational and network-level learning component of this on-going policy experiment.

Of course, the best-case scenario is that existing and potential ACOs are *not* scared off by two-sided risk and the heightened pressure to perform actual stimulates *faster* change and learning. However, based on personal experience, even the most innovative and high-performing organizations can be very resistant to change and even more reluctant to expose themselves to new sources of risk. It remains to be seen how US healthcare providers respond to this change—at the very least, it will be an important issue to monitor in the coming years.

5.5 Limitations

As is true of any work, there are many limitations that must be noted before summarizing the implications and lessons from this dissertation. First, as a study of a relatively new, and on-going, phenomenon—Medicare ACOs—the empirical findings from the two studies may be limited in generalizability due to the idiosyncrasies of the context, as well as the lack of a longer longitudinal study. Second, the empirical analyses in the two studies are limited in that they cannot demonstrate causality. Both analyses rely on variation in whole network characteristics, but it is difficult to say that these changes are exogenously driven considering that ACOs are formed voluntarily by their constituent members. That said, the robustness tests and supplementary analyses for each study provide additional support for my interpretations of the results. Moreover, as one of the first large-scale, observational studies of whole network performance across organizations, the (publicly available) data used in this dissertation represents an important methodological contribution that future work may build on.

These limitations aside, there are reasons to believe why the core theoretical contributions presented in the two studies can be translated to other contexts. First, the network morphology framework offers a different theoretical perspective on whole network outcomes that is not specific to a research context. Considering how it was developed from Blau's abstract ideas, the framework should not be limited in applicability. Second, the idea of network bounding is also grounded in basic macrosociological and social group theories. Moreover, the act of formalizing, or "bounding," certain relationships in order to protect and enhance them is somewhat universal. Aside from the particular operationalization of informal structural integration among physicians, the core relationships in Chapter 4 seem to be broadly applicable.

5.6 Final Thoughts

Network analysis is a powerful tool that can generate surprisingly intuitive insights from complex subject matter. However, we must also take care to avoid the myopia that is associated with possessing an effective implement—with a great hammer, suddenly all the world is a nail. In this sense, network analysis is excellent that describing the patterns or topologies of relationships that comprise a social group, but that does not mean that society can be fully explained by network graphs. As scholars from the early period of whole network studies noted, structure provides the possibilities but does not describe what *actually* happens (Christie et al., 1952; Mulder, 1960).

Accordingly, considerable effort was made in this dissertation to illustrate that network structure is only one part of the equation. This is perhaps most obvious in Chapter 3, in which the primary contribution was to provide a theoretical basis for examining *other* dimensions of whole networks, beyond structure. However, this theme is also present in Chapter 4 in which the performance of the whole health system networks for CABG treatment was not simply explained by structure alone. Also influential were multiplex ties, or the interplay between existing informal relationships and the intentional and goal-directed imposition of formal network ties/boundaries, underscoring the role of managerial agency in creating and shaping complex networks. That is, it was the combination of human decisions and existing network structures that, together, helped to unpack collective performance; one without the other is incomplete.

Though each study makes specific, narrower, contributions to the research streams they draw upon (summarized above and detailed in the discussions of Chapters 3.6 and 4.5), I also believe that, together, the two studies highlight opportunities for organizational and strategy research to make important contributions to societal problems that extend beyond the financial performance of individual firms. To the extent that businesses may become more influential than governments, and that complex problems in society are increasingly beyond the scope of single organizations, I believe that research must engage more deeply in problems of interorganizational collaboration and collective outcomes beyond traditional organizational boundaries.

As evidenced by this dissertation, there is likely much we can still learn from the classics, particularly with regards to *big* questions about society. Yet, we should also be cognizant of the fact that a rapidly changing world may also demand evolution in the theories we use to explain it; what was once modern to the classicists is now history. For organizational and strategy researchers, failure to extend the scope of our ideas to higher levels may not only limit opportunities to build new theories but may also further widen the chasm between management research and practice. On the contrary, moving up a level and embracing the study of organizing among organizations may reveal new pathways for cross-pollination of ideas across fields, and lead to profound new insights into our own modern society.

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VII. APPENDICES

Appendix A. Hand Coding Methodology for ACO Cultural Dimension

In hand coding ACO names, two coders independently coded a list of 697 unique terms that appeared in ACO names entities that were operating from 2013-2015. The coders focused on classifying terms as having or not having a clear connection to physicians. A list of the top twenty most frequently appearing terms can be found in Table A1 below.

Table A1: Twenty Most Frequent Terms in ACO Names (2012-2015)

LLC	MEDICAL
ACO	HEALTHCARE
CARE	COALITION
HEALTH	PHYSICIAN
ACCOUNTABLE	COLLABORATIVE
NETWORK	RURAL
PARTNERS	QUALITY
INC	CLINIC
ALLIANCE	COMMUNITY
PHYSICIANS	PRIMARY

Once each term was coded, each coders' determinations were compared and reconciled. If no agreement could be reached, a third person was brought in to resolve the dispute.

Codes were then aggregated to the ACO name level, with each name associated with a score reflecting the relative number of "physician" and "other" terms. Most names would be coded as representing a physician orientation if the name contained more physician coded versus other coded terms. Exceptions were made, however, if the name contained at least one term that was deemed to be unambiguously physician-oriented. These terms were "physician," "doctor," and "md." Names containing at least one of these terms were coded as physician orientation (C^O=1). A sample of coded ACO names can be found in Table A2. A full list of coded names is available upon request.

Table A2: Examples of Coded ACO Names

C^O=0 (Other orientation)	**C^O=1 (Physician orientation)**
Matrix ACO LLC	Care is Primary ACO LLC
Lower Shore ACO, LLC	Affiliated Physicians Medical Group ACO, Inc.
Integrated Care Alliance, LLC	Primary Care Alliance LLC
Keep Well ACO LLC	St. Luke's Clinic Coordinated Care, Ltd.
OneHealth Nebraska ACO, LLC	WakeMed Key Community Care, LLC
Arkansas Health Network LLC	Commonwealth Primary Care ACO
KentuckyOne Health Partners, LLC	Alabama Physician Network, LLC
WellStar Health Network, LLC	Physician Performance Network of Arizona, LLC

Appendix B. Machine Learning Methodology for Coding ACO Cultural Dimension

To complement the hand coding approach to creating the C^O *(cultural orientation)* variable, I also tried using a machine learning technique. In the main methodology, I was primarily interested in determining the presence or absence of a strong physician orientation based on the content of each ACO's name. However, for the machine learning approach, I was also interested in seeing what additional clusters, if any, would be detected using an established clustering methodology.

Starting with the same cleaned and standardized (i.e., punctuation removed, common abbreviations replaced) list of ACO names (N=551) used for hand coding, a large [name × term] matrix was then created, in which rows indexed each unique (cleaned, standardized) ACO name and columns indexed each unique (cleaned, standardized) term. Cell entries corresponded to the frequency with which the focal term appeared within the focal name. From this name × term matrix, a new, square, symmetric matrix, was created in which rows and columns both indexed unique ACO names, and cell entries corresponded to the Euclidean distance between focal rows and columns based on the co-occurrence of terms. Finally, using this matrix of distances, ACO names were clustered using Ward's (1963) hierarchical clustering algorithm.

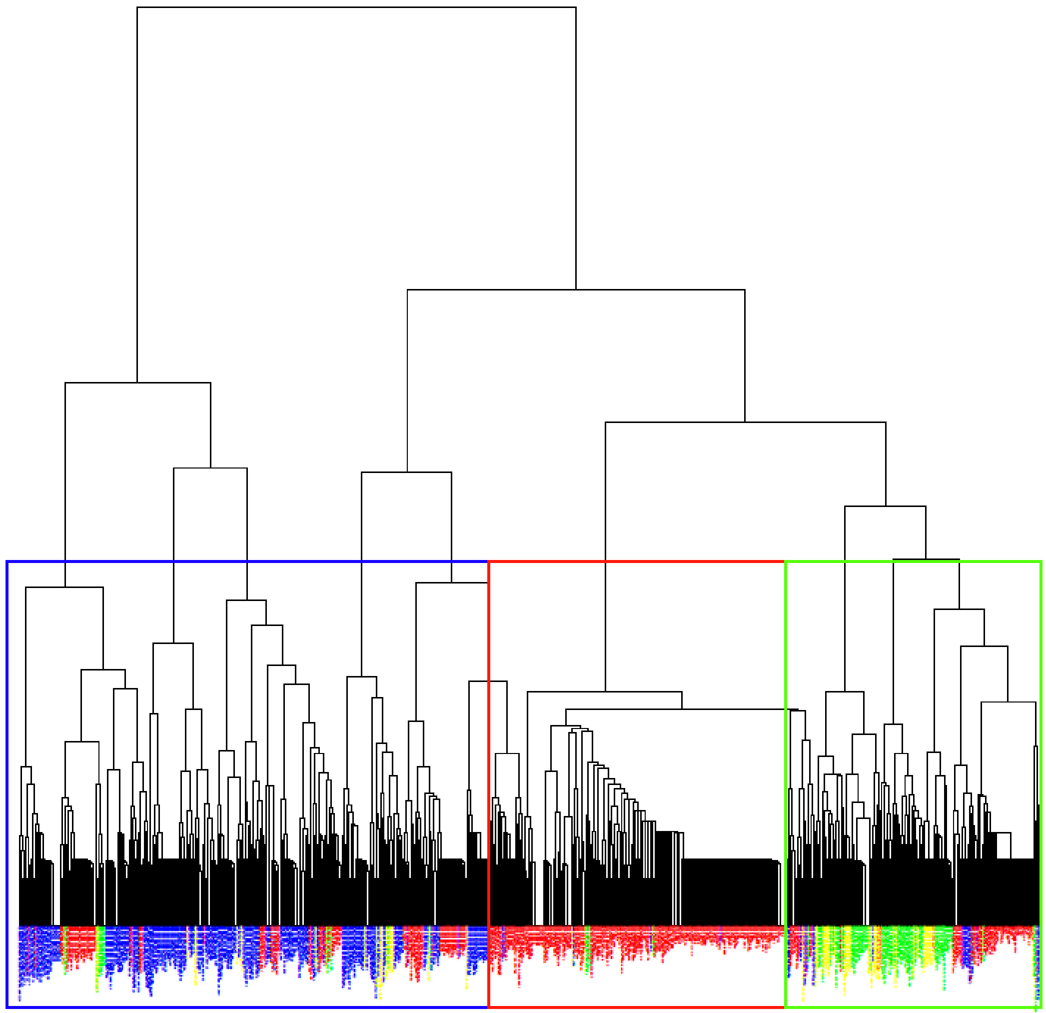

Figure A1: Dendrogram displaying results of hierarchical clustering algorithm, which grouped ACO names according to similarity. Based on these results, we identified three major clusters of cultural orientation: (1) organizational or bureaucratic orientation (left blue), (2) physician orientation (center red), and (3) community orientation (right green). The specific ACO names at the bottom-most row of the dendogram are not visible due to the large size of the image. A high-resolution version of the figure can be provided upon request.

The next step in the process was to understand the meaningful differences between the identified clusters (see dendrogram of clusters below in Figure A1). Using contextual knowledge and previous studies from healthy policy that tried to classify ACOs (e.g., Fisher & Shortell, 2012; Shortell et al., 2014), I identified three, contextually meaningful clusters of ACO names. The first comprised names that were more community or geography-focused, indicating a clear identification with the particular region they were serving. The second comprised names that were strongly connected to the physician profession, using terms such as “physician,” “doctor,” or “primary care,” which are clearly associated with medical doctors. The third cluster comprised names that reflected the organizational or bureaucratic form of the ACO, and that used terms such as “network,” “alliance,” or “coalition.”

These clusters—physician-oriented, community-oriented, and organizational—aligned well with descriptive studies of ACOs. The first, physician-oriented, seems to match ACOs which predominantly comprise private practices and physician groups (e.g., UCLA Faculty Practice Group). These ACOs often do not include a hospital or similar large, multispecialty organization (Shortell et al., 2014). The second, community-oriented, aligns with ACOs that place a greater emphasis on local communities (e.g., Piedmont Community Health Collaborative) or the health of specific populations (e.g., Asian American Accountable Care Organization). The third, organizational, is more closely aligned with ACOs that have been described as being more corporate or administrative (Kreindler et al., 2012; Shortell et al., 2014), and tend to be closely associated with larger healthcare systems that are more likely to employ physicians, rather than contract with independent physician groups.

Appendix C. Supplementary Tables

Table A3: Selection model, "ACO is a network" (Table 3.4, Model 13), first and second stages

Variable	First stage Probit, "Is a Network"	Second stage OLS
Patient and provider characteristics		
Total providers	0.00***	-0.00†
	(0.00)	(0.00)
Total beneficiaries	-2.18	0.28
	(1.52)	(0.24)
% Female beneficiaries	3.11	-9.45
	(2.74)	(15.38)
% Black & Hispanic beneficiaries	-0.13	4.25*
	(0.59)	(1.89)
% Beneficiaries aged 85+	1.97	-12.80
	(1.40)	(11.03)
% Disabled beneficiaries	2.49*	-1.81
	(1.17)	(7.21)
% Beneficiaries with ESRD	0.71	9.40
	(1.21)	(7.62)
General ACO (network) characteristics		
ACO advance payment		0.98
		(1.26)
Quality score (t+1)	-0.03***	0.04
	(0.01)	(0.03)
ACO spans noncontiguous states (1 = Yes)	4.93***	1.17
	(0.10)	(1.24)
Network size		-0.01
		(0.01)
Network isolates		-0.19
		(0.13)
% Non-referring		2.49
		(2.62)
Network turnover		-0.01
		(0.01)
Network dimensions and interactions		
Structural disconnectedness		-0.31
		(2.24)
Relational strength		-0.13***
		(0.04)
Cultural orientation (1=Physician)		7.03***
		(2.12)
Structural × Relational		-0.30***
		(0.08)
Structural × Cultural (1=Physician)		-21.87***
		(5.54)
ρ	-0.00	-
	(0.08)	-
Constant	3.32***	-13.49
	(0.93)	(15.02)
ACO fixed effects	No	Yes
Year fixed effects	No	Yes
R^2 or pseudo-R^2		0.77
N	839	736

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests); Robust standard errors in parentheses; ESRD: End-stage renal disease

Table A4: Results for Patient Deaths for "Unbound" Networks

Variable	(1) Full Sample	(2) Non-ACO	(3) Joins ACO
Disassortative mixing	-0.03***	-0.02***	-0.04***
	(0.00)	(0.01)	(0.01)
ACO-affiliated MDs	-0.00	-0.01*	0.00
	(0.00)	(0.00)	(0.00)
Patient Characteristics			
Patient Morbidity	0.10***	0.11***	0.09†
	(0.02)	(0.03)	(0.04)
Gender (0 = Male, 1 = Female)	0.02	0.05	0.00
	(0.09)	(0.11)	(0.16)
Age at Admission	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)
Black (0 = No, 1 = Yes)	0.05	0.09	0.03
	(0.20)	(0.23)	(0.41)
% Patients from Rural Area	0.19	0.13	0.51
	(0.47)	(0.47)	(1.36)
% Patients from Impoverished Area	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.02)
% Patients from Same CBSA	-0.00	0.04	-0.10
	(0.09)	(0.11)	(0.17)
Total CABG Patients	0.04***	0.03***	0.05***
	(0.01)	(0.01)	(0.02)
ED admits	0.03***	0.04***	0.02
	(0.01)	(0.01)	(0.02)
Health System Characteristics			
Total MDs per Patient	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.02)
Total Edges	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Academic Hospital (0 = No, 1 = Yes)	-0.02	0.08	-0.14
	(0.09)	(0.11)	(0.14)
Government Hospital (0 = No, 1 = Yes)	0.06	0.37*	-0.28
	(0.29)	(0.17)	(0.48)
For-profit Hospital (0 = No, 1 = Yes)	-0.00	0.01	0.27
	(0.22)	(0.19)	(0.79)
Uses EHR (0 = No, 1 = Yes)	-0.10	-0.03	-0.37
	(0.10)	(0.11)	(0.31)
Community-level Characteristics			
Total Population (log)	-0.11	-0.07	-0.19
	(0.11)	(0.13)	(0.21)
Black Population (log)	0.03	0.02	0.02
	(0.04)	(0.05)	(0.09)
Hispanic Population (log)	-0.04	-0.06	0.03
	(0.05)	(0.05)	(0.10)
Beds per 1,000 Residents	0.13	2.43***	-2.50
	(0.73)	(0.26)	(2.23)
PCPs per 1,000 Residents	0.01	0.03***	0.00
	(0.01)	(0.00)	(0.01)
Constant	-3.08	-9.54***	2.93
	(2.06)	(0.91)	(4.56)
Year Fixed Effects	Yes	Yes	Yes
Health System Fixed Effects	Yes	Yes	Yes
r2	0.20	0.20	0.20
N	4,107	2,869	1,238

†p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).