THE EFFECT OF TEACHERS' SOCIAL NETWORKS ON TEACHING PRACTICES AND CLASS COMPOSITION

By

CHONG MIN KIM

A DISSERTATION

Submitted to
Michigan State University
In partial fulfillment of the requirements
For the degree of

DOCTOR OF PHILSOPHY

Measurement and Quantitative Methods

2011

ABSTRACT

THE EFFECT OF TEACHERS' SOCIAL NETWORKS
ON TEACHING PRACTICES AND CLASS COMPOSITION

By

CHONG MIN KIM

Central to this dissertation was an examination of the role teachers' social networks play in schools as living organizations through three studies. The first study investigated the impact of teachers' social networks on teaching practices. Recent evidence suggests that teachers' social networks have a significant effect on teachers' norms, teachers' learning in communities of practice, distributed leadership, the implementation of innovations, and students' attainment including student learning and academic achievement in core subjects (Bryk & Schneider, 2002; Coburn & Russell, 2008; Frank et al., 2011; Spillane, 2006; Supovitz, Sirinides & May, 2010). Relatively little research, however, has been carried out on estimating the effect of teachers' social networks on teaching practices. The results of the first study indicated that *the formal organizational structure of the school and teachers' social network structure at time 1 affect teachers' social networks at time 2*, which *affect teachers' teaching practices at time 3*. In conclusion, the first study shows that teachers' social networks can improve teaching practice by changing formal (grade) and informal (subgroup) structure.

The second study explored the effect of teachers' social networks on class composition. Previous studies show that class composition and peer effects have an important impact on students' learning (Burns & Mason, 2002; Dreeben & Barr, 1988; Harris, 2010). Methodologically, Value-Added Models have often been used to estimate the teachers' effects on student academic achievement with the assumption of random sampling and random assignment.

Although there were studies about teachers' assignment between schools (Lankford, Loeb & Wyckoff, 2002) and students' assignment within schools (Rothstein, 2008), fewer studies have attempted to explore the effects of teachers' social networks on class composition. The results of the second study indicated that *teachers' social networks affected class composition through non-random assignment of students to teachers with respect to students' previous academic achievement as well as economic status*. Thus, the second research shows that teachers' social networks can indirectly affect students' learning by influencing class composition with respect to previous academic achievement as well as economic status.

Finally, in the third study, I quantify the robustness of the statistical inferences models in chapters 2 and 3 for valid causal inference. Generally, observational studies may have weak causal inference due to differences in unobserved preexisting conditions as well as time order of cause. By quantifying the impact threshold of a confounding variable, however, we can evaluate the sensitivity of causal claims to an unobserved confounding factor. Thus, this study evaluates Impact Threshold of a Confounding Variable (ITCV) to invalidate the causal inference in chapters 2 and 3.

In spite of limitations including missing values, reliability and validity of network measurement, and a limited sample, these chapters offer significant insight into the role teachers' social networks play in schools as organizations. Through a systematic analysis of the influence of these networks on key aspects of the student experience, this dissertation highlights the importance of teachers' social networks for teacher behaviors and in learning contexts.

Dedication

My dedication goes to my God, to my parents Soon Nyu Shin, Kwang Chul Kim, to my lovely wife Eun Joo, and to my precious daughter Claire Minjeoung.

Acknowledgements

I would like to express my deepest and sincere gratitude to chair of both my guidance and dissertation committees, Dr. Kenneth A. Frank, for his endless help and encouragement throughout the duration of my doctoral studies. Without his insightful direction and expertise of social networks and casual inference, it would not have been possible for me to complete this work. Dr. Frank was continually devoted to providing critical and insightful comments and suggestions. It has been delightful for me to conduct various projects about social networks with him. It has been especially valuable for me to learn from his cutting-edge expertise and skills of statistical analyses. It has been a great honor to have him as my advisor.

Of particular help in guiding me through my times as a doctoral student and in the completion of my dissertation has been my dissertation committee: Dr. James P. Spillane, Dr. Peter Youngs, Dr. Mark D. Reckase, and Dr. Barbara Schneider. I am especially indebted to Dr. Spillane for providing me with opportunities to expand my scope and knowledge of distributed leadership through valuable internships and projects as well as data for chapter 3 of my dissertation. I was very fortunate to be able to join the Distributed Leadership Study, which led to developing my interests in leadership theories and methods. I would also like to thank Dr. Youngs, who provided kind and detailed guidelines as well as comfort whenever I asked him about writing my dissertation. I have truly enjoy having discussions with him as a colleague and friend. I must thank Dr. Reckase for his generosity and his offering an interesting Value-Added Model course as well as other valuable measurement courses. Dr. Reckase's courses provided me with learning and practicing measurement expertise and skills through innovative and challengeable assignments. It has been a great comfort for me to visit his office to see advice as though from a father. I am very grateful to Dr. Schneider for her valuable directions throughout the course of this study.

I would like to express my deepest thanks to Dr. William Penuel and Min Sun. They are wonderful coworkers on catalyzing network expertise study (chapter 2 of my dissertation), funded by the National Science Foundation.

In addition, thanks also go to my precious academic mentors: Dr. Sang-Jin Kang, Dr. Won-sup Jang, Dr. Gue-min Lee, and Dr. Kyung-Seok Min. Dr. Kang introduced me to hierarchical linear models including educational statistics studies at Yonsei University and helped me to start the doctoral program at Michigan State University. Dr. Jang also introduced me to social capital studies at Yonsei University. Dr. Lee and Dr. Min provided invaluable advices like big brothers.

I would like to express thanks to my colleagues – Jonghwan Lee, Hyesuk Jang, Eun Hye Ham, Dr. Minh Duong, Ha Min Baik, Seung-Hwan Ham, Dr. Wang Jun Kim, Dr. Tae Seob Shin, Hosun Kang, Sun Hee Baik, Eui Jun Jeong, and Jeoung Jin Kang for their support and help.

I owe thanks to colleagues at the Distributed Leadership Study in Northwestern University, especially Dr. Becca Lowenhaupt, Dr. Linda C. Lee, Kaleen Healey, and Allison Kenney. Allison read all the chapters of this dissertation and helped me revise my arguments.

Finally, my acknowledgements go to my parents (-in-law) for their unconditional love and support and to my wife Eun Joo for her help and trust in me and to my precious daughter Claire Minjeoung. Also thanks to my entire family in Korea, especially my sister Hyun Joo and my brother Yong Gi for their emotional support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1: Theory of Teachers' Social Networks

Salancik (1995) pointed out that there was a need for a good network theory of organization and suggested that "A network theory should do either of two things: (1) It should propose how adding or subtracting a particular interaction in an organizational network will change coordination among actors in the network; or (2) It should propose how a network structure enables and disenables the interactions between two parties" (p. 348).

After criticism by Salancik (1995), some researchers tried to summarize the relevant network theories in communication (Contractor, Wasserman & Faust, 2006; Monge & Contractor, 2003) as well as organization (Kilduff & Tsai, 2003). With respect to building network theories in organization, Kilduff & Tsai (2003) classified three strategies which previous researchers have used. The first strategy is to import graph theory from mathematics and balance theory from social psychology. The second strategy is to use home-grown concepts such as the strength of weak ties (Granovetter, 1973) or structural role theory (Burt, 1992). The third strategy is to export network concepts into previous organizational theories such as resource dependence (Pfeffer & Salanick, 1978) or transaction cost economics (Williamson, 1981).

With respect to building network theories in education, educational researchers have focused on social capital theory (Daly, 2010; Finnigan & Daly, 2010; Frank, Zhao, & Borman, 2004; Moolenaar & Sleegers, 2010; Penuel et. al, 2009, 2011) and have emphasized the importance of teachers' social capital. A recent study by Häuberer (2011) pointed out the weakness of Bourdieu's, Coleman's, Putnam's, Burt's and Lin's approach to social capital and proposed a formalized concept of social capital. This researcher insisted that a social capital concept applies to a hierarchically structured society with the key notion of "a resource embedded in social relationships."

Like the above definition of social capital, teachers' social capital should include teachers' social networks. Even if the teachers' social capital is very important, we can't improve teachers' social capital without changing teachers' social networks because the core element of social capital is social networks.

Even though many researchers have used social capital theories to build social networks theories in education, they did not build specific social network theories which are appropriate in elementary school contexts. To propose and test specific social network theories in elementary school, this dissertation proposes hypotheses which investigate the relationship among social networks, structure, hierarchy and time when we examine the effects of teachers' social networks.

Hypothesis 1-1: *Previous formal organizational structure at a higher level (level 2) affects the formation of new ties of social networks at a lower level (level 1)*, as shown in Figure 1.1. For example, the formal organizational structure of the school (e.g., grade level) affects the formation of new ties in teachers' social networks (See chapter 2). If we can change the formal organizational structure at higher levels, we can change the formation of new ties in social networks at lower levels.

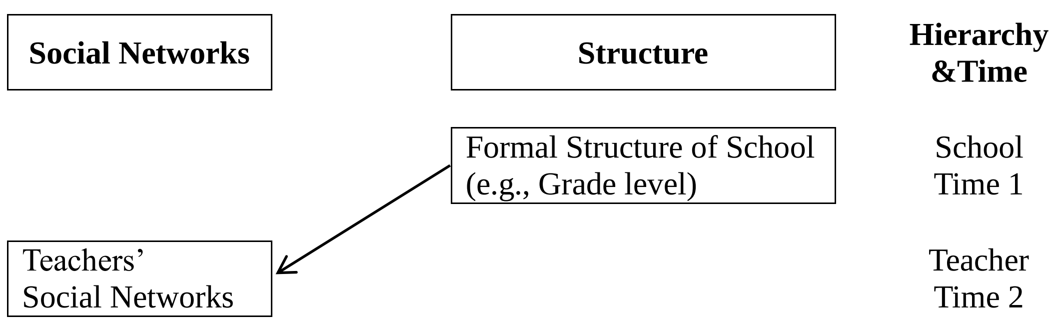

Figure 1.1. The relationship among the formal structure of school and teachers' social networks.

Hypothesis 1-2: Previous network structure at a higher level (level 2) affects the formation of new ties of social networks at a lower level (level 1), as shown in Figure 1.2. For example, teachers' formal or informal network structure (e.g. formal grade level meeting or informal cohesive subgroup) at time 1 affect the formation of new ties in teachers' social networks at time 2 (See chapter 2). If we can change the formal network structure of higher levels (e.g. formal cross grade level meeting) in 2010, we can change the formation of new ties in social networks of lower levels in 2011.

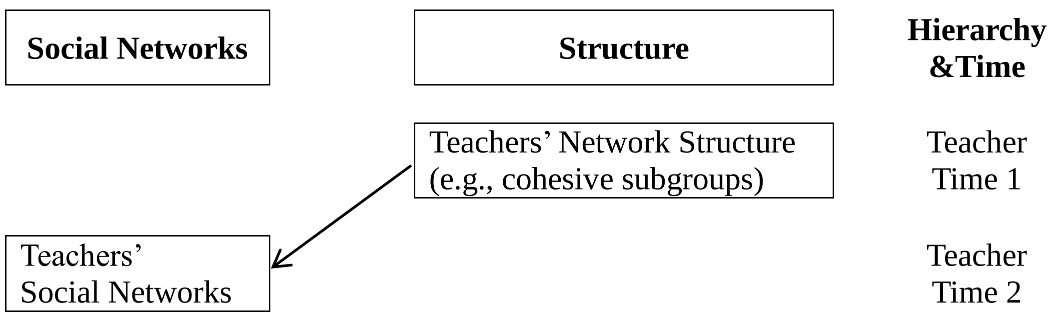

Figure 1.2. The relationship among teachers' network structure and teachers' social networks.

Hypothesis 2-1: Social networks at level 3 in time 1 affect human capital at level 2 in time 2, as shown in Figure 1.3. In other words, teachers' social network at level 3 in 2010 can affect teachers' human capital at level 2 in 2011 (See chapter 2).

Hypothesis 2-2: Previous social networks at a higher level (level 2) affect current formal organizational structure at a lower level (level 1), as shown in Figure 1.3. For example, teachers' social networks at time 1 would influence students' formal organizational structure (e.g. class composition) at time 2 (See chapter 3). If we can change the social networks at level 2 at time 1, we can change the formal organizational structure at level 1 at time 2.

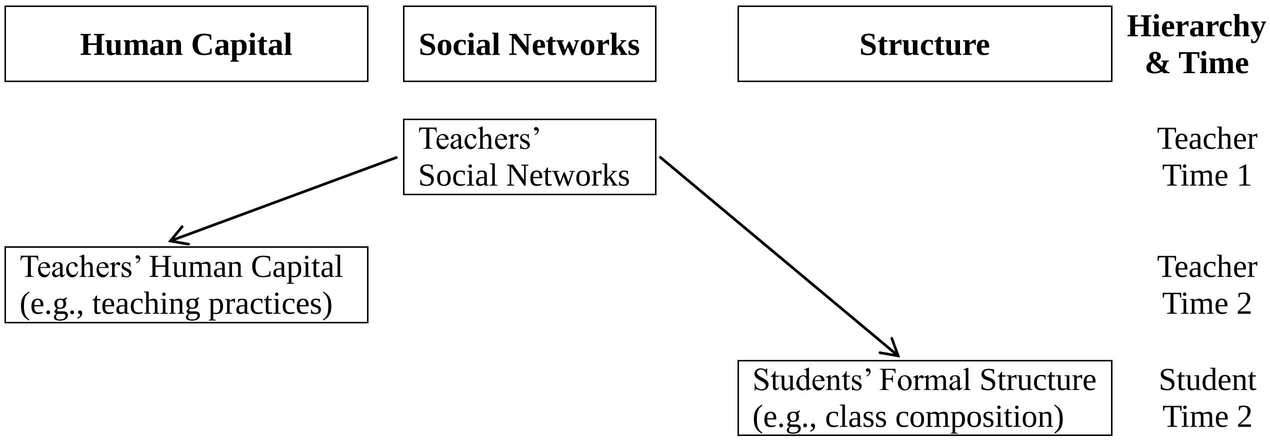

Figure 1.3. The effects of teachers' social networks on teachers' human capital and students' formal structure.

Hypothesis 3-1: Through hypothesis 1-1, 1-2, and 2-1, previous formal organizational structure and formal or informal network structure at level 3 in time 1 affect the human capital at level 1 from a coevolution perspective.

As shown in Figure 1.4, the formal organizational structure of school at level 3 in 2009 can affect teachers' social network at level 2 in 2010 (*hypothesis 1-1*) and teachers' formal or informal network structure at level 3 in 2009 can affect teachers' social network at level 2 in 2010 (*hypothesis 1-2*), which can affect teachers' human capital at level 1 in 2011 (*hypothesis 2-1*).

Hypothesis 3-2: Through hypothesis 1-1, 1-2, and 2-2, previous formal organizational structure and formal or informal network structure at level 3 in time 1 affect the formal organizational structure of level 1 from a coevolution perspective.

As shown in Figure 1.4, the formal organizational structure of the school at level 3 in 2009 and teachers' formal or informal network structure at level 3 in 2009 can affect teachers' social network at level 2 in 2010, which can affect students' formal organizational structure at level 1 in 2011 (*hypothesis 2-2*).

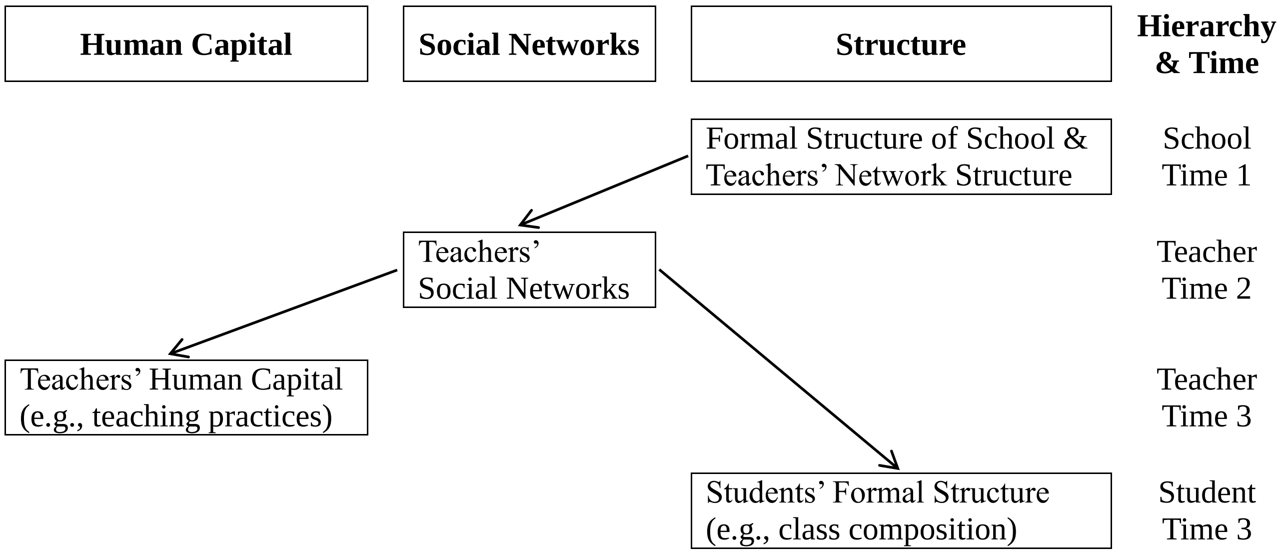

Figure 1.4. The relationship among teachers' human capital, teachers' social networks, and structure.

Hypothesis 3-1 can be applied to students as shown in Figure 1.5. Instead of testing the hypothesis, this dissertation presented relevant previous results (See chapter 3).

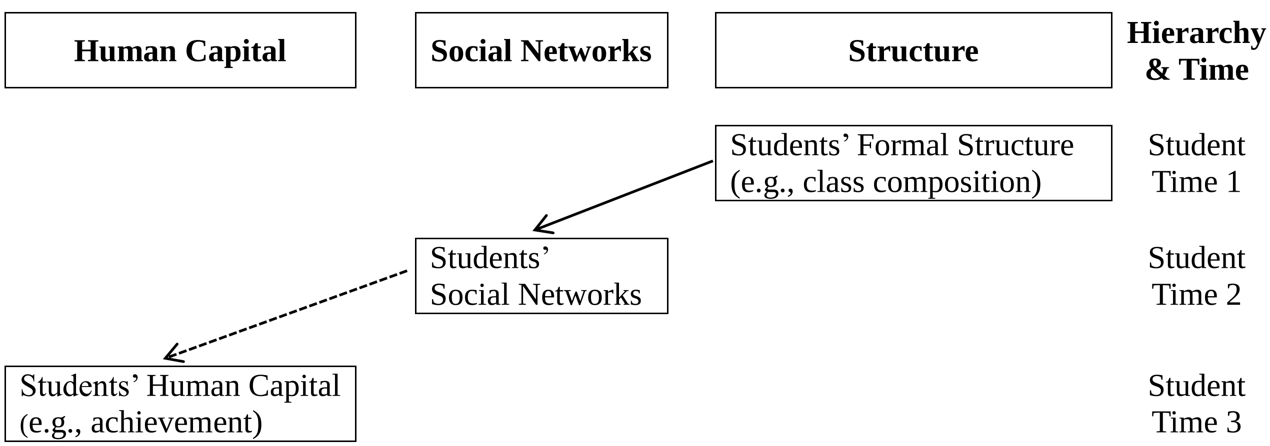

Figure 1.5. The relationship among students' human capital, structure, and social networks.

Hypothesis 4: *Human capital at a higher level (level 3) and time 2 can affect human capital at a lower level (level 1).* Instead of testing hypothesis 4, this dissertation presents relevant previous results of school and teacher effectiveness studies (See chapter 2).

Taken together, the formal organizational structure of the school and teachers' network structure can affect teachers' social networks (*Hypothesis 1-1 and 1-2)*, which can directly affect not only teachers' human capital (*Hypothesis 2-1)* but also students' formal structure (*Hypothesis 2-2).* Indirectly, teachers' social network can affect students' human capital through changing students' social network (*Hypothesis 3-1)* as well as changing teachers' human capital (*Hypothesis 4).*

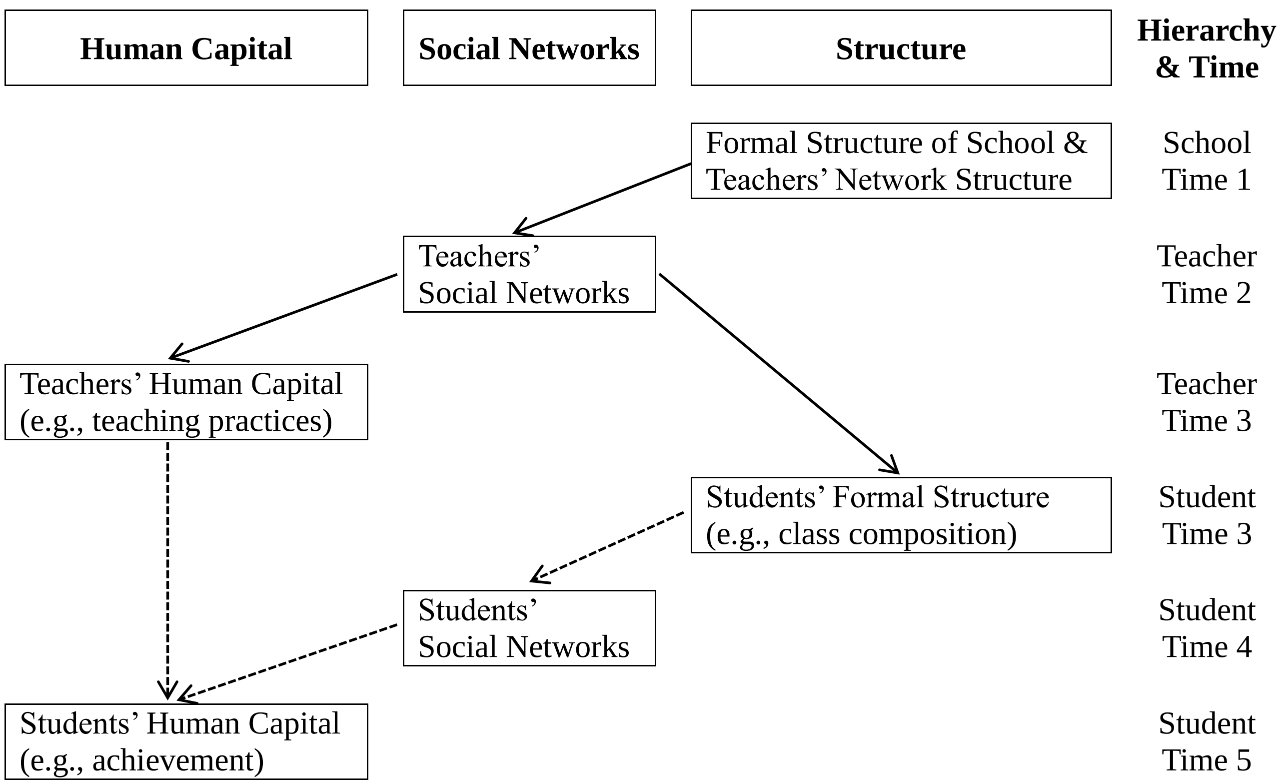

Figure 1.6. The relationship among human capital, structure, and social networks.

Specifically, in chapter 2, first, I examine whether or not the formal organizational structure of school and teachers' network structure can affect teachers' social networks (*Hypothesis 1-1 and 1-2) through selection models*. Second, I test whether or not teachers' social networks can directly affect teaching practices (*Hypothesis 2-1) through influence and dynamics models.*

Numerous researchers have found that the quality of teaching has an important impact on students' learning (Brophy & Good, 1986; Kyriakides et al., 2008; Nye et al., 2004; Teddlie & Reynolds, 2000). In recent years, many studies have reported positive outcomes of teachers' social networks as well, including teachers' norms (Bryk & Schneider, 2002); teachers' learning in communities of practice (Coburn & Russell, 2008); distributed leadership (Spillane, 2006); implementation of innovations (Frank, Zhao & Borman, 2004; Frank et al., 2011; Penuel et al., 2007, 2009); and students' attainment, students' learning, and academic achievement in core subjects (Hadfield & Jopling, 2007; Supovitz, Sirinides & May, 2010). Methodologically, however, previous studies have not estimated the dynamic interplay of teachers' social networks and teaching practices. Thus, the study in chapter 2 takes into account models of selection (the pattern of relations in a social network as a function of attributes of people) and influence (attributes of people as a function of relations in the social networks) in one dynamic model. The main research questions are: How do the mathematics teaching practices advice network and mathematics teaching practices change over two years? What can explain these changes?

Three models of selection, influence, and actor-oriented models are shown in Figure 1.7. Previous studies have investigated the effect of teachers' attributes (e.g., efficacy) on teaching practices without considering teachers' networks. Newer influence models have studied the effect of teachers' networks on teaching practices, which suggest that there are significant effects of teachers' networks on teaching practices after controlling for teachers' attributes (e.g., Frank et al., 2004). In addition, selection models have examined the effect of teachers' attributes on teachers' networks, which have shown which characteristics of actors are related to the formation of teachers' networks (e.g., Frank, 2009).

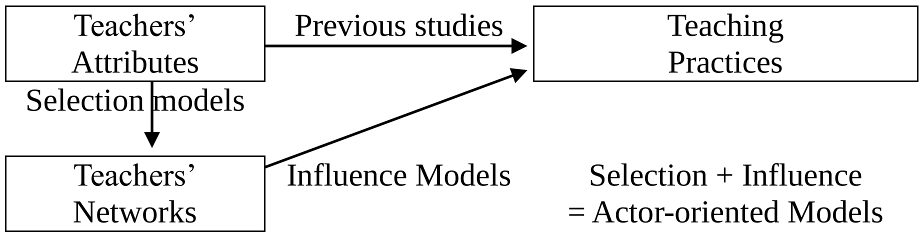

Figure 1.7. Three models of selection, influence, and actor-oriented in chapter 2.

Therefore, teachers' networks could be a dependent or independent variable depending on whether the model focuses on selection or influence. In order for both teachers' networks and teaching practices to interchange roles as dependent and independent variables, actor-oriented models have investigated both the change of teachers' networks and teaching practices.

I investigate another aspect of schooling influenced by teachers' social networks. In chapter 3, I test whether or not teachers' social networks can affect class composition (*Hypothesis 2-2)* because classroom composition and peer effects influence students' learning (Burns & Mason, 2002; Dreeben & Barr, 1988; Harris, 2010).

Methodologically, Value-Added Models have been used to estimate teachers' effects on student academic achievement relying on the assumption of random sampling and random assignment. Although some studies have explored teachers' assignment between schools (Jackson, 2009; Lankford, Loeb & Wyckoff, 2002; Miller, 2009) and students' assignment within schools (Koedel & Betts, 2009; Monk, 1987; Rothstein, 2008), little is understood about the mechanisms of assignment of teachers to students that account for teachers' social networks.

In this chapter, I analyze the effect of teachers' social networks on students' assignment with respect to students' previous academic achievement in core subjects (English/language arts and mathematics) as well as students' previous economic status in elementary schools. The main research question is: Do teachers' social networks affect class composition through non-random assignment of students to teachers with respect to students' previous academic achievement and economic status?

The relationships among teachers' attributes, teachers' social networks, and class composition are shown in Figure 1.8. Few previous studies have examined the effect of teachers' attributes (e.g., teaching experience) and social networks (e.g., advice networks) on class composition with respect to students' previous academic achievement and economic status. Thus, first, this study investigated the effect of teachers' attributes on class composition. Second, the effects of teachers' social networks on class composition are presented after controlling for teachers' attributes.

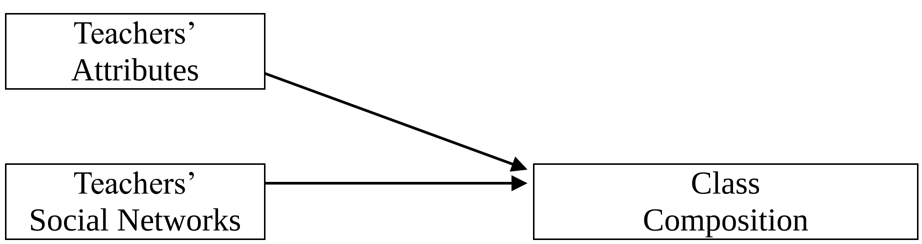

Figure 1.8. The relationship among teachers' attributes, teachers' social networks, and class composition in chapter 3.

This study is significant in that it informs whether or not teachers use their social networks to affect class composition. This information will be important when we test whether or not teachers' social network can indirectly affect students' human capital through changing students' social network.

In chapter 4, I quantify the robustness of the statistical inferences models in chapters 2 and 3 for valid causal inference. Previous studies present three conditions for valid causal inference which are 1) there is an association between cause and effect, 2) cause preexists before effect, and 3) there is no confounding variable which affect cause and effect. Generally, observational studies may have weak causal inference due to differences in unobserved preexisting conditions. By quantifying the impact threshold of a confounding variable, however, we can evaluate the sensitivity of causal claims to an unobserved confounding factor. Thus, this study evaluates the Impact Threshold of a Confounding Variable (ITCV) to invalidate the causal inference in chapters 2 and 3.

This dissertation consists of the three studies described above, as well as a concluding chapter. The chapters were organized similarly as follows. Chapter 2 describes the first study. In this chapter, I first introduce school effectiveness and social network studies. Also, the dynamic of teachers' social networks and behavior are presented with a focus on empirical studies using actor-oriented models. Second, data and method are presented including sample, dependent variables, independent variables, selection models, influence models and actor-oriented models. Third, the results of selection, influence and actor-oriented models are shared. Finally, the discussion and conclusion are presented.

In chapter 3, I discuss the second study. In this chapter, class composition studies and value-added models are introduced. Second, I present my data and methods including sample, dependent variables, and independent variables, including teachers' attributes and social networks. Third, the results about relationships between teachers' social networks and class composition are presented. Finally, the discussion and conclusion are shared.

In chapter 4, I present the third study. Causal inference and robustness indices studies are offered. In this chapter, the same data and measures as chapter 2 and 3 are used. Second, the results of ITCV in chapter 2 and 3 models are presented. Finally, the discussion and conclusion are included.

In the concluding chapter 5, policies for teachers' social networks are suggested as they relate to teachers and students in instruction and learning contexts; (1) the policy of organizational structure of school such as grade and class formation and (2) the policy of formal network structure such as grade level meetings.

In summary, the purposes of this dissertation are to test hypotheses regarding teachers' social networks through three empirical studies. In addition, the structure of this dissertation is shown as Figure 1.9.

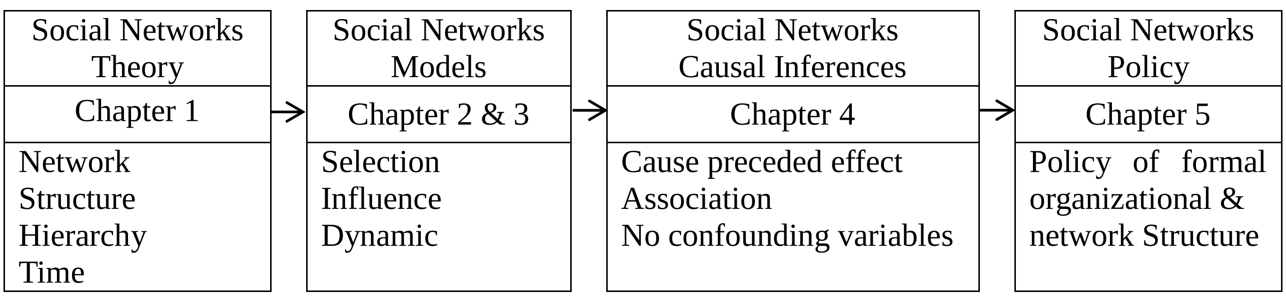

Figure 1.9. The structure of dissertation: theories, models, causal Inferences, and policy.

Taken together, these chapters offer significant insight into the role teachers' social networks play in schools as living organizations. Through a systematic analysis of the influence of these networks on key aspects of the student experience, this dissertation highlights the importance of teachers' social networks for teacher behaviors and in learning contexts.

Chapter 2: The Effect of Teachers' Social Networks on Teaching Practices

Introduction

How can we improve student achievement? Over the last two decades, school effectiveness studies have emphasized the classroom effect relative to school effects in elucidating variation on student achievement in affective as well as cognitive outcomes (Teddlie & Reynolds, 2000). Moreover, the most important factor at the classroom level is quality of teaching practices (Brophy & Good, 1986; Nye et al., 2004).

In addition, studies about teachers' cognition have emphasized teachers' knowledge, beliefs, and decision-making (Calderhead, 1996). Specifically, some studies identified the effect of teachers' knowledge (e.g., pedagogical or content knowledge) on gains in academic achievement (Hill, Rowan & Ball, 2005; Kennedy, Ahn & Choi, 2008).

We can improve teachers' knowledge to improve teaching practices. Recent studies have emphasized not only the role of professional development (Darling-Hammond et al., 2009; Desimone, 2009; Guskey & Yoon, 2009; Heck et al., 2008; Ingvarson et al., 2005; Wayne et al., 2008), but also the importance of teachers' social capital (Daly, 2010; Finnigan & Daly, 2010; Frank, Zhao, & Borman, 2004; Moolenaar & Sleegers, 2010; Penuel et. al, 2009, 2011). Social network researchers suggest that teachers' social networks have a significant effect on teachers' norms, teachers' learning in communities of practice, distributed leadership, and the implementation of innovations (Bryk & Schneider, 2002; Coburn & Russell, 2008; Penuel et al., 2007; Spillane, 2006). Specifically, recent studies pointed out peer's influence on teaching practices through social interactions (Sun & Frank, 2011) and human capital spillovers (Jackson & Bruegmann, 2009). In other words, teachers' social networks can affect teachers' human capital (e.g., teaching practices) as well as social capital (e.g., trust).

How can we estimate the effect of teachers' social networks? Social network analysis pertains not only to selection modeling of the pattern of relations in a social network as a function of attributes of people, but also to influence modeling of attributes of people as a function of relations in the social network (Frank, 1998). Selection modeling can be implemented through qualitative studies or statistical models such as p1, p2, or p*. In addition, influence modeling can be implemented through qualitative studies or statistical modeling such as multilevel models.

There have been considerable advances in estimating the effects on and of teachers' social networks through selection and influence modeling, but the previous studies were confined to estimate two models separately (Penuel et al., 2007, 2008). Actor-oriented models, however, can be evaluated for co-evolving social networks and individual behaviors (Bunt & Groenewegen, 2007; Burk et al., 2007; Pearson et al., 2006; Snijders, 2001; Steglich et al., 2006, 2010). These models can be estimated through SIENA (Simulation Investigation for Empirical Network Analysis). Although are were a few studies using dynamic modeling in education (Daly & Finnigan, 2011; Orlina, 2010), little research has been carried out to estimate the effects of teachers' social networks and teaching behavior simultaneously in education by using longitudinal data. I will do so in this study. Thus, the purpose of this study is to examine the effects of teachers' social networks on teaching practices through selection, influences and dynamic modeling.

This chapter is organized as follows. First, I present school and teacher effectiveness studies briefly and I introduce social network studies especially regarding teachers' social networks. Also, I present dynamic models of teachers' social networks and behavior with a focus on empirical studies using actor-oriented models in other fields as theoretical background. Second, data and methods are presented including sample, dependent variables, independent variables, selection model, influence model and actor-oriented models. Third, the results of selection, influence and actor-oriented model are shared. Finally, the discussion and conclusion of the dynamics of teaching practices and advice networks are presented.

Literature Review

1. School and Teacher Effectiveness Studies: **Human Capital** *or* **Social Capital**

In school effectiveness studies, emphasis has shifted from school effects to classroom effects especially concerning the quality of teaching practices in theoretical models (Kyriakides et al., 2008). Much research has documented that in explaining variation on student achievement in both cognitive and affective outcomes, the classroom effect is more fundamental than the school effect (Teddlie & Reynolds, 2000). Furthermore, quality of teaching practices is the most significant factor at the classroom level (Brophy & Good, 1986). Teddlie and Reynolds (2000) described this paradigm shift in Table 2.1.

Table 2.1 Characteristics of two school improvement paradigms

Characteristics	1960s	1980s
Orientation	Top down	Bottom up
Knowledge Base	Elite knowledge	Practitioner Knowledge
Target	Organization or curriculum based	Process based
Outcomes	Pupil outcome orientated	School process orientated
Goals	Outcomes as given	Outcomes problematic
Focus	School	Teacher
Methods	Quantitative	Qualitative
Site	Outside school	Within school
Focus	Part of school	Whole school

Source: Teddlie and Reynolds, 2000. p. 214

In addition, studies concerning teachers' cognition (e.g., efficacy) have been conducted over three decades emphasizing teachers' knowledge and beliefs, thinking, and decision-making (Calderhead, 1996). Recently, three dimensions of teacher quality as personal resources, performance and effectiveness were conceptualized (Kennedy, 2007). Among the three dimensions, personal resources focus on teachers' beliefs as well as teachers' knowledge.

Specifically, some studies pointed out the effect of teachers' knowledge (e.g., pedagogical or content knowledge) on gains in academic achievement (Hill, Rowan & Ball, 2005; Kennedy, Ahn & Choi, 2008).

Through pre-service teacher education and in-service teacher training, we can improve knowledge and teaching practices. With respect to in-service teacher training, recent studies have emphasized the role of professional development activities which included content focus, active learning, coherence, duration, and collective participation because these professional development can increase teachers' knowledge, which lead to changes in teaching practices and students' achievement (Desimone, 2009).

In addition to professional development, educational research has focused on social capital (Coleman, 1988) and emphasized the importance of teachers' social capital (Daly, 2010; Finnigan & Daly, 2010; Frank, Zhao, & Borman, 2004; Moolenaar & Sleegers, 2010; Penuel et. al, 2009, 2011). Specifically, recent studies pointed out peer's influence on teaching practices through social interactions (Sun & Frank, 2011) and human capital spillovers (Jackson & Bruegmann, 2009). In summary, the results of school and teacher effectiveness studies indicate that teaching practices can be improved through not only teachers' professional development but also teachers' social interactions and human capital spillovers. Therefore, *teachers' human capital at time 1 can affect students' human capital at time 2.*

2. Teachers' Social Networks

1) Effects on **Human Capital** *or* **Social Capital**

In recent years, many studies have reported effects of teachers' social networks, including teachers' norms (Bryk & Schneider, 2002), innovative climate (Moolenaar & Sleegers, 2010), teachers' learning in communities of practice (Coburn & Russell, 2008), distributed leadership (Spillane, 2006; Penuel et al, 2010), implementation of innovations (Frank, Zhao & Borman, 2004; Penuel et al., 2007, 2009) and students' attainment, students' learning and academic achievement in core subjects (Hadfield & Jopling, 2007; Supovitz, Sirinides & May, 2010). In other words, teachers' social networks can affect teachers' human capital (e.g., teaching practices) as well as social capital (e.g., trust).

With respect to the effects on social capital, through multilevel modeling, one study found that the relational dynamics in each school community significantly influenced meaningful school improvement efforts and relational trust, facilitators of social capital, in very disadvantaged urban school communities (Bryk & Schneider, 2002). In addition, the role of social networks through trust in supporting an innovative climate was pointed out through multilevel modeling using Dutch schools data (Moolenaar & Sleegers, 2010). Another study found that prior professional relations and proximity were key factors for trust between teachers through qualitative methods (Coburn & Russell, 2008). In summary, these results indicated that teachers' social networks can affect trust as a facilitator of teachers' social capital (Bryk & Schneider, 2002; Coburn & Russell, 2008; Moolenaar & Sleegers, 2010).

With respect to the effects on human capital, a recent study found that formal routines and informal interactions can explain how leadership is manifest in everyday practices in schools (Spillane, 2006). In explaining the significance of leadership expertise, this study emphasized that if expertise is distributed, the school leader rather than the individual leader would be the most appropriate unit for considering the improvement of leadership expertise. Other studies have shown how teachers' social networks facilitated change in school reform practices through distributed leadership (Spillane, 2006) and teachers to teachers influences (Penuel et al., 2010). Furthermore, recent studies pointed out peer's influence on teaching practices through social interactions (Sun & Frank, 2011) and human capital spillovers (Jackson & Bruegmann, 2009). In other words, these results indicated that teachers' social networks can affect teaching practices as teachers' human capital.

2) Modeling: **Selection *or* Influence**

Due to the improvement of multilevel statistical methods, the school effects model overcame the choice of unit of analysis, misestimated standard errors, heterogeneity of regression, ecological fallacy and poor precision (Hopkins, 1982; Bryk & Raudenbush, 1992; Goldstein, 1986). Finally, multilevel models solved the discordance between theoretical model and methodological model of school effect.

Although multilevel models have improved the studies of school and teacher effects, there was also a certain level of limitation because previous models did not consider teachers' social interaction as peer effects. Methodologically, previous models did not consider interdependence among teachers, which lead to biased estimates of school and teachers' effects.

Social network analysis, however, can consider interdependencies among teachers represented by social network data. Frank (1998) noted that even though multilevel models may integrate distinctiveness ascribed to both students and schools as organizations, they have not been applied to include aspects of the interaction among individuals defining the social contexts in which individuals teach and learn. To solve this limitation, relations among the people in schools have been analyzed by using social network analysis in education (Frank, 1995, 1998; Frank, Zhao and Borman, 2004).

Social network analysis pertains not only to selection modeling of the pattern of relations in a social network as a function of attributes of people, but also to influence modeling of attributes of people as a function of relations in the social network (Frank, 1998). While selection models can help us to recognize the creation of social contexts, influence models can help us to understand the effects of those contexts on individuals (Frank, 1998).

Selection modeling can be implemented through qualitative studies or statistical modeling such as p1 model (Holland & Leinhard, 1981), p2 model (Van Duijn, Snijders, & Zijlstra, 2004), or p* model (Wasserman & Pattison, 1996). In addition, influence modeling can be implemented through qualitative studies or statistical modeling such as multilevel models (Bryk & Raudenbush, 1992; Goldstein, 1986).

In summary, there have been considerable advances in estimating the effects of teachers' social networks through selection and influence modeling, but previous studies were confined to choosing appropriate methods; thus estimating two models separately (Penuel et al., 2007, 2008). In other words, although both selection and influence processes probably occur among teachers, previous studies have presented the models of selection and influence in isolation.

3. Selection ***and*** Influence: **Dynamic Modeling**

Frank et al. (2010) summarized that "A full dynamic conceptualization accounts for actors' behaviors as outcomes influenced by actors' attributes or network (influence model), and actors' networks as outcomes influenced by actors' attributes or behaviors (selection model)" (p.

230). In addition, Frank et al. (2010) argued that the network processes (e.g., knowledge flow) as both predictor and outcome could be modeled by dynamic models, which are helpful when tracking how resources flow through a network. By using simulation, parameters of actor-oriented modes are estimated from the relations and behaviors at time 1 based on random sequences in order to approximate the network and behaviors at time 2 (Frank et al., 2010).

Recent studies using actor-oriented modeling showed that both selection and influence processes played a crucial role regarding behavioral of dynamics (Bunt & Groenewegen, 2007; Burk et al., 2007; Pearson et al., 2006; Steglich et al., 2006).

Steglich et al. (2006) investigated the joint dynamics of taste in music, alcohol consumption, and friendship ties among adolescents to assess selection and influence processes by using actor-oriented models and data from teenage friends and lifestyle. This consisted of 129 cohorts of pupils at a school in the west of Scotland starting in 1995 with pupils aged 13 and ending in 1997. They found that a majority of pupils listened to music in techno and rock scales and rock preferences seemed to coincide with higher social status. Also, they found that there was a small exceptional group of mainly girls, listening to music styles in the classical scale, barely drinking alcohol, and being avoided by most of their schoolmates. Steglich et al. (2006) assessed selection and influence processes using actor-oriented models, but there are some theoretical limitations because they focused on friendship among students and students' behavior without considering organizational effects (e.g., class formation).

Burk et al. (2007) examined the co-evolution of friendship networks and delinquent behaviors in a longitudinal sample of Swedish adolescents of 260 students (132 males and 128 females) attending 52 classrooms in 9 schools in a small city in central Sweden for four annual waves. By using actor-oriented network models and longitudinal social network analysis, they found that both selection and influence processes played a substantive role in the observed dynamics of delinquent behaviors, with influence having a relatively stronger role than selection (especially in reciprocated friendships). A methodological strong point was that Burk et al. (2007) examined the co-evolution of friendship networks and delinquent behaviors by using actor-oriented models, but a theoretical weak point was that they focused on friendship among students and delinquent behaviors without considering organizational effects (e.g., formal structure of school).

In addition, Snijders and Baerveldt (2003) proposed a multilevel approach to investigating the evolution of multiple networks. They assumed that the basic evolution process was the same with different parameter values between different networks. By using stochastic actor-oriented models and Markov Chain Monte Carlo methods, this study showed that delinquent behavior similarity had a positive effect on both tie formation and tie dissolution.

Although there were a few studies using actor-oriented models in education (Daly & Finnigan, 2011; Orlina, 2010), little research has been carried out to estimate the dynamic of teachers' social networks and teaching behavior simultaneously in education by using longitudinal data. I will do so in this study.

As described in chapter 1, this study will test the following two hypotheses to examine the effects of teachers' social networks on teaching practices.

Hypothesis 1-1 and 1-2: The formal organizational structure of the school and teachers' social network structure at time 1 would affect the formation of new ties of teachers' social networks at time 2.

Hypothesis 2-1: *Teachers' social networks at time 1 can affect teachers' teaching practices at time 2.*

Data and Methods

1. Data

The current study is part of a broader project funded by the National Science Foundation to investigate catalyzing network expertise. This sub-study consists of a total of 10 elementary or middle schools. The schools are all located in California, in urban and suburban areas near major cities in Northern and Southern California.

Table 2.2 School demographic information 2007-08

ID	Student Enrollment	% White	FTE Teachers	Title I School
1	441	56.0%	25	No
3	898	0.7%	43	Yes
8	542	14.6%	27	No
26	538	27.1%	26.8	Yes
39	619	37.6%	33.3	No
45	239	77.8%	14.6	No
47	580	74.8%	24.8	No
48	554	70.6%	22.2	No
53	342	64.6%	19.2	No
54	288	25.7%	18.6	Yes

Notes: All schools met AYP in mathematics in school year of 2007-08

The student enrollment size ranged from 288 to 898 as shown in Table 2.2. Five schools had a majority of White student population. The full-time equivalent (FTE) teachers ranged from 14.6 to 43. There were three Title I schools and all schools met AYP in mathematics in the school year of 2007-08.

All faculty members were surveyed in the 10 schools in 2007 and 2008. But the sample in the final analysis differs depending on methods for treating missing values among models. The average teaching experience of the sample was 14.5 years, the mean of years working at the current school was 9 years, and 95% of the teachers had full certification (advanced professional, regular/standard/probationary) in their main assignment field shown in Table 2.3.

Table 2.3 Descriptive statistics of teacher demographics in 2007-08

Variables	Characteristics
Teaching experience (N=198)	
Mean of number of years teaching	14.5
Mean of years working at the current school	9.0
Teacher credential status (N=208)	
No state certification (no certificate or certificate not from California)	3.4%
Percentage of partial certification (temporary, provisional, or emergency state certificate)	1.9%
Percentage of full certification (advanced professional, regular/standard / probationary)	94.7%

2. Measures

1) Dependent Variables

Teachers' mathematics teaching practices advice network: the dependent variable in the selection model is the ties of interaction for each colleague (4-point scales: once or twice a year, monthly, weekly, and daily) in 2008 based on the following question: Which colleagues in this school have helped you in the past twelve months with respect to increasing the STAR mathematics test scores? For the actor-oriented model, dependent variables are the ties of interaction for each colleague in both 2007 and 2008. For analysis, the dependent variable was recoded as 0 =”no tie” and 1 =”tie existence” among teachers within a school.

Teachers' mathematics teaching practices: the dependent variable in the influence model is the extent to which teachers adopted specific teaching practices in mathematics teaching practices in 2008. In the 2008 survey, each teacher was asked to rate how often they had students do a series of activities as part of mathematics instruction *during the last month* on a five-point scale (1= “almost never,” 2= “1 or 2 times a month,” 3= “1 or 2 times a week,” 4= “almost every day," and 5= "one or more times a day."). Seven items were aggregated into a practice variable based on the results of a factor analysis (α=0.87). In the 2007 survey, each teacher was asked to rate how often he or she had students do a series of activities as part of mathematics instruction *during the last week* on a five-point scale (1= "not at all," 2= "1 or 2 times," 3= "3 or 4 time," 4= "5 or 6 times," and 5= "more than 6 times." α=0.88).

Because there was a difference in scales between 2007 (during the last week) and 2008 (during the last month), the dependent variables for the actor-oriented model are recoded on a six-point scale (0="Not at all," 1="1 or 2 times a month," 2="1 or 2 times a week," 3="3 or 4 times a week," 4="almost every day," and 5="one or more times a day.").

Table 2.4 Items for mathematics problem solving teaching practices

Items in 2007 and 2008	2007 Mean (SD)	2008 Mean (SD)
1. Solve problems that have many possible correct answers	1.72 (1.48)	2.44 (1.45)
2. Solve problems in which students have to figure out what method to use to solve them	2.49 (1.60)	3.45 (1.13)
3. Describe the procedure or algorithm they used to solve a problem	2.10 (1.55)	3.27 (1.21)
4. Explain why a procedure or algorithm they used worked to solve a problem	1.80 (1.58)	3.07 (1.34)
5. Prove that a particular method for solving a problem is valid	1.52 (1.62)	3.10 (1.29)
6. Analyze similarities or differences among methods and types of problems	1.23 (1.39)	2.77 (1.32)
7. Practice answering questions that are in the same format as the STAR test	1.71 (1.77)	2.04 (1.68)
Recoded Scales 0:Not at all 1:1 or 2 times a month 2:1 or 2 times a week 3:3 or 4 times a week 4:almost every day 5:one or more times a day	Valid N (listwise) =142 Cronbach's α =0.88 (2007)	Valid N (listwise) =144 Cronbach's α =0.87 (2008)

2) Teacher Attributes

Prior teaching practices in 2007: For the influence model, it could be that the extent to which the teachers included a mathematics teaching practices in 2008 depended on teaching experience with math in 2007. Therefore, we controlled for prior teaching practices.

Mathematics Professional Development in 2008: Mathematics professional development was controlled in the models because learning new expertise through professional development could affect mathematics advice networks and teaching practices. For the selection and influence model, the question was, in the past year, how much professional development have you had in mathematics? The variable scales from 0 to 3 (0= “None at all,” 1= “1-8 hours,” 2= “9-16 hours,” 3= “more than 16 hours,” and 9=”unsure.”).

Mathematics teaching efficacy in 2007: Mathematics teaching efficacy may be related to teaching practices because this specific belief measure teachers’ capacities to affect a student’s achievement. For the selection, influence and actor-oriented models, teachers were asked to rate the extent to which they agreed with each of the following statements (1= “Strongly disagree,” 2= “Disagree,” 3= “Agree,” 4= “Strongly Agree,” and 9=”Unsure.”): “I am responsible for students’ high achievement in mathematics”, “ Different mathematics teaching methods can affect a student’s achievement”, and “I change my teaching approach if students are not doing well in mathematics”. The average of these items was included in models (α=0.68).

Highest Grade Taught in 2008: California schools have mathematics AYP standard which is 37% of students to be proficient by the 2007-08 school year and 47.5% by the 2008-09 school year for students from the third to eighth grades. For the influence model, teachers’ highest grade taught in 2008 was controlled because we assume that teachers in higher grade levels (3rd-8th) may respond less to new norms for their teaching practices than teachers in lower grades (K-2nd).

Mathematics program coordinator role in 2008: For the selection model, teachers were asked if they had a mathematics program coordinator role at the school during the 2007-08 school year and were coded as 0 if the teacher was not a coordinator and 1 if the teacher was a coordinator.

Subgroup mean teaching practices in 2007: To investigate how teachers respond to subgroup norms about teaching practices, subgroup mean teaching practices in 2007 was included in the influence model. A sociometric item regarding professional closest colleagues was used to construct subgroup boundaries (Frank 1995, 1996). Frank's (1995, 1996) network clustering algorithm and software KliqueFinder were used for identifying subgroup membership in 2007. Grand mean centering was used to define the subgroup norm by averaging the extent to which the members of a subgroup implemented mathematics problem solving teaching practices in 2007.

Subgroup mean mathematics teaching efficacy in 2007: To investigate how teachers respond to subgroup norms about teaching efficacy, subgroup mean mathematics teaching efficacy in 2007 was included in the influence model. Grand mean centering was used to define the subgroup norm by averaging the extent to which the members of a subgroup believed their own capacities to affect a student achievement in 2007.

3) Network Variables

Direct Exposure: For the influence model, in order to estimate the effect of network on teaching practices in mathematics, direct exposure variable was:

$$Direct\ Exposure_i = \sum_{\substack{i'=1,\\ i' \neq i}}^{I} (help_{ii'}) \times (provider's\ expertise_{i'}) \times (amount\ of\ help\ provided\ to\ others_{i'})$$

Where
I is the total number of teacher *i'* that provided help to teacher *i*.
$\mathrm{help}_{ii'}$ is the extent to which teacher *i* reported receiving help with teaching mathematics from teacher *i'*.
$\mathrm{provider's\ expertise}_{i'}$ indicates teaching practice in mathematics problem solving in 2007 of teacher *i'*.
$amount\ of\ help\ provided\ to\ others_{i'}$ represents the ability of the help provider *i'* to deliver help.

As teacher *i* (help receiver) receive more help from teacher *i'* (help provider), the direct exposure will increase. In addition, as the help provider has more expertise in mathematics teaching practices and more amounts of help provided to others, the direct exposure will increase.

Same subgroup network in 2007: For the selection and actor-oriented models, after identifying cohesive subgroup within each school, same subgroup networks in 2007 were made by coding as 0 if a teacher had different subgroup membership from the other teacher within a school and 1 if a teacher had the same subgroup membership as the other teacher within a school.

Same grade taught network in 2008: For the selection and actor-oriented models, same grade taught networks in 2008 were created by coding as 0 if teachers *i* and *i'* taught different grade levels and 1 if teachers *i* and *i'* taught the same grade level.

Total of all common meeting types network in 2008: For the selection model, the following question was used to construct the total of all common meeting types: during the 2007-08 school year, in what ways and how frequently do you review annual STAR test data, either for students you are currently teaching or for students you taught last year?: ① "I participate in discussions of data as part of a formal meeting with my grade-level team", ② "I participate in discussions of data as part of a formal meeting with a cross-grade team" and ③ "I participate in discussions of data as part of a full staff meeting" (0= "never," 8= "1~8 times this year," 10= "monthly," 25= "2~3 times a month," and 40="weekly."). If both teachers answered yes to ① and they taught in the same grade level, this ① was counted for common meeting taking the minimum meeting number between actor *i* and *i'*. If both teachers answered yes to ② and they taught different grade levels, common meeting was counted by taking the minimum meeting number of ② between actor *i* and *i'*. If both teachers answered yes to ③, a common meeting of ③ was added by taking the minimum meeting number between actor *i* and *i'*. Finally, all common meetings were computed as "common meeting= minimum (① for *i*, ① for *i'*) + minimum (② for *i*, ② for *i'*) + minimum (③ for *i*, ③ for *i'*)".

For example, if 2nd grade teacher A answered 8 for ①, 10 for ②, 0 for ③ while other 2nd grade teacher B answered 10 for ①, 25 for ②, 0 for ③, all common meetings would be 8 as minimum (8=① for *i*, 10=① for *i'*) + minimum (0=② for *i*, 0=② for *i'*) + minimum (0=③ for *i*, 0=③ for *i'*) = 8+ 0 + 0 because we didn't count ② due to the same grade level taught. If 2nd grade teacher A answered 8 for ①, 10 for ②, 0 for ③ while other 3rd grade teacher B answered 10 for ①, 25 for ②, 0 for ③, all common meetings would be 10 as minimum (0=① for *i*, 0=① for *i'*) + minimum (10=② for *i*, 25=② for *i'*) + minimum (0=③ for *i*, 0=③ for *i'*)

= 0+ 10 + 0 because we didn't count ① due to the different grade level taught. Thus, all common meetings could have the five-scale value as 0, 8, 10, 25, and 40.

3. Methods

To investigate selection and influence effects, I used multilevel p2 models and two level HLM models while I used actor-oriented models and multilevel (meta-analysis) actor-oriented models to examine the dynamics in mathematics teaching practices advice networks and mathematics teaching practices by using SIENA (Simulation Investigation for Empirical Network Analysis) software. A series of descriptive statistics were employed to assess network and teaching practice in selection, influence and actor-oriented models. For SIENA outputs, there were three steps which were a convergence check, parameter values and standard errors, and a collinearity check. First, a convergence check was given to consider deviations between simulated values of the statistics and their observed values (Snijders et al., 2008). The manual for SIENA reports that "For results that are to be reported, it is advisable to carry out a new estimation when one or more of the t-ratios are larger in absolute value than 0.1" (p.32). Second, the rate parameter indicates the estimated number of changes per actor between observations. Third, the collinearity check was presented to see whether there was collinearity among variables.

Missing values of professional development in 2008 had five missing cases out of 209 cases while teaching efficacy in 2007 had 31 missing cases out of 209 cases. All missing cases were recoded as a zero value in model 1 and model 2 of multilevel selection models.

For the influence models, mathematics problem solving teaching practices in 2008 had 56 missing cases out of 209 cases. These were deleted in the two-level HLM models because this was a dependent variable and there was little relevant information for multiple imputation of missing values. After deleting the missing values of the dependent variable, there were two missing cases in teaching efficacy in 2007 and one missing case in the highest grade, which were deleted in two-level HLM models.

I used P2 4.0 version software for multilevel p2 models, HLM 6.0 version for two level HLM models, SIENA 3.2 version for actor-oriented models, and SIENA 08.exe for meta-analysis actor-oriented models.

4. Models

1) Selection Model

Through selection modeling, I will test the following hypothesis*: formal organizational structure of school and teachers' social network structure at time 1 would affect teachers' social networks at time 2*.

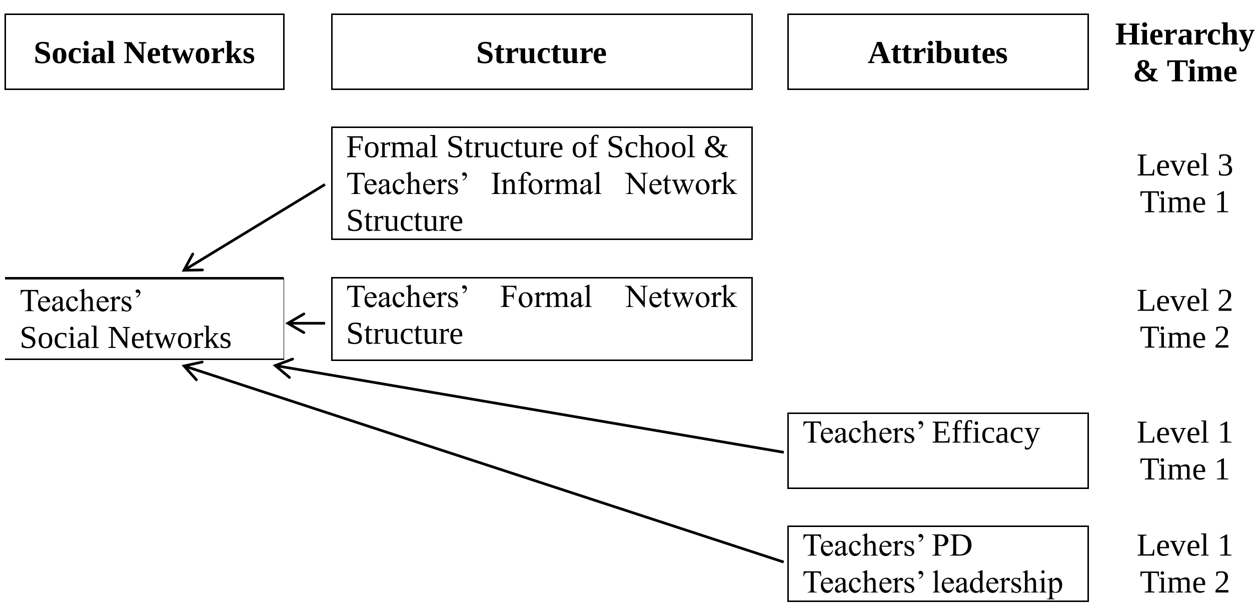

Figure 2.1. The structure of variables in multilevel p2 selection modeling

To test this hypothesis through multilevel p2 selection modeling, I consider not only endogenous network variables (density and reciprocity) but also exogenous attributes variables. In other words, teachers' efficacy, teachers' professional development, and teachers' leadership role will be included in multilevel p2 selection modeling as shown in Figure 2.1.

The selection model is a logistic model because the dependent variable is dichotomous. The dependent variable ($Help_{ii'}$) indicates whether actor *i* indicated receiving help from actor *i'*. Then $Help_{ii'}$ is modelled as a function of the tendency of actor *i'* to provide help regarding mathematics teaching practices ($\alpha_{i'}$) and the tendency of *i* to receive help (β_i). The model at level 1, for the pair of actors *i* and *i'*, is:

Level 1 (pair):

$$log\left(\frac{p[Help_{ii'}=1]}{1-p[Help_{ii'}=1]}\right) = \alpha_{i'} + \beta_i$$

To capture different bases of structuring, dummy variables were included indicating whether school actors had a tie in 2007, were members of the same subgroup, whether they taught in the same grade, and participated in regular meetings. And reciprocity was included to control for the extent to which actor *i'* provided help to *i*.

The final level 1 model was:

$$log\left(\frac{p[Help_{ii'}=1]}{1-p[Help_{ii'}=1]}\right) = \alpha_{i'} + \beta_i$$

$$+ \delta_1 \text{ (prior relationship about mathematics)}_{ii'}$$
$$+ \delta_2 \text{ (prior same subgroup)}_{ii'}$$
$$+ \delta_3 \text{ (same grade teaching assignment)}_{ii'}$$

$+ \delta_4$ (total of all meeting types in common) $_{ii'}$
$+ \delta_5$ (reciprocity: help $_{i'i}$).

The larger the value of δ_1, the more we would infer that the network structure as defined by previous ties about mathematics affects help provided at time 2. The larger the value of δ_2, the more we would infer that the network structure as defined by same subgroup memberships affects the patterns of advice sharing. Large values of δ_3 and δ_4 quantify how help is shaped by the formal organization as represented by grade level and meeting structures. The term δ_5 indicates the extent to which actors helped others who had helped them.

We modelled the tendencies of school actors to be nominated as providing and receiving help at a separate level:

Level 2a (*i'*: provider of help)

$$\alpha_{i'} = \gamma_0^{(\alpha)} + u_{oi'} .$$

Level 2b (*i*: receiver of help)

$$\beta_i = \gamma_0^{(\beta)} + v_{oi} .$$

Here, the random effects $u_{oi'}$ and v_{oi} are assumed to be normally distributed and account for dependencies associated with tendencies to provide or receive help that affect all relations in which a given individual engages. In order to estimate what attributes of the provider and receiver of help account for the patterns observed in teachers' advice networks, mathematics program coordinator role (in school 3, 45, 48 & 54) and mathematics professional development were included in provider effects in level 2a of model 1 while only mathematics professional development was included in sender effects in level 2b of model 1 because we assume that teachers with the mathematics program coordinator role tend to provide advice more than to receive advice. To estimate the effect of the teaching efficacy of provider and receiver of help, prior mathematics teaching efficacy was added to level 2a and level 2b of model 2. In other words, the only difference in model specification between model 1 and model 2 was to add prior mathematics teaching efficacy into the provider and receiver effect.

The final level 2 model was:

Level 2a (i': provider of help)

$\alpha_{i'} = \gamma_0^{(\alpha)} + \gamma_1^{(\alpha)}$ coordinator role $_{i'} + \gamma_2^{(\alpha)}$ mathematics professional development $_{i'} + \gamma_3^{(\alpha)}$ prior mathematics teaching efficacy$_{i'}$ + $u_{oi'}$.

Level 2b (i: receiver of help)

$\beta_i = \gamma_0^{(\beta)} + \gamma_1^{(\beta)}$ mathematics professional development$_i$ + $\gamma_2^{(\beta)}$ prior mathematics teaching efficacy$_i$ +v_{oi} .

In summary, the two-level logistic model was used to account for the dependencies among teachers like two-level HLM model (Generalized linear model) in order to explain the effects of dyadic level (level 1) and provider & receiver level (level 2).

2) Influence Model

Through influence modelling, I will test the following hypothesis: *Teachers' Social networks at time 1 can affect teachers' teaching practices at time 2*.

To test this hypothesis through multilevel influence modeling, I consider not only teachers' social networks (direct exposure) and organizational structure of school, but also exogenous teachers' attributes variables. In other words, teachers' efficacy, teachers' professional development, and teachers' leadership role will be included in multilevel influence modeling as shown in Figure 2.2.

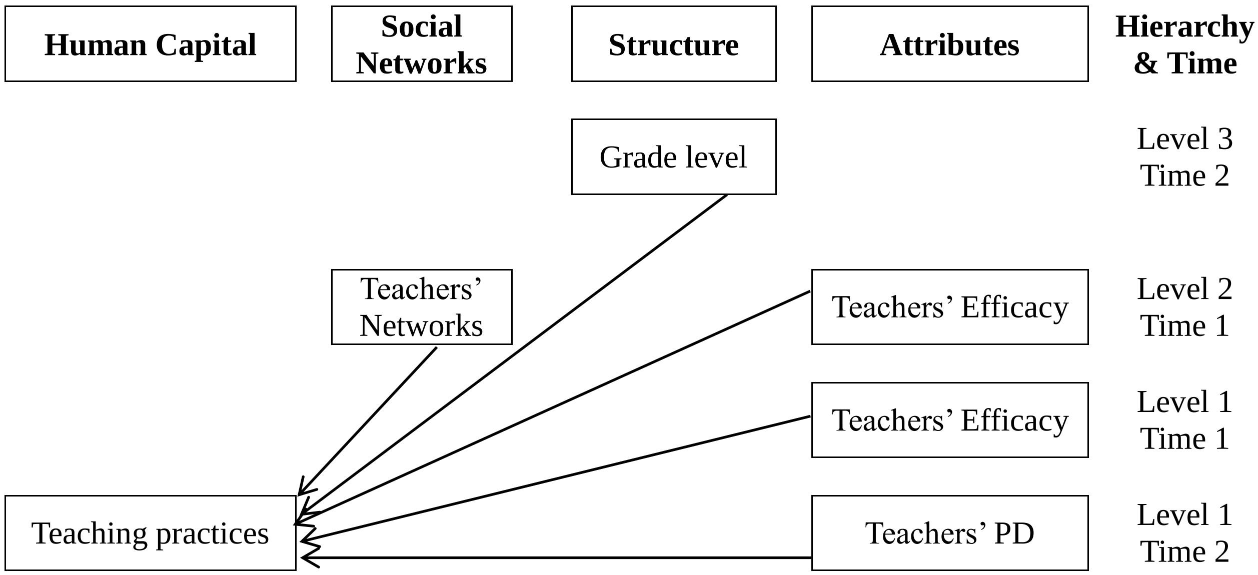

Figure 2.2. The structure of variables in multilevel influence modeling

The influence model is a two-level multilevel model (Raudenbush & Bryk, 2002) to investigate the influence of those who helped teachers with mathematics teaching practices within and between subgroups on current teacher's level of teaching practices, controlling for prior teacher's level of teaching practices, current professional development, prior mathematics teaching efficacy, and current highest grade taught.

Level-1 Model (Teacher level: i)

$$\begin{aligned} Process\ 2008_{ij} = \pi_{0j} + \pi_{1j} prior\ instruction_{ij} \\ +\pi_{2j} direct\ exposure_{ij} \\ +\pi_{3j} professional\ development_{ij} \\ +\pi_{4j}\ prior\ math\ teaching\ efficacy_{ij} \\ +\pi_{5j} highest\ grade_{ij} + e_{ij} \end{aligned}$$

Level-2 Model (Subgroup level: j)

$$\pi_{0j} = \beta_{0j} + \beta_{1j} mean\ prior\ instruction\ in\ subgroup_j$$
$$+\beta_{2j} mean\ prior\ math\ teaching\ efficacy\ in\ subgroup_{cj} + \gamma_j$$
$$\pi_{pj} = \beta_{qj}$$

Where

π_{0j} is the intercept at level one.

π_{pj}(p=1, 2, 3, 4, 5) are the level-1 coefficients that indicate the direction and strength of association between each predictor and teacher i's math in 2008.

e_{ij} is the level one residual term.

β_{0j} is the intercept at level two.

β_{1j} indicates the effect of mean prior teaching practices in subgroup j on π_{0j}.

β_{2j} indicates the effect of mean prior mathematics teaching efficacy in subgroup j on π_{0j}.

γ_j is the level two residual term.

π_{pj} (p=1, 2, 3, 4, 5)$(= \beta_{qj})$are fixed at level two.

All predictors were centered by using grand-mean to estimate the effect of influence from others.

3) Actor-Oriented Model

Dynamic models of social networks have been developed from discrete time to continuous time. Previous dynamic models of social networks in discrete time had assumed evolution of one point to the next as one jump while previous dynamic models of social networks in continuous time had assumed the probability of each network change may depend not on earlier states of the tie (continuous-time Markov chain) but on the entire current set of ties (Snijders et al., 2008). And continuous-time models were proposed by Snijders (1996, 2001) and Snijders & Van Duijn (1997).

Snijders (2005) explained that actor-oriented models assumed that actor i controls all outgoing ties and changes in the network occur only one tie at a time. The rate function determines “the moment when actor i changes one of his ties” stochastically and the evaluation function determines “the particular change that he makes”, which can depend on the network structure and on attributes represented by observed covariates.

Table 2.5 Actor-oriented model components

	Change occurrence	Rule of change
network changes	network rate function	network evaluation function
behavioral changes	behavioral rate function	behavioral evaluation function

Therefore, the actor-oriented model consists of rate and evaluation functions. Network changes consist of a network rate function and a network evaluation function while behavioural changes consist of a behavioural rate function and a behavioural evaluation function shown in Table 2.5.

(1) Micro Level: Network Analysis

Network data from 2007 and 2008 are used as the dependent variables. Based on the findings from a multilevel p2 model in the present study, actor attributes and dyadic covariates are chosen. Thus, a density effect as an out-degree effect is included into actor-oriented model as $\beta_1 S_{i1}(x)$ and a reciprocity effect is also included in the model as $\beta_2 S_{i2}(x)$.

Additionally, actor-oriented models included network structure effects which can, according to the pattern of existing interaction, identify the extent to which an actor’s decisions about whether to terminate a current network or make a new tie depending on structural effects such as transitive triplets. For example, the tendency towards triadic closure is included in the actor-oriented model as $\beta_3 S_{i3}(x)$.

In order to estimate the effect of dyadic covariates on network change, same subgroup effect is included as $\beta_4\, S_{i4}(x)$ and same grade level effect is included as $\beta_5\, S_{i5}(x)$. Both are included in the model after grand-mean centering. In order to estimate a homophily effect, an efficacy similarity measure was included as $\beta_6\, S_{i6}(x)$, where $S_{i6}(x)$ is defined as positive estimate (β_6) of efficacy similarity indicates that there is more chance to interact with another who has similar the efficacy measures.

A multilevel p2 model in this study indicated that high prior mathematics teaching efficacy is related to more probability of providing and receiving help. But, these results cannot tell us whether or not the similarity of efficacy affects the occurrence of a tie between two actors. In order to estimate homophily selection on the similarity of efficacy, the actor-oriented model included the efficacy similarity effect.

Finally, the network rate function was defined as a mathematics advice network change rate from 2007 to 2008 function, $\lambda_i^{net} = \rho_{net}$ while a mathematics advice network evaluation function was defined as a weighted sum of effects,

$f_i^{net}(\beta, x) = \sum_{k=1}^{6} \beta_k \;\; S_{ik}(x)$.

$$f_i^{net}(\beta, x) = \sum_{k=1}^{6} \beta_k \;\; S_{ik}(x)$$

$$= \beta_1\, S_{i1}(x) + \beta_2\, S_{i2}(x) + \beta_3\, S_{i3}(x) + \beta_4\, S_{i4}(x) + \beta_5\, S_{i5}(x)$$

$$+ \beta_6\, S_{i6}(x)$$

Where

β_k is weight as a statistical parameter expressing the importance of effect *k*.

$S_{ik}(x)$ is a function of the network from the point of view of actor *i*.

$S_{i1}(x) = \sum_j \text{Help}_{ij}$ is density effect defined by the out-degree.

$S_{i2}(x) = \sum_j \text{Help}_{ij}\ \text{Help}_{ji}$ is reciprocity effect defined by the number of reciprocated relations

$S_{i3}(x) = \sum_j \text{Help}_{ij} \sum_{\hbar} \text{Help}_{i\hbar}\ \text{Help}_{\hbar j}$ is transitive triplets effect defined by tendency towards triadic closure.

$S_{i4}(x) = \sum_j \text{Help}_{ij} \left(subgroup_{ij} - \overline{subgroup}\right)$ is same subgroup (centered) as a dyadic covariate.

$S_{i5}(x) = \sum_j \text{Help}_{ij} \left(grade_{ij} - \overline{grade}\right)$ is same grade taught (centered) as a dyadic covariate.

$S_{i6}(x) = \sum_j \text{Help}_{ij}\ Efficacy\ similarity_{ij}$ is prior efficacy related similarity effects as actor-dependent covariate defined by tendency to have ties to similar others (homophily selection on prior efficacy).

Behavioural data from 2007 and 2008 are used as the dependent variables. Based on the findings from the two-level HLM model in present study, actor attributes were included in the model as $S_{i1}(x)$. Behavioural rate function was defined as a teaching practices change rate from 2007 to 2008, $\lambda_i^{beh} = \rho_{beh}$ while teaching practices evaluation function was defined as a weighted sum of effects, $f_i^{beh}(\beta, x) = \sum_{k=1}^{1} \beta_k\ \ S_{ik}(x)$.

$$f_i^{beh}(\beta, x) = \beta_1\, S_{i1}(x)$$

Where

β_k is weight as a statistical parameter expressing the importance of effect *k*.

$S_{ik}(x)$ is a function of the behavior from the point of view of actor *i*.

$$S_{i1}(x) = Direct\ Exposure_i = \sum_{\substack{j=1,\\ j\neq i}}^{J} (Help_{ij}) \times (provider's\ expertise_j) \times (amount\ of\ help\ provided\ to\ others_j)$$

J is the total number of teacher *j* that provided help to teacher *i*.
$Help_{ij}$ is the extent to which teacher *i* reported receiving help with teaching mathematics from teacher *i*.
$provider's\ expertise_j$ indicates teaching practice in mathematics problem solving in 2007.
$amount\ of\ help\ provided\ to\ others_j$ represents the ability of the help provider *j* to deliver help.

The final actor-oriented models were that the behavior model included teaching practices change rate (speed), teaching practices change tendency, and direct exposure effects while the network model included mathematics teaching practices advice network change rate (speed), density, reciprocity, transitive triplets, same subgroup (centered), same grade (centered), and efficacy similarity.

(2) Macro Level: Combination of Networks

For combining results of several independent (the set of actors are disjoint, and it may be assumed that there are no direct influences from one network to another) networks, Meta-analysis for multilevel network analysis has been developed (Snijders & Baerveldt, 2003). This analysis consists of the micro level as single network evolution study (Snijders, 2001) and the macro level as combination of these network studies. In addition, this analysis combines the estimates in a meta-analysis according to the methods of Snijders and Baerveldt (2003) and a Fisher-type combination of one-sided p-values.

Through dynamic modeling, I will test two hypotheses. To test hypothesis 3-1 through dynamics modeling, however, I consider not only endogenous network variables (density, reciprocity, and transitivity), but also an exogenous attribute variable (teachers' efficacy). In other words, a transitivity variable will be added to test hierarchy in dynamics modeling but two exogenous attributes (teachers' professional development and teachers' leadership role) will be excluded in dynamics modeling.

In addition, to test hypothesis 3-2 through dynamics modeling, I only include teachers' social network. In other words, teachers' efficacy in both subgroup and individual level, teachers' professional development, and teachers' leadership role will be excluded in dynamics modeling.

Results

1. Selection Model

To test whether or not the *formal organizational structure of school and teachers' social network structure at time 1 affect the formation of new ties of teachers' social networks at time 2*, multilevel selection models were analyzed.

Table 2.6 Multilevel selection model for ten schools

Parameters	Model 1	Model 2
μ – Pair (level 1)	-5.59 (0.49)	-6.89 (1.13)
Prior relationship about mathematics, δ_1	3.52* (0.74)	3.58* (0.75)
Prior same subgroup, δ_2	1.08* (0.37)	1.13* (0.42)
Same grade, δ_3	2.08* (0.52)	2.04* (0.48)
Total of all common meeting types, δ_4	-0.00 (0.06)	0.02 (0.07)
δ_5 – Reciprocity	3.33 (0.48)	3.51 (0.52)
- Provider variance (level 2a)	0.67 (0.36)	0.71 (0.37)
Mathematics program coordinator role, $\gamma_1^{(\alpha)}$	1.79* (0.71)	1.88* (0.66)
Mathematics professional development, $\gamma_2^{(\alpha)}$	0.36* (0.12)	0.28* (0.14)
Prior mathematics teaching efficacy, $\gamma_3^{(\alpha)}$		0.15 (0.13)
- Receiver variance (level 2b)	1.86 (0.65)	1.91 (0.56)
Mathematics professional development, $\gamma_1^{(\beta)}$	0.17 (0.14)	-0.03 (0.18)
Prior mathematics teaching efficacy, $\gamma_2^{(\beta)}$		0.47* (0.16)
- Provider-receiver covariance	0.08 (0.32)	-0.09 (0.35)
-Omega for Random Density Effects	0.36 (0.29)	1.41 (2.15)

Note:* means t-ratio more than 2; The sample size was 209 in model 1 & model 2; Burn-in 4000 and sample size 20000 in MCMC estimation

The large negative value as -5.59 and -6.89 of μ (density parameter) in model 1 and model 2 indicated that when all random effects and other parameters are equal to zero, the probability of a network is much smaller than 0.5. In other words, there were sparse mathematics advice networks across ten schools. The large positive value as 3.33 and 3.51 of δ_5 (reciprocity parameter) in model 1 and model 2 indicated that actors helped others who had helped them.

To estimate the network structure effect, four network covariates were included in the density effect in level 1. The large positive values of 3.52 and 3.58 of δ_1 for models 1 and 2 indicated that having a previous tie raises the odds of having a current tie by about 33 times[1] in model 1 and about 35 times in model 2. In other words, previous ties about mathematics were much strongly related to the patterns of current advice sharing.

In addition, based on the positive values of 1.08 and 1.13 of δ_2 for models 1 and 2, having a previous same subgroup membership raises the odds of having a current tie by about two times in model 1 and model 2. In other words, we would infer that same subgroup' memberships affect the patterns of mathematics advice network.

Finally, the positive values of 2.08 and 2.04 of δ_3 for models 1 and 2 showed that having a previous same grade membership raises the odds of having a current tie by about seven times in model 1 and model 2. In other words, we would infer that advice networks were shaped by the formal organization as represented by grade level. Model 1 and 2 had, statistically non-significant, nearly zero estimate of -0.00 and 0.02 of δ_4.

In summary, the patterns of advice sharing could be, structurally, affected by 1) prior relationship about mathematics, 2) same grade level, and 3) prior same subgroup membership.

The results of including what attributes of the advice provider account for the patterns of networks showed that a mathematics program coordinator role (a positional attribute) was

[1]Note: I get odds to compute the following formula: $e^{3.52}$-1=33.78-1=32.78=3,278%

statistically significant, positively related to providing advice in both model 1 (1.79) and model 2 (1.88). In other words, having a mathematics program coordinator role raises the odds of providing advice by about five times in model 1 and model 2. Mathematics professional development also was statistically significant, positively related to providing advice in both model 1 (0.36) and model 2 (0.28). An one-unit change in mathematics professional development raises the odds of providing advice by about one half times in model 1 and about one third times in model 2.

In addition, the results of including what attributes of advice seeker account for the patterns of networks showed that prior mathematics teaching efficacy (a psychological attribute) was statistically significant and positively related to seeking advice in model 2 as 0.47. A one-unit change in mathematics professional development raises the odds of providing advice by 60% in model 2.

In summary, the results of the multilevel selection model across ten schools indicated that new ties involving mathematics teaching practices-related help were predicted strongly by having previous mathematics teaching practices help ties (time), teaching in the same grade level (the organizational structure of the school) and teachers being in the same subgroup (informal network structures) in model 1 and 2 shown in table 2.6. These results are consistent with the study of Zahorik (1987). Zahorik pointed out the importance of same grade teachers as "Teachers who teach at the same grade level understand each other's problems, can offer practical, specific help, and are close at hand" (p.394).

At the same time, a mathematics program coordinator role (a social attribute) and mathematics professional development were related to a significant shift in patterns of interaction in model 1 and 2, shown in table 2.6. In addition, prior mathematics teaching efficacy (a psychological attribute) was related to a significant shift in patterns of interaction in model 2 shown in table 2.6.

Overall, this pattern of results suggests that *formal organizational structure of school (grade level) and teachers' social network structure (subgroup) at time 1 affect the formation of new ties of teachers' social networks at time2*.

2. Influence Model

To test whether or not *teachers' social networks at time 1 affect teachers' teaching practices at time 2*, two-level and three-level multilevel models were analyzed.

Table 2.7 Variance components of unconditional model

Three-level	Math in 2008	Two-level	Math in 2008
Individual	0.759	Individual	0.548
Subgroup	0.255 (26%)	Subgroup	0.175 (24%)
School	0.00013(0.01%)		

The final model was a two-level multilevel model because school variances in three-level unconditional models were almost zero (0.01%) in Table 2.7.

1) Basic Statistics

The sample for the influence model included 150 teachers with 41 subgroups in Table 2.8. For descriptive statistics of level 1, the mean of mathematics teaching practices in 2008 was 2.88 with standard deviation (SD) 0.99 and range 0 to 4.57, while the mean of mathematics teaching practices in 2007 was 1.81 (SD, 1.13) with range 0 to 4.57. The increased means of mathematics teaching practices indicated that there was increased implementation in mathematics teaching practices from 2007 (one or two times a week) to 2008 (three or four times a week) across ten schools while the decreased standard deviation of mathematics teaching practices indicated that there were more uniform mathematics teaching practices in 2008 than 2007 across the ten schools.

Table 2.8 Descriptive statistics of multilevel influence model

Variable	M	SD	Min	Max
Level-1: Individual Teacher (N=150)				
Teaching practices in 2008	2.88	0.99	0	4.57
Teaching practices in 2007	1.81	1.13	0	4.57
Exposure between 2007 and 2008	24.17	38.18	0	216
Professional development in 2008	1.20	0.96	0	3.00
Mathematics teaching efficacy in 2007	3.43	0.46	1	4.00
Highest grade in 2007	4.11	2.19	1	9.00
Level-2: Subgroup (N=41)				
Subgroup mean of Teaching practices in 2007	1.84	0.90	0.00	4.29
Subgroup mean of math teaching efficacy in 2007	3.40	0.31	2.44	3.89

The mean of direct exposure between 2007 and 2008 was 24.17 (SD, 38.18) with range 0 to 216, which indicated that there was large variation among teachers because the sum of direct exposure was included instead of the mean of direct exposure. The mean of professional development in 2008 was 1.20 (SD, 0.96), which indicated that teachers across ten schools averaged “one to eight hours” of professional development of mathematics in 2008. The mean of mathematics teaching efficacy in 2007 was 3.43 (SD, 0.46), which showed that teachers, on average, had agreement or strong agreement with statements about prior teaching efficacy.

For descriptive statistics at level 2, the subgroup mean of mathematics teaching practices in 2007 was 1.84 (SD, 0.90) with range 0 to 4.29 while the subgroup mean of prior teaching efficacy was 3.40 (SD, 0.31) with range 2.44 to 3.89. In addition, correlations among level-one predictors are shown in Table 2.9.

Table 2.9 Correlation among level-one predictors

	Teaching practices 08	Teaching practices 07	Exposure	PD 08	Efficacy 07
Teaching practices 08					
Teaching practices 07	0.51**				
Exposure (07 to 08)	0.29**	0.34**			
PD in 08	0.17*	0.26**	0.21**		
Efficacy in 07	0.22**	0.14	0.09	0.21**	
Highest grade in 08	0.12	0.32**	0.33**	0.09	-0.05

Notes: N=150, * $p < .05$, ** $p < .001$.

The highest significant correlation was 0.51 between mathematics teaching practices in 2007 and mathematics teaching practices in 2008 while the lowest significant correlation was 0.21 between mathematics professional development in 2008 and mathematics teaching efficacy in 2007. In addition, there was statistically non-significant correlation between mathematics teaching practices in 2008 and highest grade in 2008, which indicated that current grade level may not affect current mathematics teaching practices.

2) Regression coefficient for the Multilevel Influence Model

To estimate how much *teachers' social networks at time 1 affect teachers' teaching practices at time 2*, regression coefficients (standard error) for a multilevel influence model were shown in Table 2.10.

The results of model 1 showed that prior mathematics teaching practices (coefficient of 0.36) and direct influence (coefficient of 0.005) had significant effects on current mathematics teaching practices. In order to estimate the effect of subgroup mean of prior teaching efficacy on current mathematics teaching practices, model 2 was analyzed and the results indicated that there was a significant effect (coefficient of 0.74) of subgroup mean of prior mathematics teaching efficacy. This was the source of differences in model specification and results between model 1 and model 2, which indicated that even though prior individual teaching efficacy didn't influence current teaching practices, the mean of each member's prior teaching efficacy within the same subgroup might be key factor to account for current teaching practices.

Table 2.10 Regression coefficients (standard errors) for multilevel model of mathematics problem solving teaching practices including the influences of colleagues.

Variable	Model 1	Model 2
Level-1: Individual Teacher (N=150)		
Overall mean Teaching practices in 2008	3.01 (0.20)	2.97 (0.20)
Teaching practices in 2007	0.36** (0.07)	0.37** (0.07)
Exposure between 2007 and 2008	0.005** (0.002)	0.005** (0.002)
Mathematics Professional development in 2008	0.03 (0.07)	0.03 (0.08)
Mathematics teaching efficacy in 2007	0.17 (0.17)	0.03 (0.18)
Highest grade in 2008	-0.04 (0.04)	-0.03 (0.04)
Level-2: Subgroup (N=41)		
Subgroup mean of Teaching practices in 2007	0.14 (0.18)	0.05 (0.17)
Subgroup mean of math teaching efficacy in 07	N/A	0.74* (0.34)

Note: model 2 includes subgroup mean of mathematics teaching efficacy.
* p< .05, ** p< .001.

To compare the relative impact of these estimates, standardized coefficients of regression models are presented in Table 2.11.

Table 2.11 Regression standardized coefficients for multilevel model of mathematics problem solving teaching practices including the subgroup mean of influences of colleagues.

Variable	Model 2	Model 3
Level-1: Individual Teacher (N=150)		
Overall mean Teaching practices in 08	-0.05	-0.04
Teaching practices in 07	0.42**	0.41**
Exposure between 07 and 08	0.21*	0.28**
Mathematics Professional development in 08	0.03	0.02
Mathematics teaching efficacy in 07	0.01	0.01
Highest grade in 2008	-0.07	-0.06
Level-2: Subgroup (N=41)		
Subgroup mean of teaching practices in 07	0.05	0.15
Subgroup mean of math teaching efficacy in 07	0.23*	0.22+
Subgroup mean of exposure between 07 and 08	N/A	-0.19

Note: model 3 includes subgroup mean of exposure between 2007 and 2008.
+ p=.055, * p < .05, ** p < .001.

The effect of exposure between 07 and 08 was the half times as the effect of prior teaching practices. For a two standard deviations increase in of exposure between 07 and 08, there was a two-fifth standard increase.

To estimate norm pressure of exposure between 07 and 08 at the subgroup level, model 3 included subgroup mean of exposure. The similar results indicates that mathematics teaching practices in 2007and direct exposure had influence on conducting mathematics problem solving teaching practices in 2008.

Overall, this pattern of results suggests that *teachers' social networks at time 1 affect teachers' teaching practices at time 2*.

3. Actor-Oriented Model

To examine how mathematics teaching practices advice network and mathematics teaching practices change over two years and what can explain these dynamics, actor-oriented models were analyzed.

1) Basic Statistics

There were increases in levels of mathematics teaching practices from 2007 to 2008 in all but School 48. School 54 had the largest change from 1.58 to 3.06 while school 48 had smallest change from 2.49 to 2.34.

The highest school in 2007 was school 47 (2.80) and school 8 (3.20) in 2008 while the lowest school was school 1 (1.50) in 2007 and school 8 (3.20) in 2008. The results of a paired t-test in mathematics teaching practices indicate that there were statistically significant differences between 2007 and 2008 within schools except for school 47 and 48.

Table 2.12 Change in mathematics problem solving teaching practices

Schools	School mean of math teaching practices in 2007	School mean of math teaching practices in 2008	Paired Comparison	
			Mean Differences	Std. Deviation
School 1 (N=21)	1.50 (0.70)	2.80 (0.78)	1.30**	0.71
School 3 (N=29)	1.88 (1.33)	2.82 (1.21)	0.94**	0.95
School 8 (N=19)	1.87 (0.99)	3.20 (0.81)	1.37**	1.14
School 26 (N=14)	2.00 (1.15)	3.19 (0.91)	1.19**	0.54
School 39 (N=23)	1.54 (1.04)	2.84 (0.90)	1.30**	1.03
School 45 (N=7)	1.84 (1.29)	2.71 (0.66)	0.87*	0.84
School 47 (N=9)	2.80 (1.19)	2.81 (1.21)	0.01	1.67
School 48 (N=5)	2.49 (1.30)	2.34 (1.55)	-0.15	0.79
School 53 (N=14)	1.60 (1.05)	2.62 (1.07)	1.02**	1.21
School 54 (N=11)	1.58 (1.17)	3.06 (0.87)	1.48**	0.95

Note: Paired comparison test the difference in school mean of math teaching practices between 2007 and 2008. *p <.05, **p <.001.

Table 2.13 Change in mathematics teaching practices advice networks

Networks	2007 Average degree	2008 Average degree	Change in math ties (0: no tie, 1: a tie)		
			0 → 1 (Formation)	1 → 0 (Dissolution)	1→ 1 (Constant)
School 1 (N=24)	0.217	0.217	4	4	1
School 3 (N=36)	0.629	1.714	49	11	11
School 8 (N=23)	0.682	1.000	14	7	8
School 26 (N=21)	1.100	0.400	3	17	5
School 39 (N=28)	0.926	1.074	15	11	14
School 45 (N=13)	0.333	0.500	4	2	2
School 47 (N=19)	1.222	1.056	4	7	15
School 48 (N=18)	0.235	0.294	4	3	1
School 53 (N=14)	0.923	0.769	3	5	7
School 54 (N=13)	1.667	0.583	0	13	7

Note: Average degree means that the total degrees (ties) are divided by the total number of teachers in each school. In addition, Formation means new ties in 2008 which was no ties in 2007, Dissolution means no ties in 2008 which was ties in 2007, and Constant means ties both in 2007 and 2008.

For average degree (total tie divided by sample size) in mathematics networks, there were no changes in number of ties in one school (school 1), increases in five schools (school 3, 8, 39, 45 and 48), and decreases in four schools (school 26, 47, 53, and 54) as shown in Table 2.13.

There were no mutual ties in the mathematics network in one school (school 1) for two years. School 47 had average degree of more than one in both 2007 and 2008. In addition, there was no formation of a tie in the mathematics teaching practices advice network from 2007 to 2008 in school 54 while there was dissolution and constant ties in mathematics teaching practices advice network from 2007 to 2008 in all schools.

2) Micro Level: Network Analysis

For the convergence check, there was poor convergence in school 26, 45, 47, 48, 53 and 54 because at least one t-ratio was not close to zero with an absolute value more than 0.1. For the collinearity check, there were high collinearities among variables in school 45, 48, and 54.

With respect to results of the mathematics network selection model, first, the positive network change rate indicated that there was a change in the mathematics network from 2007 to 2008 across all ten schools. Among ten schools, school 3 had the highest, most statistically significant network change rate of 5.47 as we see average degree change from 0.6 to 1.7 shown in table 2.14. Also, school 45 had the lowest, but statistically non-significant network change rate of 1.29 with average degree change from 0.3 to 0.5.

Second, a density effect as an out-degree had negative estimates just as the results of multilevel p2 models while a reciprocity effects had positive estimates among eight schools.

Third, transitive triplets' effect as a network structure effect had positive or negative estimates depending on the school. School 47 had a statistically significant positive estimate of 1.35 which indicated that the transitive triple effect was a key factor driving network change over two years in this school after controlling for same grade level and subgroup effects.

Table 2.14 Effects estimates (standard errors) in mathematics teaching practices advice networks and mathematics teaching practices

school	Mathematics teaching practices advice network (selection model)						
	Rate	Density	Reciprocity	Transitive triplets	Subgroup (Centered)	Grade (Centered)	Efficacy similarity
1	1.89	-7.59	3.62*	-1.08	5.04	0.87	-0.21
	(1.05)	(11.04)	(1.54)	(17.05)	(46.7)	(46.1)	(2.34)
3	5.47*	-2.39*	0.98*	0.64*	1.10*	0.70*	-0.18
	(1.87)	(0.23)	(0.48)	(0.21)	(0.31)	(0.29)	(0.42)
8	1.69*	-3.75*	0.81	1.40	-0.53	3.33*	2.37
	(0.54)	(1.06)	(0.99)	(0.80)	(0.93)	(1.17)	(1.27)
26	2.39*	-6.79	2.37	-0.23	2.60	0.67	-4.50
	(0.80)	(3.43)	(1.85)	(7.59)	(3.60)	1.32)	(6.60)
39	2.83*	-3.37*	0.44	0.70*	-0.11	2.04*	2.88
	(1.03)	(0.52)	(0.90)	(0.29)	(0.60)	(0.70)	(1.52)
45	1.29	-3.26	1.93	-0.84	2.25	-0.29	0.34
	(1.19)	(2.16)	(1.81)	(6.28)	(2.68)	(1.13)	(1.83)
47	1.82*	-5.66*	-1.78	1.35*	2.79	1.47	1.32
	(0.74)	(1.74)	(2.13)	(0.63)	(1.83)	(1.73)	(1.96)
48	2.29	-4.96*	-15.07	-4.61	0.96	-1.78	2.77
	(2.96)	(1.30)	(350)	(7.97)	(1.66)	(1.74)	(2.83)
53	2.21	-12.00	12.93	-0.65	-10.87	11.36	0.33
	(1.48)	(67.69)	(38.40)	(1.00)	(38.23)	(76.31)	(2.38)
54	2.03*	-8.69	4.88	0.59	3.29	1.35	-2.90
	(0.85)	(23.91)	(17.95)	(2.00)	(12.97)	(7.81)	(23.05)

School	Mathematics teaching practices (influence model)		
	Rate	Tendency	Exposure
1	1.95* (0.75)	2.12 (1.86)	0.06 (0.71)
3	2.14* (0.86)	0.88 (0.49)	-0.01 (0.01)
8	3.81 (2.55)	1.12 (0.73)	0.001 (0.02)
26	1.80* (0.47)	6.30 (31.6)	-0.04 (0.29)
39	4.32* (2.06)	0.81 (0.46)	0.02 (0.02)
45	1.49 (0.88)	9.51 (311)	-0.27 (9.58)
47	3.84 (3.25)	0.06 (0.36)	0.003 (0.005)
48	0.45 (0.42)	-85.4 (9999)	7.60 (9999)
53	8.63 (8.32)	0.40 (0.24)	0.02 (0.02)
54	2.53 (1.41)	3.38 (22.39)	0.14 (1.88)

Note:* means t-ratio more than two.

Fourth, only school 3 had a statistically significant positive same subgroup effect, which showed that same subgroup membership was a key factor explaining network change over two years although there was also a statistically significant positive network structure effect and same grade level effect.

Fifth, school 8 had statistically significant positive same grade level effect, which indicated that same grade level was a key factor explaining network change over two years.

Sixth, there was a positive estimate of efficacy similarity in schools 8, 39, 45, 47, 48 and 53, indicating that there is more chance to interact with others who have similar efficacy within schools while a negative estimate of efficacy similarity in school 1, 3 and 54 indicates that there is less chance to interact with other who have similar efficacy in these schools.

With respect to the results of mathematics teaching practices in the influence model, there were, statistically significant, positive changes in rates of mathematics teaching practices in schools 3, 8, 26, 39, 47, and 54 which indicated that teaching practices in mathematics problem solving changed over two years in these schools.

In addition, in order to estimate the effect of the network on teaching practices in mathematics problem solving, the exposure variable was made and included in the models. There were statistically non-significant, positive estimates in seven schools. These results were different from the results of the two-level HLM in the present study. It could be due to differences in model specification and the unit of analysis. In the actor-oriented models, mathematics professional development, highest grade, and teaching efficacy were not included when specifying mathematics teaching practices dynamics and unit of analysis in actor-oriented models was each school while that of two-level HLM was teachers and subgroup.

3) Macro Level: Combination of Networks

To investigate complex dynamic effects in longitudinal network models based on the results of the selection and influence modeling and generalize the results in each school, multilevel longitudinal network models were analyzed using the Meta-analysis method in SIENA 08.exe.

The results of model 1 indicate that the change in mathematics teaching practices advice networks was explained by reciprocity, same subgroup and common grade taught while the results of model 2 indicate that the change in mathematics teaching practices advice network was explained by reciprocated dyad network, transitive triplets' network, and same subgroup.

Table 2.15 the mean and variance of estimates in meta-analysis

	Parameter	Model 1	
		Mean (S.E.)	Sample school
Mathematics Teaching Practices Advice Network Change	Network Change Speed	1.89** (0.36)	3, 8, 26, 39, 45, 47, 54
	Density	-2.35** (0.17)	3, 8, 39, 45, 47, 48
	Reciprocity	1.60** (0.28)	1, 3, 8, 26, 39, 45, 47
	Transitive triplets		
	Subgroup (Centered)	1.04** (0.23)	3, 8, 39, 45, 47, 48
	Grade (Centered)	0.99** (0.26)	3, 8, 26, 39, 45, 47, 48
	Efficacy similarity	0.49 (0.35)	1, 3, 8, 39, 45, 47, 48
Mathematics Teaching practices Change	Teaching practices Change Speed	1.04** (0.21)	1, 3, 8, 26, 39, 45, 47, 48, 54
	Teaching practices Change Tendency	0.55** (0.23)	3, 8, 39, 47
	Exposure	0.003 (0.005)	3, 8, 39, 47,53
	Parameter	Model 2	
		Mean (S.E.)	Sample school
Mathematics Teaching Practices Advice Network Change	Network Change Speed	2.05** (0.29)	All school
	Density	-2.72** (0.20)	3, 8, 26, 39, 45, 47, 48
	Reciprocity	1.11* (0.54)	1, 3, 8, 26, 39, 45, 47
	Transitive triplets	0.70** (0.16)	3, 8. 39, 47, 53, 54
	Subgroup (Centered)	0.81** (0.26)	3, 8, 26, 39, 45, 47, 48
	Grade (Centered)	1.04 (0.57)	3, 8, 26, 39, 45, 47, 48
	Efficacy similarity	0.32 (0.36)	1, 3, 8, 39, 45, 47, 48, 53
Mathematics Teaching practices Change	Teaching practices Change Speed	1.42** (0.25)	1, 3, 8, 39, 45, 47, 48, 54
	Teaching practices Change Tendency	0.49** (0.17)	1, 3, 8, 39, 47, 53
	Exposure	0.004 (0.004)	1, 3, 8, 26, 39, 47,53, 54

Note: sample school was included if the standard error of each parameter was less than 5.
* p< .05, ** p < .001.

A disadvantage of this Meta-analysis is that there are inconsistencies in the results obtained for estimates and tests. For example, there were significant grade effects in three schools in the micro level analysis while there was no significant same grade effect when including the transitive triplets' effect in the Meta-analysis. Thus, there could be collinearlity problems between same grade taught and the transitive triplets' effect in model specification.

Overall, this pattern of results suggests that *the formal organizational structure of the school and teachers' social network structure at time 1 affect change of teachers' social networks between time 1 and time 2* and *teachers' social networks at time 1 may affect change of teachers' teaching practices between time 1 and time 2*.

Table 2.16 Results comparison among P2, HLM, and SIENA

Parameters	Selection Model	Influence Model	Actor-oriented Model	
	Model 2	Model 0[2]	Model 1	Model 2
Network Change Speed			1.89** (0.36)	1.42** (0.25)
Prior same subgroup	1.13* (0.42)		1.04* (0.23)	0.81* (0.26)
Same grade	2.04* (0.48)		0.99* (0.26)	1.04 (0.57)
Transitive triplets				0.70* (0.16)
Teaching practices Change Speed			2.05** (0.29)	1.42** (0.25)
Exposure between 07 and 08		0.005* (.002)	0.003 (0.005)	0.004 (0.004)

Note: * p< .05, ** p < .001.

Now, we can compare these results (SIENA) with the result of selection (p2) and influence models (HLM). Main similarity among these results was as follows. With respect to

[2]Model 0 included only teaching practices in 2007 and exposure between 07 and 08 as level 1 predictors with no level 2 predictor in a two-level multilevel model.

results of selection models between p2 and SIENA, two results were similar in that prior same subgroup and same grade were significant factors to explain the change of mathematics problem solving teaching practices advice network.

With respect to results of influence models between HLM and SIENA, two results were similar in that exposure between 2007 and 2008 was positively related to change of mathematics problem solving teaching practices, though estimates of exposure between 2007 and 2008 were not statistically significant in actor-oriented models.

Discussion and Conclusion

After investigating teachers' social networks through selection, influence, and dynamic modeling, research results indicate that *the formal organizational structure of the school and teachers' social network structure at time 1 affect the formation of new ties of teachers' social networks at time 2* and *teachers' social networks at time 1 can affect teachers' teaching practices at time 2*.

Previous studies (Penuel et al., 2009) showed similar results in selection and influence models except mathematics teaching efficacy. The main differences between previous studies and this research are the significant mathematics teaching efficacy effect in the selection model, subgroup mean mathematics teaching efficacy effect in the influence model and the transitive triplets effect in the actor-oriented model.

When controlling for prior tie, p2 models like the SIENA model can estimate network change across two time points. In addition, when including covariates like subgroup networks, p2 models can estimate structural effects. However, p2 models have a limitation in estimating change when we use longitudinal data with more than two time points and the assumption of dyads independence.

The methodological advantage of actor-oriented models over the selection and influence model is that we can analyze the network and behavior simultaneously while the disadvantage of actor-oriented model is that the model needs a larger sample size for estimation convergence and complex model specification.

If we consider teachers' turnover within schools, there might be much different patterns across the two years. Even though joining and leaving teachers (teachers' turnover) within schools might be the main cause of change in relation, there were changes in relations among the same teachers across two years after controlling for teachers' turnover. In addition, change in relation could be the predictor of change in behavior or change in behavior could be the predictor of change in relation.

Therefore, the result of the static model of network or behavior might be different from the result of dynamic model of network and behavior especially when there was transitive process, newcomers' influence, and the effect of teachers' turnover within schools.

The contextual knowledge for specific situations is more important in order to teach students well. Some teachers can seek this contextual and local knowledge from their own previous teaching practices and others may have more suitable knowledge through trial and error as teaching experience increases. But beginning teachers or new joining teachers may not have local knowledge and need more time and effort to coordinate their teaching practices to specific classes. In this situation, school mentor or subject matter (English or Math) coordinators can provide local knowledge through repeated interaction until the knowledge is partially or completely transferred to new teachers. Frank, Zhao & Borman (2004) reported that through interaction with others, elementary teachers could have more knowledge to adapt computer technology in the classroom. For teachers who do not have local knowledge, professional development could be a good source of general knowledge but professional development without interactions with others might be inefficient way for local knowledge (Frank et al., 2011).

One limitation of this study is missing values in networks and attributes data due to teacher turnover. Huisman & Steglich (2008) reported that missing actors have large effects on estimates when analyzing longitudinal network data. They showed that a reduced sample size lead to convergence problems with poor fitting evolution model and to biased parameter estimates. However, this study focuses on the same teachers during two years. Change of network and behavior could be due to not only the external condition, which is turnover (attrition, changing composition), but also internal conditions, which are professional development even if composition was the same as before.

Another limitation of this study is reliability and validity of network measurement using name generators because the 2007 survey of this study consists of three social network nominations and the 2008 survey of this study consists of five social network data and mathematics teaching practices advice network were presented as last question in both surveys. Pustejovsky & Spillane (2009) reported that multiplex social network data might be vulnerable to question-order effects.

To investigate the relationship between network and behavior, this study used three methods that had different statistical assumptions and different model specifications. Even though actor-oriented models could directly identify triadic or higher-order network effects such as closure, actor-oriented models assumed that actor *i* controls all outgoing ties and changes network only one tie at a time, and that the probability of each tie change may depend on the entire current network, but not on earlier states of the network (continuous-time Markov chain). These are very strong assumptions because actor *i* may not or cannot control the outgoing tie especially when there are restrictions in environment, law, institution and policy. In addition, actor *i* may or can change some or most ties at a time especially when there are big life events like marriage, divorce, moving to another school, state or country, participation in international conferences or workshops, or natural disasters like earthquakes or floods.

Therefore, we may need to consider event history analysis in longitudinal network analysis and future studies are needed to address this problem. Also, earlier states of the network might or could affect the current network especially when longitudinal data were collected during less than a month or a year in case of friendship network or religious network. Thus, we may need to take this into account for research design and results interpretations.

Though there are some limitations, this chapter shows that teachers' social network can improve teaching practices by changing formal (grade) and informal (subgroup) structure.

Chapter 3: The Effect of Teachers' Social Networks on Class Composition

Introduction

Recent studies show that students are non-randomly assigned to their teachers between schools (Jackson, 2009, Lankford, Loeb & Wyckoff, 2002; Miller, 2009) and within schools (Monk, 1987; Rothstein, 2008).

One study about assignment of teachers to students between schools shows that teachers tended to move to schools that served high achieving students or high socioeconomic schools (Lankford, Loeb & Wyckoff, 2002). In other words, there was an uneven composition of teacher quality across schools.

In addition, the studies about assignment of teachers to students within schools reported that principals and teachers were involved in class formation and composition (Monk, 1987; Burns & Mason, 1995; 1998). Specifically, one study showed that about two-thirds of principals included teachers formally or informally when students were assigned to their classes (Burns & Mason, 1995). Another study showed that classes were purposefully created by the majority of principals (Burns & Mason, 1995). In other words, principals and teachers control student assignment at the elementary level, resulting in potentially uneven composition of students in schools.

If so, why is this important? First, peer effects studies show that students' peers have an important impact on their learning (Burns & Mason, 2002; Harris, 2010), which leads to differences in academic achievement. In addition, student composition could affect not only interaction among students but also interaction among their parents, which can affect students' social capital.

Second, Aptitude-Treatment Interactions (ATI) studies showed that there was a remarkable interaction between students' aptitudes[3] and instructional methods (Cronbach & Snow, 1977; Snow, 1989). In other words, class composition can affect overall students' aptitudes, which can influence teachers' instructional methods. Specifically, Cronbach (1957) pointed out "persons should be allocated on the basis of those aptitudes which have the greatest interaction with treatment variables" (p. 681). Another study showed that classroom composition constrained teaching practices and student learning (Dreeben & Barr, 1988). In other words, students' assignment to their teachers could affect the nature of teaching practices for the whole class from the beginning of year, which might lead to different learning outcomes for students at the end of year.

Third, when assessing students' academic achievement, class composition affects model specification and estimates (Cronbach, 1976). Furthermore, recent results indicate that students' non-random assignment could influence gain scores, which might produce selection bias and misleading conclusions when evaluating teachers' effects on gain in students' academic achievement (Koedel & Betts, 2009; Rivkin & Ishii, 2009; Rothstein, 2009).

Although previous studies found students were non-randomly assigned to classrooms (Burns & Mason, 1995, 1998; Heck & Marcoulides, 1989; Heck et al., 1989; Jacob & Lefgren, 2007; Monk, 1987), little effort has been made to explain the mechanism of non-random assignment as a function of teachers' attributes and teachers' social networks. Thus, the purpose of this study is to explain the mechanism of assignment of students to teachers. This chapter is organized as follows. First, I introduce studies about the impact of class composition on student learning. Class composition studies and value-added models are reported with a focus on

[3] Aptitude refers to "any characteristic of the person that affects his response to the treatment" (Cronbach, 1975, p. 116)

empirical studies. Second, I present my data and methods including sample, dependent variables, and independent variables, including teachers' attributes and social networks. Third, the estimates of the relationships between teachers' social networks and class composition are presented. Finally, the discussion and conclusion are shared.

1. The Impact of Peers and Class Composition on Students' Learning

One study summarized whether school peers influence educational outcomes and explored three hypotheses that a) advantaged peers were beneficial for disadvantaged students, b) advantaged peers were harmful for disadvantaged students, and c) peers have no influence on disadvantaged students, as shown in Table 3.1 (Harris, 2010). Harris proposed a "group-based contagion theory in which students benefit from advantaged peers mainly when those peers are in the same group" (p. 1190). In addition, Harris pointed out that "peers indirectly influence one another by affecting the school resources to which they have access, especially the qualifications of the teachers who teach them" (p. 1190).

Table 3.1 Summary of theories and implications

Theory	Disciplinary Perspective	Source of Peer Influence
Advantaged Peers Beneficial		
Epidemic	Sociology	Beliefs/values
Cognitive	Psychology	Instrumental
Institutional-resources	Economics and Political Science	Instrumental
Institutional-expectations	-	Instrumental
Disruption	Economics	Instrumental
Advantaged Peers Harmful		
Relative deprivation	Sociology	Beliefs/values
Oppositional culture	Anthropology and Sociology	Beliefs/values
Signaling	Economics	Instrumental
Focus-boutique	-	Instrumental
Peers have no influence		
Home Influences	-	-
Tracking	Sociology	-

Source: Harris, 2010, p. 1177

In addition, previous Aptitude-Treatment Interactions (ATI) studies have shown that there was a remarkable interaction between students' aptitudes and instructional methods (Cronbach & Snow, 1977; Snow, 1989). Cronbach (1957) claimed that "persons should be allocated on the basis of those aptitudes which have the greatest interaction with treatment variables" (p. 681). Also, Monk (1987) pointed out that "teachers vary in their ability to achieve success with particular types of pupils, and the composition of a classroom is related to how much a particular child learns" (pp. 167-168).

Specifically, Dreeben & Barr (1988) pointed out the mechanism of the effect of classroom composition on students' learning. Dreeben & Barr described the importance of classroom composition on students' learning in that "because many low-aptitude students have to work independently at their seats while the teacher provides one group with direct attention, there will be more intrusions and time will be used less productively; as a result, there will be less learning in difficult classes" (p. 133). Although they explained the effect of classroom composition, classroom dynamics and student learning, they didn't explain which factors affect classroom composition.

With respect to relationships between classroom composition and achievement, the study by Burns & Mason (1995) reviewed previous studies and summarized that after controlling for individual scores, there are modest but statistically significant relationships between class mean scores and achievement. In addition, they reported that teacher commitment and motivation may be conditioned by classroom composition. Empirically, another study examined the relationship between class composition and student achievement in 22 elementary schools using hierarchical linear modeling to estimate composition effects (Burns & Mason, 2002). Burns & Mason (2002) argued that higher ability and more independent students were assigned to combination classes[4] by principals and teachers, which caused variation in student achievement. Though they compared the single classes to combination classes with respect to composition effects, they didn't consider teachers' social networks, which could affect class composition.

In summary, previous studies have shown that class composition and peer effects have an important impact on students' learning (Burns & Mason, 2002; Dreeben & Barr, 1988; Harris, 2010), which lead to differences in academic achievement, although few have focused on the factors that might affect assignment of students to teachers.

2. Class Composition

1) Which Factors Affect Class Composition?

The study by Heck et al. (1989) examined principals' roles concerning teacher and student assignment decisions and proposed a model of the factors that influence these decisions. They pointed out five factors which are teacher student matching, organizational concerns, internal political concerns, parent input, and data sources. Based on this model, another study by Heck & Marcoulides (1989) tested whether the principals' teacher allocation decisions were affected by district and school size using LISREL methodology; 170 Elementary school principals from three categories of California districts and school sized were selected through random interval sampling methods. They found that the proposed model fit well across schools of all sizes but did not fit well in large districts. In other words, school size does not matter in allocation decisions, consistent with the results of Monk (1987, see also Burns & Mason, 1998).

---

[4] includes students from more than one grade level at the elementary school level as self-contained classrooms

In summary, schools and districts factors (organizational concerns, internal political concerns, data sources, and district size) as well as people (teacher student matching, parent input) could affect class composition.

The study by Monk (1987) found that principal involvement (high, medium and low) varied between schools. In the case of low principal involvement, teachers met at the end of the year and distributed students to classes, and determined which teacher would teach which classes (Monk, 1987). One principal said that "Well, if you take [name] then I'd like to have [name]" and another principal "recounted an instance where veteran teachers loaded up a first-year teacher with a disproportionate number of difficult students" (Monk, 1987, p. 173). In addition, the length of a principal's tenure was positively related to the principal's involvement in assigning students to teachers (Monk, 1987).

2) How Do Principals Compose Classes?

Principals used several general strategies for student assignment, including random assignment, homogeneous classes, balanced classrooms, matching characteristics of students to teachers, and assignments by previous year's teachers (Monk, 1987). Monk summarized that regardless of principals' involvement, it was common practice to balance classes with respect to gender and race without balancing classes with respect to achievement levels, learning styles, aptitude for learning, and so on. The study by Burns & Mason (1995) described similar class formation procedures across 22 schools as five steps.

First, principal provides teachers with the grade-level configuration template;

Second, principal provides teachers with guidelines for class formation;

Third, at a grade-level meetings, teachers use student placement cards, usually color coded by gender, to create next year's classes, sorting students cards according to the principal's template and guidelines outlined in Steps 1 and 2;

Fourth, principal reviews cards, checks for potential conflicts or imbalances not noticed by teachers, incorporates parent requests, addresses any teachers' concerns;

Fifth, fall adjustments are made. (pp. 749-750).

In addition, the study by Burns & Mason (1995) reported the strategies principals use to assign students to classes and the numbers of principals reporting their use as shown in Table 3.2; 57 principals (64%) used the planned strategies involving teachers formally or informally.

Table 3.2 Strategies principals use to assign students to class and number of principals reporting their use

Strategy	Number of Principals
Strategies requiring little or no planning:	31 (34%)
Random assignment	15 (17%)
Classes roll over with adjustment	12 (13%)
Classes roll over	4 (4%)
Planned strategies:	59 (66%)
Teachers use promotion card*	32 (36%)
Teachers informally create classes+	20 (22%)
Principal and teachers decide together^	5 (6%)
Principal uses promotion cards**	2 (2%)

Note *Information cards are completed by teachers for each student. Cards reflect behavioral and academic characteristics of students, and teachers attempt to create classes based on card information. Principals can or will review class assignments and make minor adjustments.
+ Similar to above but without formal promotion cards. Teachers meet and work cooperatively to share knowledge and characteristics of each student and formulate the best assignment for each student.
^ Principals and teachers meet together and cooperatively use promotion cards or share knowledge about students for final student placements.
**Principals are given promotion cards by teachers and principals make student assignments.
Source: Burns & Mason, 1995, p. 197.

In summary, principals used not only random assignment but also the planned strategies involving teachers formally or informally. However, we don't know how teachers could influence this process informally.

3. Value-Added Models (VAM)

When estimating teacher effects on student learning by using value added models, researchers have focused on a) defining and measuring student learning (Linn, 2005), b) education production functions (Hanushek, 1979, 1986), c) test alignment and domain coverage (Porter, et al., 2007; Webb, 2007), d) scaling and growth modeling (Briggs et al., 2008), e) vertical scaling and multidimensionality (Martineau, 2006), f) the Sanders model (Sanders & Horn, 1994; Wright, Horn, & Sanders, 1997), g) models in experimental studies (Dee, 2004; Kane & Staiger, 2008), and h) model specifications (Harris & Sass, 2006; McCaffrey et al., 2004).

Specifically, one study showed that a) student and teacher heterogeneity were the most important issues with which value-added models must contend, b) covariates were inadequate replacements for individual student and teacher effects, and c) random effects models yield inconsistent estimates of model parameters due to correlation between the random effects and explanatory variables in the model (Harris & Sass, 2006). Harris & Sass also noted that the biases introduced by covariate and random effects models extend both to the estimates of the unobserved teacher quality and the effects of time-varying teacher characteristics (experience and professional development) on student achievement.

The study of Harris & Sass (2006), however, assumed that measuring interactions and coordination among teachers directly was rarely possible even though social network methods can measure interactions and coordination among teachers. In other words, they assumed that characteristics (attribute) can be measured while networks are difficult to measure. If a model includes network measures as well as attribute measures, the results may be changed significantly. Thus, social network measures need to be considered in value-added models specification.

A second study designed a random-assignment experiment in the Los Angeles Unified School District (Kane & Staiger, 2008). Kane & Staiger collected students and teachers in grades two through five and relied on an experiment in which 78 pairs of classrooms (156 classrooms and 3194 students) were randomly assigned between teachers in the school years 2003-04 and 2004-05 in the Los Angeles Unified School District.

The results of Kane & Staiger indicated that differences in mean student outcomes within each pair could be predicted by several alternative non-experimental specifications. In addition, they evaluated both the bias and predictive accuracy of the value-added estimates by seven model specifications since controls could improve the precision of estimates or reduce bias respectively. The model specifications were a) end-of-year test scores with no controls, b) end-of-year test scores with student/peer controls (included prior scores), c) end-of-year test scores with student/peer controls (included prior scores) and school fixed effects, d) end-of-year test scores with student fixed effects, e) gain scores with no controls, f) with student/peer controls, and g) with student/peer controls and school fixed effects for experimental and non-experimental data.

The study of Kane & Staiger (2008), however, excluded teachers with less than three years teaching experience in estimating effects. Excluding teachers who have less than three years teaching experience is important because teacher quality depends on teaching experience.

Due to this exclusion, we might have only very qualified teachers with little heterogeneity in teacher effects.

Furthermore, if teachers' social networks vary depending on teaching experience and there is relationship between teachers' social network and class composition, they need to test assumptions about classroom assignment of students to teachers.

In summary, random assignment, which can be implemented through experimental design, is one solution to minimize selection bias when conducting value-added models studies. Second, model specification, which can be implemented through statistical modeling, is the other solution to minimize selection bias. Previous value-added models, however, did not account for teachers' social networks which might influence random assignment as well as model specification when evaluating the teachers' effect on gain in students' academic achievement.

Using falsification tests for three widely used value-added modeling specifications, Rothstein (2008, 2010) tested assumptions about classroom assignment of students to teachers, based on the idea that future teachers cannot influence students' past achievement just as future teachers cannot have causal effects on past outcomes.

Rothstein (2008, 2010) focused on the cohort of students in the fifth grade in 2000-2001, consisting of 60,740 students from 3,040 fifth grade classrooms and 868 schools from a larger population of 99,071. The data were collected by the North Carolina Education Research Data Center. This study examined end-of-grade math and reading tests from grades 3 through 5. To construct the third grade gain score, this study used "pre-tests" given at the beginning of 3rd grade in place of the second grade scores by standardizing the scale scores separately for each subject-grade-year combination. Also, this study used a restricted sample consisting of 23,415 students from 2,116 classrooms and 598 schools.

The strength of Rothstein's research (2008, 2010) is that it challenges assumptions about random assignment of students to teachers and provides information about falsification of three widely used VAMs. At the same time, one weakness is that it does not explain what kind of factors affect non-random assignment of students to teachers. In particular, previous value-added models did not account for teachers' social networks which might influence random assignment as well as model specification when evaluating the teachers' effect on gain in students' academic achievement. Therefore, as described in chapter 1, this study tests *Hypothesis 2-2: Previous social networks at a higher level (level 2) affect current formal organizational structure at a lower level (level 1)*.

To do this, first, this study will test the first null hypothesis: *formal organizational structure at students' level are homogeneous with respect to students' previous academic achievement and economic status*. In other words, students are randomly assigned to their teachers within and between schools with respect to previous academic achievement and economic status.

Second, this study will test the second null hypothesis: *there is no relationship between teachers' social networks within schools and their students' previous academic achievement and economic status*.

Third, this study will test the third null hypothesis: *there is no effect of teachers' specific social networks within schools on their students' previous academic achievement economic status*.

Thus, the primary research question will be addressed in this study as follows:

> *After controlling for teachers' attributes, do teachers' social networks affect non-random assignment of students to teachers with respect to students' previous academic achievement and economic status?*

1. Data

Data for this analysis are drawn from a larger study of school leadership and management in one public school district in the southeastern United States.

Table 3.3 School and student characteristics in 30 elementary schools in 2006~2007

School	Title Ⅰ	Student Attendance	Student Enrollment	African American Student	White students	LEP students	Free/ Reduced Lunch
1	Yes	97%	522	93%	2%	0%	77%
2	No	95%	641	18%	73%	1%	47%
3	Yes	97%	785	95%	3%	0%	81%
4	Yes	95%	527	99%	1%	0%	92%
5	No	96%	508	44%	48%	0%	38%
6	Yes	96%	583	97%	1%	0%	92%
7	Yes	96%	519	76%	13%	1%	83%
8	Yes	97%	402	99%	0%	0%	97%
9	No	96%	622	34%	40%	11%	35%
10	Yes	95%	507	45%	44%	0%	62%
11	Yes	96%	370	98%	1%	0%	92%
12	Yes	96%	607	71%	20%	0%	62%
13	No	96%	434	24%	67%	1%	35%
14	Yes	95%	381	99%	0%	0%	84%
15	No	96%	611	6%	76%	10%	19%
16	Yes	96%	628	80%	16%	1%	77%
17	No	96%	445	60%	30%	3%	62%
18	No	97%	409	61%	33%	1%	49%
19	Yes	96%	487	74%	13%	0%	67%
20	Yes	96%	468	86%	10%	0%	80%
21	No	96%	870	26%	63%	0%	28%
22	No	96%	372	14%	74%	4%	23%
23	Yes	96%	354	38%	34%	15%	66%
24	Yes	96%	421	67%	18%	0%	67%
25	No	96%	761	49%	37%	0%	54%
26	Yes	95%	533	99%	1%	0%	97%
27	Yes	96%	603	89%	6%	0%	94%
28	No	96%	722	38%	46%	1%	47%
29	Yes	96%	646	66%	20%	2%	68%
30	No	96%	476	58%	30%	4%	53%

Note: Only school 26 did not meet AYP; school 30 was excluded from the final sample

Table 3.4 Teacher characteristics in 30 elementary schools in 2006~2007

School	Total Teacher	% Full time	% Female	% White	Years Experience
1	48	100%	88%	63%	12
2	51	94%	92%	80%	14
3	59	97%	98%	47%	13
4	56	91%	95%	32%	12
5	44	95%	89%	93%	11
6	53	96%	94%	55%	10
7	45	93%	98%	53%	14
8	41	95%	80%	37%	11
9	52	98%	98%	79%	11
10	44	100%	93%	64%	13
11	33	97%	91%	52%	10
12	54	93%	93%	83%	15
13	35	97%	97%	83%	19
14	31	97%	84%	58%	11
15	51	100%	98%	92%	16
16	52	98%	98%	87%	16
17	41	98%	93%	88%	14
18	32	97%	97%	84%	14
19	47	89%	89%	60%	15
20	43	95%	93%	72%	12
21	71	99%	94%	90%	17
22	32	100%	84%	88%	11
23	33	97%	94%	70%	13
24	45	100%	93%	67%	13
25	56	93%	96%	79%	16
26	50	90%	86%	62%	9
27	57	96%	98%	70%	10
28	51	96%	94%	88%	9
29	58	97%	93%	90%	16
30	41	98%	93%	73%	14

Note: school 30 was excluded from the final sample

In the 2006-2007 school year, the Cloverville district served 33,156 students, including 16,214 students at its 30 elementary schools. All schools except one met AYP and student attendance was more than 95%. Three schools had more than 10% Limited English Proficient (LEP) students, as shown in Table 3.3. In addition, most schools had full-time teachers with an average 10 of years of teaching experience. The final sample was 309 self-contained teachers across 29 elementary schools in 2007.

2. Measures

The dependent variables were class average English/Language Arts (ELA) achievement in 2006, class average Mathematics achievement in 2006 and class average free/reduced lunch in 2006. The attributes variables were gender, race, education, teaching experience, new teachers at the school, self-contained teachers, professional development, formal leader, the number of formal leadership roles, and several leadership roles. In addition to the attributes variables, the network variables were in-degree in ELA, Math, and combined (ELA plus Math) advice networks in 2007.

1) Dependent Variables

Class average English/Language Arts (ELA) test score in 2006 is based on a criterion-referenced-test (CRT) with multiple-choice items. The content weights for the ELA CRT in grade 2 consisted of Grammar/Phonics (60%), Sentence Construction (25%), and Research (15%) while the domains for grades 3 through 5 consisted of Grammar/Sentence Construction (60%) and Research/Writing Process (40%). There were three categories of performance standards: below 800, between 800 and 850, and above 850.

Class average Mathematics test score in 2006 is based on a criterion-referenced-test (CRT) with multiple-choice items. The content weights for ELA CRT in grade 2 consisted of Number and Operations (55%), Measurement (15%), Geometry (20%), and Data Analysis and Probability (10%) while the domains for grades 3 through 5 consisted of Number and Operations

(50%, 43%, and 38%), Measurement (18%, 17%, and 32%), Geometry (12%, 20%, 10%), Algebra (10%), and Data Analysis and Probability (10%). There were three categories of performance standards: below 300, between 300 and 350, and above 350.

Class average free/reduced lunch in 2006 ranged from 0.00 to 1.00 with a mean of 0.61 and a standard deviation of 0.28.

2) Attributes Variables

Male was coded as 0= “female” and 1= “male”.

Race had two dummy variables. One was white (68%) (0= “non-white” and 1= “white”) and the other was African American (26%) (0= “non-African American” and 1= “African American”).

Education in 2007: Teachers were asked if they had a graduate degree (e.g., Master’s degree or Ph.D.) and were coded as 0= “No” and 1= “Yes”

Teaching Experience in 2007: Teachers were asked how many years they had taught as a teacher.

New teachers at this school in 2007: Teachers with less than one year at their current school were coded as 1.

Self-contained teachers in 2007: Teachers were asked if they taught self-contained classrooms; if so, they were coded as 1.

ELA and Mathematics Professional Development in 2007: The question was: “Please indicate how many professional development sessions you participated in this year.” The variable scales were from 1 to 4 (1= “None,” 2= “1-2 sessions,” 3= “3-7 sessions,” and 4= “more than 8 sessions.”).

Formal leader in 2007: The question was: “Are you formally assigned to perform a leadership role at this school such as assistant principal, reform program coach/facilitator, subject area coordinator or chair, master/mentor teacher, or program coordinator (e.g., Title 1 coordinator)?”

The number of formal leadership roles in 2007: The total number of formal leadership roles ranged from 0 to 10.

Reading, Literacy, or English program coordinator/chair, Math program coordinator/chair, school improvement coordinator, master/mentor teacher and teacher consultant in 2007: the question was: “What percentage of your time is formally assigned to any of the following leadership roles at this school?” The variable scales from 1 to 6 (1= “0%,” 2= “1-25 %,” 3= “26-50%,” 4= “51-75%,” 5= “76-99%,” and 6= “100 %.”).

3) Network Variables

This study used advice networks as a proxy indicator instead of networks about class assignment though advice networks might not be directly related to networks about class assignment. In addition, this study assumed that networks in 2007 were similar to networks in 2006 even though there might be some change due to teacher turnover or dynamic factors. Thus, this study used networks in 2007 instead of 2006 in order to control for new teachers at this school in 2007 and due to data limitations although networks in 2006 might be more precisely related to class assignment in 2007. In other words, if we use teachers’ social networks in 2006, we need to exclude the new teachers in 2007 while if we use teachers’ social networks in 2007, we could control for new teachers in 2007 and show whether or not there was a relationship between current (2007) networks and previous (2006) achievement.

In-degree in ELA advice network in 2007: The ELA advice network consisted of the ties of interaction for each colleague (5-point scales: yearly, semiannually, monthly, weekly, and daily) in 2007 based on the following question: To whom do you turn in this school for advice or information about reading/language arts or English instruction? In-degree in ELA advice network measures the number of colleagues that were named as an advice-givers as part of their advice networks. In the case of advice networks, teachers with a higher in-degree in ELA advice networks may be considered the experts in ELA within their school because they are sought more frequently for advice in ELA subject.

In-degree in Math advice network in 2007: The Math advice network consisted of the ties of interaction for each colleague (5-point scales: yearly, semiannually, monthly, weekly, and daily) in 2007 based on the following question: To whom do you turn in this school for advice or information about mathematics instruction? In-degree in Math advice network measures the number of colleagues that were named as an advice-givers as part of their advice networks. In the case of advice networks, teachers with a higher in-degree in Math advice networks may be considered the experts in Math within their school because they are sought more frequently for advice in Math subject.

In-degree in Combined advice network (ELA plus Math advice networks) in 2007: The Combined network was based on the composite networks of ELA and math networks. In-degree in combined advice network measures the number of colleagues that were named as an advice-givers as part of their advice networks. In the case of advice networks, teachers with a higher in-degree in combined advice networks may be considered the experts in ELA or Math within their school because they are sought more frequently for advice in ELA or Math subject.

3. Methods

To test the first null hypothesis: *students are randomly assigned to their teachers within and between schools with respect to previous academic achievement and economic status,* two-level unconditional models were performed.

In addition, to test the second null hypothesis: *there is no relationship between teachers' social networks within schools and their students' previous academic achievement and economic status*, correlation analyses were performed.

Finally, to test the third null hypothesis: *there is no relationship between specific teachers' social networks within schools and their students' previous academic achievement economic status*, I explored which types of teachers' social networks and attributes affect non-random assignment between and within schools through multiple regression analyses. For this, I analyze the five models for ELA, Math and Combined networks and compare these results.

SAS 9.2 software was used to run two-level unconditional models, compute the in-degree in advice networks, analyze correlation, and run five multiple regression models.

4. Models

1) Model 1

To examine the effect of teachers' social networks on non-random assignment with respect to students' academic achievement and economic status, model 1 was specified as a multiple regression model. Model 1 controlled the following teachers' attributes: gender, race, education, teaching experience, professional development, new teachers.

$$
\begin{aligned}
&DV\ in\ 2006_i \\
&\quad = \beta_0 + \beta_1 NV\ in\ 2007_i + \beta_2 \mathrm{Grade}_2 + \beta_3 \mathrm{Grade}_3 \\
&\quad + \beta_4 \mathrm{Grade}_4 + \beta_5 \mathrm{School}_1 \sim \beta_{32} \mathrm{School}_{28} + \beta_{33} Gender_i \\
&\quad + \beta_{34} White_i + \beta_{35} Black_i + \beta_{36} Master\ degreee_i \\
&\quad + \beta_{37} Teaching\ experience_i \\
&\quad + \beta_{38} Professoinal\ development_i + \beta_{39} New_i + \varepsilon_i
\end{aligned}
$$

Where

β_0 is the intercept.

β_1 indicates the effect of Network Variables (Teachers' ELA, Math, and combined networks) in 2007 on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006

$\beta_2 \sim \beta_4$ are the effect of 2nd, 3rd and 4th grade level on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

$\beta_5 \sim \beta_{32}$ are the effect of each school on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

$\beta_{33} \sim \beta_{39}$ are the effect of each Attributes Variables(Gender, race, education, teaching experience, professional development, new teachers) on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

ε_i is the residual term.

The larger the value of β_1, the more we would infer that teachers' social networks affect non-random assignment with respect to students' academic achievement and economic status.

The larger the value of $\beta_2 \sim \beta_4$, the more we would infer that each grade level affects non-random assignment with respect to students' academic achievement and economic status.

The larger the value of $\beta_5 \sim \beta_{32}$, the more we would infer that each school affects non-random assignment with respect to students' academic achievement and economic status.

The larger the value of $\beta_{33} \sim \beta_{40}$, the more we would infer that each attribute variable affects non-random assignment with respect to students' academic achievement and economic status.

2) Model 2

Model 2 added up the formal leader variable.

$$
\begin{aligned}
DV\ in\ 2006_i &= \beta_0 + \beta_1 NV\ in\ 2007_i + \beta_2 \mathrm{Grade}_2 + \beta_3 \mathrm{Grade}_3 \\
&+ \beta_4 \mathrm{Grade}_4 + \beta_5 \mathrm{School}_1 \sim \beta_{32} \mathrm{School}_{28} + \beta_{33} Gender_i \\
&+ \beta_{34} White_i + \beta_{35} Black_i + \beta_{36} Master\ degreee_i \\
&+ \beta_{37} Teaching\ experience_i \\
&+ \beta_{38} Professoinal\ development_i + \beta_{39} New_i \\
&+ \beta_{40} Formal\ leader_i + \varepsilon_i
\end{aligned}
$$

Where

β_{40} is the effect of Attributes Variable(Formal leader) on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

3) Model 3

Model 3 replaced the formal leader variable with the total number of leadership roles.

$$
\begin{aligned}
&DV\ in\ 2006_i \\
&\quad = \beta_0 + \beta_1 NV\ in\ 2007_i + \beta_2 \mathrm{Grade}_2 + \beta_3 \mathrm{Grade}_3 \\
&\quad + \beta_4 \mathrm{Grade}_4 + \beta_5 \mathrm{School}_1 \sim \beta_{32} \mathrm{School}_{28} + \beta_{33} Gender_i \\
&\quad + \beta_{34} White_i + \beta_{35} Black_i + \beta_{36} Master\ degreee_i \\
&\quad + \beta_{37} Teaching\ experience_i \\
&\quad + \beta_{38} Professoinal\ development_i + \beta_{39} New_i \\
&\quad + \beta_{40} the\ total\ number\ of\ leadership\ roles_i + \varepsilon_i
\end{aligned}
$$

Where

β_{40} is the effect of Attributes Variable(the total number of leadership roles) on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

4) Model 4

Model 4 replaced the formal leader variable with coordinator (ELA, Math, or School improvement) roles.

$$
\begin{aligned}
&DV\ in\ 2006_i \\
&\quad = \beta_0 + \beta_1 NV\ in\ 2007_i + \beta_2 \text{Grade}_2 + \beta_3 \text{Grade}_3 \\
&\quad + \beta_4 \text{Grade}_4 + \beta_5 \text{School}_1 \sim \beta_{32} \text{School}_{28} + \beta_{33} Gender_i \\
&\quad + \beta_{34} White_i + \beta_{35} Black_i + \beta_{36} Master\ degreee_i \\
&\quad + \beta_{37} Teaching\ experience_i \\
&\quad + \beta_{38} Professoinal\ development_i + \beta_{39} New_i \\
&\quad + \beta_{40} Coordinator_i + \varepsilon_i
\end{aligned}
$$

Where

β_{40} is the effect of Attributes Variable(Coordinators) on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

5) Model 5

Model 5 replaced the formal leader variable with teacher consultant roles.

$$
\begin{aligned}
&DV\ in\ 2006_i \\
&\qquad = \beta_0 + \beta_1 NV\ in\ 2007_i + \beta_2 \mathrm{Grade}_2 + \beta_3 \mathrm{Grade}_3 \\
&\qquad + \beta_4 \mathrm{Grade}_4 + \beta_5 \mathrm{School}_1 \sim \beta_{32} \mathrm{School}_{28} + \beta_{33} Gender_i \\
&\qquad + \beta_{34} White_i + \beta_{35} Black_i + \beta_{36} Master\ degreee_i \\
&\qquad + \beta_{37} Teaching\ experience_i \\
&\qquad + \beta_{38} Professoinal\ development_i + \beta_{39} New_i \\
&\qquad + \beta_{40} Teacher\ consultant_i + \varepsilon_i
\end{aligned}
$$

Where

β_{40} is the effect of Attributes Variable(teacher consultant) on Dependent Variables (Class average ELA academic achievement score, class average Math academic achievement score, and class average free/reduced lunch) in 2006.

With respect to students' economic status, professional development variables were excluded in five models.

Results

Descriptive statistics are shown in Table 3.5.

Table 3.5 Descriptive statistics of teachers with at least 10 students except the first grade

	N	Min	Max	Mean	SD
English Language Arts (ELA) in 2006	309	785	862	820	17
Mathematics in 2006	309	284	380	329	20
Free/reduced lunch in 2006	309	0	1	.61	.27
Male teachers	309	0	1	0.09	0.29
How many years have you worked as a teacher?	307	0	47	12	9.5
White teachers	309	0	1	.70	.46
African American teachers	309	0	1	.24	.43
Graduate degree	309	0	1	.76	.43
New teachers at this school	309	0	1	.24	.43
Reading/Language Arts or English teaching professional development	304	0	3	1.28	.82
Mathematics teaching professional development	306	0	3	1.18	.76
Are you formally assigned to perform a leadership role at this school?	309	0	1	.27	.44
The total number of formal leadership roles	309	0	10	0.82	1.51
Reading, Literacy, or English program coordinator/Chair	309	0	6	0.16	0.70
Math program coordinator/Chair	309	0	6	0.18	0.75
School improvement coordinator	309	0	6	0.13	0.59
Master/mentor teacher	309	0	6	0.44	1.14
Teacher consultant	309	0	6	0.21	0.75
In-degree in ELA advice networks	309	0	8	0.84	1.13
In-degree in Math advice networks	309	0	9	0.88	1.24
In-degree in Combined (ELA plus Math) advice networks	309	0	9	1.24	1.49
Valid N (listwise)	309				

The ELA academic achievement score in 2006 was an average of 820 with standard deviation 17, and the range was from 785 to 862 while the Math academic achievement score in 2006 was an average of 329 with standard deviation 20, and the range was from 284 to 380. In addition, the percentage of students eligible for free/reduced lunch in 2006 averaged 0.61 with standard deviation 0.27, and the range from 0 to 1.

1. Heterogeneous Academic Achievement & Economic Status Within and Between Schools

After testing the first null hypothesis: *students are randomly assigned to their teachers within and between schools with respect to previous academic achievement and economic status*, the results of two-level unconditional models indicated that there was statistically significant variation in previous academic achievement among teachers (76%) while there was statistically significant variation in economic status between schools (73%), as shown in Table 3.6 (all are statistically significant at $p < .01$)

Table 3.6 Two-level (classes nested in schools) unconditional models

		Random Effects	ICC (Ratio)	Variance Estimates	S.E.	Z value	p value
ELA Achievement	Schools	Random Intercept	24%	63	21	2.96	0.0015
	Classes	Residual	76%	199	17	12.01	<.0001
Math Achievement	Schools	Random Intercept	24%	90	31	2.92	0.0018
	Classes	Residual	76%	283	24	11.99	<.0001
Free/reduced Lunch	Schools	Random Intercept	73%	0.054	0.015	3.58	0.0002
	Classes	Residual	27%	0.020	0.002	11.94	<.0001

Note: only self-contained teachers were included into models except the first grade level. ICC means intraclass correlation.

In other words, these variance estimates suggest that schools vary in students' average previous academic achievement both in ELA and mathematics and there is more variation among classes (self-contained teachers) within schools. However, there is even more variation between schools in students' average previous economic status.

In summary, these results indicated that students are non-randomly assigned to their teachers within and between schools with respect to previous academic achievement and economic status.

2. Association Between Teachers' Social Networks and Their Students' Previous Academic Achievement & Economic Status

To test the second null hypothesis: *there is no relationship between teachers' social networks within schools and their students' previous academic achievement and economic status*, correlation analyses were conducted as shown in Table 3.7.

If students were randomly assigned to their teachers regardless of their teachers' social networks, we would expect no relationship between students' previous academic achievement and their teachers' social networks. If we found the association between teachers' social networks and their students' previous academic achievement, we could infer that students were non-randomly assigned to their teachers depending on their teachers' social networks within schools with respect to academic achievement.

First, the results showed that the correlation between teachers' ELA networks in 2007 and students' ELA achievement in 2006 was statistically significant (0.25, $p<.01$) and the correlation between teachers' Math networks in 2007 and students' Math achievement in 2006 was statistically significant (0.18, $p<.01$), as shown in Table 3.7.

Table 3.7 Correlation matrix

	ELA in 2006	Math in 2006	Free lunch in 2006	In-degree in ELA in 2007	In-degree in Math in 2007
Math in 2006	.89**				
Free lunch in 2006	-.61***	-.62***			
In-degree in ELA in 2007	.25**	.22***	-.20***		
In-degree in Math in 2007	.19***	.18**	-.14*	-.41***	
In-degree in Combined	.20***	.18**	-.18**	.76***	.83***

Note: * p < .05, ** p < .01, *** p< .001.

Second, the correlation between teachers' Math networks in 2007 and students' ELA achievement in 2006 was statistically significant (0.19, p<.001) and the correlation between teachers' ELA networks in 2007 and students' Math achievement in 2006 was statistically significant (0.22, p<.001), as shown in Table 3.7.

Third, the correlation between teachers' combined networks in 2007 and students' ELA achievement in 2006 was statistically significant (0.20, p<.001) and the correlation between teachers' combined networks in 2007 and students' Math achievement in 2006 was statistically significant (0.18, p<.01), as shown in Table 3.7.

Fourth, the correlation between teachers' ELA networks in 2007 and Free/reduced lunch in 2006 was statistically significant (-0.20, p<.001) and the correlation between teachers' Math networks in 2007 and Free/reduced lunch in 2006 was statistically significant (-0.14, p<.05). In addition, the correlation between teachers' combined networks in 2007 and students' free/reduced lunch in 2006 was statistically significant (-0.18, p<.01), as shown in Table 3.7.

In summary, these results of positive correlation indicated that students were non-randomly assigned to their teachers depending on their teachers' social networks with respect to previous academic achievement. In other words, the larger social networks a teacher has within her school, the more academically advantaged students the teacher will have.

Additionally, these results of negative correlation indicated that students were non-randomly assigned to their teachers depending on their teachers' social networks with respect to previous class average free/reduced lunch. In other words, the larger social networks a teacher has within her school, the more economically advantaged students the teacher will have.

3. The Effects of Teachers' Social Networks and Attributes on Non-Random Assignment

Finally, to test the third null hypothesis: *there is no effects of teachers' particular social networks within schools on their students' previous academic achievement economic status*, I explored which types of teachers' social networks and attributes affect non-random assignment between and within schools through multiple regression analyses.

1) Students' Previous Academic Achievement

Specifically, to examine which types of teachers' social networks affect non-random assignment, three types of teachers' social networks (i.e., ELA, Math, and combined networks) were analyzed respectively in five multiple regression models.

(1) ELA Achievement

First, after controlling for teachers' attributes with school and grade-fixed effects, the results of five models indicated that teachers' ELA networks had a positive effect on non-random assignment with respect to students' previous ELA achievement. African American teachers, new teachers, and ELA professional development had a negative effect on previous ELA achievement while teaching experiences, a Master's degree, a formal leader, the total numbers and specific

Table 3.8 Effects of teachers' ELA or Math networks on students' previous ELA achievement

ELA Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	0.01	0.01	-0.01	0.00	0.00
White	0.02	-0.05	-0.01	0.01	0.00
African American	-0.06	-0.13	-0.09	-0.07	-0.09
Master's degree	0.03	0.03	0.03	0.02	0.03
Teaching experience	0.04	0.03	0.02	0.04	0.02
ELA professional development	-0.04	-0.07	-0.06	-0.05	-0.05
New teacher	-0.14*	-0.10+	-0.12*	-0.14*	-0.12*
Formal leader		0.22***			
The total number of leadership roles			0.19***		
ELA coordinator				0.08	
Teacher consultant					0.16***
In-degree in ELA networks	0.13*	0.10+	0.10+	0.12*	0.12*
R-Square	0.40	0.44	0.43	0.41	0.42
Math Networks	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Male	-0.01	0.00	-0.02	-0.02	-0.01
White	0.02	-0.05	-0.01	0.01	0.00
African American	-0.06	-0.13	-0.09	-0.07	-0.09
Master's degree	0.04	0.04	0.03	0.03	0.04
Teaching experience	0.04	0.03	0.02	0.04	0.02
ELA professional development	-0.03	-0.05	-0.05	-0.03	-0.04
New teacher	-0.14*	-0.11+	-0.13*	-0.15**	-0.13*
Formal leader		0.22***			
The total number of leadership roles			0.19***		
ELA coordinator				0.08	
Teacher consultant					0.15**
In-degree in Math networks	0.12*	0.06	0.07	0.11*	0.10*
R-Square	0.40	0.43	0.43	0.41	0.41

Notes: sample size=300, school and grade level fixed effects models.
+ p < .10, * p < .05, ** p < .01, *** p < .001.

types (e.g., teacher consultant) of leadership roles had a positive effect. In summary, these results indicated that ELA networks had a significant positive effect on non-random assignment between and within schools after controlling for teachers' attributes, as shown in Table 3.8.

Second, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' Math networks had a positive effect on non-random assignment with respect to students' previous ELA achievement. African American teachers, new teachers, and ELA professional development had a negative effect on previous ELA achievement while teaching experience, a Master's degree, a formal leader, the total numbers and specific types (e.g., teacher consultant) of leadership roles had a positive effect. In summary, these results indicate that Math networks had a positive effect on non-random assignment between and within schools after controlling for teachers' attributes, as shown in Table 3.8.

Table 3.9 Effects of teachers' combined networks on students' ELA previous achievement

Combined Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	0.00	0.00	-0.02	-0.01	-0.01
White	0.02	-0.04	-0.01	0.01	0.00
African American	-0.05	-0.13	-0.09	-0.07	-0.08
Master's degree	0.03	0.04	0.03	0.03	0.04
Teaching experience	0.04	0.03	0.02	0.04	0.02
ELA professional development	-0.04	-0.06	-0.06	-0.04	-0.05
New teacher	-0.14*	-0.10+	-0.12*	-0.14**	-0.12*
Formal leader		0.22***			
The total number of leadership roles			0.19***		
ELA coordinator				0.07	
Teacher consultant					0.15**
In-degree in Combined networks	0.12*	0.07	0.07	0.11*	0.11*
R-Square	0.40	0.43	0.43	0.41	0.42

Notes: sample size=302, school and grade level fixed effects models.
+ p < .10, * p < .05, ** p < .01, *** p < .001.

Third, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' combined networks had a positive effect on non-random assignment with respect to students' previous achievement, as shown in Table 3.9. African American teachers, ELA professional development, and new teachers had a negative effect on previous ELA achievement while teaching experience, a formal leader, the total numbers and specific types of leadership roles had a positive effect. Overall, this pattern of results suggests that three types of teachers' social network had a significant positive effect on non-random assignment of students to their teachers with respect to previous ELA academic achievement.

(2) Math Achievement

First, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' ELA networks had a positive effect on non-random assignment with respect to students' previous Math achievement. Male teachers, African American teachers, and new teachers had a negative effect on previous Math achievement while Math professional development, teaching experience, a formal leader, the total numbers and specific types of leadership roles had a positive effect. In summary, this pattern of results suggests that teachers' ELA networks had a significant positive effect on non-random assignment of students to their teachers between and within schools with respect to previous Math academic achievement after controlling for teachers' attributes, as shown Table 3.10.

Second, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' Math networks had a statistically non-significant positive effect on non-random assignment with respect to students' previous Math achievement.

Table 3.10 Effects of teachers' ELA or Math networks on students' previous Math achievement

ELA Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.01	-0.01	-0.02	-0.01	-0.01
White	0.00	-0.06	-0.03	-0.01	-0.02
African American	-0.07	-0.14	-0.10	-0.09	-0.10
Master's degree	-0.01	0.00	0.00	-0.01	0.00
Teaching experience	0.03	0.02	0.01	0.03	0.02
Math professional development	0.05	0.02	0.02	0.04	0.03
New teacher	-0.14**	-0.09+	-0.11*	-0.14**	-0.12*
Formal leader		0.20***			
The total number of leadership roles			0.20***		
Math coordinator				0.10*	
Teacher consultant					0.14**
In-degree in ELA networks	0.11*	0.08	0.08	0.11*	0.10*
R-Square	0.47	0.50	0.50	0.48	0.48
Math Networks	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Male	-0.02	-0.02	-0.03	-0.02	-0.02
White	0.00	-0.06	-0.04	-0.01	-0.02
African American	-0.07	-0.13	-0.10	-0.08	-0.09
Master's degree	-0.00	0.00	0.00	0.00	0.01
Teaching experience	0.04	0.02	0.02	0.04	0.02
Math professional development	0.04	0.01	0.01	0.03	0.02
New teacher	-0.14**	-0.10+	-0.12*	-0.14*	-0.12*
Formal leader		0.20***			
The total number of leadership roles			0.19***		
Math coordinator				0.09	
Teacher consultant					0.13**
In-degree in Math networks	0.11*	0.06	0.06	0.09+	0.10*
R-Square	0.47	0.50	0.50	0.48	0.49

Notes: Sample size=302 (ELA networks) or 303 (Math networks), school and grade level fixed effects models, + p < .10, * p < .05, ** p < .01, *** p < .001.

Male teachers, African American teachers, and new teachers had a negative effect on previous Math achievement while Math professional development, teaching experience, a Master's degree, a formal leader, the total numbers and specific types (e.g., teacher consultant) of leadership roles had a positive effect. In summary, these results indicate that Math networks had a positive effect on non-random assignment between and within schools after controlling for teachers' attributes, as shown Table 3.10.

Table 3.11 Effects of teachers' combined networks on students' math previous achievement

Combined Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.01	-0.01	-0.03	-0.02	-0.02
White	0.00	-0.06	-0.03	-0.01	-0.02
African American	-0.07	-0.13	-0.10	-0.08	-0.09
Master's degree	0.00	0.00	0.00	-0.01	0.00
Teaching experience	0.03	0.02	0.01	0.03	0.02
Math professional development	0.04	0.01	0.01	0.04	0.02
New teacher	-0.14**	-0.10+	-0.12*	-0.14*	-0.12*
Formal leader		0.20***			
The total number of leadership roles			0.20***		
Math coordinator				0.09	
Teacher consultant					0.14**
In-degree in Combined networks	0.10+	0.05	0.05	0.08	0.09+
R-Square	0.47	0.50	0.50	0.48	0.49

Notes: sample size=303, school and grade level fixed effects models,
+ p < .10, * p < .05, ** p < .01, *** p < .001.

Third, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' combined networks had, borderline statistically significant, a positive effect on non-random assignment with respect to students' previous Math achievement. Male teachers, African American teachers, and new teachers had a negative effect on previous Math achievement while Math professional development, teaching experience, a Master's degree, a formal leader, the total numbers and specific types (e.g., teacher consultant) of leadership roles had a positive effect. In summary, these results indicate that combined networks had a positive effect on non-random assignment between and within schools after controlling for teachers' attributes, as shown Table 3.11.

Overall, significant findings indicate that teachers' social networks might be a key factor in explaining the non-assignment of students to their teachers with respect to Math academic achievement as well as ELA academic achievement.

2) Students' Previous Economic Status

To estimate the effects of teachers' social networks on non-random assignment with respect to students' previous economic status, three types of teachers' social networks were analyzed.

First, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' ELA networks had a statistically non-significant negative effect on students' previous free/reduced lunch. Only new teachers at their schools had a positive effect on previous free/reduced lunch. In other words, new teachers at their schools had more economically disadvantaged students than other teachers. In summary, these results indicated that ELA networks had a negative effect but essential zero on students' previous free/reduced lunch between and within schools after controlling for teachers' attributes, as shown Table 3.12.

Table 3.12 Effects of teachers' ELA or Math networks on students' previous free/reduced lunch

ELA Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.06+	-0.05+	-0.04	-0.05	-0.05
White	-0.11+	-0.08	-0.09	-0.10+	-0.10
African American	-0.04	-0.00	-0.02	-0.01	-0.02
Master's degree	-0.01	-0.01	-0.01	-0.02	-0.02
Teaching experience	-0.04	-0.04	-0.03	-0.03	-0.03
New teacher	0.05	0.02	0.03	0.03	0.03
Formal leader		-0.11***			
The total number of leadership roles			-0.13***		
School improvement coordinator				-0.13***	
Teacher consultant					-0.12***
In-degree in ELA networks	-0.05	-0.03	-0.03	-0.03	-0.04
R-Square	0.77	0.78	0.78	0.78	0.77
Math Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.05	-0.05	-0.04	-0.04	-0.04
White	-0.11+	-0.08	-0.09	-0.10+	-0.10
African American	-0.04	-0.01	-0.02	-0.02	-0.02
Master's degree	-0.02	-0.02	-0.01	-0.02	-0.02
Teaching experience	-0.04	-0.04	-0.03	-0.04	-0.03
New teacher	0.04	0.02	0.03	0.03	0.03
Formal leader		-0.04**			
The total number of leadership roles			-0.12***		
School improvement coordinator				-0.13***	
Teacher consultant					-0.12***
In-degree in Math networks	-0.07*	-0.01	-0.04	-0.05+	-0.06+
R-Square	0.77	0.78	0.78	0.78	0.77

Notes: sample size=305, school and grade level fixed effects models.
+ p < .10, * p < .05, ** p < .01, *** p < .001.

Second, after controlling for teachers' attributes with school and grade fixed effects, the results from three models (except models 2 and 3) indicate that teachers' Math networks had a statistically significant negative effect on students' previous free/reduced lunch. Only new teachers at their schools had a positive effect on previous Free/reduced lunch. In other words, new teachers at their schools had more economically disadvantaged students than other teachers. In summary, these results indicated that Math networks had a negative effect on students' previous free/reduced lunch between and within schools, after controlling for teachers' attributes, as shown Table 3.12.Third, after controlling for teachers' attributes with school and grade fixed effects, the results from five models indicate that teachers' combined networks had a negative effect on students' previous free/reduced lunch. Only new teachers at their schools had a positive effect on previous Free/reduced lunch. In other words, new teachers at their schools had more economically disadvantaged students than other teachers, as shown Table 3.13.

Table 3.13 Effects of teachers' combined networks on students' previous free/reduced lunch

Combined Networks	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.05	-0.05	-0.04	-0.05	-0.05
White	-0.12+	-0.08	-0.09	-0.11+	-0.10
African American	-0.04	-0.01	-0.02	-0.02	-0.02
Master's degree	-0.01	-0.02	-0.01	-0.02	-0.02
Teaching experience	-0.04	-0.04	-0.03	-0.03	-0.03
New teacher	0.04	0.02	0.03	0.03	0.03
Formal leader		-0.10**			
The total number of leadership roles			-0.12***		
School improvement coordinator				-0.13***	
Teacher consultant					-0.12***
In-degree in Combined networks	-0.07*	-0.04	-0.04	-0.06+	-0.06+
R-Square	0.77	0.78	0.78	0.78	0.77

Notes: sample size=305, school and grade level fixed effects models.
+ p < .10, * p < .05, ** p < .01, *** p < .001.

Overall, significant findings indicate that after controlling for teachers' attributes with school and grade fixed effects, specific teachers' social networks (i.e., advice network in math) might be a key factor in explaining the non-assignment of students to their teachers with respect to previous students' free/reduced lunch. But, evidence is borderline.

After comparing the standardized coefficients of network effects, the results showed the similar pattern both in ELA and Math achievement, as shown in Table 3.14. However, the results showed smaller network effects on free/reduced lunch than academic achievement.

Specifically, for ELA achievement in model 1, we can interpret that an increase of one standard deviation (i.e., about one in-degree) in ELA networks results, on average, in an increase of 0.13 standard deviation (i.e., about two points, $0.13 \times 17=2.2$) in ELA achievement. Thus, an increase of four standard deviation (i.e., about four in-degree) in ELA networks results in an increase of about half standard deviation (i.e., about nine points) in class average ELA achievement.

Table 3.14 Effects of teachers' social networks on class composition in model 1 to model 5

	Model 1	Model 2	Model 3	Model 4	Model 5
ELA achievement					
In-degree in ELA networks	0.13*	0.10+	0.10+	0.12*	0.12*
In-degree in Math networks	0.12*	0.06	0.07	0.11*	0.10*
In-degree in Combined	0.12*	0.07	0.07	0.11*	0.11*
Math achievement					
In-degree ELA networks	0.11*	0.08	0.08	0.11*	0.10*
In-degree Math networks	0.11*	0.06	0.06	0.09+	0.10*
In-degree in Combined	0.10+	0.05	0.05	0.08	0.09+
Free/reduced lunch					
In-degree ELA networks	-0.05	-0.03	-0.03	-0.03	-0.04
In-degree Math networks	-0.07*	-0.01	-0.04	-0.05+	-0.06+
In-degree in Combined	-0.07*	-0.04	-0.04	-0.06+	-0.06+

Notes: school and grade level fixed effects models, + $p < .10$, * $p < .05$.

In addition, for Math achievement in model 1, we can interpret that an increase of one standard deviation (i.e., about one in-degree) in Math networks results, on average, in an increase of 0.11 standard deviation (i.e., about two points, 0.11 × 20=2.2) in Math achievement. Thus, an increase of four standard deviations (i.e., about five in-degree) in Math networks results in an increase of about half of a standard deviation (i.e., about nine points) in class average math achievement.

Finally, for free/reduced lunch in model 1, we can interpret that an increase of two standard deviations (i.e., about three in-degree) in Combined networks results, on average, in a decrease of 0.14 standard deviation (i.e., about four percentage, 0.14 × 0.27=0.0378) in class average free/reduced lunch. Thus, an increase of four standard deviations (i.e., about six in-degree) in Combined networks results in a decrease of about one fourth of a standard deviation (i.e., about eight percentage) in class average free/reduced lunch.

Table 3.15 Adjusted R-square in model 1 to model 5

	Model 1	Model 2	Model 3	Model 4	Model 5
ELA achievement					
In-degree in ELA networks	0.311	0.353	0.343	0.315	0.333
In-degree in Math networks	0.310	0.348	0.339	0.313	0.330
In-degree in Combined	0.310	0.348	0.339	0.313	0.330
Math achievement					
In-degree ELA networks	0.394	0.429	0.428	0.403	0.411
In-degree Math networks	0.396	0.427	0.426	0.401	0.411
In-degree in Combined	0.393	0.425	0.425	0.399	0.408
Free/reduced lunch					
In-degree ELA networks	0.733	0.743	0.747	0.749	0.747
In-degree Math networks	0.735	0.744	0.747	0.751	0.748
In-degree in Combined	0.735	0.744	0.747	0.751	0.748

To examine how much these models explain the variation of academic achievement and economic status, the adjusted R-square is summarized in Table 3.15. Specifically, for ELA achievement, the model with the most explanation power among five models was model 2 which explained about 35% variation of ELA achievement. For Math achievement, the model with the most explanation power among five models also was model 2 which explained about 43% variation of Math achievement. In addition, for free/reduced lunch, the model with the most explanation power among five models was model 4 which explained about 75% variation of Math achievement.

To examine how additionally teachers' social networks explained the variation of academic achievement and economic status after controlling for teachers' attributes, the models which excluded teachers' social networks in model 1 to model 5 were analyzed. Then, adjusted R-square change was computed and summarized in Table 3.16. The detailed results of each model were reported in the Appendices in Table A.1 to A.60.

Table 3.16 Adjusted R-square change in model 1 to model 5

	Model 1	Model 2	Model 3	Model 4	Model 5
ELA achievement					
In-degree in ELA networks	0.011	0.006	0.006	0.011	0.011
In-degree in Math networks	0.010	0.002	0.002	0.009	0.007
In-degree in Combined	0.010	0.001	0.002	0.009	0.007
Math achievement					
In-degree ELA networks	0.007	0.003	0.003	0.008	0.007
In-degree Math networks	0.009	0.001	0.001	0.006	0.007
In-degree in Combined	0.006	0.002	0.000	0.004	0.004
Free/reduced lunch					
In-degree ELA networks	0.001	0.000	0.000	0.000	0.001
In-degree Math networks	0.002	0.001	0.000	0.002	0.002
In-degree in Combined	0.003	0.001	0.000	0.001	0.002

The results showed that teachers' social networks additionally explained only a small amount of the variation of academic achievement (about 1%) and economic status (about 0.3%) after controlling for teachers' attributes. In other words, if we have enough information about relationship between teachers' social networks and teachers' attributes, we can control for effects of teachers' social network on class composition through value-added model specification by including relevant teachers' attributes.

In summary, to explain what kind of factors affect non-random assignment of students to teachers, the primary research question was answered as follows.

First, the results of two-level unconditional models indicate that students' academic achievement and economic status were heterogeneous within and between schools in one district. In other words, students are non-randomly assigned to their teachers within and between schools with respect to students' previous academic achievement and economic status

Second, the results of correlation analysis indicate that the significant association between teachers' social networks (English/Language Arts and Math networks) and students' previous academic achievement and economic status existed. In other words, the more social networks teachers have within schools, the more academically as well as economically advantaged students teachers have within schools.

Third, the results of multiple regression models show that teachers' social networks and attributes might be a significant factor in explaining the non-assignment of students to their teachers with respect to students' academic achievement and economic status.

Discussion and Conclusion

After examining teachers' social networks and class composition through multilevel models, correlation analyses, and multiple regression models, the results of this study indicate that *social networks at a higher level (level 2) affect formal organizational structure at a lower level (level 1).* In detail, first, students are non-randomly assigned to their teachers within and between schools with respect to students' previous academic achievement and economic status. Second, the larger a teacher' social networks within school, the more academically as well as economically advantaged students the teacher has. Third, teachers' social networks and attributes are a significant factor in explaining the non-assignment of students to teachers with respect to students' academic achievement and economic status.

This study reported results consistent with Rothstein's study (2008) that students were not randomly assigned to their teachers. The main difference between this study and previous studies is that this study focuses on the effect of teachers' social networks on non-random assignment, which has been ignored in previous studies. In addition, this study presented the results of the effect of teachers' social networks on non-random assignment after controlling for teachers' attributes; again, this is different from previous research.

However, we can doubt the effect of teachers' social networks on non-random assignment because good teachers might have larger social networks and better quality students with regard to academic achievement. That is, the networks might be confounded with quality of teaching. Even so, we could use teachers' social networks as an indicator of good teachers.

Just as students' non-random assignment between schools was a big challenge to efforts to reduce the achievement gap between schools, students' non-random assignment within schools is also an important challenge to efforts to decrease the achievement gap within schools.

With respect to teacher quality, if experienced teachers or teachers with more expertise had more high-achieving students than novice teachers, low-performing students would have less chance to improve their academic achievement. In other words, the uneven distribution of effective teachers within schools could interfere with efforts to reduce the achievement gap among students within schools. In addition, Hanushek and Rivkin (2010) pointed out that "In terms of fairness, any failure to account for sorting on unobservable characteristics would potentially penalize teachers given unobservably more difficult classrooms and reward teachers given unobservably less difficult classrooms" (p. 270).

What kind of solutions could be implemented to estimate teachers' effect on students' learning using VAMs in observational studies when there is non-random assignment of students to teachers? Steiner et al. (2010) pointed out "total bias reduction in an observational study can be achieved when (a) the outcome-related part of the selection process is quite specific… (b) a set of constructs is available that is individually less successful in bias reduction but comes from within the most crucial domains for bias reduction… and (c) a combination of expert judgment, theory, observation, and common sense is used to arrive at the rich set of domains, constructs within these domains, and even items within these constructs that might explain the selection process and be correlated with the outcome." (pp. 265-266).

Just as Steiner et al. (2010), we can consider two steps to minimize observable selection bias. First, we need to examine the process of non-random assignment. If we can identify the factors which are closely related to non-random assignment within schools, we can minimize the selection bias and lead to relevant conclusions. With respect to non-random assignment within schools, previous studies reported that principals engaged teachers formally or informally and classes were purposefully created by the majority of principals with more substantial differences in class ability. In other words, previous studies showed that most elementary schools have complex assignment processes characterized by combination of principals', teachers', or parents' selection and this study show that social networks among teachers are closely related to non-random assignment of students to their teachers.

Second, we need to include covariates in VAMs specification because Cronbach's (1976) study showed that model specification was affected by assignment rules. Specifically, Cronbach (1976) pointed out that "the unit of analysis can make a difference in the estimate of a covariate-adjusted treatment mean, when persons or classes have not been assigned to treatments at random or when the number of independent assignments to treatment is small" (p. 13). If we can identify the factors that are closely related to non-random assignment within schools, we can minimize selection bias and help produce relevant conclusions about teacher and school performance.

The limitations of this research are a) little explanation of the mechanisms of non-random assignment of students to teachers in each grade level, b) data limitation, c) no consideration of the effect of principals and parents when assigning students, d) issues related to the reliability and validity of the data on teachers' social networks, and e) causal inference. With respect to explanation of mechanisms, this study did not investigate the process of how teachers' attributes and social networks co-evolve (similar to chapter 2). Maybe teachers' attributes like being a formal leader could affect teachers' social networks and teachers using social networks could influence other teachers directly or indirectly when assigning students. Although we can conclude that teachers' social networks affect non-random assignment, we cannot answer whether teachers' social networks affect non-random assignment directly or indirectly. With respect to data limitations and consideration of the effect of principals and parents, if we have social network data about principal-teacher networks, we can identify the net effect of teacher-teacher networks after controlling for principal-teacher networks and parent-teacher networks. But I did not have access to such data for the purposes of this study.

With respect to the reliability and validity of the data on teachers' social networks, this study used proxy indicators instead of data about actual networks related to class assignment due to data limitations. In addition, the missing values of networks and measurement error of networks caused by question order could impede reliability and validity.

With respect to interdependency, selection bias, and identification problems, when using value-added models, selection bias caused by non-random assignment could lead to misleading conclusions by affecting the gain score (Rivkin & Ishii, 2009; Rothstein, 2009). In order to control for selection bias, previous studies suggested the solution as model specification. Hanushek & Rivkin (2010) examined generalizations about using Value-Added Measures of teacher quality and summarized the distribution of teacher effectiveness in various studies. They argued that "although the impact of any classroom sorting on unobservables remains an important and unresolved question, the finding of substantial variation in teacher quality appears be robust to such sorting" (p. 269).

However, when there was high interdependence and high selection bias, how can I identify the factors and specify the model? In order to estimate net effects of teachers on students' learning, new VAMs also need to identify these effects as actor-oriented models can separate selection from influence process. If we cannot disentangle these effects, internal validity will be impaired. Future studies are needed to answer this kind of question.

Even though there are some limitations, this research shows what kind of factors affect non-random assignment of students to teachers. In addition, this research shows that teachers' social networks can affect students' learning by influencing class composition, which is related to non-random assignment of students to their teachers with respect to previous academic achievement.

Chapter 4: Quantifying the Robustness of Inferences about the Effects of Teachers' Social Networks on Class Composition

Introduction

Experimental studies can provide strong cause and effect relationship while experimental studies may have weak external validity because of volunteer or convenience samples. In addition, experimental designs need random sampling and random assignment to implement successfully for strong internal validity. Observational studies can provide strong external validity when data are representative of populations while observational studies may have weak causal inference due to differences in unobserved preexisting conditions.

In order to minimize observables selection bias, we can use statistical controls in observational studies which are described as fixed effects models, instrumental variables, propensity score matching, and regression discontinuity designs (Schneider et al., 2007). However, there are also problems with these methods: the assumption of fixed effects models that omitted variables are time invariant, identifying good instruments, little or no matched cases across treatment conditions in matching propensity scores, and the assumption of regression discontinuity designs that students in the two groups have similar characteristics (Schneider et al., 2007).

To respond to these concerns, we can compute how much of the estimate of effect would have to be attributed to other factors to invalidate the causal claims (Frank, 2000). In other words, we can evaluate the sensitivity of causal claims to an unobserved confounding factor by quantifying the Impact Threshold of a Confounding Variable (ITCV). In addition, Seltzer et al. (2007) extended Frank's (2000) ITCV for multilevel models. Furthermore, Kelcey (2009) extended Frank's (2000) robust indices for applying to binominal regression models and proposed methods quantifying the Average Impact Threshold of a Confounding Variable (AITCV) with assumption that weights would change dramatically with a confounding variable in the model.

Therefore, this chapter is organized as follows. First, I present causal inference studies and the robust indices method. Second, data and methods are presented including sample, dependent variables, independent variables, and models. Third, the results are presented. Finally, the discussion and conclusion are offered with the importance of including prior information in model specification for valid causal inference.

Literature Review

1. Causal Inference Studies in Education

Shadish, Cook, & Campbell (2002) pointed out the causal relationship that “In a classic analysis formalized by the 19^{th}-century philosopher John Stuart Mill, a causal relationship exists if (1) the cause preceded the effect (2) the cause was related to the effect (3) we can find no plausible alternative explanation for the effect other than the cause” (p. 6).

The most general way to perform causal inference studies is to conduct randomized experiments. Through randomization, we assume that preexisting differences before treatments could be canceled out in each group. When we cannot randomize the subjects, quasi-experiments would be conducted.

In education settings, is randomization possible in practice? Murnane & Willett (2011) argued that “actors in the educational system typically care a lot about which experimental units (whether they be students or teachers or schools) are assigned to particular educational treatments, and they take actions to try to influence these assignments” (pp. 34-35). Thus, “Unfortunately, until fairly recently, most educational researchers did not address their causal questions by conducting randomized experiments or by adopting creative approaches to analyzing data from quasi-experiments. Instead, they typically conducted observational studies” (pp. 31-32).

Cook (2002) also claimed that “random assignment is most feasible when: treatments are shorter; they require little or no teacher training; patterns of coordination among school staff are not modified; the demand for a particular educational change outstrips its supply; two or more substantive treatments with similar goals are compared as opposed to the situation when comparing a treatment to a no-treatment; the units receiving different treatments cannot communicate with each other; and when students are the unit of assignment rather than classrooms or whole schools" (p. 184). In addition, Schneider et al. (2007) pointed out that "Implementing experiments with randomized assignment can also present problems for researchers, such as breakdowns in randomization, treatment noncompliance, and attrition" (p. 22).

One way to infer cause when using observational data or quasi-experimental designs is through statistical tools that a) control for a covariate using the general linear model as in ANCOVA, b) use an instrument variable, and c) use propensity score matching.

However, the assumption of fixed effects models that omitted variables are time invariant may not be valid while identifying good instruments is very hard with respect to instrumental variables (Schneider et al., 2007). The problem of propensity score matching can occur when there are little or no matched cases across treatment conditions whereas the assumption of regression discontinuity designs, that students in the two groups have similar characteristics, should be examined (Schneider et al., 2007).

Given these limitations, we seek to quantify the robustness of inferences with respect to violations of assumptions.

2. Sensitivity Analysis and Robustness Indices (ITCV)

Rosenbaum (2010) introduced Cornfield et al. (1959) study as the first formal sensitivity analysis in an observational study and explained the concept of sensitivity analysis in that "If the association is strong, the hidden bias needed to explain it is large" (p. 106). In addition, he proposed some models of sensitivity analysis. As a kind of sensitivity analysis, we can quantify how much of the estimate of effect would have to be attributed to other factors to invalidate the causal claims (Frank, 2000). To estimate the impact of an unmeasured confounding variable on our causal claims, Frank (2000) developed three steps for ordinary least square (OLS) regression estimates. The first step is to establish correlation between a dependent variable and one predictor, partialling for all covariates.

$$r = \frac{t}{\sqrt{(n-q-1)+t^2}}$$

Where: t taken from the result of multiple regression
n is the sample size
q is the number of parameters estimated

The second step is to define a threshold (r#) as the value of r that is just statistically significant for inference.

$$r^{\#} = \frac{t_{critical}}{\sqrt{(n-q-1)+t^2_{critical}}}$$

Where: n is the sample size
q is the number of parameters estimated
$t_{critical}$ is the critical value of the t-distribution for making an inference
$r^{\#}$ can also be defined in terms of effect sizes

The third step is to calculate the threshold for the impact necessary to invalidate the Inference by defining the impact: $k = r_{x\cdot cv} \times r_{y\cdot cv}$ and assuming $r_{x\cdot cv} = r_{y\cdot cv}$ which maximizes the impact of the confounding variable.

$$r_{x\cdot y|cv} = \frac{r_{x\cdot y} - r_{x\cdot cv} \times r_{y\cdot cv}}{\sqrt{1 - r_{y\cdot cv}^2}\sqrt{1 - r_{x\cdot cv}^2}} = \frac{r_{x\cdot y} - k}{1 - k}$$

$$ITCV = \frac{r_{x\cdot y} - \mathrm{r}^{\#}}{1 - |\,\mathrm{r}^{\#}\,|}$$

In addition, Seltzer et al. (2007) extended Frank's (2000) formula to evaluate the impact of unobserved confounding variables on coefficients of predictors in multilevel regression models. Furthermore, Kelcey (2009) extended Frank's (2000) robust indices for applying to binominal regression models because Frank (2000) developed ITCV in the linear regression models without considering nonlinear regression models. Kelcey (2009) assumed that weights could change dramatically with a confounding variable in the model and proposed the Average Impact Threshold of a Confounding Variable (AITCV).

I will apply Frank's analysis to the results in the previous chapters.

Data and Methods

I used the same data as in chapters 2 and 3. In addition, the same final selection, influence models, and multiple regression models were used for this study. Specifically, in selection models using p2 models, model 1 did not include prior relationship about math while model 2 was the same as model 2 in selection model in chapter 2. In influence models using a two-level multilevel model, model 1 did not include prior teaching practices and subgroup mean of prior teaching practices whereas model 2 did not include prior teaching practices and model 3 was the same as model 2 in the influence model in chapter 2. In multiple regression models using grade and school fixed effects, I used the same as model 1, 4, and 5 in chapter 3.

To quantify ITCV in selection and influence models, first, I estimated the effects in multilevel p2 models, two level HLM models, and multiple regression models. Second, three steps are conducted to compute ITCV in these models.

Missing values of professional development at time 2 had five missing cases out of 209 cases while teaching efficacy at time 1 had 31 missing cases out of 209 cases. All missing cases were recoded as zero value in model 1 and model 2 of multilevel selection models.

In addition, the missing values of dependent and independent values in the influence models were that teaching practices at time 2 had 56 missing cases out of 209 cases, which were deleted in the two-level HLM models because this was a dependent variable and there was little relevant information for multiple imputation of missing values. After deleting the missing values for the dependent variable, there were two missing cases in teaching efficacy at time 1 and one missing case in highest grade, which were deleted in the two-level HLM models.

I used P2 4.0 for multilevel p2 models, HLM 6.0 for two level HLM models, SAS 9.2 for multiple regression models, and Excel 2010 for computing ITCV.

Results

1. Robustness Indices (ITCV) in p2 Selection Models

To estimate how advice regarding mathematics teaching practices is related to characteristics of the actors, multilevel selection models were analyzed in Table 4.1.

Table 4.1 Regression coefficient (standard error) of selection models

Parameters	Model 1	Model 2
μ – Pair (level 1)	-7.08 (0.64)	-6.89 (1.13)
Prior advice network, δ_1		3.58* (0.75)
Prior same subgroup, δ_2	1.38* (0.35)	1.13* (0.42)
Same grade, δ_3	2.02* (0.51)	2.04* (0.48)
Total of all common meeting types, δ_4	0.02 (0.07)	0.02 (0.07)
δ_5 – Reciprocity	3.31 (0.50)	3.51 (0.52)
- Provider variance (level 2a)	0.75 (0.33)	0.71 (0.37)
Mathematics program coordinator role, $\gamma_1^{(\alpha)}$	1.84* (0.75)	1.88* (0.66)
Mathematics professional development, $\gamma_2^{(\alpha)}$	0.32* (0.14)	0.28* (0.14)
Prior mathematics teaching efficacy, $\gamma_3^{(\alpha)}$	0.12 (0.11)	0.15 (0.13)
- Receiver variance (level 2b)	1.70 (0.55)	1.91 (0.56)
Mathematics professional development, $\gamma_1^{(\beta)}$	-0.06 (0.16)	-0.03 (0.18)
Prior mathematics teaching efficacy, $\gamma_2^{(\beta)}$	0.47* (0.15)	0.47* (0.16)
- Provider-receiver covariance	0.06 (0.34)	-0.09 (0.35)
-Omega for Random Density Effects	0.37 (0.38)	1.41 (2.15)

Note:* means t-ratio more than 2; The sample size was 209 in model 1 & model 2; Burn-in 4000 and sample size 20000 in MCMC estimation

However, I am not concerned with multilevel models because the focus is a level 1 predictor as prior same subgroup. In addition, I ignored logistic nature at level 1 with the assumption that the weights would not change dramatically with a confounding variable in the model. Thus, in Model 1 shown in Table 4.1, to estimate the impact of an unmeasured confounding variable on the inference that prior same subgroup affected the current mathematics teaching practices advice network, three steps (Frank, 2000) are conducted as follows: The first step is to establish correlation between prior same subgroup and current mathematics advice network, partialling for all covariates.

$$r = \frac{t}{\sqrt{(n-q-1)+t^2}} = \frac{3.94}{\sqrt{(209-9)+3.94^2}} = 0.27$$

Where: t taken from the result of multiple regression, t=1.38/0.35=3.94
n is the sample size
q is the number of parameters estimated

The second step is to define a threshold (r#) as the value of r that is just statistically significant for inference.

$$r^{\#} = \frac{t_{critical}}{\sqrt{(n-q-1)+t^2_{critical}}} = \frac{1.96}{\sqrt{(200)+1.96^2}} = 0.138$$

Where: n is the sample size
q is the number of parameters estimated
$t_{critical}$ is the critical value of the t-distribution for making an inference
$r^{\#}$ can also be defined in terms of effect sizes

The third step is to calculate the threshold for the impact necessary to invalidate the Inference by defining the impact: $k = r_{x \cdot cv} \times r_{y \cdot cv}$ and assuming $r_{x \cdot cv} = r_{y \cdot cv}$ which maximizes the impact of the confounding

$$ITCV = \frac{r_{x \cdot y} - r^{\#}}{1-|r^{\#}|} = \frac{0.272-0.138}{1-0.138} = 0.156$$

If the impact of an unmeasured confound is more than 0.16, then inference would be invalid whereas if the impact of an unmeasured confound is less than 0.16, then inference would be valid.

In other words, when we assume $r_{x \cdot cv} = r_{y \cdot cv,}$ if a correlation between a prior same subgroup and an unmeasured confound variable ($r_{x \cdot cv}$) is more than 0.39 and the correlation between a current mathematics teaching practices advice network and an unmeasured confound variable ($r_{y \cdot cv}$) is more than 0.39, then inference would be invalid.

In Model 2 shown in Table 4.1, to estimate the impact of an unmeasured confounding variable on the inference that prior mathematics advice network affected current mathematics advice network, three steps (Frank, 2000) are conducted. If the impact of an unmeasured confound is more than 0.21, then inference would be invalid whereas if the impact of an unmeasured confound is less than 0.21, then inference would be valid. In other words, when we assume $r_{x \cdot cv} = r_{y \cdot cv,}$ if a correlation between a prior mathematics teaching practices advice network and an unmeasured confound variable ($r_{x \cdot cv}$) is more than 0.46 and correlation between a current mathematics teaching practices advice network and an unmeasured confound variable ($r_{y \cdot cv}$) is more than 0.46, then inference would be invalid.

Table 4.2 Impact threshold of a confounding variable (ITCV) in selection models

	Model 1	Model 2
Prior mathematics teaching practices advice network		0.21
Prior same subgroup	0.16	0.06
Same grade	0.15	0.18*

Note: * more robust than model 1.

Therefore, we can compare the ITCV within and between models. As shown in Table 4.2, the ITCV of the prior relationship about mathematics was 0.21 in model 2 while ITCV of prior same subgroup was 0.06 in model 2. In addition, ITCV of prior same subgroup changed from

0.16 to 0.06 when we included prior mathematics teaching practices advice network.

Based on ITCV shown as Table 4.2, we can claim that prior mathematics teaching practices advice network affects a current mathematics teaching practices advice network, which may be little sensitive to other unobserved confounding variables when the correlation between an unobserved confounding variable and a current mathematics teaching practices advice network is less than 0.46. At the same time, we can infer that a prior same subgroup network affects a current mathematics teaching practices advice network, which may be sensitive to other unobserved confounding variables when the correlation between an unobserved confounding variable and a current mathematics teaching practices advice network is less than 0.24.

In other words, if the correlation between an unobserved confounding variable and a current mathematics teaching practices advice networks exceeded 0.24, the estimate of prior same subgroup membership would be changed from having a significant t-ratio to having a non-significant t-ratio. Thus, if we did not include confounding variables exceeding correlation 0.24 (e.g., a prior mathematics teaching practices advice network as 0.46) into the model specification, we might have invalid causal claims due to the impact of an omitted confounding variable, which affects t-ratio.

2. Robustness Indices (ITCV) in Multilevel Models

To examine whether teachers' mathematics teaching practices advice networks influence their mathematics teaching practices and what factors explain this influence, two-level multilevel models were analyzed.

To compare the effect of teachers' mathematics teaching practices advice networks on their mathematics teaching practices between with prior information and without prior information, regression standardized coefficients for a multilevel influence model were shown in Table 4.3. The results of model 1 showed that Exposure between 2007 and 2008 (standardized coefficient of 0.28) and subgroup mean of math teaching efficacy in 2007 (standardized coefficient of 0.30) had significant effects on current mathematics teaching practices.

To estimate the effect of subgroup mean of prior mathematics teaching practices on current mathematics teaching practices in level 2, model 2 was analyzed and the results indicated that there was a significant effect (standardized coefficient of 0.35) of subgroup mean of prior mathematics teaching practices in level 2.

Finally, to estimate the effect of prior mathematics teaching practices and subgroup mean of prior mathematics teaching practices on current mathematics teaching practices in level 1and 2, model 3 was analyzed and the results indicated that there was a significant effect (standardized coefficient of 0.42) of prior mathematics teaching practices in level 1.

Table 4.3 Regression standardized coefficients for multilevel model of mathematics problem solving teaching practices including the influences of colleagues.

Variable	Model 1	Model 2	Model 3
Level-1: Individual Teacher (N=150)			
Overall mean Teaching practices in 2008	-0.05	-0.02	-0.05
Teaching practices in 2007			0.42**
Exposure between 2007 and 2008	0.28*	0.21*	0.21*
Mathematics professional development in 2008	0.11	0.07	0.03
Mathematics teaching efficacy in 2007	0.04	0.05	0.01
Highest grade in 2008	0.05	-0.04	-0.07
Level-2: Subgroup (N=41)			
Subgroup mean of Teaching practices in 2007		0.35*	0.05
Subgroup mean of math teaching efficacy in 07	0.30*	0.18	0.23*

Note: model 2 includes subgroup mean of mathematics teaching efficacy.
+ p= .058, * p < .05, ** p < .001.

This was the source of differences in model specification and results among four models, which indicated that prior teaching practices in mathematics problem solving was a key factor to account for current teaching practices in mathematics problem solving.

In Model 1 shown in Table 4.3, to estimate the impact of an unmeasured confounding variable on the inference that Exposure between 2007 and 2008 affected current mathematics teaching practices, three steps (Frank, 2000) are conducted as follows. The first step is to establish correlation between Exposure between 2007 and 2008 and current mathematics instruction, partialling for all covariates.

$$r = \frac{3.984}{\sqrt{(150-6)+3.984^2}} = 0.32$$

The second step is to define a threshold (r#) as the value of r that is just statistically significant for inference.

$$r^{\#} = \frac{1.96}{\sqrt{(144)+1.96^2}} = .16$$

The third step is to calculate the threshold for the impact necessary to invalidate the Inference by defining the impact: $k = r_{x\cdot cv} \times r_{y\cdot cv}$ and assuming $r_{x\cdot cv} = r_{y\cdot cv}$ which maximizes the impact of the confounding variable.

$$ITCV = \frac{.32-.16}{1-.16} = 0.19$$

If the impact of an unmeasured confound is more than 0.19, then inference would be invalid whereas if the impact of an unmeasured confound is less than 0.19, then inference would be valid.

Therefore, we can compare ITCV within and between models. As shown in Table 4.4, ITCV of prior teaching practices was 0.264 in model 3 while ITCV of exposure between prior and current changed from 0.19 to 0.09 when we included prior teaching practices and subgroup mean of prior teaching practices.

Based on the ITCV, we infer that subgroup mean of prior math teaching efficacy affects current teaching practices, which may be sensitive to other unobserved confounding variables when the correlation between an unobserved confounding variable and a current mathematics teaching practices is more than 0.30. In other words, if the correlation between an unobserved confounding variable and a current mathematics teaching practices exceeded 0.30, the estimate of subgroup mean of prior math teaching efficacy would be changed from having significant t-ratio to having non-significant t-ratio. Thus, if we cannot identify confounding variables exceeding correlation 0.30 (e.g., prior teaching practices as 0.51), we have a valid causal claims.

Table 4.4 Impact threshold of a confounding variable (ITCV) in influence models

Variable	Model 1	Model 2	Model 3
Level-1: Individual Teacher			
Teaching practices in 2007			0.26
Exposure between 2007 and 2008	0.19	0.09	0.09

We can quantify the corrected ITCV with other covariates, as shown in Table 4.5. The corrected ITCV of prior teaching practices was 0.107 in model 3 while corrected ITCV of exposure between prior and current was 0.09 in model 3. In addition, ITCV of exposure between prior and current changed from 0.098 to 0.094 when we included prior teaching practices and subgroup mean of prior teaching practices.

Table 4.5 Corrected impact threshold of a confounding variable (ITCV) with other covariates in influence models

Variable	Model 1	Model 3
Level-1: Individual Teacher		
Teaching practices in 2007		0.107
Exposure between 2007 and 2008	0.098	0.094

To compare with impact of an observed variable, I computed the impact of professional development on exposure, which was 0.04. Therefore, this result indicates that the impact threshold for exposure between 2007 and 2008 on mathematics problem solving teaching practices in 2008 is larger than the impact of professional development on exposure. An unmeasured covariate would have to have a stronger impact than the strongest measured covariate to invalidate the inference.

3. Robustness Indices (ITCV) in Multiple Regression Models

Regression Coefficients (t-ratio) of Teachers' Social Networks in Model 1, 4, and 5 were shown in Table 4.6.

Table 4.6 Regression coefficients (t-ratio) of teachers' social networks in model 1, 4, and 5

	Model 1	Model 4	Model 5
ELA achievement (N=300)			
In-degree in ELA networks	0.13* (2.30)	0.12* (2.29)	0.12* (2.28)
In-degree in Math networks	0.12* (2.20)	0.11* (2.14)	0.10* (1.97)
Math achievement (N=300)			
In-degree ELA networks	0.11* (2.07)	0.11* (2.10)	0.10*(2.06)
In-degree Math networks	0.11* (2.23)	0.09+ (1.92)	0.10* (2.08)
Free/reduced lunch (N=305)			
In-degree Math networks	-0.07* (-2.09)	-0.05+ (-1.74)	-0.06+ (-1.87)

Notes: school and grade level fixed effects models.
+ p < .10, * p < .05, ** p < .01, *** p < .001.

To estimate the impact of an unmeasured confounding variable on the inference that teachers' ELA network in 2007 affected students' ELA achievement in Table 4.6, three steps (Frank, 2000) are conducted as follows.

The first step is to establish correlation between ELA achievement and ELA network in-degree, partialling for all covariates.

$$r = \frac{2.30}{\sqrt{(300-40)+2.30^2}} = .142$$

The second step is to define a threshold (r#) as the value of r that is just statistically significant for inference.

$$r^{\#} = \frac{1.96}{\sqrt{(260)+1.96^2}} = .121$$

The third step is to calculate the threshold for the impact necessary to invalidate the Inference by defining the impact: $k = r_{x \cdot cv} \times r_{y \cdot cv}$ and assuming $r_{x \cdot cv} = r_{y \cdot cv}$ which maximizes the impact of the confounding variable. ITCV means Impact Threshold of a Confounding Variable.

$$ITCV = \frac{.142-.12}{1-.12} = .023$$

If the impact of an unmeasured confound is more than .023, then inference would be invalid whereas if the impact of an unmeasured confound is less than .023, then inference would be valid. In other words, if a correlation between in-degree in ELA networks and an unmeasured confound ($r_{x \cdot cv}$) is more than 0.15 and a correlation between ELA achievement and an unmeasured confound ($r_{y \cdot cv}$) is more than 0.15, then my causal inference would be invalid. Based on my data, two variables (a formal leader and the total number of leadership roles) had correlations more than 0.15. Therefore, when we included a formal leader or the total number of leadership roles (we could regard these variables as an unmeasured confound in model 1) into models 2 and 3, the effects of teachers' social networks on class composition was insignificant in models 2 and 3. However, if a formal leader is not a confounding variable, it may be an alternative cause or just a different measure. In addition, for valid causal inference, we need to control for prior formal leader or the total number of leadership roles.

With respect to the effects of in-degree in Math networks on previous ELA achievement, the ITCV in model 1 indicated that if a correlation between in-degree in Math networks and an unmeasured confounding variable is more than 0.126 and a correlation between previous ELA achievement and an unmeasured confounding variable is more than 0.126, then my causal inference would be invalid.

Table 4.7 Impact threshold of a confounding variable (ITCV) in multiple regression models

	Model 1	Model 4	Model 5
ELA achievement			
In-degree in ELA networks	0.023	0.023	0.022
In-degree in Math networks	0.016	0.012	0.000
Math achievement			
In-degree ELA networks	0.008	0.009	0.007
In-degree Math networks	0.018	N/A	0.008
Free/reduced lunch			
In-degree Math networks	0.009	N/A	N/A

Note: N/A means non-applicable.

We can quantify corrected ITCV with other covariates shown in Table 4.8. With respect to ELA achievement, the corrected ITCV of in-degree in ELA networks was 0.016 in model 1 while the corrected ITCV of in-degree in Math networks was 0.012 in model 1.

Table 4.8 Corrected impact threshold of a confounding variable (ITCV) with other covariates

	Model 1	Model 4	Model 5
ELA achievement			
In-degree in ELA networks	0.016	0.016	0.015
In-degree in Math networks	0.012	0.009	0.000
Math achievement			
In-degree ELA networks	0.005	0.005	0.006
In-degree Math networks	0.012	N/A	0.005
Free/reduced lunch			
In-degree Math networks	0.006	N/A	N/A

Note: N/A means non-applicable.

In summary, these results indicated that although the ITCV of in-degree in ELA networks was relatively smaller than the ITCV of variables in other studies, in-degree in ELA networks was a key factor in explaining the effects of teachers' social networks on class composition through non-random assignment with respect to ELA academic achievement because the correlation between other variables and in-degree in teachers' social networks were relatively lower than this.

In addition, the relatively high positive correlation between formal leader variable and in-degree in teachers' social networks indicate that a formal leader can influence in-degree in teachers' social networks. In spite of this, we cannot say that every formal leader has high in-degree in social networks in their schools. Therefore, we need to check the relationship between teachers' social networks and teachers' attributes when explaining the effects on teachers' social networks on class composition.

Discussion and Conclusion

After quantifying how much of an estimate would have to be attributed to other factors to invalidate the causal claims by using robust indices (Frank, 2000), results suggests that prior same subgroup (previous informal network structure) were closely related to current teaching practices advice networks (current social networks). When examining which factors affect current teaching practices advice networks, not including prior informal network structure into model specification may lead to invalid causal inference. In addition, results indicate that prior teachers' social networks had relatively significant influence on conducting current mathematics teaching practices. When we investigate which factors affect current teaching practices, we need to include prior teachers' social networks because prior teachers' social networks could be a confounding variable to invalidate our claims.

Finally, results indicated that in-degree in ELA networks was a key factor in explaining the effects of teachers' social networks on class composition through non-random assignment with respect to ELA academic achievement. Therefore, when examining which factors affect class composition, not including teachers' attributes which affect teachers' social networks into model specification may lead to invalid causal inference. In addition, we need to control for prior teachers' social networks and attributes for valid inference.

One limitation of this study is to ignore the logistic nature in level 1 when we estimate Impact Threshold of a Confounding Variable (ITCV) in selection models. When weights would not change dramatically with a confounding variable in the model, we could use Impact Threshold of a Confounding Variable (ITCV) formula for linear regression. However, if the weights changed dramatically with a confounding variable in the nonlinear regression model, we might need to use Average Impact Threshold of a Confounding Variable (AITCV) formula for nonlinear regression, which Kelcey (2009) proposed. Therefore, future studies are needed to quantify robust indices with considering weights and we need to develop Impact Threshold of a Confounding Variable (ITCV) for actor-oriented models as exponential models.

Another limitation of this study is to ignore measurement error in dependent variables, attributes variables, and network variables when we estimate Impact Threshold of a Confounding Variable (ITCV). When there was large measurement error in these variables, robustness indices might be unreliable. Thus, future studies are needed to account for measurement error in calculating Impact Threshold of a Confounding Variable (ITCV), which can be through latent variable modeling.

Even though there are two limitations in this study, this research shows that including prior information in model specification is relatively important for valid causal inference when we estimate which factors affect current mathematics advice network and teaching practices. In addition, we need to check the relationship between teachers' social networks and teachers' attributes when we estimate which factors affect class composition.

Chapter 5: Policy for Teachers' Social Networks

To propose and test specific social network theories in elementary school, this dissertation proposes four hypotheses which investigate the relationship among social networks, structure, hierarchy and time when we examine the effects of teachers' social networks, as shown as Table 5.1.

Table 5.1 The hypotheses, results, and robustness indices of this dissertation.

Structure, Hierarchy, Time, & Social networks	Hypothesis	Results	Robustness Indices
Effects of structure at level 3			
On teachers' social networks at level 2	H 1-1 H 1-2	Yes Yes	Robust Robust
On class composition at level 1	H 3-1 H 3-2	Yes Yes	
Effects of teachers' social networks at level 2			
On teaching practices at level 2	H 2-1	Yes	Robust
On class composition at level 1	H 2-2	Yes	A little Robust
Effects of teachers' teaching practices at level 2			
On students' achievement at level 1	H 4	Yes	

Note: H 1-1: Formal organizational structure at level 3 affects social networks at level 2.
H 1-2: Network structure at level 3 affects social networks at level 2.
H 2-1: Social networks at level 2 affect human capital at level 2.
H 2-2: Social networks at level 2 affect formal organizational structure at level 1.
H 3-1: Formal organizational & network structure at level 3 affects human capital at level 1.
H 3-2: Formal organizational & network structure at level 3 affect formal organizational structure at level 1.
H 4: Human capital at level 2 can affect human capital at level 1.

After investigating teachers' social networks through selection, influence, and dynamic modeling, the results of chapter 2 indicate that *formal organizational structure of school and teachers' social network structure at time 1 affect the formation of new ties of teachers' social* *networks at time 2* (H 1-1 & H 1-2) and *teachers' social networks at time 1 can affect teachers' teaching practices at time 2* (H 2-1).

In addition, the results of school and teacher effectiveness studies indicate that in explaining variation on student achievement in both cognitive and affective outcomes, the classroom effect is more fundamental than the school effect (Teddlie & Reynolds, 2000). Furthermore, the most significant factor at the classroom level is the quality of teaching practices (Brophy & Good, 1986), which can be improved through not only teachers' professional development but also teachers' social interactions and human capital spillovers. These results suggest that *teachers' human capital at time 1 can affect students' human capital at time2* (H 4).

After examining teachers' social networks and class composition through multilevel models, correlation analyses, and multiple regression models, the results of chapter 3 indicate that *teachers' social networks affect students' formal organizational structure through class composition* (H 2-2). In addition, the results of class composition and peer effects studies indicate that class composition and peer effects have an important impact on students' learning (Burns & Mason, 2002; Dreeben & Barr, 1988; Harris, 2010), which lead to differences in academic achievement (H 3-1).

Even though I did not test whether the formal organizational & network structure at level 3 affect the formal organizational structure at level 1, we can infer this based on the results of chapters 2 and 3. In other words, we can conclude that the formal organizational structure of the school (i.e., grade level) and teachers' informal network structure (i.e., cohesive subgroups) affect class composition through non-random assignment with respect to academic achievement and economic status.

Specifically, based on the results of chapter 2, we can infer that teaching practice has a dynamic change process which could be due to internal conditions (setting formal structure) as well as external conditions (e.g., teachers' turnover rate). In other words, even if teachers' composition remains constant, change in teachers' attributes such as teaching grade level or formal leadership role might affect changes in teaching practice, which may lead to improve learning and academic achievement. And, we would be wondering what kind of teachers' social networks affect teaching practices and why specific types of teachers' social networks affect teaching practices. Therefore, theoretical models which can conceptualize the framework of different kinds of teachers' social networks remain to be explained by additional research. After identifying the effects of different kinds of teachers' social networks and comparing the effects size of each type, we could build up newer models of the improvement of teaching practices.

Based on the results of chapter 3, we can infer that teachers' ELA networks have more effect on non-random assignment with respect to previous math achievement as well as ELA achievement. In addition, formal leadership roles have more effect on non-random assignment with respect to students' previous economic status as well as academic achievement. Thus, teachers' attributes and social networks could affect on class composition, which lead to different learning.

Based on the results of chapter 4, not including prior teachers' social networks and attributes into model specification may lead to invalid causal inference when examining which factors affect current teaching practices advice networks and current teaching practices. In addition, not including teachers' attributes which affect teachers' social networks into a model sand may lead to invalid causal inferences when examining which factors affect class composition; we need to control for prior teachers' social networks and attributes for valid inference.

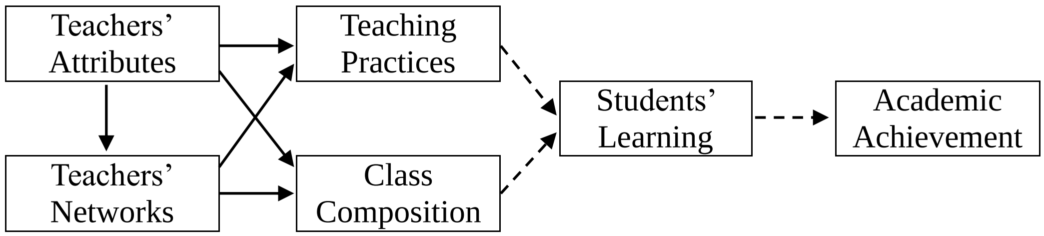

Figure 5.1. Conceptual framework of this study

Though this dissertation offered empirical evidence to the literature concerning social networks in education, there remains a range of issues to be addressed; 1) the conceptual model of teachers' social networks, teaching practices and class composition, 2) causal inference and controlling for prior and 3) policies for teachers' social networks.

Based on the results of chapters 2 and 3, the conceptual framework of this study was shown in Figure 5.1. First, teachers' attributes could affect teachers' networks, teaching practices, and class composition. Second, teachers' networks could influence teaching practices and class composition. Third, both teaching practices and class composition could affect students' learning, which may lead to different academic achievement.

Thus, future studies should be directed at examining the effect of teachers' attributes and networks on teaching practices and class composition including students' learning and academic achievement. Furthermore, future studies are needed to consider other factors which affect teachers' social networks such as principal leadership, district policy, and information technology when developing comprehensive models.

Based on the results of chapter 4, we can understand the importance of including prior information in model specification for more valid inference to satisfy the first Mill' condition (cause preceded effect). In other words, if we can control for prior information and model emergence (e.x., the formation of new ties) over time, we have more robust causal inferences than without prior in the models. In addition, we can assess the sensitivity of our causal inference using robustness indices, which is closely related to evaluating interval validity.

Based on the results of chapters 2, 3, and 4, policies for teachers' social networks are suggested as they relate to teachers and students in instruction and learning contexts; (1) the policy of organizational structure of school such as class size and composition and (2) the policy of formal network structure such as grade level meetings.

A recent study by Dee & West (2011) examined how non-cognitive skills are affected by class size in the middle school and suggested that there was relationship between smaller eighth-grade classes and improvements of school engagement. Like this, previous policymakers and researchers have argued for class size reduction policies. However, if class, even small class, formed only disadvantaged students in non-cognitive as well as cognitive skills, class size reduction policies might not be effective to improve students' human capital. Therefore, policymakers need to consider not only class size but also class composition when making effective school reforms policies if large class size constrains students' social networks, as shown in Figure 5.2.

In addition, grade size as the number of classes within one grade level might facilitate or constrain the chance to interact among teachers within grade level. Overall, the school size as the number of students and teachers within one school might facilitate or constrain the chance to interact among teachers. Therefore, policymakers need to consider appropriate grade size as well as school size when making effective school reforms policies if large grade and school size constrains teachers' social networks.

Finally, this framework could be applied to district size and district composition. In other words, if district size (the number of schools within one district) is large and the mean of school achievement and teachers' quality all are low, these conditions may constrain the chance to interact among superintendents, principals, and teachers.

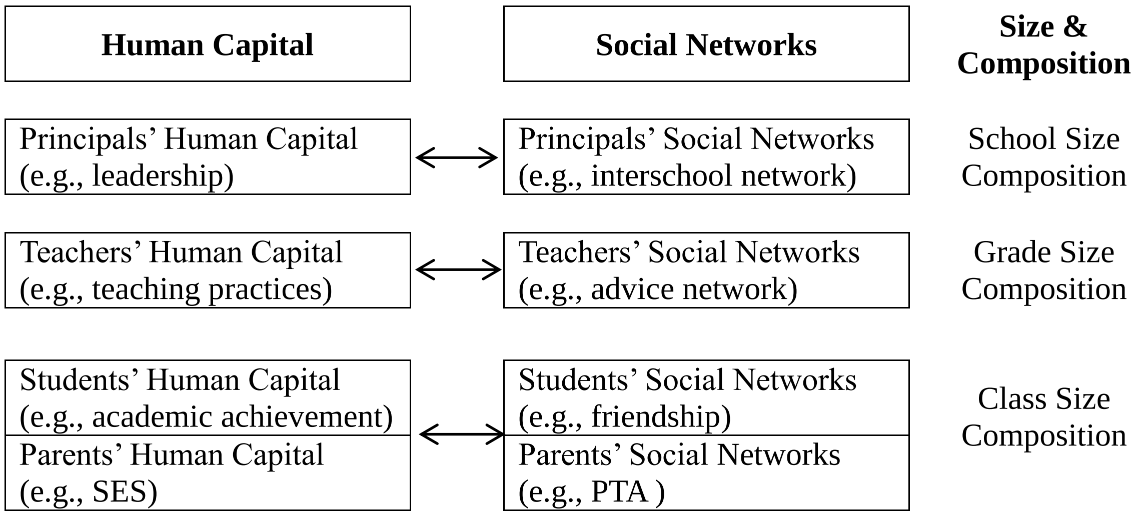

Figure 5.2. The relationship between human capital and social networks at different level

As the policy of organizational structure of school is important for teachers' social networks, we can consider the policy of formal network structure such as within and cross grade level meetings. For facilitating interaction among teachers, policymakers and practitioners (e.g., superintendents or principals) can set up formal meetings within and between schools. However, based on the results of chapter 2, these formal meetings might not be a key factor to form of new ties in teachers' social networks. Rather, too many formal meetings can be harmful for teachers' motivation and commitment. Therefore, policymakers and practitioners need to set the standard of formal meeting structure, size, time, and number.

For example, the minimum number of formal meeting is once but the maximum number of formal meeting is three within one month. And the appropriate size and time of formal meeting is six teachers within 30 minutes. In other words, teachers and school leaders together can set up these standards from the beginning of the academic year and keep revising these standards to the end of the academic year.

Through a systematic analysis and empirical evidence, in spite of some limitations, this dissertation highlights the role of teachers' social networks in education by showing that 1) social networks can improve teaching practice through changing formal and informal structure and 2) social networks can affect non-random assignment of students to their teachers with respect to previous academic achievement.

Appendices

Table A.1 Model 1 in effects of teachers' ELA networks on students' previous ELA achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	812.68	0.00	6.41	126.85	<.0001
Grade 2	-0.54	-0.02	2.81	-0.19	0.8474
Grade 3	-0.34	-0.01	2.83	-0.12	0.9042
Grade 4	4.23	0.10	3.01	1.41	0.1603
School 1003	-1.58	-0.01	7.12	-0.22	0.8244
School 1006	-4.87	-0.02	15.22	-0.32	0.7493
School 1007	23.35	0.37	5.76	4.05	<.0001
School 1009	9.01	0.08	7.13	1.26	0.2077
School 1010	-5.14	-0.07	6.16	-0.83	0.4048
School 1011	2.79	0.04	6.00	0.46	0.6425
School 1012	6.89	0.07	7.14	0.97	0.3353
School 1015	5.90	0.06	6.74	0.87	0.3828
School 1017	13.65	0.17	6.22	2.2	0.029
School 1020	5.60	0.07	6.09	0.92	0.3588
School 1021	1.51	0.02	6.20	0.24	0.8079
School 1023	18.16	0.15	7.61	2.39	0.0177
School 1024	2.33	0.02	7.01	0.33	0.7401
School 1025	8.50	0.07	7.55	1.13	0.2614
School 1026	-6.88	-0.09	6.15	-1.12	0.2646
School 1027	2.36	0.03	6.00	0.39	0.6942
School 1028	-7.39	-0.07	6.88	-1.07	0.2836
School 1029	-0.57	-0.01	6.45	-0.09	0.9291
School 1032	10.12	0.10	6.92	1.46	0.1449
School 1034	-2.25	-0.03	6.57	-0.34	0.7321
School 1035	-1.65	-0.02	6.02	-0.27	0.7842
School 1038	15.64	0.17	6.58	2.38	0.0181
School 1040	15.61	0.17	6.49	2.41	0.0168
School 1041	5.94	0.07	6.40	0.93	0.3542
School 1042	15.97	0.18	6.44	2.48	0.0138
School 1044	-3.38	-0.03	7.47	-0.45	0.6513
School 1047	6.73	0.04	9.47	0.71	0.4778
School 1049	11.26	0.11	6.83	1.65	0.1003
Male	0.51	0.01	3.02	0.17	0.8656
White	0.74	0.02	3.72	0.2	0.8422
African American	-2.34	-0.06	3.96	-0.59	0.5552
Master’s degree	1.10	0.03	2.01	0.55	0.5859
Teaching experience	0.07	0.04	0.10	0.73	0.4639
ELA professional development	-0.89	-0.04	1.09	-0.81	0.418
New teacher	-5.53	-0.14	2.22	-2.49	0.0134
In-degree in ELA networks	1.83	0.13	0.80	2.3	0.0224

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.2 Model 2 in effects of teachers' ELA networks on students' previous ELA achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	812.57	0.00	6.21	130.84	<.0001
Grade 2	0.22	0.01	2.73	0.08	0.9345
Grade 3	0.07	0.00	2.74	0.02	0.9801
Grade 4	4.51	0.11	2.91	1.55	0.1227
School 1003	-3.49	-0.03	6.92	-0.5	0.6143
School 1006	-3.09	-0.01	14.76	-0.21	0.8344
School 1007	24.69	0.39	5.59	4.41	<.0001
School 1009	9.41	0.09	6.91	1.36	0.1745
School 1010	-5.23	-0.07	5.97	-0.88	0.3818
School 1011	2.82	0.04	5.81	0.48	0.6285
School 1012	7.96	0.08	6.93	1.15	0.2514
School 1015	7.35	0.08	6.55	1.12	0.2624
School 1017	12.28	0.16	6.03	2.03	0.0429
School 1020	6.78	0.09	5.91	1.15	0.2522
School 1021	2.12	0.03	6.01	0.35	0.724
School 1023	18.62	0.16	7.38	2.52	0.0122
School 1024	4.15	0.04	6.81	0.61	0.5432
School 1025	8.53	0.07	7.32	1.16	0.2451
School 1026	-6.56	-0.08	5.96	-1.1	0.2726
School 1027	3.29	0.04	5.82	0.57	0.5721
School 1028	-7.12	-0.07	6.67	-1.07	0.2866
School 1029	-1.31	-0.01	6.25	-0.21	0.8346
School 1032	7.49	0.07	6.74	1.11	0.2676
School 1034	-0.39	0.00	6.38	-0.06	0.9512
School 1035	0.13	0.00	5.85	0.02	0.9822
School 1038	16.63	0.18	6.38	2.61	0.0097
School 1040	15.80	0.17	6.29	2.51	0.0126
School 1041	6.31	0.07	6.20	1.02	0.3097
School 1042	16.71	0.19	6.25	2.68	0.0079
School 1044	-2.91	-0.02	7.24	-0.4	0.6881
School 1047	4.68	0.03	9.20	0.51	0.611
School 1049	12.33	0.12	6.62	1.86	0.0637
Male	0.45	0.01	2.93	0.15	0.8792
White	-1.69	-0.05	3.66	-0.46	0.6453
African American	-5.10	-0.13	3.89	-1.31	0.1915
Master’s degree	1.29	0.03	1.95	0.66	0.5097
Teaching experience	0.05	0.03	0.10	0.48	0.6304
ELA professional development	-1.34	-0.07	1.07	-1.26	0.2088
New teacher	-3.82	-0.10	2.19	-1.74	0.0829
Formal leader	8.23	0.22	1.95	4.21	<.0001
In-degree in ELA networks	1.45	0.10	0.78	1.85	0.0648

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.3 Model 3 in effects of teachers' ELA networks on students' previous ELA achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	812.91	0.00	6.26	129.88	<.0001
Grade 2	0.49	0.01	2.76	0.18	0.86
Grade 3	0.48	0.01	2.77	0.17	0.8623
Grade 4	4.53	0.11	2.94	1.54	0.124
School 1003	-5.32	-0.05	7.03	-0.76	0.4499
School 1006	-2.75	-0.01	14.88	-0.18	0.8537
School 1007	23.69	0.38	5.63	4.21	<.0001
School 1009	8.94	0.08	6.97	1.28	0.2005
School 1010	-6.55	-0.09	6.03	-1.09	0.2788
School 1011	2.56	0.03	5.86	0.44	0.6628
School 1012	7.73	0.07	6.98	1.11	0.2689
School 1015	6.02	0.06	6.59	0.91	0.3614
School 1017	13.10	0.17	6.07	2.16	0.0319
School 1020	5.47	0.07	5.95	0.92	0.3585
School 1021	1.92	0.02	6.05	0.32	0.7513
School 1023	18.01	0.15	7.44	2.42	0.0162
School 1024	2.67	0.03	6.85	0.39	0.6968
School 1025	7.09	0.06	7.39	0.96	0.3383
School 1026	-6.77	-0.09	6.01	-1.13	0.2608
School 1027	0.32	0.00	5.89	0.05	0.9568
School 1028	-8.50	-0.08	6.72	-1.26	0.2075
School 1029	-1.48	-0.02	6.30	-0.24	0.8141
School 1032	8.72	0.08	6.77	1.29	0.1991
School 1034	-2.09	-0.02	6.42	-0.32	0.7455
School 1035	-0.81	-0.01	5.88	-0.14	0.8911
School 1038	15.33	0.17	6.43	2.39	0.0178
School 1040	14.98	0.16	6.34	2.36	0.0189
School 1041	5.52	0.06	6.25	0.88	0.3784
School 1042	14.73	0.17	6.30	2.34	0.0201
School 1044	-3.26	-0.03	7.29	-0.45	0.655
School 1047	2.87	0.02	9.31	0.31	0.7583
School 1049	10.29	0.10	6.67	1.54	0.1243
Male	-0.42	-0.01	2.96	-0.14	0.8862
White	-0.44	-0.01	3.65	-0.12	0.9036
African American	-3.56	-0.09	3.88	-0.92	0.3599
Master’s degree	1.09	0.03	1.97	0.56	0.5788
Teaching experience	0.04	0.02	0.10	0.39	0.6981
ELA professional development	-1.22	-0.06	1.07	-1.14	0.2552
New teacher	-4.72	-0.12	2.18	-2.16	0.0315
The total number of leadership roles	2.10	0.19	0.57	3.67	0.0003
In-degree in ELA networks	1.42	0.10	0.79	1.8	0.0736

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.4 Model 4 in effects of teachers' ELA networks on students' previous ELA achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	813.27	0.00	6.40	127.05	<.0001
Grade 2	-0.38	-0.01	2.81	-0.14	0.8916
Grade 3	-0.17	0.00	2.82	-0.06	0.9527
Grade 4	4.06	0.10	3.00	1.35	0.1766
School 1003	-2.87	-0.03	7.15	-0.4	0.6884
School 1006	-3.72	-0.01	15.20	-0.24	0.8068
School 1007	23.15	0.37	5.75	4.03	<.0001
School 1009	9.06	0.08	7.11	1.27	0.2042
School 1010	-5.79	-0.08	6.16	-0.94	0.3482
School 1011	2.96	0.04	5.98	0.49	0.6215
School 1012	7.35	0.07	7.13	1.03	0.3036
School 1015	6.18	0.06	6.73	0.92	0.3596
School 1017	13.89	0.18	6.20	2.24	0.026
School 1020	5.53	0.07	6.07	0.91	0.3628
School 1021	1.66	0.02	6.18	0.27	0.7883
School 1023	18.18	0.15	7.59	2.39	0.0173
School 1024	2.54	0.02	6.99	0.36	0.7168
School 1025	8.44	0.07	7.53	1.12	0.2636
School 1026	-6.79	-0.09	6.14	-1.11	0.2694
School 1027	1.97	0.03	5.99	0.33	0.7422
School 1028	-8.72	-0.08	6.91	-1.26	0.2082
School 1029	-0.57	-0.01	6.43	-0.09	0.93
School 1032	9.90	0.10	6.91	1.43	0.1529
School 1034	-2.17	-0.02	6.55	-0.33	0.7413
School 1035	-1.86	-0.03	6.00	-0.31	0.7574
School 1038	15.59	0.17	6.56	2.38	0.0183
School 1040	15.68	0.17	6.47	2.42	0.016
School 1041	5.37	0.06	6.39	0.84	0.4011
School 1042	15.78	0.18	6.42	2.46	0.0147
School 1044	-3.23	-0.03	7.45	-0.43	0.6653
School 1047	7.15	0.04	9.45	0.76	0.4499
School 1049	11.01	0.11	6.81	1.62	0.1072
Male	-0.13	0.00	3.04	-0.04	0.9647
White	0.36	0.01	3.72	0.1	0.923
African American	-2.89	-0.07	3.97	-0.73	0.4672
Master’s degree	0.79	0.02	2.02	0.39	0.6949
Teaching experience	0.07	0.04	0.10	0.67	0.502
ELA professional development	-0.93	-0.05	1.09	-0.85	0.3974
New teacher	-5.67	-0.14	2.22	-2.56	0.0111
ELA coordinator	1.85	0.08	1.20	1.54	0.1246
In-degree in ELA networks	1.82	0.12	0.80	2.29	0.0231

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.5 Model 5 in effects of teachers' ELA networks on students' previous ELA achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	817.82	0.00	6.52	125.51	<.0001
Grade 2	-0.37	-0.01	2.77	-0.13	0.8931
Grade 3	-0.45	-0.01	2.78	-0.16	0.8713
Grade 4	3.68	0.09	2.96	1.24	0.2152
School 1003	-3.02	-0.03	7.02	-0.43	0.6672
School 1006	-4.18	-0.01	14.98	-0.28	0.7805
School 1007	22.56	0.36	5.67	3.98	<.0001
School 1009	8.44	0.08	7.02	1.2	0.2305
School 1010	-5.72	-0.07	6.07	-0.94	0.3468
School 1011	2.21	0.03	5.90	0.37	0.7081
School 1012	7.04	0.07	7.03	1	0.3169
School 1015	5.31	0.05	6.64	0.8	0.4241
School 1017	13.14	0.17	6.12	2.15	0.0327
School 1020	5.07	0.06	5.99	0.85	0.3981
School 1021	1.19	0.02	6.10	0.2	0.8455
School 1023	17.73	0.15	7.49	2.37	0.0187
School 1024	2.15	0.02	6.90	0.31	0.7553
School 1025	7.40	0.06	7.44	1	0.3206
School 1026	-6.90	-0.09	6.05	-1.14	0.255
School 1027	0.89	0.01	5.92	0.15	0.8804
School 1028	-8.28	-0.08	6.77	-1.22	0.2226
School 1029	-2.06	-0.02	6.36	-0.32	0.7463
School 1032	7.95	0.08	6.85	1.16	0.2465
School 1034	-2.48	-0.03	6.46	-0.38	0.7019
School 1035	-0.77	-0.01	5.93	-0.13	0.8964
School 1038	14.20	0.15	6.49	2.19	0.0295
School 1040	14.37	0.15	6.39	2.25	0.0255
School 1041	5.38	0.06	6.30	0.85	0.3936
School 1042	15.95	0.18	6.34	2.52	0.0124
School 1044	-3.16	-0.03	7.35	-0.43	0.6676
School 1047	4.56	0.03	9.35	0.49	0.6257
School 1049	10.53	0.10	6.72	1.57	0.1183
Male	0.03	0.00	2.97	0.01	0.9926
White	-0.08	0.00	3.67	-0.02	0.9821
African American	-3.52	-0.09	3.92	-0.9	0.3688
Master’s degree	1.33	0.03	1.98	0.67	0.5018
Teaching experience	0.04	0.02	0.10	0.38	0.7051
ELA professional development	-1.08	-0.05	1.08	-1	0.3165
New teacher	-4.73	-0.12	2.20	-2.15	0.0327
Teacher consultant	0.91	0.16	0.29	3.11	0.0021
In-degree in ELA networks	1.79	0.12	0.79	2.28	0.0234

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.6 Model 1 in effects of teachers' Math networks on students' previous ELA achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	812.11	0.00	6.44	126.18	<.0001
Grade 2	-0.49	-0.01	2.81	-0.18	0.8608
Grade 3	0.19	0.01	2.83	0.07	0.9458
Grade 4	4.65	0.11	3.01	1.54	0.1237
School 1003	-2.08	-0.02	7.13	-0.29	0.7702
School 1006	-0.65	0.00	15.11	-0.04	0.9658
School 1007	23.61	0.38	5.76	4.1	<.0001
School 1009	8.73	0.08	7.14	1.22	0.2222
School 1010	-5.60	-0.07	6.17	-0.91	0.3656
School 1011	1.79	0.02	6.01	0.3	0.7667
School 1012	6.96	0.07	7.15	0.97	0.3314
School 1015	5.53	0.06	6.75	0.82	0.4133
School 1017	14.06	0.18	6.21	2.27	0.0243
School 1020	5.93	0.08	6.09	0.97	0.3311
School 1021	1.78	0.02	6.19	0.29	0.7745
School 1023	17.89	0.15	7.62	2.35	0.0196
School 1024	1.92	0.02	7.01	0.27	0.7842
School 1025	9.45	0.08	7.52	1.26	0.2104
School 1026	-7.07	-0.09	6.17	-1.15	0.2524
School 1027	1.14	0.02	6.06	0.19	0.8504
School 1028	-7.57	-0.07	6.88	-1.1	0.2724
School 1029	-0.87	-0.01	6.46	-0.13	0.8928
School 1032	10.44	0.10	6.92	1.51	0.1328
School 1034	-1.93	-0.02	6.57	-0.29	0.7689
School 1035	-1.76	-0.02	6.03	-0.29	0.771
School 1038	15.49	0.17	6.59	2.35	0.0195
School 1040	15.81	0.17	6.49	2.44	0.0155
School 1041	5.60	0.07	6.41	0.87	0.3833
School 1042	15.86	0.18	6.45	2.46	0.0147
School 1044	-2.94	-0.02	7.46	-0.39	0.6943
School 1047	11.11	0.07	9.36	1.19	0.2359
School 1049	12.92	0.12	6.79	1.9	0.0582
Male	-0.28	-0.01	3.00	-0.09	0.9253
White	0.68	0.02	3.73	0.18	0.8547
African American	-2.36	-0.06	3.96	-0.6	0.5515
Master’s degree	1.38	0.04	2.02	0.68	0.4957
Teaching experience	0.08	0.04	0.10	0.79	0.4274
ELA professional development	-0.63	-0.03	1.09	-0.58	0.5624
New teacher	-5.66	-0.14	2.22	-2.55	0.0113
In-degree in Math networks	1.55	0.12	0.70	2.2	0.0288

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.7 Model 2 in effects of teachers' Math networks on students' previous ELA achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	812.49	0.00	6.26	129.83	<.0001
Grade 2	0.17	0.00	2.74	0.06	0.9519
Grade 3	0.40	0.01	2.75	0.14	0.8854
Grade 4	4.75	0.11	2.93	1.62	0.1064
School 1003	-3.85	-0.03	6.94	-0.55	0.5797
School 1006	0.27	0.00	14.70	0.02	0.9852
School 1007	25.17	0.40	5.61	4.49	<.0001
School 1009	9.13	0.08	6.94	1.32	0.1893
School 1010	-5.43	-0.07	6.00	-0.9	0.3664
School 1011	2.22	0.03	5.85	0.38	0.7047
School 1012	8.06	0.08	6.95	1.16	0.2473
School 1015	7.00	0.07	6.57	1.07	0.2877
School 1017	12.90	0.16	6.04	2.13	0.0338
School 1020	6.97	0.09	5.93	1.18	0.2409
School 1021	2.65	0.03	6.02	0.44	0.6598
School 1023	18.43	0.15	7.41	2.49	0.0135
School 1024	3.68	0.04	6.83	0.54	0.5906
School 1025	9.54	0.08	7.32	1.3	0.1934
School 1026	-6.41	-0.08	6.00	-1.07	0.2859
School 1027	2.77	0.04	5.90	0.47	0.6396
School 1028	-7.21	-0.07	6.69	-1.08	0.2823
School 1029	-1.29	-0.01	6.28	-0.21	0.8375
School 1032	7.96	0.08	6.76	1.18	0.2399
School 1034	-0.14	0.00	6.41	-0.02	0.9824
School 1035	0.17	0.00	5.88	0.03	0.9776
School 1038	16.77	0.18	6.42	2.61	0.0095
School 1040	15.96	0.17	6.31	2.53	0.0121
School 1041	6.25	0.07	6.23	1	0.3169
School 1042	17.03	0.19	6.28	2.71	0.0072
School 1044	-2.42	-0.02	7.26	-0.33	0.7389
School 1047	8.01	0.05	9.13	0.88	0.3812
School 1049	13.64	0.13	6.60	2.07	0.0399
Male	-0.19	0.00	2.92	-0.06	0.9493
White	-1.70	-0.05	3.67	-0.46	0.6432
African American	-5.15	-0.13	3.92	-1.32	0.1896
Master’s degree	1.43	0.04	1.96	0.73	0.4676
Teaching experience	0.05	0.03	0.10	0.53	0.5965
ELA professional development	-1.11	-0.05	1.06	-1.04	0.297
New teacher	-4.20	-0.11	2.19	-1.92	0.0559
Formal leader	8.06	0.22	2.01	4.01	<.0001
In-degree in Math networks	0.84	0.06	0.71	1.19	0.2336

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.8 Model 3 in effects of teachers' Math networks on students' previous ELA achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	812.72	0.00	6.30	128.95	<.0001
Grade 2	0.45	0.01	2.77	0.16	0.8714
Grade 3	0.82	0.02	2.78	0.3	0.7679
Grade 4	4.79	0.11	2.95	1.62	0.1057
School 1003	-5.64	-0.05	7.05	-0.8	0.4243
School 1006	0.53	0.00	14.80	0.04	0.9716
School 1007	24.10	0.39	5.64	4.28	<.0001
School 1009	8.69	0.08	6.98	1.24	0.2146
School 1010	-6.76	-0.09	6.05	-1.12	0.2649
School 1011	1.92	0.03	5.89	0.33	0.7444
School 1012	7.82	0.08	7.00	1.12	0.2651
School 1015	5.71	0.06	6.60	0.87	0.3878
School 1017	13.61	0.17	6.08	2.24	0.0259
School 1020	5.70	0.07	5.96	0.96	0.3403
School 1021	2.35	0.03	6.06	0.39	0.6987
School 1023	17.82	0.15	7.46	2.39	0.0176
School 1024	2.27	0.02	6.86	0.33	0.7405
School 1025	8.03	0.07	7.38	1.09	0.2774
School 1026	-6.72	-0.09	6.04	-1.11	0.2669
School 1027	-0.27	0.00	5.94	-0.05	0.9637
School 1028	-8.58	-0.08	6.74	-1.27	0.2045
School 1029	-1.53	-0.02	6.33	-0.24	0.8087
School 1032	9.11	0.09	6.79	1.34	0.1807
School 1034	-1.82	-0.02	6.43	-0.28	0.7778
School 1035	-0.80	-0.01	5.90	-0.14	0.8926
School 1038	15.41	0.17	6.45	2.39	0.0176
School 1040	15.15	0.16	6.36	2.38	0.0179
School 1041	5.41	0.06	6.28	0.86	0.3894
School 1042	14.96	0.17	6.32	2.37	0.0188
School 1044	-2.82	-0.02	7.31	-0.39	0.6998
School 1047	6.21	0.04	9.26	0.67	0.5029
School 1049	11.61	0.11	6.66	1.74	0.0824
Male	-1.02	-0.02	2.95	-0.35	0.7282
White	-0.48	-0.01	3.66	-0.13	0.8957
African American	-3.62	-0.09	3.90	-0.93	0.3541
Master’s degree	1.26	0.03	1.98	0.64	0.5256
Teaching experience	0.04	0.02	0.10	0.44	0.6611
ELA professional development	-1.00	-0.05	1.07	-0.94	0.3484
New teacher	-5.00	-0.13	2.18	-2.3	0.0224
The total number of leadership roles	2.06	0.19	0.58	3.52	0.0005
In-degree in Math networks	0.94	0.07	0.71	1.32	0.1883

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.9 Model 4 in effects of teachers' Math networks on students' previous ELA achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	812.71	0.00	6.43	126.3	<.0001
Grade 2	-0.35	-0.01	2.81	-0.12	0.901
Grade 3	0.35	0.01	2.83	0.12	0.9025
Grade 4	4.48	0.11	3.01	1.49	0.1375
School 1003	-3.31	-0.03	7.16	-0.46	0.6438
School 1006	0.42	0.00	15.10	0.03	0.9777
School 1007	23.45	0.37	5.74	4.08	<.0001
School 1009	8.77	0.08	7.12	1.23	0.2189
School 1010	-6.20	-0.08	6.17	-1	0.3164
School 1011	1.97	0.03	6.00	0.33	0.7427
School 1012	7.40	0.07	7.14	1.04	0.301
School 1015	5.80	0.06	6.73	0.86	0.3902
School 1017	14.31	0.18	6.20	2.31	0.0217
School 1020	5.87	0.07	6.08	0.97	0.3353
School 1021	1.95	0.02	6.18	0.32	0.7526
School 1023	17.91	0.15	7.60	2.36	0.0192
School 1024	2.12	0.02	6.99	0.3	0.7624
School 1025	9.40	0.08	7.51	1.25	0.2115
School 1026	-6.96	-0.09	6.15	-1.13	0.2588
School 1027	0.82	0.01	6.05	0.14	0.8922
School 1028	-8.84	-0.09	6.92	-1.28	0.2028
School 1029	-0.84	-0.01	6.45	-0.13	0.8964
School 1032	10.24	0.10	6.91	1.48	0.1395
School 1034	-1.85	-0.02	6.56	-0.28	0.7781
School 1035	-1.94	-0.03	6.01	-0.32	0.7473
School 1038	15.46	0.17	6.58	2.35	0.0195
School 1040	15.88	0.17	6.48	2.45	0.0149
School 1041	5.08	0.06	6.41	0.79	0.4282
School 1042	15.71	0.18	6.44	2.44	0.0154
School 1044	-2.78	-0.02	7.45	-0.37	0.7092
School 1047	11.47	0.07	9.34	1.23	0.2206
School 1049	12.67	0.12	6.78	1.87	0.0627
Male	-0.89	-0.02	3.02	-0.3	0.7676
White	0.32	0.01	3.73	0.08	0.9324
African American	-2.90	-0.07	3.97	-0.73	0.4667
Master’s degree	1.08	0.03	2.03	0.53	0.5956
Teaching experience	0.07	0.04	0.10	0.74	0.4629
ELA professional development	-0.67	-0.03	1.08	-0.61	0.5394
New teacher	-5.81	-0.15	2.21	-2.62	0.0092
ELA coordinator	1.77	0.08	1.20	1.47	0.1426
In-degree in Math networks	1.50	0.11	0.70	2.14	0.0335

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.10 Model 5 in effects of teachers' Math networks on students' previous ELA achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	817.19	0.00	6.57	124.38	<.0001
Grade 2	-0.36	-0.01	2.77	-0.13	0.896
Grade 3	0.04	0.00	2.79	0.02	0.9876
Grade 4	4.08	0.10	2.98	1.37	0.1715
School 1003	-3.45	-0.03	7.04	-0.49	0.624
School 1006	-0.06	0.00	14.89	0	0.9968
School 1007	22.96	0.37	5.68	4.04	<.0001
School 1009	8.17	0.07	7.03	1.16	0.2465
School 1010	-6.08	-0.08	6.09	-1	0.319
School 1011	1.33	0.02	5.93	0.22	0.8226
School 1012	7.13	0.07	7.04	1.01	0.3125
School 1015	4.97	0.05	6.65	0.75	0.4559
School 1017	13.66	0.17	6.12	2.23	0.0264
School 1020	5.40	0.07	6.01	0.9	0.3692
School 1021	1.59	0.02	6.10	0.26	0.7949
School 1023	17.49	0.15	7.51	2.33	0.0206
School 1024	1.72	0.02	6.91	0.25	0.8034
School 1025	8.47	0.07	7.42	1.14	0.2548
School 1026	-6.98	-0.09	6.08	-1.15	0.2517
School 1027	-0.07	0.00	5.98	-0.01	0.9911
School 1028	-8.40	-0.08	6.79	-1.24	0.2172
School 1029	-2.20	-0.02	6.38	-0.34	0.7306
School 1032	8.42	0.08	6.86	1.23	0.2207
School 1034	-2.14	-0.02	6.48	-0.33	0.7411
School 1035	-0.86	-0.01	5.95	-0.14	0.8857
School 1038	14.22	0.15	6.51	2.18	0.0298
School 1040	14.62	0.16	6.41	2.28	0.0234
School 1041	5.15	0.06	6.32	0.82	0.4155
School 1042	16.00	0.18	6.36	2.52	0.0125
School 1044	-2.68	-0.02	7.36	-0.36	0.7158
School 1047	8.87	0.05	9.25	0.96	0.3386
School 1049	12.19	0.12	6.70	1.82	0.0699
Male	-0.73	-0.01	2.96	-0.25	0.8056
White	-0.11	0.00	3.68	-0.03	0.9754
African American	-3.53	-0.09	3.93	-0.9	0.3693
Master’s degree	1.57	0.04	1.99	0.79	0.4318
Teaching experience	0.04	0.02	0.10	0.45	0.6517
ELA professional development	-0.81	-0.04	1.07	-0.76	0.4479
New teacher	-4.97	-0.13	2.20	-2.26	0.0244
Teacher consultant	0.87	0.15	0.29	2.96	0.0033
In-degree in Math networks	1.37	0.10	0.70	1.97	0.0501

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.11 Model 1 in effects of teachers' combined networks on students' previous ELA achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	812.41	0.00	6.43	126.44	<.0001
Grade 2	-0.37	-0.01	2.82	-0.13	0.8969
Grade 3	0.08	0.00	2.83	0.03	0.9781
Grade 4	4.35	0.10	3.01	1.45	0.1496
School 1003	-2.19	-0.02	7.13	-0.31	0.7586
School 1006	-3.38	-0.01	15.18	-0.22	0.8241
School 1007	23.46	0.37	5.77	4.07	<.0001
School 1009	8.82	0.08	7.14	1.24	0.2179
School 1010	-5.55	-0.07	6.18	-0.9	0.3693
School 1011	1.99	0.03	6.01	0.33	0.7408
School 1012	6.82	0.07	7.15	0.95	0.3408
School 1015	5.63	0.06	6.75	0.83	0.4049
School 1017	13.86	0.18	6.22	2.23	0.0267
School 1020	5.61	0.07	6.09	0.92	0.3582
School 1021	1.58	0.02	6.20	0.25	0.7991
School 1023	17.89	0.15	7.62	2.35	0.0196
School 1024	2.07	0.02	7.01	0.29	0.7685
School 1025	8.16	0.07	7.59	1.07	0.2835
School 1026	-7.43	-0.09	6.19	-1.2	0.2307
School 1027	0.97	0.01	6.07	0.16	0.8727
School 1028	-7.84	-0.08	6.89	-1.14	0.256
School 1029	-1.08	-0.01	6.47	-0.17	0.8675
School 1032	10.41	0.10	6.92	1.5	0.1342
School 1034	-2.49	-0.03	6.58	-0.38	0.7058
School 1035	-2.01	-0.03	6.03	-0.33	0.7394
School 1038	14.87	0.16	6.62	2.25	0.0256
School 1040	15.76	0.17	6.49	2.43	0.0159
School 1041	5.81	0.07	6.41	0.91	0.3656
School 1042	15.63	0.18	6.47	2.42	0.0164
School 1044	-3.25	-0.03	7.47	-0.44	0.6638
School 1047	8.11	0.05	9.41	0.86	0.3894
School 1049	11.76	0.11	6.81	1.73	0.0856
Male	-0.04	0.00	3.00	-0.01	0.9894
White	0.83	0.02	3.73	0.22	0.8249
African American	-2.12	-0.05	3.97	-0.53	0.5939
Master's degree	1.28	0.03	2.02	0.64	0.5251
Teaching experience	0.07	0.04	0.10	0.72	0.4734
ELA professional development	-0.88	-0.04	1.10	-0.8	0.422
New teacher	-5.54	-0.14	2.23	-2.49	0.0135
In-degree in Combined networks	1.31	0.12	0.60	2.16	0.0315

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.12 Model 2 in effects of teachers' combined networks on students' previous ELA achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	812.65	0.00	6.25	130.12	<.0001
Grade 2	0.24	0.01	2.74	0.09	0.93
Grade 3	0.34	0.01	2.75	0.12	0.9025
Grade 4	4.58	0.11	2.93	1.57	0.1185
School 1003	-3.91	-0.04	6.94	-0.56	0.5732
School 1006	-1.24	0.00	14.76	-0.08	0.9332
School 1007	25.09	0.40	5.62	4.46	<.0001
School 1009	9.18	0.08	6.94	1.32	0.1869
School 1010	-5.41	-0.07	6.00	-0.9	0.3679
School 1011	2.33	0.03	5.84	0.4	0.691
School 1012	7.99	0.08	6.96	1.15	0.2517
School 1015	7.06	0.07	6.57	1.07	0.2835
School 1017	12.77	0.16	6.05	2.11	0.0358
School 1020	6.79	0.09	5.93	1.15	0.253
School 1021	2.54	0.03	6.03	0.42	0.6747
School 1023	18.43	0.15	7.41	2.49	0.0135
School 1024	3.77	0.04	6.83	0.55	0.5817
School 1025	8.81	0.07	7.38	1.19	0.2333
School 1026	-6.62	-0.08	6.02	-1.1	0.2721
School 1027	2.66	0.04	5.92	0.45	0.6535
School 1028	-7.36	-0.07	6.70	-1.1	0.2726
School 1029	-1.42	-0.02	6.29	-0.23	0.8221
School 1032	7.93	0.08	6.76	1.17	0.2419
School 1034	-0.45	-0.01	6.42	-0.07	0.9448
School 1035	0.02	0.00	5.89	0	0.9967
School 1038	16.42	0.18	6.45	2.55	0.0115
School 1040	15.93	0.17	6.31	2.52	0.0122
School 1041	6.36	0.07	6.23	1.02	0.3082
School 1042	16.89	0.19	6.30	2.68	0.0078
School 1044	-2.60	-0.02	7.27	-0.36	0.7207
School 1047	6.34	0.04	9.16	0.69	0.489
School 1049	13.00	0.13	6.63	1.96	0.051
Male	-0.05	0.00	2.92	-0.02	0.9859
White	-1.63	-0.04	3.68	-0.44	0.6578
African American	-5.02	-0.13	3.93	-1.28	0.2022
Master's degree	1.38	0.04	1.96	0.7	0.4824
Teaching experience	0.05	0.03	0.10	0.49	0.6272
ELA professional development	-1.25	-0.06	1.07	-1.17	0.2429
New teacher	-4.12	-0.10	2.20	-1.88	0.0617
Formal leader	8.08	0.22	2.00	4.03	<.0001
In-degree in Combined networks	0.72	0.07	0.61	1.2	0.2329

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.13 Model 3 in effects of teachers' combined networks on students' previous ELA achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	812.89	0.00	6.29	129.26	<.0001
Grade 2	0.54	0.02	2.77	0.19	0.8462
Grade 3	0.76	0.02	2.78	0.27	0.7851
Grade 4	4.61	0.11	2.95	1.56	0.119
School 1003	-5.72	-0.05	7.05	-0.81	0.4173
School 1006	-1.16	0.00	14.87	-0.08	0.9376
School 1007	23.99	0.38	5.64	4.25	<.0001
School 1009	8.75	0.08	6.99	1.25	0.2116
School 1010	-6.75	-0.09	6.05	-1.12	0.2656
School 1011	2.03	0.03	5.88	0.35	0.7296
School 1012	7.73	0.07	7.00	1.1	0.2703
School 1015	5.78	0.06	6.60	0.88	0.3823
School 1017	13.47	0.17	6.09	2.21	0.0278
School 1020	5.50	0.07	5.96	0.92	0.3572
School 1021	2.21	0.03	6.07	0.36	0.7165
School 1023	17.82	0.15	7.46	2.39	0.0176
School 1024	2.37	0.02	6.86	0.35	0.7297
School 1025	7.20	0.06	7.43	0.97	0.3332
School 1026	-6.96	-0.09	6.05	-1.15	0.2516
School 1027	-0.41	-0.01	5.96	-0.07	0.9447
School 1028	-8.75	-0.08	6.74	-1.3	0.1954
School 1029	-1.68	-0.02	6.33	-0.27	0.7908
School 1032	9.07	0.09	6.79	1.34	0.1825
School 1034	-2.16	-0.02	6.44	-0.34	0.7373
School 1035	-0.96	-0.01	5.91	-0.16	0.871
School 1038	15.01	0.16	6.48	2.32	0.0213
School 1040	15.11	0.16	6.36	2.38	0.0181
School 1041	5.52	0.07	6.27	0.88	0.3792
School 1042	14.79	0.17	6.34	2.33	0.0204
School 1044	-3.03	-0.03	7.31	-0.41	0.6794
School 1047	4.34	0.03	9.27	0.47	0.6399
School 1049	10.88	0.11	6.67	1.63	0.1042
Male	-0.88	-0.02	2.95	-0.3	0.7662
White	-0.40	-0.01	3.67	-0.11	0.9141
African American	-3.47	-0.09	3.90	-0.89	0.3756
Master's degree	1.20	0.03	1.97	0.61	0.5429
Teaching experience	0.04	0.02	0.10	0.39	0.6971
ELA professional development	-1.16	-0.06	1.08	-1.08	0.2807
New teacher	-4.91	-0.12	2.19	-2.24	0.0257
The total number of leadership roles	2.07	0.19	0.58	3.55	0.0005
In-degree in Combined networks	0.81	0.07	0.61	1.33	0.1832

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.14 Model 4 in effects of teachers' combined networks on students' previous ELA achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	813.00	0.00	6.42	126.55	<.0001
Grade 2	-0.23	-0.01	2.82	-0.08	0.9351
Grade 3	0.23	0.01	2.83	0.08	0.9346
Grade 4	4.19	0.10	3.01	1.39	0.1647
School 1003	-3.41	-0.03	7.16	-0.48	0.6347
School 1006	-2.22	-0.01	15.17	-0.15	0.8837
School 1007	23.32	0.37	5.75	4.05	<.0001
School 1009	8.86	0.08	7.12	1.24	0.2149
School 1010	-6.15	-0.08	6.18	-1	0.3205
School 1011	2.17	0.03	6.00	0.36	0.7175
School 1012	7.27	0.07	7.14	1.02	0.3098
School 1015	5.89	0.06	6.74	0.87	0.3827
School 1017	14.12	0.18	6.21	2.27	0.0238
School 1020	5.55	0.07	6.08	0.91	0.3619
School 1021	1.77	0.02	6.19	0.29	0.7756
School 1023	17.92	0.15	7.60	2.36	0.0192
School 1024	2.25	0.02	7.00	0.32	0.7478
School 1025	8.16	0.07	7.57	1.08	0.282
School 1026	-7.30	-0.09	6.17	-1.18	0.238
School 1027	0.67	0.01	6.06	0.11	0.912
School 1028	-9.09	-0.09	6.93	-1.31	0.1908
School 1029	-1.04	-0.01	6.46	-0.16	0.8726
School 1032	10.21	0.10	6.91	1.48	0.1407
School 1034	-2.39	-0.03	6.57	-0.36	0.7168
School 1035	-2.18	-0.03	6.02	-0.36	0.7178
School 1038	14.87	0.16	6.61	2.25	0.0253
School 1040	15.83	0.17	6.48	2.44	0.0152
School 1041	5.29	0.06	6.40	0.83	0.4091
School 1042	15.51	0.18	6.46	2.4	0.0171
School 1044	-3.08	-0.03	7.46	-0.41	0.6796
School 1047	8.56	0.05	9.39	0.91	0.363
School 1049	11.55	0.11	6.80	1.7	0.0906
Male	-0.66	-0.01	3.03	-0.22	0.8289
White	0.46	0.01	3.73	0.12	0.9025
African American	-2.66	-0.07	3.98	-0.67	0.5051
Master's degree	0.99	0.03	2.02	0.49	0.6262
Teaching experience	0.07	0.04	0.10	0.66	0.5089
ELA professional development	-0.91	-0.04	1.09	-0.83	0.4072
New teacher	-5.70	-0.14	2.23	-2.56	0.011
ELA coordinator	1.75	0.07	1.21	1.45	0.1469
In-degree in Combined networks	1.26	0.11	0.60	2.09	0.0377

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.15 Model 5 in effects of teachers' combined networks on students' previous ELA achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	817.49	0.00	6.55	124.81	<.0001
Grade 2	-0.24	-0.01	2.78	-0.08	0.9326
Grade 3	-0.05	0.00	2.79	-0.02	0.9846
Grade 4	3.81	0.09	2.97	1.28	0.2012
School 1003	-3.57	-0.03	7.04	-0.51	0.6121
School 1006	-2.55	-0.01	14.95	-0.17	0.8649
School 1007	22.79	0.36	5.68	4.01	<.0001
School 1009	8.25	0.07	7.03	1.17	0.242
School 1010	-6.06	-0.08	6.08	-1	0.32
School 1011	1.49	0.02	5.92	0.25	0.8018
School 1012	7.00	0.07	7.04	0.99	0.3211
School 1015	5.06	0.05	6.65	0.76	0.4478
School 1017	13.44	0.17	6.13	2.19	0.0291
School 1020	5.11	0.06	6.00	0.85	0.3959
School 1021	1.37	0.02	6.11	0.22	0.8229
School 1023	17.48	0.15	7.51	2.33	0.0206
School 1024	1.86	0.02	6.91	0.27	0.7876
School 1025	7.25	0.06	7.48	0.97	0.3334
School 1026	-7.34	-0.09	6.09	-1.2	0.2294
School 1027	-0.29	0.00	6.00	-0.05	0.9614
School 1028	-8.66	-0.08	6.79	-1.28	0.2032
School 1029	-2.44	-0.03	6.39	-0.38	0.7033
School 1032	8.34	0.08	6.85	1.22	0.225
School 1034	-2.66	-0.03	6.48	-0.41	0.6825
School 1035	-1.09	-0.02	5.95	-0.18	0.8546
School 1038	13.61	0.15	6.54	2.08	0.0384
School 1040	14.56	0.16	6.41	2.27	0.0239
School 1041	5.31	0.06	6.31	0.84	0.4008
School 1042	15.75	0.18	6.37	2.47	0.0141
School 1044	-2.98	-0.03	7.36	-0.41	0.6857
School 1047	6.12	0.04	9.29	0.66	0.5106
School 1049	11.12	0.11	6.72	1.66	0.099
Male	-0.51	-0.01	2.96	-0.17	0.8622
White	0.01	0.00	3.68	0	0.9983
African American	-3.31	-0.08	3.93	-0.84	0.3999
Master's degree	1.49	0.04	1.99	0.75	0.4533
Teaching experience	0.04	0.02	0.10	0.38	0.7061
ELA professional development	-1.05	-0.05	1.08	-0.97	0.3328
New teacher	-4.83	-0.12	2.21	-2.19	0.0296
Teacher consultant	0.89	0.15	0.29	3.01	0.0029
In-degree in Combined networks	1.19	0.11	0.60	2	0.0467

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.16 Model 1 in effects of teachers' ELA networks on students' previous Math achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	306.16	0.00	6.87	44.59	<.0001
Grade 2	18.74	0.45	3.11	6.03	<.0001
Grade 3	9.02	0.22	3.11	2.9	0.0041
Grade 4	13.83	0.28	3.33	4.15	<.0001
School 1003	1.29	0.01	7.89	0.16	0.8703
School 1006	15.03	0.04	16.84	0.89	0.3728
School 1007	27.72	0.38	6.24	4.44	<.0001
School 1009	17.06	0.13	7.82	2.18	0.03
School 1010	-2.68	-0.03	6.79	-0.39	0.6938
School 1011	8.37	0.10	6.58	1.27	0.2044
School 1012	8.87	0.07	7.88	1.13	0.261
School 1015	15.34	0.13	7.45	2.06	0.0406
School 1017	23.03	0.25	6.75	3.41	0.0007
School 1020	6.39	0.07	6.67	0.96	0.3386
School 1021	5.35	0.06	6.85	0.78	0.4355
School 1023	14.37	0.10	8.32	1.73	0.0852
School 1024	2.91	0.02	7.73	0.38	0.7071
School 1025	17.23	0.11	9.17	1.88	0.0612
School 1026	-1.75	-0.02	6.72	-0.26	0.7944
School 1027	3.98	0.05	6.63	0.6	0.5485
School 1028	-3.67	-0.03	7.57	-0.49	0.6278
School 1029	0.99	0.01	7.13	0.14	0.8894
School 1032	16.12	0.13	7.57	2.13	0.0342
School 1034	-2.28	-0.02	7.19	-0.32	0.7511
School 1035	2.41	0.03	6.66	0.36	0.7177
School 1038	25.58	0.23	7.21	3.55	0.0005
School 1040	23.74	0.22	7.11	3.34	0.001
School 1041	11.62	0.12	7.03	1.65	0.0997
School 1042	20.27	0.20	6.91	2.93	0.0036
School 1044	-2.55	-0.02	8.24	-0.31	0.7568
School 1047	18.44	0.09	10.49	1.76	0.08
School 1049	16.86	0.14	7.52	2.24	0.0257
Male	-0.34	-0.01	3.34	-0.1	0.9197
White	0.16	0.00	4.13	0.04	0.969
African American	-3.31	-0.07	4.39	-0.76	0.4508
Master’s degree	-0.32	-0.01	2.23	-0.14	0.8871
Teaching experience	0.07	0.03	0.11	0.64	0.5199
Math professional development	1.31	0.05	1.33	0.98	0.3278
New teacher	-6.32	-0.14	2.45	-2.58	0.0104
In-degree in ELA networks	1.82	0.11	0.88	2.07	0.0395

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.17 Model 2 in effects of teachers' ELA networks on students' previous Math achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	306.01	0.00	6.67	45.9	<.0001
Grade 2	19.75	0.48	3.03	6.52	<.0001
Grade 3	9.56	0.23	3.02	3.16	0.0018
Grade 4	14.41	0.29	3.24	4.46	<.0001
School 1003	-0.36	0.00	7.67	-0.05	0.9626
School 1006	17.11	0.05	16.35	1.05	0.2964
School 1007	29.71	0.41	6.08	4.89	<.0001
School 1009	18.01	0.14	7.60	2.37	0.0185
School 1010	-2.74	-0.03	6.59	-0.42	0.6778
School 1011	8.95	0.10	6.39	1.4	0.1625
School 1012	10.40	0.08	7.66	1.36	0.1756
School 1015	17.08	0.15	7.25	2.36	0.0192
School 1017	22.27	0.24	6.55	3.4	0.0008
School 1020	7.95	0.09	6.49	1.23	0.2213
School 1021	6.37	0.07	6.66	0.96	0.3392
School 1023	15.03	0.11	8.08	1.86	0.064
School 1024	5.18	0.04	7.53	0.69	0.4915
School 1025	18.46	0.12	8.90	2.07	0.0391
School 1026	-1.29	-0.01	6.52	-0.2	0.8429
School 1027	5.54	0.06	6.45	0.86	0.3906
School 1028	-3.13	-0.03	7.35	-0.43	0.6709
School 1029	0.48	0.00	6.92	0.07	0.9453
School 1032	13.71	0.11	7.38	1.86	0.0642
School 1034	-0.10	0.00	7.01	-0.01	0.9883
School 1035	4.65	0.05	6.49	0.72	0.4744
School 1038	26.92	0.24	7.01	3.84	0.0002
School 1040	24.29	0.22	6.91	3.52	0.0005
School 1041	12.47	0.12	6.83	1.83	0.0691
School 1042	21.56	0.21	6.71	3.21	0.0015
School 1044	-1.94	-0.01	8.00	-0.24	0.8088
School 1047	15.93	0.08	10.20	1.56	0.1197
School 1049	18.31	0.15	7.31	2.51	0.0128
Male	-0.39	-0.01	3.24	-0.12	0.9032
White	-2.61	-0.06	4.07	-0.64	0.5216
African American	-6.30	-0.14	4.32	-1.46	0.1463
Master’s degree	0.02	0.00	2.17	0.01	0.9909
Teaching experience	0.04	0.02	0.11	0.37	0.7139
Math professional development	0.40	0.02	1.31	0.31	0.7586
New teacher	-4.39	-0.09	2.42	-1.81	0.0711
Formal leader	8.99	0.20	2.18	4.12	<.0001
In-degree in ELA networks	1.37	0.08	0.86	1.59	0.1124

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.18 Model 3 in effects of teachers' ELA networks on students' previous Math achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	306.60	0.00	6.68	45.93	<.0001
Grade 2	20.17	0.49	3.04	6.62	<.0001
Grade 3	10.12	0.24	3.04	3.33	0.001
Grade 4	14.39	0.29	3.24	4.44	<.0001
School 1003	-2.91	-0.02	7.74	-0.38	0.7074
School 1006	17.72	0.05	16.38	1.08	0.2803
School 1007	28.54	0.39	6.07	4.7	<.0001
School 1009	17.39	0.13	7.60	2.29	0.023
School 1010	-4.36	-0.05	6.61	-0.66	0.5101
School 1011	8.56	0.10	6.39	1.34	0.1817
School 1012	10.16	0.08	7.66	1.33	0.1859
School 1015	15.59	0.13	7.25	2.15	0.0323
School 1017	22.98	0.25	6.56	3.5	0.0005
School 1020	6.41	0.07	6.48	0.99	0.3234
School 1021	6.16	0.07	6.66	0.92	0.356
School 1023	14.20	0.10	8.09	1.76	0.0803
School 1024	3.54	0.03	7.52	0.47	0.6378
School 1025	16.67	0.11	8.91	1.87	0.0625
School 1026	-1.63	-0.02	6.53	-0.25	0.8031
School 1027	1.96	0.02	6.46	0.3	0.7622
School 1028	-4.87	-0.04	7.36	-0.66	0.5086
School 1029	0.10	0.00	6.93	0.02	0.988
School 1032	14.77	0.12	7.37	2	0.0461
School 1034	-2.07	-0.02	6.99	-0.3	0.7678
School 1035	3.68	0.04	6.48	0.57	0.5711
School 1038	25.37	0.23	7.01	3.62	0.0004
School 1040	23.23	0.21	6.91	3.36	0.0009
School 1041	11.47	0.11	6.84	1.68	0.0946
School 1042	18.79	0.19	6.72	2.79	0.0056
School 1044	-2.39	-0.02	8.01	-0.3	0.7657
School 1047	13.39	0.07	10.27	1.3	0.1935
School 1049	15.89	0.13	7.31	2.17	0.0307
Male	-1.47	-0.02	3.26	-0.45	0.6531
White	-1.43	-0.03	4.04	-0.35	0.7237
African American	-4.75	-0.10	4.28	-1.11	0.2687
Master’s degree	-0.20	0.00	2.17	-0.09	0.9271
Teaching experience	0.03	0.01	0.11	0.25	0.8048
Math professional development	0.40	0.02	1.31	0.31	0.7595
New teacher	-5.25	-0.11	2.40	-2.19	0.0292
The total number of leadership roles	2.57	0.20	0.64	4.04	<.0001
In-degree in ELA networks	1.30	0.08	0.86	1.5	0.1347

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.19 Model 4 in effects of teachers' ELA networks on students' previous Math achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	306.51	0.00	6.82	44.95	<.0001
Grade 2	19.17	0.46	3.09	6.19	<.0001
Grade 3	9.63	0.23	3.10	3.11	0.0021
Grade 4	14.42	0.29	3.32	4.35	<.0001
School 1003	-0.16	0.00	7.86	-0.02	0.9836
School 1006	15.29	0.04	16.72	0.91	0.3611
School 1007	27.74	0.38	6.19	4.48	<.0001
School 1009	16.05	0.12	7.78	2.06	0.04
School 1010	-3.22	-0.04	6.74	-0.48	0.6329
School 1011	8.13	0.09	6.53	1.24	0.2143
School 1012	9.18	0.07	7.82	1.17	0.2414
School 1015	15.43	0.13	7.40	2.08	0.0381
School 1017	22.75	0.24	6.70	3.4	0.0008
School 1020	6.51	0.07	6.62	0.98	0.3265
School 1021	4.37	0.05	6.82	0.64	0.5224
School 1023	14.34	0.10	8.26	1.74	0.0837
School 1024	2.74	0.02	7.67	0.36	0.7213
School 1025	17.80	0.12	9.10	1.95	0.0517
School 1026	-1.78	-0.02	6.67	-0.27	0.7897
School 1027	2.92	0.03	6.60	0.44	0.6586
School 1028	-3.62	-0.03	7.51	-0.48	0.6305
School 1029	0.83	0.01	7.08	0.12	0.9069
School 1032	16.21	0.13	7.52	2.16	0.032
School 1034	-2.17	-0.02	7.14	-0.3	0.761
School 1035	2.06	0.02	6.61	0.31	0.7559
School 1038	25.35	0.23	7.16	3.54	0.0005
School 1040	23.86	0.22	7.06	3.38	0.0008
School 1041	10.19	0.10	7.01	1.45	0.1473
School 1042	19.43	0.19	6.87	2.83	0.005
School 1044	-2.51	-0.02	8.18	-0.31	0.7593
School 1047	18.62	0.09	10.41	1.79	0.0749
School 1049	16.88	0.14	7.46	2.26	0.0246
Male	-0.49	-0.01	3.32	-0.15	0.882
White	-0.38	-0.01	4.11	-0.09	0.9266
African American	-3.97	-0.09	4.37	-0.91	0.3645
Master’s degree	-0.46	-0.01	2.22	-0.21	0.8363
Teaching experience	0.07	0.03	0.11	0.62	0.5328
Math professional development	1.08	0.04	1.33	0.81	0.418
New teacher	-6.48	-0.14	2.43	-2.67	0.0082
Math coordinator	2.80	0.10	1.27	2.2	0.0288
In-degree in ELA networks	1.84	0.11	0.87	2.1	0.0363

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.20 Model 5 in effects of teachers' ELA networks on students' previous Math achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	311.62	0.00	7.03	44.34	<.0001
Grade 2	19.07	0.46	3.07	6.21	<.0001
Grade 3	9.02	0.22	3.07	2.94	0.0036
Grade 4	13.31	0.27	3.29	4.05	<.0001
School 1003	-0.01	0.00	7.79	0	0.999
School 1006	15.77	0.05	16.60	0.95	0.3432
School 1007	27.11	0.37	6.16	4.4	<.0001
School 1009	16.68	0.13	7.71	2.16	0.0315
School 1010	-3.34	-0.04	6.70	-0.5	0.6184
School 1011	8.03	0.09	6.49	1.24	0.2169
School 1012	9.12	0.07	7.77	1.17	0.2415
School 1015	14.78	0.13	7.35	2.01	0.0455
School 1017	22.81	0.24	6.65	3.43	0.0007
School 1020	5.90	0.06	6.58	0.9	0.3704
School 1021	5.17	0.06	6.76	0.77	0.4449
School 1023	13.85	0.10	8.21	1.69	0.0926
School 1024	2.81	0.02	7.62	0.37	0.7125
School 1025	16.57	0.11	9.04	1.83	0.068
School 1026	-1.83	-0.02	6.62	-0.28	0.7821
School 1027	2.71	0.03	6.55	0.41	0.6791
School 1028	-4.56	-0.04	7.47	-0.61	0.5422
School 1029	-0.44	0.00	7.04	-0.06	0.9499
School 1032	14.02	0.11	7.50	1.87	0.0629
School 1034	-2.58	-0.02	7.10	-0.36	0.7161
School 1035	3.43	0.04	6.58	0.52	0.6025
School 1038	24.13	0.22	7.12	3.39	0.0008
School 1040	22.57	0.21	7.03	3.21	0.0015
School 1041	11.23	0.11	6.94	1.62	0.1068
School 1042	19.69	0.20	6.81	2.89	0.0042
School 1044	-2.38	-0.02	8.13	-0.29	0.7703
School 1047	15.98	0.08	10.38	1.54	0.1249
School 1049	16.19	0.13	7.42	2.18	0.0299
Male	-0.78	-0.01	3.30	-0.24	0.8126
White	-0.79	-0.02	4.09	-0.19	0.8471
African American	-4.50	-0.10	4.35	-1.04	0.3012
Master’s degree	-0.02	0.00	2.20	-0.01	0.9923
Teaching experience	0.03	0.02	0.11	0.32	0.7497
Math professional development	0.77	0.03	1.33	0.58	0.562
New teacher	-5.42	-0.12	2.43	-2.23	0.0269
Teacher consultant	0.94	0.14	0.32	2.91	0.004
In-degree in ELA networks	1.79	0.10	0.87	2.06	0.0402

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.21 Model 1 in effects of teachers' Math networks on students' previous Math achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	306.26	0.00	6.84	44.74	<.0001
Grade 2	18.84	0.46	3.11	6.06	<.0001
Grade 3	9.65	0.23	3.11	3.1	0.0021
Grade 4	14.37	0.29	3.33	4.31	<.0001
School 1003	0.75	0.01	7.87	0.1	0.9238
School 1006	19.04	0.06	16.69	1.14	0.2549
School 1007	27.47	0.38	6.24	4.4	<.0001
School 1009	16.54	0.13	7.80	2.12	0.0349
School 1010	-3.29	-0.04	6.79	-0.48	0.6286
School 1011	7.07	0.08	6.57	1.08	0.2829
School 1012	8.69	0.07	7.87	1.1	0.2702
School 1015	14.80	0.13	7.44	1.99	0.0476
School 1017	23.07	0.25	6.73	3.43	0.0007
School 1020	6.48	0.07	6.66	0.97	0.3314
School 1021	5.41	0.06	6.84	0.79	0.4297
School 1023	13.60	0.10	8.30	1.64	0.1026
School 1024	2.31	0.02	7.70	0.3	0.7645
School 1025	19.47	0.13	9.07	2.15	0.0327
School 1026	-2.52	-0.03	6.73	-0.37	0.7089
School 1027	2.46	0.03	6.67	0.37	0.7125
School 1028	-4.15	-0.03	7.56	-0.55	0.5838
School 1029	0.46	0.00	7.13	0.06	0.9483
School 1032	16.12	0.13	7.56	2.13	0.034
School 1034	-2.47	-0.02	7.19	-0.34	0.7318
School 1035	2.15	0.03	6.65	0.32	0.7473
School 1038	24.99	0.23	7.21	3.47	0.0006
School 1040	23.66	0.22	7.10	3.33	0.001
School 1041	10.98	0.11	7.03	1.56	0.1197
School 1042	19.79	0.20	6.91	2.86	0.0046
School 1044	-2.40	-0.02	8.22	-0.29	0.7703
School 1047	22.72	0.11	10.35	2.2	0.029
School 1049	18.34	0.15	7.47	2.45	0.0148
Male	-1.21	-0.02	3.31	-0.37	0.7137
White	0.00	0.00	4.13	0	0.9995
African American	-3.14	-0.07	4.39	-0.72	0.4752
Master’s degree	0.03	0.00	2.23	0.01	0.9891
Teaching experience	0.08	0.04	0.11	0.74	0.4616
Math professional development	1.00	0.04	1.33	0.75	0.4535
New teacher	-6.40	-0.14	2.43	-2.63	0.009
In-degree in Math networks	1.73	0.11	0.77	2.23	0.0264

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.22 Model 2 in effects of teachers' Math networks on students' previous Math achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	306.41	0.00	6.67	45.96	<.0001
Grade 2	19.72	0.48	3.04	6.49	<.0001
Grade 3	9.95	0.24	3.03	3.28	0.0012
Grade 4	14.71	0.29	3.25	4.53	<.0001
School 1003	-0.74	-0.01	7.68	-0.1	0.9231
School 1006	20.15	0.06	16.26	1.24	0.2164
School 1007	29.74	0.41	6.10	4.87	<.0001
School 1009	17.52	0.13	7.60	2.3	0.022
School 1010	-3.07	-0.03	6.61	-0.46	0.6433
School 1011	8.09	0.09	6.41	1.26	0.2076
School 1012	10.27	0.08	7.67	1.34	0.1819
School 1015	16.58	0.14	7.26	2.28	0.0231
School 1017	22.52	0.24	6.56	3.43	0.0007
School 1020	7.91	0.08	6.50	1.22	0.2243
School 1021	6.66	0.07	6.67	1	0.3187
School 1023	14.43	0.10	8.09	1.78	0.0755
School 1024	4.56	0.04	7.53	0.61	0.5455
School 1025	20.21	0.13	8.83	2.29	0.0229
School 1026	-1.62	-0.02	6.56	-0.25	0.805
School 1027	4.72	0.05	6.53	0.72	0.4698
School 1028	-3.46	-0.03	7.36	-0.47	0.6389
School 1029	0.28	0.00	6.94	0.04	0.9673
School 1032	13.90	0.11	7.39	1.88	0.061
School 1034	-0.27	0.00	7.02	-0.04	0.9691
School 1035	4.51	0.05	6.51	0.69	0.4893
School 1038	26.67	0.24	7.04	3.79	0.0002
School 1040	24.21	0.22	6.92	3.5	0.0005
School 1041	12.13	0.12	6.86	1.77	0.0781
School 1042	21.47	0.21	6.75	3.18	0.0016
School 1044	-1.72	-0.01	8.01	-0.21	0.8303
School 1047	19.10	0.10	10.12	1.89	0.0602
School 1049	19.40	0.16	7.28	2.66	0.0082
Male	-1.06	-0.02	3.22	-0.33	0.7421
White	-2.66	-0.06	4.08	-0.65	0.5142
African American	-6.17	-0.13	4.34	-1.42	0.1567
Master’s degree	0.21	0.00	2.18	0.09	0.9244
Teaching experience	0.05	0.02	0.11	0.45	0.655
Math professional development	0.23	0.01	1.31	0.18	0.8584
New teacher	-4.72	-0.10	2.40	-1.96	0.0507
Formal leader	8.74	0.20	2.24	3.9	0.0001
In-degree in Math networks	0.98	0.06	0.78	1.26	0.2097

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.23 Model 3 in effects of teachers' Math networks on students' previous Math achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	306.89	0.00	6.67	46	<.0001
Grade 2	20.15	0.49	3.05	6.61	<.0001
Grade 3	10.50	0.25	3.04	3.46	0.0006
Grade 4	14.70	0.29	3.25	4.53	<.0001
School 1003	-3.21	-0.02	7.74	-0.42	0.6784
School 1006	20.57	0.06	16.27	1.26	0.2071
School 1007	28.54	0.39	6.08	4.69	<.0001
School 1009	16.96	0.13	7.60	2.23	0.0265
School 1010	-4.67	-0.05	6.62	-0.7	0.4817
School 1011	7.73	0.09	6.41	1.21	0.2287
School 1012	10.04	0.08	7.67	1.31	0.1919
School 1015	15.18	0.13	7.25	2.09	0.0372
School 1017	23.14	0.25	6.56	3.53	0.0005
School 1020	6.43	0.07	6.49	0.99	0.3223
School 1021	6.37	0.07	6.66	0.96	0.34
School 1023	13.65	0.10	8.09	1.69	0.0926
School 1024	3.02	0.02	7.51	0.4	0.6877
School 1025	18.35	0.12	8.84	2.08	0.0389
School 1026	-2.00	-0.02	6.56	-0.3	0.7609
School 1027	1.17	0.01	6.51	0.18	0.8572
School 1028	-5.16	-0.04	7.37	-0.7	0.4846
School 1029	-0.12	0.00	6.95	-0.02	0.9862
School 1032	14.88	0.12	7.38	2.02	0.0447
School 1034	-2.18	-0.02	7.00	-0.31	0.7557
School 1035	3.54	0.04	6.49	0.55	0.5859
School 1038	25.11	0.23	7.03	3.57	0.0004
School 1040	23.18	0.21	6.92	3.35	0.0009
School 1041	11.13	0.11	6.85	1.62	0.1056
School 1042	18.69	0.19	6.74	2.77	0.006
School 1044	-2.20	-0.02	8.01	-0.27	0.7839
School 1047	16.48	0.08	10.21	1.61	0.1077
School 1049	16.98	0.14	7.29	2.33	0.0206
Male	-2.07	-0.03	3.23	-0.64	0.5218
White	-1.51	-0.04	4.04	-0.37	0.7082
African American	-4.65	-0.10	4.29	-1.08	0.28
Master’s degree	0.00	0.00	2.18	0	0.9995
Teaching experience	0.03	0.02	0.11	0.32	0.7459
Math professional development	0.23	0.01	1.31	0.17	0.8615
New teacher	-5.48	-0.12	2.38	-2.3	0.022
The total number of leadership roles	2.51	0.19	0.65	3.88	0.0001
In-degree in Math networks	1.01	0.06	0.78	1.3	0.1939

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.24 Model 4 in effects of teachers' Math networks on students' previous Math achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	306.79	0.00	6.82	44.99	<.0001
Grade 2	19.14	0.46	3.10	6.18	<.0001
Grade 3	10.12	0.24	3.11	3.26	0.0013
Grade 4	14.81	0.30	3.33	4.45	<.0001
School 1003	-0.50	0.00	7.87	-0.06	0.9493
School 1006	19.33	0.06	16.61	1.16	0.2457
School 1007	27.68	0.38	6.21	4.46	<.0001
School 1009	15.63	0.12	7.78	2.01	0.0456
School 1010	-3.66	-0.04	6.76	-0.54	0.5887
School 1011	6.97	0.08	6.54	1.06	0.288
School 1012	8.99	0.07	7.83	1.15	0.2521
School 1015	14.85	0.13	7.40	2.01	0.046
School 1017	22.98	0.25	6.70	3.43	0.0007
School 1020	6.54	0.07	6.63	0.99	0.3251
School 1021	4.76	0.05	6.81	0.7	0.4851
School 1023	13.57	0.10	8.26	1.64	0.1017
School 1024	2.08	0.02	7.67	0.27	0.7861
School 1025	20.03	0.13	9.03	2.22	0.0274
School 1026	-2.35	-0.03	6.70	-0.35	0.7256
School 1027	1.82	0.02	6.65	0.27	0.7849
School 1028	-4.07	-0.03	7.52	-0.54	0.5887
School 1029	0.46	0.00	7.10	0.06	0.9483
School 1032	16.28	0.13	7.53	2.16	0.0315
School 1034	-2.35	-0.02	7.15	-0.33	0.7426
School 1035	1.93	0.02	6.62	0.29	0.7708
School 1038	24.96	0.23	7.18	3.48	0.0006
School 1040	23.76	0.22	7.07	3.36	0.0009
School 1041	9.88	0.10	7.03	1.41	0.1609
School 1042	19.29	0.19	6.89	2.8	0.0055
School 1044	-2.28	-0.02	8.19	-0.28	0.7813
School 1047	22.80	0.11	10.30	2.21	0.0277
School 1049	18.37	0.15	7.44	2.47	0.0142
Male	-1.36	-0.02	3.29	-0.41	0.6811
White	-0.47	-0.01	4.12	-0.11	0.9099
African American	-3.75	-0.08	4.38	-0.86	0.3921
Master’s degree	-0.14	0.00	2.23	-0.06	0.9503
Teaching experience	0.08	0.04	0.11	0.72	0.4713
Math professional development	0.83	0.03	1.33	0.62	0.5333
New teacher	-6.69	-0.14	2.42	-2.76	0.0062
Math coordinator	2.38	0.09	1.29	1.85	0.066
In-degree in Math networks	1.50	0.09	0.78	1.92	0.0554

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.25 Model 5 in effects of teachers' Math networks on students' previous Math achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	311.63	0.00	7.03	44.35	<.0001
Grade 2	19.12	0.46	3.07	6.23	<.0001
Grade 3	9.62	0.23	3.07	3.13	0.0019
Grade 4	13.83	0.28	3.30	4.2	<.0001
School 1003	-0.49	0.00	7.79	-0.06	0.9494
School 1006	19.70	0.06	16.48	1.2	0.233
School 1007	26.98	0.37	6.16	4.38	<.0001
School 1009	16.16	0.12	7.70	2.1	0.0369
School 1010	-3.87	-0.04	6.70	-0.58	0.5642
School 1011	6.82	0.08	6.49	1.05	0.2945
School 1012	8.95	0.07	7.77	1.15	0.2503
School 1015	14.26	0.12	7.35	1.94	0.0533
School 1017	22.92	0.25	6.65	3.45	0.0007
School 1020	5.99	0.06	6.58	0.91	0.3635
School 1021	5.32	0.06	6.75	0.79	0.4313
School 1023	13.11	0.09	8.20	1.6	0.111
School 1024	2.19	0.02	7.61	0.29	0.7734
School 1025	18.82	0.12	8.95	2.1	0.0365
School 1026	-2.49	-0.03	6.64	-0.38	0.7077
School 1027	1.39	0.02	6.60	0.21	0.8333
School 1028	-4.98	-0.04	7.47	-0.67	0.5058
School 1029	-0.84	-0.01	7.05	-0.12	0.9048
School 1032	14.13	0.12	7.50	1.88	0.0607
School 1034	-2.74	-0.03	7.10	-0.39	0.6996
School 1035	3.17	0.04	6.58	0.48	0.6303
School 1038	23.69	0.22	7.14	3.32	0.001
School 1040	22.54	0.21	7.02	3.21	0.0015
School 1041	10.67	0.11	6.95	1.54	0.1257
School 1042	19.34	0.19	6.83	2.83	0.005
School 1044	-2.19	-0.02	8.12	-0.27	0.7873
School 1047	20.23	0.10	10.25	1.97	0.0496
School 1049	17.67	0.14	7.38	2.39	0.0174
Male	-1.63	-0.02	3.27	-0.5	0.6187
White	-0.91	-0.02	4.09	-0.22	0.8235
African American	-4.31	-0.09	4.35	-0.99	0.3225
Master’s degree	0.29	0.01	2.21	0.13	0.8972
Teaching experience	0.05	0.02	0.11	0.42	0.6727
Math professional development	0.50	0.02	1.33	0.38	0.7056
New teacher	-5.60	-0.12	2.42	-2.32	0.0212
Teacher consultant	0.91	0.13	0.32	2.79	0.0056
In-degree in Math networks	1.59	0.10	0.77	2.08	0.0389

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.26 Model 1 in effects of teachers' combined networks on students' previous Math achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	306.14	0.00	6.89	44.46	<.0001
Grade 2	18.91	0.46	3.12	6.06	<.0001
Grade 3	9.47	0.23	3.12	3.04	0.0026
Grade 4	13.99	0.28	3.33	4.2	<.0001
School 1003	0.69	0.01	7.89	0.09	0.9307
School 1006	16.58	0.05	16.79	0.99	0.3243
School 1007	27.84	0.38	6.24	4.46	<.0001
School 1009	16.82	0.13	7.82	2.15	0.0325
School 1010	-3.12	-0.04	6.80	-0.46	0.6474
School 1011	7.57	0.09	6.58	1.15	0.2514
School 1012	8.76	0.07	7.89	1.11	0.2678
School 1015	15.00	0.13	7.46	2.01	0.0454
School 1017	23.26	0.25	6.75	3.45	0.0007
School 1020	6.35	0.07	6.68	0.95	0.3427
School 1021	5.45	0.06	6.86	0.79	0.4274
School 1023	13.98	0.10	8.32	1.68	0.0943
School 1024	2.55	0.02	7.73	0.33	0.7415
School 1025	17.80	0.12	9.15	1.94	0.0529
School 1026	-2.36	-0.03	6.75	-0.35	0.727
School 1027	2.67	0.03	6.70	0.4	0.6904
School 1028	-4.17	-0.03	7.58	-0.55	0.5828
School 1029	0.49	0.00	7.15	0.07	0.9452
School 1032	16.39	0.13	7.58	2.16	0.0314
School 1034	-2.64	-0.03	7.21	-0.37	0.7148
School 1035	2.05	0.02	6.68	0.31	0.7591
School 1038	24.79	0.23	7.25	3.42	0.0007
School 1040	23.83	0.22	7.12	3.35	0.0009
School 1041	11.46	0.11	7.04	1.63	0.1048
School 1042	19.97	0.20	6.93	2.88	0.0043
School 1044	-2.46	-0.02	8.25	-0.3	0.7654
School 1047	19.80	0.10	10.43	1.9	0.0587
School 1049	17.37	0.14	7.51	2.31	0.0215
Male	-0.92	-0.01	3.32	-0.28	0.7818
White	0.19	0.00	4.14	0.05	0.9633
African American	-3.05	-0.07	4.40	-0.69	0.4897
Master's degree	-0.12	0.00	2.24	-0.06	0.956
Teaching experience	0.07	0.03	0.11	0.66	0.5111
Math professional development	1.15	0.04	1.33	0.86	0.3895
New teacher	-6.38	-0.14	2.46	-2.6	0.0099
In-degree in Combined networks	1.26	0.10	0.66	1.9	0.0585

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.27 Model 2 in effects of teachers' combined networks on students' previous Math achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	306.49	0.00	6.70	45.75	<.0001
Grade 2	19.74	0.48	3.04	6.49	<.0001
Grade 3	9.84	0.24	3.03	3.25	0.0013
Grade 4	14.50	0.29	3.25	4.47	<.0001
School 1003	-0.81	-0.01	7.69	-0.11	0.9157
School 1006	19.02	0.06	16.35	1.16	0.2458
School 1007	30.08	0.41	6.10	4.93	<.0001
School 1009	17.64	0.14	7.62	2.32	0.0213
School 1010	-2.92	-0.03	6.62	-0.44	0.6593
School 1011	8.41	0.10	6.41	1.31	0.1903
School 1012	10.36	0.08	7.68	1.35	0.1789
School 1015	16.70	0.14	7.27	2.3	0.0224
School 1017	22.68	0.24	6.57	3.45	0.0006
School 1020	7.86	0.08	6.51	1.21	0.2284
School 1021	6.82	0.07	6.68	1.02	0.3085
School 1023	14.64	0.10	8.10	1.81	0.0719
School 1024	4.67	0.04	7.54	0.62	0.5358
School 1025	19.46	0.13	8.91	2.18	0.0299
School 1026	-1.42	-0.02	6.57	-0.22	0.8295
School 1027	5.03	0.06	6.54	0.77	0.4426
School 1028	-3.44	-0.03	7.37	-0.47	0.6414
School 1029	0.38	0.00	6.96	0.05	0.9569
School 1032	14.04	0.11	7.40	1.9	0.0589
School 1034	-0.29	0.00	7.04	-0.04	0.9669
School 1035	4.56	0.05	6.53	0.7	0.485
School 1038	26.70	0.24	7.07	3.78	0.0002
School 1040	24.30	0.22	6.93	3.51	0.0005
School 1041	12.45	0.12	6.86	1.82	0.0705
School 1042	21.72	0.22	6.76	3.21	0.0015
School 1044	-1.68	-0.01	8.03	-0.21	0.8342
School 1047	17.57	0.09	10.16	1.73	0.085
School 1049	18.96	0.15	7.32	2.59	0.0101
Male	-0.92	-0.01	3.23	-0.28	0.7765
White	-2.64	-0.06	4.09	-0.64	0.5196
African American	-6.23	-0.13	4.36	-1.43	0.1542
Master's degree	0.11	0.00	2.18	0.05	0.9608
Teaching experience	0.04	0.02	0.11	0.4	0.6873
Math professional development	0.30	0.01	1.31	0.23	0.8171
New teacher	-4.76	-0.10	2.42	-1.97	0.0504
Formal leader	8.93	0.20	2.24	3.98	<.0001
In-degree in Combined networks	0.60	0.05	0.66	0.9	0.3682

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.28 Model 3 in effects of teachers' combined networks on students' previous Math achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	306.95	0.00	6.70	45.78	<.0001
Grade 2	20.19	0.49	3.05	6.61	<.0001
Grade 3	10.40	0.25	3.04	3.42	0.0007
Grade 4	14.48	0.29	3.25	4.46	<.0001
School 1003	-3.34	-0.03	7.75	-0.43	0.667
School 1006	19.37	0.06	16.36	1.18	0.2375
School 1007	28.84	0.40	6.08	4.74	<.0001
School 1009	17.09	0.13	7.62	2.24	0.0257
School 1010	-4.56	-0.05	6.63	-0.69	0.4922
School 1011	8.05	0.09	6.41	1.26	0.2103
School 1012	10.12	0.08	7.68	1.32	0.1891
School 1015	15.27	0.13	7.26	2.1	0.0364
School 1017	23.31	0.25	6.57	3.55	0.0005
School 1020	6.34	0.07	6.50	0.98	0.3298
School 1021	6.51	0.07	6.68	0.97	0.3311
School 1023	13.85	0.10	8.10	1.71	0.0884
School 1024	3.12	0.03	7.53	0.41	0.6785
School 1025	17.50	0.11	8.91	1.96	0.0506
School 1026	-1.82	-0.02	6.57	-0.28	0.7825
School 1027	1.38	0.02	6.53	0.21	0.8325
School 1028	-5.18	-0.04	7.38	-0.7	0.4836
School 1029	-0.05	0.00	6.96	-0.01	0.9942
School 1032	15.04	0.12	7.38	2.04	0.0427
School 1034	-2.25	-0.02	7.01	-0.32	0.7485
School 1035	3.56	0.04	6.51	0.55	0.5844
School 1038	25.09	0.23	7.05	3.56	0.0004
School 1040	23.25	0.21	6.93	3.35	0.0009
School 1041	11.44	0.11	6.86	1.67	0.0965
School 1042	18.87	0.19	6.75	2.79	0.0056
School 1044	-2.18	-0.02	8.03	-0.27	0.7858
School 1047	14.80	0.07	10.23	1.45	0.1489
School 1049	16.45	0.13	7.31	2.25	0.0253
Male	-1.94	-0.03	3.24	-0.6	0.5499
White	-1.45	-0.03	4.05	-0.36	0.72
African American	-4.66	-0.10	4.30	-1.08	0.2798
Master's degree	-0.11	0.00	2.18	-0.05	0.9614
Teaching experience	0.03	0.01	0.11	0.28	0.7833
Math professional development	0.30	0.01	1.32	0.23	0.8186
New teacher	-5.53	-0.12	2.40	-2.3	0.0221
The total number of leadership roles	2.57	0.20	0.65	3.96	<.0001
In-degree in Combined networks	0.64	0.05	0.66	0.97	0.3336

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.29 Model 4 in effects of teachers' combined networks on students' previous Math achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	306.71	0.00	6.86	44.74	<.0001
Grade 2	19.23	0.47	3.11	6.18	<.0001
Grade 3	9.99	0.24	3.11	3.21	0.0015
Grade 4	14.50	0.29	3.33	4.36	<.0001
School 1003	-0.62	0.00	7.88	-0.08	0.9374
School 1006	17.21	0.05	16.71	1.03	0.3039
School 1007	28.01	0.39	6.21	4.51	<.0001
School 1009	15.82	0.12	7.80	2.03	0.0435
School 1010	-3.53	-0.04	6.77	-0.52	0.6024
School 1011	7.39	0.08	6.55	1.13	0.2604
School 1012	9.06	0.07	7.85	1.15	0.2493
School 1015	15.02	0.13	7.42	2.02	0.044
School 1017	23.13	0.25	6.71	3.45	0.0007
School 1020	6.42	0.07	6.64	0.97	0.3344
School 1021	4.77	0.05	6.83	0.7	0.486
School 1023	13.90	0.10	8.28	1.68	0.0944
School 1024	2.28	0.02	7.69	0.3	0.7667
School 1025	18.60	0.12	9.11	2.04	0.0423
School 1026	-2.22	-0.02	6.71	-0.33	0.7416
School 1027	1.96	0.02	6.67	0.29	0.7692
School 1028	-4.09	-0.03	7.54	-0.54	0.5879
School 1029	0.48	0.00	7.11	0.07	0.946
School 1032	16.53	0.13	7.54	2.19	0.0293
School 1034	-2.49	-0.02	7.17	-0.35	0.7282
School 1035	1.84	0.02	6.64	0.28	0.7824
School 1038	24.78	0.23	7.21	3.44	0.0007
School 1040	23.91	0.22	7.09	3.38	0.0008
School 1041	10.24	0.10	7.04	1.46	0.1467
School 1042	19.42	0.19	6.90	2.81	0.0053
School 1044	-2.32	-0.02	8.21	-0.28	0.7772
School 1047	20.28	0.10	10.38	1.95	0.0517
School 1049	17.53	0.14	7.47	2.35	0.0198
Male	-1.11	-0.02	3.30	-0.33	0.7379
White	-0.33	-0.01	4.13	-0.08	0.9372
African American	-3.70	-0.08	4.39	-0.84	0.4
Master's degree	-0.28	-0.01	2.23	-0.13	0.9003
Teaching experience	0.07	0.03	0.11	0.65	0.5151
Math professional development	0.95	0.04	1.33	0.71	0.4761
New teacher	-6.69	-0.14	2.45	-2.73	0.0067
Math coordinator	2.50	0.09	1.29	1.94	0.0536
In-degree in Combined networks	1.09	0.08	0.66	1.64	0.1021

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.30 Model 5 in effects of teachers' combined networks on students' previous Math achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	311.58	0.00	7.06	44.11	<.0001
Grade 2	19.20	0.46	3.08	6.23	<.0001
Grade 3	9.45	0.23	3.07	3.07	0.0023
Grade 4	13.47	0.27	3.30	4.09	<.0001
School 1003	-0.57	0.00	7.80	-0.07	0.9416
School 1006	17.45	0.05	16.58	1.05	0.2935
School 1007	27.31	0.38	6.17	4.43	<.0001
School 1009	16.41	0.13	7.72	2.12	0.0346
School 1010	-3.72	-0.04	6.72	-0.55	0.5801
School 1011	7.27	0.08	6.50	1.12	0.2644
School 1012	9.01	0.07	7.79	1.16	0.248
School 1015	14.43	0.12	7.36	1.96	0.0511
School 1017	23.10	0.25	6.66	3.47	0.0006
School 1020	5.86	0.06	6.59	0.89	0.3751
School 1021	5.36	0.06	6.77	0.79	0.4291
School 1023	13.45	0.10	8.22	1.64	0.1028
School 1024	2.41	0.02	7.63	0.32	0.7521
School 1025	17.28	0.11	9.04	1.91	0.057
School 1026	-2.35	-0.03	6.66	-0.35	0.7246
School 1027	1.57	0.02	6.62	0.24	0.8128
School 1028	-5.01	-0.04	7.48	-0.67	0.5041
School 1029	-0.83	-0.01	7.07	-0.12	0.9062
School 1032	14.36	0.12	7.52	1.91	0.0572
School 1034	-2.90	-0.03	7.11	-0.41	0.6838
School 1035	3.10	0.04	6.60	0.47	0.6393
School 1038	23.49	0.21	7.17	3.28	0.0012
School 1040	22.68	0.21	7.04	3.22	0.0014
School 1041	11.11	0.11	6.95	1.6	0.1114
School 1042	19.50	0.19	6.85	2.85	0.0047
School 1044	-2.25	-0.02	8.14	-0.28	0.7829
School 1047	17.52	0.09	10.32	1.7	0.0909
School 1049	16.77	0.14	7.42	2.26	0.0245
Male	-1.36	-0.02	3.28	-0.42	0.6779
White	-0.75	-0.02	4.10	-0.18	0.8546
African American	-4.24	-0.09	4.37	-0.97	0.3319
Master's degree	0.15	0.00	2.21	0.07	0.947
Teaching experience	0.04	0.02	0.11	0.35	0.7291
Math professional development	0.63	0.02	1.33	0.48	0.6344
New teacher	-5.57	-0.12	2.44	-2.28	0.0232
Teacher consultant	0.92	0.14	0.33	2.82	0.0051
In-degree in Combined networks	1.15	0.09	0.65	1.76	0.0788

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.31 Model 1 in effects of teachers' ELA networks on students' previous free/reduced lunch

Model 1	B	Beta	S. E.	t value	p value
Intercept	0.93	0.00	0.06	15.11	<.0001
Grade 2	0.01	0.01	0.03	0.3	0.7635
Grade 3	0.04	0.08	0.03	1.54	0.1255
Grade 4	0.02	0.04	0.03	0.81	0.4179
School 1003	-0.11	-0.06	0.07	-1.5	0.1339
School 1006	-0.25	-0.05	0.15	-1.6	0.1109
School 1007	-0.54	-0.54	0.06	-9.45	<.0001
School 1009	-0.24	-0.13	0.07	-3.36	0.0009
School 1010	0.01	0.01	0.06	0.19	0.8473
School 1011	-0.37	-0.31	0.06	-6.19	<.0001
School 1012	-0.08	-0.05	0.07	-1.14	0.2557
School 1015	-0.24	-0.15	0.07	-3.53	0.0005
School 1017	-0.50	-0.39	0.06	-8.18	<.0001
School 1020	-0.55	-0.42	0.06	-9.02	<.0001
School 1021	-0.03	-0.02	0.06	-0.45	0.6535
School 1023	-0.26	-0.13	0.08	-3.43	0.0007
School 1024	-0.09	-0.05	0.07	-1.31	0.1904
School 1025	-0.71	-0.36	0.08	-9.3	<.0001
School 1026	0.02	0.01	0.06	0.25	0.8008
School 1027	-0.08	-0.07	0.06	-1.38	0.1675
School 1028	0.02	0.01	0.07	0.33	0.742
School 1029	-0.21	-0.14	0.07	-3.19	0.0016
School 1032	-0.18	-0.11	0.07	-2.58	0.0105
School 1034	0.00	0.00	0.07	-0.06	0.9516
School 1035	-0.12	-0.10	0.06	-1.96	0.0508
School 1038	-0.69	-0.45	0.07	-10.49	<.0001
School 1040	-0.29	-0.19	0.07	-4.43	<.0001
School 1041	-0.45	-0.33	0.06	-7.07	<.0001
School 1042	-0.41	-0.30	0.06	-6.51	<.0001
School 1044	-0.03	-0.01	0.08	-0.36	0.7225
School 1047	-0.61	-0.22	0.10	-6.37	<.0001
School 1049	-0.45	-0.26	0.07	-6.46	<.0001
Male	-0.05	-0.06	0.03	-1.67	0.0968
White	-0.07	-0.11	0.04	-1.78	0.0766
African American	-0.02	-0.04	0.04	-0.61	0.5452
Master’s degree	-0.01	-0.01	0.02	-0.34	0.7327
Teaching experience	0.00	-0.04	0.00	-1.22	0.222
New teacher	0.03	0.05	0.02	1.37	0.1721
In-degree in ELA networks	-0.01	-0.05	0.01	-1.36	0.174

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.32 Model 2 in effects of teachers' ELA networks on students' previous free/reduced lunch

Model 2	B	Beta	S. E.	t value	p value
Intercept	0.94	0.00	0.06	15.53	<.0001
Grade 2	0.00	0.01	0.03	0.13	0.8972
Grade 3	0.04	0.07	0.03	1.49	0.1362
Grade 4	0.02	0.03	0.03	0.79	0.4323
School 1003	-0.09	-0.05	0.07	-1.32	0.1888
School 1006	-0.26	-0.06	0.15	-1.74	0.0825
School 1007	-0.56	-0.55	0.06	-9.88	<.0001
School 1009	-0.25	-0.14	0.07	-3.52	0.0005
School 1010	0.01	0.01	0.06	0.19	0.8488
School 1011	-0.38	-0.31	0.06	-6.36	<.0001
School 1012	-0.09	-0.05	0.07	-1.3	0.1933
School 1015	-0.25	-0.16	0.07	-3.78	0.0002
School 1017	-0.50	-0.38	0.06	-8.2	<.0001
School 1020	-0.56	-0.43	0.06	-9.38	<.0001
School 1021	-0.04	-0.03	0.06	-0.58	0.5612
School 1023	-0.27	-0.14	0.07	-3.6	0.0004
School 1024	-0.11	-0.06	0.07	-1.57	0.117
School 1025	-0.71	-0.36	0.07	-9.51	<.0001
School 1026	0.01	0.01	0.06	0.16	0.873
School 1027	-0.09	-0.08	0.06	-1.56	0.1198
School 1028	0.02	0.01	0.07	0.27	0.7906
School 1029	-0.20	-0.13	0.06	-3.17	0.0017
School 1032	-0.16	-0.09	0.07	-2.35	0.0196
School 1034	-0.02	-0.02	0.06	-0.35	0.724
School 1035	-0.13	-0.11	0.06	-2.24	0.0259
School 1038	-0.70	-0.46	0.06	-10.85	<.0001
School 1040	-0.29	-0.19	0.06	-4.58	<.0001
School 1041	-0.45	-0.34	0.06	-7.31	<.0001
School 1042	-0.42	-0.30	0.06	-6.81	<.0001
School 1044	-0.03	-0.02	0.07	-0.44	0.6609
School 1047	-0.60	-0.22	0.09	-6.32	<.0001
School 1049	-0.46	-0.27	0.07	-6.74	<.0001
Male	-0.05	-0.05	0.03	-1.69	0.0924
White	-0.05	-0.08	0.04	-1.28	0.2029
African American	0.00	0.00	0.04	-0.05	0.963
Master’s degree	-0.01	-0.01	0.02	-0.44	0.6572
Teaching experience	0.00	-0.04	0.00	-1.05	0.2937
New teacher	0.02	0.02	0.02	0.7	0.485
Formal leader	-0.07	-0.11	0.02	-3.43	0.0007
In-degree in ELA networks	-0.01	-0.03	0.01	-0.95	0.3455

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.33 Model 3 in effects of teachers' ELA networks on students' previous free/reduced lunch

Model 3	B	Beta	S. E.	t value	p value
Intercept	0.93	0.00	0.06	15.58	<.0001
Grade 2	0.00	0.00	0.03	-0.05	0.9641
Grade 3	0.04	0.06	0.03	1.31	0.1912
Grade 4	0.02	0.03	0.03	0.78	0.4358
School 1003	-0.07	-0.04	0.07	-0.96	0.3361
School 1006	-0.27	-0.06	0.15	-1.81	0.0715
School 1007	-0.55	-0.54	0.06	-9.84	<.0001
School 1009	-0.24	-0.13	0.07	-3.48	0.0006
School 1010	0.03	0.02	0.06	0.43	0.6711
School 1011	-0.37	-0.31	0.06	-6.36	<.0001
School 1012	-0.09	-0.05	0.07	-1.31	0.1911
School 1015	-0.24	-0.15	0.07	-3.65	0.0003
School 1017	-0.50	-0.39	0.06	-8.35	<.0001
School 1020	-0.55	-0.43	0.06	-9.28	<.0001
School 1021	-0.03	-0.03	0.06	-0.57	0.5709
School 1023	-0.26	-0.13	0.07	-3.55	0.0005
School 1024	-0.10	-0.06	0.07	-1.42	0.1568
School 1025	-0.69	-0.36	0.07	-9.36	<.0001
School 1026	0.01	0.01	0.06	0.19	0.8469
School 1027	-0.06	-0.05	0.06	-1.06	0.2903
School 1028	0.03	0.02	0.07	0.48	0.6295
School 1029	-0.20	-0.13	0.06	-3.13	0.002
School 1032	-0.17	-0.10	0.07	-2.46	0.0144
School 1034	-0.01	-0.01	0.06	-0.14	0.8903
School 1035	-0.13	-0.11	0.06	-2.16	0.0318
School 1038	-0.69	-0.45	0.06	-10.76	<.0001
School 1040	-0.28	-0.19	0.06	-4.48	<.0001
School 1041	-0.44	-0.33	0.06	-7.21	<.0001
School 1042	-0.40	-0.29	0.06	-6.49	<.0001
School 1044	-0.03	-0.02	0.07	-0.4	0.6883
School 1047	-0.57	-0.21	0.09	-6.06	<.0001
School 1049	-0.44	-0.26	0.07	-6.5	<.0001
Male	-0.04	-0.04	0.03	-1.38	0.1702
White	-0.05	-0.09	0.04	-1.48	0.1387
African American	-0.01	-0.02	0.04	-0.29	0.7691
Master’s degree	-0.01	-0.01	0.02	-0.36	0.718
Teaching experience	0.00	-0.03	0.00	-0.9	0.3677
New teacher	0.02	0.03	0.02	0.94	0.3477
The total number of leadership roles	-0.02	-0.13	0.01	-3.97	<.0001
In-degree in ELA networks	-0.01	-0.03	0.01	-0.79	0.4323

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.34 Model 4 in effects of teachers' ELA networks on students' previous free/reduced lunch

Model 4	B	Beta	S. E.	t value	p value
Intercept	0.86	0.00	0.06	13.95	<.0001
Grade 2	0.01	0.02	0.03	0.52	0.6008
Grade 3	0.05	0.09	0.03	1.88	0.0608
Grade 4	0.03	0.05	0.03	1.19	0.2332
School 1003	-0.11	-0.06	0.07	-1.51	0.1323
School 1006	-0.26	-0.05	0.15	-1.73	0.0852
School 1007	-0.53	-0.53	0.06	-9.62	<.0001
School 1009	-0.23	-0.13	0.07	-3.33	0.001
School 1010	0.02	0.02	0.06	0.34	0.7356
School 1011	-0.37	-0.30	0.06	-6.3	<.0001
School 1012	-0.09	-0.05	0.07	-1.23	0.2196
School 1015	-0.24	-0.15	0.07	-3.7	0.0003
School 1017	-0.49	-0.38	0.06	-8.16	<.0001
School 1020	-0.54	-0.42	0.06	-9.2	<.0001
School 1021	-0.02	-0.01	0.06	-0.27	0.7859
School 1023	-0.26	-0.13	0.07	-3.49	0.0006
School 1024	-0.09	-0.05	0.07	-1.3	0.1939
School 1025	-0.70	-0.36	0.07	-9.43	<.0001
School 1026	0.02	0.01	0.06	0.29	0.7757
School 1027	-0.06	-0.05	0.06	-1.09	0.2749
School 1028	0.04	0.02	0.07	0.54	0.5906
School 1029	-0.21	-0.14	0.06	-3.38	0.0008
School 1032	-0.15	-0.09	0.07	-2.28	0.0236
School 1034	-0.01	0.00	0.06	-0.11	0.9158
School 1035	-0.13	-0.11	0.06	-2.22	0.0274
School 1038	-0.69	-0.45	0.06	-10.76	<.0001
School 1040	-0.27	-0.18	0.06	-4.28	<.0001
School 1041	-0.44	-0.33	0.06	-7.2	<.0001
School 1042	-0.41	-0.29	0.06	-6.72	<.0001
School 1044	-0.01	-0.01	0.07	-0.18	0.8584
School 1047	-0.57	-0.21	0.09	-6.12	<.0001
School 1049	-0.44	-0.26	0.07	-6.61	<.0001
Male	-0.04	-0.05	0.03	-1.51	0.1322
White	-0.06	-0.10	0.04	-1.68	0.0945
African American	-0.01	-0.01	0.04	-0.23	0.817
Master’s degree	-0.01	-0.02	0.02	-0.53	0.5974
Teaching experience	0.00	-0.03	0.00	-1	0.3171
New teacher	0.02	0.03	0.02	0.92	0.3573
School improvement coordinator	-0.01	-0.13	0.00	-4.36	<.0001
In-degree in ELA networks	-0.01	-0.03	0.01	-1.05	0.2943

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.35 Model 5 in effects of teachers' ELA networks on students' previous free/reduced lunch

Model 5	B	Beta	S. E.	t value	p value
Intercept	0.87	0.00	0.06	14.06	<.0001
Grade 2	0.01	0.01	0.03	0.26	0.7987
Grade 3	0.05	0.08	0.03	1.65	0.1003
Grade 4	0.03	0.05	0.03	1.15	0.2521
School 1003	-0.09	-0.05	0.07	-1.28	0.2021
School 1006	-0.26	-0.05	0.15	-1.71	0.088
School 1007	-0.53	-0.53	0.06	-9.58	<.0001
School 1009	-0.24	-0.13	0.07	-3.37	0.0009
School 1010	0.02	0.02	0.06	0.32	0.7497
School 1011	-0.37	-0.30	0.06	-6.26	<.0001
School 1012	-0.08	-0.05	0.07	-1.19	0.2336
School 1015	-0.23	-0.15	0.07	-3.52	0.0005
School 1017	-0.50	-0.39	0.06	-8.32	<.0001
School 1020	-0.55	-0.42	0.06	-9.17	<.0001
School 1021	-0.03	-0.02	0.06	-0.42	0.6765
School 1023	-0.26	-0.13	0.07	-3.48	0.0006
School 1024	-0.09	-0.05	0.07	-1.32	0.1877
School 1025	-0.70	-0.36	0.07	-9.36	<.0001
School 1026	0.01	0.01	0.06	0.24	0.8127
School 1027	-0.07	-0.05	0.06	-1.11	0.2683
School 1028	0.03	0.02	0.07	0.49	0.6246
School 1029	-0.19	-0.12	0.06	-2.97	0.0033
School 1032	-0.15	-0.09	0.07	-2.25	0.0252
School 1034	0.00	0.00	0.06	-0.04	0.968
School 1035	-0.13	-0.11	0.06	-2.19	0.0297
School 1038	-0.68	-0.44	0.06	-10.49	<.0001
School 1040	-0.27	-0.18	0.06	-4.32	<.0001
School 1041	-0.44	-0.33	0.06	-7.18	<.0001
School 1042	-0.41	-0.29	0.06	-6.59	<.0001
School 1044	-0.03	-0.02	0.07	-0.41	0.6834
School 1047	-0.58	-0.21	0.09	-6.23	<.0001
School 1049	-0.44	-0.26	0.07	-6.51	<.0001
Male	-0.05	-0.05	0.03	-1.53	0.1274
White	-0.06	-0.10	0.04	-1.55	0.1232
African American	-0.01	-0.02	0.04	-0.25	0.8015
Master’s degree	-0.01	-0.02	0.02	-0.5	0.6184
Teaching experience	0.00	-0.03	0.00	-0.85	0.3961
New teacher	0.02	0.03	0.02	0.88	0.3818
Teacher consultant	-0.01	-0.12	0.00	-3.98	<.0001
In-degree in ELA networks	-0.01	-0.04	0.01	-1.34	0.1817

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.36 Model 1 in effects of teachers' Math networks on students' previous free/reduced lunch

Model 1	B	Beta	S. E.	t value	p value
Intercept	0.93	0.00	0.06	15.26	<.0001
Grade 2	0.01	0.01	0.03	0.28	0.7798
Grade 3	0.04	0.07	0.03	1.42	0.1562
Grade 4	0.02	0.03	0.03	0.7	0.4834
School 1003	-0.11	-0.06	0.07	-1.46	0.1441
School 1006	-0.27	-0.06	0.15	-1.77	0.0775
School 1007	-0.54	-0.53	0.06	-9.41	<.0001
School 1009	-0.24	-0.13	0.07	-3.35	0.0009
School 1010	0.02	0.01	0.06	0.27	0.7883
School 1011	-0.36	-0.30	0.06	-6.05	<.0001
School 1012	-0.08	-0.05	0.07	-1.12	0.2628
School 1015	-0.24	-0.15	0.07	-3.52	0.0005
School 1017	-0.50	-0.39	0.06	-8.17	<.0001
School 1020	-0.55	-0.43	0.06	-9.09	<.0001
School 1021	-0.03	-0.02	0.06	-0.41	0.6825
School 1023	-0.26	-0.13	0.08	-3.4	0.0008
School 1024	-0.09	-0.05	0.07	-1.3	0.1959
School 1025	-0.71	-0.36	0.08	-9.39	<.0001
School 1026	0.02	0.02	0.06	0.37	0.7124
School 1027	-0.07	-0.06	0.06	-1.14	0.2559
School 1028	0.03	0.02	0.07	0.37	0.7109
School 1029	-0.20	-0.13	0.07	-3.11	0.0021
School 1032	-0.18	-0.10	0.07	-2.57	0.0108
School 1034	0.00	0.00	0.07	-0.06	0.9518
School 1035	-0.12	-0.10	0.06	-1.91	0.057
School 1038	-0.69	-0.45	0.07	-10.43	<.0001
School 1040	-0.29	-0.19	0.06	-4.45	<.0001
School 1041	-0.44	-0.33	0.06	-6.96	<.0001
School 1042	-0.41	-0.29	0.06	-6.43	<.0001
School 1044	-0.03	-0.01	0.08	-0.36	0.7225
School 1047	-0.64	-0.23	0.09	-6.78	<.0001
School 1049	-0.45	-0.27	0.07	-6.65	<.0001
Male	-0.05	-0.05	0.03	-1.52	0.1295
White	-0.07	-0.11	0.04	-1.78	0.076
African American	-0.03	-0.04	0.04	-0.65	0.5177
Master’s degree	-0.01	-0.02	0.02	-0.48	0.6292
Teaching experience	0.00	-0.04	0.00	-1.28	0.2017
New teacher	0.03	0.04	0.02	1.26	0.2083
In-degree in Math networks	-0.01	-0.07	0.01	-2.09	0.0373

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.37 Model 2 in effects of teachers' Math networks on students' previous free/reduced lunch

Model 2	B	Beta	S. E.	t value	p value
Intercept	0.94	0.00	0.06	15.58	<.0001
Grade 2	0.00	0.01	0.03	0.13	0.8962
Grade 3	0.04	0.07	0.03	1.42	0.1569
Grade 4	0.02	0.03	0.03	0.72	0.4737
School 1003	-0.09	-0.05	0.07	-1.3	0.1949
School 1006	-0.28	-0.06	0.15	-1.86	0.0636
School 1007	-0.55	-0.55	0.06	-9.82	<.0001
School 1009	-0.24	-0.14	0.07	-3.49	0.0006
School 1010	0.01	0.01	0.06	0.24	0.8127
School 1011	-0.37	-0.30	0.06	-6.25	<.0001
School 1012	-0.09	-0.05	0.07	-1.28	0.2002
School 1015	-0.25	-0.16	0.07	-3.76	0.0002
School 1017	-0.50	-0.38	0.06	-8.21	<.0001
School 1020	-0.56	-0.43	0.06	-9.4	<.0001
School 1021	-0.03	-0.03	0.06	-0.56	0.576
School 1023	-0.27	-0.14	0.07	-3.57	0.0004
School 1024	-0.11	-0.06	0.07	-1.54	0.1247
School 1025	-0.71	-0.36	0.07	-9.58	<.0001
School 1026	0.01	0.01	0.06	0.23	0.8157
School 1027	-0.08	-0.07	0.06	-1.39	0.1658
School 1028	0.02	0.01	0.07	0.3	0.7666
School 1029	-0.20	-0.13	0.06	-3.12	0.002
School 1032	-0.16	-0.09	0.07	-2.36	0.019
School 1034	-0.02	-0.01	0.06	-0.34	0.7363
School 1035	-0.13	-0.11	0.06	-2.19	0.0293
School 1038	-0.70	-0.46	0.06	-10.78	<.0001
School 1040	-0.29	-0.19	0.06	-4.58	<.0001
School 1041	-0.45	-0.34	0.06	-7.22	<.0001
School 1042	-0.42	-0.30	0.06	-6.73	<.0001
School 1044	-0.03	-0.02	0.07	-0.44	0.6606
School 1047	-0.62	-0.22	0.09	-6.61	<.0001
School 1049	-0.46	-0.27	0.07	-6.87	<.0001
Male	-0.05	-0.05	0.03	-1.59	0.1141
White	-0.05	-0.08	0.04	-1.3	0.1936
African American	0.00	-0.01	0.04	-0.1	0.9205
Master’s degree	-0.01	-0.02	0.02	-0.53	0.5988
Teaching experience	0.00	-0.04	0.00	-1.1	0.2722
New teacher	0.02	0.02	0.02	0.7	0.4869
Formal leader	-0.06	-0.10	0.02	-3.16	0.0018
In-degree in Math networks	-0.01	-0.04	0.01	-1.28	0.1999

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.38 Model 3 in effects of teachers' Math networks on students' previous free/reduced lunch

Model 3	B	Beta	S. E.	t value	p value
Intercept	0.93	0.00	0.06	15.64	<.0001
Grade 2	0.00	0.00	0.03	-0.04	0.9666
Grade 3	0.03	0.06	0.03	1.25	0.2113
Grade 4	0.02	0.03	0.03	0.72	0.4736
School 1003	-0.07	-0.04	0.07	-0.96	0.3366
School 1006	-0.28	-0.06	0.15	-1.91	0.057
School 1007	-0.55	-0.54	0.06	-9.8	<.0001
School 1009	-0.24	-0.13	0.07	-3.47	0.0006
School 1010	0.03	0.02	0.06	0.46	0.6468
School 1011	-0.37	-0.30	0.06	-6.26	<.0001
School 1012	-0.09	-0.05	0.07	-1.29	0.1969
School 1015	-0.24	-0.15	0.07	-3.64	0.0003
School 1017	-0.50	-0.39	0.06	-8.34	<.0001
School 1020	-0.55	-0.43	0.06	-9.3	<.0001
School 1021	-0.03	-0.03	0.06	-0.54	0.5879
School 1023	-0.26	-0.13	0.07	-3.53	0.0005
School 1024	-0.10	-0.06	0.07	-1.41	0.1612
School 1025	-0.70	-0.36	0.07	-9.42	<.0001
School 1026	0.02	0.01	0.06	0.26	0.7939
School 1027	-0.06	-0.05	0.06	-0.93	0.3525
School 1028	0.03	0.02	0.07	0.5	0.6168
School 1029	-0.20	-0.13	0.06	-3.08	0.0023
School 1032	-0.17	-0.10	0.07	-2.46	0.0144
School 1034	-0.01	-0.01	0.06	-0.13	0.8928
School 1035	-0.13	-0.11	0.06	-2.12	0.0349
School 1038	-0.69	-0.45	0.06	-10.71	<.0001
School 1040	-0.28	-0.19	0.06	-4.49	<.0001
School 1041	-0.44	-0.33	0.06	-7.14	<.0001
School 1042	-0.40	-0.28	0.06	-6.44	<.0001
School 1044	-0.03	-0.02	0.07	-0.4	0.6887
School 1047	-0.59	-0.21	0.09	-6.31	<.0001
School 1049	-0.44	-0.26	0.07	-6.62	<.0001
Male	-0.04	-0.04	0.03	-1.3	0.1932
White	-0.06	-0.09	0.04	-1.5	0.1353
African American	-0.01	-0.02	0.04	-0.33	0.7418
Master’s degree	-0.01	-0.01	0.02	-0.44	0.6587
Teaching experience	0.00	-0.03	0.00	-0.95	0.3439
New teacher	0.02	0.03	0.02	0.9	0.3664
The total number of leadership roles	-0.02	-0.12	0.01	-3.73	0.0002
In-degree in Math networks	-0.01	-0.04	0.01	-1.18	0.24

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.39 Model 4 in effects of teachers' Math networks on students' previous free/reduced lunch

Model 4	B	Beta	S. E.	t value	p value
Intercept	0.86	0.00	0.06	14.09	<.0001
Grade 2	0.01	0.02	0.03	0.5	0.618
Grade 3	0.05	0.08	0.03	1.79	0.0753
Grade 4	0.03	0.05	0.03	1.1	0.2735
School 1003	-0.10	-0.06	0.07	-1.48	0.1398
School 1006	-0.28	-0.06	0.15	-1.86	0.0634
School 1007	-0.53	-0.52	0.06	-9.58	<.0001
School 1009	-0.23	-0.13	0.07	-3.33	0.001
School 1010	0.02	0.02	0.06	0.4	0.6891
School 1011	-0.36	-0.30	0.06	-6.18	<.0001
School 1012	-0.08	-0.05	0.07	-1.21	0.2255
School 1015	-0.24	-0.15	0.07	-3.69	0.0003
School 1017	-0.49	-0.38	0.06	-8.16	<.0001
School 1020	-0.55	-0.42	0.06	-9.26	<.0001
School 1021	-0.01	-0.01	0.06	-0.23	0.8158
School 1023	-0.25	-0.13	0.07	-3.47	0.0006
School 1024	-0.09	-0.05	0.07	-1.3	0.1963
School 1025	-0.70	-0.36	0.07	-9.5	<.0001
School 1026	0.02	0.02	0.06	0.39	0.6999
School 1027	-0.05	-0.04	0.06	-0.89	0.3729
School 1028	0.04	0.02	0.07	0.57	0.5697
School 1029	-0.21	-0.14	0.06	-3.3	0.0011
School 1032	-0.15	-0.09	0.07	-2.27	0.0239
School 1034	-0.01	0.00	0.06	-0.1	0.9169
School 1035	-0.13	-0.11	0.06	-2.17	0.0309
School 1038	-0.68	-0.45	0.06	-10.7	<.0001
School 1040	-0.27	-0.18	0.06	-4.3	<.0001
School 1041	-0.44	-0.32	0.06	-7.11	<.0001
School 1042	-0.41	-0.29	0.06	-6.64	<.0001
School 1044	-0.01	-0.01	0.07	-0.18	0.8594
School 1047	-0.59	-0.22	0.09	-6.45	<.0001
School 1049	-0.45	-0.26	0.07	-6.77	<.0001
Male	-0.04	-0.04	0.03	-1.4	0.1618
White	-0.06	-0.10	0.04	-1.68	0.0932
African American	-0.01	-0.02	0.04	-0.28	0.7831
Master’s degree	-0.01	-0.02	0.02	-0.64	0.5199
Teaching experience	0.00	-0.04	0.00	-1.05	0.2949
New teacher	0.02	0.03	0.02	0.82	0.4128
School improvement coordinator	-0.01	-0.13	0.00	-4.29	<.0001
In-degree in Math networks	-0.01	-0.05	0.01	-1.74	0.0827

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.40 Model 5 in effects of teachers' Math networks on students' previous free/reduced lunch

Model 5	B	Beta	S. E.	t value	p value
Intercept	0.87	0.00	0.06	14.17	<.0001
Grade 2	0.01	0.01	0.03	0.24	0.8088
Grade 3	0.04	0.07	0.03	1.54	0.1252
Grade 4	0.03	0.04	0.03	1.04	0.2993
School 1003	-0.09	-0.05	0.07	-1.24	0.2143
School 1006	-0.28	-0.06	0.15	-1.88	0.0611
School 1007	-0.53	-0.53	0.06	-9.55	<.0001
School 1009	-0.23	-0.13	0.07	-3.35	0.0009
School 1010	0.02	0.02	0.06	0.38	0.7024
School 1011	-0.36	-0.29	0.06	-6.13	<.0001
School 1012	-0.08	-0.05	0.07	-1.18	0.2398
School 1015	-0.23	-0.14	0.07	-3.5	0.0005
School 1017	-0.50	-0.38	0.06	-8.32	<.0001
School 1020	-0.55	-0.42	0.06	-9.22	<.0001
School 1021	-0.02	-0.02	0.06	-0.39	0.6939
School 1023	-0.25	-0.13	0.07	-3.44	0.0007
School 1024	-0.09	-0.05	0.07	-1.3	0.1954
School 1025	-0.70	-0.36	0.07	-9.45	<.0001
School 1026	0.02	0.02	0.06	0.34	0.737
School 1027	-0.05	-0.04	0.06	-0.9	0.3683
School 1028	0.04	0.02	0.07	0.52	0.6002
School 1029	-0.18	-0.12	0.06	-2.91	0.0039
School 1032	-0.15	-0.09	0.07	-2.25	0.025
School 1034	0.00	0.00	0.06	-0.04	0.9672
School 1035	-0.13	-0.11	0.06	-2.14	0.0335
School 1038	-0.67	-0.44	0.06	-10.44	<.0001
School 1040	-0.27	-0.18	0.06	-4.34	<.0001
School 1041	-0.44	-0.33	0.06	-7.08	<.0001
School 1042	-0.40	-0.29	0.06	-6.52	<.0001
School 1044	-0.03	-0.02	0.07	-0.41	0.6803
School 1047	-0.61	-0.22	0.09	-6.63	<.0001
School 1049	-0.45	-0.26	0.07	-6.7	<.0001
Male	-0.04	-0.04	0.03	-1.39	0.1664
White	-0.06	-0.10	0.04	-1.55	0.1217
African American	-0.01	-0.02	0.04	-0.29	0.7698
Master’s degree	-0.01	-0.02	0.02	-0.62	0.5353
Teaching experience	0.00	-0.03	0.00	-0.91	0.3625
New teacher	0.02	0.03	0.02	0.82	0.4144
Teacher consultant	-0.01	-0.12	0.00	-3.88	0.0001
In-degree in Math networks	-0.01	-0.06	0.01	-1.87	0.062

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.41 Model 1 in effects of teachers' combined networks on students' previous free/reduced lunch

Model 1	B	Beta	S. E.	t value	p value
Intercept	0.94	0.00	0.06	15.26	<.0001
Grade 2	0.01	0.01	0.03	0.22	0.8278
Grade 3	0.04	0.07	0.03	1.45	0.148
Grade 4	0.02	0.03	0.03	0.78	0.4332
School 1003	-0.10	-0.06	0.07	-1.46	0.1454
School 1006	-0.25	-0.05	0.15	-1.61	0.1095
School 1007	-0.54	-0.53	0.06	-9.45	<.0001
School 1009	-0.24	-0.13	0.07	-3.39	0.0008
School 1010	0.02	0.01	0.06	0.26	0.7912
School 1011	-0.37	-0.30	0.06	-6.12	<.0001
School 1012	-0.08	-0.05	0.07	-1.12	0.2618
School 1015	-0.24	-0.15	0.07	-3.54	0.0005
School 1017	-0.50	-0.39	0.06	-8.18	<.0001
School 1020	-0.55	-0.43	0.06	-9.07	<.0001
School 1021	-0.02	-0.02	0.06	-0.38	0.7032
School 1023	-0.26	-0.13	0.08	-3.44	0.0007
School 1024	-0.09	-0.06	0.07	-1.34	0.1826
School 1025	-0.70	-0.36	0.08	-9.19	<.0001
School 1026	0.02	0.02	0.06	0.38	0.7027
School 1027	-0.07	-0.06	0.06	-1.13	0.2584
School 1028	0.03	0.02	0.07	0.38	0.7021
School 1029	-0.20	-0.13	0.07	-3.09	0.0022
School 1032	-0.18	-0.11	0.07	-2.59	0.01
School 1034	0.00	0.00	0.07	-0.02	0.9845
School 1035	-0.11	-0.10	0.06	-1.88	0.061
School 1038	-0.68	-0.45	0.07	-10.35	<.0001
School 1040	-0.29	-0.19	0.06	-4.47	<.0001
School 1041	-0.44	-0.33	0.06	-7.02	<.0001
School 1042	-0.41	-0.29	0.06	-6.42	<.0001
School 1044	-0.02	-0.01	0.08	-0.33	0.7401
School 1047	-0.61	-0.22	0.09	-6.45	<.0001
School 1049	-0.44	-0.26	0.07	-6.49	<.0001
Male	-0.05	-0.05	0.03	-1.61	0.1085
White	-0.07	-0.12	0.04	-1.82	0.0698
African American	-0.03	-0.04	0.04	-0.69	0.489
Master's degree	-0.01	-0.01	0.02	-0.44	0.6629
Teaching experience	0.00	-0.04	0.00	-1.2	0.2306
New teacher	0.03	0.04	0.02	1.19	0.2369
In-degree in Combined networks	-0.01	-0.07	0.01	-2.06	0.0403

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.42 Model 2 in effects of teachers' combined networks on students' previous free/reduced lunch

Model 2	B	Beta	S. E.	t value	p value
Intercept	0.94	0.00	0.06	15.57	<.0001
Grade 2	0.00	0.00	0.03	0.09	0.9272
Grade 3	0.04	0.07	0.03	1.44	0.1516
Grade 4	0.02	0.03	0.03	0.77	0.4416
School 1003	-0.09	-0.05	0.07	-1.3	0.1961
School 1006	-0.26	-0.06	0.15	-1.75	0.0804
School 1007	-0.55	-0.55	0.06	-9.85	<.0001
School 1009	-0.25	-0.14	0.07	-3.52	0.0005
School 1010	0.01	0.01	0.06	0.23	0.8149
School 1011	-0.37	-0.31	0.06	-6.3	<.0001
School 1012	-0.09	-0.05	0.07	-1.29	0.1995
School 1015	-0.25	-0.16	0.07	-3.77	0.0002
School 1017	-0.50	-0.38	0.06	-8.22	<.0001
School 1020	-0.56	-0.43	0.06	-9.39	<.0001
School 1021	-0.03	-0.03	0.06	-0.54	0.5878
School 1023	-0.27	-0.14	0.07	-3.59	0.0004
School 1024	-0.11	-0.06	0.07	-1.57	0.1187
School 1025	-0.71	-0.36	0.07	-9.42	<.0001
School 1026	0.01	0.01	0.06	0.24	0.8101
School 1027	-0.08	-0.07	0.06	-1.39	0.1666
School 1028	0.02	0.01	0.07	0.3	0.7612
School 1029	-0.20	-0.13	0.06	-3.11	0.0021
School 1032	-0.16	-0.10	0.07	-2.38	0.0182
School 1034	-0.02	-0.01	0.06	-0.31	0.7553
School 1035	-0.13	-0.11	0.06	-2.17	0.0307
School 1038	-0.70	-0.46	0.07	-10.71	<.0001
School 1040	-0.29	-0.19	0.06	-4.6	<.0001
School 1041	-0.45	-0.34	0.06	-7.27	<.0001
School 1042	-0.42	-0.30	0.06	-6.72	<.0001
School 1044	-0.03	-0.02	0.07	-0.43	0.671
School 1047	-0.60	-0.22	0.09	-6.4	<.0001
School 1049	-0.46	-0.27	0.07	-6.76	<.0001
Male	-0.05	-0.05	0.03	-1.64	0.1019
White	-0.05	-0.08	0.04	-1.32	0.1863
African American	-0.01	-0.01	0.04	-0.13	0.8995
Master's degree	-0.01	-0.02	0.02	-0.5	0.6196
Teaching experience	0.00	-0.04	0.00	-1.05	0.2942
New teacher	0.01	0.02	0.02	0.65	0.5157
Formal leader	-0.06	-0.10	0.02	-3.17	0.0017
In-degree in Combined networks	-0.01	-0.04	0.01	-1.26	0.2098

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.43 Model 3 in effects of teachers' combined networks on students' previous free/reduced lunch

Model 3	B	Beta	S. E.	t value	p value
Intercept	0.94	0.00	0.06	15.62	<.0001
Grade 2	0.00	0.00	0.03	-0.08	0.9373
Grade 3	0.03	0.06	0.03	1.27	0.2055
Grade 4	0.02	0.03	0.03	0.77	0.4443
School 1003	-0.07	-0.04	0.07	-0.96	0.3385
School 1006	-0.27	-0.06	0.15	-1.81	0.0714
School 1007	-0.55	-0.54	0.06	-9.82	<.0001
School 1009	-0.24	-0.13	0.07	-3.49	0.0006
School 1010	0.03	0.02	0.06	0.46	0.6477
School 1011	-0.37	-0.30	0.06	-6.31	<.0001
School 1012	-0.09	-0.05	0.07	-1.3	0.1963
School 1015	-0.24	-0.15	0.07	-3.66	0.0003
School 1017	-0.50	-0.39	0.06	-8.35	<.0001
School 1020	-0.55	-0.43	0.06	-9.29	<.0001
School 1021	-0.03	-0.03	0.06	-0.53	0.5997
School 1023	-0.26	-0.13	0.07	-3.55	0.0005
School 1024	-0.10	-0.06	0.07	-1.43	0.1544
School 1025	-0.69	-0.35	0.07	-9.28	<.0001
School 1026	0.02	0.01	0.06	0.27	0.7878
School 1027	-0.06	-0.05	0.06	-0.93	0.3551
School 1028	0.03	0.02	0.07	0.51	0.6117
School 1029	-0.20	-0.13	0.06	-3.07	0.0024
School 1032	-0.17	-0.10	0.07	-2.48	0.0138
School 1034	-0.01	0.00	0.06	-0.11	0.9116
School 1035	-0.12	-0.11	0.06	-2.1	0.0365
School 1038	-0.69	-0.45	0.06	-10.65	<.0001
School 1040	-0.29	-0.19	0.06	-4.5	<.0001
School 1041	-0.44	-0.33	0.06	-7.18	<.0001
School 1042	-0.40	-0.28	0.06	-6.43	<.0001
School 1044	-0.03	-0.01	0.07	-0.39	0.6989
School 1047	-0.57	-0.21	0.09	-6.14	<.0001
School 1049	-0.44	-0.26	0.07	-6.53	<.0001
Male	-0.04	-0.04	0.03	-1.35	0.1767
White	-0.06	-0.09	0.04	-1.52	0.1298
African American	-0.01	-0.02	0.04	-0.36	0.7226
Master's degree	-0.01	-0.01	0.02	-0.42	0.6782
Teaching experience	0.00	-0.03	0.00	-0.9	0.3676
New teacher	0.02	0.03	0.02	0.86	0.3918
The total number of leadership roles	-0.02	-0.12	0.01	-3.74	0.0002
In-degree in Combined networks	-0.01	-0.04	0.01	-1.17	0.2446

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.44 Model 4 in effects of teachers' combined networks on students' previous free/reduced lunch

Model 4	B	Beta	S. E.	t value	p value
Intercept	0.87	0.00	0.06	14.08	<.0001
Grade 2	0.01	0.02	0.03	0.45	0.656
Grade 3	0.05	0.09	0.03	1.81	0.0713
Grade 4	0.03	0.05	0.03	1.17	0.2437
School 1003	-0.10	-0.06	0.07	-1.48	0.1408
School 1006	-0.26	-0.05	0.15	-1.72	0.0862
School 1007	-0.53	-0.53	0.06	-9.61	<.0001
School 1009	-0.23	-0.13	0.07	-3.36	0.0009
School 1010	0.02	0.02	0.06	0.4	0.6904
School 1011	-0.36	-0.30	0.06	-6.24	<.0001
School 1012	-0.08	-0.05	0.07	-1.22	0.2248
School 1015	-0.24	-0.15	0.07	-3.72	0.0002
School 1017	-0.49	-0.38	0.06	-8.17	<.0001
School 1020	-0.54	-0.42	0.06	-9.24	<.0001
School 1021	-0.01	-0.01	0.06	-0.21	0.8362
School 1023	-0.26	-0.13	0.07	-3.5	0.0005
School 1024	-0.09	-0.05	0.07	-1.33	0.1847
School 1025	-0.69	-0.35	0.07	-9.32	<.0001
School 1026	0.02	0.02	0.06	0.4	0.6901
School 1027	-0.05	-0.04	0.06	-0.88	0.3777
School 1028	0.04	0.02	0.07	0.58	0.5624
School 1029	-0.21	-0.14	0.06	-3.29	0.0011
School 1032	-0.15	-0.09	0.07	-2.29	0.0227
School 1034	0.00	0.00	0.06	-0.07	0.9445
School 1035	-0.13	-0.11	0.06	-2.14	0.033
School 1038	-0.68	-0.45	0.06	-10.62	<.0001
School 1040	-0.27	-0.18	0.06	-4.31	<.0001
School 1041	-0.44	-0.33	0.06	-7.16	<.0001
School 1042	-0.41	-0.29	0.06	-6.63	<.0001
School 1044	-0.01	-0.01	0.07	-0.16	0.876
School 1047	-0.57	-0.21	0.09	-6.18	<.0001
School 1049	-0.44	-0.26	0.07	-6.63	<.0001
Male	-0.04	-0.05	0.03	-1.48	0.1405
White	-0.06	-0.11	0.04	-1.72	0.087
African American	-0.01	-0.02	0.04	-0.31	0.7538
Master's degree	-0.01	-0.02	0.02	-0.61	0.5443
Teaching experience	0.00	-0.03	0.00	-0.98	0.3265
New teacher	0.02	0.03	0.02	0.75	0.4526
School improvement coordinator	-0.01	-0.13	0.00	-4.3	<.0001
In-degree in Combined networks	-0.01	-0.06	0.01	-1.74	0.083

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.45 Model 5 in effects of teachers' combined networks on students' previous free/reduced lunch

Model 5	B	Beta	S. E.	t value	p value
Intercept	0.88	0.00	0.06	14.17	<.0001
Grade 2	0.00	0.01	0.03	0.18	0.8547
Grade 3	0.04	0.07	0.03	1.56	0.1189
Grade 4	0.03	0.05	0.03	1.12	0.2652
School 1003	-0.09	-0.05	0.07	-1.24	0.2162
School 1006	-0.26	-0.05	0.15	-1.73	0.0853
School 1007	-0.53	-0.53	0.06	-9.58	<.0001
School 1009	-0.24	-0.13	0.07	-3.39	0.0008
School 1010	0.02	0.02	0.06	0.38	0.703
School 1011	-0.36	-0.30	0.06	-6.19	<.0001
School 1012	-0.08	-0.05	0.07	-1.18	0.2391
School 1015	-0.23	-0.15	0.07	-3.52	0.0005
School 1017	-0.50	-0.38	0.06	-8.33	<.0001
School 1020	-0.55	-0.42	0.06	-9.21	<.0001
School 1021	-0.02	-0.02	0.06	-0.36	0.7157
School 1023	-0.26	-0.13	0.07	-3.48	0.0006
School 1024	-0.09	-0.05	0.07	-1.34	0.1827
School 1025	-0.69	-0.35	0.07	-9.26	<.0001
School 1026	0.02	0.02	0.06	0.35	0.7252
School 1027	-0.05	-0.04	0.06	-0.89	0.3748
School 1028	0.04	0.02	0.07	0.54	0.5918
School 1029	-0.18	-0.12	0.06	-2.89	0.0042
School 1032	-0.15	-0.09	0.07	-2.28	0.0237
School 1034	0.00	0.00	0.06	0	0.9974
School 1035	-0.12	-0.11	0.06	-2.11	0.0359
School 1038	-0.67	-0.44	0.06	-10.36	<.0001
School 1040	-0.28	-0.18	0.06	-4.36	<.0001
School 1041	-0.44	-0.33	0.06	-7.14	<.0001
School 1042	-0.40	-0.29	0.06	-6.5	<.0001
School 1044	-0.03	-0.01	0.07	-0.39	0.6969
School 1047	-0.59	-0.21	0.09	-6.33	<.0001
School 1049	-0.44	-0.26	0.07	-6.55	<.0001
Male	-0.04	-0.05	0.03	-1.47	0.1429
White	-0.06	-0.10	0.04	-1.59	0.1136
African American	-0.01	-0.02	0.04	-0.33	0.7383
Master's degree	-0.01	-0.02	0.02	-0.58	0.5612
Teaching experience	0.00	-0.03	0.00	-0.84	0.4021
New teacher	0.02	0.03	0.02	0.74	0.46
Teacher consultant	-0.01	-0.12	0.00	-3.9	0.0001
In-degree in Combined networks	-0.01	-0.06	0.01	-1.89	0.0601

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.46 Model 1 in effects of teachers' attributes on students' previous ELA achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	813.63	0.00	6.45	126.24	<.0001
Grade 2	-0.82	-0.02	2.83	-0.29	0.7716
Grade 3	-0.15	0.00	2.85	-0.05	0.9574
Grade 4	4.27	0.10	3.03	1.41	0.1598
School 1003	-2.08	-0.02	7.18	-0.29	0.7721
School 1006	-0.43	0.00	15.22	-0.03	0.9773
School 1007	24.83	0.40	5.77	4.3	<.0001
School 1009	8.51	0.08	7.19	1.18	0.2375
School 1010	-4.95	-0.06	6.21	-0.8	0.426
School 1011	2.58	0.03	6.05	0.43	0.6696
School 1012	7.26	0.07	7.20	1.01	0.3144
School 1015	5.39	0.06	6.79	0.79	0.4285
School 1017	15.11	0.19	6.23	2.42	0.016
School 1020	5.72	0.07	6.14	0.93	0.352
School 1021	3.11	0.04	6.21	0.5	0.6163
School 1023	18.01	0.15	7.67	2.35	0.0197
School 1024	1.49	0.01	7.06	0.21	0.8335
School 1025	10.51	0.09	7.56	1.39	0.166
School 1026	-5.84	-0.07	6.18	-0.94	0.346
School 1027	3.00	0.04	6.04	0.5	0.62
School 1028	-7.34	-0.07	6.93	-1.06	0.2905
School 1029	0.09	0.00	6.49	0.01	0.9889
School 1032	11.12	0.11	6.97	1.6	0.1116
School 1034	-1.79	-0.02	6.62	-0.27	0.7867
School 1035	-1.13	-0.02	6.06	-0.19	0.8525
School 1038	16.62	0.18	6.62	2.51	0.0126
School 1040	15.84	0.17	6.54	2.42	0.0161
School 1041	6.47	0.08	6.44	1	0.3164
School 1042	17.55	0.20	6.46	2.72	0.007
School 1044	-2.34	-0.02	7.51	-0.31	0.7556
School 1047	10.35	0.06	9.42	1.1	0.2727
School 1049	12.97	0.13	6.84	1.9	0.059
Male	-0.30	-0.01	3.02	-0.1	0.9215
White	0.60	0.02	3.75	0.16	0.8734
African American	-2.71	-0.07	3.99	-0.68	0.497
Master's degree	1.06	0.03	2.03	0.52	0.6012
Teaching experience	0.08	0.04	0.10	0.77	0.4432
ELA professional development	-0.55	-0.03	1.09	-0.5	0.6152
New teacher	-6.67	-0.17	2.18	-3.05	0.0025

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.47 Model 2 in effects of teachers' attributes on students' previous ELA achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	813.30	0.00	6.23	130.62	<.0001
Grade 2	0.05	0.00	2.74	0.02	0.9866
Grade 3	0.24	0.01	2.75	0.09	0.9318
Grade 4	4.56	0.11	2.93	1.56	0.1207
School 1003	-3.98	-0.04	6.95	-0.57	0.5673
School 1006	0.45	0.00	14.71	0.03	0.9756
School 1007	25.91	0.41	5.58	4.64	<.0001
School 1009	9.05	0.08	6.94	1.3	0.1937
School 1010	-5.09	-0.07	6.00	-0.85	0.3971
School 1011	2.66	0.04	5.84	0.46	0.6494
School 1012	8.30	0.08	6.96	1.19	0.234
School 1015	7.04	0.07	6.57	1.07	0.2856
School 1017	13.35	0.17	6.04	2.21	0.0279
School 1020	6.94	0.09	5.93	1.17	0.2435
School 1021	3.40	0.04	6.00	0.57	0.5707
School 1023	18.52	0.16	7.41	2.5	0.0131
School 1024	3.59	0.03	6.83	0.52	0.6003
School 1025	10.09	0.08	7.31	1.38	0.1686
School 1026	-5.73	-0.07	5.97	-0.96	0.3382
School 1027	3.84	0.05	5.84	0.66	0.5118
School 1028	-7.07	-0.07	6.70	-1.06	0.2923
School 1029	-0.83	-0.01	6.28	-0.13	0.895
School 1032	8.13	0.08	6.76	1.2	0.2306
School 1034	0.06	0.00	6.41	0.01	0.9923
School 1035	0.63	0.01	5.87	0.11	0.9148
School 1038	17.44	0.19	6.40	2.73	0.0068
School 1040	15.98	0.17	6.32	2.53	0.012
School 1041	6.75	0.08	6.23	1.08	0.2796
School 1042	17.98	0.20	6.24	2.88	0.0043
School 1044	-2.08	-0.02	7.26	-0.29	0.7748
School 1047	7.39	0.04	9.12	0.81	0.4187
School 1049	13.72	0.13	6.61	2.08	0.0389
Male	-0.19	0.00	2.92	-0.06	0.949
White	-1.92	-0.05	3.67	-0.52	0.6009
African American	-5.54	-0.14	3.91	-1.42	0.1576
Master's degree	1.27	0.03	1.96	0.65	0.5176
Teaching experience	0.05	0.03	0.10	0.5	0.6192
ELA professional development	-1.11	-0.05	1.06	-1.04	0.2997
New teacher	-4.61	-0.12	2.16	-2.13	0.0339
Formal leader	8.65	0.23	1.95	4.44	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.48 Model 3 in effects of teachers' attributes on students' previous ELA achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	813.65	0.00	6.27	129.72	<.0001
Grade 2	0.35	0.01	2.77	0.13	0.9003
Grade 3	0.68	0.02	2.78	0.25	0.8066
Grade 4	4.58	0.11	2.95	1.55	0.1214
School 1003	-5.96	-0.05	7.05	-0.85	0.3987
School 1006	0.76	0.00	14.82	0.05	0.9593
School 1007	24.84	0.40	5.62	4.42	<.0001
School 1009	8.56	0.08	6.99	1.22	0.2221
School 1010	-6.50	-0.09	6.06	-1.07	0.2841
School 1011	2.39	0.03	5.88	0.41	0.6853
School 1012	8.07	0.08	7.01	1.15	0.2507
School 1015	5.65	0.06	6.61	0.85	0.3937
School 1017	14.17	0.18	6.07	2.33	0.0204
School 1020	5.56	0.07	5.97	0.93	0.353
School 1021	3.16	0.04	6.04	0.52	0.6008
School 1023	17.87	0.15	7.47	2.39	0.0174
School 1024	2.06	0.02	6.87	0.3	0.7646
School 1025	8.50	0.07	7.38	1.15	0.2502
School 1026	-5.98	-0.08	6.02	-0.99	0.3214
School 1027	0.66	0.01	5.91	0.11	0.9116
School 1028	-8.54	-0.08	6.75	-1.26	0.2071
School 1029	-1.05	-0.01	6.32	-0.17	0.8688
School 1032	9.38	0.09	6.79	1.38	0.1687
School 1034	-1.73	-0.02	6.44	-0.27	0.7889
School 1035	-0.35	0.00	5.90	-0.06	0.9524
School 1038	16.05	0.17	6.44	2.49	0.0134
School 1040	15.10	0.16	6.37	2.37	0.0184
School 1041	5.89	0.07	6.27	0.94	0.3488
School 1042	15.84	0.18	6.30	2.52	0.0125
School 1044	-2.47	-0.02	7.31	-0.34	0.7358
School 1047	5.33	0.03	9.25	0.58	0.565
School 1049	11.52	0.11	6.67	1.73	0.0852
Male	-1.10	-0.02	2.95	-0.37	0.7089
White	-0.64	-0.02	3.67	-0.17	0.8626
African American	-3.93	-0.10	3.89	-1.01	0.3137
Master's degree	1.07	0.03	1.97	0.54	0.5899
Teaching experience	0.04	0.02	0.10	0.39	0.6951
ELA professional development	-0.99	-0.05	1.07	-0.93	0.3545
New teacher	-5.52	-0.14	2.15	-2.57	0.0107
The total number of leadership roles	2.24	0.21	0.57	3.95	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.49 Model 4 in effects of teachers' attributes on students' previous ELA achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	814.22	0.00	6.44	126.45	<.0001
Grade 2	-0.66	-0.02	2.83	-0.23	0.8157
Grade 3	0.02	0.00	2.84	0.01	0.9939
Grade 4	4.10	0.10	3.02	1.36	0.1762
School 1003	-3.39	-0.03	7.21	-0.47	0.6387
School 1006	0.70	0.00	15.20	0.05	0.9634
School 1007	24.62	0.39	5.76	4.28	<.0001
School 1009	8.56	0.08	7.17	1.19	0.2334
School 1010	-5.61	-0.07	6.21	-0.9	0.367
School 1011	2.76	0.04	6.03	0.46	0.648
School 1012	7.71	0.07	7.18	1.07	0.2839
School 1015	5.68	0.06	6.78	0.84	0.4031
School 1017	15.34	0.19	6.22	2.47	0.0143
School 1020	5.66	0.07	6.12	0.92	0.356
School 1021	3.26	0.04	6.19	0.53	0.5991
School 1023	18.02	0.15	7.65	2.36	0.0193
School 1024	1.71	0.02	7.04	0.24	0.8086
School 1025	10.43	0.09	7.54	1.38	0.1681
School 1026	-5.76	-0.07	6.17	-0.93	0.3514
School 1027	2.60	0.04	6.03	0.43	0.6669
School 1028	-8.70	-0.08	6.97	-1.25	0.2131
School 1029	0.09	0.00	6.47	0.01	0.9884
School 1032	10.89	0.11	6.95	1.57	0.1183
School 1034	-1.71	-0.02	6.60	-0.26	0.7959
School 1035	-1.34	-0.02	6.05	-0.22	0.8244
School 1038	16.55	0.18	6.60	2.51	0.0128
School 1040	15.90	0.17	6.52	2.44	0.0154
School 1041	5.89	0.07	6.44	0.92	0.3608
School 1042	17.34	0.20	6.44	2.69	0.0076
School 1044	-2.19	-0.02	7.49	-0.29	0.77
School 1047	10.75	0.06	9.40	1.14	0.2537
School 1049	12.70	0.12	6.82	1.86	0.0637
Male	-0.95	-0.02	3.04	-0.31	0.7555
White	0.21	0.01	3.75	0.06	0.9551
African American	-3.27	-0.08	3.99	-0.82	0.4141
Master's degree	0.75	0.02	2.03	0.37	0.7121
Teaching experience	0.07	0.04	0.10	0.71	0.4809
ELA professional development	-0.59	-0.03	1.09	-0.54	0.5883
New teacher	-6.80	-0.17	2.18	-3.12	0.002
ELA coordinator	1.88	0.08	1.21	1.55	0.1214

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.50 Model 5 in effects of teachers' attributes on students' previous ELA achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	818.82	0.00	6.55	124.95	<.0001
Grade 2	-0.64	-0.02	2.79	-0.23	0.8172
Grade 3	-0.27	-0.01	2.80	-0.1	0.9237
Grade 4	3.71	0.09	2.99	1.24	0.215
School 1003	-3.53	-0.03	7.08	-0.5	0.6184
School 1006	0.16	0.00	14.98	0.01	0.9914
School 1007	24.00	0.38	5.68	4.22	<.0001
School 1009	7.94	0.07	7.07	1.12	0.2624
School 1010	-5.54	-0.07	6.11	-0.91	0.3659
School 1011	2.00	0.03	5.95	0.34	0.7364
School 1012	7.40	0.07	7.08	1.05	0.2969
School 1015	4.81	0.05	6.69	0.72	0.4724
School 1017	14.56	0.18	6.13	2.37	0.0183
School 1020	5.19	0.07	6.04	0.86	0.3912
School 1021	2.75	0.03	6.11	0.45	0.6524
School 1023	17.57	0.15	7.55	2.33	0.0208
School 1024	1.33	0.01	6.94	0.19	0.8486
School 1025	9.35	0.08	7.45	1.25	0.2108
School 1026	-5.89	-0.07	6.08	-0.97	0.3339
School 1027	1.50	0.02	5.96	0.25	0.8021
School 1028	-8.24	-0.08	6.83	-1.21	0.2282
School 1029	-1.43	-0.02	6.40	-0.22	0.8235
School 1032	8.90	0.09	6.89	1.29	0.1975
School 1034	-2.03	-0.02	6.51	-0.31	0.7553
School 1035	-0.25	0.00	5.97	-0.04	0.9663
School 1038	15.14	0.16	6.53	2.32	0.0212
School 1040	14.57	0.16	6.45	2.26	0.0246
School 1041	5.89	0.07	6.34	0.93	0.3536
School 1042	17.49	0.20	6.35	2.76	0.0063
School 1044	-2.14	-0.02	7.39	-0.29	0.7722
School 1047	8.07	0.05	9.29	0.87	0.386
School 1049	12.19	0.12	6.73	1.81	0.0712
Male	-0.77	-0.01	2.98	-0.26	0.7963
White	-0.23	-0.01	3.70	-0.06	0.9499
African American	-3.91	-0.10	3.94	-0.99	0.3229
Master's degree	1.30	0.03	2.00	0.65	0.5155
Teaching experience	0.04	0.02	0.10	0.41	0.6815
ELA professional development	-0.76	-0.04	1.08	-0.7	0.484
New teacher	-5.82	-0.15	2.17	-2.69	0.0076
Teacher consultant	0.92	0.16	0.30	3.13	0.002

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.51 Model 1 in effects of teachers' attributes on students' previous Math achievement

Model 1	B	Beta	S. E.	t value	p value
Intercept	307.90	0.00	6.86	44.9	<.0001
Grade 2	18.45	0.45	3.13	5.9	<.0001
Grade 3	9.28	0.22	3.13	2.97	0.0033
Grade 4	13.86	0.28	3.35	4.14	<.0001
School 1003	0.65	0.00	7.93	0.08	0.935
School 1006	19.26	0.06	16.82	1.15	0.253
School 1007	28.87	0.40	6.25	4.62	<.0001
School 1009	16.19	0.12	7.86	2.06	0.0404
School 1010	-2.57	-0.03	6.83	-0.38	0.7072
School 1011	7.85	0.09	6.61	1.19	0.2364
School 1012	8.95	0.07	7.93	1.13	0.2599
School 1015	14.60	0.13	7.49	1.95	0.0523
School 1017	24.09	0.26	6.77	3.56	0.0004
School 1020	6.17	0.07	6.71	0.92	0.3586
School 1021	6.80	0.07	6.86	0.99	0.3221
School 1023	13.67	0.10	8.36	1.63	0.1034
School 1024	1.74	0.01	7.76	0.22	0.8225
School 1025	19.87	0.13	9.13	2.18	0.0304
School 1026	-1.14	-0.01	6.75	-0.17	0.8657
School 1027	4.42	0.05	6.67	0.66	0.5075
School 1028	-3.93	-0.03	7.61	-0.52	0.6059
School 1029	1.48	0.01	7.17	0.21	0.8366
School 1032	16.76	0.14	7.61	2.2	0.0286
School 1034	-2.31	-0.02	7.24	-0.32	0.7503
School 1035	2.78	0.03	6.70	0.42	0.6784
School 1038	26.18	0.24	7.25	3.61	0.0004
School 1040	23.62	0.21	7.16	3.3	0.0011
School 1041	11.84	0.12	7.08	1.67	0.0954
School 1042	21.39	0.21	6.93	3.09	0.0022
School 1044	-1.77	-0.01	8.28	-0.21	0.8306
School 1047	21.92	0.11	10.42	2.1	0.0363
School 1049	18.36	0.15	7.53	2.44	0.0154
Male	-1.22	-0.02	3.33	-0.37	0.7152
White	-0.05	0.00	4.16	-0.01	0.9901
African American	-3.59	-0.08	4.41	-0.81	0.4173
Master's degree	-0.34	-0.01	2.24	-0.15	0.8783
Teaching experience	0.08	0.04	0.11	0.74	0.4609
Math professional development	1.20	0.05	1.34	0.89	0.373
New teacher	-7.51	-0.16	2.40	-3.13	0.0019

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.52 Model 2 in effects of teachers' attributes on students' previous Math achievement

Model 2	B	Beta	S. E.	t value	p value
Intercept	307.29	0.00	6.64	46.3	<.0001
Grade 2	19.58	0.47	3.04	6.45	<.0001
Grade 3	9.78	0.23	3.03	3.23	0.0014
Grade 4	14.47	0.29	3.24	4.46	<.0001
School 1003	-0.92	-0.01	7.69	-0.12	0.9051
School 1006	20.35	0.06	16.28	1.25	0.2123
School 1007	30.66	0.42	6.06	5.06	<.0001
School 1009	17.41	0.13	7.61	2.29	0.023
School 1010	-2.67	-0.03	6.61	-0.4	0.6871
School 1011	8.59	0.10	6.40	1.34	0.181
School 1012	10.53	0.09	7.68	1.37	0.1714
School 1015	16.62	0.14	7.27	2.29	0.023
School 1017	23.01	0.25	6.55	3.51	0.0005
School 1020	7.86	0.08	6.50	1.21	0.2278
School 1021	7.50	0.08	6.64	1.13	0.2596
School 1023	14.54	0.10	8.10	1.8	0.0737
School 1024	4.43	0.04	7.53	0.59	0.5568
School 1025	20.48	0.13	8.84	2.32	0.0213
School 1026	-0.82	-0.01	6.53	-0.13	0.9003
School 1027	5.95	0.07	6.46	0.92	0.3581
School 1028	-3.29	-0.03	7.37	-0.45	0.6555
School 1029	0.81	0.01	6.94	0.12	0.907
School 1032	14.06	0.11	7.40	1.9	0.0583
School 1034	-0.01	0.00	7.03	0	0.9986
School 1035	5.03	0.06	6.50	0.77	0.4398
School 1038	27.43	0.25	7.02	3.91	0.0001
School 1040	24.23	0.22	6.93	3.5	0.0005
School 1041	12.68	0.13	6.85	1.85	0.0653
School 1042	22.45	0.22	6.71	3.35	0.0009
School 1044	-1.33	-0.01	8.02	-0.17	0.8684
School 1047	18.39	0.09	10.11	1.82	0.0702
School 1049	19.49	0.16	7.29	2.67	0.008
Male	-1.05	-0.02	3.23	-0.33	0.745
White	-2.91	-0.07	4.08	-0.71	0.4769
African American	-6.65	-0.14	4.33	-1.54	0.126
Master's degree	0.02	0.00	2.17	0.01	0.9921
Teaching experience	0.05	0.02	0.11	0.43	0.6704
Math professional development	0.28	0.01	1.31	0.21	0.833
New teacher	-5.18	-0.11	2.38	-2.18	0.0305
Formal leader	9.43	0.21	2.17	4.34	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.53 Model 3 in effects of teachers' attributes on students' previous Math achievement

Model 3	B	Beta	S. E.	t value	p value
Intercept	307.84	0.00	6.64	46.36	<.0001
Grade 2	20.04	0.48	3.05	6.57	<.0001
Grade 3	10.37	0.25	3.04	3.41	0.0008
Grade 4	14.45	0.29	3.25	4.45	<.0001
School 1003	-3.59	-0.03	7.74	-0.46	0.6435
School 1006	20.82	0.06	16.29	1.28	0.2023
School 1007	29.39	0.40	6.06	4.85	<.0001
School 1009	16.80	0.13	7.61	2.21	0.0282
School 1010	-4.38	-0.05	6.63	-0.66	0.5093
School 1011	8.21	0.09	6.40	1.28	0.201
School 1012	10.29	0.08	7.68	1.34	0.1816
School 1015	15.10	0.13	7.26	2.08	0.0384
School 1017	23.71	0.25	6.55	3.62	0.0004
School 1020	6.26	0.07	6.50	0.96	0.3362
School 1021	7.22	0.08	6.64	1.09	0.2781
School 1023	13.70	0.10	8.10	1.69	0.092
School 1024	2.76	0.02	7.52	0.37	0.7133
School 1025	18.48	0.12	8.85	2.09	0.0377
School 1026	-1.20	-0.01	6.54	-0.18	0.8547
School 1027	2.15	0.02	6.48	0.33	0.7398
School 1028	-5.12	-0.04	7.38	-0.69	0.4882
School 1029	0.39	0.00	6.94	0.06	0.9547
School 1032	15.13	0.12	7.38	2.05	0.0414
School 1034	-2.07	-0.02	7.01	-0.3	0.768
School 1035	4.00	0.05	6.49	0.62	0.538
School 1038	25.78	0.23	7.02	3.67	0.0003
School 1040	23.11	0.21	6.93	3.33	0.001
School 1041	11.62	0.12	6.85	1.7	0.0912
School 1042	19.49	0.19	6.72	2.9	0.0041
School 1044	-1.84	-0.01	8.02	-0.23	0.8192
School 1047	15.54	0.08	10.20	1.52	0.1287
School 1049	16.88	0.14	7.30	2.31	0.0216
Male	-2.14	-0.03	3.23	-0.66	0.5083
White	-1.67	-0.04	4.04	-0.41	0.6809
African American	-5.01	-0.11	4.29	-1.17	0.2433
Master's degree	-0.21	0.00	2.17	-0.1	0.9229
Teaching experience	0.03	0.01	0.11	0.29	0.7692
Math professional development	0.28	0.01	1.31	0.21	0.8342
New teacher	-6.02	-0.13	2.35	-2.57	0.0108
The total number of leadership roles	2.71	0.21	0.63	4.31	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.54 Model 4 in effects of teachers' attributes on students' previous Math achievement

Model 4	B	Beta	S. E.	t value	p value
Intercept	308.26	0.00	6.81	45.26	<.0001
Grade 2	18.87	0.46	3.11	6.06	<.0001
Grade 3	9.89	0.24	3.12	3.17	0.0017
Grade 4	14.45	0.29	3.34	4.33	<.0001
School 1003	-0.80	-0.01	7.91	-0.1	0.9197
School 1006	19.56	0.06	16.70	1.17	0.2425
School 1007	28.90	0.40	6.21	4.65	<.0001
School 1009	15.17	0.12	7.82	1.94	0.0533
School 1010	-3.11	-0.04	6.79	-0.46	0.647
School 1011	7.61	0.09	6.57	1.16	0.248
School 1012	9.26	0.08	7.87	1.18	0.2407
School 1015	14.68	0.13	7.44	1.97	0.0495
School 1017	23.82	0.25	6.72	3.54	0.0005
School 1020	6.28	0.07	6.66	0.94	0.3466
School 1021	5.84	0.06	6.82	0.86	0.3929
School 1023	13.63	0.10	8.31	1.64	0.102
School 1024	1.56	0.01	7.70	0.2	0.8392
School 1025	20.46	0.13	9.07	2.25	0.025
School 1026	-1.16	-0.01	6.70	-0.17	0.8623
School 1027	3.37	0.04	6.64	0.51	0.6117
School 1028	-3.88	-0.03	7.56	-0.51	0.6082
School 1029	1.32	0.01	7.12	0.19	0.8528
School 1032	16.85	0.14	7.56	2.23	0.0267
School 1034	-2.20	-0.02	7.19	-0.31	0.7601
School 1035	2.43	0.03	6.65	0.37	0.7148
School 1038	25.96	0.24	7.20	3.61	0.0004
School 1040	23.74	0.22	7.11	3.34	0.001
School 1041	10.43	0.10	7.06	1.48	0.1407
School 1042	20.57	0.20	6.89	2.99	0.0031
School 1044	-1.72	-0.01	8.22	-0.21	0.8344
School 1047	22.14	0.11	10.35	2.14	0.0333
School 1049	18.38	0.15	7.48	2.46	0.0146
Male	-1.38	-0.02	3.31	-0.42	0.6771
White	-0.59	-0.01	4.14	-0.14	0.887
African American	-4.24	-0.09	4.39	-0.96	0.3359
Master's degree	-0.48	-0.01	2.23	-0.22	0.8283
Teaching experience	0.08	0.04	0.11	0.72	0.4719
Math professional development	0.97	0.04	1.33	0.72	0.4695
New teacher	-7.68	-0.17	2.38	-3.23	0.0014
Math coordinator	2.77	0.10	1.28	2.16	0.0313

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.55 Model 5 in effects of teachers' attributes on students' previous Math achievement

Model 5	B	Beta	S. E.	t value	p value
Intercept	313.38	0.00	7.02	44.65	<.0001
Grade 2	18.79	0.45	3.09	6.09	<.0001
Grade 3	9.28	0.22	3.09	3.01	0.0029
Grade 4	13.34	0.27	3.31	4.03	<.0001
School 1003	-0.65	0.00	7.84	-0.08	0.9337
School 1006	19.93	0.06	16.58	1.2	0.2305
School 1007	28.23	0.39	6.17	4.58	<.0001
School 1009	15.81	0.12	7.75	2.04	0.0423
School 1010	-3.24	-0.04	6.74	-0.48	0.6309
School 1011	7.52	0.09	6.52	1.15	0.2503
School 1012	9.20	0.08	7.82	1.18	0.2404
School 1015	14.05	0.12	7.39	1.9	0.0584
School 1017	23.85	0.26	6.67	3.57	0.0004
School 1020	5.68	0.06	6.62	0.86	0.3916
School 1021	6.59	0.07	6.76	0.98	0.3304
School 1023	13.15	0.09	8.25	1.59	0.1121
School 1024	1.67	0.01	7.65	0.22	0.8278
School 1025	19.16	0.12	9.01	2.13	0.0344
School 1026	-1.24	-0.01	6.66	-0.19	0.8529
School 1027	3.14	0.04	6.59	0.48	0.6345
School 1028	-4.82	-0.04	7.51	-0.64	0.5217
School 1029	0.02	0.00	7.08	0	0.9973
School 1032	14.62	0.12	7.54	1.94	0.0537
School 1034	-2.61	-0.02	7.14	-0.37	0.7152
School 1035	3.80	0.04	6.61	0.57	0.566
School 1038	24.72	0.22	7.16	3.45	0.0007
School 1040	22.44	0.20	7.07	3.17	0.0017
School 1041	11.44	0.11	6.98	1.64	0.1023
School 1042	20.78	0.21	6.83	3.04	0.0026
School 1044	-1.61	-0.01	8.17	-0.2	0.8442
School 1047	19.38	0.10	10.31	1.88	0.0613
School 1049	17.65	0.14	7.43	2.38	0.0182
Male	-1.65	-0.02	3.29	-0.5	0.6161
White	-1.01	-0.02	4.11	-0.24	0.8069
African American	-4.78	-0.10	4.37	-1.09	0.2752
Master's degree	-0.05	0.00	2.22	-0.02	0.9838
Teaching experience	0.04	0.02	0.11	0.41	0.6812
Math professional development	0.66	0.03	1.33	0.49	0.6228
New teacher	-6.58	-0.14	2.38	-2.76	0.0062
Teacher consultant	0.95	0.14	0.33	2.91	0.0039

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.56 Model 1 in effects of teachers' attributes on students' previous free/reduced lunch

Model 1	B	Beta	S. E.	t value	p value
Intercept	0.92	0.00	0.06	15.03	<.0001
Grade 2	0.01	0.02	0.03	0.36	0.7192
Grade 3	0.04	0.07	0.03	1.48	0.1408
Grade 4	0.02	0.03	0.03	0.81	0.4212
School 1003	-0.10	-0.06	0.07	-1.45	0.1481
School 1006	-0.27	-0.06	0.15	-1.77	0.0773
School 1007	-0.55	-0.54	0.06	-9.61	<.0001
School 1009	-0.24	-0.13	0.07	-3.29	0.0011
School 1010	0.01	0.01	0.06	0.17	0.8638
School 1011	-0.37	-0.30	0.06	-6.14	<.0001
School 1012	-0.08	-0.05	0.07	-1.15	0.2514
School 1015	-0.24	-0.15	0.07	-3.47	0.0006
School 1017	-0.51	-0.39	0.06	-8.29	<.0001
School 1020	-0.55	-0.42	0.06	-8.99	<.0001
School 1021	-0.04	-0.03	0.06	-0.59	0.5582
School 1023	-0.26	-0.13	0.08	-3.38	0.0008
School 1024	-0.09	-0.05	0.07	-1.22	0.2232
School 1025	-0.72	-0.37	0.08	-9.47	<.0001
School 1026	0.01	0.01	0.06	0.19	0.8533
School 1027	-0.09	-0.07	0.06	-1.43	0.1546
School 1028	0.02	0.01	0.07	0.35	0.7288
School 1029	-0.21	-0.14	0.07	-3.24	0.0014
School 1032	-0.18	-0.11	0.07	-2.63	0.009
School 1034	0.00	0.00	0.07	-0.07	0.9444
School 1035	-0.12	-0.10	0.06	-2	0.0463
School 1038	-0.70	-0.46	0.07	-10.54	<.0001
School 1040	-0.29	-0.19	0.07	-4.41	<.0001
School 1041	-0.45	-0.34	0.06	-7.09	<.0001
School 1042	-0.42	-0.30	0.06	-6.64	<.0001
School 1044	-0.03	-0.02	0.08	-0.42	0.6741
School 1047	-0.63	-0.23	0.09	-6.67	<.0001
School 1049	-0.45	-0.27	0.07	-6.61	<.0001
Male	-0.05	-0.05	0.03	-1.51	0.1332
White	-0.07	-0.11	0.04	-1.75	0.0813
African American	-0.02	-0.03	0.04	-0.55	0.5816
Master's degree	-0.01	-0.01	0.02	-0.33	0.739
Teaching experience	0.00	-0.04	0.00	-1.27	0.2055
New teacher	0.04	0.06	0.02	1.72	0.0858

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.57 Model 2 in effects of teachers' attributes on students' previous free/reduced lunch

Model 2	B	Beta	S. E.	t value	p value
Intercept	0.93	0.00	0.06	15.52	<.0001
Grade 2	0.00	0.01	0.03	0.16	0.87
Grade 3	0.04	0.07	0.03	1.45	0.1472
Grade 4	0.02	0.03	0.03	0.78	0.4348
School 1003	-0.09	-0.05	0.07	-1.28	0.2031
School 1006	-0.28	-0.06	0.15	-1.87	0.062
School 1007	-0.56	-0.56	0.06	-10.03	<.0001
School 1009	-0.24	-0.13	0.07	-3.47	0.0006
School 1010	0.01	0.01	0.06	0.18	0.8602
School 1011	-0.37	-0.31	0.06	-6.33	<.0001
School 1012	-0.09	-0.05	0.07	-1.32	0.1887
School 1015	-0.25	-0.16	0.07	-3.75	0.0002
School 1017	-0.50	-0.39	0.06	-8.29	<.0001
School 1020	-0.56	-0.43	0.06	-9.38	<.0001
School 1021	-0.04	-0.03	0.06	-0.68	0.4956
School 1023	-0.27	-0.14	0.07	-3.58	0.0004
School 1024	-0.11	-0.06	0.07	-1.52	0.1297
School 1025	-0.72	-0.37	0.07	-9.66	<.0001
School 1026	0.01	0.01	0.06	0.11	0.9122
School 1027	-0.09	-0.08	0.06	-1.6	0.1111
School 1028	0.02	0.01	0.07	0.28	0.7829
School 1029	-0.20	-0.13	0.06	-3.2	0.0015
School 1032	-0.16	-0.10	0.07	-2.38	0.0181
School 1034	-0.02	-0.02	0.06	-0.37	0.7116
School 1035	-0.14	-0.12	0.06	-2.28	0.0235
School 1038	-0.71	-0.46	0.06	-10.92	<.0001
School 1040	-0.29	-0.19	0.06	-4.58	<.0001
School 1041	-0.46	-0.34	0.06	-7.35	<.0001
School 1042	-0.43	-0.31	0.06	-6.92	<.0001
School 1044	-0.04	-0.02	0.07	-0.49	0.6262
School 1047	-0.61	-0.22	0.09	-6.54	<.0001
School 1049	-0.46	-0.27	0.07	-6.88	<.0001
Male	-0.05	-0.05	0.03	-1.58	0.1143
White	-0.05	-0.08	0.04	-1.24	0.2153
African American	0.00	0.00	0.04	0.01	0.9923
Master's degree	-0.01	-0.01	0.02	-0.44	0.6587
Teaching experience	0.00	-0.04	0.00	-1.08	0.2821
New teacher	0.02	0.03	0.02	0.9	0.3665
Formal leader	-0.07	-0.11	0.02	-3.58	0.0004

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.58 Model 3 in effects of teachers' attributes on students' previous free/reduced lunch

Model 3	B	Beta	S. E.	t value	p value
Intercept	0.93	0.00	0.06	15.6	<.0001
Grade 2	0.00	0.00	0.03	-0.02	0.9823
Grade 3	0.03	0.06	0.03	1.27	0.2046
Grade 4	0.02	0.03	0.03	0.78	0.4379
School 1003	-0.07	-0.04	0.07	-0.92	0.3586
School 1006	-0.29	-0.06	0.15	-1.92	0.0554
School 1007	-0.55	-0.55	0.06	-9.97	<.0001
School 1009	-0.24	-0.13	0.07	-3.45	0.0007
School 1010	0.03	0.02	0.06	0.42	0.6746
School 1011	-0.37	-0.31	0.06	-6.34	<.0001
School 1012	-0.09	-0.05	0.07	-1.32	0.1869
School 1015	-0.24	-0.15	0.07	-3.63	0.0003
School 1017	-0.51	-0.39	0.06	-8.44	<.0001
School 1020	-0.55	-0.43	0.06	-9.27	<.0001
School 1021	-0.04	-0.03	0.06	-0.65	0.5154
School 1023	-0.26	-0.13	0.07	-3.53	0.0005
School 1024	-0.09	-0.06	0.07	-1.37	0.1709
School 1025	-0.70	-0.36	0.07	-9.48	<.0001
School 1026	0.01	0.01	0.06	0.15	0.8784
School 1027	-0.06	-0.05	0.06	-1.08	0.2831
School 1028	0.03	0.02	0.07	0.5	0.6189
School 1029	-0.20	-0.13	0.06	-3.15	0.0018
School 1032	-0.17	-0.10	0.07	-2.49	0.0133
School 1034	-0.01	-0.01	0.06	-0.15	0.8843
School 1035	-0.13	-0.11	0.06	-2.19	0.0294
School 1038	-0.69	-0.46	0.06	-10.81	<.0001
School 1040	-0.28	-0.19	0.06	-4.48	<.0001
School 1041	-0.45	-0.33	0.06	-7.24	<.0001
School 1042	-0.40	-0.29	0.06	-6.57	<.0001
School 1044	-0.03	-0.02	0.07	-0.44	0.6596
School 1047	-0.58	-0.21	0.09	-6.24	<.0001
School 1049	-0.44	-0.26	0.07	-6.61	<.0001
Male	-0.04	-0.04	0.03	-1.28	0.201
White	-0.05	-0.09	0.04	-1.46	0.1449
African American	-0.01	-0.02	0.04	-0.25	0.7996
Master's degree	-0.01	-0.01	0.02	-0.36	0.7209
Teaching experience	0.00	-0.03	0.00	-0.92	0.3588
New teacher	0.02	0.04	0.02	1.13	0.2597
The total number of leadership roles	-0.02	-0.13	0.01	-4.13	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.59 Model 4 in effects of teachers' attributes on students' previous free/reduced lunch

Model 4	B	Beta	S. E.	t value	p value
Intercept	0.85	0.00	0.06	13.93	<.0001
Grade 2	0.02	0.03	0.03	0.57	0.5666
Grade 3	0.05	0.09	0.03	1.85	0.0661
Grade 4	0.03	0.05	0.03	1.2	0.2319
School 1003	-0.10	-0.06	0.07	-1.47	0.1428
School 1006	-0.28	-0.06	0.15	-1.87	0.0627
School 1007	-0.54	-0.53	0.06	-9.75	<.0001
School 1009	-0.23	-0.13	0.07	-3.28	0.0012
School 1010	0.02	0.02	0.06	0.32	0.7457
School 1011	-0.36	-0.30	0.06	-6.26	<.0001
School 1012	-0.09	-0.05	0.07	-1.24	0.2157
School 1015	-0.24	-0.15	0.07	-3.66	0.0003
School 1017	-0.49	-0.38	0.06	-8.26	<.0001
School 1020	-0.54	-0.42	0.06	-9.18	<.0001
School 1021	-0.02	-0.02	0.06	-0.37	0.7093
School 1023	-0.25	-0.13	0.07	-3.45	0.0007
School 1024	-0.08	-0.05	0.07	-1.23	0.2187
School 1025	-0.70	-0.36	0.07	-9.58	<.0001
School 1026	0.01	0.01	0.06	0.23	0.8151
School 1027	-0.07	-0.05	0.06	-1.12	0.2627
School 1028	0.04	0.02	0.07	0.56	0.5785
School 1029	-0.22	-0.14	0.06	-3.42	0.0007
School 1032	-0.16	-0.09	0.07	-2.31	0.0215
School 1034	-0.01	0.00	0.06	-0.11	0.9096
School 1035	-0.13	-0.11	0.06	-2.25	0.025
School 1038	-0.69	-0.45	0.06	-10.81	<.0001
School 1040	-0.27	-0.18	0.06	-4.26	<.0001
School 1041	-0.44	-0.33	0.06	-7.23	<.0001
School 1042	-0.42	-0.30	0.06	-6.83	<.0001
School 1044	-0.02	-0.01	0.07	-0.23	0.8218
School 1047	-0.59	-0.21	0.09	-6.36	<.0001
School 1049	-0.45	-0.26	0.07	-6.74	<.0001
Male	-0.04	-0.04	0.03	-1.39	0.1666
White	-0.06	-0.10	0.04	-1.66	0.0991
African American	-0.01	-0.01	0.04	-0.18	0.8549
Master's degree	-0.01	-0.02	0.02	-0.53	0.5993
Teaching experience	0.00	-0.03	0.00	-1.03	0.3025
New teacher	0.03	0.04	0.02	1.18	0.2393
School improvement coordinator	-0.01	-0.14	0.00	-4.46	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

Table A.60 Model 5 in effects of teachers' attributes on students' previous free/reduced lunch

Model 5	B	Beta	S. E.	t value	p value
Intercept	0.86	0.00	0.06	13.98	<.0001
Grade 2	0.01	0.01	0.03	0.31	0.7547
Grade 3	0.04	0.08	0.03	1.59	0.1128
Grade 4	0.03	0.05	0.03	1.14	0.254
School 1003	-0.09	-0.05	0.07	-1.23	0.2214
School 1006	-0.28	-0.06	0.15	-1.88	0.0606
School 1007	-0.54	-0.54	0.06	-9.73	<.0001
School 1009	-0.23	-0.13	0.07	-3.3	0.0011
School 1010	0.02	0.01	0.06	0.3	0.7651
School 1011	-0.36	-0.30	0.06	-6.21	<.0001
School 1012	-0.08	-0.05	0.07	-1.2	0.2296
School 1015	-0.23	-0.14	0.07	-3.46	0.0006
School 1017	-0.51	-0.39	0.06	-8.43	<.0001
School 1020	-0.54	-0.42	0.06	-9.14	<.0001
School 1021	-0.03	-0.03	0.06	-0.55	0.5816
School 1023	-0.25	-0.13	0.07	-3.42	0.0007
School 1024	-0.08	-0.05	0.07	-1.23	0.2196
School 1025	-0.70	-0.36	0.07	-9.53	<.0001
School 1026	0.01	0.01	0.06	0.17	0.8646
School 1027	-0.07	-0.06	0.06	-1.15	0.2509
School 1028	0.03	0.02	0.07	0.51	0.6122
School 1029	-0.19	-0.13	0.06	-3.01	0.0028
School 1032	-0.16	-0.09	0.07	-2.3	0.0221
School 1034	0.00	0.00	0.06	-0.05	0.961
School 1035	-0.13	-0.11	0.06	-2.23	0.0269
School 1038	-0.68	-0.45	0.06	-10.54	<.0001
School 1040	-0.27	-0.18	0.06	-4.3	<.0001
School 1041	-0.45	-0.33	0.06	-7.21	<.0001
School 1042	-0.41	-0.30	0.06	-6.71	<.0001
School 1044	-0.03	-0.02	0.07	-0.47	0.6367
School 1047	-0.60	-0.22	0.09	-6.52	<.0001
School 1049	-0.45	-0.26	0.07	-6.66	<.0001
Male	-0.04	-0.04	0.03	-1.37	0.1715
White	-0.06	-0.09	0.04	-1.52	0.1302
African American	-0.01	-0.01	0.04	-0.2	0.8439
Master's degree	-0.01	-0.02	0.02	-0.49	0.6238
Teaching experience	0.00	-0.03	0.00	-0.89	0.3729
New teacher	0.03	0.04	0.02	1.21	0.2285
Teacher consultant	-0.01	-0.12	0.00	-4	<.0001

Note: B=unstandardized coefficients, Beta=standardized coefficients, and S.E.=Standard Errors.

BIBLIOGRAPHY

BIBLIOGRAPHY

Briggs, D., Weeks, J., Wiley, E. (2008, April). *The sensitivity of value-added modeling to the creation of a vertical score scale*, presented at the National Conference on Value-Added Modeling, Madison, WI.

Brophy, J., and Good, T. I., (1986). Teacher behavior and student achievement. In M. C. Wittrock (Ed.), *Handbook of research on teaching* (3rd ed.). pp. 328-375. New York: Math instruction Millan.

Bryk. A. S., & Raudenbush. S. W. (1992). *Hierarchical linear models,* first edition. London: Sage.

Bryk, A. S., & Schneider, B. (2002). *Trust in schools: A core resource for improvement*. New York; Russell Sage Foundation.

Burk, William J., Steglich, Christian E.G., & Snijders, Tom A. B. (2007). Beyond dyadic interdependence: Actor-oriented models for co-evolving social networks and individual behaviors. *International Journal of Behavioral Development, 31*, 397-404.

Burns, R. & Mason, D. (1995). Organizational constraints on the formation of elementary school classes. *American Journal of Education, 103* (2), 185-212.

Burns, R. & Mason, D. (1998). Class formation and composition in elementary schools. *American Educational Research Journa,l 35* (4), 739-772.

Burns, R. & Mason, D. (2002). Class composition and student achievement in elementary schools. *American Educational Research Journal, 39* (1), 207-233.

Burstein, L. (1980). The analysis of multilevel data in the presence of heterogeneous within-class regressions. *Journal of Educational Statistics, 3*, 347-383.

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Calderhead, J. (1996). Teachers: Beliefs and knowledge. In D. C. Berliner and R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 709-725). New York: Simon & Schuster Macmillan.

Coburnn, C. E., & Russell, J. L. (2008). District policy and teachers' social networks. *Educational Evaluation and Policy Analysis, 30*(3)*,* 203-235.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, 95-120.

Contractor, N. S., Wasserman, S., & Faust, K. (2006). Testing multitheoretical multilevel hypotheses about organizational networks: An analytic framework and empirical example. *Academy of Management Review, 31*(3), 681-703.

Cook, T. D. (2002). Randomized experiments in educational policy research: A critical examination of the reasons the educational evaluation community has offered for not Doing Them. *Educational Evaluation and Policy Analysis, 24*(3), 175-199.

Cornfield, J., Haenszel, W., Hammond, E., Lilienfeld, A., Shimkin, M., & Wynder, E. (1959). Smoking and lung cancer: Recent evidence and a discussion of some questions. *Journal of the National Cancer Institute, 22*, 173-203.

Cronbach, L. J. (1957). The two disciplines of scientific psychology. *American Psychologist, 12*, 671-684.

Cronbach, L. J. (1976). *Research on classrooms and schools: Formulation of questions, design, and analysis*. Occasional paper of the Stanford Evaluation Consortium, Stanford University, Stanford, CA.

Cronbach, L. J. & Snow, R. (1977). *Aptitudes and instructional methods: A handbook for research on interactions*. New York: Irvington.

Daly, A. J. (2010). Mapping the terrain: Social network theory and educational change. In A. J. Daly (ed.), *Social Network Theory and Education Change*. (Ch. 1, pp. 1-16). Cambridge, MA: Harvard Education Press.

Daly, A. J. & Finnigan, K. S. (2011). The ebb and flow of social network ties between district leaders under high stakes accountability. *American Education Research Journal, 48*(1), 39-79.

Darling-Hammond, L., Wei, R. C., Andree, A., Richardson, N., & Orphanos, S. (2009). *Professional learning in the learning profession: A status report on teacher development in the United States and abroad*. National Staff Development council.

Dee, T. (2004). Teachers, race, and student achievement in a randomized experiment. *The Review of Economics and Statistics, 86*(1), 195-210.

Dee, T. S., & West, M. R. (2011). The non-cognitive returns to class size. *Educational Evaluation and Policy Analysis*, *33*(1), 23-46.

Desimone, L. M. (2009). Improving impact studies of teachers' professional development: toward better conceptualizations and measures. *Educational Researcher, 38*, 181-199.

Dreeben, R., & Barr, R. (1988). Classroom composition and the design of instruction. *Sociology of Education 61*(3), 129-142.

Finnigan, K. S., & Daly, A. J. (2010). Learning at a system level: Ties between principals of low-performing schools and central office leaders. In A. J. Daly (ed.), *Social Network Theory and Education Change*. (Ch. 10, pp. 179-196). Cambridge, MA: Harvard Education Press.

Frank, K. A. (1995). Identifying cohesive subgroups, *Social Networks*, *17*, 27-56.

Frank, K. A. (1996). Mapping interactions within and between cohesive subgroups. *Social Networks*, *18*, 93-119.

Frank, K. A. (1998). The social context of schooling: Quantitative methods. *Review of Research in Education 23*, chapter 5: 171-216.

Frank, K. A. (2000). Impact of a confounding variable on the inference of a regression coefficient. *Sociological Methods and Research, 29*(2), 147-194.

Frank, K.A. (2009). Quasi-ties: Directing resources to members of a collective. *American Behavioral Scientist*, *52*, 1613-1645.

Frank, K., A., Kim, C., & Belman, D. (2010). Utility theory, social networks, and teacher decision making: Modeling networks' influences on teacher attitudes and practices. In A. J. Daly (ed.), *Social Network Theory and Education Change*. (Ch. 12, pp. 223-242). Cambridge, MA: Harvard Education Press.

Frank, K. A., & Zhao, Y. (2005). Subgroups as a meso-level entity in the social organization of schools. In L. Hedges & B. Schneider (Eds.), *Social organization of schools* (Ch. 10, pp. 279-318). New York: Sage.

Frank, K. A., Zhao, Y., & Borman, K. (2004). Social capital and the diffusion of innovations within organizations: Application to the implementation of computer technology in schools. *Sociology of Education*, *77*, 148-171.

Frank, K. A., Zhao, Y., Penuel, W. R., Ellefson, N., & Porter, S. (2011). Focus, fiddle, and friends: Experiences that transform knowledge for the Implementation of Innovations. *Sociology of Education*, *84*(2), 137-156.

Goddard, Y., Goddard, R., & Tschannen-Moran, M. (2007). A theoretical and empirical investigation of teacher collaboration for school improvement and student achievement in public elementary schools. *Teachers College Record*, *109*(4), 877-896.

Goldhaber, D., & Brewer, D. (2000). Does teacher certification matter? High school teacher certification status and student achievement. *Educational Evaluation and Policy Analysis*, *22*(2), 129–145.

Goldstein, H. (1986). Multilevel mixed liner model analysis using iterative generalized least squares, *Biometrika*, *73*, 43-56.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology, 78*, 1360-1380.

Guskey, T. R., & Yoon, K. (2009). What works in professional development? *Phi Delta Kappan, 90*(7), 495-500.

Hadfield, M. & Jopling, M. (2007). *The potential of collaboratives to support schools in complex and challenging circumstances*. Nottingham:NCSL.

Hanushek, E. (1979). Conceptual and empirical issues in the estimation of educational production functions. *Journal of Human Resources, 14*(3), 351-388.

Hanushek, E. (1986). The economics of schooling: Production and efficiency in the public schools, *Journal of Economic Literature*, *XXIV* (3), 1141-78.

Hanushek, E. & Rivikin, S. (2010). Generalizations about using value-added measures of teacher quality. *the American Economic Review 100*(2), 267-271.

Harris, D. N. (2010). How do school peers influence student educational outcomes? Theory and evidence from economics and other social sciences. *Teachers College Record, 112*(4), 1163-1197.

Harris, D. N. & Sass, T. (2006). *Value-added models and the measurement of teacher quality*, Unpublished Draft.

Häuberer, J. (2011). *Social capital theory: Towards a methodological foundation*. Germany: Springer Fachmedien Wiesbaden

Heck, D. J., Banilower, E. R. Weiss, I. R., & Rosenberg, S. L. (2008). Studying the effects of professional development: The case of the NSF's local systemic change through teacher enhancement initiative. *Journal for Research in Mathematics Education, 39*(2), 113-152.

Heck, R., & Marcoulides, G. (1989, October). *Evaluating the effects of organizational size on administrative decision making*. Paper presented at the Annual Meeting of the American Evaluation Association, San Francisco, California.

Heck, R., Marcoulides, G., & Glasman, N. (1989). The application of causal modeling techniques to administrative decision making: The Case of Teacher Allocation. *Educational Administration Quarterly 25*, 253-267.

Hill, H. C., Rowan, B., & Ball, D. L. (2005). Effects of teachers' mathematical knowledge for teaching on student achievement, *American Educational Research Journal, 42*(2), 371–406.

Holland, P. W., & Leihhardt, S. (1981). An exponential family of probability distribution for directed graphs. *Journal of the American Statistical Association. 76*, 33-65.

Hopkins, K. D. (1982). The unit of analysis: Group means versus individual observations. *American Educational Research Journal*, *19(1)*, 5-18.

Huisman, M. & Steglich, M C. (2008). Treatment of non-response in longitudinal network studies. *Social network, 30*, 297–308.

Jackson, C. K. (2009). Student demographics, teacher sorting, and teacher quality: Evidence from the end of school desegregation. *Journal of Labor Economics, 27*(2), 213-256.

Jackson, C. K., & Bruegmann, E. (2009). Teaching students and teaching each other: The importance of peer learning for teachers. *American Economic Journal: Applied Economics, 1*(4), 1-27.

Jacob, B. A., & Lefgren, L. (2007). What do parents value in education? An empirical examination of parents' revealed preferences for teachers. *Quarterly Journal of Economics, 122*, 1603-1637.

Kane, T. & Staiger, D. (2008). *Are teacher-level value-added estimates biased? An experimental validation of non-experimental estimates*, NBER Working Paper No. 14607.

Kelcey, B. M. (2009). *Improving and assessing propensity score based causal inferences in multilevel and nonlinear settings.* Unpublished Doctoral Dissertation, University of Michigan.

Kennedy. M. (2007, April). *Monitoring and assessing teacher quality*. Paper presented at the Annual Meeting of the American Educational Research Association, Chicago, IL.

Kennedy, M., Ahn, S., & Choi, J. (2008). The value-added by teacher education. In Cochran-Smith, M., Feiman-Nemser, S., and McIntyre, J. (3rd ed.). *Handbook of Research in Teacher Education*. New York: Routledge / Taylor & Francis Group.

Kilduff, M., & Tsai, W. (2003). Social networks and organizations. London: Sage.

Koedel, C., & Betts, J (2009). *Does student sorting invalidate value-added models of teacher effectiveness? An extended analysis of the Rothstein critique*. Working Papers 0902, Department of Economics, University of Missouri.

Kyriakides, L., Creemers, B. P. M., & Antoniou, P. (2008). Teacher behavior and student outcomes: Suggestions for research on teacher training and professional development, *Teaching and Teacher Education*, 1-12.

Ingvarson, L., Meiers, M. & Adrian, B. (2005). Factors affecting the impact of professional development programs on teachers' knowledge, practice, student outcomes & efficacy. *Education Policy Analysis Archives, 13*(10), 1-26.

Lankford, H., Loeb, S., & Wyckoff, J. (2002). Teacher Sorting and the plight of urban schools:

A descriptive analysis. *Educational Evaluation and Policy Analysis, 24*(1), 37-62.

Linn, R. L. (2005, June 28). Conflicting demands of No Child Left Behind and state systems: Mixed messages about school performance. *Education Policy Analysis Archives, 13*(33). Retrieved from http://epaa.asu.edu/epaa/v13n33/.

Martineau, J. (2006). Distorting Value Added: The use of longitudinal, vertically scaled student achievement data for growth-based, Value-Added Accountability, *Journal of Educational and Behavioral Statistics, 31*(1), 35-62.

McCaffrey, D., Lockwood, J.R., Louis, T., & Hamilton, L. (2004). Models for value-added models of teacher effects. *Journal of Educational and Behavioral Statistics, 29*(1), 67-101.

Miller, C. (2009). *Teacher sorting and own-race teacher effects in elementary school*. Stanford Institute for Economic Policy Research No. 08-36, CA.

Murnane, R. J., & Willett, J. B. (2011). *Methods matter: Improving causal inference in educational and social science research*, New York: Oxford University Press.

Sun. M., & Frank, K. A. (2011, April). *Peer's influence on teachers' mathematical knowledge for teaching and instructional practices*. Paper presented at the Annual Meeting of the American Educational Research Association, New Orleans, LA.

Monge, P. R., & Contractor, N. S. (2003). *Theories of communication networks*. New York: Oxford University Press.

Monk, D. (1987). Assigning elementary pupils to their teachers. *Elementary School Journal*, *88*, 167-187.

Moolenaar, N. M., & Sleegers, P. J. (2010). Social networks, trust, and innovation: The role of relationships in supporting an innovative climate in Dutch schools. In A. J. Daly (ed.), *Social Network Theory and Education Change*. (Ch. 6, pp. 97-114). Cambridge, MA: Harvard Education Press.

Nye, B., Konstantopoulos, S., & Hedges, L. (2004). How large are teacher effects? *Educational Evaluation and Policy Analysis*, *26*, 237-257.

Orlina, E. C. (2010). *Information seeking, trust, and turnover: Three essays examining middle school instructional advice networks*. Unpublished Doctoral Dissertation, Northwestern University.

Pearson, M., Steglich, C. E. G., & Snijders, T.A.B. (2006). Homophily and assimilation among sport-active adolescent substance users. *Connections*, *27*(1), 47-63.

Penuel, W. R., Frank, K. A., & Krause, A. (2007, April). *A social network approach to examining the effects of distributed leadership in schoolwide reform initiatives,* Paper presented at the Annual Meeting of the American Educational Research Association, Chicago, IL.

Penuel, W.R., Frank, K. A., Belman, D., Kim, C., & Sun, M. (2008, March). *Teacher unions in institutional and local context*. Paper presented at the Annual Meeting of the American Educational Research Association, New York, NY.

Penuel, W. R., Riel, M., Krause, A., & Frank, K. A. (2009). Analyzing teachers' professional interactions in a school as social capital: A social network approach. *Teachers College Record*, *111*, 124-163.

Penuel, W. R., Frank, K. A., & Krause, A. (2010). Between leaders and teachers: Using social network analysis to examine the effects of distributed leadership. In A. J. Daly (ed.), *Social Network Theory and Education Change*. (Ch. 9, pp. 159-178). Cambridge, MA: Harvard Education Press.

Penuel, W. R., Frank, K. A., Sun, M., & Kim, C. (2011). Teachers' social capital and implementation of schoolwide reforms. In S. Kelly (Ed.), *Understanding Teacher Effects* (Ch. 9). New York: Teachers College Press.

Pfeffer, J., & Salancik, G. R. (1978). *The external control of organizations*. New York: Harper & Row.

Porter, A. C., Smithson, J., Blank, R. & Zeidner, T. (2007). Alignement as a teacher variable. *Applied Measurement in Education, 20*(1), 27-51.

Pustejovsky, J. E., & Spillane, J. P. (2009). Question-order effects in social network name generators. *Social Networks, 31*, 221-229.

Raudenbush. S. W., & Bryk. A. S. (2002). *Hierarchical linear models*, Second Edition. London:Sage.

Rivkin, S. G. & Ishii, J. (2009). Impediments to the estimation of teacher value added. *Education Finance and Policy, 4*(4), 520-536.

Rosenbaum, P. R. (2010). *Observational studies*. Second Edition, New York:Springer.

Rothstein, J. (2008). *Teacher quality in educational production: Tracking, decay, and student achievement.* NBER Working Paper Series, Working Paper 14442, http://www.nber.org/papers/w14442.

Rothstein, J. (2009). Student sorting and bias in value-added estimation: Selection on observables and unobservables. *Education Finance and Policy, 4*(4), 537-571.

Rothstein, J. (2010). Teacher quality in educational production: Tracking, decay, and student achievement. *Quarterly Journal of Economics, 125*(1), 175-214.

Salancik, G. R. (1995). Wanted: A good network theory of organization. *Administrative Science Quarterly, 40*(2). 345-349.

Sanders, W. & Horn, S. (1994). The Tennessee value-added assessment system (TVAAS): Mixed-model methodology in educational assessment. *Journal of Personnel in Education, 8*, 299-311.

Schneider, B., Carnoy, M., Kilpatrick, J., Schmidt, W. H., & Shavelson, R. J. (2007). *Estimating causal effects using experimental and observational designs* (report from the Governing Board of the American Educational Research Association Grants Program). Washington, DC: American Educational Research Association.

Scott, J. (2000). *Social network analysis*. Second Edition. London: Sage.

Seltzer, M. H., Frank, K. A., & Kim, J. (2007, April). *Studying the sensitivity of inferences to possible unmeasured confounding variables in multisite evaluations.* Paper presented at the Annual Meeting of the American Educational Research Association, Chicago, IL.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston: Houghton Mifflin.

Snijders, T.A.B. (1996). Stochastic actor-oriented models for network change. *Journal of Mathematical Sociology 21*, 149–172.

Snijders, T.A.B. (2001). The statistical evaluation of social network dynamics. In M. E., Sobel, and Becker, M. P. (Eds.), *Sociological methodology* 2001, pp. 361-395. Boston and London: Basil Blackwell.

Snijders, T.A.B. (2005). Models for longitudinal network data. In Carrington, P.J., Scott, J., Wasserman, S. (Eds.), *Models and Methods in Social Network Analysis*. pp. 215–247. New York: Cambridge University Press.

Snijders, T.A.B., & Baerveldt, C. (2003). A multilevel network study of the effects of delinquent behavior on friendship evolution. *Journal of mathematical sociology 27*, 123-151.

Snijders, T.A.B., Steglich, C.E.G., Schweinberger, M., Huisman, M. (2008). *Manual for SIENA version 3.2,* University of Groningen, ICS, Groningen. University of Oxford, Oxford.

Snijders, T.A.B., & Van Duijn, M. A. (1997). Simulation for statistical inference in dynamic network models. In Conte, R., Hegselmann, R., and Terna, P. (eds.), *Simulating Social Phenomena*, pp. 493-512. Berlin: Springer.

Snow, R. (1989). Aptitude-Treatment Interaction as a framework for research on individual differences in learning. In P. Ackerman, R.J. Sternberg, & R. Glaser (ed.), *Learning and Individual Differences*. New York: W.H. Freeman.

Spillane, James P. (2006). *Distributed leadership*. San Francisco, CA: Jossey-Bass.

Steglich, C.E.G., Snijders, T.A.B., & West, P. (2006). Applying SIENA: An illustrative analysis of the co-evolution of adolescents' friendship networks, taste in music, and alcohol consumption. *Methodology, 2*, 48-56.

Steglich, C.E.G., Snijders, T.A.B., & Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology*. *40*(1), 329-393.

Steiner, P. M., Cook, T. D., Shadish, W. R., & Clark, M. H. (2010). The importance of covariate selection in controlling for selection bias in observational studies. *Psychological Methods*. *15* (3), 250-267.

Supovitz, J., Sirinides, P., & May, H. (2010). How principals and peers influence teaching and learning. *Educational Administration Quarterly*, *46*(1), 31-56.

Teddlie, C., & Reynolds, D. (2000). *The international handbook of school effectiveness research*. London : Falmer Press.

Van. de Bunt, G.G., & Groenewegen, P. (2007). An actor-oriented dynamic network approach: The case of interorganizational network evolution. *Organizational Research Methods, 10*, 463-482.

Van Duijn, M. A., Snijders, T. A. B., & Zijlstra, B. J. H. (2004). P2: A random effects model with covariates for directed graphs, *Statistica Neerlandica, 58*, 234-254.

Wasserman, S., & Pattison, P. (1996). Logit models and logistic regression for social networks: An introduction to Markov graphs and P*, *Psychometrika*, *61*, 401-425.

Wayne, A. J., Yoon, K., Zhu, P., Cronen, S., & Garet, M. S. (2008). Experimenting with teacher professional development: Motives and methods. *Educational Researcher, 37*, 469-479.

Webb, N. L. (2007). Issues related to judging the alignment of curriculum standards and assessments. *Applied Measurement in Education, 20*(1), 7-25.

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American Journal of Sociology, 87*, 548-577.

Wright, S., Horn, S., & Sanders, W. (1997). Teacher and classroom context effects on student achievement: Implications for teacher evaluation. *Journal of Personnel Evaluation in Education, 11*, 57–67.

Zahorik, J. A. (1987). Teachers’ collegial interaction: An exploratory study. *The Elementary School Journal, 87*(4), 385-396.