Processes of Peer Selection and Influence in Adolescents' Academic Achievement

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Abstract

LORRIE SCHMID: Processes of peer selection and influence in adolescents' academic achievement (under the direction of Jill V. Hamm)

In this dissertation study, I focused on changes in peer affiliations within a grade-based network and students' academic achievement, as measured through curricular grades from 7th to 9th grade. Specifically, my intent was to assess the independent roles of selection and influence on both peer affiliations within the network and grades over time. This study was unique in that I explore the processes of peer selection and influence independently of each other within a statistical modeling framework, stochastic actor modeling, which considers changes in network affiliations as well as changes in individuals' behaviors simultaneously. Stochastic actor modelling using Siena was implemented to examine the following research questions:

1) What is the nature of changes to adolescents' affiliative patterns within the grade-level peer network?
2) To what extent and in what ways do network structural characteristics; (i.e., density, reciprocity, transitivity, and hierarchy), influence affiliative patterns?
3) To what extent and in what ways do individual characteristics derived from network analysis and individual demographic characteristics change the network?
4) To what extent and in what ways do selection and influence account for the co-evolution of changes to peer affiliations within the network and academic achievement?
5) To what extent and in what ways do individual characteristics derived from network analyses and demographic characteristics of adolescents influence academic achievement?

6) To what extent and in what ways do these individual demographic moderate the relationships between peer selection and peer influence, and academic achievement?

This study used four waves of data on peer affiliations and academic achievement from the Processes of Peer Influence Study (Golonka et al., 2007), collected from 2002 to 2007, in a magnet school in an urban district in North Carolina. Overall, the results revealed that, 1) processes of peer selection, not influence, were important to understanding academic achievement and 2) different patterns of peer selection occur for African American and European American students. Implications for understanding adolescent peer networks and academic achievement were discussed.

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Before starting graduate school six years ago, I worked on issues of peer affiliation and education at the Center for Child and Family Policy. One of the studies that I was involved with was the Processes of Peer Influence study which is the data used for this dissertation study. Thank you to Dr. Philip Costanzo for allowing me to use this data. In addition to the data, I was fortunate enough to work with several individuals that continue to support and cheer me on. Thank you to Dr. Megan Golonka and Adam Mack, who I met many years ago and still continue to provide useful insights to my past, present, and future work.

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Table of Contents

List of Tables

Tables

List of Figures

Figures

INTRODUCTION

In schools, adolescents are embedded in a broad network of peers, known as peer networks. A peer network is formally defined as a representation of a set of affiliations between individuals, bounded together in a researcher-defined context (Wasserman & Faust, 1994). In schools, peer networks are typically grade-based; each student in the grade selects same-grade peers as affiliates. Peer network activities are central to adolescents' academic achievement, with numerous studies demonstrating the potential for aspects of peer network affiliations to change adolescents' academic adjustment (Crosnoe, Cavanagh, & Elder, 2003; Ryan, 2001; Wentzel, 2009). The precise mechanisms through which peer affiliations contribute to members' academic achievement are not fully understood. Specifically, there has been little attention to how the *selection* of peers and peer *influence* independently alter adolescents' academic achievement across time. Selection and influence are foundational to understanding peer affiliative networks and their resulting effects on members' behaviors. For instance, high academic achieving students are both more likely to affiliate with other high academic achieving peers and be influenced by their peers to achieve. However, high achieving individuals who affiliate with lower academically achieving peers may either be more likely to change their peer affiliations to better reflect their academic achievement or to adapt their academic achievement to better align with their peer affiliates (Berndt & Murphy, 2002).

In this dissertation study, I focus on changes in peer affiliations within a grade-based network, and students' academic achievement, as measured through grade point average (i.e., GPA), during the middle grades and early high school years. Specifically, my intent is to assess the independent roles of selection and influence on both peer affiliations within the network and grades, over time. This study is unique in that I explore the processes of peer selection and influence independently of the other within a statistical modeling framework, stochastic actor modeling, which considers changes in network affiliations as well as changes in individuals' behaviors simultaneously. Both network affiliations and individual behaviors can determine changes in network affiliations and individual behaviors; thus, there is a mutual dependence between both the network and the behavior across time. Researchers have defined this mutual dependence occurring across time as "the co-evolution of networks and behavior dynamics" (Snijders, Steglich, & Schweinberger, 2007, p. 1). Therefore, changes in peer affiliative networks and academic achievement across this time span can be modeled simultaneously, parsing peer selection and peer influence effects on affiliations and achievement with the same population.

Three main types of characteristics are involved in understanding the co-evolving processes of peer affiliations within the network and behavioral changes: network structural characteristics, individual characteristics derived from network analyses, and individuals' demographic characteristics. Peer networks have structural characteristics, which reflect general tendencies found among the affiliations among individuals (Wasserman & Faust, 1994). Affiliations within a peer network are constrained by these network structural characteristics, in that these broader network structures help to shape individuals' affiliative choices (Snijders, 2011). The network structural characteristics examined in this study include: hierarchy, density, reciprocity, and transitivity. For example, networks can be characterized by the degree of hierarchy that defines them, that is, by the ordering of affiliations that is found in the network. Some networks, like the armed services, have a well-defined hierarchy within the network; whereas other networks, such as a book club, may have little hierarchy. The degree to which a network is hierarchical affects the pattern of affiliation choices for the individual. If a network is strongly hierarchical, individuals will have few affiliations; and if a network is more egalitarian, variability in the number and types of affiliations is expected. In the current study, I will examine these network structural characteristics, specifically focusing on their impact on peer affiliations and changes to individuals' academic achievement from 7th grade to 9th grade.

Two different types of individual characteristics are examined in this study: individual characteristics that are derived from network analyses and individuals' demographic characteristics. Individuals within peer networks can differ from one another in significant ways through the affiliations they receive from others, send to others, or reciprocate with one another. For example, some individuals are more "popular", receiving more peer affiliations compared to other peers in the network (Snijders, van de Bunt, & Steglich, 2010, p.48). Demographic characteristics are included to determine if differences in the co-evolution of peer networks and academic achievement vary systematically with regards to the gender and race of the members. Therefore, in the current study, I examine if there are differences in peer affiliations and academic achievement based on individual level characteristics derived from network analyses (e.g., popularity), or individual demographic characteristics (e.g., gender and race). In addition, the processes of peer selection and influence are examined to determine if there are systematic differences in how these processes operate by any of the individual demographic characteristics.

In summary, the current study specifically addresses the following research questions:

1) What is the nature of changes to adolescents' affiliative patterns within the grade-level peer network from 7th grade to 9th grade?
2) To what extent and in what ways do network structural characteristics; such as density, reciprocity, transitivity, and hierarchy, influence affiliative patterns within networks from 7th grade to 9th grade?

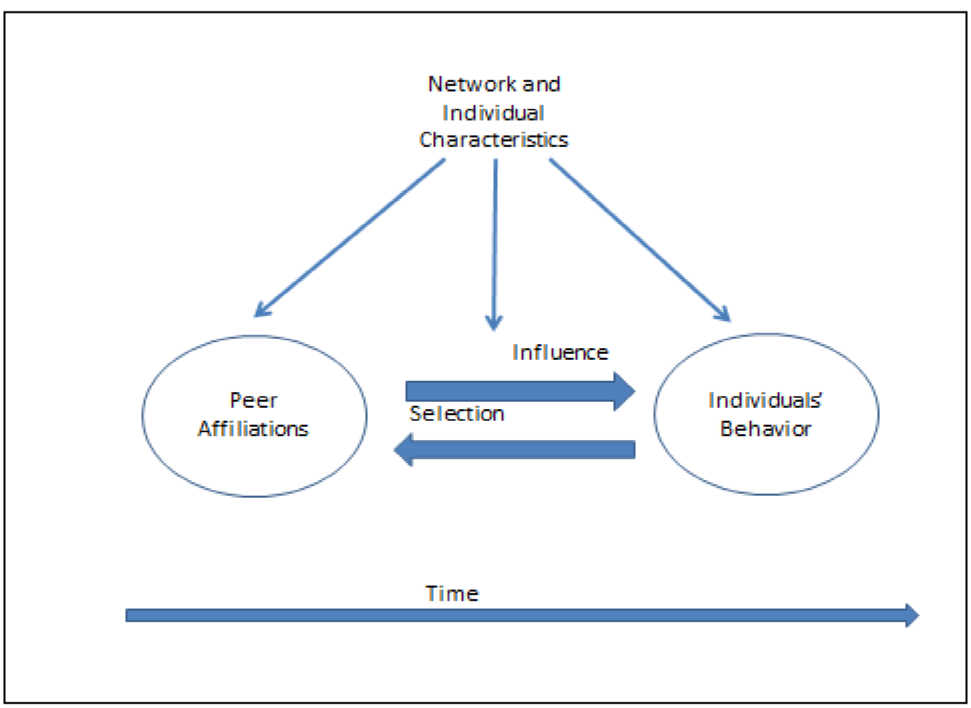
3) To what extent and in what ways do individual characteristics derived from network analyses (i.e., popularity, activity and assortativity) and individual demographic characteristics (i.e., gender and race) change the peer affiliation network from 7^{th} grade to 9^{th} grade?
4) To what extent and in what ways do selection and influence account for the co-evolution of changes to peer affiliations within the network and academic achievement across 7^{th} grade to 9^{th} grade?
5) To what extent and in what ways do individual characteristics derived from network analyses and demographic characteristics of adolescents influence academic achievement?
6) To what extent and in what ways do these individual demographic characteristics (i.e., gender and race) moderate the relationships between peer selection and peer influence, and academic achievement across 7^{th} grade to 9^{th} grade?

Theoretical Background

During adolescence, peer networks are dynamic with changes occurring within individual relationships as well as within the broader network. Research has focused on either individual's perspectives on relationships or on network structures, without considering the two simultaneously (Cairns, Xie, & Leung, 1998). The current study attempts to overcome the focus on either the individual or the network by focusing on peer selection and peer influence in changes to peer network and academic achievement across time, from 7^{th} grade to 9^{th} grade (see Figure 1 for a general conceptualization of the current study). A basic premise of the study is that changes in individuals' behaviors cannot be fully understood independently of the peer network. Changes to individuals' academic achievement cannot be understood separately from the peer network; in addition, individuals' academic achievement may change the peer network over time. Therefore, a complete study of selection and influence must include a longitudinal assessment of both peer networks and individual behaviors; in this case, academic achievement, as they co-evolve over time. Three types of characteristics are conceptualized in this study to relate to both the peer affiliation network as well as individuals' behaviors. The first set of characteristics is the network structural characteristics (i.e., density, reciprocity, transitivity, and hierarchy) which describe the overall structure of the network. The second set of characteristics is individual characteristics derived from network analysis. The final set of characteristics is based on individuals' demographic characteristics (i.e., race and gender). Both types of individual characteristics allow for understanding how individuals differ across the network due their affiliation patterns or in their demographic characteristics. These differences can result in different affiliations within the network and academic achievement over time.

Figure 1.

General conceptualization of the co-evolution of peer affiliations and behaviors



Thus, I focus on the key theoretical foundations that contribute to the aspects of this conceptual framework (see Figure 1). First, I focus on the processes of peer selection and peer influence, and how each may change peer affiliations and behaviors across time. Then, I provide a conceptual explanation of the co-evolution of adolescents' peer affiliations within the network and academic achievement and how selection and influence impact both affiliations and behaviors. Next, I conceptualize the characteristics of the network structure that can constrain peer affiliative networks and individuals' behaviors. Finally, I conceptualize two types of individual characteristics, one derived from network structure and the other derived from self-reported demographic data and how they relate to peer affiliations and behaviors over time. Taken together, this section will provide a theoretical argument for examining the relationships between peer affiliations within a network and academic achievement across time; separating the effects of peer selection and peer influence in terms of choices in affiliates and academic achievement.

Peer Homophily: Selection and Influence

An important concept to understand within a peer network is *homophily*, which is the inherent tendency for individuals to affiliate with similar others (Lazarsfeld & Merton, 1954). Homophily has been used as both a description of peer affiliations and as a predictor for peer affiliation. A long-standing research question has focused on why similarities occur among affiliates within a network. That is, are individuals similar to one another before they affiliate which leads them to select one another on the basis of their similar characteristics? Or, do peer affiliates become more similar to one another after they select one another, based on their interactions and influence on each other? Until recently, researchers could only identify the homophily among peer affiliations, not the independent contributions of selection and influence on homophily within a relationship. A key component to this study is to determine the extent to which selection and influence each contribute to changes in individuals' peer affiliations and behaviors over time within the larger context of the school-based network. This study addresses how the processes of selection and influence contribute to peer homophily and impacts academic achievement in the network.

Homophily has been theorized to assume two main forms. *Status homophily* encompasses similarities between peers in terms of demographic characteristics such as gender, race, age, SES, and religious affiliation (McPherson, Smith-Lovin, & Cook, 2001). In this study, gender and race are assessed to determine if there is a homogeneous grouping within the network by gender and by race. For adolescents in a school-based network, gender and race are presumed to be the most salient demographic characteristics; and homophilous networks have been found by gender and race throughout many different school environments (Epstein, 1989; Hallinan & Williams, 1990; Shrum, Cheek, & Hunter, 1988). However, it is unknown whether processes of selection and influence operate differently by gender and race.

Value homophily is defined as peer similarities in attitudes, values and thoughts. In this study, individual characteristics derived from network analyses (i.e., popularity, activity, and assortativity) will be used to explore issues of value homophily. *Popularity* represents individuals' status in the network; those with greater numbers of affiliates are conceptualized as being more popular than those with fewer affiliates. *Activity* represents individuals' level of selection of affiliates in the network; those who select greater numbers of affiliates are conceptualized as being more active than those who select fewer affiliates. *Assortativity* is the extent to which individuals' associate with others who have similar patterns of affiliation, in this case, similar popularity and activity levels. These individual characteristics derived from network analyses are used to determine individual differences in affiliations and behaviors across time. Within this study, I examine the extent to which adolescent students affiliate with others who have similar academic achievement, and how each process (i.e., selection and influence) is related to changes in both peer affiliation and academic achievement.

Homophily in the schooling context. Differences across school environments may support or diminish the opportunities for peers to affiliate with dissimilar others, potentially allowing for the sharing or resources and behaviors (Chang, 2004; Epstein, 1989; Neckerman, 1996). Common organizational practices in middle and high schools such as academic ability tracking, small schools within schools, and other practices can restrict the pool of possible peers available to affiliate with (Barber & Olsen, 2004; Epstein, 1989). These school organizational practices can artificially constrain peer affiliations within a school- or grade- based network to only include the effective network of these smaller organizational groups. For example, academic ability tracking within the school may limit possible peer affiliations by limiting the students that can interact with one another, creating sub-networks with the grade-level network (Moody, 2001). This means that students, in effect, only have opportunities to interact with those that belong to their academic ability track. Use of organizational practices that structure students' contact can result in greater homophily, especially if the organization is based on academic achievement and other salient characteristics (Epstein, 1989; Moody, 2001). Greater homophily among peer affiliates may have a significant effect on students' academic success and failure. School-based peer relationships can foster information and resources regarding students' academic and social decision-making within the school (Coleman, 1988). Individuals might select new peer affiliates to alter the resources (e.g., both supports and hindrances) available to them (Crosnoe et al., 2003). New peer affiliates may have knowledge, abilities, and skills related to schooling and academics as well as exposure to broader achievement-oriented networks. However, these resources may not be diverse if the student body of the school has been significantly segmented into homogeneous networks through ability tracking or other environmental constraints (Moody, 2001). The current study focused on a magnet school, for which students apply via a lottery to gain admission. In addition, organization strategies including academic ability tracking were used. Taken together, the overall grade-level network within the school may already have a homophilous student body, due to the self-selection into the school; and the academic ability tracking which may artificially segment the grade into even more homophilous subgroups.

Selection. Selection is a key mechanism in peer affiliation formation. A theory used to understand relationship formation is *assortative pairing*, which describes individuals' desire for valued and similar attributes, statuses, and behaviors in their peer affiliations (Kandel, 1978). Individuals first define what is important to them in terms of characteristics, attitudes, values and behaviors; then they search for those characteristics and behaviors in others and affiliate with peers who share those characteristics. When applied to adolescents, assortative pairing theories can describe the rapid changes in peer networks, as individuals and affiliates are changing their values, characteristics, and behaviors rapidly and new affiliations are often sought to maintain similarities. In the general conceptualization of the model for this study (see Figure 1), the selection of peer affiliates occurs after individuals consider their own attributes and behaviors. For example, adolescents who are poor students are more likely to select peer affiliates with similarly low achievement, whereas adolescents who are academically strong students are more likely to select peer affiliates who share their successful academic behaviors (Kindermann, 1993).

Propinquity is defined as proximity or closeness in physical space. Relationships are more likely to form between individuals who frequently meet and interact with one another (Crosnoe, 2000; Epstein, 1989). Proximity can limit the pool of possible peers available for affiliation, leading to demographic, behavioral, and attitudinal similarities between network members (Epstein, 1989). Stated another way, individuals are more likely to affiliate with peers similar to themselves because they attend the same schools, are tracked into the same classrooms, and experience similar activities (Epstein, 1989).

Another selection process involved in affiliation formation is peer *similarity* to the self. This process reflects the similarity-attraction hypothesis which theorizes that individuals are attracted to those who they perceive to be similar to them and leads to affiliating with others who are similar to oneself (Byrne & Griffitt, 1966). Thus, the similarity between the self and others is a *process* of selection. However, similarity may also arise out of interactions with others, indicating an influence effect. Therefore, a key purpose of this study is to distinguish the processes of selection and influence in peer homophily in academic achievement within a school-based network across time.

Influence. Influence is a key mechanism in the maintenance of peer affiliations and changes to individuals' behaviors. Once affiliates are selected, individuals and their affiliates continue to build similarities with one another through a process of mutual interaction and influence called *socialization* (Adler & Adler, 1995; Kandel, 1978). Peer affiliates can socialize academic achievement in both positive and negative ways through activities such as direct academic support, modeling behaviors and peer norms regarding achievement (Berndt & Murphy, 2002; Juvonen, 2007; Ryan, 2000). In the proposed study, peer influence is theorized to occur after the selection of peer affiliates (see Figure 1). Thus, students might improve their academic achievement due to the influence of peer affiliates who themselves are academically successful; or students might have declines in their academic achievement due to the influence of lower achieving peer affiliates.

Both selection and influence processes are significant to the development of homophilous peer networks, in which members may hold similar affiliations as well as behaviors (see Figure 1). However, selection and influence can be identified temporally within a relationship life cycle. The selection of peers occurs in the early stages of a relationship, whereas peer influence is involved the maintenance and continuation of relationships over time. Although the distinction between selection-based versus influence-based homophily can be explained conceptually, the analytic means to determine the contributions of selection and influence processes has only recently become available. It is unclear to what extent adolescents select others with similar academic achievement or to what extent academic achievement changes over time due to the influence of peers. Only through considering both peer affiliations and behaviors simultaneously, across time, can the conceptual distinction between selection and influence be independently and directly studied.

Co-evolution of the Peer Affiliative Network and Academic Achievement

An elusive goal for researchers has been to understand the unique contributions of peer selection and peer influence to changing peer affiliations and behaviors. Both individual behaviors and network affiliations change over time, and these changes can alter the other. Dynamic social network analytic models, such as stochastic actor models, enable scholars to examine specific peer processes of selection and influence and how these processes change individuals' behaviors and affiliative patterns across time (Burk, Kerr & Stattin, 2008; Snijders et al., 2007). These models are helpful for assessing changes in peer networks and adolescents' behaviors (e.g., academic achievement) especially when changes are occurring in both peer affiliations and behaviors across time. Snijders and his colleagues have termed the relationship between peer affiliations within the network and the members' behaviors as co-evolving (Snijders et al., 2007; Snijders et al., 2010). That is, not only can changes to peer affiliations within a network alter individuals' behaviors but individuals' behaviors can alter peer affiliative patterns within the network. Moreover, patterns of affiliations and members' behaviors can be altered by the overall network structural characteristics, by the individual characteristics derived from network analyses and individuals' demographic characteristics (see Figure 1). Thus, the mutual dependence of peer affiliations within the network and behaviors (e.g., academic achievement) evolve together over time. According to Snijders et al. (2010):

> "Since the network and behavior variables both influence the dynamics of the network ties and of the actors' behavior, the sequence of changes in the network ties and of the actors' behaviors, the sequence of changes in the other, generates a mutual dependence between network dynamics and behavior dynamics (p.54).

Stochastic Actor Modeling: Rational Choice and Key Assumptions

This complicated co-evolution of affiliations and behaviors is modeled using an individual-oriented perspective, based upon a rational choice framework (Wittek, Snijders, & Lee, 2013). Rational choice theory, in the simplest form, assumes that individuals seek to make choices for themselves by maximizing rewards and minimizing costs (Coleman, 1990; Homans, 1960). Therefore, all choices made within the stochastic model, whether they involve peer affiliations or behaviors, are made by individuals, based on rational calculations that serve their needs and minimize their risks. Additionally, the stochastic actor model assumes that individuals have complete control over their affiliation choices (Snijders, 2013). As part of the complete control in determining one's peer affiliation, individuals also are assumed to have complete knowledge about the entire network, in this case, the grade-level network. This would also include complete knowledge of the affiliations that already constitute the network, which may or may not be possible, depending on the size of the network and the organization structures of the grade (Wittek et al., 2013).

The stochastic actor model conceptualizes actors' optimization of their affiliation and behavior choices, through a utility function (Snijders, 2013). The utility function is maximized when peer affiliations are closely aligned with other affiliations in the network, which leads individuals to become more integrated into the network. The utility function is underutilized when individuals are affiliated with others who they are not closely connected to in the network. Therefore, individuals are more likely to affiliate and maintain affiliations with those who help them connect to the broader network, and are less likely to affiliate and maintain affiliations with peers who are less likely to provide this connection. Overall, this means that the stochastic actor modeling algorithm attempts to maximize network structural characteristics, such as density, reciprocity and transitivity through individual choices on affiliations (Snijders, 2013).

Network Structural Characteristics

Researchers using social network analysis and stochastic actor models employ a conceptual framework that examines how individuals within a shared context interact, the pattern of those interactions, and what those interactions suggest generally about affiliations and behaviors (Gest, Osgood, Feinburg, Bierman, & Moody, 2011). Network structural characteristics represent the general features of the network. Through an understanding of these network structural characteristics, scholars can have a more accurate understanding of peer selection and peer influence effects. Several network structural characteristics are used in this study to define the overall peer network as well as to understand the changes in affiliation patterns (e.g., affiliation formation and dissolution). In this study, the network structural characteristics include: density, reciprocity, transitivity and hierarchy. *Density* represents the overall interconnectedness of affiliations between all of the individuals in the network. Density is the ratio of the number of affiliations across the network divided by the total number of all possible affiliations in the network (Wasserman & Faust, 1994). Networks can be dense, with all individuals affiliating with all other individuals in the network. However, most peer networks are less dense, with individuals preferring to affiliate with only a few others (Veenstra & Dijkstra, 2012). *Reciprocity* reflects the tendency for individuals to connect with one another; that is, if one individual selects an affiliate, that affiliate is more likely to select that individual as an affiliate. Reciprocity across a network is defined as the extent to which all relationships are reciprocated. High reciprocity reflects a network of mostly bidirectional (i.e., mutual) ties; whereas low reciprocity indicates many asymmetrical (i.e., non-mutual) ties between individuals (Wasserman & Faust, 1994). *Transitivity* is a conceptual extension of reciprocity that involves larger subsets (e.g., groups of three individuals or triads) rather than the dyadic reciprocal relationships within the network. Like reciprocity, transitivity among triads is common, reflecting the idea that, "my friends' friend is more likely to be my friend" (Holland & Leinhardt, 1977). Finally, network *hierarchy* reflects the ordering of individuals within a network. Some network hierarchies are organized formally by roles or numerical ordering, such as teams or rank order in grades. Other hierarchies are more informal and have an organization that reflects the status of members, such as peer groups or book clubs. There are expected relationships between network reciprocity, transitivity, and hierarchy. For example, if a network is fully hierarchical, in which each individual is only connected asymmetrically to a single other individual, there would be no reciprocity or transitivity in the network, because no reciprocal relationships exist within a full hierarchy (Snijders, 2011). Under a fully egalitarian network, all individuals would be affiliated with all other members, leading to a higher reciprocity and transitivity score.

Individual Characteristics

Within a peer network, individuals differ in terms of the pattern of their affiliations as well as having differences in behaviors, and these characteristics help to explain differences among individuals within the network (Gest et al., 2011; Snijders et al., 2010). In the current study, I am interested in two types of individual characteristics: individual characteristics derived from network analysis and individual demographic characteristics. Both types of individual characteristics are presumed to be related to changes in both peer affiliations within the network and behavior changes across time (Ripley, Snijders, Boda, Voros, & Preciado, 2014; Snijders et al., 2010).

The peer network is comprised of a set of individuals who have identified a set of affiliates. In addition, each individual is identified as an affiliate within the network. Thus, there are sets of relationship ties from an individual to others, and sets of relationship ties from others to each individual. These relationship ties differ among individuals in the network. Individuals select others to affiliate with and that is defined as *activity* (Snijders et al., 2010). Individuals who name many affiliates are characterized as more active in the network, compared to those who send out fewer relationship ties. The number of affiliations received by others is conceptualized as *popularity* (Snijders et al., 2010). Individuals who receive a lot of peer nominations are conceptualized as more popular within the network than those who receive fewer affiliations. Individuals within a network differ in their activity and popularity statuses, with some individuals sending and receiving more affiliative ties than others. Finally, the similarities between individuals and their affiliations are examined through assortativity. *Assortativity* is defined as an individual's tendency to choose to affiliate with others of a similar activity or popularity status (Newman, 2002; Ripley et al., 2014). Assortativity can be conceptualized as a measure of homophily in terms of affiliative status; that is, similarities are expected to be found between individuals and their affiliates in terms of their solicitation and reception of affiliative ties.

The other set of characteristics include individuals' demographic characteristics, including gender (i.e., male or female) and race (i.e., European American or African American). In the proposed study, these characteristics may systematically alter the peer affiliative network, the behavior (i.e., academic achievement) or both the network and achievement. Peer affiliation homophily has been found in both gender and race (McPherson et al., 2001). In addition, these demographic characteristics will be used to determine, what, if any differences in the processes of peer selection and peer influence systematically occur by gender and race (See Figure 2 for a conceptualization of the co-evolution of peer affiliations and academic achievement).

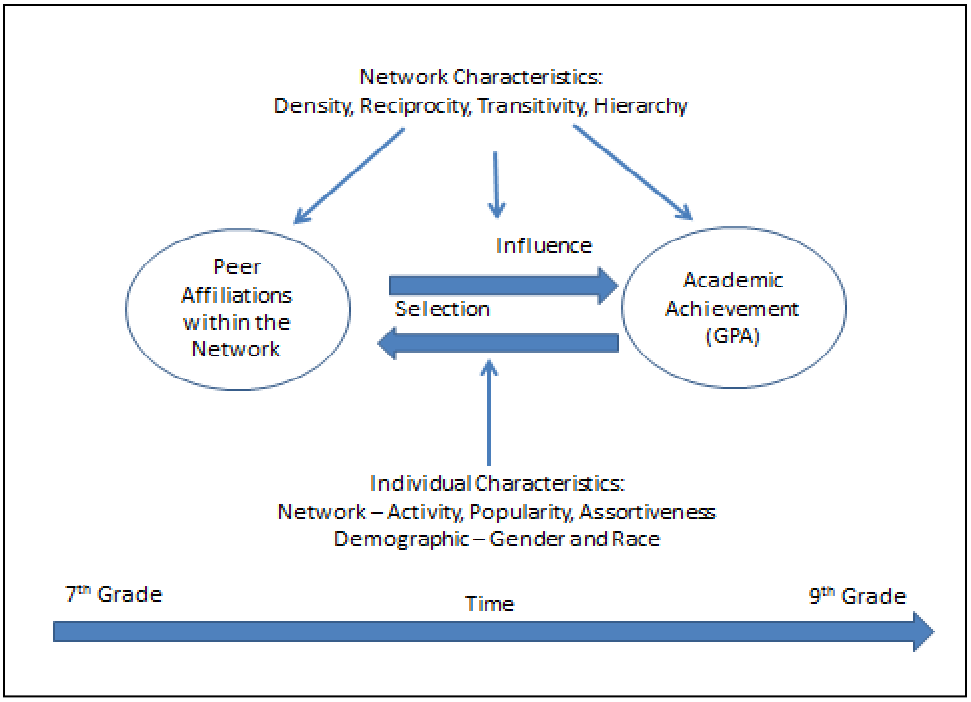
Summary

In summary, I propose an integrated theoretical model that draws on social psychological theories of relationship formation and homophily as well as social network analysis perspectives that examine individuals' affiliations and behaviors within the broader network across time. Based on this model, I propose that adolescents' peer affiliations and academic achievement will change in relation to the processes of selection and influence within the grade-level peer network. Furthermore, I propose that network structural characteristics, individual characteristics derived from the network analysis and demographic characteristics such as race and gender will alter both peer affiliations and academic achievement. This approach addresses several conceptual and methodological issues that have been ongoing dilemmas within existing studies of peer selection and influence, most notably, the determination of how much of an individual's academic achievement is due to peer selection and how much is due to peer influence. Thus, the results of this study have the potential to add to an understanding of the independent and combined effects of peer selection and influence and their relationship to academic achievement over time.

I conceptualize a co-evolving and mutually dependent relationship between peer affiliation networks and academic achievement. Peer networks are patterns of affiliations within a single grade in a school, across four time points, from 7^{th} to 9^{th} grade. Individuals who are affiliated are typically similar to one another, displaying homophily. These similarities arise out of processes of selection and influence. In line with this conceptual framework, I will use social network analysis and, in particular, stochastic actor modeling, to disentangle peer selection and peer influence effects in academic achievement across three schooling years from 7^{th} grade to 9^{th} grade.

Figure 2.

Conceptualization of the co-evolution of peer affiliation and academic achievement



LITERATURE REVIEW

In this review, I provide the empirical basis for the components of my conceptual framework depicted in Figure 2. First, I substantiate the bidirectional relationship between peers and academic achievement during adolescence; specifically, the attitudes, norms, and actions that are used to support or hinder achievement within peer networks. Specifically, I review studies that examine the processes of peer selection and peer influence and how they support the relationship between peer affiliations and academic achievement. Second, I review and critique earlier methods for studying peer selection and peer influence, with specific attention to three issues: the use of cross-sectional or short-term longitudinal studies, a lack of attention to network dynamics, and an overestimation of peer selection or peer influence effects due to an inexact parsing of these processes. Third, I review stochastic actor modeling as a method to overcome the limitations of these earlier methods. In addition, stochastic actor modeling allows the researcher to examine all components found within my conceptual model in a single framework to determine the extent to which co-evolution is occurring between the peer affiliative networks and academic achievement over time. Moreover, I reviewed studies that examined academic achievement using this modeling technique. Finally, three different characteristic types have been conceptualized as part of my theoretical framework: network structural characteristics, individual characteristics derived from network analysis, and demographic characteristics. For each characteristic type, relevant literature focusing on peer affiliative networks and academic achievement will be reviewed. In summary, I focus the review on the components of my theoretical framework; specifically, the processes of peer selection and peer influence in understanding peer affiliations and academic achievement, from 7th grade to 9th grade within a school-based grade network.

Peer Affiliates' Selection and Influence on Academic Achievement

School-based peer affiliations play multifaceted roles in adolescents' academic achievement. At a basic level, individuals who have school-based peer affiliates have been found to have higher academic achievement, compared to those who do not affiliate with others (Wentzel, 2009). However, there are specific ways peers can support academics within school; including providing information, resources, and support that occur through peer interactions within the network. In addition, research findings indicate that peers aid students in general school or class issues, class course-taking, and strategies on how to engage with others in the school environment (Cook, Deng, & Morgano, 2007; Crosnoe et al., 2003; Frank, Muller, Schiller, Riegle-Crumb, Strassman-Mueller, Crosnoe, & Pearson, 2008; Ryan, 2000). Specifically, peers have been shown to support academic achievement through aiding their affiliates in homework, class projects and study groups (Cook et al., 2007; Crosnoe et al., 2003; Kindermann, 2007). In addition, peers provide clarification, help with specific tasks, and offer general reassurance and support (Patrick, Hicks, & Ryan, 1997; Wentzel, 2009).

The relationship between peer affiliations within the school network and academic achievement has been theorized to be enhanced by a sense of school belonging, which is assessed through four components: attachment, commitment, involvement, and belief (Goodenow, 1993; Wentzel, 2009). Peer affiliates support academic achievement through these more indirect ways by providing emotional support and belonging within the school environment; specifically, building an attachment to school and academics (Goodenow, 1993; Patrick et al., 1997; Ryan, 2001). Research findings have indicated that peer relationships are necessary for a sense of school belonging (Hamm & Faircloth, 2005). School belonging can lead to an increase in academic motivation and engagement whereas a lack of school belonging can lead to alienation, failure, and dropout (Osterman, 2000). Thus, peer relationships can provide emotional support and belonging, thereby leading to higher academic engagement and achievement (Hamm & Faircloth, 2005; Wentzel, 2003).

Peers have also been found to articulate and display behaviors that run counter to achievement and to endorse norms that oppose achievement (Juvonen & Murdoch, 1995). Recent research has indicated that these norms tend to be localized within segments in the network. Peer groups, which are self-selected groups of individuals who interact with one another, have been found to share distinct within-group norms that vary in their support for or rejection of academic achievement (Hamm, Schmid, Farmer, & Locke, 2011; Juvonen & Murdoch, 1995). Norms that oppose academic achievement can lead students to disengage from the academic process, leading to declines in academic achievement (Hamm et al., 2011; Juvonen & Murdoch, 1995; Kindermann, 2007). This indicates that the roles of peer selection and influence can lead to different academic outcomes, based on the norms and resulting practices that individuals and their affiliates endorse.

Methodologies of Examining Peer Selection and Influence

Researchers have been interested in understanding peer influence processes among adolescents for over forty years (Kandel, 1978). Earlier studies were limited in their capacity to distinguish processes of selection and influence because they were designed as cross-sectional studies that could not examine changes in relationships across time (Billy & Urdy, 1985; Bauman & Fisher, 1986; Cohen, 1977). Specifically, cross-sectional and short-term longitudinal studies do not provide any information about affiliation formation, maintenance, and discontinuation. Thus, an accurate measure of selection was not available because formation was not assessed. These studies overestimated peer influence because they could not take these selection effects into account; therefore, peer homophily was explained as a function of only peer influence. Additionally, concurrent data on both peer affiliations and behaviors do not allow for a temporal understanding of what comes first: the peer affiliation or the behavior. Thus, the cause of the behavior cannot be ascertained, only behavioral similarity among affiliates can be measured, because the temporal ordering of effects cannot be assessed. In summary, early studies provided information about peer homophily across different behaviors, but could not examine the roles of peer selection and influence processes in these behaviors.

Researchers have worked to overcome some of the shortcomings in earlier works by collecting information on individuals and their affiliates across time. In addition, these studies have begun to analyze data at the relationship level rather than the individual level. Studies have been focused on two types of relationships: friendship dyads (Cohen, 1983; Hallinan & Williams, 1990; Kandel, 1978; Kiuru, Salmela-Aro, Nurmi, Zettergren, Andersson, & Bergman, 2012; Popp, Laursen, Kerr, Stattin, & Burk, 2008) and peer groups (Cohen, 1977; Ennett, Bauman, Hussong, Faris, Foshee, & Cai, 2006; Kindermann, 2007; Ryan, 2001). There are a number of advantages to analyzing dyads and peer groups, rather than individuals, to determine the roles of selection and influence. Analyzing behaviors at the relationship level allows the researcher to model interdependencies between individuals, allowing for a more accurate representation of similarities found across individuals and within dyads or peer groups. Stated another way, similarities are expected to occur in dyads and groups more often than they would occur by chance. Through including network interdependencies, homophily among individuals that are affiliated can be more accurately examined.

Studies of friendship dyads and peer groups improved on earlier studies' shortcomings by using longitudinal data and incorporating the relationship between individuals in their analyses. However, problems remained that led to an imprecise parsing of peer selection and peer influence in understanding homophily (Kandel, 1996). Specifically, dyadic and peer group studies do not control for network structural characteristics (Veenstra & Steglich, 2012), which means that these studies do not fully account for the role that the overall peer context plays in homophily. Importantly, studies of dyads and peer groups include individuals and their selection of affiliates; however, these studies do not include individuals who are not affiliated with one another. This artificial limitation of affiliation choice restricts understanding of how the selection process works, potentially leading to an inaccurate estimation of homophily through selection effects. By including all members of the network, researchers can model network structural characteristics such as density, reciprocity, transitivity and hierarchy, which allow for a more precise understanding of peer selection and peer influence, after controlling for similarity within the entire network context (Snijders, 2011). If network structural characteristics are not taken into consideration, all peer affiliations across the network have the same probability of occurring over time. Network structural characteristics can indicate affiliations that are more likely to occur, due to tendencies such as reciprocity or transitivity. Thus, better understanding of the patterns of peer affiliation can only occur when network structural characteristics are included in the model. The proposed study attempts to overcome the limitations of these earlier methods by taking into account network dependencies across time through the inclusion of network structural characteristics when assessing peer affiliations and academic achievement.

It is still unclear the extent to which the independent yet interrelated processes of selection and influence play in peer affiliate homophily in academic achievement. Peer influence on behaviors have been studied in many ways across time, but a significant confound in many past studies is the role of selection in homophily. In order to accurately measure the processes of peer selection and influence, complete network and behavior data, collected longitudinally and assessed in a social network framework is needed. Selection and influence occur in a temporal order and to examine the selection processes in relationship formations, individuals' behavior must be assessed prior to the beginning of the affiliations. To accurately determine the process of peer influence, studies must control for peer homophily in the selection process before again assessing behavioral similarities among peer affiliates. Finally, network studies must be conducted so that the interdependence of the affiliations across the network can be addressed. All potential peer affiliates are not the same; some are more likely to occur due to the overall structure of the peer network. Only through including all of these elements can an accurate examination of the processes of selection and influence on peer homophily in academic achievement be assessed.

Stochastic Actor Models

Stochastic actor modeling is a technique designed to analyze peer affiliations within networks across time, using both network structural characteristics and individual characteristics derived from network analysis, to examine changes in both affiliations and behaviors. Stochastic actor models allow for the analysis of both network affiliations and behaviors within a single model, allowing for the examination of the independent contributions of peer selection and peer influence. By including changes in affiliations across time, selection effects can be assessed for similarities in behaviors prior to affiliation. In addition, influence effects can be assessed through changes in the behavior over time, after network selection has been determined. Focusing on a single component of the model, without controlling for the other model components, leads to a partial understanding of the processes of selection and influence. By including network and individual characteristics focused on understanding the co-evolution of network affiliations and behaviors, a more precise parsing of selection and influence can be attained. In addition, stochastic actor models can be used to determine when and for whom processes of selection and influence occur by examining interactions between individual demographic characteristics and individual characteristics derived from network analysis and how they relate to patterns of affiliation and behavior.

An example of a stochastic actor model is called the Simulation Investigation for Empirical Network Analysis (Siena; Snijders et al., 2007) which is used in the current study. Siena models refine the examination of selection and influence through the use of complete network data, including all network members, collected longitudinally at two or more time points. Thus, Siena modeling techniques control for the network dependencies, leading to more precise assessments of peer affiliations across time. Additionally, the models allow for the inclusion of network structural characteristics, individual characteristics derived through network analysis, and other individual characteristics to address both overall network changes and individual differences within the network (Snijders et al., 2010). Siena models include the simultaneous assessment of network affiliations and behaviors, which allow researchers to independently determine the effects of peer selection and peer influence, controlling for the other. In addition, statistical effects can be calculated in Siena, which allows for hypothesis testing of overall network characteristics, differences in individual characteristics, the effects of selection and influence, and the moderation of selection and influence (Ripley et al., 2014).

Like any methodological or statistical technique, stochastic actor modeling includes assumptions about the modeling process and data; specifically, regarding the nature of time, and the natures of network and behavior change. The Siena modeling technique assumes time to be continuous; even though the data are collected at discrete time points. This means that during the modeling simulation processes, peer affiliations within the network can be formed or disbanded at any time. Analytically, this means that a continuous co-evolving simulation of affiliations and behavior is conducted to estimate changes between each discrete time period (Snijders, 2011). Therefore, the modeling process simulates the changing patterns of affiliations and behaviors in continuous time to determine the ordering of changes in both affiliations and behaviors. To determine the selection and influence effects on homophily, it is necessary to determine the ordering of peer affiliations and behaviors. If affiliates are similar on the behavior prior to affiliation, this indicates a selection effect. If affiliates become more similar on a behavior after their affiliation, that indicates an influence effect.

Siena modeling involves assumptions about the nature of individuals in the network, specifically, how peer affiliations and behaviors change. First, the modeling technique includes the assumption that individuals control and choose their own affiliations within the network, indicating a rational choice model of peer selection (Snijders, 2013). Additionally, within the simulation, individuals cannot simultaneously change both their affiliations and their behavior; rather, only one choice can be made at a time. This means that two individuals cannot jointly determine a relationship; rather, one individual first selects the other, and then the affiliation can be reciprocated. In addition, a single individual cannot change an affiliation and a behavior at the same time, one must follow the other. Siena's algorithms have been designed so that only one decision, called a *microstep*, is made at a time by each individual within the simulated space (Snijders et al., 2010; Steglich et al., 2010). This is an important assumption for parsing peer selection and peer influence; each step has been reduced to a single individual choice on affiliation or behavior, and the resulting pattern of choices can help determine the temporal ordering necessary for understanding changes in peer affiliations and behaviors.

Based on these assumptions about the nature of time, network, and behavior changes, two functions are used to construct the model: the *rate* and *objective* functions. When assessing the co-evolution of peer affiliations within a network and changes in a behavior, two rate and two objective functions are created: one for assessing changes in peer affiliations, and one for assessing changes in behaviors. Each individual's opportunity for change is defined through the *rate function*. The rate function is the overall network opportunity to make a change, whereby individuals have an opportunity to change either their peer affiliations or behaviors. The rate function does not determine whether or not a change is made in peer affiliations or behaviors;

rather, it only provides an opportunity for change. Higher rate functions indicate more opportunities to change compared to lower rate functions. The *objective function* is the probability that individuals change either their peer affiliations or behaviors, based on the network structural characteristics, individual characteristics derived from network analyses and other demographic characteristics and behaviors. Therefore, after having had the possibility to make a change based on the rate function, the objective function determines when changes are actually made. Stated another way, the objective function determines the probabilities of changes in the overall network, given that each individual has an opportunity to make a change.

In order to model network and behavior change over time, longitudinal data on both peer affiliations and behaviors must be collected. Three main criteria are necessary to execute a Siena model: an adequate number of individuals in with the network, time points, and changes between time points. Using simulation data, researchers have determined that stochastic actor modeling processes can be used for networks varying in size from approximately 20 individuals to several hundred (Snijders et al., 2010). More individuals in the network allow for more possible changes in both peer affiliations and behaviors between time points, which can lead to more explanatory power. However, too many individuals in a single network can be a problem. The Siena theoretical framework assumes that each and every individual could be affiliated to every other individual in the network and this premise becomes untenable if the network is too large.

In addition to the requirements regarding the number of individuals, peer network data and behavior data must be collected longitudinally for at least two time points and no more than ten time points (Snijders et al., 2010). The modeling process assumes time homogeneity in the peer network and behaviors, and tests for this assumption are part of the model (Lospinoso, Schweinberger, Snijders, & Ripley, 2011). For researchers using Siena, the concern is if these differences across time exist and are not accounted for, that the true selection and influence parameters can not be estimated. However, if the Siena time test indicates that there are differences in the number of affiliations or large differences in network parameters found across time, dummy variables can be constructed to account for those differences. In addition network stability that is measured in the time test, there also needs to be changes in affiliations and behaviors across time so that effective modeling is possible. Changes in the networks and behaviors provide the researcher with more information about the nature of the affiliations and behaviors (Snijders et al., 2010). Stated another way, if a network is completely stable across time, there is no variability to be explained by changes in affiliations and how they relate to changes in behaviors. However, if the network is completely random, no predictions regarding the changes in affiliates and behaviors can be ascertained. Therefore, both stability and change must occur in the network and behavior across time.

Review of Studies using Siena

Stochastic actor modeling allows for the study of social networks and behaviors over time. This study uses stochastic actor modeling, specifically Siena, to model the co-evolution of peer affiliations and academic achievement over time (Snijders et al., 2007). Siena is a relatively new modeling procedure and has not been widely used in applied research projects; thus, I reviewed studies using Siena that assessed the co-evolution of peer networks and behaviors, focusing on academic achievement.

Two manuscripts reviewed focused on academic achievement: Flashman (2012) and Lomi, Snijders, Steglich and Torlo (2011) and are further examined for their applicability to this study. The Lomi et al. (2011) study focused on the selection and influence of peer affiliations on academic performance, using a sample of Italian MBA students. The authors looked at two different peer networks: friendship and advice-seeking about the program; and how it related to academic grades. Data were collected on networks and members' behaviors at three time points across a single calendar year while the students were in the MBA program. Both selection and influence parameters were assessed on both the friendship network and the advice-seeking network. The selection parameter, that is, the similarity in ability prior to peer selection for both the advice and friendship network was non-significant. The influence parameter, that is, the similarity in behaviors after controlling for peer selection for both networks was statistically significant and strongly positive (Lomi et al., 2011). Thus, these results would indicate that homophily in academic achievement is a function of peer influence, not peer selection.

However, the authors further probed the processes of selection and influence by academic achievement. They found that the selection processes, not influence, operated differently for different students, based on their achievement level. High ability students were less likely to select new peers over time; whereas, lower ability students were more likely to select new affiliates, especially for their advice networks. Thus, high achieving students were more likely to be selected as an affiliate for the advice-seeking network than to be selected as a friend (Lomi et al., 2011). In addition, homophily by academic achievement was found in the friendship network, with peers having similar achievement to their affiliates. Therefore, depending on the analysis, both selection and influence were found to play a role in changing networks and academic achievement, leading to a more nuanced understanding of these networks and their impact on academic achievement over time.

The Flashman (2012) article focused on the selection and influence of friendship networks and academic achievement, using a sample of eight small, rural K-12 schools. The study was designed to explore the extent to which homophily in academic achievement occurs within friendships. In addition, the author investigated how and to what extent selection and influence processes change peer friendships and academic achievement. To address these questions, the author first conducted a cross-sectional analysis of the data. This analysis did not assess network structural characteristics, or changes in affiliations within the network over time, or parse the temporal ordering of selection and influence. Using this method, Flashman (2012) found that students with higher GPAs were more likely to be nominated as a friend compared to individuals with lower GPAs. In addition, there was a homophily effect with high achieving friends being more likely to affiliate with others high achieving students.

However, when the same friendship networks across the eight schools were assessed longitudinally, using Siena, correcting for the shortcomings above, the results indicated that there was no relationship between network affiliations and academic achievement within six of the eight schools. Therefore, in these six schools, differences in affiliation were not found by GPA, and no differences by academic achievement occurred in the pattern of nominations. For the two schools that had significant effects, both selection and influence played significant roles (Flashman, 2012). Friendship homophily did not occur with regards to academic achievement; that is, high achieving students were no more likely to affiliate with other high achieving students than those with lower achievement status. In addition, the nomination structure did not differ for those who were high achieving students, compared to those who were less academically successful. The author interprets these findings to indicate that smaller schools in smaller communities are more egalitarian and that the friendship ties exist for reasons other than academic achievement (Flashman, 2012).

More generally within the literature that applies Siena, there was great variability in how the selection and influence parameters were constructed and interpreted. The most common approach included the a set of parameters on the *network objective function*, focused on changes in network affiliation; and a set of parameters on the *behavior objective function*, focused on changes in behavior. The *selection* parameter was derived within the network objective function and was defined as the similarity in behaviors. The *influence* parameter was derived from affiliates' similarities on the behavior and derived in the behavior objective function, after controlling for selection in the network objective function (see Baerveldt, Voelker, & VanRossem, 2008; Knecht, Burk, Wessie, & Steglich, 2011 for examples of this). In this study, I use this structure to organize my findings.

Many different behaviors have been assessed using Siena techniques and these findings have differed. Some behaviors appear to occur prior to selection of new peer affiliates, indicating a selection effect (e.g., smoking), whereas other behaviors (e.g., drinking and school-based motivations) appear to be influenced by peers (see Delay, Laursen, Kiuru, Nurmi, & Salmela-Aro, 2013; Kiuru, Burk, Larsen, Salmela-Aro, & Numi, 2010; Ojanen, Sijtsema, Hawley, & Little, 2010). However, other behaviors, such as delinquency, depression, and social anxiety, were found to have both selection and influence effects (see Baerveldt et al., 2008; Gileta, Burk, Scholte, Engels, & Prinstein, 2013; vanZalk, vanZalk, Kerr, & Stattin, 2011). These findings indicate differences in the processes of peer selection and influence, depending on the behavior being studied. This study demonstrates the processes of peer selection and peer influence on academic achievement, through independent and simultaneous assessment of peer affiliations and academic achievement from 7th to 9th grade.

Network Level Structural Characteristics

Network structural characteristics provide an overview of how individuals and their affiliates within the network interact as a cohesive and structural unit. Generally, taking the network context into account allow for a more precise understanding of individual changes across time (Snijders, 2011). Through understanding the overall network composition, researchers can better predict when and how affiliations change within the network. For example, in networks with higher reciprocity, there is a higher probability for bidirectional relationships than in networks with low reciprocity. Thus, network structural characteristics can be understood as an overall constraint to changes in affiliations and behaviors within the network. This section will focus on the literature that is relevant to the four key network structural characteristics: density, reciprocity, transitivity, and hierarchy.

Density is a measure of overall connectedness of individuals within the network. If everyone reported affiliations with all other affiliates, density would be 100%. However, in reality, density is usually quite low, with less than 20% of possible affiliations actually occurring (Snijders et al., 2010; Veenstra & Steglich, 2012). This indicates that individuals are selective with whom they affiliate. However, density may also be lower due to measurement decisions made regarding the data collection of peer relationships. Individuals might be asked to list all affiliations within a network, which is defined as unconstrained choice (Cillensen, 2009; Gest, Moody, & Rulison, 2007). Another strategy is to restrict individuals' nomination choices, prompting individuals to identify their top three affiliations (e.g., Coie, Dodge, & Coppotelli, 1982) or five affiliations (e.g., Gest et al., 2007). If peer nominations are constrained, the density parameter may also be artificially attenuated (Cillensen, 2009). For example, network density would never equal 100% if a constrained choice option is used because individuals do not have the opportunity to select all others. Therefore, networks defined as low density may occur organically, due to individuals' preferential selection processes, or because of measurement decisions, specifically, constrained choice procedures that only allow individuals to select a few affiliates. In this study, I use an unconstrained measurement process whereby all adolescents could select any and all others as affiliates. Thus, my estimates of density should be accurate, since choice is not artificially compressed.

Few studies have assessed how network density might relate to the patterns of affiliations and academic achievement. One study indicated that school-based adolescent network density had no direct relationship to academic achievement, but that the interaction between peer affiliates' academic achievement and network density had a strong relationship to academic achievement. Specifically, individuals within a highly dense network are more strongly influenced by peers than those in less dense networks (Maroulis & Gomez, 2008). However, this amplification effect may lead to either positive or negative outcomes in achievement. Thus, students with highly dense networks of high achieving peers were found to have higher GPAs, whereas students with highly dense networks of low achieving peers were found to have lower GPAs. Therefore, density can either help or hinder academic achievement outcomes, depending on the norms and practices of students' peer affiliates (Maroulis & Gomez, 2008; Rizzuto, LeDoux, & Hatala, 2009).

Reciprocity is the tendency for individuals to have bidirectional relationships between one another, that is, to reciprocate nominations of one another. Adolescent peer networks typically include many reciprocal affiliations across time (Veenstra & Steglich, 2012). Reciprocity also operates as a constraint on the affiliations within the network. For example, unreciprocated affiliations at an earlier time are likely to be reciprocated or discontinued by the next time point; unreciprocated affiliations, also known as asymmetric ties, are less likely to be maintained over time. Thus, if a network has a high level of reciprocity, asymmetric ties are less likely to occur or be maintained, compared to reciprocal ties.

Several researchers have focused on reciprocated friendships and academic achievement. Findings suggest that homophily in academic achievement among reciprocated dyads occurs from early adolescence to adulthood (Veronneau, Vitaro, Dishion, Brendgen, & Tremblay, 2010). Additionally, these effects appear to be far-reaching, with reciprocated best friends at age 14 having similar academic achievement and educational expectations at age 16, as well as similar educational attainment at age 26 (Kiuru et al., 2012). Thus, it appears that reciprocated relationships are especially pertinent for understanding both short-term and long-term network effects on academic achievement (Kiuru et al., 2012; Veronneau et al., 2010). Both selection and influence processes appear to account for dyadic academic homophily across time. Peers selected affiliates who were similar to themselves in intelligence, indicating that adolescents used selection processes that reflected an attraction to similarities in achievement. In addition, the dyads became increasingly similar in academic achievement across time, indicating peer influence effects (Kiuru et al., 2012). These findings indicate that there is a strong relationship between dyadic reciprocity and academic achievement; however, these studies did not examine broader peer networks. In this study, reciprocity is examined across the network and assesses how network reciprocity might account for homophily in academic achievement.

An extension of reciprocity is transitivity, where relationships between three or more individuals are assessed. *Transitivity* is defined as the extent to which an affiliate's nominated affiliate is also nominated as the individuals' affiliate (Holland & Leinhardt, 1977). Stated another way, positive transitivity scores indicate that individuals tend to affiliate with those who are also nominated by their affiliates. In adolescent peer networks, transitivity is expected to be positive, with more reciprocated triadic relationships found than expected (Ripley et al., 2014). Transitivity often operates as a network constraint, similarly to reciprocity, but including larger sets of affiliations. Ties between three individuals who have some set of reciprocal ties among them are more likely to become transitive than relationships between three unrelated individuals. No study has directly examined how transitivity might impact academic achievement within the peer network. I contend that transitivity is a significant network structural characteristic, over and above reciprocity, indicating that larger sets of connected affiliates are more homophilous in terms of academic achievement than unconnected individuals within the network; and that both the affiliations and behaviors strengthen over time.

A final network structural characteristic that is assessed in the study is *hierarchy*, defined as an arrangement in which individuals are ranked above or below others in some ordered manner.

Adolescents' peer networks vary in their amount of hierarchy, with some networks being fully egalitarian and decentralized, and other peer networks are strongly hierarchical and centralized (Gest, Davidson, Rulison, Moody, & Welch, 2007; Rodkin & Ahn, 2009; Wilson, Karimpour, & Rodkin, 2011). Research findings suggest that highly hierarchical networks are more likely to include individuals with higher rates of aggression, and are less likely to include individuals who are academically successful (Rodkin & Ahn, 2009; Wilson et al., 2011). However, these studies only assessed hierarchy in smaller contexts, such as dyads and peer groups, not networks. In addition, although these studies included network hierarchy other network characteristics (e.g., density, reciprocity) were not assessed; thereby, the unique contribution of hierarchy on the network may be misstated. Finally, it is unclear how stable hierarchy is across the network over time and what impact that stability or instability has on achievement. This study assesses hierarchy in the network, across time, and what effects, if any, that it has on academic achievement.

Individual Characteristics

To more precisely understand the processes of peer selection and peer influence, it is necessary to assess not only the overall network structural effects but also differences between individuals in the network. Individuals within the network differ in the affiliations that they have with others; some have many affiliates, where others have fewer relationships. The individual characteristics that pertain to the nature of affiliative patterns within the network in this study are: popularity, activity and assortativity.

Across studies, popularity has been conceptualized and defined in different ways. For instance, indicators of popularity have encompassed behavioral components, such as being well-liked (Wentzel & Caldwell, 1997), or being perceived as cool (Troop-Gordon, Viscounti, & Kuntz, 2011). Individuals who are well-liked are typically prosocial and would be categorized as sociometric popular; whereas, individuals who are cool, deviant and disruptive would be categorized as perceived popular (Cillessen, Schwartz, & Mayeux, 2011). These differences in definitions have likely contributed to differential findings in terms of how popularity is related to academic achievement. In the proposed study, *popularity* is defined by the number of peer affiliations received, as well as the ability to attract more affiliations over time, due to this popular status (Ripley et al., 2014). Stated differently, popularity is not focused on differences in behavioral characteristics, rather, it examines differences in the number of affiliations received across the network. Therefore, in the proposed study, popularity is a measure of network affiliative prominence that might contain both behavioral elements of likeability and coolness.

Several studies have explored the relationship between these descriptive forms of popularity and academic achievement; however, differences in the definition of popularity have led to different findings on academic achievement across adolescence. Using the well-liked definition of popularity, many studies have found an association between being popular and having higher academic achievement (Kindermann, 2007; Wentzel & Asher, 1995; Wentzel & Caldwell, 1997). However, in other studies using the same definition, no relationships were found between popularity and academic achievement (Schwartz, Gorman, Nakamato, & McKay, 2006; Wentzel, 2003). Using the definition of popularity focused on being cool, studies found that being popular was associated with poorer academic achievement outcomes (Farmer, Irvin, Leung, Hall, Hutchins, & McDonough, 2010; Killeya-Jones, Costanzo, Malone, Quinlan, & Miller-Johnson, 2007; Troop-Gordon et al., 2011). In addition, the opposite of popularity (e.g., “unpopular”) was found to be associated with higher GPAs throughout early adolescence (Bellemore, 2011). Thus, different measures for popularity have different relationships with academic achievement.

Activity is defined by the number of peer affiliations solicited of others. Individuals who are more active in the network solicit more affiliations in the network compared to less active individuals. Activity is also conceptualized as self-reinforcing across time, with individuals soliciting affiliations based on their previous activity status (Ripley et al., 2014). Therefore, the parameters for popularity and activity are the inverse of one another; with popularity focused on the affiliations received by others, and activity focused on the affiliations solicited to others. There has been little study in the relationship between activity and academic achievement. It may be that individuals who perceive many connections to others (e.g., a high activity score) will feel more integrated into the school and, therefore, be more academically adjusted. However, these connections have not been determined yet in the literature. This study examines the role that activity has on both the development of peer affiliations and its relation to academic achievement over time.

Assortativity is a measure of homophily, which indicates an individuals' tendency to affiliate with others who have a similar popularity or activity status (Snijders et al., 2010). Therefore, assortativity indicates the extent to which individuals share similar popular and/or active levels. Research on early adolescents has indicated that popular students, defined as either likeable, or cool, or having high number of affiliates, tend to affiliate with one another (Farmer et al., 2010; Flashman, 2012; Wentzel, 2003). However, the extent to which assortativity is found among students with similar activity level is unknown. In the current study, assortativity is expected on both popularity and activity status, but the extent to which assortativity is related to academic achievement is unknown.

In addition to the individual characteristics derived from network analysis, individual differences in peer affiliations and academic achievement have been examined by gender and race. Broadly speaking, peer affiliations throughout childhood and adolescence are typically homogeneous with regards to gender and race (Maccoby, 1998; McPherson et al., 2001; Shrum et al., 1988). However, in many schooling networks, peer homogeneity may be due to a lack of demographic variability (Epstein, 1989). In the current study, I expect peer affiliate homophily within the network in regards to gender and race. However, since the school from which the proposed sample is taken is equally mixed by gender and race, I anticipate that there will be some heterogeneity in these affiliations.

Differences in academic achievement by gender and race have also been studied. Typically, girls have been found to have higher school engagement and motivation compared to boys, although these findings do not always translate to gender differences in GPA (Cairns & Cairns, 1994; Kindermann, 2007; Ryan, 2001). In addition, there is a long-standing and persistent academic achievement gap within the United States, with African American students consistently scoring lower on achievement tests compared to their European American counterparts (Allen, Hombo, & Stoeckel, 2005; Goza & Ryabov, 2009). In this study, similarities of affiliates in terms of gender and race will be assessed, as well as differences in academic achievement by gender and race. More importantly, the processes of peer selection and influence will be examined by gender and race to determine if different selection and influence operate differently for different demographic groups.

Peer relationships tend to be homophilous with respect to gender, with long-standing finding of gender segregation within dyads and peer groups (Maccoby, 1998; McPherson et al., 2001). Preferences to affiliate with the same gender starts early, with young children identifying gender differences and selecting affiliates based on that demographic characteristic, making same-gender relationships normative for most of childhood and into adolescence (McPherson et al., 2001). Gender homophily has been examined in several stochastic actor model studies with respect to different behaviors. Findings have indicated that selection and influence processes may operate differently for girls and boys across many behaviors. For example, boys are more likely than girls to select peers based on their aggressive behaviors, and to be more susceptible to peer influence to engage in aggressive behaviors (Burk et al., 2008; Dijkstra et al., 2011; Veenstra & Dijkstra, 2012). Another set of studies found gender difference in peer selection and influence differences that were associated with difference in the rates of depression and social anxiety. Girls, rather than boys, were more susceptible to peers' influence on depression and social anxiety, with an intensification of those behaviors when girls interacted with others who have a shared pattern of depression and anxiety (Brechwald & Prinstein, 2011; VanZalk et al., 2011). No study has examined how different patterns of peer selection and influence might exist by gender with regards to differences academic achievement.

Another often studied source of peer relationship homophily is race; with research findings indicating that a high level of racial homogeneity found in peer networks across the life course (Goza & Ryabov, 2009; Hamm, 2000; McPherson et al., 2001; Shrum et al., 1998). Racial homophily may occur, in part, from the traditional segregation of the school setting (Coleman, 1961; Goza & Ryabov, 2009; Hamm, Brown, & Heck, 2005; Moody, 2001). However, even with desegregation strategies, schools may remain relatively homogeneous due to tracking policies, which likely contributes to racial homophily in adolescents' peer relationships (Moody, 2001). Race and ethnicity have been examined in a few stochastic actor modeling studies and the results replicate the prior findings that showed racial and ethnic homophily among affiliates (Baerveldt et al., 2008; Knecht et al., 2011; Mercken, Snijders, Steglich, & deVries, 2009). These studies examined European samples and it is unclear whether being a minority in Europe is comparable to being a minority in the United States.

It is further unknown whether the processes of peer selection and peer influence operate similarly for different racial and ethnic groups. For example, the results of some studies suggest that African American students may be more dissimilar to their peers in academic achievement compared to their European American counterparts; which may indicate a different selection effect (Gutman, Sameroff, & Eccles, 2002; Hamm, 2000). In this study, I examine racial homophily among peer affiliates to determine if and what relation it has to differences in academic achievement. Finally, I examine the roles of peer selection and influence on academic achievement and how these processes might differ based on one's racial group.

Current Study

This study addresses changes in students' peer affiliations and academic achievement within a school-based network, from 7th grade to 9th grade. As part of this study, I examine the co-evolution of changes in peer affiliation and academic achievement, including network structural characteristics (i.e., density, reciprocity, transitivity, and hierarchy), and individual characteristics derived from network analysis (i.e., popularity, activity, and assortativity). In addition, individual demographic characteristics (i.e., gender and race) are assessed to determine if there are systematic differences in network affiliation patterns, academic achievement, or both constructs, based on race and gender. Specifically, this study will focus on the co-evolution and mutual change in both peer network affiliations and academic achievement across this time period from middle school into high school. By modeling both peer network affiliations and achievement behavior simultaneously, selection and influence processes can be independently examined. In the current study, I estimate a model that incorporates both selection and influence. By assessing the similarity in academic achievement within the network objective functions, I am measuring the selection process, independently of influence. Likewise, by assessing the similarities of peer affiliates' academic achievement within the behavior objective function, I measure peer influence, controlling for selection processes. Taken together, findings from the current study contribute to a greater understanding of how school-based peer affiliations operate; specifically, how the processes of peer selection and peer influence contribute to changes in academic achievement during adolescence.

The use of stochastic actor modeling allows me to analyze differences between peer selection and peer influence independently of the other. Specifically, I can determine the extent to which changes in peer affiliations across the network lead to changes over time in academic achievement; and, correspondingly, how changes in academic achievement lead to changes over time in peer affiliation. In addition, I examine which network and individual characteristics are important for understanding these changes, and, specifically, when and for whom are they most salient. Six research questions address these issues; the first three research questions focus only on the analysis of peer affiliations across time; while the final three research questions analyze the co-evolving changes in peer affiliation networks and academic achievement.

1) What is the nature of changes to adolescents' affiliative patterns within the grade-level peer network from 7th to 9th grade?

This research question focuses on changes in peer affiliations across time, assessing when new affiliations occur, established affiliations continue, and other affiliations are discontinued within the network (Snijders et al., 2010). Multiple parameters are used to assess the change and stability in affiliations across time (e.g., Moran's *I*, Jaccard index,). The *rate function* has been conceptualized as the "waiting time" for each individual before they have the opportunity to make an affiliation change (Steglich et al., 2010). Rates of change are dependent on network structural characteristics and individual characteristics. Although no specific hypotheses are derived to address the predicted rate change in affiliations, based on previous research (e.g., Lansford, Killeya-Jones, Miller, & Costanzo, 2009; Neckerman, 1996; Schmid, 2009), I anticipate that there will be a moderate change in peer affiliations across time, indicating that a significant proportion of relationships established are maintained.

2) To what extent and in what ways do network structural characteristics, such as density, reciprocity, transitivity and hierarchy, alter affiliative patterns within networks from 7th to 9th grade?

Four network structural characteristics are essential for understanding adolescent peer networks: density, reciprocity, transitivity, and hierarchy. Although there are network structural parameter findings that I anticipate (e.g., reciprocity will be strongly positive), no formal hypotheses are advanced. Rather, the network structural characteristics are best viewed as constraints or boundaries within which individuals interact and behaviors change. For example, if two unrelated affiliates are connected to many similar others, they are more likely to become affiliated. Thus, network structural characteristics describe the overall network context, the network boundaries and rules for changes in peer affiliations.

Density is the overall interconnectedness of affiliations across the network. Based on other research using stochastic actor modeling, the density parameter is expected to be negative (Burk et al., 2008; Veenstra & Steglich, 2012), indicating that most individuals only select a few affiliates. *Reciprocity* is the tendency for individuals to have bidirectional relations between one another; that is, to select one another as affiliates. As with other studies, reciprocity is expected to be positive, with most adolescents reporting reciprocal affiliations to one another (Veenstra & Steglich, 2012). An extension of the dyadic relationship reciprocity is *transitivity*, where the relationships between three or more individuals are assessed. Several different methods have been derived to assess network transitivity. In this study, all transitivity parameters are expected to be positive; that is, complete triads will be found more often in the network than expected by chance (Ripley et al., 2014). *Hierarchy* reflects the extent to which some individuals are ranked above others in an ordered manner across the network (Wasserman & Faust, 1994). Research on adolescents show some hierarchy in their networks (Gest, Davidson, et al., 2007; Wilson et al., 2011). The three-cycle indicator assesses how close the peer network is to complete reciprocity between each actor in the network, with a negative parameter indicating hierarchy (Ripley et al., 2014). In this study, some network hierarchy is expected; therefore, the three-cycle parameter is expected to be negative.

3) To what extent and in what ways do individual characteristics derived from network analysis (i.e., popularity, activity, and assortativity) and individual demographic characteristics (i.e., gender and race) change the peer affiliation network from 7th to 9th grade?

Unlike the earlier research questions, I propose specific hypotheses regarding the individual characteristics derived from network analysis and demographic characteristics. Moreover, analyses designed to test these hypotheses control for the network structural characteristics already defined. It is important to determine when and how individuals differ in their patterns of affiliations. *Popularity* is based on the individuals' ability to attract more affiliations due to their popular status (Ripley et al., 2014). *Activity* is based on the individuals' propensity to select affiliates and solicit affiliates based on their activity status (Ripley et al., 2014). Both the popularity and activity parameters are expected to be positive, indicating that both behaviors are reinforcing over time. *Assortativity* is based on individuals' tendency to affiliate with others who have similar popular and activity status (Ripley et al., 2014).

Gender and race are also used to assess differences in choices of affiliates among individuals. In the current study, gender and race are analyzed to determine if and when individuals affiliate with those of the same race and gender. The *homophily* effect assesses whether individuals are more likely to affiliate with others who share the same demographic characteristics; in this study, gender and racial homophily. Based on prior research findings (i.e., Maccoby, 1998; McPherson et al., 2001) both gender and race are expected to have a homophily effect, with those individuals with the same gender and race more likely to affiliate with each other.

H3.1: Popular (and active) adolescents are more likely to associate with others who are popular (and active).

H3.2: Adolescents will affiliate with others who share their gender and racial demographic characteristics.

4) To what extent and in what ways do selection and influence account for the co-evolution of changes to peer affiliations within the network and academic achievement across 7th grade to 9th grade?

This research question focuses on the simultaneous changes in peer affiliations and academic achievement within the network. Both peer affiliative networks and behaviors can determine changes in affiliations and academic achievement; thus, there is a mutual dependence in these constructs across time. To model changes in both peer affiliations within a network and members' academic achievement simultaneously, the procedures used in the earlier research questions are expanded to include academic achievement. Thus, there will be two rate and objective functions; one to explain the peer affiliations within the network (i.e., network functions) and one to explain academic achievement (i.e., behavior functions).

When using these modeling techniques, there are two shape parameters that define the basic behavioral objective function: linear and quadratic (Steglich et al., 2010). The *linear* effect describes linear growth in the behavior over time (Ripley et al., 2014). An example of a positive linear effect would be alcohol use across adolescence, where use is lower at the beginning and becomes more normative across the network over time. Overall network changes in academic achievement are not expected; that is, the average GPA across the grade-based network is not expected to systematically rise or fall. The *quadratic* shape effect assesses the extent to which individual changes in behavior continue over time; that is, if they are self-reinforcing (Ripley et al., 2014). For this study, it is anticipated that the quadratic parameter will be positive; indicating individuals' changes in academic achievement over time will be self-reinforcing (Cook et al., 2007).

5) To what extent and in what ways do individual characteristics derived from network analyses and demographic characteristics of adolescents influence academic achievement?

This research question focuses on the simultaneous changes in affiliations and academic achievement, controlling for all characteristics defined in the network function, as well as the systematic academic achievement effects (i.e., shape parameters) within the behavior function, while introducing individual characteristics derived from network analysis and individual demographic characteristics to the behavior function. The *popularity behavior* effect assesses the relationship between popularity status and academic achievement, with a positive effect indicating that popular individuals also have higher grades (Steglich et al., 2010). The *activity behavior* effect assesses the relationship between activity status and academic achievement, with a positive effect indicating that those with higher activity scores also have higher grades (Steglich et al., 2010). I contend that activity may be a proxy for engagement in the network; with a higher activity status indicating a greater perceived sense of belonging in the network (Goodenow, 1993). In this study, I postulate both a positive popularity behavior effect and a positive activity behavior effect, indicating that individuals with higher statuses also have higher grades.

In addition to assessing popularity and activity, individual demographic characteristics are examined in relation to changes in affiliations and academic achievement over time. Past research has indicated that adolescent girls will have higher grades compared to boys (Kindermann, 2007; Ryan, 2001) and that adolescent European American students will have higher grades than African American students (Allen et al., 2005; Goza & Ryabov, 2009). Although hypotheses have not been generated for these models, the results for these demographics are addressed in the findings.

H5.1: There will be a positive relationship between popularity (activity) and academic achievement across the network and time; that is, more popular (active) individuals are expected to have higher grades compared to less popular (active) students.

6) To what extent and in what ways do these individual characteristics (i.e., gender and race) moderate the relationships between peer selection and peer influence, and academic achievement from 7th to 9th grade?

Peer selection is a process whereby similar affiliates come together on the basis of those attributes (Byrne & Griffitt, 1966; Kandel, 1978). Therefore, similarities between individuals occur prior to the affiliation process; thus, selection is part of the network objective function, not the behavior process. Stated another way, selection is associated with the decisions made about peer affiliations in the network but not part of understanding the change in behaviors. The selection effect, defined through the similarities found in grades in the network objective function, are hypothesized to be positive, indicating that those with similar academic achievement are more likely to affiliate with one another.

Prior studies have shown that affiliate selection differs by gender and race (McPherson et al., 2001; Veenstra & Dijkstra, 2012). Specifically, girls are more likely to affiliate with others girls and boys are more likely to affiliate with other boys. Similarly, African American students are more likely to affiliate with other African American students while European American students are more likely to affiliate with other European American students. If girls have higher grades compared to boys and girls are more likely to select other girls as peer affiliates, then it is expected that the homophily in achievement by gender will be found, with girls having higher grades. Additionally, if African American students have lower grades compared to European American students and African American students are more likely to select other African American students as affiliates, then it is expected that the similarities in achievement by race will be found, with African American students having lower grades.

Peer influence occurs after affiliations have been established, through the direct and indirect attitudes and interactions that support or hinder academic achievement. Therefore, peer influence is measured as part of the behavior objective function, defined as affiliates' similarities on academic achievement. Stated differently, peer influence is measured as the relative strength between individuals' affiliate behaviors compared to one's own behavior (Ripley et al., 2014). In this study, influence is expected to be positive, with peer affiliates' grades similar to the grades of the individuals who affiliate with those peers (Cook et al., 2007; Crosnoe et al., 2003).

Peer influence has been theorized and empirically found to be moderated by individual demographic characteristics, such as gender and race. For example, boys are more susceptible to peer influence that leads them to act out in more aggressive ways and to engage in delinquent activities (Baerveldt et al., 2008; Burk et al., 2008). In addition, girls have been found to be more susceptible to peer influences regarding depression and anxiety, leading girls to manifest more internalizing symptoms across time (VanZalk et al., 2010; VanZalk et al., 2011). Currently in the literature, there is no suggested pattern of differences due to peer influence on academic achievement by gender or race; therefore, no specific hypotheses are undertaken. However, results are addressed and interpreted in the findings.

H6.1: Selection processes will be positive, indicating that individuals affiliate with others who have similar grades to themselves.

H6.2: Influence processes will be positive, indicating the individuals become more similar to their affiliates over time.

METHODS

As part of a longitudinal intervention study, data were collected from students in an urban North Carolina magnet school that served 6th to 12th grade (North Carolina Department of Public Instruction (NCDPI), 2007). The intervention study involved the implementation of a peer leadership-based program designed to convince peer group leaders to deliver anti-drug messages to their peers (Golonka, Peairs, Grimes, & Costanzo, 2007). This study included data from the control sample that was collected in the year prior to the intervention implementation. All students in the 7th grade were invited to participate, and data collection included 4 time points following participants from 7th to 9th grade. Peer network affiliations, student characteristics, and academic achievement were assessed on each consented student at each time point. Time 1 data collection occurred in the Fall of 7th grade, time 2 data collection occurred in the Spring of 7th grade, Time 3 data collection occurred in the Fall of 8th grade, and time 4 data collection occurred in the Fall of 9th grade.

School Characteristics

Participants in the sample attended a magnet school for grades 6 through 12 in a midsize city in the southeast United States, as designated by the National Center for Education Statistics (NCES)[1]. The entire 6 to12 grade school's student body during the first year of data collection was 1,412 students, with a teacher / student ratio of 15.02 students for each teacher (NCDPI, 2007). During the same time frame, there were 203 students in the 7th grade and all were recruited to be part of this study. The NCES data indicated that, for the year of initial participation in the study, 58% of the students in the school were at grade level for reading, and 75% of students were at

[1] Locale 12 being defined as "Within a Mid-size City" (U.S. Department of Education, 2007)

grade level for mathematics (U.S. Department of Education, 2007). This was significantly higher than the overall district, for which 41% of the students were at grade level for reading and 56% of students were at grade level for mathematics (U.S. Department of Education, 2007). Additionally, the participating school had fewer students who were eligible for free / reduced lunch, compared to the district average (38% vs. 62%, NCDPI, 2007). Therefore, this school may be different from the rest of the district in terms of student academic achievement and family income, which may make it difficult to generalize these findings to the entire district.

Participants

One hundred sixty-eight students were consented and completed the 7th grade survey. Specifically, the rate of consent across time was: 83% at Time 1, 84% at Time 2, 81% at Time 3, and 63% at Time 4.[2] The sample was balanced in terms of gender, with 51% of the sample self-identifying as female. The sample was racially diverse, with comparable proportions of African American (42%) and European American (41%) students, as identified through student self-report.

Procedures

At each time point, paper-and-pencil surveys were administered to students during two 50-minute class periods during science class. Students were reminded that their answers were confidential, that they could omit any questions they were not comfortable answering, and that they could stop at any time. The teachers remained in the room during the survey administration but were not involved in the survey. Students received $5 for the completion of the survey at each time point.

[2] The response rate drops at Time 4 after a transition from middle school to high school where many of the students decided to leave to go to another high school.

Measures

The measures included in this study were part of a larger assessment battery. Measures assessed individual characteristics, peer network affiliations, and academic achievement. To construct the network, students were asked who they affiliated with. In addition, data were collected on student's demographics, peer behavior nominations, and administrative data on curriculum grades and end-of-grade (EOG) tests.

Demographics. Students were asked to report on their self-identified gender and race. Within the analysis, participants' gender was dummy coded, with female students as the reference group. Two different dummy codes for race were constructed, one with being African American as the reference group, and one with being European American as the reference group.

Peer behavior nominations. Students were provided with a roster of all possible affiliates in their current grade and asked to make unlimited nominations of peers who fit various behavioral descriptors. Overt aggression was based on nominations for the descriptor, "fight a lot, hit others, or say mean things to them". Prosocial leadership was comprised of the item, "are leaders and good to have in charge". Deviant leadership was based on the descriptor, "good at getting others to break the rules". For each item, the number of nominations a student received was converted into a standardized *z* score, where zero was the mean score on the attribute, a negative number indicated lower than average attribute levels and a positive number indicated higher than average levels on the attribute (DeRosier & Thomas, 2003).

Peer network affiliations. Peer affiliations within the network across time were derived from the sociometric nomination prompt, "Who do you hang around with?" (Miller-Johnson, Costanzo, Coie, Rose, Browne, & Johnson, 2003) A roster list of all students in the grade was listed below the prompt. Students could select any other students in the grade, whether they were consented to participate in the survey or not. A matrix of peer affiliations at each time point was constructed from each individual's pattern of affiliations derived from the sociometric prompt. The matrix included rows, representing all individuals in the network; and columns, representing all possible affiliates within the network. Each cell of the matrix described the relationship between the individual and possible affiliates; a 0 indicated no relationship and a 1 indicated an affiliation. The affiliation matrix was used as the basis of the peer network analyzed as part of this study using stochastic actor modeling procedures. In addition, this matrix was used to derive the network structural characteristics and individual characteristics derived from network analysis.

Academic achievement. School administrative data were collected on each consented students at the end of 6th, 7th, 8th, and 9th grades. Curricular grades in language arts, math, science and social studies were summed together to constitute a total grade score. The stochastic actor modeling approach requires the dependent variable to be discrete (Snijders et al., 2010). Following procedures established in studies of networks and academic achievement, a single grade variable for each time point was created, with five categories (Flashman, 2012). First, curricular grades across the four academic content areas were summed, so that maximum variability between scores could be ascertained. The sum scores could range from 0 (0% for all 4 academic courses) to 400 (100% in all 4 courses). For Grade 6, 107 (64%) of the sample's grades were available, with a summed grade score of 341.00 (*SD* = 38.57). For Grade 7, 161 (96%) of the sample's grades were available, with a summed grade score of 338.21 (*SD* = 39.72). For Grade 8, 144 (85%) of the sample's grades were available with a summed grade score of 340.84 (*SD* = 37.45). Finally, for Grade 9, 130 (77%) of the sample's grades were available with a summed grade score of 343.45(*SD* = 43.45).The distributions of the summed scores at each time point were assessed and quintiles were derived, so that students with the lowest grades were represented in category 1 and those students with the highest grades were in category 5.

Additionally, end-of-grade (EOG) test data were collected at the end of 6th, 7th, 8th, and 9th grade, and were used as another indicator of academic achievement. Students were assessed on both reading and math; and the raw assessment scores were scaled into an achievement level score, ranging from 1 equaling “insufficient mastery” to 4 equaling “superior performance” (NCDPI, 2007). Grade level proficiency includes level scores of 3 and 4. For Grade 6, 157 students (93%) had EOG reading and math scores, with 80.25% scoring at or above grade in reading and 94.90% scoring at or above grade in math. For Grade 7, 164 students (98%) had EOG scores with 89.02% scoring at or above grade in reading and 87.80% scoring at or above grade in math. For Grade 8, 130 students (77%) had EOG scores with 97.69% scoring at or above grade in reading and 65.38% scoring at or above grade in math. Finally, for Grade 9, 126 students (75%) had EOG scores with 84.13% scoring at or above grade in reading and 79.36% scoring at or above grade in math.

The grade and test score data were moderately to highly correlated (*r’s* ranging from 0.51 to 0.71) across the four time points. Moderate to high correlations between grades and standardized test scores (*r*’s ranging from 0.40 to 0.70) have been reported in diverse populations (see Duckworth, Tsukayama, & Quinn, 2011). Both grades and test scores are designed to measure students’ academic skills, but use different characteristics to rate those skills. Grade data includes not only the subject content being assessed through curricular tests, but also homework and classroom effort and conduct. Standardized tests, on the other hand, are derived from content based on standards that may or may not be part of the curriculum being taught in the classroom. However, these tests are the same for all students across all classrooms, which allow for academic ability to be measured consistently across educational systems. Therefore, both achievement indicators are used within this analysis and may not lead to the same interpretations because of the differences in measurement constructs.

Missing Data

There are two main types of missing data that can occur in longitudinal network analysis; one is defined as non-response at the actor characteristic level and the second is non-response at the relationship affiliation level (Biemer & Lyberg, 2003; Huisman & Steglich, 2008). Actor characteristic non-response has been described more broadly as survey non-response (Biemer & Lyberg, 2003). Survey non-response has been examined in many studies and findings indicate that the greater the amount of missing data, the larger the probability of bias, or systematic variability of the results compared to the population. In addition, survey non-response can lead to unstable estimates of variance parameters, which are evidenced by larger standard errors than expected (Biemer & Lyberg, 2003).

Several researchers have assessed the effects of non-response on the structural components of cross-sectional social networks. Specifically, higher levels of non-response have been shown to decrease power for testing the strength between ties, resulting in unstable network structural characteristics (Kossinets, 2006; Marsden, 1990). In longitudinal social network analysis, there are two different types of non-response. *Unit non-response* indicates that the individual did not nominate any others in the network; therefore, these individuals have no outgoing ties. However, they are still part of the network and may be nominated by their peers, thus leading to having a certain popularity status, as well as being included in the structural network. Another type of non-response in longitudinal network analysis is *wave non-response*, which occurs when individuals are missing all data at one or more time points. These individuals are not able to send or receive nominations because they are not part of the network at that time (Huisman & Steglich, 2008).

Following other studies (e.g., Huisman & Steglich, 2008), I have defined two different types of missing data: one for unit non-response (i.e., identified as 'NA' in the dataset) and one for wave non-response (i.e., identified as '10' in the data set). Both values were used across the data set, and were identified in both the network data, as well as the behavior data (i.e., academic achievement). It is important to note that the unit non-response (i.e., ‘NA’ value) was used only as an individual attribute. However, wave non-response was used with both the actor (i.e., rows) and the affiliates (i.e., columns). Therefore, if a student was missing data for a specific wave, they were not expected to have outgoing or incoming nominations.

Within Siena, all missing data are identified as missing at random and imputed (Huisman & Steglich, 2008). Simulations are carried out on all variables as if data were 100% complete. Missing data in the peer affiliative network are typically set to zero, indicating no ties between individuals. For all variables, if there is data at any earlier time point prior to the missing data, those values are used to impute the current value; however, if there are no earlier values, the variables are set to zero. This imputation strategy is called the last observation carry forward option and is used for longitudinal analysis even though it typically underestimates variance parameters and may lead to bias estimates (Lepkowski, 1989). However, this is somewhat mitigated in the Siena model, where the imputed data is only used in the simulations and not in the results. The results only include those individuals with non-missing data across all components.

Missing at random indicates that there is no relationship between the variables of interest and the reasons individuals did not participate in the survey or were missing certain items (Biemer & Lyberg, 2003). In the current study, survey participation drops from 81% in 8th grade to 63% in 9th grade. This is due to the fact that 24 students decided to attend high school at another school in the district (Schmid, 2008). A separate analysis of student mobility indicated that panel attrition was random across demographic characteristics such as gender and race as well as academic achievement indicators (Schmid, 2008). However, it is unclear whether or not these data constitute missing at random because the relationship between leaving the school and academic achievement can not be probed. Thus, the assumption of missing at random may not be warranted, leading to possible bias in the results.

Analysis Plan

The first analysis involves the use of descriptive statistics to describe characteristics of the sample, specifically the network affiliations. To do so, the number of affiliations created, maintained, and discontinued between each time point was determined, as well as an examination of network structural characteristics at each time point. In addition, elements that make up individual characteristics derived from network analysis were also examined.

There are assumptions that must be met in order to conduct a study using Siena modeling techniques. First, to properly identify a Siena model, some change in peer affiliations across time is necessary; however, some degree of stability in peer affiliations is also necessary. Thus, the amount of change and stability in the peer affiliative network across time was examined by conducting a Jaccard index. Second, when studying the co-evolution of networks and behaviors, it is important to remember that behaviors, in this case, academic achievement, are on an ordinal scale. The grade indicator is a set of quintiles, based on a ranked ordering of a summed curricular grade, and the EOG test data used a achievement level based on a continuous scale. Third, the strength of the relationship between peer affiliations and academic achievement was examined using the network autocorrelation coefficient, Moran's *I* (Moran, 1950; Steglich et al., 2010; Veenstra & Steglich, 2012). In the present study, some association between peer affiliations and academic achievement over time was expected. A final key assumption is time homogeneity, that is, that there are no systematic changes in any key variables between any two time periods. For example, the number of overall affiliations in the network should be relatively stable, indicating that the same population was being analyzed. To ascertain time heterogeneity in stochastic actor-oriented models, a time test was conducted to determine if there are significant differences between any time points (Lopinoso et al., 2011).

1) **What is the nature of changes to adolescents' affiliative patterns within the grade level peer network from 7th to 9th grade?**

This first model is best understood as an empty model, whereby rate functions from each time point were derived and interpreted. This research question does not formally include hypotheses. Rather, a general understanding of the amount of change in affiliations across time was assessed. This was determined through the analysis of the Jaccard index as well as the descriptive changes in peer affiliations in the network across time.

2) **To what extent and in what ways do network structural characteristics, such as density, reciprocity, transitivity and hierarchy, influence affiliative patterns within networks from 7th to 9th grade?**

Working from the empty model described above, different network structural characteristics were added to the network objective function (Ripley et al., 2014). The final model included all network structural characteristics. Results for each model included the parameter's point estimate, the standard error and a Wald-type *t*-test, which is interpreted the same as a standardized *z* score (Ripley et al., 2014). The *t*-test is derived from dividing the point estimate from the standard error. Snijders described the *t*-test as a ratio of signal to noise, indicating the strength of the estimate after taking error into account (Snijders, 2011). Although it is named a *t*-ratio, it approximates a *z* distribution and statistical significance is derived from the normal distribution, allowing for hypothesis testing (Ripley et al., 2014). Although I suggested the possible direction and strength of the network structural characteristics I did not hypothesize about those relationships, since they are primarily serving as control variables for later research questions.

3) **To what extent and in what ways do individual characteristics derived from network analysis (i.e., popularity, activity, and assortativity) and individual demographic characteristics (i.e., gender and race) change the peer affiliative network from 7th to 9th grade?**

This set of analysis controlled for network structural characteristics and introduced individual characteristics into the model, including those derived from the network analysis as well as demographic characteristics.

H 3.1: Popular (active) adolescents are more likely to associate with others who are popular (active).

This hypothesis was tested by including the *popular* parameter and the *activity* parameter into the model that includes network structural characteristics as control variables. The popular indicator assessed the impact of popularity on network ties; the activity indicator assessed the impact of activity on network ties. Positive popularity and activity indicators imply that popularity and activity are self-reinforcing. In this study, I expect both the popular and activity parameters are statistically significant and positive, based on a significant *t*-test score and a positive point estimate, indicating that popular individuals were more likely to affiliate with other popular individuals, and active individuals were more likely to affiliate with other active individuals.

H 3.2: It is hypothesized that adolescents will affiliate with others who share their gender and racial characteristics.

This hypothesis was tested by including the *homophily effect* parameter into the model that already includes network structural characteristics as control variables. The homophily effect assessed similarities between individuals and their affiliates, with positive parameter values indicating affiliates share the same demographic characteristics. Homophily effect parameters were examined for both race and gender. In this study, I expect the homophily effect indicator regarding gender and race to be statistically significant and positive, indicating that affiliations were more likely to occur between individuals who share the same race and gender characteristics.

4) To what extent and in what ways do selection and influence account for the co-evolution of changes to peer affiliations within the network and academic achievement across 7th grade to 9th grade?

This research question focused on both changes in peer affiliations and academic achievement within the network; thus, the co-evolution of changes in the network and behaviors. When studying networks and behaviors simultaneously, two rate and two objective functions are created: one for the network effects and one for the behavior effects. This set of analyses first controls for the network structural characteristics (described in research question 2) and individual characteristics (described in research question 3). Additionally, after controlling for these other components, this research question focused on the parameters regarding academic achievement that are part of the behavior objective function.

Like the network model, the behavior model has three rate parameters (i.e., Time 1 to Time 2, Time 2 to Time 3, and Time 3 to Time 4) that were examined. Additionally, two shape parameters were examined in the model. The *linear* indicator assessed overall growth in the behavior across time, with positive parameter values indicating a systematic rise in the behavior across the network. The *quadratic* indicator assessed self-reinforcement of behaviors over time, with positive parameter values indicating a systematic reinforcement of individuals' behavior over time.

5) To what extent and in what ways do individual characteristics derived from network analyses and demographic characteristics of adolescents influence academic achievement?

This research question extends the study of both changes in peer affiliations and academic achievement within the network, by operationalizing the individual characteristics in the behavior objective function, continuing to control for elements that are part of the network objective function. Defined in research question 4, the behavior objective function included both the linear and quadratic effects on behavior as control variables. This research question focused on the individual characteristics, both derived from network analysis and demographics and how they relate to the behavior objective function, that is, academic achievement outcomes. Hypotheses of relationships between the individual characteristics and academic achievement were advanced.

H 5.1: There will be a positive relationship between popularity (activity) and academic achievement across the network and time; that is, more popular individuals are expected to have higher grades compared to less popular (active) students.

This hypothesis was tested by including the *popularity behavior* effect and *activity behavior* effect into the model that already has controlled for all network-related components as well as the general shape functions for behaviors. The popularity behavior effect assesses the relationship between network popularity and academic achievement, with higher parameter values indicating that those individuals who are highly popular also have higher academic achievement. The activity behavior effect assesses the relationship between network activity and academic achievement, with higher parameter values indicating that those individuals who are highly active also have higher academic achievement. By soliciting many affiliations, I contend that individuals with high activity levels feel a high sense of engagement with the network, leading to a sense of belonging. A higher sense of belonging has been shown to lead to higher engagement as well as indirectly leading to higher academic achievement outcomes (Goodenow, 1993). I expect both the popularity behavior and activity behavior indicators to be positive and statistically significant.

In addition, gender and race effects were tested using the three dummy codes described above (e.g., female vs. male; African American students and all other students; European American students and all other students). The gender effect assesses the relationship between gender and academic achievement, with positive parameter values indicating that males have higher academic achievement scores than girls and negative parameter values indicating females have higher academic achievement scores compared to males. The two race parameters assessed the relationship between race and academic achievement. A positive African American race parameter indicates that African American students have higher academic achievement scores compared to all students of other races. A positive significant European American race parameter indicates that European American students have higher academic achievement scores compared to all students of other races.

6) To what extent and in what ways do these individual demographic characteristics (i.e., gender and race) moderate the relationships between peer selection and peer influence, and academic achievement from 7^{th} to 9^{th} grade?

This research question focused on both changes in peer affiliations and academic achievement within the network, controlling for all other significant parameters tested in the earlier research questions, allowing for an examination of the processes of peer selection and influence. As with the previous research questions, estimates, standard errors, and the *t*-test for each parameters were reported. In addition, the log odds ratio for each significant result was reported. The log odds ratio is calculated by taking the exponential of the ratio of the parameter estimate and the range of the behavior minus 1 (for the grade data that is 4; Ripley et al., 2014). Log odds ratios provide an indication of the strength of the relationship, with positive values indicating that achievement will contribute for a formation of an affiliation and a negative value indicating the dissolution of an affiliative tie. Peer selection operates within the network objective function while peer influence operates within the behavior objective function. Both selection and influence were modeled separately and combined. In addition, the interactions between peer selection and peer influence were analyzed; however, no specific hypotheses were endorsed, because there is no suggested pattern of differences described currently in the literature. Hypotheses of particular relationships regarding the selection and influence were tested.

H 6.1: Selection processes will be positive, indicating that individuals affiliate with others who have similar grades to themselves.

This hypothesis was tested by including the *grades similarity* parameters into the *network* objective function. The grades similarity parameters determine the extent to which individuals and their affiliates share similar academic achievement outcomes across time. Higher grades similarity parameters indicated the selection of peers based on an already occurring similarity in academic achievement. I expect the grades similarity parameters to be positive and statistically significant.

H 6.2 Influence processes will be positive, indicating that individuals become more similar to their affiliates over time.

This hypothesis was tested by including the *grades similarity* parameters into the *behavior* objective function. The grades similarity parameters determine the extent to which individuals and their affiliates share the same academic achievement outcomes across time. Higher grades similarity parameters in the behavior objective function indicate peer influence based on a growing similarity in academic achievement after controlling for peer selection processes. I expect the grades similarity parameter to be positive and statistically significant.

RESULTS

Descriptive Network Statistics

Network analyses were first independently conducted for each time point to allow for a better understanding of each network and to aid in the identification of differences between networks across time. Each network at each time point was assessed to determine general network structural components including size, density, reciprocity, and transitivity. In addition, the average indegree and outdegree across the network were estimated. All descriptive analyses were conducted using Ucinet, version 6 (Borgatti, Everett & Freeman, 2002) and RSiena, version 4 (Ripley et al., 2014). All research questions were modeled in RSiena, version 4 (Ripley et al., 2014). Due to sizing constraints and for better flow, complete models are found in the Appendix B, and only pertinent parameters are shown within tables in the text.

An affiliative tie was signified by a ‘1’; a non-relationship resulted in a ‘0’. Individuals who did not consent to be part of the study could receive relationship ties (e.g., participants could affiliate with them) but they did not complete the survey; and therefore, did not select any others with whom to affiliate. Table 1 presents the number of individuals in the network, the number of participants in the network, the total number of relationship ties across the network, and the proportion of missing data that were not defined as structurally missing.

Table 1.

Network size, number of ties and missing data

	# Total Network	# Consented	# Ties	% Missing
Time 1	203	168	4045	17%
Time 2	195	163	4721	14%
Time 3	191	155	4310	13%
Time 4	213	134	3033	11%

Each of the network structural characteristics was assessed to determine the general structural tendencies within the network at each time point. The characteristics described include density, reciprocity and transitivity. *Density* was calculated as the number of ties between all individuals across the network divided by the total number of possible affiliations in the network (Wasserman & Faust, 1994), ranging from 0 (i.e., no network ties) to 1 (i.e., all individuals were connected to one another). Table 2 includes the density scores from Time 1 to Time 4. In the grade-level network, density ranged from .07 to .12, which indicated low peer network density across all time points. In general, this network characteristic was similar to findings from other studies indicating adolescent peer networks were not very dense and that individuals selectively affiliate with others (Veenstra & Dijkstra, 2012).

Reciprocity is the tendency for individuals to affiliate with those who choose to affiliate with them; that is, to be part of a bi-directional relationship. One way that reciprocity was assessed is through a census of all dyadic ties at each time point (see Appendix A, Table A1 for the dyad census). The dyad census for the current study indicated that around 30% of the ties are reciprocated at each of the four time points. Another way that these relationships can be assessed is through a network reciprocity score that uses an arc-based parameter that ranges from 0 (i.e., no reciprocal relationships) to 1 (i.e., complete network reciprocity, Borgatti et al., 2002). In this network, reciprocity was relatively stable, ranging from 0.35 to 0.39. Like the dyadic census, this indicated that 30% to 40% of ties were reciprocated at each time point. This was probably a conservative estimate, since those who were not consented but selected as affiliates were included in the network and their ties were, of course, not reciprocated. Table 2 included the reciprocity network scores from Time 1 to Time 4.

Transitivity is the expansion of reciprocity to include larger sets of relationships (e.g., triads) in the network. One way to assess transitivity is through the use of a triad census. The triad census is a categorization of all types of relationships available; there are 16 different types of relationships that are found between three actors (Wasserman & Faust, 1994). Each of the 16 relationships and the resulting number of triads are listed in Appendix A, Table A2. Transitivity can be assessed in a variety of ways, including transitive triplets (e.g., a <-> b <-> c <-> a) in the network compared to some possible number of triplets; in this study, the numerator is the total number of possible triplets in the network (Borgatti et al., 2002; Wasserman & Faust, 1994). Table 2 includes the transitivity parameters on the network from Time 1 to Time 4. The estimates suggested that transitivity occurs in about 35% to 45% of triadic relationships across time. Moreover, like reciprocity, these findings may be conservative, as they include affiliative relationships from the non-participants.

Table 2.

Network summary statistics

	Density	Reciprocity	Transitivity
Time 1	0.111	0.391	0.359
Time 2	0.124	0.356	0.426
Time 3	0.113	0.381	0.410
Time 4	0.077	0.355	0.434

Indegree and outdegree are important for understanding individual differences between selections of affiliates. The average of nominations sent to others (i.e., outdegree) and nominations received by others (i.e., indegree) were assessed at each time point, and the mean, standard deviation, and range for both outdegree and indegree are presented in Table 3. As expected, the average network scores for indegree and outdegree were the same; however, the standard deviations differ remarkably. The outdegree standard deviations are twice that of the indegree standard deviations, indicating wider variability in the number of nominations sent compared to the nominations received. Therefore, some individuals nominated all or almost all others as affiliates (e.g., outdegree ranges close to 200); but individuals only received affiliative nominations from, at most, a quarter of the network population (e.g., indegree ranges close to 50). The discrepancies between in degree and outdegree indicate the overall selectivity of most of the actors within the network. Individual level parameters including popularity, activity and assortativity were derived from these degree parameters.

Table 3.

Average Network Outdegree and Indegree Parameters

	Outdegree			Indegree		
	M	*SD*	Range	*M*	*SD*	Range
Time 1	20.37	20.25	0-121	20.37	9.67	3-49
Time 2	24.42	29.99	0-194	24.42	9.38	0-46
Time 3	22.98	25.77	0-191	22.98	9.21	4-45
Time 4	19.32	24.73	0-160	19.32	7.57	4-39

Model Assumptions for Estimating a Stochastic Actor Model

There are several assumptions that ought to be met to use stochastic actor modeling in an appropriate and useful way (Snijders, 2007; Veenstra & Dijkstra, 2012). First, there must be some stability as well as change in the peer network over time. Second, there should be some relationship between the peer networks and the behaviors being assessed; in this case, academic achievement. Finally, Siena assumes time homogeneity, that is, no systematic changes in the variables between any two time periods. Each of these assumptions were assessed and reported prior to estimating the Siena models.

To address the amount of change and stability in the peer affiliative network to see if a Siena model could be undertaken, a Jaccard index was used. The Jaccard index examines the number of stable affiliations from one time point to the next, compared to the total number of affiliations across the same time period (Veenstra & Steglich, 2012). In this study, Jaccard indices were calculated at each set of time points. The Jaccard index between Time 1 and Time 2 was 33.7%; the Jaccard index between Time 2 and Time 3 was 35.5%; and, the Jaccard index between

Time 3 and Time 4 was 27.8%. Results of studies have suggested that a Jaccard index of 30% indicates reasonable stability in the network; however, it is unclear what effect lower indices have on the stability of the parameter (Steglich et al., 2010; Veenstra & Steglich, 2012).

Second, the existence and strength of the relationship between the peer network and academic achievement was examined using a Moran's *I* (Veenstra & Steglich, 2012). The Moran's *I* is a network autocorrelation coefficient and is similar to a correlation (Moran, 1950; Steglich et al., 2010). Moran's *I* values range from -1 indicating a completely random relationship between network affiliation and academic achievement to +1 indicating a perfect association between network affiliation and academic achievement. In the current study, some association between peer network affiliations and academic achievement over time was expected; therefore, Moran's *I* was expected to be weakly positive. In fact, the Moran's *I* at Time 1 was statistically significant yet close to zero (0.025, $p<.05$), the Moran's *I* at Time 2 was 0.09 ($p<.05$), the Moran's *I* at Time 3 was 0.30 ($p<.05$) and the Moran's *I* at Time 4 was 0.40 ($p<.05$). Taken together, this indicates that there is a statistically significant and positive association between the network affiliations and academic achievement that increases in magnitude across time.

A final key assumption is time homogeneity, that is, that there are no systematic changes in any of the key variables between any two time periods across the network. For example, the number of overall affiliations between individuals in the network should be relatively stable. If there were a significantly different number of affiliations between Time 2 and Time 3 compared to the other time points, that might indicate that the same population was not being analyzed. In that case, it would be more appropriate to assess each set of time points independently rather than examine changes across the entire set of time points. To determine if there are systematic changes across time, I conducted a time heterogeneity test, which involved the analysis of network structural characteristics to determine if there are significant differences between any time points

(Lopinoso et al., 2011). This was conducted on the first (null) model and the complete model. No significant differences were found between the time points in the null model, thus, running the model combined across the four time points was appropriate.

Question 1: What is the nature of changes to adolescents' affiliative patterns within the grade level peer network from 7^{th} to 9^{th} grade?

This first model is best understood as an empty model, whereby rate functions from each time point are derived. This research question does not formally include hypotheses. Rather, a general understanding of the amount of change in affiliations across time was determined through the analysis of the Jaccard index, the descriptive changes in peer affiliations in the network across time, and the calculation of rate functions.

In addition to the cross-sectional analyses reported at each time point, it is necessary to understand the relationships between affiliations created, maintained and discontinued between each time point. A summary of those relationships across time is shown in Appendix A, Table A3. Due to the overall selectivity of the network, most individuals were not affiliated with all others in the network. Across all possible network ties, 81% to 84% were non-relationships at each time point. Two types of change occur in the network: creating a tie (i.e., No -> Yes) or dissolving a tie (i.e., Yes -> No). Different patterns were found between tie creation and dissolution. The net creation and net dissolution parameters were measured by determining the sum between the affiliations created and dissolved. More ties were created than dissolved between Time 1 and Time 2; and more ties were dissolved than created from Time 2 to Time 3 and Time 3 to Time 4. Finally, stability in peer affiliations across time is assessed through the relationships that were maintained from one time to the next (i.e., Yes-> Yes). The rate of affiliation ties is relatively stable, with 6% of ties from Time 1 to Time 2 maintained, 7% of ties from Time 2 to Time 3 maintained, and 4% of ties from Time 3 to Time 4 maintained.

The Jaccard index signifies stability in the network and is a calculation of the number of stable affiliations from the first time point to the second time point divided by the total number of new, lost and stable affiliations within the time period. The Jaccard index at Time 1 to Time 2 was 33.7%; Time 2 to Time 3 was 35.5%; and Time 3 to Time 4 was 27.8%. The drop in the Jaccard index was due, in part, to the net dissolution in ties between Time 3 and Time 4. The network dissolution may be exacerbated by the attrition in the network between Time 3 and Time 4, when students left the school for a different high school.

Stochastic actor modeling comprises two different functions that describe changes in the network: the rate function and the objective function. The rate function defines the amount of change whereby the objective function defines the direction of change. Specifically, the rate function refers to the frequency with which a given actor changes a relationship. The rate parameters slow down from 7th grade to 9th grade; a rate of 40.46 (*SD* = 0.89) from Time 1 (7th grade) to Time 2; to a rate of 35.38 (*SD* = 0.77) from Time 2 (7th grade) to Time 3; and finally, from Time 3 (8th grade) to Time 4 (9th grade), a rate of 25.16 (*SD* = 0.58). This may be due to two different processes occurring during this time period. First, the number of actors declined throughout the study and more rapidly between Time 3 and Time 4. This was also reflected in the number of network ties, which declined from 4,310 at Time 3 to 3,033 at Time 4. In addition, it may be that affiliation choices have become solidified, with fewer changes occurring in the network that is still intact. Unfortunately, this would not be reflected in the Jaccard index, which also included those who leave the network entirely within the time period.

Question 2: To what extent and in what ways do network structural characteristics, such as density, reciprocity, transitivity and hierarchy, influence affiliative patterns within networks from 7th to 9th grade?

The second model builds upon the first model, through analyzing the set of network structural characteristics (i.e., density, reciprocity, transitivity and hierarchy). For each model, point estimates, standard errors and *t*-test results are presented for each parameter. The *t* test is a ratio of the estimate and standard error and is used to determine statistical significance. Key parameters for each research question are shown in the tables in the results section; all results for all models are shown in Appendix B. The fully converged[3] model results are shown in Table 4, and all of the network structural characteristics are statistically significant. *Density* is derived from the total network affiliations compared to the total number of possible affiliations; the literature suggests that adolescent peer networks are not very dense, relative to network size (Maroulis & Gomez, 2008; Steglich et al., 2010). In the current study, the density parameter, as expected, was negative, indicating that peers were selective in the ties that they made. *Reciprocity* is defined by the ratio of bidirectional ties compared to the number of possible ties; in earlier studies, reciprocity has been found to be strongly positive (Kiuru et al., 2012; Steglich et al., 2010). In this network, the reciprocity parameter was positive as expected, signaling that the network has a high level of bidirectional relationships over time. *Transitivity*, or the cohesion of the network at the triadic level, was measured using three different measures: transitive triplets, balance, and distance 2 effects. All three transitivity parameters indicated greater transitivity in the network. *Hierarchy* is the extent to which individuals are ranked within the network. Adolescent peer networks have been found to be somewhat hierarchical, as defined through a negative 3 cycle parameter. As expected, the 3 cycle parameter was negative, indicating hierarchy in the network.

[3] Convergence is measured through an assessment of *t* results in the model; results estimates should be less than 0.2 on each parameter.

Table 4.

Model for Q2: Network Structural Characteristics

Parameter	Estimate	*SE*	*t*
Density	-1.5408	0.0151	-102.04***
Reciprocity	1.2987	0.0318	40.84***
Transitive Triples	0.0901	0.0020	45.05***
Balance	0.0015	0.0003	5.00***
Distance 2	-0.0175	0.0024	-7.29***
3-cycle / anti-hierarchy	-0.1242	0.0038	-32.68***

*Note: *p<.05; **p<.01, and *** p<.0001*

Question 3: To what extent and in what ways do individual characteristics derived from network analysis (i.e., popularity, activity, and assortativity) and individual demographic characteristics (i.e., gender and race) change the peer affiliative network from 7th to 9th grade?

After controlling for network structural characteristics, as described above, this research question introduced two types of indicators: individual characteristics derived from network analyses and individual demographic characteristics. Three parameters were used to ascertain individual differences in peer affiliations due to network position: popularity, activity and assortativity. *Popularity* is based on the individuals' ability to attract more affiliations due to their high status (Cillensen, 2011; Ripley et al., 2014). *Activity* is based on the individuals' propensity to select affiliates and solicit affiliates based on the activity status. *Assortativity* is based on individuals' tendency to affiliate with others who have a similar popular status and activity status. Individuals are expected to associate with others who have the same network status. The results from this model are found in Table 5. Convergence was defined as *t*-ratios smaller than 0.2. The model with all variables did not converge; upon further assessment, the assortativity parameters had high *t*-ratios, which indicated a lack of model fit (*t* = .52 for activity; *t* = .48 for popularity). In later models, assortativity is not included due to these problems with model convergence.

Table 5.

Model for Q3: Characteristics derived from network analysis

Parameter	Estimate	*SE*	*t*
Popularity	0.0217	0.0071	3.06*
Activity	0.0129	0.0018	7.17***

*Note: *p<.05; **p<.01, and *** p<.0001*

H3.1: Popular (and active) adolescents are more likely to associate with others who are popular (and active). The popularity parameter indicated that popularity was self-reinforcing from 7th to 9th grade. In this study, the popularity parameter was positive, indicating that popular individuals become more popular over this time period. The activity parameter indicated that activity was self-reinforcing, indicating that individuals who solicit many peer affiliations continue to do so from 7th to 9th grade.

Next, differences in choices of affiliates among individuals were examined by race and gender. Typically, effects are conducted on covariate attributes to determine the relative similarity on the attribute across members of the network. When assessing race and gender, it is not appropriate to measure similarity; rather, the interest is in whether or not individuals share the *same* characteristic (African American or not, European American or not, Male or Female). Thus, the covariate parameter assessed whether the individuals share the same characteristic or not. Additionally, an interaction term assessing individual's reciprocity to those affiliates who share the same demographic characteristics was conducted. A positive interaction parameter between reciprocity and the demographic covariate indicated that reciprocal ties were more likely to occur between individuals who share the same demographic characteristics. The results from this model are found in Table 6.

Table 6.

Model for Q3: Characteristics derived from demographics

Parameter	Estimate	*SE*	*t*
Same race (African American)	0.1737	0.0254	6.84 ***
Same race x reciprocity (African American)	-0.0117	0.0645	-0.18
Same race (European American)	0.1251	0.0256	4.89 *
Same race x reciprocity (European American)	-0.2634	0.0676	-3.90 *
Same gender (Male)	0.1990	0.0195	10.20 ***
Same gender x reciprocity (Male)	0.1036	0.0537	1.93 ***

*Note: *p<.05; **p<.01, and *** p<.0001*

H3.2: Adolescents affiliate with others who share their gender and racial demographic characteristics. Both gender and racial homophily were found in the network from 7th to 9th grade. A statistically significant and positive estimate for those of the same race was found, indicating that both African American students and European American students were more likely to select same-race peers. Next, the interaction between being of the same race and reciprocity between dyads was assessed. The interaction between both partners being African American and having a reciprocated relationship was not significant. Surprisingly, the interaction between being a European American student and in a reciprocated relationship was significant and negative, indicating that relationships between European American student dyads were less likely to be reciprocated, compared to cross-race relationships. These findings run counter to many other studies which have found strong reciprocity within race versus across racial categories (McPherson et al., 2001; Moody, 2001; Vaquera & Kao, 2008).

Positive gender homophily was found across the network, based on a statistically significant and positive parameter found by gender. This means that adolescents were more likely to select affiliates of the same gender as themselves. In addition, a statistically significant and positive interaction was found between gender and being part of a reciprocal relationship with a peer of the same gender. Therefore, same-gender relationships were more likely to be reciprocated than are cross-gender relationships.

Question 4: To what extent and in what ways do selection and influence account for the co-evolution of changes to peer affiliations within the network and academic achievement across 7th grade to 9th grade?

The first set of research questions focused on understanding network affiliations over time. Here, I begin to address both changes in the network and academic achievement simultaneously; thus, specifying the co-evolution of changes in the network and behavior over time. Like affiliations in networks, changes in behavior can be assessed across time. A summary of changes in grades for the sample is given in Tables 7. Models using two different ordinal measures of academic achievement were examined using grade quintiles (i.e., grades ranging from 1 to 5) and standardized test score levels (i.e., scores ranging from 1 to 4). The results for grades are described within the text, while the standardized test score results are found within the Appendix A, Table A4 and Appendix B, Table B12. The results for both achievement measures follow similar patterns, and since grades were included in all models, it was determined that it would be the one reported on within the text. For grades, over half of the individuals belong to the same achievement category across time. Additionally, roughly 20% of network members have positive changes in their grade quintile scores and slightly fewer have grades that decrease over time.

Table 7.

Changes in Grades across time

	T1 -> T2	T2 -> T3	T3 -> T 4
% where grades went up	21.70	20.41	20.00
% where grades went down	22.64	18.37	15.71
% where grades were stable	55.66	61.22	64.28

As described in the first research question, stochastic actor modeling is based on two different functions that describe changes in the network. In order to accurately assess the co-evolution of networks and behaviors over time, an additional rate and objective function for behavior (i.e., grades) was calculated along with the network rate and objective function that define changes in affiliations. The behavior rate function refers to the probability of a given actor to change his or her academic achievement. The grade rate parameter declines over time; from 1.04 (*SD* = 0.22) at Time 1 to Time 2, 0.90 (*SD* = 0.15) from Time 2 to Time 3, and 0.87 (*SD* = 0.15) from Time 3 to Time 4. The lower rate parameter indicates a greater proportion of students' grades were stable over time, rising from 56% to 64% from 7th to 9th grade.

In addition, the behavior model also includes two standard behavior parameters that help define the behavior objective function: the linear and quadratic parameters. The linear parameter describes overall growth in academic achievement over time; the quadratic parameter assesses the extent to which changes in achievement continue over time. The results of this model are found in Table 8. In this study, the linear and quadratic shape parameters were not significant, indicating that there are no systematic changes in grades across time.

Table 8.

Model for Q4: Behavior (Grades) shape parameters

Parameter	Estimate	*SE*	*t*
Linear shape	0.0371	0.0774	0.48
Quadratic shape	0.0627	0.0437	1.43

*Note: *p<.05; **p<.01, and *** p<.0001*

Question 5: To what extent and in what ways do individual characteristics derived from network analyses and demographic characteristics of adolescents influence academic achievement?

This question first examined the individual characteristics derived from network analysis, popularity and activity, and their effects on changes in grades across 7th to 9th grade. The popularity behavior parameter reflects the relationship between network popularity and academic achievement; with positive findings indicating that students who receive more nominations were more likely to have higher grades, and negative findings indicating that students who receive fewer nominations were more likely to have higher grades. The activity behavior parameter reflects the relationship between network activity and academic achievement. Positive activity parameters indicate that active students (i.e., those who affiliate with many other individuals in the network) were more likely to have higher grades, whereas negative effects indicate that non-active students (i.e., those that affiliate with fewer individuals in the network) were more likely to have higher grades. The results of this model are found in Table 9.

Table 9.

Model for Q5: Popularity and Activity behavior effects

Parameter	Estimate	*SE*	*t*
Popularity behavior effect	-0.0015	0.0112	-0.13
Activity behavior effect	-0.0083	0.0039	-2.13 *

*Note: *p<.05; **p<.01, and *** p<.0001*

H5.1: There will be a positive relationship between popularity (activity) and academic achievement across the network and time; that is, more popular (active) individuals are expected to have higher grades compared to less popular (active) students. Unexpectedly, the popularity behavior effect was not significant within the academic achievement behavior model. This means no relationship between popularity and grades was found. Additionally, the activity behavior effect was significant, but was a negative effect, counter to the hypothesized positive relationship. The observed effect indicated that individuals who affiliated with fewer individuals in the network were more likely to have higher grades.

In addition, the effects of demographic data, specifically, race and gender, on academic achievement were also examined. Although no specific hypotheses were advanced, the role of these characteristics was important to understanding the complex interplay between peer relationships and academic achievement. Table 10 includes the results of race and gender main effects on grades across time.

Table 10.

Model for Q5: Demographic behavior effects

Parameter	Estimate	*SE*	*t*
Male effect on Grades	0.2595	0.1743	1.49
African American effect on Grades	0.1414	0.2657	0.53
European American effect on Grades	0.5403	0.2737	1.97 *

*Note: *p<.05; **p<.01, and *** p<.0001*

There were no significant findings for being male, indicating that after controlling for all other characteristics, boys and girls have similar grades across time. Additionally, being an African-American student (as opposed to any other race) was examined. The non-significant effect indicated that there was no difference in academic achievement between African American students and students of another race. Finally, being a European American student (as opposed to any other race) was examined. This effect was significant and positive indicating that being a European American student was positively associated with grades over time. It was somewhat surprising that the European American student effect was significant and the African American student effect was not. Upon closer review, there was a noticeable difference between African American students' and European American students' mean GPA at Time 1 (*m* = 79, *m* = 89 respectively). This difference was not detected when African Americans students were combined with students of all other ethnicities because students of other racial/ ethnic groups (e.g., Hispanic students, multiracial students) have GPAs similar to African American students (*m* = 81 for Hispanic students, *m* = 84 for multiracial students).

Question 6: To what extent and in what ways do these individual demographic characteristics (i.e., gender and race) moderate the relationships between peer selection and peer influence, and academic achievement from 7th to 9th grade?

A key theme of this research study has been to understand how peer selection and peer influence independently contribute to understanding changes in academic achievement. For this research question, different sets of models were examined to assess aspects of selection and influence: one with selection indicators only, one with selection indicators and moderators of selection, one with influence indicators only, and one with influence indicators as well as moderators of influence. Finally, a model including selection and influence effects as well as the moderators of the selection and influence effects was conducted and the results are described within the text. In addition to the estimates, standard errors, and t-test results that have been reported for all parameters, log odds ratios were also reported for significant results. Log odds ratios provide an indication of the strength of the relationship. All the model results can be found in Appendix B.

H6.1: Selection processes will be positive, indicating that individuals affiliate with others who have similar grades to themselves. Selection was assessed through three different parameters: grade ego, grade alter and grade similarity. The results of these three indicators using grades as the achievement measure are shown in Table 11. The *grade ego effect* indicates whether or not those individuals with higher grades also tend to be more active in the network by nominating more peer affiliates. In this study, the grade ego effect was not significant, meaning that there were no differences in the number of peer nominations made by those with high grades compared with students with lower grades. The *grade alter effect* indicates whether or not individuals with higher grades are also more popular in the network, compared to those with lower grades. Popularity is derived by the number of peers who affiliate with one another. In this study, the grade alter effect was not significant, meaning there were no differences in the nominations received and grades. The *grade similarity effect* is a measure of homophily, that is, whether affiliative ties tend to occur more often between peers who have similar grades. In this study, the grade similarity effect was statistically significant and positive, indicating that students with similar achievement patterns tended to affiliate with one another; that is, high achieving students affiliate with other high achieving students, and lower achieving students affiliate with other lower achieving students. The log odds ratio was 1.09, indicating a 9% greater probability in fostering a relationship with someone who shares a similar academic achievement compared to someone who has a dissimilar academic achievement record.

Table 11.

Model for Q6: Selection effects by grades

Parameter	Estimate	*SE*	*t*
Grade Ego Effect	0.0026	0.0133	0.19
Grade Alter Effect	0.0145	0.0106	1.37
Grade Similarity Effect	0.3485	0.0709	4.92 ***

*Note: *p<.05; **p<.01, and *** p<.0001*

In addition, moderators of the selection effects were examined, including being a Male student, being an African American student, and being a European American student. The results for each type of selection interaction effect are shown in Tables 12-14. The grade ego parameter measured the relationship between academic achievement and network activity. The interaction term for grade ego and being an African American student assessed how achievement and being African American related to network activity. In this study, the interaction between grades and African American ego effects were significant and positive, demonstrating that when African American students have higher grades, they are more connected to the peer network, as indicated through higher nomination activity. The log odds ratio was 1.02 indicating a 2% greater probability for African American students with higher grades to be more active in the network, compared to less academically successful African American students. The same selection interaction term was estimated for European American students and was not significant, indicating that network activity was not related to an interaction term between grades and being an European American student. Additionally, the interaction term for grade ego and being male assessed how grades relate to the network activity. In this study, the interaction between grades and being Male was significant and negative, indicating that female students with high grades, not males, were more connected to the peer network, as measured through network affiliation activity. However, the log odds ratio was 1.01, indicating little difference between the results and what is expected by chance.

Table 12.

Model for Q6: Selection effects using grade ego moderators

Parameter	Estimate	*SE*	*t*
African American	0.0682	0.0327	2.08 *
European American	0.0289	0.0336	0.86
Male	-0.0565	0.0254	-2.22 *

*Note: *p<.05; **p<.01, and *** p<.0001*

The grade alter parameter measured the relationship between grades and popularity in the network. The interaction term for grade alter and a demographic characteristic assessed how the relationship between belonging to the demographic group and having a certain grades affected their popularity in the network. In this study, the interaction terms for grade alter and being African American, being European American, and being Male were all non-significant. Therefore, the main effect for grade alter as well as the interactions between grade alter and demographic characteristics did not relate to differences in popularity across the network.

Table 13.

Model for Q6: Selection effects using grade alter moderators

Parameter	Estimate	*SE*	*t*
African American	0.0154	0.0335	0.46
European American	-0.0088	0.0541	-0.16
Male	-0.0057	0.0203	-0.28

*Note: *p<.05; **p<.01, and *** p<.0001*

The grade similarity effect is a measure of homophily. When assessing the main effect, positive effects indicated that peers affiliate with others who have similar grades. The interaction terms for grade similarity and African American similarity was significant and negative, indicating that African American students with higher grades were less likely to affiliate with other African American peers, compared to lower achieving African Americans. However, lower achieving African Americans were more likely to affiliate with other African American peers, compared to their higher achieving African American counterparts. The log odds ratio was 1.07, indicating a 7% greater probability in fostering a relationship with cross-race affiliates if one was a higher achieving African American student. This finding was replicated among European American students. European American students with higher grades were more likely to associate with students of other races. However, lower achieving European American students were more likely to associate with peers of their own race. Although this result was statistically significant, the log odds was 1.00, indicating no differences between the results and what was expected by chance.

Table 14.

Model for Q6: Selection effects using grade similarity moderators

Parameter	Estimate	*SE*	*t*
African American	-0.2911	0.1878	-1.55 *
European American	-0.3431	0.2016	-1.70 *
Male	0.0084	0.1721	0.05

*Note: *p<.05; **p<.01, and *** p<.0001*

H6.2: Influence processes will be positive, indicating the individuals become more similar to their affiliates over time. Influence was assessed through three different parameters: grade average similarity, grade total similarity, and grade average alter. The *grade average similarity effect* was an indicator of similarity in grades that compares individuals to each of their affiliates, regardless of the number of affiliates. The *grade total similarity* effect was a proportional indicator of similarity in grades, comparing the individual to each affiliate, based on the number of affiliates. The *grade average alter* effect indicator assessed the affiliates' average value on the behavior. In this study, none of the influence effects were statistically significant, meaning that influence did not appear to play a role in understanding academic achievement as measured by grades. The results of these influence indicators are shown in Table 15.

Table 15.

Model for Q6: Influence grade effects

Parameter	Estimate	*SE*	*t*
Grade Average Similarity	30.6226	128.1934	0.239
Grade Total Similarity	-0.2239	1.0725	-0.209
Grade Average Alter	5.3470	25.0236	0.214

*Note: *p<.05; **p<.01, and *** p<.0001*

Like selection effects, influence was also assessed by the three covariate variables: being African American, being European American, and being Male. As before, each influence effect (i.e., average similarity, total similarity, and average alter) were assessed using each covariate. Thus, nine interaction variables were constructed and the results are shown in Tables 16. As with the main effects, none of the moderation terms were statistically significant. This indicated that peer affiliates were not significantly influencing others after selection was accounted for; and additionally, that there were no differences in peer influence on grades by gender and race.

Table 16.

Model for Q6: Influence Grade Moderators

Parameter	Estimate	*SE*	*t*
Average Similarity			
African American	-45.5351	403.0485	-0.11
European American	13.9315	603.0375	0.02
Male	0.0737	12.4375	0.01
Total Similarity			
African American	0.9133	9.7214	0.09
European American	0.5042	11.0979	0.04
Male	-0.1924	0.3690	-0.52
Average Alter			
African American	-1.2510	10.0559	-0.12
European American	12.8400	72.5075	0.18
Male	1.1060	2.3999	0.46

*Note: *p<.05; **p<.01, and *** p<.0001*

Post-hoc Analyses

Post-hoc analyses were conducted to examine variables that were not specified in these research questions but could provide insight into the findings already described. The post-hoc model incorporated actor characteristics that could change over time, in contrast to the stable demographic characteristics earlier assessed. Three behavioral characteristics were tested in the analysis: levels of aggression, prosocial leadership, and deviant leadership. Students were rated by their peers on these three behavioral components, and a *z* score was derived for each individual at each time point. Aggression was based on the descriptor, “fight a lot, hit others, or say mean things”; prosocial leadership was based on the descriptor, “leaders and good to have in charge”; and deviant leadership was based on the descriptor, “good at getting others to break the rules” (DeRosier & Thomas, 2003). The results from the model incorporating these three actor covariates were shown in Appendix B, Table B13.

Again, selection and influence effects on grades were analyzed, including the three time-varying individual characteristics of aggression, leadership and deviance. Within the model, only selection effects, not influence, were significant. Specifically, as in earlier estimated models, the grade similarity parameter was significant (t = 3.51, p<.001) indicating that homophily in grades was still evident even controlling for other changing behavioral characteristics. In addition, these individual behavioral covariates which change over time were significant in understanding peer affiliations within the network. Specifically, homophily in peer affiliates by deviant leadership and aggression was found, indicating that peers who shared similar attributes in regards to aggression (t = 3.67, p<.001) and deviant leadership (t = 3.23, p<.001) were more likely to be affiliated with one another. This finding was not replicated for prosocial leadership, where similarities in prosocial leadership did not lead to greater expectations for affiliation. Although behavior homophily was found among affiliates with similar deviant leadership and aggression levels, these individuals were no more likely to have reciprocated relationships compared to other affiliations (aggression x reciprocity t = -0.31, p=n.s.; deviant leadership x reciprocity t = -1.06, p = n.s.). Thus, although aggression and deviant leadership similarity might lead individuals to affiliate, it does not indicate any reciprocation or stability of the affiliation over time.

DISCUSSION

This study focused on changes in peer affiliations within a school-based network and academic achievement during middle school and into high school. Specifically, the goal of the study was to assess the independent contributions of peer selection and peer influence in understanding the changes occurring in the co-evolving grade-level network and academic achievement from 7th to 9th grade. By using a framework based on social network analysis, I examined how individuals in this shared context formed affiliations and how those affiliations affected members' behaviors. This study allowed for the probing of peer selection and peer influence to better determine when and how those mechanisms interacted with changes in academic achievement.

Peer Selection and Influence

Over the past twenty years, research has progressed on the creation of concepts and methods to study peer homophily in behaviors within the context of dynamic change (Cairns & Cairns, 1994; Dishion, 2013). Past work has demonstrated peer homophily in terms of academic achievement, using diverse methods (Kindermann, 2007; Ryan, 2001; Wentzel, 2009). In the context of peer affiliations and their relationships to academic achievement, peers have been found to provide cognitive stimulation and reinforcement, social and emotional support, and to serve as role models for behaviors, attitudes, and knowledge (Hartup, 2009; Patrick et al., 1997; Wentzel, 2009). In previous studies, peer influence was described as a significant mechanism for understanding how peers relate to and change their academic achievement outcomes (Altermatt & Pomerantz, 2003; Cook et al., 2007; Kindermann, 2007; Ryan, 2001). However, these past studies failed to examine network structural characteristics, changes in both peer affiliations and academic achievement over time, or to use multiple indicators of selection and influence. By including all of these components within the current study, a more precise analysis of processes of peer selection and peer influence related to academic achievement over time was demonstrated.

The findings from the current study lend support to the role of homophily in peer affiliations and academic achievement, with peer affiliates sharing the same demographic characteristics and similar academic achievement outcomes. This finding has long been supported in the literature; peer affiliates have tended to be part of the same demographic groups and to share similar attitudes and behaviors (Kindermann & Gest, 2009; McPherson et al., 2001; Ryan, 2001; Wentzel, 2009). In brief, adolescents in the present study were more likely to select peers who had similar grades compared to other peers in the network; that is, academic achievement was an important characteristics used to select affiliations. However, after accounting for overall network similarities on academic achievement and selection processes, no further academic achievement similarities were found, indicating that influence mechanisms did not play a significant role in changes to students' academic achievement.

Selection was measured by three different parameters that examined the relationship between affiliation patterns and academic achievement: how grades was related to activity (i.e., the ego parameter), how grades was related to popularity (i.e., the alter parameter), and whether or not academic achievement similarities were found between affiliates (i.e., the similarity parameter). According to the findings of the current study, the selection of peer affiliations, that is, activity and academic achievement were not related. A trend toward significance suggested that students who had higher grades were more likely to be selected as affiliates (i.e., were more popular), compared to those with lower grades. Finally, students were found to affiliate with peers of similar grades, rather than to affiliate with students who had different grades. In past studies, peer influence was described as similarity among peers and often did not capture the similarity between individuals prior to affiliation (see Cook et al., 2007; Kindermann, 2007; Ryan, 2001). As the findings from the current study indicated, similarity on grades between affiliates was significant at the start of the affiliation and did not change over time.

Influence was assessed using three different parameters: one parameter that compared individuals' behavior to all of their affiliates' behavior (i.e., average similarity), a parameter that compared individuals' behavior to the average behavior of their affiliates (i.e., total similarity), and a parameter that compared the average behavior of affiliates to individuals' behavior (i.e., average alter). None of these mechanisms on influence were significantly related to academic achievement in this study. The overall absence of an influence effect was counter to many earlier studies which reported significant peer influence effects (Cook et al., 2007; Kindermann, 2007; Ryan, 2001). However, these earlier studies did not include measures of peer selection or network structural effects. Therefore, it appears that earlier studies were also measuring network-wide similarities across the schooling context as well as components of peer selection within their influence parameters. When those network characteristics and peer selection were specified and independently measured in the current study, peer influence was no longer significant.

The present study extends the understanding of the contributions of peer selection and influence to academic achievement by including information on network structural characteristics (e.g., density, reciprocity) as well as processes of peer selection (Flashman, 2012). In prior studies, researchers did not take into account network homogeneity which for adolescent populations typically occurs in schools. In addition, these studies typically focused on friendship dyads or peer groups, without accounting for other students who were part of the shared network but not identified as part of the group. Students who attend the same school are more likely to be similar to their classmates, than to students in other schools (Crosnoe, 2000). Thus, early studies may have misinterpreted the strength and magnitude of the similarities between affiliates by not parsing the overall network similarity on academic achievement from the measurement of affiliate similarity on achievement. By including network structural characteristics into the analysis of peer affiliates' influence on behavior, a more accurate understanding of the unique elements within peer affiliations across a shared environment can be ascertained.

Previous studies have characterized selection processes as fixed, with any changes in behavior attributed to peer influence (Kindermann, 1993; Ryan, 2001; Wentzel & Caldwell, 1997). Because selection processes have been conceptualized as fixed and unchanging, selection has not been a key focus in understanding behavior homophily and was often not studied (Kindermann, 2007; Ojanen et al., 2010). However, selection can be viewed as active and dynamic, as a process whereby individuals sort themselves into homogenous affiliations (Kindermann, 2007; Veenstra & Dijkstra, 2012). Therefore, studies of peer influence that did not account for peer selection may have misinterpreted similarity among peers as part of the processes of influence, leading to an overestimation of the strength and magnitude of this process. This study suggests that the similarity between peer affiliations on academic achievement that was found may be best understood as a function of the overall school environment as well as the sorting process that occurs during affiliation selection.

Peer influence, when separated from both network characteristics and selection effects, may not be the key mechanism for understanding academic achievement among affiliates within a network. In earlier studies, similarity among affiliates may have been misspecified, including characteristics of the overall network and the selection process. If homogeneity with respect to academic achievement occurs at both the network level and/or the selection process, few differences should be found among the affiliates in terms of academic achievement. The lack of variance in academic achievement in the current study may be due to these network and selection processes that maximize grade similarities. Peer influence, by definition, can only occur among affiliates who differ on behaviors, with the goal to make peer members more homogeneous. Stated differently, if during the peer selection process students sorted themselves into homophilous relationships that maximized similarity, it is unknown if remaining differences between affiliates can still be altered through peer influence (Altermatt & Pomerantz, 2003; Kindermann, 2007).

Additionally, it may be that academic achievement is not a behavior that is susceptible to peer influence, contrary to interpretations of previous results (Ryan, 2000; Wentzel, 2009). Among the studies using Siena, some behaviors, such as aggression and substance use, appear to include both processes of peer selection and influence (de la Haye, Green, Kennedy, Pollard, & Tucker, 2013; Osgood et al., 2013; Rulison, Gest, & Loken, 2013). However, it appears that other behaviors, such as smoking cigarettes, were affected by selection, but not peer influence (Delay et al., 2013). In the Delay et al. (2013) study, peer affiliates typically shared similar smoking behaviors; but when discrepancies occurred, individuals were more likely to dissolve their affiliations than to engage in influence processes that would lead to changes in behavior. Thus, for academic achievement, individuals appear to be more likely to share similarity with peers, selecting grade-mates who share their achievement behaviors and changing affiliations when their behaviors no longer align.

More study is warranted on the timing of selection and influence on peer affiliations, and the relationship of this timing to academic achievement during adolescence. In the present study and for all studies using Siena, there is a direct temporal ordering of selection and influence (Dishion, 2013; Veenstra, Dijkstra, Steglich, & Van Zalk, 2013). This aligns with the theory of assortative pairing, in which individuals first define what they value and then select affiliates who can support those values (Kandel, 1978). In both the Siena and assortative pairing conceptualizations, peer selection of affiliates occurs before behaviors; influences are examined after behaviors first occur (Steglich et al., 2010). However, it is unclear if it is appropriate for processes of peer selection and influence to be temporally fixed, as some researchers have argued that influence processes may actually occur prior to selection (Dishion, 2013). For example, individuals might aspire to affiliate with peers who take part in particular behaviors. Thus, adolescents might engage in certain behaviors (e.g., smoking cigarettes, academic engagement) prior to affiliating with similar peers, which would reflect the role of influence prior to selection. A future study might test the temporal ordering of selection and influence to determine if individuals were influenced by others prior to selection. Testing this alternative hypothesis on the timing of selection and influence through experimental design would be helpful to determine if the assumptions of the current study (i.e., the timing of selection prior to influence) were appropriately defined.

Moderators of Peer Selection and Influence

The findings of the current study help to clarify the mechanisms of peer selection and influence, by examining the extent to which selection and influence are differentially affected by student characteristics. In general, research on the contributions of peer selection and influence to behaviors has not focused on any moderators of these mechanisms, merely attending to the mechanisms themselves (see Brechwald & Prinstein, 2011). Additionally, studies using stochastic actor models have focused primarily on selection and influence, including network structural characteristics, with minimal attention to individual characteristics that could affect selection and influence of behaviors (see Veenstra & Dijkstra, 2012). However, several of the studies in the special issue on network-behavior dynamics pointed to the growing need to analyze moderator effects to better understand differences between individuals, their affiliates, and how they relate to behaviors (Molano, Jones, Brown, & Aber, 2013; Ojanen et al., 2013; Veenstra et al., 2013). In the literature extant, only a single study using stochastic actor modeling has focused on adolescent peer networks and their relationship to academic achievement (Flashman, 2012). The author included some network structural characteristics (i.e., reciprocity and transitivity) but not others (i.e., density or hierarchy) as well as an indicator of individual difference, popularity. The processes of peer selection and influence, and their effects on academic achievement were studied, but no moderators were included (Flashman, 2012). The present study represents an advancement over Flashman's study, by not only including a full array of structural characteristics and individual differences, but also moderators of selection and influence, to assess different demographic patterns of in peer affiliations and academic achievement

In the present study, patterns of selection were differentially affected by achievement and race for both African American and European American students. African American students with higher grades nominated more affiliates than their lower achieving counterparts; that is, they were more active in the network. African American students with higher grades have higher activity rates, indicating their propensity to nominate significantly more affiliates compared to African American students with lower grades. Prior work has shown that activity in the network, that is, nominating many others to affiliate with, may be related to a sense of school belonging, that is, feeling connected and supported by other peers in the school network (Goodenow, 1993; Gutman et al., 2002; Osterman, 2000). Thus, the higher activity rate for African American students with higher grades may be related to a sense of belonging, which also may be related to higher academic achievement. Future study should measure a sense of school belonging along with network and behavior data to determine the exact link between these concepts. African American students with higher grades did not differ from African Americans students with lower grades in the number of nominations they received from others (i.e., popularity); meaning that there were no differences found by popularity among African American students who had low grades versus high grades. European American students had a different pattern of results, with a different pattern of affiliation by academic achievement. Neither activity nor popularity differed for European American students with high grades compared to European American students with lower grades. This means that for European American students, there were no systematic patterns of difference between the nominations sent and received by those with higher grades compared to those with lower grades. It may be that for European American students other characteristics are more salient to the solicitation and receiving of peer affiliate nominations   In one prior study, European American students were surveyed and indicated that academic achievement was not a salient characteristic in selecting peer affiliations (Berndt & Keefe, 1992). Future work could identify which attributes are most salient for understanding the selection of peer affiliates.

In the present study, higher achieving African American and European American students were more likely to affiliate with students who were not of their race. However, lower achieving African American and European American students were more likely to affiliate with students who share the same race. These findings lend support to the results of previous work that has reported academic benefits to cross-race relationships (see Goza & Ryabov, 2009; Hallinan & Williams, 1990; Hamm et al., 2005). The current study extends these prior findings by examining cross-race relationships across time, race, and achievement level. By examining cross-race relationships across time, a better understanding of the dynamics of reciprocity and stability can be garnered, and how those attributes relate to academic achievement. It may be that cross-race relationships afford students a greater diversity of educational resources, which leads to higher academic achievement (Coleman, 1988; Crosnoe et al., 2003). Or, it may be that students of both races who have higher grades have more opportunities to explore cross-race affiliations, which leads to most of the educational resources residing with high achieving students (Wilson et al., 2011).

The interactions between gender and grades and their relationship to activity (i.e., the number of nominations sent to peer affiliates in the network), popularity (i.e., the number of nominations received by peer affiliates in the network), and cross-gender relationships were also addressed in the present study. The results indicated that higher achieving male students selected fewer affiliates than did higher achieving female students. This may be an indicator of school belonging, which would suggest that higher achieving female students may have a higher sense of school belonging, compared to their higher achieving male counterparts. Academic achievement of boys and girls was not related to popularity in the network, as measured through the number of nominations received from others. Popularity, in this study, was defined as having high overall network status, which has been theorized to be similar to direct measures of sociometric popularity and perceived popularity (Moody, Brynildsen, Osgood, Feinberg, & Gest, 2012). Given that, these results appear to agree with previous findings using more direct measures of popularity that indicated that there was no linear relationship between popularity and academic achievement (see Schwartz et al., 2006). Finally, no differences were found between grades and cross-gender relationships, meaning that academic achievement and gender did not change the patterns of cross-gender affiliations.

Interactions between academic achievement and demographics were found in students' nomination patterns, indicating that different patterns of selection occurred by achievement, race, and gender. Those same interactions were examined to determine if different patterns of influence occurred. In the current study, no differences in the influence processes were found among African American students by grades, European American students by grades, or between male and female students by grades. This was counter to the hypotheses stated but not unexpected, since both the influence effects for the entire network and the influence effects by demographic characteristics were not significant. That is, overall, there were no differences in influence across the network, or any significant influence effects by race or gender on academic achievement. These results also counter previous findings in which peer influence affected academic achievement outcomes (Wentzel, 2009). However, as described previously, it may be that what has been interpreted as peer influence in prior studies can be better defined as three interrelated components: similarities across individuals within the same schooling context, sorting processes in selecting peers to maximize similarities, and processes of peer influence to reinforce or increase similarity across time.

Examining Networks and Behaviors Together

The present study applied stochastic actor modeling to study the co-evolution of network and academic achievement across time (Snijders et al., 2010). Using this modeling approach, I have studied differences in students' behaviors, how students affiliate with other peers, the extent to which these patterns of affiliations are similar or different across students, and how these characteristics are aggregated across the network. The current findings were consistent with the results of prior studies with regard to the structural characteristics of adolescent peer affiliative networks (Veenstra & Dijkstra, 2012). As with these other studies, all network structural characteristics were significant (e.g., density) and continued to be significant, even when individual level characteristics were included in the model (see Ojanen et al., 2013; Steglich et al., 2010; Van Workum, 2013).

In addition to network structural characteristics, past research findings have shown that individual characteristics derived from network analyses provide useful differentiation among members of the network, and how these differences relate to behavioral differences (Snijders et al., 2010; Veenstra & Dijkstra, 2012). In the current study, both popularity and activity parameters were significant and positive, indicating the reinforcement of individuals' popularity and activity status through their patterns of affiliation. This means that individuals who nominated many other affiliates continued to do so over time. In addition, those who were nominated as affiliates more often continued to be selected over time. The reinforcement of popularity effects as defined in the current study were consistent with findings from other studies that have employed stochastic actor modeling, supporting the argument that popularity is a reinforcing construct over time (Osgood et al., 2013; Snijders et al., 2010; Veenstra & Dijkstra, 2012). Fewer studies have reported on the reinforcement of activity over time, and these results have been mixed (see de la Haye et al., 2013 for an example of a negative activity effect). Activity is derived from the number of nominations sent to others; researchers have differed in how they have operationalized activity, with some constraining the choice of affiliations to a select few and others allowing individuals to select as many affiliates as there are in the network (Cillessen, 2009; Coie et al., 1982; Kindermann & Gest, 2009). In the current study, individuals had an unconstrained selection of affiliates, which means that they could select as many affiliates in the network as they wanted. Therefore, differences in activity across studies might be due to these different measurement strategies.

The current study focused on academic achievement, a salient, universal behavior in U. S. adolescents' lives (Juvenon, 2007). The majority of the studies using Siena have focused on problem behaviors such as aggression, violence or substance use; or, to a lesser degree, internalized problem behaviors such as depression, eating disorders, and suicide risk (Veenstra et al., 2013). Few studies using Siena have focused on behaviors that are a universal engaged in by all adolescents such as academic achievement. In the study of problematic behaviors, the aims focus on whether or not individuals engaged in the behavior. In the study of universal behaviors, such as academic achievement, all individuals are engaged in the behavior, so that all receive some rating on the behavior. Relatively few adolescents are involved in behaviors such as weapons carrying or cutting but all adolescents take part in the schooling environment (Dijkstra, Lindenberg, Veenstra, Steglich, Isaacs, & Hodges, 2010; Giletta et al., 2013). Therefore, by focusing on a universal behavior like academic achievement, I have addressed issues that relate to the daily lives of all adolescents.

Limitations and Future Opportunities

The goal of the study was to examine the independent processes of peer selection and influence on academic achievement over time. Several aspects of the sample and methods may limit the generalizability of the results. First, the network and behavior data on the sample were taken from a single grade within a single magnet school. The school was unique in that the student body differed significantly from the rest of the school district, and potentially, from other public middle and high schools. Second, the attrition in the present sample may limit the power to detect findings or may have led to biased findings. Third, the Siena modeling process includes several assumptions which likely limit the generalizability of the results. Specifically, the Siena modeling framework is based on rational choice theory, which maximizes individual utility and minimizes error. Fourth, Siena is a relatively new process, and it remains unclear how to best implement a modelling program that continues to be developed while determining how to interpret the documentation of these changing processes. Finally, further dissemination of results is warranted to help researchers determine robust versus erroneous findings.

Sample characteristics. In the present study, networks were limited to peer affiliates who were within the same school and grade. Despite these restrictions, academic achievement was affected by peer selection, but not influence. Results from a number of studies have indicated that non-school peers, especially for African American students, influence students' achievement in both positive and negative ways (see Dubois & Hirsch, 1990; Gutman et al., 2002). Future studies might find different findings if they include peer nomination data across grade level or non-school friends. Specifically, this might strengthen the selection effect found in the current study and potentially detect influence effects.

The study's sample was collected in a magnet school, which may differ from neighborhood public schools in significant ways. Magnet schools tend to be less racially and economically disadvantaged compared to similar schools that are not magnets (Gamoran, 1996). Importantly, students choose to attend the magnet schools, whereas in traditional public schools, the majority of students do not select their schools. In addition to these demographic characteristics, students in magnet schools have higher scores on standardized tests, compared to students in similar neighborhood schools. It is unclear why significant differences in academic achievement have been found between these two types of schools. It may be that some magnet schools receive additional financial support. Also, there might be significant differences in school climate and family support with magnet schools that is lacking within neighborhood schools (Gamoran, 1996).

Like the general characteristics of the magnet schools described above, the sample appeared to differ in significant ways from the neighborhood schools in the district. The participating school had a more racially and economically diverse student population. The participating school had more students who were self-identified as being European American and fewer students eligible for free and reduced lunches, compared to the other middle schools within the district (NCDPI, 2007). In addition, students in the magnet school had significantly higher reading and math standardized test scores compared to students attending the neighborhood schools in the district (NCDPI, 2007).

It is unclear why differences in academic achievement were found between the magnet school and the other schools in the district. The participating magnet school did not receive any additional funding compared to the other schools in the district. It may be that parents of students at the magnet school are more actively involved in their children's' education compared to other schools. Consequently, the participating school may have had norms toward academic achievement that differed from the rest of the system (see Chang, 2004). It may be that these differences limit the generalizability of this study to the rest of the middle schools and high schools in the district. Future study focused on broader representation of students and their families may lead to different findings.

Finally, the rate of student participation in the study declined from 83% in 7th grade to 63% in 9th grade. Much of this attrition occurred because students left the school to attend other high schools within the district (Schmid, 2008). However, an assessment of the differences in students who stayed at the school versus students who left the school found no significant differences in demographic characteristics and academic measures (Schmid, 2008). Few studies have focused on the role of missing data in stochastic actor models and therefore, the impact of attrition on the models is not clear (Huisman & Steglich, 2008; Veenstra & Dijkstra, 2012). As with other studies, low participation rates can result in limited statistical power that can interfere with the researcher's ability to detect significant findings (Biemer & Lyberg, 2003). In addition, missing data within network studies is an even greater problem due to the dependencies between individuals and affiliates. Missing data can limit the understanding of the relationships between individuals and affiliates as well as the interconnectedness of the entire network that is constructed from aggregating all of the affiliations (Huisman & Steglich, 2008; Marsden, 1990). Furthermore, the imputation strategies that researchers use in employing stochastic actor models may lead to biased estimates as well as underestimated variance parameters which may also exacerbate the detection of significant findings (Huisman, 2009; Lepkowski, 1989). Future study should determine when and how missing data is problematic when using these models.

To better understand homophily effects over time, future studies need to address how often data are collected on network affiliations and member's behaviors (Kindermann & Gest, 2009). Specifically, the current study addressed peer selection and influence on academic achievement over a three year time span, with data collection on networks and behaviors at four different time points. Most of the studies using Siena have included multiple data points across a several year time span (Veenstra & Dijkstra, 2012). However, peer affiliations are not stable across time; findings suggest that at least half of relationships change between yearly assessments (Neckerman, 1996; Schmid, 2009). No published research has focused on the optimal timing of data collections to understand adolescent peer affiliations. More frequent data measurement would allow for more precise tracking of changes as well as better understandings of affiliation creation and dissolution. Future work must determine the optimal timing of measurement to best understand the changing peer ecology and its effects on behaviors.

Siena model assumptions. A basic premise in this study was that individuals' behavior cannot be divorced from the behaviors of their affiliations. Counter to this concept of the interrelated dependencies between individuals and affiliates in the network are the incremental process that Siena uses to construct an accurate representation of the network. Siena uses a series of individual decisions extended from rational choice theory, described as a microstep, to simulate the individual changes which increment across the entire network processes (Snijders, 2013). The concept of the microstep assumes that each individual makes decisions and changes based only on their own self-interest and complete knowledge of all affiliations in the network (Snijders et al., 2010). This conflict between how network affiliations were conceptualized and the individual nature underpinning the modeling process has not been addressed (see Snijders, 2013 for a description of the theory).

In addition to the microstep, the stochastic actor model assumes that individuals attempt to maximize their own rewards in the network while minimizing any cost. The maximization of reward is defined as integrating oneself fully into the network through maximizing similarity with one's affiliates. Any selection choice that does not follow this maximization principle is defined as error. Error is detected through simulating the network results under these premises and determining how the real affiliation data differs from those simulations. Stated another way, the random element in stochastic actor modeling procedure can be viewed as a discontinuity between affiliations observed across time and the findings with the simulations that maximize the network utility function (Snijders, 2013). In the current study, the random error, defined as discontinuity between the model and the actual data, may contain important information regarding the affiliation choices that individuals make, as well as differences in behaviors between individuals. A key decision that researchers must contend with is whether or not they believe that individuals form affiliations within a network, looking to maximize network structural characteristics, like reciprocity, and behavior similarities across affiliations. Maximization of network structural characteristics might be useful when studying structural issues across the network but may be less useful when understanding the patterns of relationships among individuals in the network. Future work should focus on how the model assumptions relate to model findings and highlight when and how Siena modeling is most appropriately used.

Development of stochastic actor modeling techniques. Siena is a relatively new statistical modeling technique and thus, the development and applications continue to evolve. Although the conceptual and mathematical properties were first described in 2001, the first application was published in 2007, and the first application of the co-evolution of networks and behaviors was published in 2010 (Burk et al., 2007; Snijders, 2001; Steglich et al., 2010). Major changes were undertaken in 2010 to move Siena within the R software framework. Although the main statistical processes of Siena have been developed, active modification and expansion continues. Siena is being developed by multiple users within the R platform, which is a strength in that development can occur and be deployed more rapidly and also be geared to researcher's needs. However, this presents challenges to researchers trying to determine which elements have been adequately developed, documented, and disseminated. In the two years since I started working with Siena, six or more updates have occurred. It is difficult to determine when enough development has occurred to ameliorate the majority of the errors within the parameters. Thus, there are elements being developed, such as the goodness-of-fit statistic, that have been modified and continue to be modified throughout the past two years. Therefore, I decided to only use Siena model elements that were developed and documented in the manual. In addition to these development activities, more work needs to focus on improving efficiency in the programming code. In the current study, a single model including networks and behaviors takes a day to implement, even while using parallel processing. To have wider applications using Siena, development of the programming must address these issues.

In addition to these programming elements, further dissemination of Siena and associated processes need to be extended. There are now approximately 50 articles that apply Siena techniques to networks and behaviors (Veenstra et al., 2013). Applied researchers continue to vary in their use and interpretation of the model parameters, and great variability in how peer selection and influence were constructed and interpreted persists (Snijders et al., 2010; Steglich et al., 2010; Veenstra et al., 2013). At the present time, researchers are only using the network structural effects and a few main individual effects to address selection and influence among different behaviors, with moderators rarely reported (Veenstra & Dijkstra, 2012). This may be due to the lack of clarity on moderators in the Siena documentation as well as the lack of dissemination of moderators using this framework (Ripley et al., 2014). Specifically, the manual does not include any guidance for how to interpret the moderator results, and in key articles using Siena, no moderators were included (Snijders et al., 2010; Steglich et al., 2010). It is unclear why the developers have not described this more fully, considering the depth of analysis and description on network effects (see Snijders et al., 2010) and the co-evolution of network and behavior effects (see Steglich et al., 2010).

Conclusion

Adolescents are embedded in peer networks, defined as a set of affiliations between individuals who are bounded together in an environmental context, in this case, school (Wasserman & Faust, 1994). Peer affiliations within a school network are central to adolescents' academic achievement outcomes over time (Crosnoe et al., 2003; Kindermann, 2007; Ryan, 2001; Wentzel, 2009). Members of peer networks tend to share demographic characteristics, as well as similar attitudes, values, and behaviors (Kindermann & Gest, 2009; McPherson et al., 2001). However, the precise mechanisms through which peer affiliations contribute to academic achievement have not been well-understood, with little attention on how selection and influence independently alter adolescents' academic achievement. Using stochastic actor modeling, selection and influence effects can be independently parsed through studying the co-evolution in peer networks and behaviors simultaneously (Snijders et al., 2010). The present study provided valuable contributions to the literature by testing the nature of changes in affiliation at the individual and network level as well as changes in behavior over time; by assessing the individual differences in these affiliations and behaviors; and deriving an independent parameter of selection and influence, controlling for individual and network effects. Processes of peer selection, not peer influence, were related to changes in academic achievement. It may be that once similarities shared across the network as well as processes of selection which sort on similarity are accounted for, the processes of peer influence cannot be detected.

Appendix A. Descriptive Network Statistics

Table A1.

Dyad Census

Tie	T1	T2	T3	T4
Mutual	791	841	822	538
Asymmetrical	1641	2173	1860	1399
Total Ties	2432	3014	2682	1937
Total Possible Ties	15018	16313	16161	17691

Table A2.

Triad Census

Triad Type	T1	T2	T3	T4
003	404186	922220	287811	171242
012	169695	356976	148320	84260
102	82620	103065	70681	37478
021D	344460	62500	284640	173505
021U	6059	12325	73822	3275
021C	8036	13309	8525	4590
111D	8660	8256	25341	4097
111U	102971	31640	91138	51132
030T	47277	11278	65764	29175
030C	128	144	172	77
201	10360	4703	202062	326870
120D	22977	3037	25775	12809
120U	107392	7078	22031	61426
120C	5782	1781	7909	2969
210	37262	3953	155825	267767
300	15836	1200	73649	313393

Table A3.

Relationship affiliations across time

Tie	Time 1 to Time 2	Time 2 to Time 3	Time 3 to Time 4
No -> No	29599	29651	31061
No -> Yes	2464	1950	1439
Yes -> No	1812	2345	2655
Yes -> Yes	2170	2360	1575

Table A4.

Changes in EOG scores across time

	T1 -> T2	T2 -> T3	T3 -> T 4
% actors whose EOG went up	27.85	6.15	22.22
% actors whose EOG went down	16.45	51.54	23.01
% actors whose EOG was stable	55.06	41.54	53.97

Appendix B. Siena Model Results

Table B1.

Model Q3: Characteristics derived from network analysis

Parameter	Estimate	SE	*t*
Density	-0.6347	0.1512	-4.20**
Reciprocity	1.3212	0.0330	40.04***
Transitive Triples	0.0951	0.0066	14.41***
3-cycle / anti-hierarchy	-0.0298	0.0050	-5.96***
Balance	-0.0009	0.0034	-0.26
Actors at Distance 2	-0.0185	0.0064	-2.89*
Popularity	0.0217	0.0071	3.06*
Activity	0.0129	0.0018	7.17***
Out-out assortativity	-0.0499	0.0080	-6.24
In-in assortativity	-0.0393	0.0151	-2.60

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B2.

Model Q3: Characteristics derived from demographics

Parameter	Estimate	SE	*t*
Density	-2.6222	0.0627	-41.82***
Reciprocity	1.2952	0.0614	21.09 ***
Transitive Triples	0.0319	0.0036	8.86 ***
3-cycle / anti-hierarchy	-0.0297	0.0063	-4.71 *
Balance	0.0181	0.0013	13.92 ***
Actors at Distance 2	-0.0048	0.0031	-1.55
Popularity	0.0055	0.0012	4.58 **
Activity	0.0208	0.0013	16.00 ***
Same race (African American)	0.1737	0.0254	6.84 ***
Same race x reciprocity (African American)	-0.0117	0.0645	-0.18
Same race (European American)	0.1251	0.0256	4.89 *
Same race x reciprocity (European American)	-0.2634	0.0676	-3.90 *
Same gender (Male)	0.1990	0.0195	10.20 ***
Same gender x reciprocity (Male)	0.1036	0.0537	1.93 ***

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B3.

Model for Q4: Behavior shape parameters

Parameter	Estimate	SE	*t*
Density	-2.8612	0.0660	-43.35 ***
Reciprocity	1.4207	0.0572	24.84 ***
Transitive Triplets	0.0184	0.0039	4.72 ***
3-cycle / anti-hierarchy	-0.0117	0.0063	-1.86 *
Balance	0.0211	0.0014	15.07 ***
Actors at Distance 2	-0.0180	0.0030	-0.60
Popularity	0.0089	0.0010	8.90 ***
Activity	0.0243	0.0015	16.20 ***
Same race (African American)	0.1946	0.0243	8.01 ***
Same race x reciprocity (African American)	-0.0927	0.0618	-1.50
Same race (European American)	0.1456	0.0255	5.71 ***
Same race x reciprocity (European American)	-0.2951	0.0646	-4.57 ***
Same gender (Male)	0.2309	0.0189	12.22 ***
Same gender x reciprocity (Male)	0.0599	0.0492	1.22
Behavior Effects			
Linear shape	0.0371	0.0774	0.48
Quadratic shape	0.0627	0.0437	1.43

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B4.

Model for Q5: Popularity and Activity behavior effects

Parameter	Estimate	SE	*t*
Density	2.9160	0.0632	46.14 ***
Reciprocity	1.4451	0.0639	22.61 ***
Transitive Triplets	0.0154	0.0036	4.28 *
3-cycle / anti-hierarchy	-0.0076	0.0059	-1.29
Balance	0.0219	0.0013	16.85 ***
# actors - distance 2	-0.0006	0.0034	-0.18
Popularity	0.0094	0.0009	10.44 ***
Activity	0.0254	0.0015	16.93 ***
Same race (African American)	0.1976	0.0224	8.82 ***
Same race x reciprocity (African American)	-0.1046	0.0659	-1.59
Same race (European American)	0.1480	0.0234	6.32 ***
Same race x reciprocity (European American)	-0.3054	0.0608	-5.02 ***
Same gender (Male)	0.2335	0.0185	12.62 ***
Same gender x reciprocity (Male)	0.0497	0.0536	0.93
Behavior Effects			
Linear shape	0.3051	0.2772	1.10
Quadratic shape	0.0529	0.0484	1.09
Popularity behavior effect	-0.0015	0.0112	-0.134
Activity behavior effect	-0.0083	0.0039	-2.13

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B5.

Model for Q5: Demographic behavior effects

Parameter	Estimate	SE	*t*
Density	-3.0783	0.0597	-51.56 ***
Reciprocity	1.5109	0.0597	25.31 ***
Transitive Triplets	0.0086	0.0032	2.69 *
3-cycle / anti-hierarchy	0.0014	0.0054	0.26
Balance	0.0238	0.0012	19.83 ***
Actors at Distance 2	0.0035	0.0032	1.09
Popularity	0.0110	0.0010	11.00 ***
Activity	0.0279	0.0013	21.46 ***
Same race (African American)	0.2100	0.0251	8.37 ***
Same race x reciprocity (African American)	-0.1309	0.0627	-2.09 *
Same race (European American)	0.1591	0.0252	6.31 ***
Same race x reciprocity (European American)	-0.3350	0.0642	-5.22 ***
Same gender (Male)	0.2479	0.0191	12.98 ***
Same gender x reciprocity (Male)	0.0212	0.0492	0.43
Behavior Effects			
Linear shape	0.1211	0.3388	0.36
Quadratic shape	-0.0259	0.0575	-0.45
Popularity behavior effect	0.0065	0.0133	0.49
Activity behavior effect	-0.0092	0.0046	-2.00 *
Male behavior effect	0.2595	0.1743	1.49

African American behavior effect	0.1414	0.2657	0.53
European American behavior effect	0.5403	0.2737	1.97 *

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B6

Selection Effects Only

Parameter	Estimate	SE	*t*
Density	-2.9123	0.0731	-39.84 ***
Reciprocity	1.4234	0.0582	24.46 ***
Transitive Triplets	0.0157	0.0039	4.02 ***
3-cycle / anti-hierarchy	-0.0086	0.0061	-1.41
Balance	0.0214	0.0013	16.46 ***
Actors at Distance 2	0.0010	0.0035	0.28
Popularity	0.0095	0.0011	8.64 ***
Activity	0.0251	0.0015	16.73 ***
Same race (African American)	0.1852	0.0255	7.26 ***
Same race x reciprocity (African American)	-0.1205	0.0647	-1.86 *
Same race (European American)	0.1318	0.0260	5.07 ***
Same race x reciprocity (European American)	0.2815	0.0669	4.21
Same gender (Male)	0.2312	0.0186	12.43 ***
Same gender x reciprocity (Male)	0.0498	0.0499	1.00
Grade ego	0.0012	0.0074	0.16
Grade alter	0.0098	0.0067	1.46
Grade similarity	0.3017	0.0475	6.35 ***
Behavior Effects			
Linear shape	0.1361	0.2862	0.47
Quadratic shape	-0.0251	0.0562	-0.45

Grade indegree	0.0058	0.0123	0.47
Grade outdegree	-0.0093	0.0045	-2.07 *
Male behavior effect	-0.2619	0.1911	-1.37
African American behavior effect	-0.1473	0.2628	-0.56
European American behavior effect	0.5315	0.2765	1.92 *

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B7.

Selection Effects with Moderators

	Estimate	SE	*t*
Density	-2.9284	0.0605	-48.40 ***
Reciprocity	1.3964	0.0612	22.82 ***
Transitive Triplets	0.0165	0.0034	4.85 ***
3-cycle / anti-hierarchy	-0.0094	0.0055	-1.71 *
Balance	0.0214	0.0012	17.83 ***
Actors at Distance 2	0.0037	0.0034	1.09
Popularity	0.0094	0.0011	8.54 ***
Activity	0.0251	0.0013	19.31 ***
Same race (African American)	0.2062	0.0275	7.50 ***
Same race x reciprocity (African American)	-0.0931	0.0688	-1.35
Same race (European American)	0.1494	0.0265	5.64 ***
Same race x reciprocity (European American)	-0.2573	0.0676	-3.81 **
Same gender (Male)	0.2363	0.0197	11.99 ***
Same gender x reciprocity (Male)	0.0446	0.0505	0.88
Grade ego	0.0027	0.0073	0.40
Grade alter	0.0151	0.0071	2.13 *
Grade similarity	0.3413	0.0470	7.26 ***
Grade ego x African American ego	0.0598	0.0267	2.24 *
Grade ego x European American ego	0.0225	0.0268	0.84
Grade ego x Male ego	-0.0531	0.0141	-3.76 **

Grade alter x African American alter	0.0162	0.0269	0.60
Grade alter x European American alter	-0.0133	0.0283	-0.47
Grade alter x Male alter	-0.0015	0.0145	-0.10
Grade similarity x African American	-0.2784	0.1347	-2.07 *
Grade similarity x European American	-0.3313	0.1442	-2.30 *
Grade similarity x Male	0.0158	0.0971	0.16
Behavior Effects			
Linear shape	0.1378	0.3230	0.43
Quadratic shape	-0.0274	0.0584	-0.47
Grade indegree	0.0057	0.0135	0.42
Grade outdegree	-0.0092	0.0051	-1.80 *
Male behavior effect	-0.2605	0.1786	-1.46
African American behavior effect	-0.1379	0.2690	-0.51
European behavior effect	0.5432	0.2721	2.00 *

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B8.

Influence Effects Only

	Estimate	SE	*t*
Density	-3.1110	0.0627	-49.62 ***
Reciprocity	1.5316	0.0602	25.44 ***
Transitive Triplets	0.0073	0.0036	2.03 *
3-cycle / anti-hierarchy	0.0029	0.0057	0.51
Balance	0.0240	0.0014	17.14 ***
Actors at Distance 2	0.0041	0.0035	1.17
Popularity	0.0114	0.0010	11.40 ***
Activity	0.0284	0.0015	18.93 ***
Same race (African American)	0.2137	0.0262	8.16 ***
Same race x reciprocity (African American)	-0.1387	0.0667	-2.08 *
Same race (European American)	0.1615	0.0245	6.59 ***
Same race x reciprocity (European American)	-0.3421	0.0660	-5.18 ***
Same gender (Male)	0.2523	0.0200	12.61 ***
Same gender x reciprocity (Male)	0.0116	0.0542	0.21
Behavior Effects			
Linear shape	-0.1885	0.4570	-0.41
Quadratic shape	0.3656	0.9151	0.40
Grade indegree	0.0121	0.0192	0.63
Grade outdegree	-0.0059	0.0058	-1.02
Male behavior effect	-0.2384	0.2446	-0.97

African American behavior effect	0.3121	0.4876	0.64
European American behavior effect	0.3443	0.4043	0.85
Average Similarity	12.1900	15.6944	0.78
Total Similarity	-0.0650	0.0807	-0.80
Average Alter	0.5267	2.3927	0.22

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B9.

Influence Effects with Moderators

	Estimate	SE	*t*
Density	-3.0197	0.0679	-44.47 ***
Reciprocity	1.4909	0.0798	18.68 ***
Transitive Triplets	0.0111	0.0050	2.22 *
3-cycle / anti-hierarchy	-0.0019	0.0075	-0.25
Balance	0.0230	0.0018	12.78 ***
Actors at Distance 2	0.0017	0.0036	0.47
Popularity	0.0105	0.0011	9.54 ***
Activity	0.0269	0.0020	13.45 ***
Same race (African American)	0.2067	0.0332	6.22 ***
Same race x reciprocity (African American)	-0.1248	0.0929	-1.34
Same race (European American)	0.1546	0.0331	4.67 ***
Same race x reciprocity (European American)	-0.3221	0.0854	-3.77 **
Same gender (Male)	0.2438	0.0406	6.00 ***
Same gender x reciprocity (Male)	0.0281	0.0680	0.41
Behavior Effects			
Linear shape	-1.8422	13.2259	-0.14
Quadratic shape	0.3181	1.6592	0.19
Grade indegree	-0.0007	0.0496	-0.01
Grade outdegree	-0.0149	0.0230	-0.65
Average Similarity	40.6581	199.5298	0.20

Total Similarity	-0.2111	1.0832	-0.19
Average Alter	8.8870	59.5183	0.15
Male behavior effect	0.1738	0.8861	0.20
Average Similarity x Male	-1.0988	13.7329	-0.08
Total similarity x Male	-0.1777	0.5626	-0.31
Average Alter x Male	1.6675	2.3043	0.72
African American behavior effect	1.0983	6.3610	0.17
Average Similarity x African American	-48.5820	230.3934	-0.21
Total Similarity x African American	0.7724	4.6195	0.17
Average Alter x African American	-3.3285	11.0244	-0.30
European American behavior effect	-3.7273	34.5158	-0.11
Average Similarity x European American	32.2178	532.9947	0.06
Total Similarity x European American	0.2488	5.5365	0.04
Average Alter x European American	21.0470	154.6515	0.14

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B10.

Selection and Influence Effects Only

	Estimate	SE	*t*
Density	-3.0383	0.0744	-40.84 ***
Reciprocity	1.4859	0.0624	23.81 ***
Transitive Triplets	0.0110	0.0041	2.68 **
3-cycle / anti-hierarchy	-0.0027	0.0064	-0.42
Balance	0.0224	0.0015	14.93 ***
Actors at Distance 2	0.0037	0.0037	1.00
Popularity	0.0110	0.0011	10.00 ***
Activity	0.0267	0.0017	15.70 ***
Same race (African American)	0.1997	0.0257	7.77 ***
Same race x reciprocity (African American)	-0.1460	0.0672	-2.17 *
Same race (European American)	0.1419	0.0253	5.61 ***
Same race x reciprocity (European American)	-0.3073	0.0623	-4.93 ***
Same gender (Male)	0.2456	0.0186	13.20 ***
Same gender x reciprocity (Male)	0.0186	0.0543	0.34
Grade ego	0.0014	0.0071	0.20
Grade alter	0.0095	0.0069	1.38
Grade similarity	0.3024	0.0461	6.56 ***
Behavior Effects			
Linear shape	-0.2706	0.4296	-0.63
Quadratic shape	0.2286	0.7325	0.31

Grade indegree	0.0134	0.0167	0.80
Grade outdegree	-0.0053	0.0055	-0.96
Average similarity	10.7308	11.6981	0.92
Total similarity	-0.0679	0.0702	-0.97
Average Alter	0.6713	1.8900	0.35
Male behavior effect	-0.2456	0.2303	-1.07
African American behavior effect	0.2441	0.3785	0.64
European American behavior effect	0.3111	0.3840	0.81

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B11.

Selection and Influence Effects with Moderators

	Estimate	SE	*t*
Density	-3.0537	0.1632	-18.71 ***
Reciprocity	1.4457	0.1006	14.37 ***
Transitive Triplets	0.0112	0.0101	1.6 *
3-cycle / anti-hierarchy	-0.0024	0.0124	-0.19
Balance	0.0226	0.0025	9.04 ***
Actors at Distance 2	0.0067	0.0047	1.42
Popularity	0.0108	0.0016	6.75 ***
Activity	0.0269	0.0030	8.97 ***
Same race (African American)	0.2182	0.0354	6.16 ***
Same race x reciprocity (African American)	-0.1135	0.0828	-1.37
Same race (European American)	0.1579	0.0322	4.90 ***
Same race x reciprocity (European American)	-0.2795	0.0954	-2.93 *
Same gender (Male)	0.2502	0.0288	8.69 ***
Same gender x reciprocity (Male)	0.0184	0.0614	0.30
Grade ego	0.0026	0.0133	0.19
Grade alter	0.0145	0.0106	1.37
Grade similarity	0.3485	0.0709	4.91 ***
Grade similarity x African American	-0.2911	0.1878	-1.55
Grade similarity x European American	-0.3431	0.2016	-1.70 *
Grade similarity x Male	0.0084	0.1721	0.05

Grade ego x African American ego	0.0682	0.0327	2.08 *
Grade ego x European American ego	0.0289	0.0336	0.86
Grade ego x Male ego	-0.0565	0.0254	-2.22 *
Grade alter x African American alter	0.0154	0.0335	0.46
Grade alter x European American alter	-0.0088	0.0541	-0.16
Grade alter x Male alter	-0.0057	0.0203	-0.28
Behavior Effects			
Linear shape	-1.6375	7.4516	-0.22
Quadratic shape	0.1551	1.4132	0.11
Grade indegree	0.0047	0.0410	0.11
Grade outdegree	-0.0071	0.0189	-0.37
Average Similarity	30.6226	128.1934	0.24
Total Similarity	-0.2239	1.0725	-0.21
Average Alter	5.3470	25.0236	0.21
Male behavior effect	0.0306	0.9105	0.03
Average Similarity x Male	0.0737	12.4275	0.01
Total Similarity x Male	-0.1924	0.3690	-0.52
Average Alter x Male	1.1060	2.3999	0.46
African American behavior effect	0.7030	5.9627	0.12
Average Similarity x African American	-45.5351	403.0485	-0.11
Total Similarity x African American	0.9133	9.7214	0.09
Average Alter x African American	-1.2510	10.0559	-0.12
European American behavior effect	-2.9352	21.1033	-0.14

Average Similarity x European American	13.9315	603.0375	0.02
Total Similarity x European American	0.5042	11.0979	0.04
Average Alter x European American	12.8400	72.5075	0.18

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B12.

Selection and Influence effects using End of Grade (EOG) tests

	Estimate	SE	*t*
Density	-3.1037	0.0600	-51.73 ***
Reciprocity	1.5135	0.0616	24.57 ***
Transitive Triplets	0.0097	0.0034	2.85 **
3-cycle / anti-hierarchy	0.0006	0.0055	0.11
Balance	0.0242	0.0013	18.61 ***
Actors at Distance 2	0.0051	0.0034	1.50
Popularity	0.0105	0.0010	10.50 ***
Activity	0.0282	0.0014	20.14 ***
Same race (African American)	0.1896	0.0259	7.32 ***
Same race x reciprocity (African American)	-0.1322	0.0259	-1.89 *
Same race (European American)	0.1853	0.0257	7.21 ***
Same race x reciprocity (European American)	-0.3568	0.0650	-5.49 ***
Same gender (Male)	0.2529	0.0194	13.04 ***
Same gender x reciprocity (Male)	0.0217	0.0537	0.40
EOG ego	0.0127	0.0093	1.36
EOG alter	-0.0003	0.0087	-0.03
EOG similarity	0.1636	0.0828	1.97 *
EOG similarity x African American	0.1395	0.1732	0.80
EOG similarity x European American	-0.3015	0.1793	-1.68 *

EOG similarity x Male	-0.2088	0.1429	-1.46
EOG ego x African American ego	-0.0224	0.0285	-0.78
EOG ego x European American ego	0.0073	0.0280	0.26
EOG ego x Male ego	-0.0219	0.0158	-1.39
EOG alter x African American alter	0.0391	0.0254	1.54
EOG alter x European American alter	0.1051	0.0259	4.06 ***
EOG alter x Male alter	0.0074	0.0164	0.45
Behavior Effects			
Linear shape	0.1895	0.2823	0.67
Quadratic shape	-0.0615	0.2177	-0.28
EOG indegree	0.0064	0.0114	0.56
EOG outdegree	-0.0241	0.0107	-2.25 *
Average Similarity	-10.5439	10.3846	-1.01
Total Similarity	0.3448	0.1806	1.91 *
Average Alter	1.4065	0.8355	1.68 *
Male behavior effect	-0.0646	0.2642	-0.24
Average Similarity x Male	0.7198	4.4810	0.16
Total Similarity x Male	-0.0244	0.1020	-0.24
Average Alter x Male	0.4676	0.7036	0.66
African American behavior effect	-0.0731	0.4754	-0.15
Average Similarity x African American	0.8217	9.3700	0.08
Total Similarity x African American	-0.2646	0.5437	-0.49
Average Alter x African American	-0.5341	1.3259	-0.40

European American behavior effect	-0.5671	0.6212	-0.91
Average Similarity x European American	-7.2889	10.6800	-0.68
Total Similarity x European American	-0.0833	0.5641	-0.15
Average Alter x European American	2.6768	1.6164	1.66 *

*Note: *p<.05; **p<.01, and *** p<.0001*

Table B13.

Peer Networks and Grades: Examining Behavioral Attributes

	Estimate	SE	*t*
Density	-3.0625	0.0697	-43.94 ***
Reciprocity	1.4541	0.0819	17.75 ***
Transitive Triplets	0.0110	0.0040	2.75 **
3-cycle / anti-hierarchy	-0.0053	0.0058	-0.91
Balance	0.0208	0.0016	13.00 ***
Actors at Distance 2	0.0016	0.0046	0.35
Popularity	0.0122	0.0012	10.17 ***
Activity	0.0258	0.0018	14.33 ***
Same race (African American)	0.1553	0.0356	4.36 ***
Same race x reciprocity (African American)	-0.1070	0.0739	-1.45
Same race (European American)	0.1611	0.0270	5.97 ***
Same race x reciprocity (European American)	-0.3144	0.0668	-4.71 ***
Same gender (Male)	0.2477	0.0229	10.82 ***
Same gender x reciprocity (Male)	0.0228	0.1066	0.21
Similar Aggression	0.3159	0.0854	3.67 **
Similar Aggression x reciprocity	-0.0469	0.1504	-0.31
Similar Leadership	0.0607	0.0483	1.26
Similar Leadership x reciprocity	0.1348	0.1305	1.03
Similar Deviance	0.2503	0.0774	3.23 **

Similar Deviance x reciprocity	-0.1879	0.1774	-1.06
Grade Ego	-0.0130	0.0096	-1.35
Grade Alter	-0.0071	0.0153	-0.46
Grade Similar	0.2142	0.0610	3.51 **
Behavior Effects			
Linear shape	-1.0938	3.4932	-0.31
Quadratic shape	-0.0659	1.1234	-0.06
Grade indegree	-0.0019	0.0706	-0.03
Grade outdegree	-0.0039	0.0160	-0.24
Average Similarity	17.8238	43.7338	0.41
Total Similarity	-0.1683	0.6017	-0.28
Average Alter	1.7491	11.7933	0.15
Male behavior effect	0.1547	1.3126	0.12
Average Similarity x Male	7.4162	25.3470	0.29
Total Similarity x Male	-0.3448	0.8128	-0.42
Average Alter x Male	1.2533	4.0461	0.31
African American behavior effect	0.5110	2.4205	0.21
Average Similarity x African American	-20.8770	135.8856	-0.15
Total Similarity x African American	0.4667	3.4811	0.13
Average Alter x African American	0.2059	4.0639	0.05
European American behavior effect	-1.1597	10.4800	-0.11
Average Similarity x European American	-2.6151	209.4073	-0.01
Total Similarity x European American	0.5009	3.9636	0.13

Average Alter x European American	6.4491	30.1811	0.21
Aggression behavior effect	-0.4776	0.4887	-0.98
Average Similarity x Aggression	-7.9554	9.6948	-0.82
Total Similarity x Aggression	0.1740	0.2899	0.60
Average Alter x Aggression	-0.4381	1.2043	-0.36
Leadership behavior effect	0.2953	0.3167	0.93
Average Similarity x Leadership	0.5551	9.1786	0.06
Total Similarity x Leadership	0.0107	0.1715	0.06
Average Alter x Leadership	-0.1980	0.7048	-0.28
Deviance behavior effect	-0.5131	1.4029	-0.36
Average Similarity x Deviance	4.2835	8.8762	0.48
Total Similarity x Deviance	-0.0717	0.2348	-0.30
Average Alter x Deviance	-0.6642	2.3715	-0.28

*Note: *p<.05; **p<.01, and *** p<.0001*

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