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Understanding Teacher Effectiveness with Complexity and Network Theories

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UNDERSTANDING TEACHER EFFECTIVENESS WITH COMPLEXITY
AND NETWORK THEORIES

A Dissertation
Presented to
the Graduate School of
Clemson University

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Doctor of Philosophy
Educational Leadership

by
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ABSTRACT

This study seeks to understand teacher effect on student test scores with perspectives from complexity and network theories. The assumptions are that network relationships and interactive dynamics are important to individual productivity in knowledge intensive organizations such as schools. Data were collected from students, faculty and staff in ten elementary schools in one school district in the southeast US. The analytical framework included: network analyses, hierarchical linear modeling, Lenth's analysis, response surface methodology and multiple regression. Results support the assumptions. Teacher's network measures exhibited complex linear, curvilinear and interactive effects on student test scores. Teachers who are central in the advice network and who broker trust are especially effective. Implications and future studies are discussed.

DEDICATION

I dedicate this dissertation to my late father. Although he was only with me for the first ten years of my life, at a very young age, he instilled in me the drive to pursue excellence in academics. His conscientious efforts in my early education and his encouragement for my smallest achievements have inspired me throughout my lifetime. I hope my earning the PhD will in some small way fulfill his own higher education dream.

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I sincerely appreciate in a deeply personal way the contributions of those whose names will be mentioned. Just as Ein Stein would not have derived the theory of relativity if he were isolated from birth on a deserted island (see *The Edge of Organization*), it would not have been possible to complete my dissertation without the web of support from the following people.

To my dear Captain Roger Chamberlin: without you, I would not be where I am. You made sure I did not pass up this opportunity to study with Dr. Marion while I was on excursion in China; you provided me a comfortable home to work from, a safe haven to rest in and a power station to draw energy from; your unwavering support, genuine encouragement and wise advice are the wind beneath my wings. Your support day in and day out is weaved into this dissertation. I look forward to continued growth with your love and support.

To my advisor and chair of my committee, Dr. Russ Marion: you are the best mentor I have ever had in my professional life. You inspire me in the pursuit of excellence, and model excellence with your own achievements; you give me opportunities to learn, and accompany me in the process with your love and patience; you point me to the future, and inspire me with your encouragement and faith. I look forward to the coming years of learning, collaborating and growing together!

To the rest of my committee members: Dr. Robert Knoeppel, for your expertise in the subject matter, for your insightful critique, and for all the opportunities you have given me in teaching and learning; Dr. Eileen Kraemer, for your invaluable suggestions

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CHAPTER ONE

INTRODUCTION

When it comes to student test scores, it is well established that teachers differ in their effectiveness. Depending on the subject matter and student population, teacher effect accounts for 7-21% of variation in student test scores (Nye, Konstantopoulos, & Hedges, 2004). For example, Nye et al. (2004) analyzed math and reading achievement scores for students from kindergarten to third grade in a large-scale experimental study. They found similar results as previous field-design studies, that teacher effect on math was about 12% to 14%, and that on reading was about 7%. They also found that teacher effect was much bigger than school effect. For reading test scores, the teacher variance component was over twice as large as the school variance component (3%) at Grade 2 and over three times as large at Grade 3 (2%). The pattern was similar in mathematics. This finding points to a compelling reality that the teacher a student happens to get within a school matters more than the school the student happens to attend.

Evaluating teachers based on their impacts on student test scores is called value-added (VA) approach (Chetty, Friedman, & Rockoff, 2014a). Data shows that the VA measures are valid because they exhibit little or no bias by student sorting (Chetty, Friedman, & Rockoff, 2014a). In addition, these impacts do not disappear fast; rather, elementary school teacher effects last even into young adulthood. With an exceptionally large longitudinal data set (over one million students spanning over 20 years), Chetty et al. (2014b) found that high VA teachers have students who are more likely to attend

college, earn higher salaries, and less likely to have children as teenagers. This finding further confirms the importance of teacher effectiveness.

Some might argue that student characteristics are much better indicators of test scores. For example, Goldhader, Brewer, and Anderson (1999) found that student characteristics that include gender, ethnicity, socio-economic status, parental education and family structure explained about 60% of the variation in student test scores. This number looks more impressive compared to 7-21% of teacher effect. But these student characteristics are out-of-school factors that are well beyond the reach of educators. Relative to the small set of factors that education policies might directly influence, teacher effectiveness seems to be the most critical.

With the increasingly important role standardized tests play in monitoring and shaping American education, this issue of instructor behaviors and student test scores becomes a worthy question to pursue. A series of milestone movements have placed increasingly intense accountability demands on schools as measured by students' standardized test scores. This is particularly evident for K-12 schools, but test scores are important in higher education institutions as well.

The first such movement in K-12 schools was on educational equity. The Coleman Report in the 1960s brought attention to racial and socioeconomic gaps based on standardized achievement test results (Coleman, 1968), and consequently the National Assessment of Educational Progress (NAEP) was established and served as the nation's report card to help monitor national progress in educational equity (Jencks & Phillips, 1998). The second movement shifted educational policy from equity to excellence. This

movement was initiated with *A Nation at Risk* report of 1983 (National Commission on Excellence in Education, 1983) that called for an end to the minimum competency testing movement and replacing it with proficiency. The latest policy effort in this regard was *No Child Left Behind Act of 2001* (NCLB, 2002), which was aimed at accomplishing high academic standards for all students and closing achievement gaps among racial and social groups (Lee, 2015).

In higher education, student test scores are important both for admissions and for the evaluation of student learning. For undergraduate admission, high school grade point average (GPA) and admission test scores (such as ACT and SAT) are typically used to predict student success (Breland, Maxey, Gernand, Cumming, & Trapani, 2002). Both measures have been proven to be effective predictors of moderate levels of first-year GPA in college, with ACT scores more effective at predicting higher levels of first-year GPA (Noble & Sawyer, 2004). Similarly, for graduate admission, standardized tests (such as GRE) are found to be an effective predictor of student success in graduate school. In addition, when combined with undergraduate GPA, standardized tests yielded the most accurate predictions of success (Kuncel & Hezlett, 2007). To evaluate student learning during college, two approaches are commonly used: GPA (Carini, Kuh, & Klein, 2006), or class specific knowledge gains (Cassidy & Eachus, 2000).

Given the significance of test scores, educational institutions are invested in finding out how to improve test scores. Layers of complexity play into student test scores. Those that reflect what the educational systems can do include: features of state and district policies and practices, conditions in schools, principal leadership, classrooms (e.g.

classroom size), teachers' professional community, and the interactions among these factors (Louis, Leithwood, Wahlstron, & Anderson, 2010). This study puts the spotlight on teachers because of the pivotal role of teachers in efforts to advance education (York-Barr & Duke, 2004).

Human Capital Assumptions

Since teachers are so important, the question becomes: what makes one teacher more effective than another? One stream of research seeks to answer this question from a human capital perspective. Human capital can be defined as "an individual's cumulative abilities, knowledge, and skills developed through formal and informal education and experience" (Becker, 1964; Pil & Leana, 2009, p. 1103). Typical variables included in such studies are teachers' college rating, education level (or years of education), certification level, years of experience, subject knowledge and verbal ability (Darling-Hammond & Younds, 2002; Pil & Leana, 2009; Wayne & Youngs, 2003). However, these variables did not yield satisfactory results. Nye et al. (2004) found that neither teacher experience, nor teacher education explained the variance in teacher effects (never more than 5%). Of these traditional measures of teacher quality, only experience is consistently correlated with more effective teaching (Wayne & Youngs, 2003).

The human capital assumption yields limited results because it ignores the interaction and interdependency among faculty and staff. First of all, teachers are not static. They collaborate and interact with each other, and change and grow as a result. They access each other's human capital through social capital. Information exchange is essential to effective teaching (Pil & Leana, 2009), and individual teacher's access to and

participation in information flow plays an essential role in their effectiveness. Second, educational institutions are complex organizations with multiple aims, diverse players, and driven by complex, interactive mechanisms. To create and disseminate knowledge effectively, educational institutions need to maintain networked relationships and generate complex dynamics to process large amount of information. Human capital assumption does not address these aspects of individual and organizational effectiveness.

Assumptions of This Study

To compensate for the limit in the human capital assumptions, this study approaches teacher effect on student test scores from a social capital perspective. This perspective assumes that outcomes are influenced more by relationships among group members and interactive dynamics in a group (Gronn, 2002; Liden & Maslyn, 1998; Pearce & Sims, 2000; Uhl-Bien, Marion, & McKelvey, 2007; Yammarino, Salas, A., Shirreffs, & Shuffler, 2012). Specifically, this study draws from network theory and complexity theory to explain teacher effect on student test scores.

Marion, Christiansen, Klar, Schreiber, and Erdener (2016) defined the complexity approach as "the interaction of people, information and structures in ways that process internal and external information and that influence organizational outcomes" (p.243). McKelvey (2008) explained this approach with an analogy: the collective, more than the individual, acts as the processor of information, much as the collective of neurons in the brain rather than neurons alone process human knowledge. In summary, the complexity approach assumes that the collective dynamics drive outcomes.

From the network perspective, the social environment such as a school can be expressed as "patterns or regularities in relationships among interacting units" (Wasserman & Faust, 1994, p. 3). In addition to the relational concepts, the network perspective also acknowledges the following central principles: agents are interdependent, relational ties are channels for distribution of resources, network structural environments provide opportunities for or constraints on individual actions, and relational patterns among agents are lasting (Wasserman & Faust, 1994). This study conceptualizes network structure as channels for information flow. The structural position of agents affects their access to information distributed in the network. Therefore, the network approach investigates outcomes at the intersection of network structure and information flow process (Borgatti & Halgin, 2011).

From these two perspectives, social capital can be defined as access to information (Burt, 2005; Coleman, 1990; Lin, 1999) as well as access to interactive dynamics of information (Uhl-Bien, Marion, & McKelvey, 2007) as a function of an individual's network position. Social capital is further operationalized as each individual teacher's network measures as calculated with network analysis methods.

The complexity approach values heterogeneity in exerting internal tension for creativity and adaptation (Uhl-Bien et al., 2007), while the network approach balances this view point by stating that homogeneity strengthens trust and collaboration (Burt, 2005; McPherson, Smith-Lovin, & Cook, 2001). Therefore this study is also interested in the effect of heterogeneity and homogeneity in teacher's network relationships on student test scores. Homogeneity is operationalized as the level of structural equivalence for each

teacher with other members of the network and calculated with network analysis methods as well.

Informal Leadership

Consistent with complexity and network theory, teachers are conceptualized as informal leaders who engage in the information flow process and possess social capital. Informal leaders can be defined as individuals who occupy strategic network positions and as a result, actively engage in and benefit from information flow processes. According to complexity theory, any individual can be an informal leader and participate in the interactive dynamics of information flow; no assumptions are made about their formally appointed positions in the organization.

As informal leaders, teachers can develop their capacity in enhancing the information flow process, and schools can organize their structure to enhance teachers' informal leadership.

Research Gap

Six studies (Briley, 2016; Daly, Chrispeels, & Moolenaar, 2011; Friedkin & Slater, 1994; Marion, Jiang, Buchanan, Bridges, Knoeppel, Gordon, 2017; Moolenaar, Sleegers, & Daly, 2012; Pil & Leana, 2009) investigated student test scores from the social capital perspective. These studies collected network data from either faculty alone or faculty and staff, and used resulting network measures to explain student test scores. Some studies (Friedkin & Slater, 1994; Moolenaar, Sleegers, & Daly, 2012; Pil & Leana, 2009) calculated network measures at the school or team level, while others (Briley,

2016; Daly, Chrispeels, & Moolenaar, 2011; Marion, Jiang, Buchanan, Bridges, Knoeppel, Gordon, 2017) used more fine-grained teacher-level network variables.

But they all lacked in the following aspects: 1) none of them examined curvilinear relationship and interactive effects between network measures and test scores; 2) none of them investigated the teacher network conditions for best student performance; 3) none of them examined the relationship from the joint complexity and network perspectives.

Purpose Statement

This study will investigate teacher effects on student test scores from social capital and group dynamic lens. The theoretical framework will be built upon complexity theory and network theory; they offer complementary explanations on how social capital and group dynamics affect outcomes. A quantitative design will be used, and it involves collecting both student and teacher data from ten elementary schools in one school district in the southeastern U. S. Student test scores, as well as student and teacher demographic information will be collected from the district office. Teacher advice, social and trust network data will be collected with online surveys and analyzed with network analysis methods. Teacher-level network variables are indicators of each teacher's social capital and relationship patterns.

This study employs polynomial regression and response surface methodology (RSM) to examine the relationship between teacher network variables and their effect on student test scores. RSM utilizes polynomial regression to examine how combinations of two or more predictor variables relate linearly, curvilinearly, and interactively to an

outcome (Shanock, Baran, Gentry, Pattison, & Heggestad, 2010). Besides standard regression statistics, RSM also produces several plots that identify the optimum outcome and corresponding input measures. In addition, to control for the exogenous school and student variables, hierarchical linear modeling will be used.

Research Questions

Three research questions lead this research study: 1) What is the relationship between teacher network variables and student test scores? Specifically, this study is interested in curvilinear and interaction effects that influence outcomes; 2) What is the effect of homogeneity in teacher's network relationships on student test scores? 3) What combinations of teacher network variables have the optimal effect on student performance?

Significance of the Study

Standardized test scores, particularly of the scope needed for this study, are much more difficult to obtain in higher education than in K-12. This study utilizes K-12 data to develop an analytical framework for student achievement that is generalizable to higher education. Further, teacher effectiveness is conceptualized as informal leadership, and leadership is independent of the context in which it is practiced (Rost, 1991).

Several audiences will benefit from this study. First, policymakers who advocate for academic excellence and student competency will learn a new perspective about the organization of educational structures. Second, educational administrators who are at the forefront of accountability pressures will get confirmation about the effectiveness of collaborative efforts in their institutions, and learn about suggestions to steer such

collaboration to productivity. Third, instructors who are at the center of instructional efforts will further recognize the importance of their social networks for their teaching effectiveness, and learn about important network positions that will optimize their effectiveness. Last but not least, fellow educational researchers will be informed of a promising new area in educational research, and be encouraged to pursue this line of inquiry.

Summary

In summary, teacher effectiveness is important for student test scores. Given the accountability pressure, educators are interested in learning about ways to improve teacher effectiveness. Traditional human capital assumptions in investigating teacher effect on student test scores have serious limits. This study conceptualizes teachers as informal leaders, and approaches this topic with network and complexity assumptions that take into account the interdependency and interaction of educational professionals in organizational information processing. In addition, this study fills in the literature gap with both its theoretical framework and analysis strategies.

The next chapter delineates the theoretical framework that guides the research design and interpretation of results.

CHAPTER TWO

THEORETICAL FRAMEWORK

Educational institutions are complex organizations with multiple aims, diverse players, and driven by complex, interactive mechanisms. Compared to factories where the production process is well defined and routine, educational institutions require much more context-specific decision-making and local problem solving. To create and disseminate knowledge effectively, educational institutions need to be adaptive, creative and learning-oriented. Therefore, the social dynamics in such work places are very important to its productivity and individual's engagement in such dynamics is important to their personal (and the group's) effectiveness. In this theoretical framework section, the process that leads to productivity in knowledge-intensive organizations will be introduced from two complementary perspectives: the interactive dynamics perspective and the strategic structural positions perspective. Complexity leadership theory provides the framework for the interactive dynamics perspective, while network theory lays the foundation for the network position perspective. Both theories address the productivity process from three aspects: informal leadership, information flow and social capital. Relationship among these concepts is illustrated in Figure 2.1.

This section provides an overview of supporting literature, and introduces the key terms associated with the two theories.
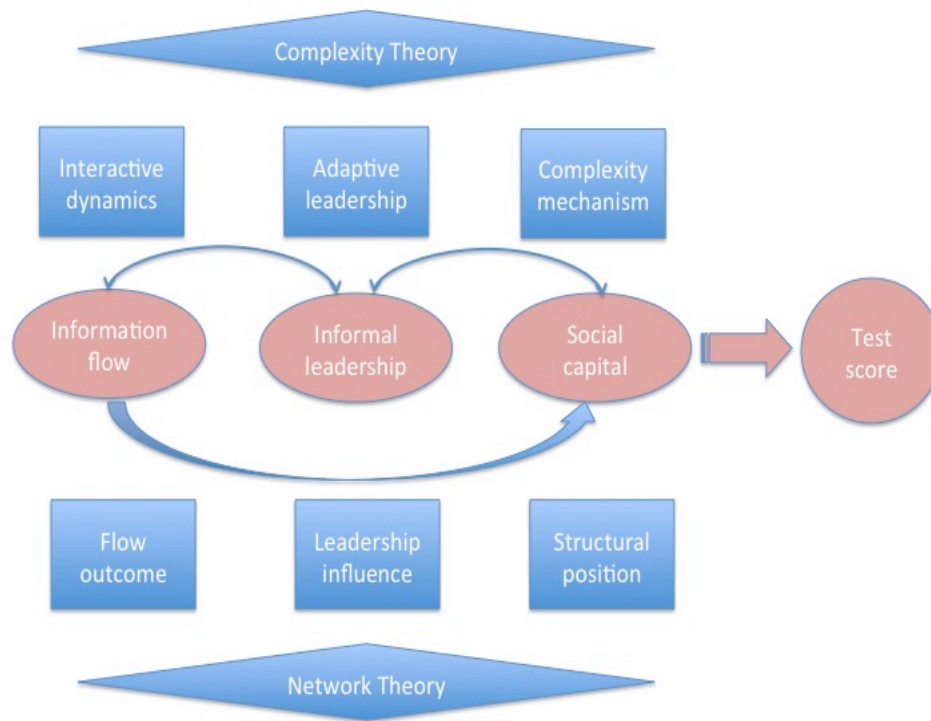
Figure 2. 1. Theoretical framework

Overview of Complexity and Network Theory

Complexity Leadership Theory

There are two ways to conceptualize leadership. The first is to examine leadership as a property of individuals and their behaviors; this is also called the human capital perspective (Balkundi & Kilduff, 2006). The second is to examine leadership as "a collective phenomenon that is distributed or shared among different people, potentially fluid, and constructed in interaction" (Denis, Langley, & Sergi, 2012, p. 212). This is a collectivism perspective.

Several theories fall under the umbrella of the second perspective, collectivism, including relational theory, distributed leadership theory, collaborative leadership theory,

shared leadership theory, leader-member exchange theory and complexity leadership theory (Gronn, 2002; Liden & Maslyn, 1998; Pearce & Sims, 2000; Uhl-Bien et al., 2007; Yammarino et al., 2012). Complexity leadership theory, one stream in the collectivism movement, perceives leadership as emergence through the synergistic (people reacting to each other but not in conformity with one another), dynamic interaction of information among organizational members.

Complexity leadership theory (CLT) is a framework for leadership in organizations "that enables the learning, creative, and adaptive capacity of complex adaptive systems (CAS) in knowledge-producing organizations or organizational units" (Uhl-Bien et al., 2007, p. 304). In short, CLT studies how to lead complex dynamics in an organization.

CLT has its root in complexity theory. Complexity theory, when applied in social science contexts, sees organizations as complex adaptive systems (CAS) composed of a diversity of agents who interact with one another, mutually affect one another and generate emergent behaviors as a result (Marion, 1999). Properties common to such systems include: simple components or agents (simple relative to whole system), nonlinear interactions among components, with no central control yet they produce emergent behaviors such as hierarchical organization, information processing, dynamics, evolution and learning (Mitchell, 2011). The complex dynamics, synergy and synchrony created through such interaction as a whole cannot be reduced to any individual part, and cannot be understood with a simplistic summary of the parts (Uhl-Bien et al., 2007).

The CLT framework includes three leadership functions: administrative, enabling, and adaptive leadership (Uhl-Bien et al., 2007). This leadership theory acknowledges the role of formal administrative or bureaucratic structure in the development of leadership and organizations. It defines the leadership exercised by people in formal leadership positions as administrative leadership. One of the key roles that such leaders can play is to create connections between, or to harmonize administrative structures and adaptive structures in organizations. Adaptive leadership refers to adaptive, creative, and learning actions that emerge from the interactions of CAS. Adaptive leadership is one form of informal leadership. Enabling leadership creates the organizational conditions to foster the informal emergent dynamic as well as facilitate the information flow from adaptive to administrative structures. It can be seen as an extension of administrative leadership in the complexity context.

Enabling leadership creates conditions within an organization to foster complex dynamics. These conditions include elements such as interaction in network relationships, interdependency and pressure over conflicting constraints and appropriate levels of heterogeneity (Uhl-Bien et al., 2007). The following paragraphs elaborate on these conditions in a school context.

From a complexity point of view, relationships are no longer just about the leader-follower relationship; instead, it is about enabling effective networks, the ambiance that fosters interactive dynamics (Marion & Uhl-Bien, 2001; Uhl-Bien et al., 2007). School administrators can, for example, promote interaction by arranging the master schedule so that teachers from different grades can plan together.

Conflicting constraints arise when one person can achieve their preferences at the expense of one or more other persons. When interdependent agents are confronted with conflicting constraints, they seek to oppose or negotiate the constraint; negotiation can lead the conflicting agents to refine or realign their information to accommodate each other; as a result, information evolves and, often, something new and surprising emerges if they find unique, new solutions. Conflicting constraints are opportunities to promote creativity, learning, and adaptability. They are particularly potent when complexly distributed over an interactive, interdependent network of individuals such that solutions in one situation can generate constraints in another.

Heterogeneity stimulates interdependency because they enhance conflicting constraints. With heterogeneity of ethnicity, preferences, or worldviews, agents are pressured to negotiate and adapt to their differences.

Yet too much conflicting constraints and heterogeneity can inhibit information flow because, when spread across an interdependent network, the scope of cascading, interactive constraints become impossible to resolve. Homogeneity, on the other hand, significantly reduces constraints and fosters cooperation (Burt, 2005; McPherson et al., 2001); consequently there is little pressure to elaborate and change. School leaders can instead work to create an ideal mixture of heterogeneity (such as diverse ideas about teaching) and homogeneity (such as common understanding that good teaching is important for effective learning), seeking a balance that promotes pressures and change without generating so much interdependent pressure that useful decisions and change becomes impossible.

Network Theory

No single or all-encompassing network theory exists. However, all related work in social networks builds upon the assumption of "the importance of relationships among interacting units" (Wasserman & Faust, 1994, p. 4). The network perspective is interested in "the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups" (Borgatti & Halgin, 2011, p. 1168). This study is interested in the information flow mechanism and process where the network structure is seen as the channel for distribution of information.

The network perspective has been used to explain a range of social phenomena, such as innovation climate (Moolenaar et al., 2010; Moolenaar & Sleegers, 2010; Tortoriello et al., 2014), leadership influence (Brass, 1984, White et al, 2016), productive capacity (Marion et al., 2016), adaptability (Schreiber & Carley, 2008), teacher beliefs (Siciliano, 2016), and student test scores (Friedkin & Slater, 1994; Moolenaar et al., 2012).

Graph theory provides the vocabulary to label and denote many network structural properties, and the mathematical foundation to quantify and measure these properties. Graph theory represents social networks in two-dimensional space, comprising of a set of points (agents, units, actors or nodes) and a set of lines (linkages, ties, edges, relationships or connections) connecting the points (Freeman, 1979). The lines may be non-directional or directional. Directional networks distinguish between "choices made" and "choices received" (Wasserman & Faust, 1994, p. 198). This study has a combination of directional and non-directional relationships. In social network

analysis, the graphic representation of social links that a person has is also called

sociogram (Moreno, 1934). Figure 2.2 is an image of sociogram.
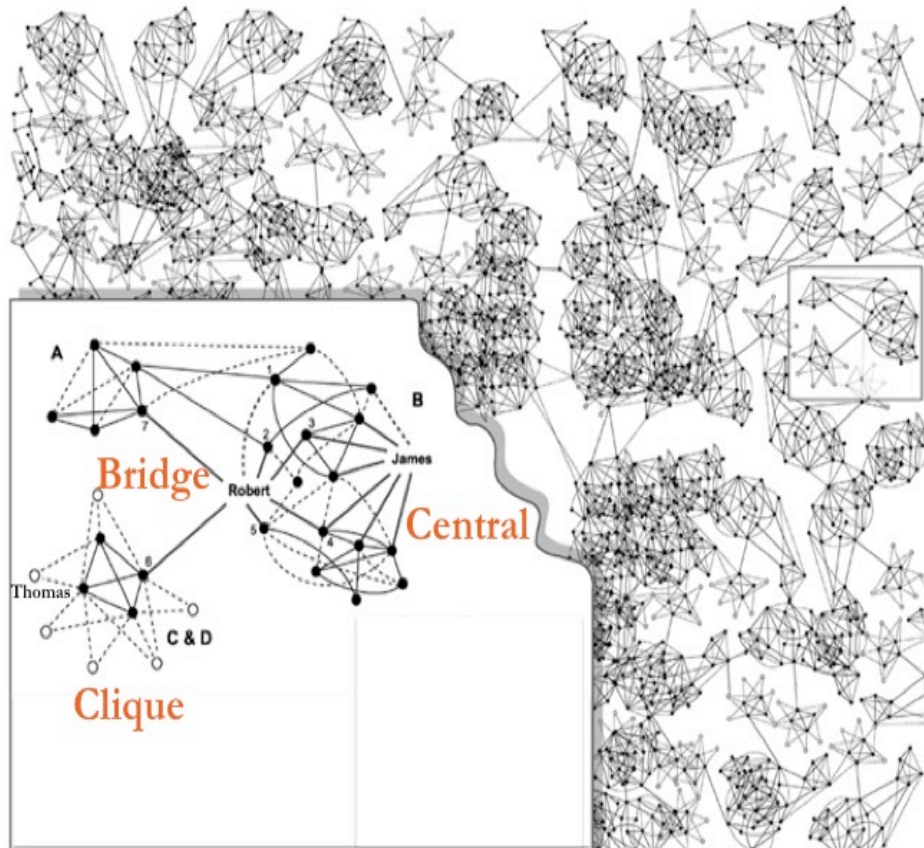
Figure 2. 2.Three network positions: bridge, central and clique. Dots represent people,

and solid lines represent ties between people (dashed lines are negligible weak

connections). Adapted from Brokerage and closure: an introduction to social capital

(p.14), by R. S. Burt, 2005, New York, NY: Oxford University Press. Copyright 2005 by

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Social network analysis is most interested in two aspects of the network: the

structural properties of the network and the content of the tie. The structural properties

include the network as a whole and individual's structural position in the network.

Measures for structure of a network as a whole are commonly referred to as "network-level measures", as represented by the typology of the sociogram in Figure 2.2. Measures for individual's structural positions are called "agent-level measures", as represented by the positions occupied by James, Robert and Thomas in Figure 2.2. This study focuses on agent-level measures for each teacher. James is in a central position; Robert is in a bridging position, and Thomas is in a clique. These three positions are most widely studied because of their strategic significance. In the following sections, advantages associated with each of structural positions will be discussed in detail.

The content of the tie refers to the nature of relationship between two agents, as represented by the solid lines in Figure 2.2. Tie content is typically categorized as *instrumental* versus *expressive* (Ibarra, 1993). Instrumental relationships arise out of interaction over work, such as advice about task-related issues (Friedkin & Slater, 1994; Krackhardt & Hanson, 1993; Moolenaar et al., 2012). Expressive relationships are affective in nature, and involve exchange of things such as friendship (Brass, 1984; Mehra et al., 2001), social support (Ibarra, 1993), and trust (Bryk & Schneider, 2003). This study will examine both types of ties.

The network perspective recognizes the importance of interdependency among units, and incorporates such interdependency in its methodology, social network analysis. In social network analysis, the unit of analysis is "an entity consisting of a collection of individuals and linkages among them", and is operationalized as "dyads (two actors and their ties), triads (three actors and their ties), or larger systems (subgroups of individuals, or entire networks)" (Wasserman & Faust, 1994, p. 5).

To study relationships among individuals in an organization such as a school, the network is typically bounded to include everybody in the network. But how to define the boundary can be challenging. Brass (1984) argued that in an organization there could be several units of references, such as an immediate work group, within department or within the entire organization. It is important to consider the appropriate unit of reference because different structural positions in different units have different implications. For example, in his study of a newspaper publishing company, Brass (1984) found that contacts beyond the immediate work group were important for technical-core personnel to gain influence, but not for support staff. This study involves all the professional staff members that comprise the education-related environment, equivalent to the entire organization in Brass' term.

Information Flow, Informal Leadership, and Social Capital

This section discusses the process that leads to organizational or group productivity from three aspects: information flow, informal leadership and social capital. Both the complexity perspective and the network perspective, as well as how these two perspectives integrate, will be elaborated.

An emerging new field in leadership research uses social network analysis methods and theory to study the micro dynamics of how leadership is enacted (Balkundi & Kilduff, 2006; Friedrich, Vessey, Schuelke, Ruark, & Mumford, 2009; White, Currie, & Lockett, 2016). Scholars in this field view information flow and network as essential for leadership emergence. For example, Friedrich et al. (2009) called information the "currency" of leadership and network the "channel" for information exchange (p. 942).

Interactive and interdependent networks of people provide the context in which information interacts and emerges. From a network perspective, such people occupy strategic structural positions in the network, and can access, disseminate, mediate or control information in ways that can benefit or harm the entire network (Friedrich et al., 2009). From a complexity perspective, they engage more effectively in interactive dynamics of information flow, and benefit from such dynamics. Both mechanisms lead to higher informal leadership and social capital. The following sections elaborate on these ideas.

Information Flow

Complexity perspective. Information flow is the mechanism underlying complex dynamics that generate emergent outcomes. Information, carried and transmitted by people in the system, has the potential to interact, merge and transform into something creatively new, different from its original form and at a higher level of sophistication (Marion et al., 2016). This is an irreducible process in that information, after it is processed by interdependent interaction, is qualitatively different from before. People then act on the new information and as a result, outcomes such as learning, innovation and adaptability emerge (Uhl-Bien et al., 2007).

The complexity perspective examines individuals' degree of engagement in the information flow process, and recommends organizational contexts that empower such interactive dynamics—networked relationships are one such recommended context.

Network perspective. Information is amplified and empowered when embedded in networked, interactive dynamics. The linkages between agents serve as conduits for

information flow (Borgatti & Halgin, 2011; Wasserman & Faust, 1994). The structure and composition of an individual's network provides both opportunities and constraints. Strategic location in an organizational network allows the agent to identify strategic opportunities, marshal resources, assemble teams, and win support for innovative projects (Sparrowe & Liden, 2005).

Borgatti and Halgin (2011) summarized the theoretical proposition of two well-established network theories as the "flow model". In such models, networks are seen as the channel for the flow of information. As information flows through the network, nodes in strategic positions have advantages related to flow outcome, such as the speed, the frequency, and the quality of information received by the node. For example, central nodes may receive information more quickly than other nodes because they have many connections through which to receive the information. Nodes in bridging positions connect across clusters, and therefore have access to diverse information and have control over the distribution of such information (Burt, 2005).

Nodes are rewarded for the roles they play in the information flow process, therefore, these flow outcomes are related to other constructs, such as effective performance (Cross & Cummings, 2004; Mehra, Kilduff, & Brass, 2001), leadership influence (Brass, 1984; Ibarra, 1993), and bargaining power (Burt, 1992). In this way, network theory consists of "elaborating how a given network structure interacts with a given process (such as information flow) to generate outcomes for the nodes or the network as a whole" (Borgatti & Halgin, 2011, pp. 1172-1173).

Informal Leadership

Complexity perspective. From a complexity perspective, informal leadership, complex dynamics and information flow are closely related to each other. Informal leadership influences complex dynamics by enhancing information flow (Marion et al., 2016). Informal leadership reflects the complexity perspective of effective leadership, which is to "capitalize on interactive dynamics" (Marion & Uhl-Bien, 2001, p. 394).

Any individual can be an informal leader and participate in the interactive dynamics of information flow; no assumptions are made about their formally appointed positions in the organization. Many avenues exist for informal leaders to engage in and enhance information flow. For example, informal leaders can become information hubs because they are connected with many people, or they can transmit information to isolated parties, or they can engage in intense information processing within their subgroups. Each of these activities is related to a strategic network position.

Network perspective. Network analysis methods have been applied in studying leadership processes (Friedrich et al., 2009) such as emergence, informal leadership, and leader performance. From this perspective, leadership can be understood as social capital that collects around certain individuals–whether formally designated as leaders or not–based on the structure and content of their social ties (Balkundi & Kilduff, 2006).

In celebrating the potential synergy between leadership research and social network approaches, Balkundi and Kilduff (2006) made the argument that informal leadership is often equated with network centrality. Summarizing several empirical studies, they identified *degree centrality* (defined as the number of links of an agent

normalized by the maximum number of such links) with positive affect on team performance, *betweenness centrality* (defined as the percentage of times when an agent lies on the shortest path between two other agents) as predictors of leadership perception and emergence, and *eigenvector centrality* (defined as the degree that an agent is connected with other agents who are themselves well connected) with improved team effectiveness. Other researchers have found that a person's centrality in advice networks and social support networks is related to positive perception of leadership influence (Brass, 1984; Ibarra, 1993; White et al., 2016).

It has been established that an individual's network position affects information flow outcome, as well as others' perception of his or her leadership influence. Based on the discussion in the last two paragraphs, an inference could be drawn that information flow is the mechanism for the emergence of leadership influence. This is the same conclusion reached by advocates of the complexity perspective. Therefore, informal leaders can be defined as individuals who occupy strategic network positions and as a result, actively engage in and benefit from information flow processes.

Social Capital

Network perspective. Social capital, as a concept, is rooted in social network and social relations. Researchers of social capital have two differential focuses: resources embedded in social networks, and network locations to access such resources (Lin, 1999). This study focuses on the network location aspect of social capital.

According to Coleman (1990):

Social capital is defined by its function. It is not a single entity but a variety of different entities having two characteristics in common: They all consist of some aspect of social structure, and they facilitate certain actions of individuals who are within the structure. Like other forms of capital, social capital is productive, making possible the achievement of certain ends that would not be attainable in its absence (p. 302).

Burt (2005) also acknowledged network location as a key element of identifying social capital, and defined social capital as advantages for individuals occupying strategic locations in social networks. He defined social capital in terms of closure within a group and brokerage beyond the group. Closure within a group reinforces status quo, enhances new relationships between friends of friends, and amplifies trust or distrust. Brokerage between groups affords access to creative information and ways to implement such information that is outside the target group. These two forms of social capital enhance each other because closure facilitates the trust and collaborative alignment needed to deliver the value of brokerage.

Complexity perspective. The complexity perspective of information flow extends the concept of social capital. Besides access to existing information flow, complexity theorists identify access to the interactive dynamics of information flow in the network as social capital. Information can transform through the interactive dynamics and produce outcomes such as innovation and learning as a whole that transcends the sum of isolated information without such interaction. Everybody involved in the interactive dynamics, in turn, benefits and gains social capital this way.

These three dimensions, information flow, informal leadership and social capital are mutually reinforcing and complementary, and all lead to productivity (as measured by test scores in this study). When teachers are engaged in information flow, the likelihood that their students will produce higher test scores increases. Teachers' engagement in information flow also facilitates better test scores by strengthening both each teacher's informal leadership and social capital. When teachers exercise informal leadership, information flow within the network is enhanced, as is the social capital of every teacher. Social capital, on the other hand, reinforces informal leadership by virtue of access to information flow afforded by strategic network positions. Teachers who engage in information flow, exercise informal leadership and possess social capital will be more effective in helping students to achieve higher test scores.

Specific strategic network positions and tie contents, related network measures and projected effect on productivity will be elaborated in the next section.

Network Structural Position and Content of Tie

This section delves into details of network analysis. As briefly mentioned in the overview section, networks are evaluated by their structure (structural positions) and the content of their ties (network types). This section provides justifications for both structural positions and network types investigated in this study.

Strategic Structural Positions and Related Network Measures

Three strategic structural positions, *bridging*, *central* and *clique engagement* are most commonly associated with different forms of social capital. Network measures formalize the concept of social capital (Altman, Carley, & Reminga, 2017; Borgatti,

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Candace, & Martin, 1998; Burt, 1992; Freeman, 1979; Newman, 2010), and distinguish agents in strategic positions. Network measures are grouped according to the degree they relate to these three positions. Table 2.1 summarizes the names of the measures, their definition and significance, and Appendix A has the formula for each measure. How these network measures relate to various constructs of productivity are also elaborated in the following sections.

Bridging position (see Robert in Figure 2.2). A bridge is a well-developed network position that links two or more groups. Granovetter's (1973) notion of bridges was expressed as the strength of weak ties. According to the strength of weak ties theory, people with more weak ties have social capital because weak ties bridge a person with someone who is not connected to his or her other friends, and thus capture novel information (Granovetter, 1973). This argument was further elaborated and formalized by Burt in his notions of structural holes and constraints. In the structural holes theory, Burt (1992) termed the missing links between an agent's neighbors as structural holes. The person who fills structural holes is in a bridging position and is often called a broker between different groups. Burt, Kilduff, and Tasselli (2013) explained the relationship between structural hole, brokerage and broker as "a structural hole is a potentially valuable context for action, brokerage is the action of coordinating across the hole with bridge connections between people on opposite sides of the hole, and network entrepreneurs, or more simply, brokers, are the people who build the bridges" (p.531).

Brokers have three advantages: access to a wider diversity of information, early access to that information, and control over information diffusion (Burt, 2005). Such

people have the advantage of "information arbitrage" (p. 17), or the strategic deployment of information to create value. As a result, they are often identified as opinion leaders, found to be responsible for the spread of new ideas and behaviors and are rewarded for their integrative work.

Brokers are rewarded in many ways, such as positive individual and team evaluations, higher compensations than peers, faster promotion, and better performance ratings. For example, Cross and Cummings (2004) examined the effect of individual's network position on individual performance within a company and ties that bridged various social divides. They collected data from two knowledge intensive work environments on information and awareness networks as well as the number of ties outside the organization and outside the department, the number of ties spanning physical barriers, and the number of ties with people in higher hierarchical levels. Their conclusion was that any kind of bridging relationship that spans a social divide is positively related to performance.

Burt (1992) developed two measures of structural holes: *effective size*, and *constraint*. *Effective size* is calculated as the number of connections, weighted by strength of tie, that a person is directly connected to, minus a "redundancy" factor.

Table 2. 1

Name, Definition and Significance for Agent-Level Network Measures

Name	Definition	Significance	Reference
Central Position: many connections or short distances			
†In-Degree Centrality	It is the number of links directed into a node normalized by the maximum number of such links.	It measures the connections that the node of interest receives from other nodes. For example, in the citation network, the number of citations a paper receives from other papers measures the influence of this paper.	Altman, Carley & Reminga, 2017
†Out-Degree Centrality	It is the number of links emanating from a node normalized by the maximum number of such links.	It measures the connections that the node of interest nominates other nodes. For example, in the trust network, this measures the number of people the central node trusts.	Altman, Carley & Reminga, 2017
Total-Degree Centrality	It is the normalized sum of its in-Degree and out-Degree.	Individuals who have connections to many others might have more influence, more access to information, or more prestige than those who have fewer connections.	Altman, Carley & Reminga, 2017; Newman, 2010

†Eigenvector Centrality	The principal eigenvector of the network. A node is central to the extent that its neighbors are central.	Node has high score if connected to many nodes that are themselves well connected. For example, individuals who are connected to many otherwise isolated individuals or organizations will have much lower score in this measure than those that are connected to groups that have many connections themselves.	Altman, Carley & Reminga, 2017
†Katz Centrality	This computes the centrality of each entity based on the centrality of its neighbors. Alpha should be chosen such that its absolute value is less than the reciprocal of the largest eigenvalue of N.	It is essentially measuring the same thing as eigenvector centrality. This measure solves the problem of eigenvector centrality where only vertices that are in a strongly connected component of two or more vertices, or the out-component of such a component, can have non-zero eigenvector centrality.	Altman, Carley & Reminga, 2017; Newman, 2010
PageRank Centrality	This calculates the importance of a node based on the importance of its in-coming neighbors.	This measure calculates the centrality a node derives from his neighbors as proportional to their centrality divided by their out-degree. This way vertices that point to many others pass only a small amount of centrality on to each of those others, even if their own centrality is high.	Altman, Carley & Reminga, 2017; Newman, 2010
Authority Centrality	A node is authority-central to the extent that its in-links are from nodes that have many out-links.	Individuals or organizations that act as authorities are receiving information from a wide range of others each of whom sends information to a large number of others.	Altman, Carley & Reminga, 2017

†*Hub Centrality	A node is hub-central to the extent that its out-links are to nodes that have many in-links.	Individuals that act as hubs are sending information to a wide range of others each of whom has many others reporting to them.	Altman, Carley & Reminga, 2017
In-Closeness Centrality	The closeness of all other nodes to a node in the network. It is the inverse of sum of distances in the network to a node and from all other nodes.	Nodes that are separated from others by only a short geodesic distance might have better access to information at other vertices, or more direct influence on other vertices.	Altman, Carley & Reminga, 2017; Newman, 2010
Closeness Centrality	The closeness of a node to other nodes in a network (also called out-closeness). It is the inverse of the sum of distances in the network from a node to all other nodes.	High scoring nodes could monitor the information flow in an organization better than most others, and will often times have the best picture of what is happening in the network as a whole.	Altman, Carley & Reminga, 2017
†*in-Inverse Closeness Centrality	The average closeness from all other nodes to a node in a network considering only paths from all other nodes to the node. It is the sum of the inverse distances between a node and all other nodes.	Nodes that are separated from others by only a short geodesic distance might have better access to information at other vertices, or more direct influence on other vertices.	Altman, Carley & Reminga, 2017; Newman, 2010

Inverse Closeness Centrality	The average closeness of a node to the other nodes in a network (also called out-inverse closeness centrality). Inverse Closeness is the average inverse distances from a node to all other nodes.	High scoring nodes could monitor the information flow in an organization better than most others, and will often times have the best picture of what is happening in the network as a whole.	Altman, Carley & Reminga, 2017 Altman, Carley & Reminga, 2017
Bonacich Power Centrality	This computes the centrality of each entity based on the centrality of its neighbors.	This measure tells us who is connected to the most powerful (e.g. other highly connected) people.	
Capability	The formula discounts for the fact that most agents have some connections and assumes that there is a general discount to having large numbers of connections.	Detects entities with high or low degree relative to other entities.	Altman, Carley & Reminga, 2017
Cognitive Demand	Measures the total amount of cognitive effort expended by each agent to do its tasks, need to move, connecting others, and so on.	This measure identifies emergent leaders because of the amount of cognitive effort inferred to be expended based on the individual's position in the meta-network.	Altman, Carley & Reminga, 2017
Radiality Centrality	The normalized sum of its closeness to all other nodes.	This measures identifies people who are close to many other people in the network.	Altman, Carley & Reminga, 2017

Shared Situation Awareness	Individuals or organizations that are high in group awareness are those that by virtue of their connections to others, what resources they use, what knowledge there is, what tasks there are - have a better understanding of what others are doing.	This measure identified people who are in the know.	Altman, Carley & Reminga, 2017

Bridging Position: connecting otherwise disconnected parts

Betweenness Centrality	The Betweenness Centrality of node v in a network is defined as: across all node pairs that have a shortest path containing v, the percentage that passes through v.	This measure indicates the extent that an individual is a broker of indirect connections among all others in a network. Such people are thought of as gatekeeper of information flow.	Altman, Carley & Reminga, 2017
Ego Betweenness Centrality	It is the betweenness score within a node's own ego network, which contains the node itself, its immediate neighbors nodes, and all links between them	This measures indicates the degree that a node connects his immediate neighbors.	Altman, Carley & Reminga, 2017
Information Centrality	It accounts for indirect as well as shortest (geodesic) paths among entities. Information centrality is similar to betweenness, except that betweenness considers only shortest paths geodesics, whereas information centrality also considers	This measure indicates the extent that an individual is a broker of indirect connections among all others in a network. Such people are thought of as gatekeepers of information flow.	Altman, Carley & Reminga, 2017

	more circuitous paths weighted by the inverse of the path length (the number of links along the path).		
*Potential Boundary Spanner	The degree to which a node spans disconnected groups in a network. This is calculated as the ratio of betweenness centrality to total degree centrality. This is a composite measure that is high when the agent is potentially influential but is not in the know.	The individual or organization may be connected to only one or a few members of each group. This measures finds an individual who could likely have great potential to interact with other parts of an organization based on their existing connections.	Altman, Carley & Reminga, 2017 Burt, 1992
Structural Holes Constraint	The degree to which each node in a square network is constrained from acting because of its existing links to other nodes.	This measure identifies the missing links that keep the node form accomplishing tasks.	
*Structural Holes Effective Network Size	It is a node's ego network based on redundancy of ties.	This measures a node's bridging ability.	Burt, 1992
*Structural Holes Efficiency	The fraction of nodes in an ego network that are not redundant. This is calculated as effective network size divided by the number of nodes in each ego network.	This measures a node's bridging ability.	Altman, Carley & Reminga, 2017

Clique Engagement: cohesive subgroup

Clique Count	A clique is defined as a group of three or more nodes that are all connected together and that cannot be made larger by adding another node.	The more cliques a node belongs to, the more engaged is this node in cliques.	Altman, Carley & Reminga, 2017
Clustering Coefficient	Measures the degree of clustering in a network by averaging the clustering coefficient of each node, which is defined as the density of the node's ego network.	The clustering coefficient gives a sense of the local characteristics of the network--how information spreads by means of employee groups. A higher clustering coefficient supports local information diffusion as well as a decentralized infrastructure because employees are likely to share information and know what is happening in their work group.	Carley et al., 2013
Simmelian Ties	This measures for each node the fraction of nodes to which it has a Simmelian tie. A Simmelian tie is a tie embedded in cliques and is often associated with brokers inside such cliques.	This measures three-way reciprocal relationships.	Altman, Carley & Reminga, 2017
*Triad Count	Triadic analysis is based on sub-graphs, where the number of nodes is three. A triad is a sub-graph consisting of three nodes and three lines among them.	The more triads a node belongs to, the more engaged is this node in cliques.	Wasserman & Faust, 1994; Altman, Carley & Reminga, 2017

	Heterogeneity: diverse information		
*Correlation Similarity	This is a natural scale for similarity measure of structural equivalence. It measures the degree to which each pair of rows has overlapping data.	It measures the degree of homogeneity in a node's network relationships.	Altman, Carley & Reminga, 2017; Newman, 2010
Correlation Distinctiveness	Measures the degree to which each pair of rows has complementary data, expressed as the percent of total data.	It measures the degree of heterogeneity in a node's network relationships.	Altman, Carley & Reminga, 2017
Correlation Expertise	Measures the degree to which each pair of rows has complementary data, expressed as a fraction of the data of the first row.		Altman, Carley & Reminga, 2017

Note. * These measures are significant in one or more of the RSM/regression models.

† These measures are not calculated for the social network (non-directional).

Please refer to Appendix A for the formula for each measure.

Constraint is calculated as the extent to which all of a person's relational investments directly or indirectly involve a single connection. Later researchers developed related measures, such as *structural holes efficiency*, calculated as the fraction of nodes in an ego network that are not redundant (Altman et al., 2017). Another measure of the bridging capacity of a network position is *betweenness centrality*(L. C. Freeman, 1979), calculated as the number of times a person falls along the shortest path between two other actors.

Clique engagement (see Thomas in Figure 2.2). Engagement in cliques is another important structural position. According to graph theory, a clique is a "maximal complete sub-graph of three or more nodes" (Wasserman & Faust, 1994, p. 254). A clique is a formal representation of "cohesive subgroups", where people communicate within their sub-groups more than they communicate with agents outside the group (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013). Cliques are different from silos in that they interact actively with other agents and cliques. In other words, they are not isolated from the larger network (Marion et al., 2016). Cliques are found to incubate new ideas, nurture minority needs and empower their voices (Rodan & Galunic, 2004), process diverse information (McPherson et al., 2001), and process large amounts of information effectively (Marion, Christiansen, Klar, Schreiber, & Akif Erdener, 2016). Cliques can be seen as "hot spots" in a network where new and diverse ideas are incubated and nurtured before entering into the bigger network, and where information is processed quickly because of the cohesion in the structure.

A Simmelian tie is related to cliques in that a Simmelian tie is embedded in a clique. A Simmelian tie is formed when three people are reciprocally connected to one other and each is reciprocally connected to another, third party (Krackhardt, 1998). Yet Simmelian ties are qualitatively different from isolated dyads and dyads embedded in a clique in three ways: they mitigate the pursuit of individuals' self-interests, reduce the bargaining power of single individuals, and facilitate cooperation and conflict resolution (Krackhardt, 1999). Tortoriello and Krackhardt (2010) investigated the effect of Simmelian bridging ties on innovation. Their data on 276 research and development scientists and engineers revealed that a strong bridging tie embedded in a dense clique-like structure that transcended formal organizational boundaries explained difference in individuals' innovation capacity.

Newman (2010) introduced *clustering coefficient* as an approximate measure for cliques. *Clustering coefficient* measures "the average probability that two neighbors of a vertex are themselves neighbors" (p. 262). In effect, it measures the density of triangles in a network. *Simmelian tie* measures the fraction of agents to which an agent has a Simmlian tie (Altman et al., 2017).

Central position (see James in Figure 2.2). Central position is yet another strategic location. To occupy a central position in a bounded network, a person can have connections with many people, or be linked to many people by relatively few intervening nodes (i.e., short distances). Distance (a.k.a. geodesic distance) between two vertices in a network is defined as "the minimum number of edges one would have to traverse in order to get from one vertex to the other" (Newman, 2010, p. 9). For instance, two friends

would have geodesic distance 1 in a friendship network because there is a single edge directly connecting them, while the friend of your friend would have distance 2 from you.

Agents in central locations receive and disseminate information quickly, and have the opportunity to interact with many other agents (Borgatti & Halgin, 2011). Such people are central to an organization, have great situation awareness, and are "in the loop" with agents who are well connected (Altman et al., 2017). Tsai (2001) investigated the effect of a business unit's central position on its innovation and performance. They collected data from 24 business units in a petrochemical company and 36 business units in a food-manufacturing company, and then constructed knowledge-sharing networks. They measured in-degree centrality for each unit's information or knowledge access networks and found that in-degree centrality for both networks has a significant and positive effect on innovation. Burt (2005) discussed the advantage of central agents in terms of network closure. Network closure delivers the value of brokerage by facilitating collaboration and trust.

Freeman (1979) categorized two measures for central location and both are positively related to social capital. The first measure is *degree centrality*. It is based on the number of connections, and serves as index of activity. The second is *closeness centrality*. It is based on the geodesic distance between points, and serves as an index of independency or efficiency. These two measures can be applied to both directional and non-directional relations. In case of directional relations, measures for "out" (e.g., out-degree) means "choices made", while measures for "in" (e.g., in-degree) means "choices received". Such distinction is important, since agents who have high in-degree centrality

measures are the recipient of extensive ties, and can be considered "prestigious" (Wasserman & Faust, 1994, p. 174).

Newman (2010) defined new measures related to *degree centrality*, including *eigenvector centrality*, *Katz centrality*, *PageRank*, *hub centrality* and *authority centrality*.

Eigenvector centrality gives each node a score proportional to the sum of the score of its neighbors, instead of awarding the same score for every neighbor. This way eigenvector centrality measures the degree that a node is connected with other important nodes. *Katz centrality* improves upon eigenvector centrality in dealing with nodes that do not have many connections. It computes centrality of each entity based on the centrality of its neighbors and selects a free parameter alpha to govern the balance for nodes without many connections. *Page rank* is a variation of *Katz centrality* in that it takes into account the out-degree of a node's neighbors. If a node's neighbor sends ties to many other nodes, this neighbor is important. By being connected with this neighbor, this node becomes important too according to *Katz centrality*. However, this importance is overstated because this node is only one of many out- links that this neighbor has. *PageRank* calculates a node's centrality proportional to this node's neighbor's centrality divided by their out-degrees. This way a node that receives ties from an important node that is sending ties to many others becomes less important.

Authority centrality and *hub centrality* are differentiated by the direction of links. A node is authority-central to the extent that its in-links are from nodes that have many out-links. Individuals or organizations that act as authorities are receiving information from a wide range of others, each of whom sends information to a large number of others.

A node is hub-central to the extent that its out-links are to nodes that have many in-links. Hubs and authorities are a natural generalization of eigenvector centrality. A high hub actor points to many good authorities and a high authority actor receives from many good hubs (Altman et al., 2017).

This study categorizes all agent-level network measures into the three groups discussed above: bridging, central and clique engagement. Please refer to Table 2.1 for the complete list of measures in each category, their definitions and significance and Appendix A for the formulas.

Based on importance of the three network positions, the following hypothesis is proposed:

Hypothesis 1: Measures of central location, bridging location, and clique engagement
will all have a significant effect on student test scores.

The Content of Tie

It was established in the last section that the structure of a network can predict a variety of outcomes, and a hypothesized relationship between the structural network measures and test scores was proposed. But this is only one aspect of the network. The other aspect is the content of the tie, which determines the nature of information that flow through the structure. So besides structural locations, network measures can also be categorized according to the content of tie.

Researchers in social sciences are interested in a variety of networks formed by different ties. These ties may be formal in nature, such as workflow, defined as "the formally prescribed set of interdependencies between employees established by the

division of labor in the organization"(Mehra et al., 2001, p. 130), or formal ties that are

more fluid than those found on organizational charts, such as committee, task force,

teams networks (Ibarra, 1993). These connections could also be informal in nature,

involving "more discretionary patterns of interaction" (Ibarra, 1993, p. 58) with no trace

in any formal organizational documents. These informal relationships enhance

employees' ability to communicate, collaborate, and influence (Krackhardt & Hanson,

1993), and are far more reflective of the operating structure than organizational charts.

This study is interested in informal connections among teachers. Informal

connections are often categorized as instrumental versus expressive network relationships

(Ibarra, 1993). Instrumental ties arise from interaction over work, such as advice about

work. Expressive ties are more personal and affective, and involve exchange of things

such as friendship, social and emotional support, or trust. Instrumental and expressive ties

are not mutually exclusive, and there tends to be an overlap in the two types of networks

(Borgatti & Foster, 2003). But the primary content of the two types of ties are

theoretically distinct (Balkundi & Harrison, 2006), as not all advice relationships are

friendships, and vice versa.

This research is interested in three networks: advice (instrumental), social and

trust (expressive).

Instrumental ties. Instrumental relationships arise out of interaction over work,

such as advice on task-related issues (Friedkin & Slater, 1994; Krackhardt & Hanson,

1993; Moolenaar et al., 2012). Work-related information flows through the advice

network, and is instrumental in facilitating individual job performance. Strategic

positions in the advice network reflect an individual's involvement in exchanging assistance with coworkers and engaging in mutual problem solving. Such individuals not only accumulate knowledge (Baldwin, Bedel, & Johnson, 1997) related to work and become better problem-solvers, but also accumulate advantage for future exchange of valued resources (Cook & Emerson, 1978).

Previous research that examined the effect of centrality in advice networks on other related constructs, such as power (Brass, 1984), innovation (Ibarra, 1993), and individual performance (Sparrowe, Liden, & Kraimer, 2001), all reported positive relationships.

Expressive ties. Expressive relationships are affective in nature, and involve exchange of things such as friendship (Brass, 1984; Mehra et al., 2001), social support (Ibarra, 1993), and trust (Bryk & Schneider, 2003). Such relationships derive from mutual liking, similarity of attitudes, or personal choices. Compared with instrumental networks, expressive ties like friendship represent more individual choice and initiatives because agents have more discretion in the choice. Mehra et al. (2001) found that betweenness centrality in friendship networks among employees of a chemical company had a positive effect on individual performance while network size had a negative effect.

Trust is a less studied expressive relationship, and is somewhat overlooked. But trust is a foundation of social capital (Coleman, 1988). Trust refers to willingness to be vulnerable to another party with the expectation that the other party will behave in the focal individual's best interest (Maye, Davis, & Schoorman, 1995). Burt (2005) defined trust as "you trust someone when you commit to a relationship before you know how the

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other person will behave" (p.93), and stated that trust facilitates collaboration that delivers the value of brokerage. Louis (2007) argued that trust is as important as professional community and organizational learning in changing school cultures for the benefit of student learning. Empirical studies support such claims. Bryk and Schneider (2002) examined reform efforts in the Chicago school district and found that the level of trust among teachers was the distinguishing factor in comparisons of schools that thrived under reform and schools that did not. In addition, Goddard, Tschannen-Moran, and Hoy (2001) found in their quantitative study of 452 teachers in 47 elementary schools that teacher trust in students and parents is related to higher student achievement after all contextual variables are controlled for.

Given the significance of the advice (instrumental), social and trust (expressive) networks, the following hypothesis is proposed:

Hypothesis 2: Measures from advice, social and trust networks will have a significant

effect on student test scores.

Curvilinear Relationship

This section builds a rationale for curvilinear relationships between teacher network variables and student test scores. Coupling and social capital will be used to make the argument. Coupling is concerned with information flow while social capital approaches this topic from a resource perspective. The commonality among these two aspects is how they explain the mechanism for "diminished return": a certain amount of ties facilitates productivity because of access to information, but too many ties cause resource drain as a result of conflicting constraints.

Coupling and Information Flow

For networks to effectively channel information, a certain amount of interaction and interdependence among the agents in the network must exist (Balkundi & Kilduff, 2006). This condition could be described with coupling. Coupling refers to the number of links among the units of a system or the nature and strength of relationships between units. A tightly coupled system is a result of a high number or short distance of links among units, and a loosely coupled system is a result of a low number or high distance of links among units (Marion, 1999). In tightly coupled organizations, different elements are closely knit and information has easy access to the entire system. Yet because of too many conflicting constraints, people do not have room to negotiate and adapt. On the other hand, in a loosely coupled organization, information flows slowly because the elements of loosely coupled systems have little effect on one another, thus exert little pressure to negotiate and adapt. The individual parts are not themselves typically difficult to access; rather, the problem lies in diffusing the information across the network. So neither structure, tight or loose coupling, is conducive to productive information flow.

Moderately coupled systems are tight enough to produce change-demanding constraints and to share resources, but loose enough to enable flexibility needed to negotiate creativity and change (Marion, 1999). Such systems are ideal for productive information flow. Kauffman (1993) demonstrated with simulation data that the excessive linkages of tightly coupled organizations created so much information and constraint that it overwhelmed the network, while loosely coupled systems move too little information and have too few constraints to be useful. He showed with a formal model that moderate

levels of coupling are optimal for information processing. Using similar logic, Marion et al. (2016) found a curvilinear relationship between agents' cluster engagement and an organization's productivity.

An individual's degree of coupling is governed by the same logic as organizational coupling. Individuals who are more integrated into the overall network are more tightly coupled. In terms of network measures, they have higher degree centrality, closeness centrality, effective network size, and are in more cliques (K. Carley, personal communication, May 13, 2017). Tightly coupled individuals face too many conflicting constraints, while loosely coupled individuals do not have adequate access to information flow. Moderately coupled individuals are engaged in information flow in a way that is most conducive to productivity.

Diminished Returns of Social Capital

The previous section of network positions elaborated on the benefit of social capital. Social capital, however, comes at a cost. As Coleman (1990) pointed out, ' a given form of social capital that is useful for facilitating certain actions may be useless or harmful for others' (p. 302). For example, friendship is an important form of social capital. However task conflicts involving friends bring no benefit to team performance, while non-friend task conflicts tend to be beneficial for team performance (Hood, Cruz, & Bachrach, 2017).

Similarly, Adler and Kwon (2002) observed that:

Investments in social capital, like investments in physical capital, are not

costlessly reversible or convertible. Therefore, unbalanced investment or

overinvestment in social capital can transform a potentially productive asset into a constraint and a liability. (p. 28)

Some researchers have attributed the reasons for such diminished return of social capital as limited attentional capability, time to maintain relationships, and hindrance behavior (Rotolo & Petruzzelli, 2013). Other researchers have pointed out that large numbers of ties could drain an individual's own resources because these relationships are laborious to maintain, and create more role demands and information overload (Mayhew & Levinger, 1976).

Empirical studies support this notion of diminished returns of social capital. Several studies examining the relationship between authors' network and scientific productivity have found negative curvilinear relationships (inverted U-shape) between network centrality and indicators of productivity (Badar, Hite, & Ashraf, 2015; Mcfadyen & Cannella, 2004; Rotolo & Petruzzelli, 2013).

Based on the logic of coupling an social capital, the following hypothesis is proposed:

Hypothesis 3: Social capital, in the form of network structural position within the school's advice, social and trust networks, is expected to have a curvilinear effect (inverted U-shape) on teachers' effectiveness. Effectiveness is optimized for teachers with moderate levels of social capital.

Homogeneity versus Heterogeneity

Another central concept in social network analysis is that of similarity between agents according to their relationship patterns (Newman, 2010). Two agents are

structurally equivalent if "they share many of the same network neighbors" (Newman, 2010, p. 211). An example measure is *correlation cosine similarity*, which measures the degree to which each pair of rows has overlapping data (Altman et al., 2017). The higher this similarity measure, the more homogenous is the focal node's relationship.

According to CLT (Uhl-Bien et al., 2007), heterogeneity enhances the diversity of information flow in a network. Similarly, network theory stated that one mechanism that produced the advantage for bridging position is access to diverse information (Burt, 2005). One recent study of email traffic between people in a small headhunter organization showed that headhunters in closed networks who exchange diverse information with contacts have as high performance as network brokers (Aral & Van Alstyne, 2011). This further supports the point that that information diversity is the key factor predicting performance, and network position is an indicator of access to such diverse information. Complexity theory and network theory are in agreement regarding the importance of heterogeneity.

Other empirical studies also support the benefit of heterogeneity. For example, Phillips, Liljenquist and Neale (2009) found through their experimental study that the affective pain of adding socially distinct newcomers into a group is worth the cognitive gains. Results showed that groups with out-group new comers (i.e., heterogeneous groups) performed better than groups with in-group new comers (i.e., homogeneous groups). Heterogeneous groups perceived their interactions as less effective (affective pains), but they were better at accomplishing the task presented in the study (cognitive gains).

However, heterogeneous pressures increase conflicting constraints in a system, thus it is difficult to resolve differences. When heterogeneity is excessive, it can promote a condition in which constraints are too complex to resolve (Kauffman, 1993; Uhl-Bien et al., 2007). Both Kauffman and Uhl-Bien et al. argue, then, that moderate levels of conflicting constraints are optimal for organizational productivity.

Homogeneity, on the other hand, fosters cooperation and network ties (Burt, 2005). Homogeneity indicates shared knowledge, and therefore breeds ease of communication, shared cultural tastes, and other features that smooth the coordination of activity and communication (McPherson et al., 2001). However, homogeneity alone, in the absence of other pressures, does not foster conflicting constraints needed to enable change and creativity. Rather, it fosters group thinking and stifles creativity and learning. According the McWilliams, Dawson and Tan (2001), a mixture of homogeneity and heterogeneity is optimal. Such admixture is not explored in this study, however, and consequently this study proposes a hypothesis for heterogeneity only.

Based on the logic discussed above, the following hypothesis is proposed:

Hypothesis 4: Measures of heterogeneity will exhibit a curvilinear relationship (inverted U Shape) with teacher effectiveness. Effectiveness is optimized for teachers with low to moderate levels of heterogeneity.

Social Network Analysis and Student Test Scores

Six studies that used network analysis to examine student test scores are examined from three aspects: network boundary, network type and level of measurement. The design and finding of these six studies are presented in Table 2.2.

Table 2. 2

Studies of Network Analysis and Student Test Scores

	Moolenaar, Sleeger & Daly, 2012	Daly, Chrispeels & Moolenaar, 2011	Pil & Leana, 2009	Friedkin & Slater, 1994	Briley, 2016	Marion, et al., 2017
Network Boundary	all teaching personnel	reading teachers	math teacher at grade level	all teaching personnel	all teaching personnel and staff	all teaching personnel and staff
Avg. No. of Agents/ Network	15	18	4	21	75	53
No. of Bounded Networks	53	5	239	17	1	7
Network Types	instrumental &expressive advice network	instrumental : interaction over subject knowledge	instrumental : interaction over subject instruction	instrumental : discuss and advice expressive: friendship	instrumental : advice expressive: social and trust	instrumental : advice expressive: social and trust
Level of Network Measure	Two network-level	Three agent-level	Network-level and agent-level	Three Network-level	Ten agent-level	Seven agent-level
Significant Measures	density	In-degree	Tie strength	in-degree and density	seven from expressive, three from instrumental	Five from expressive, two from instrumental
Test Score	School level: mean score for math and language in Grade 6	Student level: reading in Grades 2-5	Student level: math in Grades 4 & 5 (with previous year as control)	School level: four-year average of reading, language and math scores in Grades 3 and 6	Student Level: math, ELA and reading in Grades 6 -8	Student level: math, ELA, reading in Grades 3-5

Friedkin and Slater (1994) collected data from 364 teachers in 17 elementary schools in California, with an average of 21 teachers in each school. This network boundary is equivalent to Brass's (1984) "within department" unit of reference. They collected data on two instrumental networks (discuss and advice), and one expressive network (friendship), and calculated each principal's degree centrality (in-degree and out-degree) and each school's density in each of the three networks. All nine measures (principals' in-degree centrality, out-degree centrality and density in all three networks) were treated as network-level measures, and were used as predictors for school performance, which was based on a four-year average of the standardized scores from reading, language and mathematics in Grades 3 and 6. They found that principal's in-degree centrality in advice network and the density of professional ties among teachers in two instrumental networks all had positive effects on school performance.

Pil and Leana (2009) explored growth in student achievement in math from human and social capital perspectives. They collected data from 1,013 teachers, who were members of 239 grade teams from Grades 4 and 5 in about 200 elementary schools. On each team, they had on average four members, comprising of only teachers who taught math in that specific grade level. This network boundary is equivalent to Brass's (1984) "immediate work group" unit of reference. On the issue of social capital, they analyzed both individual teacher level and team level ties. On the individual teacher level, they developed a composite score for horizontal tie strength (meaning ties between teachers) from frequency of interaction over subject instruction and reported closeness to other teachers on the team. Similarly they calculated each teacher's vertical tie strength,

which measured a focal teacher's frequency of interaction and reported closeness with the principal. The team level tie scores were the average of each individual teacher on the team after controlling for team size. They found that individual teacher's vertical tie strength as well as grade team's horizontal tie strength significantly predicted students' growth in score. Importantly, this study used both individual-level and network-level measures to predict student test score growth. To account for the different levels of variances as a result of the nested data, this study utilized hierarchical linear modeling (HLM).

Daly et al. (2011) investigated the joint effects of teacher human and social capital on students' reading test scores in five elementary schools in one school district in California. An average of 18 teachers who taught the tested subject were included in each of the five bounded networks. This network boundary is equivalent to Brass's (1984) "within department" unit of reference. On the social capital side, three agent-level measures were calculated for each teacher regarding their interaction network over reading knowledge. They found that teacher's in-degree centrality had an effect on student test scores.

Moolenaar et al. (2012) examined the relationship between teacher instrumental and expressive advice networks and student achievement in math and language as a function of collective efficacy beliefs in 53 Dutch elementary schools. Data were collected from all teaching personnel in each school, and the average number of participants on each of the 53 teams was 15. This network boundary is also the equivalent to Brass's (1984) "within department" unit of reference. Two group-level measures

(density and centralization) for each team were produced. Their conclusion was that the density of both instrumental and expressive advice network types positively affected teachers' perceptions of collective efficacy, which in turn was associated with increased student achievement. Network centralization, the other group-level measure, did not show any significance.

Briley (2016) used network analysis to understand the effect of agent-level network measures on student test scores from two semesters and school year growth score in math, reading and English language. She collected data from all 75 faculty and staff on their instrumental (advice) and expressive (social and trust) networks and calculated agent-level measures for each participant. This network boundary is equivalent to Brass's (1984) "entire organization" unit of reference. She found ten significant measures: seven from the expressive networks and three from the instrumental networks; six measures of central location (e.g., closeness centrality), three measures of clique engagement (e.g., Simmelian ties), and one measure of bridging location (brokerage).

Marion, Jiang, Buchanan, Bridges, Knoeppel, Gordon (2017) collected instrumental (advice) and expressive (social and trust) network data from all faculty and staff in seven elementary schools and students' math, ELA and reading scores in Grades 3-5. After controlling for school and student contextual variables, they found seven significant measures for student test scores: five from the expressive networks, two from the instrumental networks; six measures of central location (e.g. closeness centrality), one measure of bridging location (e.g. betweenness centrality).

The results from studies that used agent-level measures to understand student test scores were summarized (Briley, 2016; Daly et al, 2011; Marion et al., 2017) in Table 2.3. This synthesis of literature shows that instrumental networks were examined more often, and as a result, found to be significant more often. In terms of locations, measures for central location were the most frequent predictors of student test scores. These two patterns lead to the refinement of Hypotheses 1 and 2.

Hypothesis 1 Refined: Measures of central location, bridging location, and clique engagement will all have significant effects on student test scores. Central locations measures will dominate the results.

Hypothesis 2 Refined: Measures from advice, social and trust networks will all have significant effect on student test scores. Measures from the advice network will dominate the results.

However, none of the studies examined the potential curvilinear relationships between teacher network measures and student test scores, nor did they examine the interactive effects between the network measures. This is a "gap" that this study seeks to fill.

Table 2. 3

Synthesis of Results from Test Score Studies with Agent-level Network Measures

	Advice	Social	Trust
Bridge			Betweenness, Brokerage
Central	Closeness, Degree, Information	Eigenvector, Information, Shared-Situation- Awareness	Authority, Closeness, Hub Information
Clique	Clique Count	Simmelian Ties	Clique Count

Summary

In summary, this theoretical framework delineates the assumptions of this study. The central argument in complexity theory is that interactive dynamics among agents and information are responsible for organizational outcome (Uhl-Bien et al., 2007). The central argument in network theory is an individual's network position indicates his or her advantaged or disadvantaged access and control in the information flow process, and the advantage is then translated into outcomes such as higher performance, better compensation, positive evaluations, fast promotion (Burt et al., 2013).

Further, specific measures for network positions and levels of heterogeneity were introduced and related to concepts in complexity theory and network theory, thus

building the rationale for including these measures as predictor variables. In addition,

rationale for curvilinear relationships between predictor and outcome variables was built,

relevant literature was synthesized, and consequently four hypotheses were proposed.

The following design section presents details about the methodology for this

study.

CHAPTER THREE

RESEARCH DESIGN

The design for this study is organized sequentially in four stages: In Stage 1, agent-level network measures for each participant within their schools' bounded networks are calculated. Stage 2 refines the dependent variables for the study. Hierarchical linear modeling (HLM) is used to control contextual variables for student test scores and to produce teacher effect scores (dependent variables, or DV) to refine raw test scores for each subject. Each subject is analyzed separately. Stage 3 is exploratory in that a large set of network measures are screened with Lenth analysis to select the measures actively affect the DVs; different combinations of selections are then tested in Stage 4, regression analysis and response surface methodology, and the best models are selected.

This research design is exploratory in that a large set of network measures are screened and tested in Stages 3 and 4 to identify the measures with the largest influence on teacher effect. The best model for each subject is selected after experimenting with combinations of different variables.

The research design is assembled into a visual model in Figure 3.1.
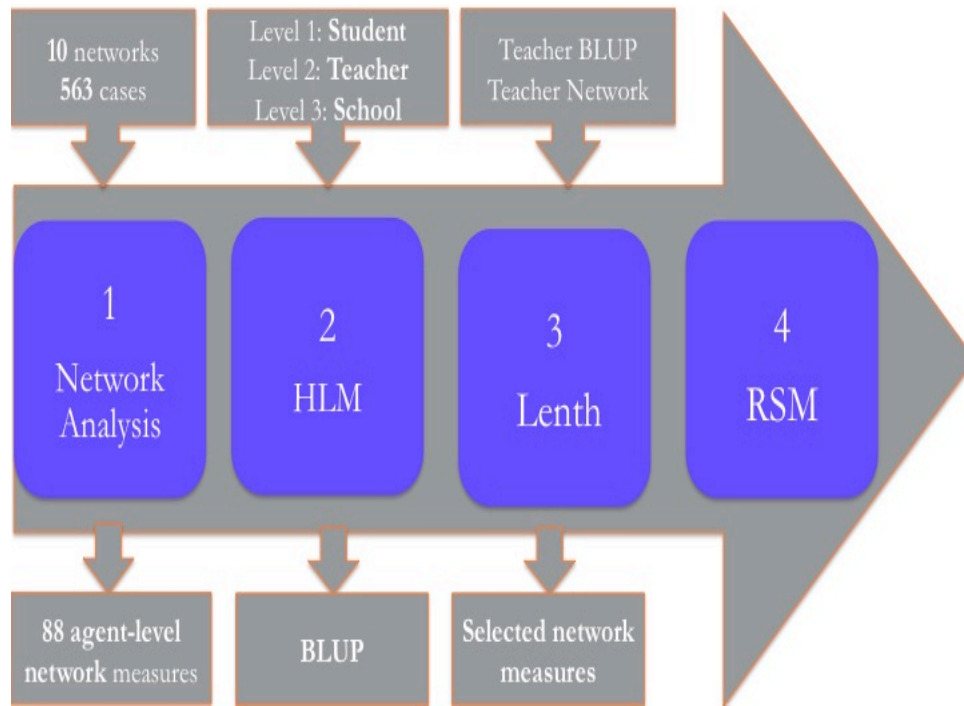
Figure 3. 1. Research design

Sample

      This research was conducted with all ten elementary schools in one school district in the southeastern United States. In the 2015-2016 school year, this school district had a total enrollment of 12,925 students, 22 schools, and 867 teachers.

      Students in Grades 3 to 8 were administered the SC Ready test as an end-of-year standardized test. SC Ready is a statewide assessments in English language arts (ELA) and mathematics that meet all of the requirements of Acts 155 and 200, the Elementary and Secondary Education Act (ESEA), the Individuals with Disabilities Education Improvement Act (IDEA), and the Assessments Peer Review guidance (South Carolina Department of Education, 2017). In 2016, 44.9% of students in this school district met or

exceeded expectations in math, while the number for the whole state was 42.6%. For ELA, 41.5% of students in this school district met or exceeded expectations, compared to 43% in the whole state. So this school district is about average in terms of student performance for the SC Ready test.

Students in Grades 4 to 8 were administered the SCPASS test as an end-of-year standardized test for science and social studies. SCPASS test items measure student performance on the South Carolina Academic Standards. The SCPASS test items are aligned to the standards for each subject and grade level (South Carolina Department of Education, 2017). In 2016, 67.5% of students met expectation and above in science, compared to 68.8% in the whole state. For social studies, 76.9% of students met expectation and above, compared to 74.4%. So student performance on the SCPASS test in this school district was at or above average as well.

For SC Ready, this study includes all 2927 students in Grades 3, 4 and 5. For SCPASS, this study includes all 1915 students from Grades 4 and 5.

Teacher-level participants in each school include all professional personnel who interact with one another and who influence the overall school environment that exerts influence on student test scores. The sample includes teachers (plus part-time professionals in specialized subjects such as speech pathology), teacher aides, administrative staff, and related support staff (such as school nurses). Employees who are not likely to interact with professionals on issues pertinent to education, such as custodians, cafeteria workers, and bus drivers, are excluded. This network boundary is

equivalent of Brass's (1984) "entire organization" unit of reference described in Chapter 2.

Five hundred and sixty-three professional personnel were invited to participate in the survey. Of these participants, 129 are teachers who teach tested subjects discussed above.

Data Collection

Student test scores, student and teacher demographic information were collected from the district office. Teacher advice, social and trust network data were collected with online surveys during school meetings.

Student-level

Student-level data includes standardized achievement test scores for math, ELA, science and social studies, lunch status, ethnicity, gender, and school and teacher assignments. These data were obtained from school district records with student name anonymized.

Teacher-level

Teacher-level data includes teacher demographic and network data. Teacher demographic data includes teacher ethnicity, gender and years of teaching experience, and were obtained from school district record.

Teacher network data were collected through a network survey during the same semester standardized tests were administered to students. The survey is designed to solicit responses about who socializes with whom (social network), who advises whom on work-related issues (advice network), and who trusts whom (trust network).

Participants completed the online survey during one of their professional development meetings, where researchers personally solicited their participation. A research team were organized and trained to present the research project to all participants in each school and solicited participation in person to ensure a high participation rate. The link to the survey was delivered via Qualtrics to the participants' email boxes half an hour before the meeting, and participants filled out the survey at the professional development meeting.

Each participant was provided a roster with names of all the professional staff in his or her school. This bounded network method provides a more complete picture of the network than the egocentric method where participants list people they have relationships with from their memory. As a result, the bounded method reduces measurement error (Scott, 2000).

To help ensure reliability, specific questions that provide details on the construct of interest were used (Cross & Cummings, 2004). For example, to obtain data on advice network, the following question was asked "from the following list, identify the people you would go to for advice on work-related issues). In addition, the questions only assess "typical interactions" rather that specific ones (e.g., in the last week) because of the accuracy of recall for such interactions (Freeman, Romney, & Freeman, 1987). For example, to obtain data on social network, the following question was asked, "from the following list, identify the people with whom you regularly socialize either inside or outside school". Words such as "regular" indicate the frequency of interaction solicited. Typical interactions address stable patterns of interactions, which are of most interest to

researchers because they yield insight into the "true" structure of the network (Wasserman & Faust, 1994).

To help ensure validity, reverse questions were asked on directional networks (advice and trust). As introduced in the theoretical framework section, directional networks distinguish between "choices made" and "choices received" while non-directional networks do not make such distinctions. Advice and trust networks are directional because agent i seeks advice from or trusts agent j is not the same as agent j seeks advice from or trusts agent i. In other words, this relationship is not automatically reciprocal. On the other hand, the social network is non-directional because if agent i socializes with agent j, agent j automatically reciprocates the relationship.

Specifically, five questions were used to generate the social, advice and trust networks. To generate the social network, the following question will be asked: "From the following list, identify the people with whom you regularly socialize either inside or outside school (choose all that apply)". To generate the advice network, the following two questions were asked: "From the following list, identify the people you would go to for advice on work-related issues (e.g., teaching strategy, discipline, curriculum, etc.; choose all that apply)" and "Now reverse this question: Which of the following people regularly seek advice from you about such work-related issues (choose all that apply)". To generate the trust network, the following two questions were asked: "From the following list, identify the people with whom you share confidential information (choose all that apply)" and "Now reverse this question: Which of the following people come to you to share confidential information (choose all that apply)".

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Data from the reverse questions (column vectors) were used to complete missing data in the row vectors of the original questions (row vectors record respondents' answers).

The network survey is part of a larger study where other questions were also asked. For a complete list of the survey questions, and the informed consent form, please refer to Appendix B.

Data Analysis

Network data are analyzed with network analysis, and agent-level network variables are produced. Student test scores are analyzed with hierarchical linear modeling (HLM) to produce teacher effect on student test scores, the dependent variables for this study. Lenth's analysis is used to screen the network variables, and response surface methodology is used to examine the relationships between the independent and dependent variables.

Stage 1: Network analysis

The first step in network analysis is to replace missing data for participants who did not return the survey. This step is necessary because analyses have shown that this approach yields more accurate results than leaving missing data empty (Borgatti, Everett, & Johnson, 2013). This step is different for non-directional networks and directional networks.

For the social network (non-directional), if agent i did not return the survey, but agent j in the column vector for agent i selects agent i as a person he socializes with (cell j, i =1), then I enter 1 in cell i, j. In network analysis, the convention is that the i, jth cell is coded 1 if agent i has a relationship with agent j, and coded 0 if agent i does not have a

relationship with agent j. For the advice and trust network (directional), missing data is replaced with reverse question. If agent i did not return the survey, but agent j selects agent i as one of the person who seeks advice from him or trusts him (cell j, i =1 in the reverse advice/trust question), then I fill in cell i, j as 1 in the original advice/trust question. To do this, my assumption is that agent j is accurate in the perception of his social, advice and trust relationships.

The second step is to cross-validate the data (Cross & Cummings, 2004; Krackhardt & Hanson, 1993). A validated relationship is one whose existence is confirmed by both parties. This process is different for directional and non-directional networks.

In the social network (non-directional), for each pair (i, j), a validated relationship exists if agent i selects agent j and agent j selects agent i as the person they socialize with. In the advice networks (directional), for each pair (i, j), a validated relationship exists if agent i indicates that he turns to agent j for advice and agent j confirms that agent i turns to him for advice (the reverse advice/trust question). So for the advice network, the matrix is based on relationships in which agreement exists between the matrix of advice-receiving relationships and the transpose of the matrix of advice-giving relationships. To validate the trust network, I will follow the same procedure as the advice network. Using validated data, I will construct square agent-by-agent matrices for each school's social, advice and trust network.

After these two steps, the three agent-by-agent network matrices for each of the ten school will be entered separately into ORA, a specialized network analysis software

developed at Carnegie Mellon University (Altman et al., 2017). ORA produced 26 relevant agent-level measures from the social network (non-directional), and 31 relevant agent-level measures from advice and trust networks (directional) (refer to Table 2.1) for each of 563 participants. Altogether there are 87 agent-level measures for each participant. Non-directional (social) networks have six measures less than directional (advice and trust) networks because these measures were calculated based on the direction of relationships. This will be explained further in the results section.

Stage 2: HLM

The dependent variables in this study are teacher-effect on student test scores. This explains how these DVs are calculated and how contextual effects are controlled. Each tested subject (math, ELA, science and social studies) is analyzed separately.

Since the data is nested (students nested under teacher, teacher nested under school), HLM are used to control for school and student contexts, as well as teacher and student interaction terms. HLM has the capacity to model and statistically evaluate structural relations in nested data (Field, 2013). The purpose of this step is to calculate teacher effects on student test scores by partialing out pertinent school- and student-levels contextual variables.

Student test scores are mean-centered at grade level to standardize differences by grades, and these scores for each subject will be the dependent variable in the HLM.

Following the precedent of similar quantitative studies, the following variables are used to control for school and student context: school name (school level), students' gender, ethnicity and socio-economic status, and teacher interaction with student

demographics (student level) (Friedkin & Slater, 1994; Leana & Pil, 2006; Marks & Printy, 2003; Pil & Leana, 2009). These contextual variables are the independent variables for the HLM model. The fixed effects for the analysis include: school name, student gender, lunch status and ethnicity. The random effects include teacher name nested under school, teacher interaction with student gender, lunch status and ethnicity.

Restricted Maximum Likelihood procedures are used to estimate the "best linear unbiased predictors" (denoted as BLUPs) of the teacher effects for each subject. BLUPs measure teacher effect (test scores) after contextual variances are partialed from the model. It is sometimes referred to as "shrinkage" estimates since the smaller the ratio of the teacher variation to the total variation, the closer the BLUP estimate of teacher effect is to the overall average. BLUPs for teacher-effect in each subject will be used as dependent variables for Lenth and RSM analyses.

Stage 3: Lenth Analysis

Lenth's method is an objective method for deciding which effects are active in the analysis of unreplicated experiments, when the model is saturated and hence there are no degrees of freedom for estimating the error variance (Lenth, 2006). It was employed in this study to reduce the 87 network measures to meaningful subsets for each subject. The Lenth method calculates for each effect a standard-error-like quantity, called the pseudo standard error or PSE. The effects of each of the original 87 variables are then judged relative to the PSE to decide whether there is enough evidence for them to be deemed active in its effect on the dependent variable. For more details please refer to the Lenth reference above.

The Lenth analysis selected two to three "active" network measures for each test from all the 87 agent-level measures, and these measures will be used as independent variables in Stage 4.

Stage 4: Response Surface Methodology

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes (Myers, Montgomery, & ANderson-Cook, 2016). The most extensive applications of RSM are in the industrial world where it is used to test several input variables (e.g., time and temperature) to determine an optimal combination for producing a desired outcome (e.g., taste of a cookie). The performance measures or quality characteristics are called response or dependent variable, and the input variables are called factors or independent variables.

There is increasing interest from social sciences in this methodology. One example is multisource feedback research, where the congruence and discrepancy between self-rating and observer rating is examined (Shanock et al., 2010). Broadly speaking, this technique can be used for any situation in which researchers are interested in how combinations of two or more predictor variables relate to an outcome (Shanock et al., 2010).

To explore the relationship between responses and factors, second-order polynomial models are most widely used because of their flexibility, ease of estimation and accurate prediction (Myers et al., 2016). In a second-order polynomial model, the following terms are included: first-order term (main effects), interaction terms and

quadratic terms. Besides polynomial statistics, RSM also generates a three-dimensional response surface, a two-dimensional contour plot and a two-dimensional desirability plot. The surface is a curved quadratic surface and shows how the dependent variable changes as functions of two independent variables. Most common types of surfaces are simple maximum, stationary ridge, rising ridge, or saddle (a.k.a. min-max) (Myers et al., 2016). The individual contours represent points of constant response, much like a topographical map, shown as functions of two independent variables on the dependent variable (Anderson & Whitcomb, 2017). Examining and manipulating the desirability plots can identify the combinations of input variables for optimal output (SAS Institute Inc, 2015).

In this study, a second-order model will be used. The dependent variable will be BLUPs of test scores produced from HLM, and the independent variables will be teacher network variables calculated with network analysis and selected with Lenth analysis. These selected network variables will be entered into the RSM model to test for linear, curvilinear and interactive effects. This step is repeated for each of the four subjects (math, ELA, science and social studies). The final model for each subject was decided based on two criteria: whether the overall model was significant, and how big was the explanatory power. The models with parameters that yielded the highest explanatory power were selected.

Standardized residuals and Cook's D were used to test the assumptions of normal distribution of residuals. Cases that are inappropriately influential were removed from the datasets.

JMP Pro 12 (SAS Institute Inc, 2015) was used to conduct this analysis.

Even though the agent-level network measures are calculated and selected with all participants, only teachers who taught tested subjects and have corresponding BLUPs for each subject are included in Stage 3 and 4 of the analysis.

Summary

In summary, data were collected on students and teachers, and analyzed with a series of network analysis and statistical methods. The next chapter presents results from the analysis.

CHAPTER FOUR

RESULTS

Introductory Overview

This study examines the degree to which social relationships and interactive dynamics play a role in teacher effectiveness measured as their value-add on student test scores. Three research questions motivated this research study: 1) what is the relationship between teacher network variables and student test scores? Specifically, this study is interested in curvilinear and interaction effects that influence outcomes; 2) what is the effect of homogeneity in teacher's network relationships on student test scores? 3) what combinations of teacher network variables have the optimal effect on student performance?

Four hypotheses were proposed based on the theoretical framework:

Hypothesis 1: Measures of central location, bridging location, and clique engagement will all have significant linear effects on student test scores. Central locations measures will dominate the results.

Hypothesis 2: Measures from advice, social and trust networks will all have significant linear effect on student test scores. Measures from the advice network will dominate the results.

Hypothesis 3: Social capital, in the form of network structural position within the school's advice, social and trust networks, is expected to have a curvilinear effect (inverted U shape) on teachers' effectiveness. Effectiveness is optimized for teachers with moderate levels of social capital.

Hypothesis 4: Measures of heterogeneity will exhibit a curvilinear relationship (inverted

U shape) with teacher effectiveness. Effectiveness is optimized for teachers with

low to moderate levels of heterogeneity.

This section presents results from data analysis that support or reject the

hypotheses.

Description of Respondents

Data were collected from ten elementary schools in the southeast of the US.

Student math and ELA test scores from Grades 3-5 and science and social studies test

scores from Grades 4 and 5 were included. For students from Grades 3-5, 48.8% are

female; 53.6% are white, 31.3% are African American, 7.4% are Hispanic, 5.8% are

multiracial, and 1.8% are other races combined. Students' lunch status was used as a

proxy for their socio-economic status. Of these students, 56.8% are on free lunch, 5.3%

are on reduced lunch, and 37.9% are on paid lunch. Students from Grades 4 and 5 have

similar demographic characteristics.

Teacher network data were collected with network survey. Of these participants,

129 were teachers who taught tested subjects and were included in the statistical analysis.

Specifically, there were 120 math teachers (94% white, 93% female, on average 9.57

years of experience); 125 ELA teachers (94% white, 93% female, on average 9.97 years

of experience); 70 science teachers (91% white, 91% female, on average 9.51 years of

experience); and 70 social studies teachers (93% white, 91% female, on average 9.69

years of experience). Please refer to Table 4.1 for detailed teacher demographics

information.

Table 4. 1

Demographics of Teachers Who Taught End-of-year Tests

			Math	ELA	Science	Social Studies
		N	120	125	70	70
Race	Black	n	7	7	6	5
	White	n	113	118	64	65
Gender	Female	n	111	116	64	64
	Male	n	9	9	6	6
Years of Teaching	Mean		9.57	9.97	9.51	9.69

Description of Data

Network data. All 563 professional personnel from ten schools were invited to participate in the network survey; 502 returned the survey, with an average return rate of 89%. School 2 has the highest return rate of 98%, and School 5 has the lowest return rate of 69%. For return rate for each school, please refer to Table 4.2. Strategies for replacing missing data were different for directional (advice and trust) and non-directional networks (social).

Table 4. 2

Network Survey Return Rate by School

School Name	No. of Reponses	No. of Participants	Return Rate
School 1	53	56	95%
School 2	62	63	98%
School 3	59	61	97%
School 4	57	60	95%
School 5	48	70	69%
School 6	38	54	70%
School 7	47	55	85%
School 8	53	55	96%
School 9	35	36	97%
School 10	50	53	94%
Summary	502	563	89%

Network data were validated by including only connections acknowledged by both parties (Cross & Cummings, 2004; Krackhardt & Hanson, 1993). As a result, on average only 50% of the advice links, 32% of the social links and 48% of the trust links remained (Table 4.3). More links were removed than remained. The procedure's strength lies in the fact that it avoids over-exaggeration of network connections. Krackhardt and Hanson (1993) recommended cross-validating network data because they found that when network data were collected within an organization, some people tended to over

select relationships for fear of offending their colleagues. In addition, U. Matzat and Snijders (2010) found in an experimental study that online data collection yielded higher network densities than did face-to-face data collection; that is, people tend to report more connections in online surveys. Network data in this study were collected through an online survey, and this cross-validation procedure could help reduce the over-exaggeration problem. Such procedures are conservative in that they assume that one-sided relationships (i.e. relationships reported by only one person) do not exist.

Agent-level network measures produced by ORA were reviewed to identify and remove measures that were perfectly correlated with each other. For example, social network is non-directional, so several measures that were calculated based on the direction of ties are identical with each other. Example measures include in-degree centrality (the number of links directed into a node normalized by the maximum number of such links), out-degree centrality (the number of links directed from this node normalized by the maximum number of such links). Five such measures from the social network were removed

Table 4. 3

Density and Links for Each Network Before and After Validation

| | **Before Validation** | | | | | |
| | Social | | Advice | | Trust | |
	Density	All Links	Density	All Links	Density	All Links
School 1	0.324	999	0.165	519	0.151	466
School 2	0.188	747	0.107	418	0.08	313
School 3	0.201	785	0.131	510	0.099	386
School 4	0.251	888	0.151	542	0.109	392
School 5	0.354	1711	0.166	802	0.121	583
School 6	0.194	556	0.108	309	0.084	240
School 7	0.263	781	0.134	399	0.076	227
School 8	0.287	852	0.147	437	0.105	311
School 9	0.263	331	0.176	222	0.147	185
School 10	0.313	863	0.19	524	0.163	448
	After Validation					
	Social		Advice		Trust	
School 1	0.175	270	0.088	272	0.087	268
School 2	0.102	199	0.066	256	0.044	172
School 3	0.12	234	0.07	287	0.042	163
School 4	0.156	277	0.063	224	0.06	211
School 5	0.293	708	0.074	356	0.055	264
School 6	0.137	196	0.049	140	0.039	113
School 7	0.171	254	0.068	203	0.047	141
School 8	0.185	257	0.078	232	0.056	166
School 9	0.168	106	0.119	150	0.06	75
School 10	0.178	245	0.079	219	0.045	123

Percentage of Links Remained

	Network size	Social	Advice	Trust
School 1	56	27%	52%	58%
School 2	63	30%	61%	55%
School 3	63	31%	56%	42%
School 4	60	41%	41%	54%
School 5	70	35%	44%	45%
School 6	54	33%	45%	47%
School 7	55	30%	51%	62%
School 8	55	32%	53%	53%
School 9	36	28%	68%	41%
School 10	53	28%	42%	27%
Summary	565	32%	50%	48%

Test score data. Test score data were mean centered to account or differences by grade level**.**

Some students included in the datasets were in gifted or in self-contained special education classes. The patterns of results in these classes were different than patterns observed among regular teachers: Students scores were largely independent of teacher effects (i.e., students scored high in gifted and low in remedial classes with little variance attributable to teacher). Because of this, and since there were few such students (less than 2% of the data), they were removed from the final analysis, and only results for regular students and their teachers are shown here. Table 4.4 shows the number of regular students and teachers in each subject area dataset.

HLM Analyses

HLM analysis revealed that variation across the ten schools, student socio-economic status (free, reduced or paid lunch status) and student ethnicity consistently had significant effect on student-level test scores. Student gender had significant effect only on science test scores. The explanatory power of all the three levels of variables combined (school, teacher, student) on student test scores ranged from 0.27 for ELA and social studies to 0.34 for math (see Model 1 in Table 4.5).

Teacher-effects for each subject (operationalized as teacher BLUPs, or coefficients that controlled for student and school level effects) were calculated from the HLM and used as dependent variables for subsequent analyses.

Table 4. 4

Demographics of Regular Students

Test	SC Ready	SCPASS
Grades	3, 4, 5	4, 5
N	2874	1878
% Female	49.1%	49.3%
% White	54.8%	55.6%
% African American	31.0%	29.7%
% Hispanic	7.5%	7.4%
% Multiracial	5.9%	5.6%
% Other races	0.9%	1.7%
% Free Lunch	52.6%	51.8%
% Reduced Lunch	4.9%	5.1%
% Paid lunch	42.4%	43.1%

Lenth's Analysis

Lenth's analysis is an exploratory procedure that separates active effects
(variables) on a dependent variable from inactive effects. Lenth analysis identified two to
three significant terms for each subject, and these terms were used in the subsequent
analysis as independent variables.

Table 4. 5

Results from HLM, Lenth, RSM and Multiple Regression

Variables	Math	ELA	Science	Social Studies
	Model 1: HLM			
	F	F	F	F
Context				
School	6.37**	7.83**	12.64**	8.71 **
Student Gender	1.38	10.42	10.76**	9.94
Student Lunch Status	68.70**	69.55**	44.90**	44.33**
Student Ethnicity	28.76**	23.97**	16.60**	8.95**
R^2	0.34	0.27	0.32	0.27
R^2Adjusted	0.34	0.27	0.31	0.26
	Model 2: RSM/Regression			
Network Measures	β	β	β	β
Linear				
correlationSimilarity-Social			-0.42**	
hubCentrality-Advice			0.47**	
inInverseClosenessCentrality-Advice			0.40**	0.43**
potentialBoundarySpanner-Social	0.2*			
structuralHolesEffectiveNetworkSize-Trust	0.18*			0.26*
structuralHolesEfficiency-Trust		0.20*		
triadCount-Advice		-0.12		
triadCount-Social				-0.33*
Curvilinear				
correlationSimilarity-Social^2			0.23	
hubCentrality-Advice^2			-0.53 **	
inInverseClosenessCentrality-Advice^2			-0.16	
structuralHolesEfficiency-Trust^2		-0.25**		
triadCount-Advice ^2		-0.13		
Interactive				
hubCentrality*correlationSimilarity			0.52**	
hubCentrality*inInverseClosenessCentrality			-0.17	
inInverseClosenessCentrality*correlationSimilarity			-0.11	
structuralHolesEfficiency*triadCount		0.14		
F	5.02**	4.4**	3.68**	5.12**
R^2	0.08	0.16	0.36	0.19
R^2Adjusted	0.06	0.12	0.26	0.15
N	118	123	69	69

Note: * p<.05, **p<.01

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Regression and RSM

Variables identified as active from the Lenth's analysis were then subjected to regression and to quadratic and interaction equation (response surface methods, or RSM) procedures in order to support or reject the hypotheses. After the full model was developed, assumptions of normal distribution of residuals were tested. Standardized residuals were examined as indicator of influence on the regression line. Results suggested that one case in math (z-score of residual > $|4.0|$) and one case in ELA (z-score of residual > $|4.0|$) were inappropriately influential. After these two cases were removed, assumptions for math and ELA were met. There were no influential cases in science and social studies.

The explanatory power of the final models ranged from 8% for math to 36% for science. The final models for ELA and science included curvilinear and interaction terms, while math and social studies models had only linear effects.

Overall results showed three significant terms for bridging positions in the network, two significant terms for central position, and one significant term for clique engagement (see Table 4.6). For tie content, results showed two significant terms for each of the advice, social, and trust networks. The advice network had a significant, central position measure; the social network had significant measures for bridging position and clique engagement, the trust network had significant bridging position measures. These results provided support for Hypotheses 1 and 2, which predicted significant linear effect of network measures on teacher effectiveness. However, neither advice network nor central location measures dominated the results.

Table 4. 6

Results in Terms of Network Position and Tie Content

	Advice	Social	Trust
Bridge		Potential Boundary Spanner	Structural Holes Effective Network Size; Structural Holes Efficiency (^2)
Central	Hub Centrality (^2); In-Inverse Closeness Centrality		
Clique	Triad Count	Triad Count	

Hypothesis 3 predicted negative curvilinear relationship (which plot as inverted U-shaped) between social capital measures and teacher effectiveness. As indicated in Model 2 of Table 4.5, results support this hypothesis. For science, the coefficient for hub centrality-advice squared is negative and significant (β=-0.51), hence plotting as an inverted U. Similarly for ELA, the coefficient for structural holes efficiency squared is negative and significant (β=-0.25).

Hypothesis 4 predicted that levels of heterogeneity plot as curvilinear relationships with teacher effectiveness. No measure of heterogeneity was shown to have a significant effect on test scores, so Hypothesis 4 is rejected. Correlation similarity-social, a measure of homogeneity, did show significance in the science network,

however; the effects were positive indicating a U shaped plot. Careful examination of the RSM plot in Figure 4.2 indicates what is going on. The surface plane from left to right on the correlation similarity-social scale is cupped, thus accounting for the positive effect. But correlation similarity-social interacts with hub centrality-advice, and there are different patterns of effect for low and high hub centrality. Where hub centrality is negligible, the effect on science BLUPs decreases as correlation similarity-social increases. This supports the claims of McWilliams et al. (2001) and of Uhl-Bien et al. (2007) that high levels of homogeneity fosters group-think-like effects.

Below the detailed results for each tested subject are presented.

Math

Potential Boundary Spanner-Social (β=0.20). This bridging variable measures the degree to which a node connects disconnected groups in a network, and identified agents that are potentially influential but who are not, 'in-the-know' in the social network. This measure has significant and positive impact on math scores: The more a math teacher spans social boundaries, the higher test scores his or her students exhibit. Thus the linear effect predicted in Hypotheses 1 and 2 was confirmed.

Structural Holes Effective Network Size-Trust (β=0.18). This measures the effective size of a node's ego network based on redundancy of ties. It evaluates the structural holes (i.e. missing relations that inhibit information flow between people) of the focal agent's ego network, and consequently reveals this agent's bridging capacity. The bigger network size with non-redundant ties a math teacher has, the more effective

this math teacher is. Therefore, its linear, positive bridging affect in the trust network for math teacher was confirmed, as predicted by Hypothesis 1 and 2.

ELA

Structural Holes Efficiency-Trust (β =0.2 for its linear term; β=-0.25 for its quadratic term). This term is calculated as effective network size divided by the number of nodes in each ego network, and measures the fraction of nodes in an ego network that are not redundant. From a linear perspective, higher values of this measure are related to higher ELA scores.

Structural holes efficiency-trust interacts with triad count-advice. Close examination of this relationship in Figure 4.1 reveals that the linear term exists when triad count-advice is high, thus the linear effect predicted in Hypotheses 1 and 2 were confirmed. Its curvilinear effect (inverted U) exists when triad count-advice is low, thus the curvilinear effect predicted by Hypothesis 3 was confirmed.

An examination of the desirability plot and surface plot shows that BLUP is optimal at 0.025 (on a scale of -0.6-0.1) when structural holes efficiency trust = 0.625 (on a scale of -0.4-1.2) and triad count-advice = 5 (on a scale of 0-50).
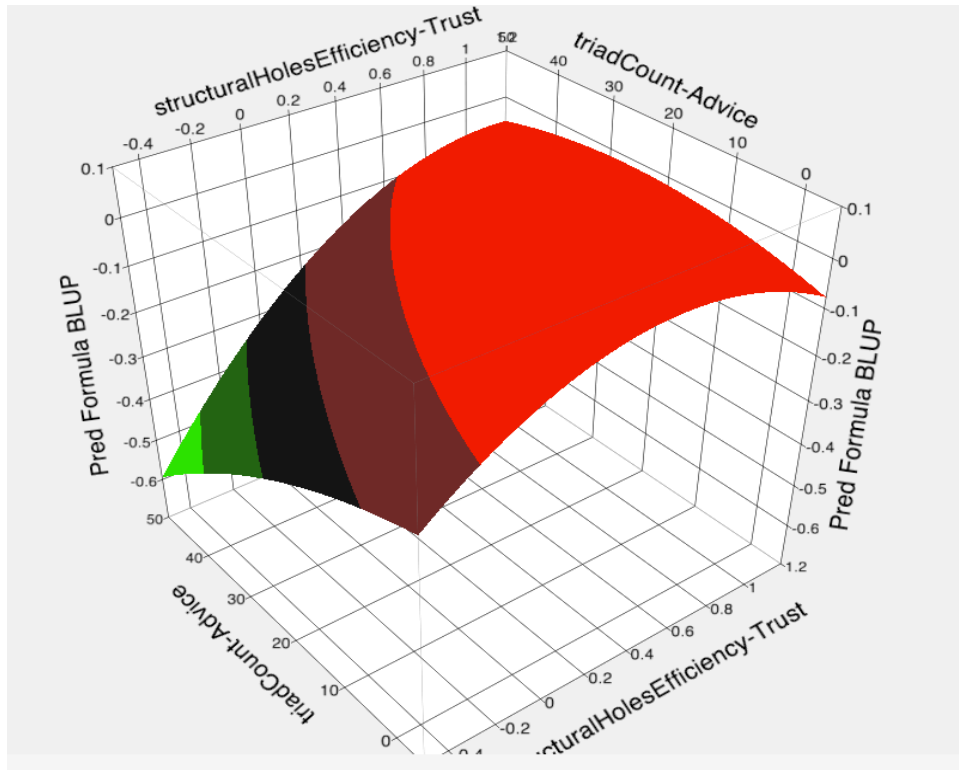
Figure 4. 1. ELA surface plot

Dependent Variable: ELA Teacher BLUP

Independent Variables: Structural Holes Efficiency-Trust, Triad Count-Advice

Science

Correlation Similarity-Social (β=-0.42). This measures the degree of structural equivalence for each agent in the social network. Agents high on this measure have social patterns that are similar to those of many other agents, and are thus more homogeneous. The more homogenous the science teacher is in the social network, the less effective this teacher becomes. Therefore, a negative effect of homogeneity in the social network on science teacher effectiveness was confirmed. This was not hypothesized but such relationships were described as likely in the literature review.

In-Inverse Closeness Centrality-Advice (β=0.40). This is the sum of the inverse distances from all other nodes to a focal node. In the advice network, many nodes can reach a target node with high in inverse closeness centrality; that is, there are relatively few steps (intervening nodes) between others and the target node. Thus, the more a science teacher's advice is available to others, the more effective this teacher is. A positive linear effect of central location in the advice network on science teacher effectiveness was confirmed in this analysis, as predicted in Hypothesis 1 and 2.

Hub Centrality-Advice (β=0.46 for its linear term; β=-0.53 for its curvilinear term). A node is hub-central to the extent that its out-links are to nodes that have many in-links. In the context of the advice network, such individuals seek advice from individuals who give advice to a lot of people. Overall, as the hub centrality measure of central location in the advice network increases linearly, science teacher effectiveness increases, as predicted in Hypothesis 1 and 2.

Hub-centrality advice interacts with correlation similarity-social. Examination of this interaction in Figure 4.2 explains its linear and curvilinear effects. Hub centrality is curvilinear at low values of correlation similarity-social and linear at high values of correlation similarity-social. In addition, hub-centrality advice is curvilinear at both high and low levels of in-inverse closeness centrality-advice (Figure 4.3). Hypotheses 1 and 2 regarding linear effects and Hypothesis 3 regarding curvilinear effects on outcomes were all supported.

Hub Centrality-Advice* Correlation Similarity-Social (β=0.52). This positive interaction term indicates that the effect of hub centrality in the advice network for

science teacher effectiveness interacts with level of correlation similarity in the social

network, as described just above. There was no hypothesis for interaction but this finding

strengthens the support for Hypotheses 1 and 2.

BLUP is maximized at 0.046 (on a scale of -0.15-0.10) when in-inverse closeness

centrality advice = 0.07 (on a scale of -0.05-0.30), hub centrality advice = 0.28 (on a

scale of -0.05-0.30), and correlation similarity =0.30 (on a scale of -0.05-0.30).
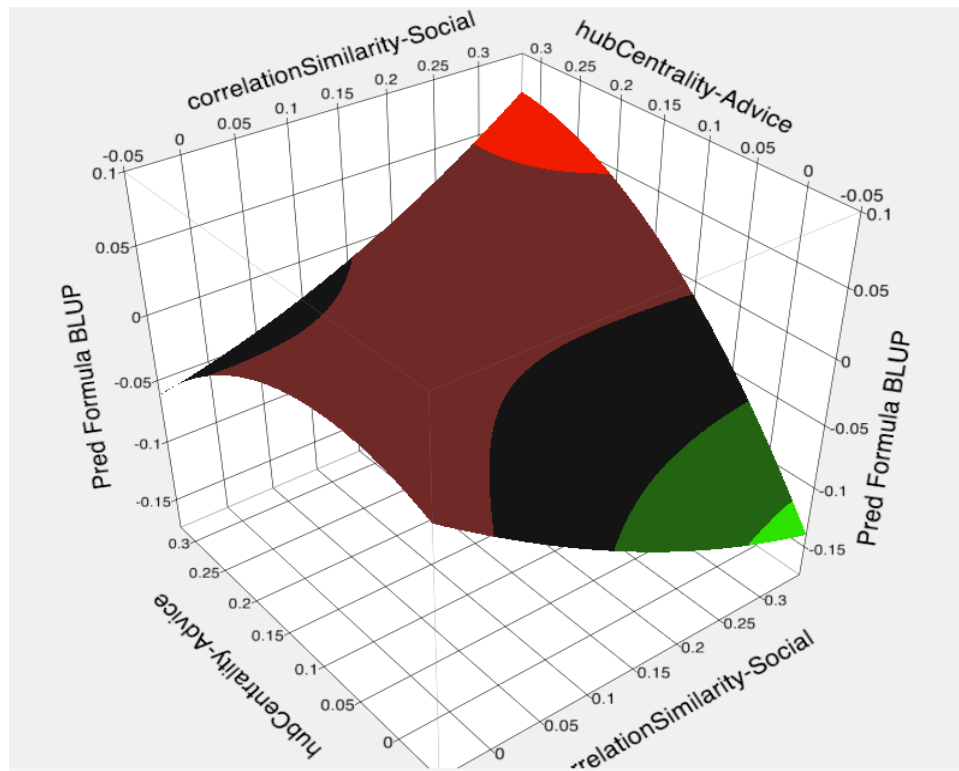
Figure 4. 2 Science surface plot 1

Dependent Variable: Science Teacher BLUP

Independent Variable: Hub Centrality-Advice and Correlation Similarity-Social

Hold values: In-inverse closeness Centrality-Advice=0.147 (Median value)
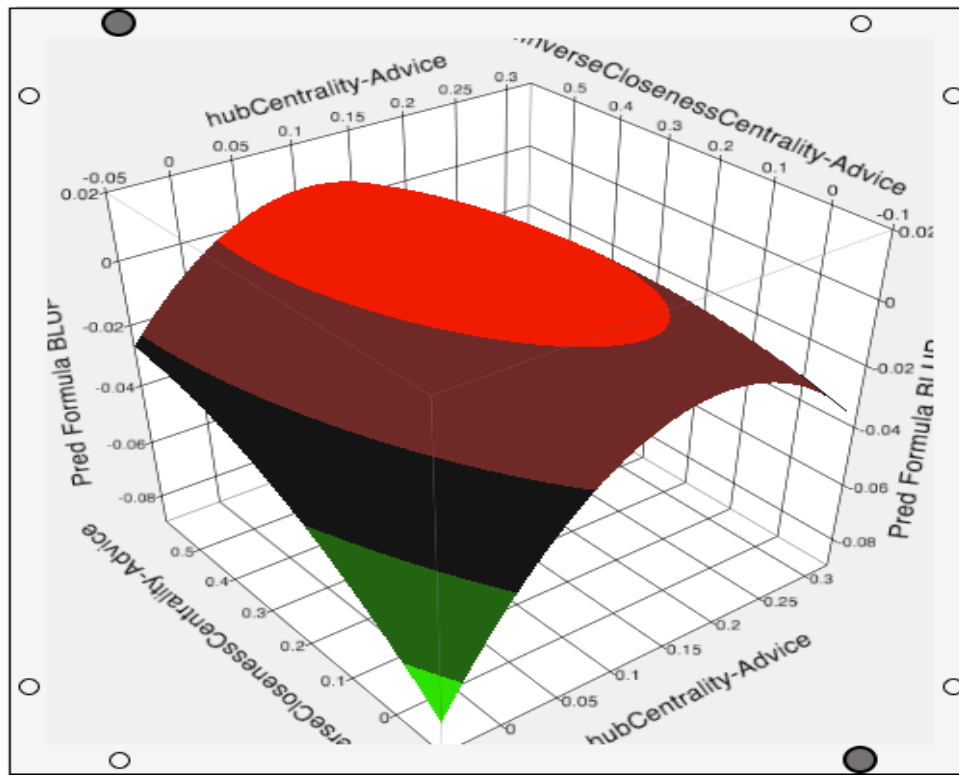
Figure 4. 3. Science surface plot 2

Dependent Variable: Science Teacher BLUP

Independent Variable: Hub Centrality-Advice and In-inverse closeness Centrality-Advice

Hold values: Correlation Similarity-Social =0.086 (Median value)

Social Studies

In-Inverse Closeness Centrality-Advice (β=0.43). As explained in the results for science, many nodes can reach agents high in this measure. As observed with science teachers, the more a social studies teacher's advice is accessible to other teachers, the more effective this teacher is. A positive linear effect for this central position measure in the advice network supports Hypotheses 1 and 2.

Structural Holes Effective Network Size-Trust ($\beta=0.26$). As explained in the results for math, this measure evaluates the structural holes of the focal agent's ego network, a bridging capacity. Like math teachers, the larger the network size with non-redundant ties a social studies teacher has, the more effective this social studies teacher is. The positive effect for this bridging variable in the trust network of social studies supports Hypotheses 1 and 2.

Triad Count-Social ($\beta=-0.33$). The triads that comprise this measure consist of three nodes and three sides such that all nodes are connected to one other node. The direction of the sides is unimportant, so there are several possible configurations of these triads. Results in this study indicate that the more triads that a social studies teacher belongs to, the less effective this teacher is. Further investigation reveals that triad-count social is also highly correlated with correlation similarity-social ($r=0.73$), thus indicating that these triads in the social networks are based on more homogenous relationships. As noted above, complexity theorists argue that high levels of homogeneity are not conducive to effectiveness because of the group think effect.

Research Questions Answered

Question 1: what is the relationship between teacher network variables and student test scores? Are there curvilinear and interaction effects that influence outcomes?

Teacher network variables exhibited linear, curvilinear and interactive effects on student test scores. For math and social studies, only linear effects existed; for ELA, both linear and curvilinear effects existed and science teachers' network measures exhibited linear, curvilinear and interactive effects on their students' test scores.

Question 2: what is the effect of homogeneity in teacher's network relationships on student test scores?

Homogeneity in teacher's network relationships exhibited negative linear effect and positive interactive effect (with hub centrality advice) on student test scores.

Question 3: what combinations of teacher network variables have the optimal effect on student performance?

This question is only answered for ELA and Science.

ELA teachers are most effective when they are engaged in brokering trust (structural holes efficiency trust = 0.6 on a scale of -0.4-1.2), and in the meantime have a lower level of clique engagement in advice (triad count-advice = 5 on a scale of 0-50). Science teachers are most effective when they are actively engaged in the advice network with their colleagues who are similar to them socially (when both hub centrality advice and correlation similarity are at a high level).

Summary

In summary, findings from this study support Hypotheses 1, 2, and 3. Hypothesis 4 was not supported directly, but similar dynamics as predicted by this hypothesis were discovered. In particular, central position in the advice network and bridging position in the trust networks exerted the most influence with multiple significant measures on more than one subject (i.e. in-inverse closeness centrality-advice for science and social studies, and structural holes effective network size-trust for math and social studies) and both linear and curvilinear effects (i. e. hub centrality-advice and structural holes efficiency-trust).

The next chapter interprets the findings guided by the theoretical framework in Chapter 2, and discusses the implications for theory and practice.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

This study seeks to understand teacher effectiveness through complexity and network lenses. The central argument in complexity theory is that interactive dynamics among agents and their information are responsible for organizational outcome, and the collective of interdependent and interactive people, rather than the individual, acts as the processer of information in an organization and resultant, emergent outcomes (Uhl-Bien et al., 2007). The central argument in network theory is that network structure is the channel for information distribution, and an individual's network position determines his or her level of access and control in this distribution, and individuals acting on advantage are rewarded with outcomes such as higher performance, better compensation, positive evaluations, and fast promotion (Burt et al., 2013). Complexity theory argues that agents who perform these functions exercise informal leadership, defined as agents who, in various ways, enhance the flow of information.

The outcome investigated in this study is teacher effectiveness as measured by their value-add on student test scores. It is hypothesized that teacher's engagement, or informal leadership, in the network dynamics, as measured by network variables, will exhibit linear, curvilinear and interactive effects on student test scores.

Interpretation of Findings

The theoretical framework section presented the assumption that access to information flow and interactive dynamics as afforded by teachers' network positions within each school affect teacher effectiveness. This assumption is supported by the

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general pattern in the findings that teachers more engaged in the network dynamics are more effective than those who are disengaged. Specifically, the theoretical framework section presented three logics for the productivity process: information flow, informal leadership and social capital. Teachers who engage in the information flow dynamics generate social capital and emerge as informal leaders. Teachers' network positions and relationship patterns impact their engagement in network dynamics, which, in turn, impact their effectiveness. This theoretical framework will be used to guide the interpretation of findings from this study.

Math

Potential boundary spanner-social and structural holes effective network size-trust exhibit positive linear effect on math test scores. Both are measures of bridging position.

Agents in bridging positions broker novel information and facilitate interdependency. Specifically, findings from this analysis indicate that individuals who exhibit great potential to interact with other parts of an organization socially (i.e. potential boundary spanner-social) and individuals who do not have excessively redundant trust ties (i.e. structural holes effective network size-trust) are especially high in effectiveness in math.

According to network theory, such individuals have many advantages that could be summarized as information breadth (less redundant information), timing (early access to that information) and arbitrage (control over information flow) (Burt et al., 2013). For example, they are likely to access a wider diversity of information because of their non-redundant connections. They can also exert control over information diffusion because

sometimes they are the only channels through which information could be passed (if two friends of agent i are not connected, then they can only learn about each other from agent i; this way i can control the flow of that information).

Such individuals also facilitate interdependency among groups. According to complexity theory, interdependency and conflicting constraints create pressure to adapt and improve. Individuals who are highly interdependent with other parts of the organization are likely to benefit from such pressure and to improve their effectiveness. They are likely to emerge as informal leaders, and possess high levels of social capital.

ELA

Structural holes efficiency-trust exhibits both linear and curvilinear effects on ELA test scores. Close examination of Figure 4.1 reveals that its linear effect exists when triad count-advice is high, and its negative curvilinear effect (inverted U) exists when triad count-advice is low. In either case, ELA scores increase with structural holes efficiency-trust, it's just that it increases linearly in the presence of numerous triads and curvilinearly in their absence.

Structural holes are places in an *ego* network in which different people or groups are not connected. An *ego* network is the network of direct relationships a given person has. If the ego has links to a person in each of two otherwise unlinked networks, then he or she fills a structural hole and has access to the information in those groups. An *efficient* group in an ego network is one in which there are many individuals in the group who have unique, or non-redundant, information. By connecting to subgroups that each contains significant numbers of nodes with non-redundant information, the ego has

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unique access to that diverse, non-redundant information, and is positioned to broker the information between groups.

Triad counts identify the number of triads for each person in a network (two other people with which a given person is linked) and sum them for each person. Persons with high count, then, are members of numerous sets of triads of individuals.

ELA teacher effectiveness rises strongly with structural holes-efficiency, but it dips a bit at high structural holes and low triad count-advice, thus giving it the curvilinear effect observed along the right wall in Figure 4.1. This dip is not observed on the opposite wall, where triad count is higher. Higher triad levels apparently empower the efficacy of structural holes. At the higher triad counts and greater structural holes-efficiency, ego finds more opportunity to broker with triads; at lower levels of triad counts, that opportunity is lost.   It is possible that the availability of triads in advice network increases the diversity of information that ego can tap and thus provides an information flow advantage.

Alternatively, the curvilinear term for structural holes efficiency trust could be understood in terms of closure and brokerage. Burt (2005) sees brokerage and closure as complementary to each other in enhancing social capital. Closure refers to groups, such as triads, that have no open links (opposite to structural holes). Network closure is about strengthening connections and getting more effective at what is already known. Brokerage refers to connections across otherwise unconnected sub-groups to engage diverse information. Network closure decreases the heterogeneity in a group, enforces the status quo of the group, and strengthens relationships within the group. As a result,

network closure has the capacity to facilitate trust and collaborative alignment needed to deliver the value of brokerage. Initially, people high on brokerage but low on closure benefit from novel information.

However, as their network connections become too diverse, they lack the network cohesion to deliver the value of novel information—for example, they cannot find enough support to implement new ideas. In addition, maintaining the connections drains their resources and takes time away from accomplishing their goals, described by Coleman (1988) as the cost of social capital. As a result, their effectiveness suffers, as illustrated by the dip in Figure 4.1.

Science

The findings for science exhibited linear, curvilinear, and interaction effects for hub centrality advice, correlation similarity social, and in-inverse closeness centrality advice (Table 4.5, Model 2).

Hub centrality and closeness centrality reference agents in central positions. Nodes in central positions receive and disseminate information quickly and are actively engaged in the complex dynamics of the network. Hub centrality advice identifies agents who seek advice from individuals who give advice to a lot of other agents. In-inverse closeness centrality advice identifies agents who are active in giving advice; agents high in this measure receive many nominations as the go-to person for advice. Such teachers gain valuable insights in their teaching, become better problem solvers, and accumulate advantages for future exchange of valued resources (Baldwin et al., 1997; Cook & Emerson, 1978). According to network theory, such individuals have advantages because

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they receive high quantity of information earlier than others (Borgatti & Halgin, 2011). These measures also indicate levels of engagement in the interaction of information. According to complexity theory, interaction of information via informal leadership could result in information transformation and individuals engaged in the process benefit from the information flow and emerge as informal leaders.

Correlation similarity social identifies individuals who are socially homogeneous to numerous other nodes. Its negative effect comes from lack of diverse information and group-thinking effects.

Hub centrality-advice is curvilinear (inverse U shaped) at low values of correlation similarity-social and linear at high values of correlation similarity-social.

When correlation similarity-social is low, hub centrality can be seen as a measure of the degree of coupling (Kauffman, 1993) for an individual. The higher the hub centrality measure, the more tightly coupled the individual is. As behaviors move across the surface plot from loose coupling (low hub centrality) to moderate coupling (moderate level of hub centrality), effectiveness increases because of increasing pressure to elaborate and experiment. However, as behaviors move into more tightly coupled regions, the conflicting constraints afford little room for creative change. As a result, effectiveness suffers, as observed in the lower right regions of Figure 4.2.

Higher levels of correlation similarity apparently empower the efficacy of hub centrality, as hub centrality rises strongly at higher levels of correlation similarity. This points to benefits of homogeneity in network relationships. Teachers who are homogenous in their social relationships, because of the common ground to work from,

have enhanced capacity to implement new ideas gained from new advice. This is consistent with the argument from Burt (2005) that network closure facilitates trust and cooperation, and delivers the value of new information. However, the mechanism that translates social homogeneity and advice engagement into effectiveness is unclear and deserves further investigation.

Science teacher effectiveness is optimal when both correlation similarity-social and hub centrality-advice are at a high level (Figure 4.2). That is, science teachers are most effective when they seek advice from their colleagues who are similar to them socially.

Hub centrality-advice is curvilinear (inverse U shaped) at both high and low values of in-inverse closeness centrality-advice. Science teacher effectiveness is optimal when hub centrality-advice is at a medium level and in-inverse closeness centrality-advice is at moderate to high level (Figure 4.3). That is, science teachers are most effective when they are actively engaged in advice giving, and moderately engaged in advice seeking from those go-to persons for advice.

Social Studies

For social studies, there were three significant linear predictors: in inverse closeness centrality-advice (individuals who have ready access to advice from numerous others), structural holes effective network size trust (connected to subgroups that each contain significant numbers of nodes with non-redundant trust relationships), and triad count-social (three-way relationships).

Please refer to the interpretation of science results for the positive effect of in-inverse closeness centrality advice, and the interpretation of ELA results for the positive effect of structural holes effective network size-trust.

Cliques are found to incubate new ideas, nurture minority needs and empower their voices (Rodan & Galunic, 2004), process diverse information (McPherson et al., 2001), and process large amounts of information effectively (Marion, Christiansen, Klar, Schreiber, & Erdener, 2016). Triads are indicative of cliques and triad-count social had a negative effect on teacher effectiveness for social studies. This finding seems to be contradictory to the theory. There could be two possible reasons. First, the nature of the relationship in which triads were measured was social. It could be that clique benefits for effectiveness are unlikely to emerge in social networks. Some research, for example, report that workplace friendship had negative association with individual performance outcomes (Mehra et al., 2001).

Second, a closer look revealed that this triad measure is closely correlated with correlation similarity in the social network, which is a measure of homogeneity (r=0.73), and correlation similarity-social likewise has a negative effect on science teacher effectiveness. The combination of findings (negative effects of both correlation similarity and triad count) confirmed previous research that high levels of homogeneity in closed networks are dysfunctional for learning and creativity. When cliques are formed around homogenous relationships, they lack access to diverse information, and are likely to fall victim to the group-think effect.

Contributions to Theory and Research

Several findings from this study are of interest to theory and research.

First, in support of complexity theory, the findings suggest important benefits to students derived from the interactive dynamics and interdependency among the faculty and staff in school (Uhl-Bien et al., 2007). Synthesizing results in this paper with findings from previous studies (Briley, 2016; Daly et al, 2011; Marion et al., 2017), students with teachers who engage in interaction over advice and in facilitating interdependence in trust seem to consistently have higher test scores. However, after a certain threshold value, the benefit diminishes. This confirms to the optimal information processing capacity of moderate coupling.

The findings also advance complexity theory by revealing nuanced roles homogeneity plays in different contexts. Homogeneity enhances trust and collaboration, and therefore can magnify the value of interaction and interdependence. However, when homogeneity is combined with cliques, it does disservice to productivity because of redundant information and group-think effect.

Second, this study contributes to network theory by confirming the advantages associated with network positions in the school context (Burt, 2005). Results show that teachers' central positions in the advice network and bridging positions in the trust network are beneficial for their students' test scores, although once a threshold is reached, the benefits diminish. The diminished return for the central position points to the cost of social capital (Coleman, 1988)—the maintenance of too many ties takes time away from working on one's goals. The diminished return for the bridging position

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suggests a need to maintain balance between brokerage and closure---closure delivers the benefit of brokerage by enhancing trust and collaboration (Burt, 2005).

Implications for K-12 Schools

Practitioners and policy makers devoted a lot of effort in developing teacher human capital, ranging from reforming teacher certification program to improving teacher subject matter knowledge and verbal skills (Darling-Hammond & Younds, 2002; Department of Education, 2002). However, less attention has been devoted to incentives and regulations that might foster social capital and interactive dynamics within schools. This study, together with several other similar studies (Friedkin & Slater, 1994; Pil & Leana, 2009) provided convincing evidence that the "social" aspect of teacher's professional life is equally, if not more important as the human capital aspect. Therefore, practitioners and policy makers should consider reframing the incentives and control mechanisms under which school professionals work, and make it a priority to promote productive collaboration among educators.

There are signs that the educational communities are recognizing the ineffectiveness of the "isolated culture of teaching" (York-Barr & Duke, 2004, p. 256). The recent paradigm shift with regard to teacher professional development (Bleicher, 2013) is an example. This shift emphasizes collaboration in addition to individual skills. Professional learning communities (PLC) are one typical model in the new paradigm (Vescio, Ross, & Adams, 2008). The key concept behind PLC is that teachers who engage in the collaborative culture of PLC will increase their professional knowledge and enhance student learning. Vescio et al. (2008) reviewed eight studies that examined the

relationship between teachers' participation in PLC and student achievement, and reported that all eight studies found significant improvement in student achievement at either the primary or the secondary levels. The authors attributed the success of PLC to "a persistent focus on student learning and achievement by the teachers in the learning communities" (Vescio et al., 2008, p. 87). Results from this study indicate that interactive dynamics among teachers within these communities could contribute as much to improved student achievement, and further studies could consider approaching the effectiveness of PLC from this perspective. K-12 schools should definitely continue and promote such collaborative efforts.

Other organizational mechanisms that promote interaction and interdependency of teachers could also be explored. Complexity theory advocates that interactive dynamics cannot be reduced to any individual part. Therefore, engaging the whole faculty and staff on issues such as student discipline, textbook selection and instructional objectives could produce unexpectedly creative ideas, and help to build common understanding. Designing good schools is about organizing the work of adults so that they can work coherently together as a whole for the development of the children.

Implications for Leadership Development

As discussed in Chapter 2, leadership, more than the property of individuals and their behaviors, can be conceptualized as "a collective phenomenon that is distributed or shared among different people, potentially fluid, and constructed in interaction" (Denis et al., 2012, p. 212). Results from this study support the significance of collective dynamics as a result of networked interactions. In line with this collectivist line of thinking about

leadership, the focus of leadership development could be expanded beyond individual's knowledge, skills and abilities to include the networked patterns of social relationships.

Cullen-Lester, Maupin, and Carter (2017) summarized three approaches for network-enhancing leadership development strategies:(1) Individuals developing social competence; (2) individuals shaping networks; and (3) collectives co-creating networks. Empirical evidence shows that even a little network training could produce substantial improvement in learning to see and benefit from network connections. For example, Burt and Ronchi (2007) conducted a field experiment in which executives were taught to understand the network structure of social capital. They found that those trained showed significant improvement in performance evaluation, promotion and retention compared to the control group of untrained but equally capable peers. Similarly, Janicik and Larrick (2005) found through five studies of schematic processing differences in encoding and recalling of incomplete networks that people could become schematic for complex, incomplete social networks.

These theoretical and experimental studies all support the notion that people can be trained to understand and take advantage of networks, and this network-enhancing ability should be an important part of leadership development. Educational institutions of both K-12 and higher education could consider incorporating such leadership development programs into their faculty professional development plans. Individual faculty, likewise, could pay attention to strategies to better understand and manage their networks as part of their efforts to improve effectiveness.

Limitation and Future Studies

This study has several limitations.

First, this study approaches teacher effectiveness only from their value-add on student test scores. Student test scores are imperfect indicators of teacher classroom practices, and they might not be the best embodiment of student learning. Policy makers favor them because they can be implemented at a large scale rather inexpensively, and they give the public a straightforward way of understanding educational progress (Linn, 2000). There are, however, other more subtle indicators of teacher effectiveness, such as structured in-person observations of teacher practice (Carey, 2017) or other teachers' evaluations (American Federation of Teachers, 2003). The analytical model in this study may predict teacher effectiveness on student standardized test scores, but would the results hold if the outcome of interest were other measures of teacher effectiveness? Future studies could explore this area.

Second, this study does not have student test scores from previous years. Several studies showed that students' prior achievements are one of the most significant predictors of their current achievement (Nye et al., 2004; Pil & Leana, 2009). However, in their analysis of both achievement gains (with control for prior achievement) and achievement status (without control for prior achievement), Nye et al. (2004) found that the magnitude of teacher effects were comparable in these two sets of analysis. For examples, for third grade math, teacher effect accounted for 12.3% of the variation in gains in student test scores (with control for second grade math), and 10.4% of the variation in student test scores (without control for second grade math). The results

provide evidence that without controlling for prior achievement, the current study is still able to estimate teacher effect on student test scores with relative accuracy. Yet it is suggested that future studies include student prior achievement if such data is available.

Third, this study captured social capital and network dynamics with agent level network variables. There are several issues related to this approach. To begin with, the network boundary restricted the participants to be faculty and staff within the school. However, social dynamics that influence student test scores are much broader than what happens within the school. For example, the dynamic between teacher and parent is an important one. Empirical evidence shows that teacher trust in students and parents is related to higher student achievement (Goddard et al., 2001). On the other hand, teachers also need parental support in establishing trusting relationships with students (A. S. Bryk & Schneider, 2002). This teacher-parent dynamic would be important to examine regarding teacher effectiveness, especially at the elementary level. Other important dynamics include teacher and principal, teacher and student, and even teacher and the community that schools are located in (Bryk & Schneider, 2002).

Another aspect is about the inherent limit in model building. As Box and Draper (1987) pointed out, "essentially, all models are wrong, but some are useful" (p. 424). The network analysis model seeks to capture social capital and network dynamics through "typical interactions". This of course, is a legitimate and proven strategy. However, the underlying assumption is that all social relationships and interactive dynamics are measurable. This is similar to assuming that student learning could be captured with student test scores. But many subtle and elusive aspects of relationships and dynamics

cannot be captured with any statistical tools. For example, a new teacher could be inspired by the wisdom shared by a principal who is about to retire, and translated this inspiration into his teaching career. Such interactions are random yet profound, and are well beyond the reach of "typical interactions" targeted in this study.

Yet another aspect is the network data cross validation procedures used in this study, which is conservative and might bias the results. These procedures were described in detail in Chapter 3 and results reported in Chapter 4. To count as a valid relationship, only connections acknowledged by both parties were included. As a result, on average only 50% of the advice links, 32% of the social links and 48% of the trust links remained. More links were removed than remained. The questions worth considering are: is it appropriate to remove these relationships just because they are not confirmed by both parties? What could be the reasons that a relationship is not confirmed by both parties? Measurement error could be one reason. For example, one party might go through the name list too fast, and left out a typical interaction by mistake. In this case, the relationship reported by the other party should be kept. Difference in perceptions could be another. For example, if agent i selected agent j as a person with whom he has frequent social interaction, but agent j did not select agent i, could it because they have different perceptions of what counts as "social interaction"? If so, whose perception is accurate? What are the parameters to make that decision? Unfortunately, there is no ready answer to this question. Future study could consider comparing results from network data that have been validated and those that have not, and further investigate the differences.

Fourth, this study did not include any human capital measures. Human capital is foundational to teacher effectiveness. Other studies have found several human capital measures such as teacher experience (Wayne & Youngs, 2003), subject-specific teaching ability (Pil & Leana, 2009) to exert significant influence on student test scores. How will such human capital measures interact with the social capital measures used in this study is an interesting topic to pursue.

Lastly, this study did not specify any assumptions about human agency (Burt et al., 2013). Complexity theory is focused on how interactive dynamics are related to productivity and network theory is focused on how network structure is related to advantages in outcomes. Both theories take human agency as secondary consideration.

Complexity theory assumes that humans are carriers of information, and they act on the interactive dynamics of information. But how effective is the "carrier", and what influences the course of actions taken? These questions are not explored in complexity theory. Similarly, network theory assumes that achievement springs directly from a network. However, networks do not act, but people act. So how much does the human agency matter? A deeper recognition of personality and cognitive ability in network analysis is called for.

There are studies that examine the effect of personality traits such as self-monitoring (defined as individual differences in the control of self-representations for situational appropriateness) (Mehra et al., 2001; Sasovova, Mehra, Borgatti, & Schippers, 2010), leader charisma (a personality dimension evaluated by the reports of subordinates) (Balkundi, Kilduff, & Harrison, 2011) and empathy (understanding of others' intentions

and attending to their emotional states)(Kardos, Leidner, Pléh, Soltész, & Unoka, 2017) on network position or size. Results indicated that high self-monitors tend to have more structural holes; leader charisma did not predict leaders' centrality in team advice network but formal leaders central in team advice networks tended to be seen as charismatic by subordinates; and empathetic abilities predicted how many close relationships people maintain.

Other studies investigated the effect of social cognitive capacity on network size. They found that mentalising ability (the ability to correctly infer and remember others' higher-order intentions and desires) predicted people's network size (Stiller & Dunbar, 2007).

Future studies could investigate how human agency such as personality and cognitive ability influences the complex dynamics in educational institutions.

Future Directions

Results from this study showcase the importance of social capital and interactive dynamcis in knowledge intensive organizations. Many digital tools are available to enhance such complex dynamics. In fact, Lin (1999) argued that "cyber-network" represents one of the "revolutionary rise of social capital" (p.45). For K-12 schools and higher educational institutions, it is a worthy cause to explore how digital technology could be creatively utilized to strengthen social capital for individuals and organizations. Digital technology complements to face-to-face interactions, and provides great leverage to strengthen professional networks.

Many web-based platforms already exist for academia. Internet Discussion Group

(IDG) such as newsgroup and mailing list is one such example (Uwe Matzat, 2004). IDG has been used as informal tools for communication among researchers for a long time. Statistics show that IDG enhances social capital of users through establishing weak contacts. Yet the same study found no substantial numbers of new collaborations from these weak ties. This seems to indicate that not enough network closure exists to deliver the benefit of brokerage developed through weak ties (Burt, 2005).

Various social media-like platforms are other examples. Such platforms seek to harness the web for academics to communicate and network, and to publicize scholarly outputs (Thelwall & Kousha, 2014).

These platforms include citation management products such as Mendeley, Zotero, and CiteULike. In addition to managing citations for users, these products also have social media features, allowing users to find and follow each other. These platforms also include academic social network sites like academia.edu and Research Gate, which focus on the producers of research. Such sites allow users to create profiles for themselves, upload their own papers and datasets, and grant access to requests. They also provide publication analytics and facilitate the exchange of information, including posting public questions to the community (Ovadia, 2014). Universities could take advantage of such platforms by establishing and maintain university specific sites. Researchers from the same university or a coalition of universities could align their interests, communicate their expertise, and establish collaboration. Universities could facilitate such collaboration with institutional support such as financial reward or promotions.

Universities could also borrow ideas about online networking from the business world. For example, enterprise social media (ESM) is a platform that is gaining popularity in businesses. ESM refers to a collection of web-based platforms that enable professionals within an organization to communicate with each other, post, edit, and sort text and files linked to themselves or others, and most importantly, view the messages, connections, text, and files communicated, posted, edited and sorted by anyone at any time (Leonardi, Huysman, & Steinfield, 2013). There are four ways (Majchrzak, Faraj, Kane, & Azad, 2013) that ESM could engage professionals and enhance their network: 1) metavoicing where professional engage in the ongoing online knowledge conversation by reacting online to others' presence, profiles, content and activities; 2) triggered attending where professionals engage in the online knowledge conversation by remaining uninvolved in content production or the conversation until a timely automated alert informs the individual of a change to the specific content of interest; 3) network-informed associating where professionals engage in the online knowledge conversation informed by relational and content ties; 4) generative role-taking where professionals engage in the online knowledge conversation by enacting patterned actions and taking on community-sustaining roles in order to maintain a productive dialogue among participants. University faculty, especially those in the same discipline or in disciplines that are highly complementary, can use such platforms to connect with each other and align their interests.

ESM could strengthen professional networks in several ways. First, such platforms increase participants' social capital by developing and maintaining

relationships between entities (people to people, people to information) (Fulk & Yuan, 2013; Vaast & Kaganer, 2013). The concrete ways ESM enhances social capital include: enhance strong ties by contextualizing knowledge sharing (Tsoukas, 2009), build productive bridging ties to friends' friends to fill structural holes or fit expertise need, increase diversity and size of network ties, increase network density and reciprocity, and build new connections or weak ties through personalized, informal, up-to-date recommendation system (Fulk & Yuan, 2013). Establishing bridging ties is one of the biggest contributions of ESM. As discussed earlier in the theoretical framework section, bridging ties provide opportunity to access new resources, information and contacts because of lack of overlapping in the connections (Granovetter, 1973).

Second, such platforms facilitate emergence, both in terms of problem solving and in terms of knowledge production, and both processes connect people in organic ways. According to complexity leadership theory (Uhl-Bien et al., 2007), one mechanism for emergence is the reformulation of existing elements to produce outcomes that are qualitatively different from the original elements. Since the conversations on ESM are intended as peer-to-peer rather than a centralized spoke in the wheel through a leader, the manner in which conflicts such as complaints, frustrations, and arguments get resolved becomes an emergent process.

Third, ESM also provides an online platform (McAfee, 2006) with a constantly changing structure built by distributed, autonomous and largely self-interested peers without central coordination. On this platform, authoring creates content; links and tags knit it together; and search, extensions, tags and signals make emergent structures and

patterns in the content visible, and as more people engage in the process, the emergent structure becomes increasingly fine-grained. According to complexity theory, one key feature of complex adaptive systems is that global pattern emerges through interaction among autonomous individuals without central control (Mitchell, 2011). The affordances of ESM facilitate the complex interactive dynamic among knowledge professionals in the process of knowledge production.

Findings from the current study suggest that bridging positions are positively related to outcomes, however it takes network closure to deliver the value of brokerage. Social media offers tremendous opportunities to build bridges among researchers, and universities possess unique resources such as physical proximity and control over institutional policy to enhance network closures. If designed and implemented properly, digital technology could bring revolutionary changes to research productivity in higher educational institutions.

Conclusion

This study conceptualizes schools as knowledge intensive organizations, and assumes that in such organizations, network relationships and interactive dynamics are important to teacher effectiveness. Teacher network variables were used to measure each teacher's engagement in network relationships and complex dynamics, and various statistical procedures were used to analyze the effect of these teacher network variables on student test scores. Based on arguments of information flow, informal leadership and social capital, this study finds that network relationships and interactive dynamics facilitate teacher effectiveness. This study also offers insight into more nuanced

curvilinear and interactive effects of these network variables, suggesting the complexity of social dynamics.

Results from this study offer important insights for theory and practice. They confirmed the importance of interaction and interdependence among school faculty and staff, and advantages associated with different strategic network positions. The results further highlight the cost of social capital, and the effectiveness of moderate coupling. The results also advance complexity theory by revealing the advantage and disadvantage of homogeneity under different circumstances.

Based on results from this study, practices that facilitate network relationships and dynamics should be encouraged. Current collaborative practices such as professional learning communities should be promoted. In addition, digital technologies, because of their potential in facilitating social capital and emergence of knowledge, should be used creatively to transform network dynamics into research productivity in educational institutes at all levels.

APPENDICES

Appendix A

Formula for Network Measures

1. in-Degree Centrality

Formula

let A be the input network with maximum link value V

In-Degree Centrality = colsum(A) / V*rows(A)

Note: if the network A is unimodal and not using the diagonal, then the measure is normalied by V*(rows(A)-1).

Reference: Altman, Carley & Reminga, 2017, p. 1146

2. out-Degree Centrality

Out-Degree Centrality = rowsum(A) / V*cols(A)

Note: if the network A is unimodal and not using the diagonal, then the measure is normalized by V*(cols(A)-1).

Reference: Altman, Carley & Reminga, 2017, p. 1191

3. Total-Degree Centrality

let A be the input network with N nodes and maximum link value V

Total-Degree Centrality for node i = (sum(A(i,:)) + sum(A(:,i)) - A(i,i)) / 2*V*(N-1)

Note: if the network A is symmetric, then the measure is normalized by V*(N-1).

Note: if the network A allows self-loops, then the normalize value is incremented.

Reference: Altman, Carley & Reminga, 2017, p. 1299

4. Eigenvector Centrality

Formula

Eigenvector Centrality is not directly computed on networks with multiple components. Some tools only calculate it on one component with varying rules as to which component to use. ORA calculates the measure on all components separately (values are scaled according to the component size), and combines them into a single result vector.

let A be the unimodal input network (if not symmetric, links are added to make it symmetric) with N nodes

let K be the number of components in the network A

let N_k be the nodes in the kth component.

let V_k be the dominant eigenvector computed on the sub-network induced by the nodes N_k

Scale the V_k values by multiplying them by N_k/N

Eigenvector Centrality is the combined vector of all scaled component V_k values.

Note: Hub Centrality and Authority Centrality measures are generalizations of the Eigenvector Centrality measure and take into account directed links.

Reference: Altman, Carley & Reminga, 2017, p. 1126

5. Katz Centrality

Formula

Let A = adjacency representation of the network N. Then Katz Centrality for the network is the solution c to the following system of linear equations:

inverse(I - alpha*A')*c = alpha*A'*e : I is an identity matrix, and e is a vector of ones

The solution vector c is then normalized by dividing by the absolute value of the largest element.

The magnitude of alpha affects the degree to which distant ties are taken into account. By default, alpha is chosen to be as large as possible (it must be < 1/lambda, where lambda is the magnitude of the largest eigenvalue) so as to approximate eigenvector centrality.

Note: the input network is transposed, and the meaning of the link (i,j) should be that i chooses or 'gives influence to' node j

Reference: Altman, Carley & Reminga, 2017, p. 1163

6. PageRank Centrality

A node's score is based on the scores of its in-coming neighbor nodes, and in a way analogous to computing Eigenvector Centrality.

The algorithm models someone surfing the web, moving from one page node to another via hyperlinks. Starting from a page, he moves to a hyperlinked page with probability proportional to the link value. If a page with no hyperlinks is encountered, then any one page is chosen uniformly at random.

In addition, the web surfer can jump to any page at random with a small probability, and if a page has no out-links, then a page is chosen uniformly at random.

let A = input network with N nodes where A >= 0

let rowsum = vector of row sums of A

let C = N x N network with links: (i,j) = (sum(A(i,:)) == 0), that is, transform each empty row of A into a row of ones

let A(i,j) = A(i,j) ./ sum(A(i,:)), that is, normalize each link by the sum of the values in its row to convert A into a stochastic matrix

let E = N x N network with each cell equal to 1/N, which is the random transition matrix

let the Google matrix G = alpha*A + (1 - alpha)*E

PageRank is the dominant eigenvector of the matrix G.

Note: by default alpha = .85 and therefore G > 0, and therefore an all positive dominant eigenvector exists; alpha = 0 would mean that all transitions are based on the probabilities of A, and alpha = 1 would mean that all transitions follow the uniform probabilities of E.

Reference: Altman, Carley & Reminga, 2017, p. 1219

7. Authority Centrality

Formula

Authority Centrality is the Eigenvector Centrality of the network A'*A, where A is the input network.

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Reference: Altman, Carley & Reminga, 2017, p. 1056

8. Hub Centrality

Formula

Hub Centrality is the **Eigenvector Centrality** of the network A*A', where A is the input network.

Reference: Altman, Carley & Reminga, 2017, p. 1121

9. in-Closeness Centrality

Formula

let A be the unimodal input network with N nodes, minimum link value v, and maximum link value V

let D be the distance network defined as:

$D(i,j)$ = shortest path length from i to j, if a path exists from i to j

$D(i,j)$ = N*V, if no path exists from i to j

$D(i,i) = 0$

The following computes the sum of shortest path lengths from all other nodes to node i:

let $d = \sum D_{u,i}$: for all nodes u

Closeness Centrality value for node i = v*(N-1) / d

Reference: Altman, Carley & Reminga, 2017, p. 1143

10. Closeness Centrality

Formula

let A be the unimodal input network with N nodes, minimum link value v, and maximum link value V

let D be the distance network defined as:

  D(i,j) = shortest path length from i to j, if a path exists from i to j

  D(i,j) = N*V, if no path exists from i to j

  D(i,i) = 0

The following computes the sum of shortest path lengths from node i to all other nodes:

  let d = $\sum D_{i,j}$: for all nodes j

Closeness Centrality value for node i = V*(N-1) / d

Reference: Altman, Carley & Reminga, 2017, p. 1077

  11. Inverse Closeness Centrality

Formula

let A be the unimodal input network with N nodes, minimum link value v, and maximum link value V

let D be the distance network defined as:

  D(i,j) = shortest path length from i to j, if a path exists

D(i,j) = 0, if no path exists

D(i,i) = 0

The following computes the sum of shortest path lengths from node i to all other nodes:

let d = $\sum(1/D_{i,u})$: for all nodes u where $D_{i,u} > 0$

Inverse Closeness Centrality value for node i = $v*(N-1) / d$

Reference: Altman, Carley & Reminga, 2017, p. 1158

12. Bonacich Power Centrality

Formula

Let A = adjacency representation of the network N. Then Bonacich Power Centrality for the network is the solution c to the following system of linear equations:

inverse(I - beta*A)*c = A*e : I is an identity matrix, and e is a vector of ones

The solution vector c is then normalized by dividing by the absolute value of the largest element.

The magnitude of beta affects the degree to which distant ties are taken into account. By default, beta is chosen to be as large as possible (it must be < 1/lambda, where lambda is the magnitude of the largest eigenvalue) so as to approximate eigenvector centrality.

Note: the meaning of the link (i,j) should be that i is influenced by node j

Note: if **beta** is 0, then Bonacich Centrality equals the In-Degree Centrality of each node.

Reference: Altman, Carley & Reminga, 2017, p. 1066

13. Capability

Formula

Let A be the input network in matrix form

Let d = vector of row degrees of the nodes

Normalize d by the maximum degree score, that is, d = d / max(d)

Then the Capability of node i is computed as:

$$1 / (1 + \exp(10 * (0.5 - d[i])))$$

Reference: Altman, Carley & Reminga, 2017, p. 1070

14. Radiality Centrality

Formula

Consider a network with N nodes, and a minimum link value of value v.

let D(i,j) = shortest path length from node i to j (or 0 if no path exists)

let diameter be the maximum D(i,j) over all (i,j) pairs

Radiality Centrality of node i = sum(diameter - D(i,:)) / (N-1)*(diameter - v)

Note: the maximum value of 1 is achieved for the center node of a star network.

Note: isolates have a score of 0

Reference: Altman, Carley & Reminga, 2017, p. 1233

15. Shared Situation Awareness

Formula

let alpha, beta, delta, gamma, mu be decimal numbers.

let A = Agent x Agent interaction/communication network.

let P = Agent x Agent physical proximity network.

let S = Agent x Agent social demographic similarity network.

let e = eigenvector centrality measure computed on A.

let G = geodesics between agents computed on A.

Then the SSA between agents i and j is:

SSA(i,j) = alpha*e[i]*e[j] + beta*P(i,j) +
delta*S(i,j)/(gamma*G(i,j)) + mu*A(i,j)*A(j,i)

let ssa = rowsum(ssa)

The node level output is ssa / max(ssa)

Reference: Altman, Carley & Reminga, 2017, p. 1273

16. Betweenness Centrality

let D be the distance network for the input network; D(i,j) =
shortest path distance from i to j, and zero if no path exists

let C be the network of the number of shortest paths for the input
network (so that C(i,j) = number of shortest paths from i to j, and
zero if no path exists

The following computes the total fraction of shortest paths that node
i lies on:

$\Sigma(C_{u,i}*C_{i,v})/C_{u,v}$: for (u,v) where $D_{u,v} = D_{u,i} + D_{i,v}$

This value is then normalized by the maximum number of shortest
paths possible to get the betweenness centrality.

Reference: Altman, Carley & Reminga, 2017, p. 1060

17. Potential Boundary Spanner

let betweennessCentrality = Betweenness Centrality values for the input network

let totalDegreeCentrality = Total-Degree Centrality values for the input network

Potential Boundary Spanner = betweennessCentrality ./ totalDegreeCentrality

Reference: Altman, Carley & Reminga, 2017, p. 1288

18. Structural Holes Constraint

$$(2.4) \qquad \left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2, \qquad q \neq i, j.$$

i, p, q are three agents in the network; p_{qj} is the proportional strength of q's relationship with j, as p_{ij} is the proportion strength of i's relation with j.

Reference: Burt, 1992, p. 52

19. Structural Holes Effective Network Size

$$\text{Effective size of } i\text{'s network} = \sum_J \left[1 - \sum_q p_{iq} m_{Jq} \right], \qquad q \neq i, j,$$

i, p, q are three agents in the network; p_{iq} is the proportional strength of i's relationship with q, as m_{jq} is the marginal strength of j's relation with q (interaction with q divided by the strongest of j's relationships with anyone)

Reference: Burt, 1992, p. 52

20. Clustering Coefficient

let **G=(V,E)** be the graph representation of a square network.

Define for each node $v \in V$ its Clustering Coefficient cc_v:

let **Gv = ego network of entity v**

Then Clustering Coefficient for entity:

$$\text{entity } v = cc_v = density(Gv)$$

Then Clustering Coefficient for graph:

$$graph = \frac{\sum_{v \in V} cc_v}{|V|}$$

Reference: Carley, et al., 2013, p.855

21. Simmelian Ties

Formula

let A be the unimodal, binary input network

Symmetrize network A by reducing or removing link values

All Cliques of size >= 3

let N_i be the number of distinct nodes that are in a clique with node i

Simmelian Ties for node i = N_i / (N-1), where N is the number of nodes in A

Reference: Altman, Carley & Reminga, 2017, p. 1277

22.   Triad Count

Formula

let A be the binary, unimodal input network

We create a new network called TriadCount such that:

TriadCount(i,j) = number of triads using link (i,j) = cardinality{ k | A(i,j)*A(j,k)*A(i,k) = 1 ∀i,j,k distinct}

The Triad Count for node i = sum(TriadCount(i,:))

Reference: Altman, Carley & Reminga, 2017, p. 1302

23. Corrrelation Similarity

For each pair of rows (i,j) we compute the number of bits they have in common, and then normalize this by the sqrt of the product of their number of knowledge bits.

The Cosine Similarity of rows i and j of A is defined as:

let common = sum(A(i,:) .* A(j,:))

SC(i,j) = common / (sum(A(i,:)) + sum(A(j,:)) - common)

Note: by definition, SC(i,i) = 1, and SC is symmetric.

The node-level output value for node i = ($\sum SC_{i,j}$)/(rows(A)-1) : for i ≠ j

This is the average Cosine Similarity row i has with the other rows.

Reference: Altman, Carley & Reminga, 2017, p. 1106

24. Correlation Distinctiveness

Let A be the input network.

For each pair of rows (i,j) we compute the number of knowledge bits they have exactly opposite. Then normalize this sum by the total number of knowledge bits. In effect, this is the exclusive-OR of their knowledge vectors.

The Distinctiveness Correlation between rows i and j of A is defined as:

$$DC(i,j) = sum(A(i,:) .* \sim A(j,:)) + sum(\sim A(i,:) .* A(j,:))$$

$$DC = DC / cols(A)$$

Note: by definition, $DC(i,i) = 0$, and DC is symmetric.

The node-level output value for node i = $(\Sigma DC_{i,j})/(rows(A)-1)$: for i ≠ j

This is the average Distinctiveness Correlation row i has with the other rows.

Reference: Altman, Carley & Reminga, 2017, p. 1116

25. Correlation Expertise

Formula

Let A be the input network.

For each pair of rows (i,j) we compute the number of bits that j has that i does not have. Then normalize this sum by the total number of bits that row i does not have.

The Expertise Correlation of rows i and j of A is defined as:

$$CE(i,j) = sum(\sim A(i,:) .* A(j,:)) / (cols(A) - sum(A(i,:)))$$

Note: $CE(i,i) = 0$, and the output is not necessarily symmetric.

The node-level output value for node i = $(\Sigma CE_{i,j})/(rows(A)-1)$: for i ≠ j

This is the average Expertise Correlation row i has with the other rows.

Reference: Altman, Carley & Reminga, 2017, p. 1133

Appendix B

Network Survey

Information about Being in a Research Study

Clemson University

Collectivist Dynamics and Student Test Scores in Elementary Education

Description of the Study and Your Part in It

Russ Marion, Rob Knoeppel, Hans Klar and Gemma Jiang invite you to take part in a research study. Drs. Marion, Knoeppel, and Klar are professors at Clemson University; Ms. Jiang is a PhD student at Clemson University and assistant to Dr. Marion. The purpose of this research is to explore the effects of network relationships and relationships with your leader on student test scores in elementary schools.

Your part in the study will be to respond to a survey about interaction patterns at your school. It will take you about 15 minutes complete.

Risks and Discomforts

Participants could experience mild risks or discomforts if responses were leaked to other participants in the school. As described below, we will take significant precautions to see that this does not happen.

Possible Benefits

This research will help us understand how to help your school improve the test scores of its students. Depending on findings, suggestions could involve changes such as how faculty interact, how leaders provide leadership, or how teachers and staff participate in decision making.

Protection of Privacy and Confidentiality

We will do everything we can to protect your privacy and confidentiality. While we must request your name when the data is collected in order to prepare the data for analysis, names will be removed as soon as the data is prepared for analysis and will not be associated with your responses in subsequent analyses (about 3 weeks after all data is in). Data is collected in a confidential manner and will be maintained on password-protected computers at Clemson University. The research team will share the summarized results of the study but, unless you state otherwise, no information will be provided that could possibly identify you personally.

However, the results of the survey will allow us to identify informal leaders in your school. If we find that you are an informal leader, we would like to reveal that fact, and only that fact, to administrators. We will ask for your permission at the beginning of the survey and will notify you again before releasing any information (you will be asked if you want to opt-out at this point). We will not otherwise tell anybody outside of the research team what your responses were or even that you were in this study. The program we use to collect data leaves no record of responses on your computer (once closed) that could be recovered by others.

The Clemson University Research Ethics Committee (Institutional Research Board) has certified this research and all its investigators.

We might be required to share the information we collect from you with the Clemson University Office of Research Compliance and the federal Office for Human

Research Protections. If this happens, the information would only be used to find out if we ran this study properly and protected your rights in the study.

Choosing to Be in the Study

You do not have to be in this study. You may choose not to take part and you may choose to stop taking part at any time. You will not be punished in any way if you decide not to be in the study or to stop taking part in the study.

Contact Information

If you have any questions or concerns about this study or if any problems arise, please contact Russ Marion at Clemson University at 864 654-3464 or at marion2@clemson.edu.

If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) at 864-656-6460 or irb@clemson.edu. A copy of this form will be provided to you.

<div align="right">**CONTINUE TO NEXT PAGE**</div>

If we find that you are an informal leader in your school, would you be willing to allow us to reveal that fact to you and then to your school's administration?

What is your name? (This is very important; your name will be deleted as soon as the data is formatted and before analysis). _____

About how many years have you been a teacher? _____

About how many years have you been a teacher AT THIS SCHOOL? _____

1. From the following list, identify the people with whom you regularly socialize either inside or outside school (choose all that apply)?

2. From the following list, identify the people you would go to for advice on work-related issues (e.g., teaching strategy, discipline, curriculum, etc.; choose all names that apply)?

3. Now reverse this question: Which of the following people regularly seek advice from you about such work-related issues (choose all that apply)?

4. From the following list, identify the people with whom you share confidential information (choose all that apply)?

5. Again reversing the question, which of the following people come to you to share confidential information?

6. Which of the following tasks do you perform on a regular basis at this school (choose all that apply)?

Teach pre-k	Teach Gr 4	Teach Special Ed	Teach Art	Administration
Teach k	Teach	Teach remedial	Coordinate Title I	Financial

	Gr5	lessons	Activities	monitoring
Teach Gr1	Teach Art	Teach computers	Teach, other	Other support services
TeachGr2	Teach PE	Teach music	Counseling/Psychology	
Teach Gr3				

7. In the following list, identify the skills at which you are <u>particularly</u> adept (choose all that apply).

School Budgeting	Finding resources	Differentiating instruction	Music	Technology
Community partnerships	Subject area content	Recreation/physical development	Organizational management	Clerical
Student tests Interpretation	Subject area content standards	Student discipline	IEPs Implementation	Instruction
IEP Writing	Curriculum development	Classroom management	Funds accounting	

8. Which of the following resources do you *regularly* use to perform your tasks at this school (choose all that apply)?

Art supplies	Materials for	STEM	Computers	Psychological

	students with disabilities	resources		testing
Music supplies	Online teaching program	Resource teacher	Smart board technology	District policy makers
PE supplies	Instructional software	Professional learning communities	Counseling/psychological services	Community clubs, volunteers, etc.
IEP software	Curriculum standards/manuals	Professional library	Remediation services	Rec department, tech school, etc.
IEPs	Learning games	Policy manuals	Computers	

In numbers 9-19, please rate your beliefs about your relationship with your principal (leader) on the following scale, ranked Strongly Disagree to Strongly Agree:

9. I like my leader very much as a person.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

10. My leader the kind of person one would like to have as a friend.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

11. My leader is a lot of fun to work with.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

12. I feel that my leader would defend my work actions to a superior, even without complete knowledge of the issue in question.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

13. My leader would come to my defense if I were "attacked" by others.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

14. My leader would defend me to others in the organization if I made an honest mistake.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

15. I do work for my leader that goes beyond what is specified in my job description or what is normally expected of me.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

16. I am willing to apply extra effort, beyond that normally required to further the interests of my work group.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

17. I am impressed with my leader's knowledge of the job.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

18. I respect my leader's knowledge of and competence on the job.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

19. I admire my leader's professional skills.

Strongly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Strongly Agree

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