THREE ESSAYS ON NONCOGNITIVE FACTORS,

FRIENDSHIP NETWORKS AND EDUCATION OUTCOMES

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A DISSERTATION

in

Education

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2020

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DEDICATION

For Jaeyoon Chung, my loving husband.

ACKNOWLEDGMENT

I am extremely grateful to the incredible individuals who provided encouragement, support and guidance throughout this project. I am thankful to Dr. Robert Boruch for his unwavering patience and guidance for the last seven years. I always felt welcomed knocking on his door with numerous questions and ideas and I left each meeting with more energy than I had arrived with. Those conversations were the highlights of my graduate school experience and I will miss them dearly. I would also like to thank Dr. Michael Rovine for spending many hours advising me on this project. Dr. Rovine always had the clearest explanations to the most complex materials and I am deeply humbled and inspired by his dedication to excellence. I am also extremely thankful to Dr. Wendy Chan for readily lending an ear whenever I ran into methodological challenges and always guiding me to the right paths. I would also like to thank Dr. Rand Quinn, whom I consider a mentor, for providing constant support and encouragement throughout this journey. I am also grateful to Christine Lee and Linda Chandler of the Quantitative Methods division whose support made graduate school an unforgettable chapter in my life. I would also like to extend my heartfelt gratitude to Zach Nachsin who helped me tremendously with data security and software management as I conducted all my analyses in the data secure room. Finally, I am extremely grateful to my colleagues, friends and family who supported with encouragement and genuine advice throughout. I am deeply thankful to each one of you.

This research uses data from Add Health, a program project directed by Kathleen Mullan Harris and designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill, and funded by grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 23 other federal agencies and foundations. Information on how to obtain the Add Health data files is available on the Add Health website (http://www.cpc.unc.edu/addhealth). No direct support was received from grant P01-HD31921 for this analysis.

This research uses data from the AHAA study, which was funded by a grant (R01 HD040428-02, Chandra Muller, PI) from the National Institute of Child Health and Human Development, and a grant (REC-0126167, Chandra Muller, PI, and Pedro Reyes, Co-PI) from the National Science Foundation. This research was also supported by grant, 5 R24 HD042849, Population Research Center, awarded to the Population Research Center at The University of Texas at Austin by the Eunice Kennedy Shriver National Institute of Health and Child Development. Opinions reflect those of the authors and do not necessarily reflect those of the granting agencies.

ABSTRACT

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Robert F. Boruch

With an increasing focus on noncognitive factors in education, understanding their measurement of growth is more important than ever. Yet, little research systematically examines noncognitive factors during adolescence. Adolescence is a highly transitional time when friendships become critical to the development of noncognitive factors and academic performance. Using data from the National Longitudinal Survey of Adolescent Health, this dissertation consists of three essays that focus on the interplay between noncognitive factors, friendship networks and high school outcomes. Chapter 1 studies the dimensionality and measurement of change in noncognitive factors during adolescence through examination of eleven survey questionnaires. Exploratory Factor Analysis and Confirmatory Factor Analysis are used to analyze the dimensionality of the survey items which tap into managerial skills, sense of belonging and self-esteem. Longitudinal scalar invariance was achieved for sense of belonging factor. We use common-factor model combined with the second-order factor model with factor loadings obtained from the scalar invariance model to examine growth in sense of belonging and find evidence of its growth during adolescence. However, significant variances in the intercept and slope of the second-order factor models suggest variations between students, inviting further research. Chapter 2 investigates the relationship between family income, friendship network centrality and sense of belonging in school. This study explores friendship network centrality as a possible mediator between family income and differential school belongingness reported by adolescents from different family income backgrounds. Results from mediation analysis suggests that friendship network centrality mediated the positive effect of family income on sense of belonging in school. This result remained consistent when we replicated the analysis using multilevel structural equations modeling framework. Chapter 3 examines the relationship between friendship network closure during ninth grade year and two subsequent high school academic outcomes: on-time high school graduation and course failures. The study uses propensity score matching and Cox proportional hazards model. We find limited evidence of causal relationship between ninth grade friendship network closure and high school academic outcomes but find its association to other ninth grade predictors of high school success, such as GPA and getting along with teachers.

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Background

The importance of noncognitive skills in academic and professional domains is well established. Intrapersonal skills such as self-discipline, grit, locus of control, sense of belonging, and growth-mindset are important predictors of school achievements, labor outcomes and upward social mobility (Brunello & Schlotter, 2011; Coleman & DeLeire, 2003; Duckworth & Seligman, 2005; Farrington et al., 2012; Heckman et al., 2013; Reeves et al., 2014). The growing consensus on the importance of noncognitive skills has prompted education researchers to focus on psychological interventions aimed at improving these noncognitive skills (Cohen et al., 2009; Hulleman & Harackiewicz, 2009). With the use of brief mindset interventions conducted in on-line or laboratory settings, research suggests possibility of scaling up mindset interventions which were traditionally delivered in person (Paunesku et al., 2015). Evidence suggests that the benefits may be more pronounced among underperforming students (David Yeager et al., 2014).

Despite the early success of these educational interventions, gaps in the current literature remain. Noncognitive skills are multifaceted and the definition of noncognitive skills remains a debate (Farrington et al., 2012; Heckman & Rubinstein, 2001). Unlike the cognitive skills which measurement has been well-documented through standardized tests, literature on measurement of noncognitive skills remains disparate and scare. Conflicting research evidence surrounds the malleability of noncognitive skills as well. Although the underlying assumptions behind the psychological interventions is that noncognitive skills are malleable and can be taught, research evidence on the long-term effects is divided. One research indicates that an online intervention improved growth mindset and resiliency in the short-term but the changes were not sustained (Donohoe et al., 2012).

Noncognitive skills

Literature around noncognitive skills developed through multiple disciplines. One of the early studies to use the term “noncognitive skills” was in the economics literature when Heckman and Rubinstein (2001) used the term to refer to general skillsets valued in the labor market and schools but not captured in traditional standardized testing. Upon examining the lower earnings of the General Education Degree (GED) recipients compared to ordinary high school graduates with comparable test scores, Heckman and Rubinstein (2001) attributed the reason for the difference in their income to the difference in noncognitive skills. However, lack of reliable measures for noncognitive skills made it difficult to identify which specific skill was the most important.

Studies of noncognitive skills in the economics literature used data from large, national surveys and the research focus was largely driven by the survey items included in those surveys. For example, using the National Longitudinal Survey of Youth (NLSY), Heckman et al.(2006) distinguished between self-esteem and locus of control as separate dimensions of noncognitive skills in studying their effects on schooling and employment decisions. Similarly, Judge and Hurst (2007) also used the NLSY and found that positive self-evaluations enhanced the benefits of high socioeconomic status and academic achievement.

How do noncognitive skills change academic outcomes? Research documents that noncognitive skills operate to help make decisions related to academic outcomes. Drawing from the human capital investment model and psychologists' concept of locus of control, Coleman and DeLeire (2003) showed that the locus of control, the extent to which an individual believes their actions will affect their outcomes, affects teenagers' decisions to invest in education.

Economists have viewed noncognitive skills as malleable, which are highly influenced by parents (Heckman & Masterov, 2007) and argued that early childhood interventions would have higher returns (Cunha et al., 2010; Cunha & Heckman, 2008). In a longitudinal Perry Preschool Study, in which 3-4 year old children participated in the randomized early childhood intervention, Heckman et al. (2013) found that the participants had positive life outcomes on education, income, marriage and health. The researchers noted that the program generated the positive outcomes, not through improvements in cognitive skills but by changing various noncognitive skills.

Personality traits

Noncognitive skills have been largely viewed as personality traits in psychology literatures. Using a well-known framework, the Big Five personality model, which comprises of: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, researchers have found that these personality traits could account for variations in academic outcomes that cognitive skills alone could not explain. The positive association between Conscientiousness and academic success is the most well-established (Bauer & Liang, 2003; Conard, 2006; Duff et al., 2004; O'Connor & Paunonen, 2007; Vedel, 2014). Evidence suggests that Conscientiousness affects academic performance through behavioral mediators, such as attendance (Conard, 2006) or setting sleep schedule (Gray & Watson, 2002). Studies show mixed results in relationship between Openness to Experience and academic success. Some studies found positive effects of Openness to Experience (Farsides & Woodfield, 2003; Lounsbury et al., 2003; Paunonen & Ashton, 2001), but others failed to do so (Conard, 2006; Furnham & Chamorro-Premuzic, 2004). Positive associations between Agreeableness and academic outcomes are also documented (Farsides & Woodfield, 2003; Poropat, 2009) and similar to Conscientiousness, evidence suggests that Agreeableness affects academic outcomes by changing behaviors; Agreeableness was found to improve final grades by changing attendance (Farsides & Woodfield, 2003). Neuroticism and extraversion were found to be negatively associated with academic outcomes (Chamorro-Premuzic & Furnham, 2003; Furnham & Chamorro-Premuzic, 2004; Sanchez et al., 2001).

The Big Five psychology factors model provides a clearer way to conceptualize and define noncognitive skills with reliable measurement tools, and there is a preponderance of empirical evidence linking each factor to academic outcomes. However, much of the evidence comes from post-secondary education settings, with overrepresentation of psychology department students (Vedel, 2014). In addition, researchers have also identified variance in academic performance that the Big Five model alone could not account for; other motivational aspects, such as work drive, was separately identified to explain variance in academic performance (Lounsbury et al., 2003).

Beliefs, Motivation and Mindsets

Researchers have identified beliefs, motivation and mindsets to be important predictors of academic success. Dweck and Leggett (1988) argued that students' mindset about intelligence, specifically, their beliefs on whether intelligence is fixed or malleable, is a crucial element to students' academic success. Their research showed that children who believed intelligence is malleable pursued learning goals, whereas students who believed intelligence is fixed focused on securing positive judgement of others (Dweck & Leggett, 1988). Empirical evidence supports this theory; seventh graders who believed intelligence was malleable were found to have upward trajectory in mathematics achievement in junior high school, compared to those who believed intelligence was fixed (Blackwell et al., 2007).

Duckworth et al. (2007) approached noncognitive skills from a motivational perspective. They showed that grit, defined as "perseverance and passion for long-term goals" was a strong predictor of education attainment, retention in military academy and ranking in National Spelling Bee. Grit was found to have high correlations with Conscientiousness from the Big Five personality model but was found to have its own predictive validity distinct from Conscientiousness. Some researchers have tried to increase motivation by changing beliefs or interests. Hulleman & Harackiewicz (2009) demonstrated that classroom activities designed to connect the course materials to students' daily lives increased motivation and interest. Similarly, Yeager et al. (2014) found that teaching self-transcendent purpose for learning through a brief psychological intervention improved high school science and math GPAs.

Sense of belonging is one of the important academic mindsets evidenced to improve academic performance (Farrington et al., 2012). Sense of belonging has been found to build mindsets helpful in academic settings (Goodenow, 1992; Wentzel & Caldwell, 1997) and protect students from negative identity threat established in an environment, which can hurt academic performance (Cohen and Garcia, 2008). Walton and Cohen (2011) demonstrated that mindset interventions aimed at alleviating belongingness doubts could improve GPA.

Noncognitive Factors

Farrington et al.(2012) attempted to organize and structure the differences in definitions of noncognitive skills. In a comprehensive review, Farrington et al.(2012) broadened the usage of the term *noncognitive skills* to *noncognitive factors* to encapsulate a broader definition which includes "sets of behaviors, skills, and strategies that are crucial to academic performance in their classes, but that may not be reflected in their scores on cognitive tests" (Farrington et al., 2012). The current study will use the term noncognitive factors as defined by Farrington et al. (2012), which comprises of five categories: Academic Behaviors, Academic Perseverance, Academic Mindsets, Learning Strategies and Social Skills. The first category, the Academic Behaviors are defined as "behaviors that are commonly associated with being a good student such as being punctual, paying attention in class, participate in classroom activities and abilities to complete homework" (Farrington et al., 2012). This definition encompasses the broad behavioral management skills that are indicative of one's abilities to learn by managing one's own behaviors. The second category, the Academic Perseverance, refers to "students' tendency to complete school assignments in a timely and thorough manner, to the best of one's ability, despite distraction, obstacle, or level of challenge" (Farrington et al., 2012). The third category, the Academic Mindsets are psychological beliefs and attitudes one has about oneself in relation to the academic work, while the fourth category, the Learning Strategies are a set of strategies crucial to learning, such as goal setting and time management. Finally, the fifth noncognitive factor is Social Skills, which are defined as "interpersonal qualities such as cooperation, assertion, responsibility, and empathy" (Farrington et al., 2012).

Changes in Noncognitive Factors during Adolescence

Research studies on changes in noncognitive factors often revolve around specific dimensions for which valid measurement exist, such as intrinsic motivation and self-esteem. Some studies suggest that noncognitive factors change as people go through changes in their lives. In a three-year longitudinal analysis that followed 646 students from eighth through tenth grades, Otis et al.(2005) found that students experienced declines in intrinsic motivation as they transitioned from junior to senior high school. Evidence of declines in noncognitive factors during transitional time was found among younger groups as well; students were found to experience decrease in self-efficacy during transition from elementary to secondary school (Bouffard et al., 2001). Corpus et al. (2009) focused on changes in motivational skills during the course of the school year and illustrated that students' perception of school goals drove the changes in motivational skills. In examinations of third through eighth grade students, significant declines in both intrinsic and extrinsic motivation from fall to spring semester were detected (Corpus et al., 2009).

Self-esteem is one of the widely studied dimensions of noncognitive factors. However, existing studies that examine changes in self-esteem have shown inconsistent results. Using data from the Family Health Study (FHS), Baldwin and Hoffmann (2002) examined 7-year changes in self-esteem of adolescents who were 11 to 16 year old during the first wave of data collection. Age was found to have a curvilinear relationship with self-esteem; in the beginning, self-esteem increased with age, but this relationship reversed as students became older. Some studies found evidence for positive growth in self-esteem during adolescence. Using data of individuals aged 14 to 30 from the National Longitudinal Survey of Youth, Erol and Orth (2011) showed that self-esteem increased during adolescence but slowed down in young adulthood. On the other hand, a 17-year longitudinal analyses of 1,083 adolescents from age of 13 to 30 documented that self-esteem was highly stable during adolescence, although there were considerable inter-individual differences (Birkeland et al., 2012).

The Current Study

Young adulthood, including adolescence, is a crucial time when personality traits are more prone to changes than any other periods of the life course (Roberts et al., 2006). Yet, close examination of noncognitive factors during this period has been limited by lack of clear definitions and understanding of the psychometric properties of the measurement. This study is motivated by the need to fill these gaps by studying the growth of noncognitive factors, examining how different dimensions of noncognitive factors are interrelated, and investigating if they grow during adolescence. A better understanding of how noncognitive factors change during adolescence is an important step toward designing effective interventions and identifying the right age groups to target. The current study examines sequential responses to the repeatedly asked survey questions on the National Longitudinal Survey of Adolescent Health (Add Health) that are purported to measure different dimensions of noncognitive factors. The purpose of this study is threefold. First, we seek to identify and determine the interrelationships between different components of noncognitive factors measured by the Add Health survey items. Second, we assess whether changes in noncognitive factors can be studied by evaluating longitudinal measurement invariance of the identified factors. Lastly, we investigate if there is evidence of growth in noncognitive factors during adolescence. For the second and third research questions, we examine each cohort of four grades separately (8^{th} grade – 11^{th} grade at baseline). The three questions under the investigation are the followings:

1) What is the dimensionality and factor structure of the survey items that tap into noncognitive factors?
2) Does the factor structure hold stable across three different time points of measurement?
3) Is there evidence of growth in noncognitive factors during adolescence?

Data and Methods

The National Longitudinal Study of Adolescent Health (Add Health)

The study uses data from Add Health, a nationally representative adolescents in grades 7-12 in the United States in 1994-95 who were followed through their adolescence and transition into adulthood (Harris, 2013). The study was mandated by the U.S. Congress with the original intent to investigate the causes of adolescent health and behaviors with a focus on understanding the effects of multiple contexts in adolescent life.

In this section, we provide a general overview of the Add Health but emphasize on the details of the administration of the Wave 1 In-School Survey, Wave 1 In-Home Survey, and Wave 2 In-Home Survey, in which the current study draws its data from.

The Add Health used a school-based design. The primary sampling frame of the Add Health survey was obtained from the Quality Education Database (QED). A sample of 80 high schools (defined as having 11th grade with enrollment of at least 30 students) were chosen from a stratified sample with probability proportional to size. Schools were stratified by region, urbanity, school type, ethnic composition and size. For each selected high school, a feeder school, a school that included 7th grade and sent its graduates to the selected high school was also recruited to participate, comprising one school pair in 80 different U.S. communities. Because some schools spanned from grades 7 to 12, the final sample included 132 schools, each associated with 80 different communities.

The Wave I In-School survey was administered between September of 1994 and April of 1995, surveying over 90,000 students on a single day during a 45 to 60-minute class period. Questions on the Wave I In-School survey included items on friendship networks, school activities, school context, grades, social, behavioral and health related items. During the Wave I In-School survey, school administrator from each school was also asked to complete a 30-minute survey covering questions about the school characteristics.

The Wave 1 In-Home survey was conducted few months after the Wave 1 In-School survey during 1994-1995. From the union of students who were on the school rosters and students who were not on the rosters but completed the Wave 1 In-School survey, a sample was chosen to participate in a 90-minute Wave 1 In-Home interview.

The sample was selected using stratified sampling by school, grade and gender where about 20 students from each strata were chosen to yield about 200 students from each pair of schools (Harris, 2013). Overall, there were 20,745 participants in the Wave 1 In-Home survey. Among them, the core sample of 12,105 students in grades 7 to 12 were chosen to comprise the core in-home sample, which provides a nationally representative sample of American adolescents in grades 7 to 12 and served as the basis for the consequent longitudinal follow-ups. Black/African American students with college-educated parents, Cuban and Puerto Rican adolescents, Chinese students, and physically disabled students were oversampled.

It is important to note that the data collection method during the in-home interviews differed from the Wave 1 In-School survey. During the in-home interviews, students were interviewed using a Computer-Assisted Personal Interview (CAPI)/Audio Computer-Assisted Self Interview (ACASI). Data were recorded on laptop computers; less sensitive materials were entered by the interviewer and more sensitive materials were entered by the respondent.

Wave II In-Home interviews were conducted during April-August of 1996 on the participants of the Wave 1 administrations. Students who were 12^{th} graders at Wave 1 In-School and In-Home Survey were excluded in the Wave II In-Home interview. 14,736 respondents were surveyed in Wave 2 In-Home survey. In order to avoid confusion, from now on, I refer to Wave I In-School survey as Time 1, Wave I In-Home survey as Time 2 and Wave II In-Home survey as Time 3.

Analytic Sample

The analytic sample were students who were in grade 8, 9, 10, or 11 either in Time 1 or Time 2 who were attempted to be interviewed for Time 3. The cohort of 12^{th} graders in Time 1 were excluded in the current study because Time 3 follow-up interview was not attempted, although the attempts were made at later waves of the Add Health. Students who were interviewed in the months of July and August were also removed in the analytic sample because some of the questions regarding sense of belonging and managerial skills referenced teachers and other students when school was in session and measurement time far too removed from the school year can cause recall bias prevalent in survey research (Sudman & Bradburn, 1973). This reduced the final analytic sample to 4,340 adolescents. About 52% of the final analytic sample were female, 64% were White, and about 32% of the students had college-educated mothers (Table 1.1). All measurements for Time 1 were taken in months of October, November and December and for Time 2 and Time 3, in the months of April, May, and June.

Measures

We reviewed the Add Health survey items and identified eleven repeatedly asked survey questionnaires that tap into the three purported dimensions of noncognitive factors.

Managerial skills. We use four survey items which are purported to measure general managerial skills relevant for academic success. The student was asked to respond to a question in five-point scale ranging from 0 (*never*) to 4 (*everyday*), followed by the stem, "since school started this year, how often have you had trouble…"

Item 1. Getting along with other students
Item 2. Paying attention in school
Item 3. Getting homework done

Item 4. Getting along with teachers

Because the four managerial skills related questions were negatively worded, I reverse-coded the variables such that 5 would indicate higher level of managerial skills and 1 would indicate lower level of managerial skills. The four items are not derived from an already existing scale, but the items had high composite reliability[1] at Time 1 (CR = 0.84) and acceptable composite reliability at Time 2 (CR= 0.69) and Time 3 (CR = 0.69).

Sense of Belonging. Three items measuring sense of belonging were also identified. Each survey item was measured using a five-point scale ranging from 1 (*strongly agree) to* 5 (*strongly disagree*) in their agreement to the following statements:

Item 5. I feel close to people at school
Item 6. I feel like I am part of this school
Item 7. I am happy at this school

The items are modified versions of perceived cohesion scale (Bollen & Hoyle, 1990) and have been used in previous studies to measure sense of belonging or school connectedness (Moody & White, 2003; Russell & Toomy, 2013). We recoded the variables in the analyses so 5 (*strongly agree*) indicated a greater level of sense of belonging and 1 (*strongly disagree*) indicated a lower level of sense of belonging. The three items had high composite reliability at Time 1 (CR = 0.77), Time 2 (CR = 0.76) and at Time 3 (CR = 0.76).

Self Esteem. We also include four survey questions that tap into self-esteem. Respondents were asked the respond to the degree to which they agreed with the

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[1] Although Cronbach's coefficient alpha is the most widely used to estimate reliability, it has been criticized for being the lower bound of the true reliability. We report composite reliability, which is a popular alternative to the Cronbach's coefficient alpha. In the exploratory factor analysis on the split sample (Table 1.3), we report Cronbach's coefficient alpha as a comparison to the composite reliability reported for all samples.

following statements in a five-point scale, ranging from 1 (*strongly agree*) to 5 (*strongly disagree*):

Item 8. You have a lot of energy
Item 9. You have lots of good qualities
Item 10. You have a lot to be proud of
Item 11. I feel like I am doing everything right

Items 9-11 are modified items from the well-established Rosenberg scale (Rosenberg, 1965) and Item 8 has been used in previous studies to measure global self-esteem (Daniels & Leaper, 2006). I recoded the variables in the analyses so 5 (*strongly agree*) indicated greater level of self-esteem and 1 (*strongly disagree*) indicated lower level of self-esteem. The three items had high composite reliability at Time 1 (CR = 0.77), Time 2 (CR = 0.75) and Time 3 (CR = 0.76).

Missing Data

3,034 cases (70%) had no missing data on any of the 11 items measured three times. This meant that listwise deletion would have resulted in loss of about 30% of the original sample, which is quite substantial. Missing data patterns were examined. At Time 1, 86% had no missing data, and 4% were missing on the four managerial skills items. And 3% were missing on all items—meaning that they were simply not surveyed during the Wave 1 In-Home Survey. At Time 2, 99% had no missing data in any of the variables, and 1% of the data were missing on the four self-esteem related items. There were 10 missing patterns, which all were less than 1%. At Time 3, 81% had no missing data in any of the variables, 14% had missing data on all of the items, which means that 14% were attrited from the sample. Item-level missingness is provided in Table 1.2. Data is said to be Missing at Random (MAR) when the probability of missing data on the variable is unrelated to its value, after controlling for other variables. When data is MAR, full information maximum likelihood estimated is generally regarded as the best method for handling missing data in most CFA and SEM applications (Allison, 2003). We assumed data is MAR and implemented the analyses with full information maximum likelihood estimation.

Statistical Methods

Exploratory Factor Analysis

In order to determine the appropriate factor structure for the items, Exploratory Factor Analysis (EFA) with maximum likelihood estimation method was fitted on the randomly split sample (n= 2,141) separately for each time of measurement. We decided to conduct EFA prior to the CFA analyses because some of the survey items have not been previously validated to comprise a distinct factor. Moreover, EFA allows items to freely load on different factors and we were interested if some items would load on multiple factors. Based on the factor correlations from EFA with oblique factors exceeding 0.32, we fitted EFA using promax rotation extraction (Brown, 2006). Exploratory Factor Analysis (EFA) was conducted using psych package (Revelle, 2017) in R Version 3.5.2 (R Core Team, 2018).

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was followed by EFA in order to confirm the acceptability of the factor structures suggested by the EFA. CFA was fitted on the randomly-split sample of 2,199 students. Acceptability of CFA was evaluated based on multiple fit indices: comparative fit index (CFI), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR) and tucker lewis index (TLI)

(Brown, 2006). A good fit is achieved when TLI and CFI are close to 0.95; RMSEA is close to 0.06 and SRMR is close to 0.08 (Hu & Bentler, 1999). Each model was determined to have an adequate fit when RMSEA was below 0.08; CFI and TLI values above 0.90 (Browne & Cudeck, 1993; West et al., 2012). CFA was conducted using lavaan package (Rosseel et al., 2014) in R Version 3.5.2 (R Core Team, 2018).

Longitudinal Measurement Invariance

Factorial invariance ensures that the same construct is measured over time and in the same metric (Meredith & Horn, 2001; Meredith & Teresi, 2006). Because this study is interested in whether there is a growth curve for each factor, longitudinal measurement invariance was assessed for each factor separately for each cohort. The sample size and characteristics of the four cohorts are displayed in Table 1.8. This study extends the common factor model to longitudinal invariance model as described in Grimm, Ram, & Estabrook (2017). Three models were considered: (1) configural invariance model, (2) metric invariance model and (3) scalar invariance model.

Measurement invariance for the more restrictive model is established when there is no substantial difference in the model fit statistics as suggested by non-significance of chi-square test or minimal shift in changes in CFI and RMSEA (Muthén & Asparouhov, 2002). However, previous research suggests that chi-square test can falsely reject the null hypothesis in large samples so we focus on examining changes in CFI and RMSEA where suggested cutoffs for comparing the nested models with increasing constraints are at ΔCFI ≤ 0.01 and ΔRMSEA ≤ 0.015 (Cheung & Rensvold, 2002, Chen, 2007). The general path diagram of a longitudinal factor model is illustrated in Figure 1.1. In order to identify the model and scale the latent variables, the mean of the common factor at Time

1 was constrained to 0 and the variance was constrained to 1. The common factors were allowed to covary over time and factor correlations were estimated since they provide information about the stability of the latent variable over time (Grimm et al., 2017). Items were also allowed to covary across time.

Second-Order Growth Model

If scalar invariance model is achieved, I use the second-order growth model approach to examine changes (Hancock et al., 2001). The second order model combines the longitudinal common factor model with the growth model. As illustrated in Figure 1.2, the common factor model comprises the first order factors. The intercepts and slopes, which are the growth factors comprise the second order factor. In order to achieve identification of the Second-Order Growth Model, I fixed one factor loading for each latent variable at 1 and the mean of the second order intercept at 0. These identification constraints ensure that the first-order latent variable is standardized (Grimm et al., 2017). The slope in the Second-Order Growth Model is the shape factor. The first and last factor loadings were fixed at 0 and 1 respectively, and the second factor loading was estimated from the data with unstructured model specification.

Results

Item Analyses

The summary of each survey item is presented in Table 1.2. Most of the items were consistently skewed to the left. This was especially the case for the four items that measured the self-esteem. Nonetheless, none of the items had skewness substantially worrying to be of departure from normality as suggested absolute value of skewness to detect non-normality is greater than 2 (West et al., 1995). The kurtosis of all items was also below 7, as recommended to be the cutoff for departure from normality in large samples (West et al., 1995). The changing behaviors of four items that measure managerial skills raised some concerns. For example, while the item, "I have trouble getting along with other students" (reverse-coded), had a skewness of -0.5 at Time 1, its skewness almost tripled at Time 2 and Time 3 (-1.4 and -1.6).

Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) with maximum likelihood estimation method was fitted to extract one, two and three factors. Time 1 measurement had the first two eigenvalues above the Kaiser-Guttman rule; Time 2 and Time 3 measurements had the first three eigenvalues above the Kaiser-Guttman rule. Although the Kaiser-Guttman rule is widely used, previous research suggested that this method results in either under-factoring, or over-factoring (Cattell & Vogelmann, 1977; Zwick & Velicer, 1986). Based on results from parallel analyses, a three-factor solution was found to be appropriate for each time point. Table 1.3 reports the final three-factor EFA solution with promax rotation for each wave of the survey. There was a clear pattern of factor loadings with all items with moderate to high loading in one factor. The weakest factor loading corresponded to item 1, "trouble getting along with other students" at Time 2, which had factor loadings of 0.3. There were no multiple loaders. Overall, the results provided support for a three-factor structure for the eleven Add Health survey items.

Confirmatory Factor Analysis

Based on the evidence obtained from EFA solution, a three-factor solution was specified in which item 1-4 loaded onto the latent variable *managerial skills,* item 5-7 loaded onto the *sense of belonging* and item 8-11 loaded on the *self-esteem*. The standardized loadings from the CFA model ranged from 0.46 to 0.84 and all eleven indicators had a substantial loading that was significant at 0.001 level (Table 1.5). The fit of the model (RMSEA < 0.06, CFI > 0.95) was good for each time point (Table 1.6). The factor correlations from the three-factor CFA model (Table 1.7) suggested that managerial skills, sense of belonging and self-esteem were related to one another. The factor correlations between self-esteem and sense of belonging tended to be higher than with the managerial skills.

Longitudinal measurement invariance

Managerial Skills. Table 1.9 provides fit statistics for the three measurement invariance models for each cohort. For managerial skills, configural invariance model fitted the data well for all cohorts (RMSEA ≤ 0.05, CFI > 0.95), thereby supporting the notion of a single common managerial skills factor in all time points of measurement. However, evidence for metric invariance was weak for Cohort 2 (ΔCFI = 0.026), Cohort 3 (ΔCFI = 0.016) and Cohort 4 (ΔCFI = 0.014) based on the large changes in CFI above the suggested cutoff at 0.01. Moving from the metric invariance to the scalar invariance model, there was weak evidence of scalar invariance for Cohort 1, as demonstrated by the large change in CFI (ΔCFI = 0.02). We also note that the fit indices from the scalar invariance model suggest only adequate fit. Because we did not find strong evidence for scalar invariance for any of the cohorts under investigation, we determined that managerial skills factor did not meet longitudinal scalar invariance.

Sense of Belonging. Table 1.10 provides fit statistics for the three measurement invariance models for each cohort. For sense of belonging, configural invariance model fitted the data very well for all cohorts (RMSEA ≤ 0.03, CFI > 0.99). The change in

RMSEA for Cohort 3 was above the recommended 0.023, but this cohort had RMSEA of zero for the configural model and the change in CFI was low (0.003). Therefore, we determined that the change in RMSEA was not too worrisome. There was evidence for scalar invariance was for Cohort 2, Cohort 3 and Cohort 4 based on the changes in fit statistics. The changes in fit statistics for Cohort 1 (ΔRMSEA = 0.019, ΔCFI = 0.012) were slightly above the recommended cutoffs. However, Cohort 1 produced good fit statistics for the scalar invariance model (RMSEA = 0.045, CFI = 0.983) and the deviation from the cutoffs were only minimal. Therefore, we determined that there was enough evidence to support longitudinal scalar invariance for the sense of belonging factor.

Table 1.11 provides the parameter estimates from the scalar invariance longitudinal common factor mode. As stated previously, the mean of the first factor (measurement at Time 1) was constrained to be 0 and the variance was constrained at 1 in order to identify and scale the latent variable. The means and variances are estimated for the latent factor measured at Time 2 and Time 3. The factor loadings and factor intercepts are constrained to be the same at each point of measurements. For Cohort 1, the mean of latent variable at Time 2 and 3 were 0.17 and 0.08 respectively. This suggests that from fall of 8th grade to the spring of 8th grade, the mean of sense of belonging changed 0.17 standardized deviation of the fall 8th grade distribution and in the spring of 9th grade year, the mean of sense of belonging changed 0.08 standardized deviation from the fall of 8th grade year. For Cohort 2, the pattern was similar; the mean of sense of belonging increased 0.19 standard deviation in the spring of 9th grade year from the fall of 9th grade year and increased 0.08 standard deviation in the spring of 10th grade year from the fall of

9th grade year. Similar patterns were observed for Cohort 3 and Cohort 4 as well; the factor means increased between Time 1 and Time 2, which is within-school year change but decreased slightly at Time 3, when moving from one school year to the next. The common factors were modeled to covary over time to estimate between-time correlations. The factor correlations between each time point ranged 0.42 to 0.67 with higher correlations detected in Cohort 3 and Cohort 4. This suggests that sense of belonging is relatively stable during adolescence with higher stability found among the older cohorts.

Self-esteem. Table 1.12 provides fit statistics for the three measurement invariance models for each cohort. For self-esteem, configural invariance model fitted the data very well for all cohorts (RMSEA ≤ 0.05, CFI > 0.97). There was also strong evidence for metric invariance for all cohorts (ΔRMSEA ≤ 0.015 and ΔCFI ≤ 0.01). However, the changes in RMSEA and CFI were both above the recommended cutoffs as we moved from the metric invariance model to scalar invariance model for all cohorts. Because the changes in RMSEA and CFI suggested that the longitudinal scalar invariance for the self-esteem factor may not have been met, we decided not to proceed with the growth model for this factor. Nonetheless, the overall fit statistics for the scalar invariance model suggested that the self-esteem factor produced an adequate to good fit of the model (RMSEA < 0.07, CFI >0.94). Therefore, we proceed with interpretation of the parameter estimates for the scalar invariance longitudinal common factor model.

Table 1.13 provides parameter estimates from the scalar invariance longitudinal model. The mean of the first factor (measurement at Time 1) was constrained at 0 and the variance was constrained at 1 in order to identify and scale the latent variable. The means and variances are estimated for the latent factor measured at Time 2 and Time 3. For

Cohort 1, the mean of latent variable at Time 2 and 3 were 0.28 and 0.31 respectively. This suggests that from the fall of 8^{th} grade year to spring of 8^{th} grade year, the mean in self-esteem changed about 0.28 standard deviation of the 8^{th} grade fall distribution and 0.31 standard deviation of the 8^{th} grade fall distribution as they moved to the spring of 9^{th} grade year. Similar patterns were observed in other cohorts. For Cohort 2, the mean of the latent variable at Time 2 and Time 3 were 0.29 and 0.39 respectively, suggesting that from the fall of 9^{th} grade year to spring of 9^{th} grade year, the mean in self-esteem changed about 0.29 standard deviation of the 9^{th} grade fall distribution and 0.39 standard deviation of the 9^{th} grade fall distribution as they moved to the spring of 10^{th} grade year. Similar patterns were observed in Cohort 3 and Cohort 4. The factor correlations between each time point of measurement ranged 0.45 to 0.62 across all cohorts, suggesting moderate to high stability in the self-esteem factor over time.

Second-Order Growth Model

Sense of Belonging. The second order latent basis model for sense of belonging factor produced good fit for all cohorts under investigation (CFI > 0.98, RMSEA <0.04). Table 1.14 provides parameter estimates from the second-order growth models. The mean of slope was positive for all cohorts, suggesting positive changes in sense of belonging. Because we imposed identification constraints on the models where we specified the total variance of the first-order factor at Time 1 to be approximately one, for Cohort 1 and Cohort 2, the mean change from Time 1 through Time 3 represents about 0.07 standard deviation increase when compared to the amount of between-person differences in sense of belonging at Time 1. For Cohort 3, the mean change from Time 1 through Time 3 represents about 0.14 standard deviation increase when compared to the amount of between-person differences in sense of belonging at Time 1. For Cohort 4, the mean change from Time 1 through Time 3 represents about 0.18 standard deviation increase when compared to the amount of between-person difference in sense of belonging at Time 1. We find that the variance of the second-order intercept and shape factors were both significant for all cohorts under investigation, suggesting that students significantly varied in their levels of sense of belonging and rate of growth for all grade level groups. The covariance between the second-order intercept and shape factors was negative and significant, implying that students with higher sense of belonging had lower rate of growth over time. We use changes in factor loading to examine the within-person rate of change. We constrained the first factor loading to zero and the third factor loading to one and freely estimated the second factor loading. For Cohort 1, 71% of the predicted changes between fall of grade 8 and spring of grade 9 in sense of belonging occurred between fall of grade 8 and spring of grade 9. Our finding suggests that changes in sense of belonging was not linear with time. For all cohorts under investigation, more than half of the predicted changes occurred between Time 1 and Time 2, indicating that school context may be important to its growth.

Discussions

Existing research on the growth of noncognitive factors has been hindered by lack of clear definitions and understanding in their psychometric properties. The main goals of this research were to examine the dimensionality and factor structures of the eleven survey items that tap into different dimensions of noncognitive factors using data from a large national survey and assess growth for each identified factor. While most of survey items behaved consistently at each point of measurement, we found that Item 1 (trouble getting along with students) and Item 4 (trouble getting along with teacher) had lower factor loadings on their purported dimension at Time 2 and Time 3 compared to at Time 1. The items also had higher skewness and kurtosis at Time 2 and Time 3 compared to Time 1. This observation can be evidence of method effects, which occurs when variance of an item is attributable to the method of measurement (Podsakoff et al., 2003).Different measurement methods were used for data collection at Time 1 and Time 2 & 3; data from Time 1 were collected using a paper-pencil survey during an in-class period in schools, whereas data collections for Time 2 & Time 3 took place through interviewers who visited students at home. Interviewers entered responses to non-sensitive questions on a laptop, but respondents were allowed to enter responses to sensitive questions themselves. Although we do not know for sure if Item 1 and Item 4 were determined as sensitive questions in Add Health survey collection, it is possible that the presence of an interviewer, changes in setting and different modalities of the survey collection contributed to the sensitivity in respondents' answers to the survey items. Item 1 and Item 4 may have been especially prone to the method effect because students may feel less inclined to provide honest answers to negative questions on social relations when interacting with the interviewer. This is an important practical issue for researchers when using data from longitudinal surveys to examine longitudinal changes.

Despite the possible presence of method effects, our final results from exploratory and confirmatory factor analyses supported a three-factor solution with each item having salient loadings on the purported dimension. The factor correlations derived from the confirmatory factor analyses suggest that managerial skills, self-esteem and sense of belonging may be interrelated with one another during adolescence. The current study found evidence for longitudinal scalar invariance for the sense of belonging, but we did not find strong evidence for longitudinal scalar invariance for the self-esteem factor or managerial skills factor. Given that existing research on growth of self-esteem has shown mixed results, our finding invites further investigation into the longitudinal measurement invariance of this factor. Although we did not find strong evidence of longitudinal scalar measurement invariance for the self-esteem factor, the fit statistics still produced adequate to good fit. Results from the longitudinal scalar invariance common factor model suggested that both sense of belonging and self-esteem are moderately stable during adolescence. For the sense of belonging factor, the between-time correlations were slightly higher for the older cohorts, a finding which is in accord with previous literature which suggests that noncognitive factors tend to stabilize as one ages. Moderate to high positive correlations were found for the self-esteem factor as well. The correlations were stronger among the older cohorts with the exception of the oldest cohort who were 11^{th} graders at Time 1, when correlations dropped slightly. One possibility for this observation is that the transition from 11^{th} grade to 12^{th} grade year might be a more sensitive period compared to other years in high school. Given that 11^{th} and 12^{th} grade years tend to be filled with college preparation and college admission decisions are made during this period, it is possible that students' self-esteem is becomes stable.

The latent growth model was fitted only for the sense of belonging factor, which achieved longitudinal scalar invariance for all cohorts under investigation. Results from the second-order model suggested statistically significant positive slopes for the sense of belonging, suggestive of positive growth. However, we find that the growth is unlikely to be linear with time. Rather, our evidence suggests that school context might be important to the growth of sense of belonging, as shown by greater changes between Time 1 and Time 2, which were within-school-year changes, compared to between Time 2 and Time 3, which were between-school-year changes. This finding is consistent with previous research which found that students' motivation changed with the school context (Corpus et al., 2009). This finding can have important implications for designing interventions attempting to address sense of belonging in school; the timing of the interventions might matter and any changes in students' sense of belonging during a given school year may only be temporary- as a new school year might set another beginning for this dimension to start afresh. Moreover, we also found evidence for substantial between-student variations in the intercept and growth factor of sense of belonging. We did not test for any student-level characteristics that can explain the between-individual differences as it was beyond the scope of the current study. Nonetheless, our results invite further research investigating variables that can explain the differences.

This study has a number of limitations. First, this study only included self-rated items. Past research has shown that self-reports on attitudes and behaviors are highly affected by the features of the instrument, such as reference points, ordering of questionnaires, and question formats (Knowles, 1988; Schwarz, 1999). Second, the Add Health survey used a school-based design where individuals were sampled with unequal probability. Not accounting for the hierarchical nature of the data can result in underestimation of standard errors and increase the probability of Type 1 errors. Finally, this study used latent growth modeling to examine longitudinal changes in sense of belonging among adolescents. A limitation of the latent growth modeling is that it assumes everyone in the model is drawn from a homogeneous population and single parameters are used to describe the changes in every individual, when in fact, there can be unobserved classes of subpopulations (Wang & Bodner, 2007). Attempting to identify a single growth curve when multiple subpopulations exist can result in conflicting findings depending on the characteristics of the sample (Wang, 2007). This study has found that there are significant between-student variations in both the intercept and the slope of adolescents' sense of belonging. Future research will focus on identifying individual characteristics associated with the differences.

Table 1. 1. Sample Demographic Characteristics

	%
Demographic Information	
Female	52.4%
White	64.1%
African American	23.6%
Asian	7.5%
Mother has a college degree	32.2%
School Characteristics	
Enrollment	
< 125	1.7%
126-350	6.4%
351-775	27.1%
>776	64.8%
Metro	
Urban	28.1%
Suburban	53.3%
Rural	18.5%
Region	
West	21.6%
Midwest	24.9%
South	38.3%
Northeast	15.2%
N	4,340

Table 1.2. Summary of Survey Items (N= 4,340)

Items of constructs	Time	Mean	S.D	Skewness	Kurtosis	% Missing
Item1. Get along with other students	1	3.45	1.48	-0.54	1.81	4.80
	2	4.14	0.96	-1.43	5.04	1.10
	3	4.23	0.90	-1.57	5.83	23.10
Item 2. Pay attention in school	1	3.21	1.35	-0.23	1.75	5.00
	2	3.78	1.00	-0.82	3.25	1.10
	3	3.84	1.01	-0.85	3.31	23.10
Item 3. Get homework done	1	3.22	1.37	-0.26	1.76	4.80
	2	3.81	1.05	-0.89	3.32	1.10
	3	3.85	1.05	-0.88	3.23	23.10
Item 4. Get along with teachers	1	3.79	1.30	-0.94	2.68	4.70
	2	4.13	0.95	-1.35	4.88	1.10
	3	4.27	0.86	-1.48	5.60	23.10
Item 5. Feel close to people at school	1	3.57	1.08	-0.61	2.80	8.40
	2	3.73	0.97	-0.78	3.38	1.20
	3	3.63	0.99	-0.65	3.02	23.10
Item 6. Feel part of school	1	3.56	1.17	-0.62	2.60	9.20
	2	3.86	0.99	-0.94	3.58	1.10
	3	3.83	1.00	-0.87	3.41	23.10
Item 7. Happy to be at this school	1	3.57	1.21	-0.68	2.63	9.80
	2	3.73	1.08	-0.79	3.05	1.10
	3	3.71	1.07	-0.77	3.02	23.10
Item 8. Have a lot of energy	1	3.97	0.90	-0.79	3.49	8.00
	2	4.13	0.81	-0.97	4.13	0.10
	3	4.06	0.83	-0.93	3.98	16.30
Item 9. Have lots of good qualities	1	4.13	0.85	-1.04	4.43	10.20
	2	4.27	0.66	-0.63	3.63	0.20
	3	4.33	0.64	-0.68	3.87	16.30
Item 10. Have a lot to be proud of	1	4.09	0.95	-1.02	3.75	10.30
	2	4.28	0.71	-0.88	4.10	0.30
	3	4.35	0.69	-0.89	3.91	16.30
Item 11. Do everything right	1	3.28	1.04	-0.21	2.54	10.40
	2	3.70	0.89	-0.51	2.84	0.10
	3	3.84	0.88	-0.62	3.10	16.30

Table 1.3. Rotated Factor Pattern Loadings from Three-Factor Exploratory Factor Analysis of Add Health Survey Items using Maximum Likelihood with Promax Rotation (N=2,141)

Items of constructs	I	II	III	*Communality*	I	II	III	*Communality*	I	II	III	*Communality*
Managerial skills		*α=0.84*				*α=0.65*				*α=0.68*		
Item 1. Trouble getting along with other students	**0.70**	0.01	-0.03	0.48	**0.30**	0.21	-0.07	0.18	**0.40**	0.2	-0.07	0.23
Item 2. Trouble paying attention in school	**0.84**	-0.02	0.05	0.7	**0.86**	-0.12	0	0.64	**0.82**	-0.06	-0.02	0.63
Item 3. Trouble getting homework done	**0.80**	-0.01	0.04	0.64	**0.69**	-0.08	0.03	0.43	**0.71**	-0.1	0.02	0.46
Item 4. Trouble getting along with teacher	**0.68**	0.04	-0.03	0.47	**0.41**	0.13	-0.11	0.22	**0.45**	0.02	-0.01	0.21
Sense of belonging		α=0.79				*α=0.78*				*α=0.80*		
Item 5. Feels close to people at school	-0.03	**0.67**	0.03	0.47	-0.1	**0.79**	-0.04	0.54	-0.09	**0.85**	-0.08	0.62
Item 6. Feels part of school	-0.02	**0.88**	-0.06	0.7	-0.09	**0.86**	0.02	0.68	-0.05	**0.80**	0.05	0.65
Item 7. Happy to be at this school	0.04	**0.68**	0.02	0.49	0.04	**0.66**	-0.02	0.46	0.05	**0.68**	-0.02	0.47
Self-esteem		α=0.76				*α=0.74*				*α=0.75*		
Item 8. Has lots of energy	-0.06	0.12	**0.46**	0.3	0.04	0.15	**0.43**	0.27	0.02	0.11	**0.42**	0.23
Item 9. Has good qualities	0.03	-0.07	**0.80**	0.58	-0.03	-0.03	**0.75**	0.54	-0.04	-0.04	**0.77**	0.54
Item 10. Has a lot to be proud of	0.04	-0.03	**0.81**	0.64	0	-0.02	**0.84**	0.68	-0.01	-0.05	**0.86**	0.7
Item 11. Doing everything right	0.04	0.03	**0.56**	0.34	0.11	0.04	**0.48**	0.3	0.09	0.07	**0.56**	0.4

Note. Items 1-4 were reverse-coded.

Table 1.4. Factor Correlations from Exploratory Factor Analysis: Three-Factor Model with Promax rotation (N=2,141)

	Managerial skills	Sense of Belonging	Self-esteem
		Time 1	
Managerial skills	1.00		
Sense of Belonging	0.20	1.00	
Self-esteem	0.64	0.13	1.00

	Managerial skills	Sense of Belonging	Self-esteem
		Time 2	
Managerial skills	1.00		
Sense of Belonging	-0.51	1.00	
Self-esteem	0.29	-0.39	1.00

	Managerial skills	Sense of Belonging	Self-esteem
		Time 3	
Managerial skills	1.00		
Sense of Belonging	0.34	1.00	
Self-esteem	0.42	0.44	1.00

Table 1.5. Standardized Factor Loadings from Three-factor Confirmatory Factor Analysis with Correlated Factors (N=2,199)

	Standardized factor loadings		
Items of constructs	Time 1	Time 2	Time 3
Managerial skills			
Item 1. Trouble getting along with other students	0.70	0.50	0.46
Item 2. Trouble paying attention in school	0.84	0.76	0.80
Item 3. Trouble getting homework done	0.80	0.68	0.71
Item 4. Trouble getting along with teacher	0.69	0.49	0.46
Sense of belonging			
Item 5. Feels close to people at school	0.67	0.72	0.71
Item 6. Feels part of school	0.81	0.82	0.85
Item 7. Happy to be at this school	0.75	0.71	0.66
Self-esteem			
Item 8. Has lots of energy	0.58	0.51	0.48
Item 9. Has good qualities	0.73	0.71	0.75
Item 10. Has a lot to be proud of	0.79	0.81	0.84
Item 11. Doing everything right	0.61	0.58	0.60

Note. Items 1-4 were reverse-coded.

Table 1.6. Goodness of Fit Statistics from Three-factor Confirmatory Factor Analysis with Correlated Factors (N=2,199)

	Time 1	Time 2	Time 3
CFI	0.98	0.96	0.95
RMSEA	0.05	0.05	0.06
SRMR	0.03	0.04	0.05
TLI	0.97	0.95	0.94

Table 1.7. Factor Correlations from Confirmatory Factor Analysis: Three-Factor Model (N=2,199)

	Managerial skills	Sense of Belonging	Self-esteem
		Time 1	
Managerial skills	1.00		
Sense of Belonging	0.12	1.00	
Self-esteem	0.11	0.61	1.00

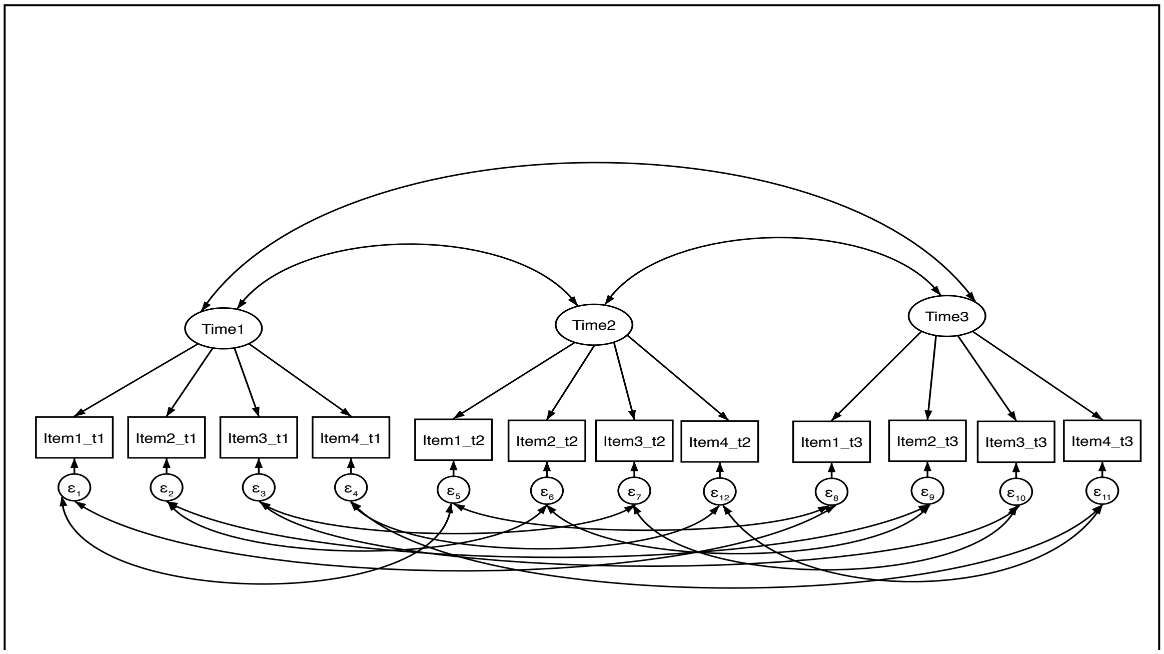
	Managerial skills	Sense of Belonging	Self-esteem
		Time 2	
Managerial skills	1.00		
Sense of Belonging	0.39	1.00	
Self-esteem	0.33	0.40	1.00

	Managerial skills	Sense of Belonging	Self-esteem
		Time 3	
Managerial skills	1.00		
Sense of Belonging	0.32	1.00	
Self-esteem	0.23	0.37	1.00

Table 1.8. Sample Demographic Characteristics by Cohort: Longitudinal Measurement Invariance and Growth Models (N=4,340)

	Cohort 1	Cohort 2	Cohort 3	Cohort 4
	%	%	%	%
Demographic Information				
Female	54.0%	51.9%	51.3%	53.0%
White	65.3%	69.6%	62.3%	60.4%
African American	26.4%	21.0%	24.7%	23.1%
Asian	5.1%	3.5%	9.4%	10.6%
Mother has a college degree	35.0%	32.8%	30.0%	32.1%
School Characteristics				
Enrollment				
< 125	2.3%	1.7%	1.6%	1.3%
126-350	8.5%	6.9%	5.5%	5.6%
351-775	33.3%	29.6%	23.1%	24.7%
>776	55.8%	61.8%	69.8%	68.4%
Metro				
Urban	29.4%	30.1%	25.9%	27.9%
Suburban	52.5%	47.6%	56.3%	56.0%
Rural	18.1%	22.3%	17.8%	16.2%
Region				
West	15.1%	14.1%	26.9%	27.4%
Midwest	24.7%	26.3%	24.8%	23.8%
South	43.6%	42.1%	33.8%	35.9%
Northeast	16.6%	17.5%	14.5%	12.9%
N	819	1,077	1,256	1,188

Note. Cohort 1 were 8th graders in Time 1; Cohort 2 were 9th graders in Time 1; Cohort 3 were 10th graders in Time 1, and Cohort 4 were 11th graders in Time 1.



Note. Factor intercepts are not shown in the figure.

Figure 1.1. Generic Common Factor Longitudinal Measurement Invariance Model with Four Items and Three Time Points of Measurement

Table 1.9. Fit Statistics from Managerial Skills Longitudinal Measurement Invariance Models by Cohort

Fit statistics	Configural invariance	Metric invariance	Scalar invariance
Cohort 1 (N=819)			
$\chi^2(df)$	124.36 (39)	151.813 (45)	216.953 (51)
RMSEA	0.050	0.054	0.063
ΔRMSEA	-	*0.004*	*0.009*
CFI	0.971	0.964	0.944
ΔCFI	-	*0.007*	*0.02*
Cohort 2 (N=1,077)			
$\chi^2(df)$	127.937 (39)	227.588 (45)	334.456 (51)
RMSEA	0.046	0.061	0.072
ΔRMSEA	-	*0.015*	*0.011*
CFI	0.975	0.949	0.921
ΔCFI	-	*0.026*	*0.028*
Cohort 3 (N=1,256)			
$\chi^2(df)$	122.938 (39)	197.382 (45)	256.487 (51)
RMSEA	0.041	0.052	0.057
ΔRMSEA	-	*0.011*	*0.005*
CFI	0.981	0.965	0.952
ΔCFI	-	*0.016*	*0.013*
Cohort 4 (N=1,188)			
$\chi^2(df)$	188.663 (39)	243.760 (45)	273.709 (51)
RMSEA	0.057	0.061	0.061
ΔRMSEA	-	*0.004*	*0*
CFI	0.958	0.944	0.937
ΔCFI	-	*0.014*	*0.007*

Note. Cohort 1 were 8th graders in Time 1; Cohort 2 were 9th graders in Time 1; Cohort 3 were 10th graders in Time 1, and Cohort 4 were 11th graders in Time 1.

Table 1.10. Fit Statistics from Sense of Belonging Longitudinal Measurement Invariance Models by Cohort

Fit statistics	Configural invariance	Metric invariance	Scalar invariance
Cohort 1 (N=819)			
$\chi^2(df)$	17.885 (15)	29.355 (19)	60.704 (23)
RMSEA	0.015	0.026	0.045
ΔRMSEA	-	*0.011*	*0.019*
CFI	0.999	0.995	0.983
ΔCFI	-	*0.004*	*0.012*
Cohort 2 (N=1,077)			
$\chi^2(df)$	23.402 (15)	29.674 (19)	55.436 (23)
RMSEA	0.023	0.023	0.036
ΔRMSEA	-	*0*	*0.013*
CFI	0.997	0.997	0.99
ΔCFI	-	*0*	*0.007*
Cohort 3 (N=1,256)			
$\chi^2(df)$	9.728 (15)	30.097(19)	61.909 (23)
RMSEA	0.00	0.022	0.037
ΔRMSEA	-	*0.022*	*0.015*
CFI	1.00	0.997	0.991
ΔCFI	-	*0.003*	*0.006*
Cohort 4 (N=1,188)			
$\chi^2(df)$	32.116 (15)	53.885 (19)	72.787 (23)
RMSEA	0.031	0.039	0.043
ΔRMSEA	-	*0.008*	*0.004*
CFI	0.996	0.991	0.988
ΔCFI	-	*0.005*	*0.003*

Note. Cohort 1 were 8^{th} graders in Time 1; Cohort 2 were 9^{th} graders in Time 1; Cohort 3 were 10^{th} graders in Time 1, and Cohort 4 were 11^{th} graders in Time 1.

Table 1.11. Parameter Estimates from Sense of Belonging Scalar Invariance Longitudinal Common Factor Model by Cohort

	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Factor loadings				
Item 5. Feels close to people at school	0.74	0.76	0.77	0.81
Item 6. Feels part of school	0.91	0.95	0.94	0.98
Item 7. Happy to be at this school	0.86	0.81	0.83	0.84
Factor means				
Sense of Belonging Time 1	0.00	0.00	0.00	0.00
Sense of Belonging Time 2	0.17	0.19	0.27	0.32
Sense of Belonging Time 3	0.08	0.08	0.21	0.28
Factor intercepts				
Item 5. Feels close to people at school	3.67	3.59	3.48	3.41
Item 6. Feels part of school	3.78	3.69	3.55	3.50
Item 7. Happy to be at this school	3.64	3.60	3.53	3.45
Factor variances				
Sense of Belonging Time 1	1.00	1.00	1.00	1.00
Sense of Belonging Time 2	0.77	0.85	0.78	0.73
Sense of Belonging Time 3	0.76	0.79	0.84	0.82
Factor correlations				
Time 1, Time 2	0.53	0.50	0.66	0.63
Time 2, Time 3	0.56	0.56	0.65	0.67
Time 1, Time 3	0.42	0.53	0.54	0.53
N	819	1,077	1,256	1,188

Note. All factor loadings are statistically significant ($p < .001$).
Cohort 1 were 8th graders in Time 1; Cohort 2 were 9th graders in Time 1; Cohort 3 were 10th graders in Time 1, and Cohort 4 were 11th graders in Time 1.

Table 1.12. Fit Statistics from Self-esteem Longitudinal Measurement Invariance Models by Cohort

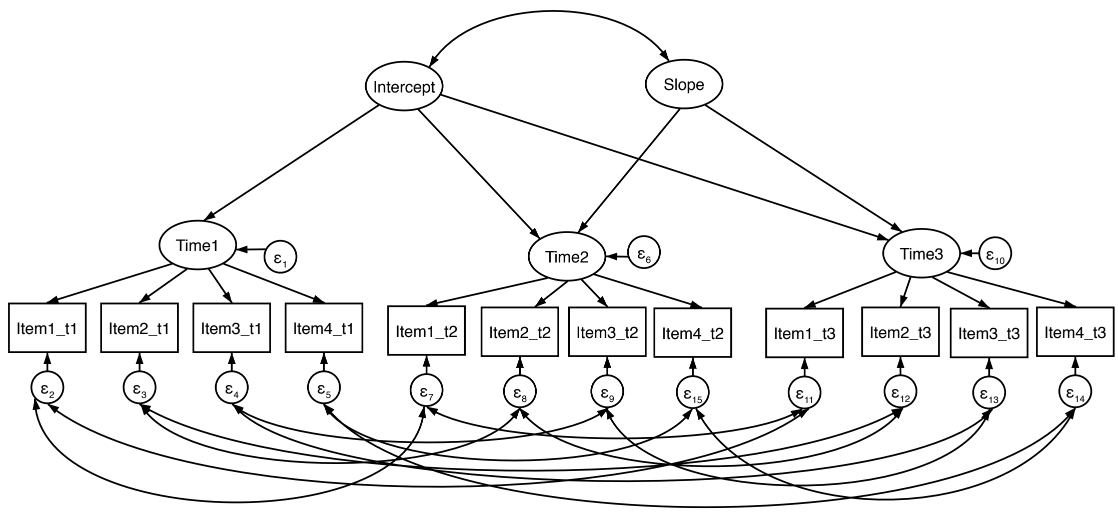
Fit Statistics	Configural invariance	Metric invariance	Scalar invariance
Cohort 1 (N=819)			
$\chi^2(df)$	60.480 (39)	70.045 (45)	145.703 (51)
RMSEA	0.026	0.026	0.048
ΔRMSEA	-	*0*	*0.022*
CFI	0.993	0.992	0.969
ΔCFI	-	*0.001*	*0.023*
Cohort 2 (N=1,077)			
$\chi^2(df)$	90.89 (39)	104.94 (45)	218.15 (51)
RMSEA	0.035	0.035	0.055
ΔRMSEA	-	*0*	*0.02*
CFI	0.988	0.986	0.961
ΔCFI	-	*0.002*	*0.025*
Cohort 3 (N=1,256)			
$\chi^2(df)$	104.85 (39)	113.39 (45)	249.79 (51)
RMSEA	0.037	0.035	0.056
ΔRMSEA	-	*0.002*	*0.021*
CFI	0.987	0.986	0.96
ΔCFI	-	*0.002*	*0.026*
Cohort 4 (N=1,188)			
$\chi^2(df)$	139.839 (39)	154.776 (45)	303.993 (51)
RMSEA	0.047	0.045	0.065
ΔRMSEA	-	*0.002*	*0.02*
CFI	0.978	0.976	0.945
ΔCFI	-	*0.002*	*0.031*

Note. Cohort 1 were 8th graders in Time 1; Cohort 2 were 9th graders in Time 1; Cohort 3 were 10th graders in Time 1, and Cohort 4 were 11th graders in Time 1.

Table 1.13. Parameter Estimates from Self-esteem Scalar Invariance Longitudinal Common Factor Model by Cohort

	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Factor loadings				
Item 8. Have a lot of energy	0.48	0.45	0.48	0.46
Item 9. Have lots of good qualities	0.66	0.64	0.62	0.57
Item 10. Have a lot of be proud of	0.76	0.77	0.76	0.70
Item 11. Do everything right	0.67	0.73	0.66	0.65
Factor means				
Self-esteem Time 1	0.00	0.00	0.00	0.00
Self-esteem Time 2	0.28	0.29	0.34	0.34
Self-esteem Time 3	0.31	0.39	0.45	0.44
Factor intercepts				
Item 8. Have a lot of energy	4.08	3.99	3.91	3.85
Item 9. Have lots of good qualities	4.41	4.07	4.07	4.11
Item 10. Have a lot of be proud of	4.12	4.03	4.02	4.05
Item 11. Do everything right	3.63	3.46	3.41	3.41
Factor Variances				
Self-esteem Time 1	1.00	1.00	1.00	1.00
Self-esteem Time 2	0.58	0.56	0.60	0.64
Self-esteem Time 3	0.62	0.56	0.54	0.68
Factor Correlations				
Time 1, Time 2	0.55	0.60	0.61	0.58
Time 2, Time 3	0.53	0.56	0.50	0.45
Time 1, Time 3	0.62	0.63	0.66	0.63
N	819	1,077	1,256	1,188

Note. All factor loadings are statistically significant ($p < .001$).
Cohort 1 were 8th graders in Time 1; Cohort 2 were 9th graders in Time 1; Cohort 3 were 10th graders in Time 1, and Cohort 4 were 11th graders in Time 1.



Note. Factor intercepts are not shown in the figure. When scalar factorial invariance is imposed, the model will constrain the factor loadings and the factor intercepts of the first-order measurement model to be equal. The first factor loading for each latent variable is fixed at 1 and the mean of latent variable intercept is fixed at 0 for identification.

Figure 1.2. Path Diagram of a Second-Order Growth Model with Four Items and Three Time Points of Measurement

Table 1.14. Parameter Estimates for Sense of Belonging Second Order Model from Second-Order Latent Basis Model by Cohort

	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Intercept				
Sense of Belonging 1	1	1	1	1
Sense of Belonging 2	1	1	1	1
Sense of Belonging 3	1	1	1	1
Slope				
Sense of Belonging 1	0	0	0	0
Sense of Belonging 2	0.71***	1.15***	0.60***	0.71***
Sense of Belonging 3	1	1	1	1
Means				
Intercept	0	0	0	0
Slope	0.07***	0.07***	0.14***	0.18***
Covariance				
Intercept ~~ Slope	-0.17***	-0.10***	-0.15***	-0.19***
Variance				
Intercept	0.37***	0.37***	0.44***	0.49***
Slope	0.21***	0.09**	0.21***	0.25***
Residual Variances				
Sense of Belonging 1	0.18***	0.21***	0.15***	0.15***
Sense of Belonging 2	0.18***	0.21***	0.15***	0.15***
Sense of Belonging 3	0.18***	0.21***	0.15***	0.15***
N	819	1,077	1,256	1,188

Note. p*<0.10, p**<0.05,p***<0.01.The estimates from the first-order factors are omitted because there were not much changes from the estimates from the common factor measurement invariance model. Cohort 1 were 8th graders in Time 1; Cohort 2 were 9th graders in Time 1; Cohort 3 were 10th graders in Time 1 and Cohort 4 were 11th graders in Time 1.

Chapter 2: Family Income and School Belongingness: A Mediation Analysis

Background

Despite the decrease in racial and gender gaps in education, socioeconomic status-based achievement gaps continue to prevail (Gamoran, 2001) and income-based achievement gap is one of the biggest threats to educational inequality in the United States (Reardon, 2018). While psychological interventions aimed to improve students' mindset, attitudes and noncognitive skills have recently shaped queries around reducing achievement gaps, little research has been conducted to investigate possible systematic differences in the noncognitive domains through which income generates differential academic outcomes.

The socioeconomic status-based achievement gradient has been studied extensively in education research. In Coleman (1968)'s seminal work, "The Equality of Opportunity Report," he unearthed that the achievement gap was mostly explained by educational and economic status of the parents. Since the publication of Coleman's paper, the socioeconomic-based achievement gap has become even more pronounced. A recent paper finds that the achievement gap between children from high and low income families is about 35 percent larger among children born in 2001 than among children born twenty-five years prior (Reardon, 2018).

Psychological interventions which focus on building mindsets, beliefs, motivational and socio-emotional skills have proliferated in education research (Okonofua et al., 2016; Paunesku et al., 2015; Walton & Cohen, 2011). Promising evidence from these studies suggests psychological interventions can potentially address equity at little economic costs; these interventions tend to be brief and can be implemented in individualized settings—making these interventions scalable. However, because these interventions are often conducted in decontextualized settings, many of them arguably do not take environmental factors into careful consideration.

Given that a student's learning environment is comprised of intricate relationships, one's networks can be viewed as an environment which provides opportunities and constraints for individuals' decisions and actions (Wasserman & Faust, 1994). Peer networks can also serve as a resource and channel for exchange of information, support, norms and values (Cherng, Calarco, & Kao, 2013; Eisenkopf, 2010; Harris, Graham, & Mason, 2006). Research studies document that peer networks are important contexts that determine adolescents' decisions and behaviors (Bearman & Moody, 2004; Christakis & Fowler, 2008; Mundt et al., 2012; Schaefer et al., 2012).

Social network analysis can be a useful tool in studying friendships because it does not constrain the study of peer relations to dyadic interactions but allows one to examine relations as embedded in a larger network of relationships (Harris, 2013). A deeper understanding in adolescents' friendship networks can better inform the design of a growing number of education interventions that focus on students' psychological aspects.

Socioeconomic status, academic achievement and psychological factors

Farkas (2003) detailed three theoretical paradigms under which families of different social classes produce different developmental outcomes for their children. The first concerns the different levels of economic investments families put into human capital (Schultz, 1960). The second concerns with different levels of cultural capital (Bourdieu, 1973; Lareau, 1987; Swidler, 1986). Lastly, the third involves social capital which stems from social networks such as parental and neighborhood networks (Coleman, 1988; Lin, 1999).

Family income influences developments of socio-emotional skills among young children (Fletcher & Wolfe, 2016). In the longitudinal analysis of the Early Childhood Longitudinal Study-Kindergarten Cohort Data (ECLS-K), the authors showed that there was sizable family income gradient with regard to socio-emotional skills at the entry of kindergarten. The family income gradient steepened over the course of six subsequent years under investigation. The direct influence of family income was present on diverse dimensions of noncognitive skills, such as self-control, organization, eagerness to learn, interpersonal skills, adaptability and approaches to learning.

The linkage between socioeconomic backgrounds and psychological factors is also evidenced in research conducted outside the United States. In examination of the national sample of high school students from Chile, Claro et al (2016) found strong positive association between socioeconomic backgrounds and academic achievement. The study also uncovered positive effects of the *growth mindset*, the belief that intelligence is not fixed and can be developed (Dweck, 2007) on academic achievement. The positive association between the growth mindset and academic achievement was present across all socioeconomic strata in the study. However, the study also illuminated that students from low-income families were less likely to hold growth mindset compared to students from wealthier families. This finding invites research that investigates the interaction between socio-economic and psychological factors.

Evidence from public health literature has indicated that the relationship between psychological factors and life outcomes may interact with economic resource. One research found that *striving*, defined as relentless determination to succeed, had unexpected consequences on the physical health of adolescents from economic hardships. In this research, African American students with high striving but economic hardships at the age of 16 developed higher risks of developing Type II diabetes by the time they reached 29 compared to their *non-striving* counterparts, despite their superior outcomes in education, income, and psychological health (Brody et al., 2016). This unanticipated finding suggests that the highly motivated students from economic hardships may have dealt with stressors by compromising important aspects of their physical health, pointing to the need for addressing contextual factors that may underlie the complex relationships.

Sense of belonging, socioeconomic status, and networks

Research studies have demonstrated myriad ways in which sense of belonging positively affects various outcomes. Sense of belonging is associated with improved psychological and physical health (Ma et al., 2005). Sense of belonging helps building mindsets crucial in academic settings (Cohen & Garcia, 2008; Goodenow, 1992; Wentzel & Caldwell, 1997). In higher education research, studies collectively point to sense of belonging to be crucial to college retention (Hausmann et al., 2009; Hoffman et al., 2002; Morrow & Ackermann, 2012). In particular, socioeconomic class has been found to be strongly associated with sense of belonging in higher education institutions- motivating a deeper understanding in the extent to which socioeconomic class affects college retention through sense of belonging (Ostrove & Long, 2007). Using student responses from the Student Experience in the Research University (SERU) survey project, Soria and Stebleton (2013) empirically demonstrated that students from working-class backgrounds experience lower sense of belonging compared to students from middle/upper-class backgrounds. In addition, the study also illuminated evidence in statistically lower social capital for students from working-class backgrounds, further implying the connection between sense of belonging and social capital.

Literatures have construed sense of belonging largely as a psychological concept. For instance, Walton and Cohen (2007) introduced the idea of *belonging uncertainty,* a psychological state where people become sensitive to information that is diagnostic of the quality of social connections. Interventions seeking to improve students' sense of belonging center on changing their psychological state by providing opportunities to build nonthreatening narratives to their social relations (Stephens et al., 2014; Walton et al., 2015; Walton & Cohen, 2011).

Some research implies a possibility that a *social-belonging intervention* designed to change psychological aspects could also change social relations. Walton et al. (2015) showed that a social-belonging intervention helped female engineering students in selective engineering programs integrate into a male-dominated field through increased friendships with male engineering students. Although this study raised an intriguing possibility that changing the psychological aspect of belongingness can also help students change friendship formations, it lacked analyses of friendship network to illustrate the structural aspects; the study only looked at the number of male friends in its proportion to the total number of male students.

Socioeconomic status affects how they activate social ties. People who perceive themselves to be low status tend to have a winnowing networking behaviors when they perceive themselves to be under threat (Smith et al., 2012). In a research that combined analysis of General Social Surveys (GSS) with a laboratory experiment, the authors found that individuals who perceived themselves to be low status activated smaller and closed subsections of their networks, whereas people who perceived themselves to be high status expanded their networks when they perceived threats to their job security.

Different networking styles can lead to different levels of social capital and information asymmetry. Lareau (1987, 2011) pointed out that working and middle-class parents have different levels of information on their children's schooling because the two groups differed in their social networks; the working-class parents had strong ties with their kinships, such as their siblings, parents, and other relatives in their neighborhoods. On the other hand, the middle-class parents developed strong networks with parents of their children's classmates, using these ties as a resource to get additional information about their children's school lives.

The socioeconomic status-based differences in organized activity participation may also contribute to differential networking styles and social capital. Lareau (2011) discussed how children from middle class families engaged in organized activities designed to cultivate diverse interests, whereas students from working class families were less prone to be involved in organized activities. The socioeconomic status of parents was important in activating their children's cultural and social capital.

Social Network Analysis

In order to address the social aspect of sense of belonging, we use social networks analysis in our study. Social network analysis studies relationships (*tie*s) among individuals (*nodes*) and includes a broad array of quantitative methods, both descriptive and inferential (Sweet, 2016). Descriptive methods include use of various network measures to summarize the whole network or individual nodes in the network; inferential methods include tools for modeling social networks, such as exponential random graph models and latent space models (Sweet, 2016). The current study focuses on the descriptive method in social network analysis.

Network data can be stored in various formats and the two most common representation of network data are *edgelist* and *adjacency matrix*. An edgelist comprises of two columns, which represent a dyad of two individuals. Each pair of tie formation data represents a row and an absence of row between possible pair of dyads in the network would indicate an absence of a tie. On the other hand, an adjacency matrix stores information on a *n x n* matrix, where all possible relationships between two nodes are identified as 1 or 0; 0 denotes an absence of a tie between two nodes and 1 denotes a presence of a tie between two nodes. An adjacency matrix is symmetric for non-directed graphs but non-symmetric for directed graphs. *Isolates* refer to nodes that do not have any direct ties to other nodes in the network.

Network Centrality

Various measures have been proposed to conceptualize an individual node's network position. Network centrality, one of widely used measures to describe how central an individual node is, can be broadly categorized into four types: degree centrality, closeness centrality, betweenness centrality, and prestige/power/eigenvector centralities (Jackson, 2010). In this section, we provide a definition of each type of network centrality, illustrate each network centrality visually (Figure 2.1) and provide their calculations (Table 2.1).

The *degree centrality* (Nieminen, 1974) represents the total number of direct connections a node has a tie to. In a directed network, degree centrality can be represented in two ways, *in-degree*, the number of ties that point into the node and *out-degree*, the number of ties that point out from the node. Examining the degree centrality can be a useful way to summarize the number of direct ties for a node.

The second form of centrality is *closeness centrality*. Closeness centrality focuses on how close a node is to any other nodes in the network on average. The closeness centrality is estimated from the inverse of the total distance between a node *i* and *j* where *j* is any other nodes in the network G and the total distance is the *geodsic*[2] distance between the two nodes (Sabidussi, 1966). Closeness centrality is not appropriate for capturing centrality in disconnected networks with many *isolates* (Grunspan et al., 2014).

$$\boxed{\text{Closeness centrality (i)} = \frac{1}{\sum_{j \in G} \text{dist(i,j)}}} \qquad \textbf{(1)}$$

The third form of centrality is *betweenness centrality* (Freeman, 1977). The betweenness centrality measures how well a node is positioned to serve as a bridge connecting other nodes in the overall network. As shown in equation (2), $\boxed{\sigma\ (j, k|i)}$ is the total number of shortest paths between *j* and *k* that pass through *i* and $\boxed{\sigma\ (j, k)}$ is the number of shortest paths between *j* and *k*. Nodes with high betweenness centrality are most likely be the link with the shortest *average path length*[3] between any two nodes.

$$\boxed{\text{Betweenness centrality (i)} = \sum_{i \neq j \neq k} \frac{\sigma\ \text{(j,k|i)}}{\sigma\ \text{(j,k)}}} \qquad \textbf{(2)}$$

The last form of centrality, *prestige/power, and eigenvector related centrality* measures are more complex forms of network centralities. They are built on the idea that a network's centrality is largely determined by how important its neighbors are (Bonacich,

[2] *Geodesics* is the length of the shortest path between two nodes. If there is no path between two nodes, then the geodesic between the two nodes is infinite.
[3] Average path length is the average number of ties that must be traversed in the shortest path between any two pair of nodes in a network.

1972, 1987; Katz, 1953). Bonacich centrality is one of the widely used eigenvector centrality measures and was developed by extending Katz (1953)'s idea on measuring power or prestige of a node in a given network.

Katz (1953) proposed that the power or prestige of a given node can be measured by differentially weighting the importance of the *weighted* sum of the walks that emanate from it. For example, a walk of length 1 would be worth α, a walk of length 2 will be worth α^2 and so forth for some parameter α that is greater than 0 but less than 1. By using this method, we can give higher weight to nodes that are within shorter distance from the node and decaying weight to nodes that are farther from the node.

Suppose that $g11$ (where 11 is the n x 1 vector of 1s) is the vector of degrees of nodes, which informs how many walks of length 1 emanates from each node. Then, $g^k 11$ is the vector whose i^{th} entry is the total number of walks of length of k from each node. This idea can be expressed as:

$$\text{Katz power index }(g, \alpha) = (1 + \alpha g + \alpha^2 g^2 \ldots)\alpha g11 \quad \mathbf{(3)}$$

This value becomes finite when *a* is small enough and can be rewritten as below where *II* is the identity matrix:

$$\text{Katz power index }(g, \alpha) = (II - \alpha g)^{-1}\alpha g11 \quad \mathbf{(4)}$$

Bonacich (1972) extended this idea by introducing β *parameter that is different from* α. This makes β a decay factor that evaluates how much value of being connected to another node decreases with distance, while α becomes a normalizing scalar that captures the base value on each node.

$$\text{Bonacich centrality }(g, \alpha, \beta) = (II - \beta g)^{-1}\alpha g11 \quad \mathbf{(5)}$$

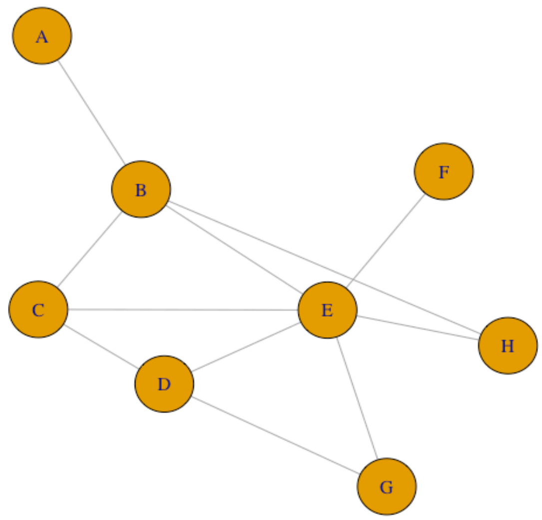
Figure 2.1 illustrates an undirected network with 8 nodes and 11 ties. Each circle denotes an individual node in the network and each line represents a tie between nodes. Table 2.1 provides estimates of the four different network centralities we described above. As shown in Figure 2.1 and Table 2.1, node *E* has the highest centrality as measured by all four different types of centralities. On the other hand, node *A* has the lowest centrality as measured by all four different types of centralities. The four network centralities are positively correlated with one another but having the same value on one network centrality measure does not necessarily mean they are also equal on other centrality measures.

Table 2.1. Network centrality for the Eight Nodes from Figure 2.1.

Node	Degree centrality	Closeness centrality	Betweenness centrality	Bonacich centrality
A	1	0.06	0	0.21
B	4	0.10	6.5	0.72
C	3	0.09	1	0.70
D	3	0.08	0.5	0.65
E	6	0.13	12	1.00
F	2	0.08	0	0.49
G	1	0.07	0	0.30
H	2	0.08	0	0.51

Note. Network centralities were calculated using the igraph package in R.

Figure 2.1. An Undirected Network with Eight Nodes and Eleven Ties



The Current Study

Networks can serve as a mechanism through which social inequality deepens if they are organized in such a way that predicts an individual's decisions to adopt certain behaviors (DiMaggio & Garip, 2012). Research studies have identified various ways this can occur in adolescent friendships. Adolescent friendships are shaped and clustered by preferences for the same race (Leszczensky & Pink, 2015; Moody, 2001; Smith et al., 2016), by academic achievement (Flashman, 2012), and by motivation levels in classrooms (Kindermann, 2007). Our aim is to understand how friendship networks operate to shape the relationship between family income and belongingness in school, thereby expanding our conceptualization of sense of belonging from a de-contextualized psychological construct to a domain that is intricately intertwined with its environment.

We use Sullivan's interpersonal theory of development (Sullivan, 1953) and Bourdieu's theory of social and cultural reproduction (Bourdieu, 1973). Sullivan's interpersonal theory of development stresses interactions with others as a critical component to the formation of sense of self and feelings of security. We draw on evidence documenting that peer acceptance mediates the relationship between sports participation and global self-esteem (Daniels & Leaper, 2006).

Bourdieu's theory of social and cultural reproduction stipulates that the socializing influence of educational institutions recreates the privileges of the upper class through cultural and social reproductions. We also draw from evidence that participation in organized activities differ by social class (Lareau, 2011) and that parents from different social classes also vary in their social capital to navigate their children's academic lives (Lareau, 1987; Lareau & Horvat, 1999). Based on prior research which delved into class-based differences in social capital (Lareau, 1987; Ostrove & Long, 2007; Smith et al., 2012), this research hypothesize that students with higher family income will occupy more central friendship network positions. Secondly, building on findings from prior literature which suggested that networks influence emotional attachments to groups (Paxton & Moody, 2003), I further postulate that students who are central in their friendship networks will experience a higher sense of belonging in school. The current study put forward the following hypothesis:

Hypothesis. Friendship network centrality will positively mediate the relationship between family income and sense of belonging.

Data and Methods

The National Longitudinal Survey of Adolescent Health

This study uses data from the National Longitudinal Study of Adolescent Health, also known as Add Health (Harris, 2013). Add Health is a longitudinal survey of nationally representative sample of adolescents in grades 7-12 in the United States in 1994-95 who were followed through their transition into adulthood in multiple waves of interviews. General overview of the Add Health has been provided in the previous chapter, so this section focuses on the administration of the Wave 1 In-School Survey, Wave 1 In-Home Survey, and Wave 1 Parent Survey, which the current study draws its data from.

The Wave I In-School survey was administered between September 1994 and April 1995, surveying over 90,000 students on a single day during a 45 to 60-minute class period. Questions on the Wave I In-School survey included items on friendship networks, school activities, school context, grades, social, behavioral and health related questions. Wave 1 In-School survey also collected friendship nomination data and we use the network module to measure friendship network centrality.

The Wave 1 In-Home survey was conducted few months after the Wave 1 In-School survey during 1994-1995. From the union of students who were on the school rosters and students who were not on the rosters but completed the Wave 1 In-School survey, a sample of adolescents was chosen to participate in 90-minute Wave 1 In-Home interview. The sample was selected using stratified sampling by school, grade and gender where about 20 students from each strata were chosen to yield about 200 students from each pair of schools (Harris, 2013). Overall, there were 20,745 participants in the Wave 1 In-Home survey. Wave 1 In-Home survey included questions about sense of belonging in school and we use student responses to these questions to measure sense of belonging.

Parents were interviewed during the first wave of Add Health survey in 1995. A parent, preferably the mother of each adolescent respondent interviewed in Wave I survey were asked to complete an interviewer-assisted survey of which topics included the parents' education, employment and parents' familiarity with the adolescents' friends and their parents. If the adolescent's mother did not reside in the household, the next appropriate respondent was interviewed. About 85% of the parent in-home survey were biological mother, followed biological father (4%). The survey response rate for the Wave 1 Parent Survey was about 85% for the child-specific data. The Wave 1 In-Home Parent Survey included a question on family income, and we use parents' response to this question to measure family income.

Analytic Sample

The analytic sample for the mediation analysis includes students who were interviewed in both Wave I In-School Survey and Wave I In-Home survey and whose parents were interviewed in the In-Home Parent survey. There were 90,118 students in the In-School survey, 75,871 of whom whose network measures were estimated. Among them, 14,319 were interviewed during the Wave 1 In-Home survey. Of these students, 12,286 had their parents survey completed. Students who changed schools between Wave 1 In-School survey and Wave 1 In-Home survey were removed from the analytic sample.

The response rate of parent survey among was about 85% among the initially identified 14,319 sample from Wave 1 In-School and Wave 1 In-Home student respondents. Disproportionately large percentage of foreign-born students had their parent survey data missing; about 30% of the foreign-born students' parents were not surveyed. Of the surveyed parents, 292 parents had missing value on the income questionnaire because the family income question was never reached, and additional 1,280 parents had missing value because they refused to answer the question about income.

Altogether, about 20% of the analytical sample had missing values on the family income variable, which is the independent variable in our study. Data is said to be Missing at Random (MAR) when the probability of missing data on the variable is unrelated to its value, after controlling for other variables. This was not true in our case because people who have low or high income are more likely to refuse to respond to the question, making our data Missing not at Random (MNAR). While various methods for treatment of MNAR data have been proposed, some have argued that they do not always perform better than listwise deletion (Enders, 2011), which removes any observations with missing data. Studies have also suggested that listwise deletion still produces trustworthy estimates when the missingness is not too severe (Bennett, 2001; Dong & Peng, 2013). Given that listwise deletion still resulted in a large sample, listwise deletion was chosen to handle the missingness. The final analytic sample included 10,418 students from 121 schools.

Measures

Sense of Belonging. Sense of belonging is the dependent variable in the mediation model and was measured by three Wave 1 In-Home survey questionnaires. The questions asked respondents to answer in ranges between 1 (strongly disagree) to 5 (strongly agree) in their agreement to the following statements; *I feel close to people at school* (M = 3.73, SD = 0.99); *I feel like I am part of this school* (M = 3.86, SD = 1.0); and *I am happy at this school* (M = 3.73, SD = 1.09). The three items had high internal consistency and the scree plot suggested that one factor solution was appropriate (Figure 2.2). We used principal components analysis to derive factor scores from the three survey items (*M* = 0.01, *SD* = 1.44) and used this as a measure of sense of belonging.

Bonacich centrality. Bonacich centrality is the mediator variable in our study. Bonacich centrality is measured from the friendship nomination module in Wave I In-School survey where students were asked to nominate up to five male and five female friends from the roster of all students enrolled in the respondent's school and in the sister school. The Add Health provides Bonacich centrality for students who attended schools where survey response rates for the network module was more than 50%. We use this variable in the analysis. If out-degree is zero, Bonacich centrality was estimated as zero. About 8 percent of the friendship nominations occurred to individuals whose names were not in the rosters. These nominations were not uniquely identifiable and not included in the estimation of Bonacich centrality. The Bonacich centrality (*M* = 0.80, *SD* = 0.64) in our sample ranged between 0 to 4.29.

$$\boxed{\text{Bonacich centrality of X } (\alpha, \beta) = \alpha(\mathbf{I} - \beta\mathrm{X})^{-1}\mathrm{X}1} \quad \textbf{(6)}$$

Equation (6) expresses Bonacich centrality as measured by the Add Health: $\boxed{\alpha}$ is a scaling vector, $\boxed{\beta}$ is the power weight which reflects the degree of dependence on the extent to which the prestige of the other nodes to whom the focal node has ties to (set to 0.1), $\boxed{\boldsymbol{I}}$ is the identity matrix, **X** is an adjacency matrix that contains all friendship nominations; **1** is columns of 1s.

Family income. Family income was measured in Wave 1 Parent Survey through the question, "About how much total income, before taxes did your family receive in 1994? Include your own income, the income of everyone else in your household, and income from your welfare benefits, dividends and all other sources." Because the income variable was highly skewed to the right (skewness = 9.51, kurtosis = 141.62), I used log transformation to normalize the data.

Statistical Methods

Mediation analysis allows one to determine the extent to which the relationship between the independent and dependent variable is attributable to a third, mediating variable. This study uses mediation analysis with a single mediator introduced by Baron and Kenny (1986) and employs the assessment procedures and criteria suggested by Zhao et al. (2010). Figure 2.4 illustrates a single-mediator model. *X* denotes the independent variable, *M* is the mediator and *Y* is the dependent variable. *a* denotes the relation of *X* to *M*, *b* represents the relationship between *M* to *Y* adjusted for *X*, and c denotes the relation of *X* to *Y* adjusted for *M*. The mediated effect can either be captured by a x b or by c'- c where c' denotes the total effect and c denote the direct effect of X on Y. In full-mediation, c is equal to zero and a x b is equal to c'.

According to Baron and Kenney (1986), establishing mediation requires three conditions: First, X must significantly affect M in equation (7). Second, X must significantly affect in Y in equation (8). Third, M must affect Y when the controlling for X in equation (9).

$$M = i_1 + aX + e_1 \quad \textbf{(7)}$$

$$Y = i_2 + c'X + e_2 \quad \textbf{(8)}$$

$$Y = i_3 + cX + bM + e_3 \quad \textbf{(9)}$$

Finally, Baron and Kenney (1986) suggested performing Sobel z-test to test the statistical significance of path a x b, which is the indirect, or the mediated effect.

Zhao et al. (2010) disputed the original Barron and Kennedy (1986) on three points. First, although Barron and Kennedy (1986) proposed that the strength of mediation is demonstrated by the lack of direct effect when the indirect effect is included in the model, Zhao et al. (2010) argued that it is the size of the indirect effect that should be of foremost importance in mediation, not the absence of direct effect.

Second, while Barron and Kennedy (1986) propounded that statistically significant zero-order effect of X on Y needs to be established for the effect of the mediator on the dependent variable (equation (8)), Zhao et al. (2010) argued that this is not a necessary condition. The authors pointed out that mathematically, the zero-order effect of X on Y turns out to be equivalent to the total effect of X on Y. It is then the mediated effect a x b that needs to be statistically significant for the mediation to be established. We follow this approach and focus on significance of the indirect effect to establish mediation.

Finally, Zhao et al. (2010) advised against the Sobel z-test and recommended using bootstrap test (Preacher & Hayes, 2004). The authors illuminated that because the sampling distribution of products and Sobel's z is not normal, when a x b is positive, its sampling distribution will be positively skewed, and the confidence intervals will often erroneously include zero. The bootstrap test (Preacher & Hayes, 2004) accounts for this by generating empirical sampling distributions of a x b from repeated replications. Following this approach, we will report bootstrap sampled standard errors from 200 replications in our analyses.

Another possible problem with our current design in mediation is the multilevel nature of our samples. Because students are nested within schools, it is likely that students within the same school are more similar to each other than students attending other schools. The current study has 1-1-1 design in that all the variables in the mediation model are measured at the individual level, but all individuals are nested in schools. In multilevel settings, the traditional mediation approaches can lead to biased standard errors because the assumption of independence of observations is violated.

We report the intraclass correlation coefficient (*ρ)* to assess the presence of statistical independence. The intraclass correlation coefficient (*ρ*) is estimated as the ratio of between-group variance (τ^2) over the total variance ($\tau^2 + \sigma^2$), where σ^2 is the within-group variance. When the intraclass correlation coefficient is large, this implies that there is a greater group dependence and evidence for violation of the independence of observations.

$$\boxed{\text{Intraclass correlation coefficient } (\rho) = \frac{\tau^2}{\tau^2 + \sigma^2} \quad \mathbf{(10)}}$$

There have been several recommended procedures for multilevel mediation analyses within the standard multilevel modeling framework. However, Preacher et al. (2010) pointed out that the mediation analyses under the traditional multilevel modeling framework is not suitable in 1-1-1 design because the use of one slope fails to fully separate between-group and within-group effects, introducing bias in the estimation. The current study follows the multilevel structural equation modeling (MSEM) approach suggested by Preacher et al. (2010) and include a random intercept in each equation at the school level. We estimate the indirect effects from the MSEM and compare against the indirect effects estimated from the single-level mediation model. All statistical analyses were conducted using STATA software, version 14 (StataCorp, 2015).

Results

Students (N = 10,418) nested within schools (J = 121) were considered in the final model. Characteristics of the sample in the study are summarized in Table 2.2. 58.6% of our analytical sample were White and 22.9% were Black/African American students. About half of the sample under study were females. Students were distributed in their grades from 6 through 12. Majority of the analytical sample attended schools in the suburban area (54.9%), followed by urban (26.6%) and rural areas (18.5%). About 8% of the sample received public assistance and 15.2% reported that they did not participate in any clubs, organizations or team activities.

Preliminary analyses revealed some notable differences in the variables in the current study by student participation in extracurricular activities and we report the findings in Table 2.5. Compared to students who reported having participated in at least one extracurricular activity (N = 8,833), students who did not participate in any extracurricular activity (N = 1,585) had lower Bonacich centrality (0.84 vs. 0.61), had lower average log of family income (3.56 vs. 3.38), reported lower levels of sense of belonging as measured by the overall belongingness factor score (0.09 vs. -0.51) but also for each of the three survey items: I feel close to people at school (3.77 vs. 3.49), I feel like I am part of this school (3.94 vs. 3.46), and I am happy at this school (3.78 vs. 3.46).

Our mediation hypothesis was confirmed in the single mediation model (Model 1, Table 2.6). As expected, the total effect of family income on sense of belonging was positive and statistically significant ($\beta = 0.1$, $p < 0.001$). The indirect effect of log of income on sense of belonging through the friendship network centrality was also positive and statistically significant ($\beta = 0.04$, $p < 0.001$). The mediated effect was in the same direction as the total effect, accounting for about 40% of the total effect.

In order to assess possible clustering, intraclass correlations coefficients clustered at the school level were estimated for each variable: family income ($\rho = 0.21$), Bonacich centrality ($\rho = 0.01$), and sense of belonging ($\rho = 0.03$). The intraclass correlations indicated that school-level clustering may not have been severe, but we proceeded with the mediation model using the multilevel structural equations modeling framework (MSEM) to compare against the results from the single-level model. We included a random intercept in each equation at the school level.

Our mediation hypothesis was confirmed in the MSEM model (Model 2, Table 2.6). The total effect of family income on sense of belonging was positive and statistically significant ($\beta = 0.1$, $p < 0.001$). Consistent with results from the single-level mediation, we found evidence for statistically significant positive indirect effect of log of family income on sense of belonging through Bonacich centrality ($\beta = 0.05$, $p < 0.001$). The mediated effect was in the same direction as the total effect and was slightly greater than the estimate from the single-level mediation, accounting for about 50% of the total effect.

Discussions

Existing research on sense of belonging has overwhelmingly focused on its psychological aspect. Although previous literature has documented associations between socioeconomic status and sense of belonging, the role of friendship networks as a possible mediator has been largely absent from the discussion. The goal of this paper was to focus on the social aspect of sense of belonging by using a network measure derived from friendship nomination and document its association to sense of belonging and further investigating its association to family income in the mediation analysis, thereby proposing a mechanism through which family income can affect an important noncognitive aspect of adolescents' development.

This study clearly identified and decomposed the indirect effects of family income in sense of belonging through friendship centrality. The current study found that friendship network centrality mediated the positive relationship between family income and sense of belonging. The statistically significant, positive indirect effect was found in both single-level mediation approach and MSEM approach. Findings from current study show that friendship network centrality and family income both matter in terms of how adolescents feel they belong in school, paving a direction for future research and informing the design of educational interventions focused on improving students' sense of belongingness in schools.

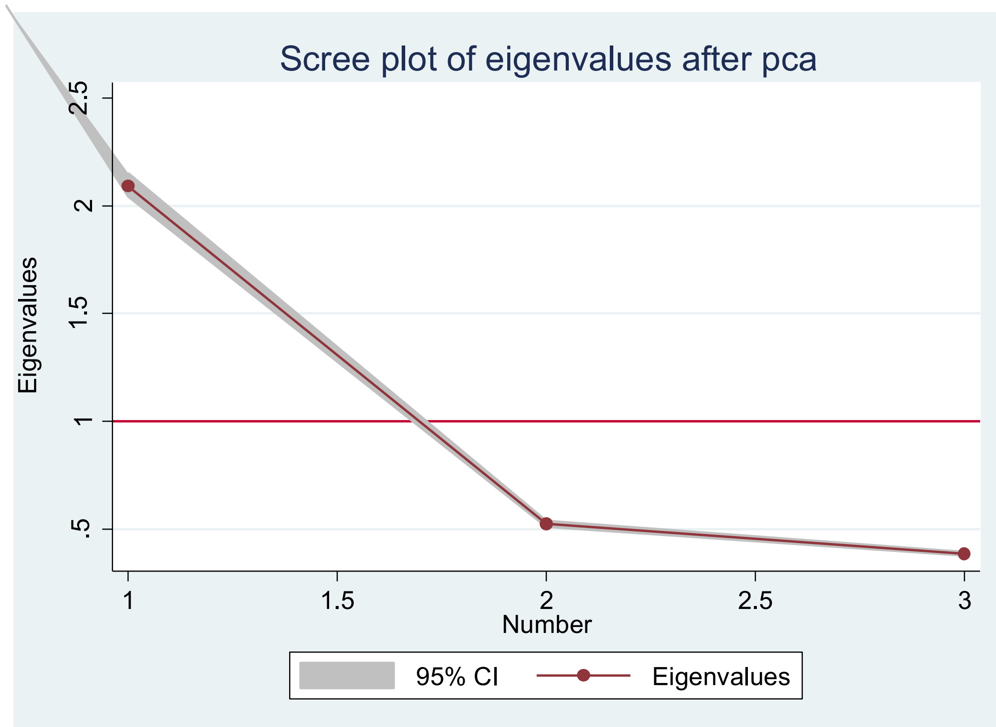
The current study has important limitations and future work will address them. Barron and Kenney (1986)'s approach to mediation analysis assumes that the total effect of X on Y is summation of the indirect effect (a x b) and the direct effect (c). This assumption does not consider possible interaction effect between X (family income) and M (Bonacich centrality). In addition, the traditional mediation analysis also does not consider possible unmeasured confounders in the M-Y path. Cognizant of these limitations in the traditional approach, future work will consider employing causal mediation analysis approach (Imai et al., 2010), which extends the traditional mediation analysis to address their limitations.

Despite the limitations, our study has several methodological strengths, including the use of a descriptive network measure derived from the friendship network. We also considered possible school-level clustering and replicated the single-level analyses using the MSEM approach. As such, findings from the current study contributes to the emerging body of literature utilizing network data in studying social capital and establishes a foundation for future research that takes friendship networks into consideration in studying sense of belonging. Furthermore, results from the current study contribute to understanding the pathways through which family income can create differential outcomes in a noncognitive factor, an area that has not been explored extensively in previous research.

The current study did not fully explore the role of extracurricular activity in the mediation model. However, results from the preliminary analyses motivate future research centered on this question. In our exploratory analyses, we showed that participation in extracurricular activity was associated with all the variables in the mediation model: family income, Bonacich centrality, and sense of belonging, implying that participation in extracurricular activity may be an important variable to explore in future research. This observation is largely in accord with existing research studies which have pointed to the importance of participation in organized activities in formation of social capital, friendships and positive academic outcomes (Camacho & Fuligni, 2015; Gibbs et al., 2015; Vandell et al., 2015). We will explore this area in future research.

Table 2.2. Sample Demographic Characteristics (N=10,418)

	%
Demographic information	
White	58.6%
Black/African Americans	22.9%
Female	50.4%
Grade	
6	0.2%
7	14.2%
8	13.8%
9	19.3%
10	20.5%
11	18.1%
12	14.1%
Receives public assistance	8.1%
Unable to pay the bills	18.2%
Does not participate in any extracurricular activities	15.2%
School characteristics	
School size	
125 or fewer students	1.8%
126-350 students	7.7%
351-775 students	26.0%
776 or more students	64.5%
% White	
0%	11.1%
1-66%	37.9%
67-93%	27.2%
94-100%	23.9%
Metro	
Urban	26.6%
Suburban	54.9%
Rural	18.5%
N	10,418



Note. The three questions were measured in five point-likert scale to statements: "I feel close to people at school", "I feel like I am part of this school", and "I am happy at this school"

Figure 2.2. Scree Plot of Eigenvalues after Principal Component Analysis on the Three Sense of Belonging Survey Questions (N=10, 418)

Table 2.3. Descriptive Summary of Variables and Measures in the Mediation Model (N=10,418)

	M	SD	Min	Max
Log (family income)	3.53	0.81	0.00	6.91
Bonacich centrality	0.80	0.64	0.00	4.29
Sense of belonging (factor scores)	0.01	1.45	-4.68	2.06
I feel close to people at school	3.73	0.99	1.00	5.00
I feel like I am part of this school	3.86	1.01	1.00	5.00
I am happy at this school	3.73	1.09	1.00	5.00

Note. The three survey questions were measured on a five point-likert scale between 1 (strongly disagree) to 5 (strongly agree).

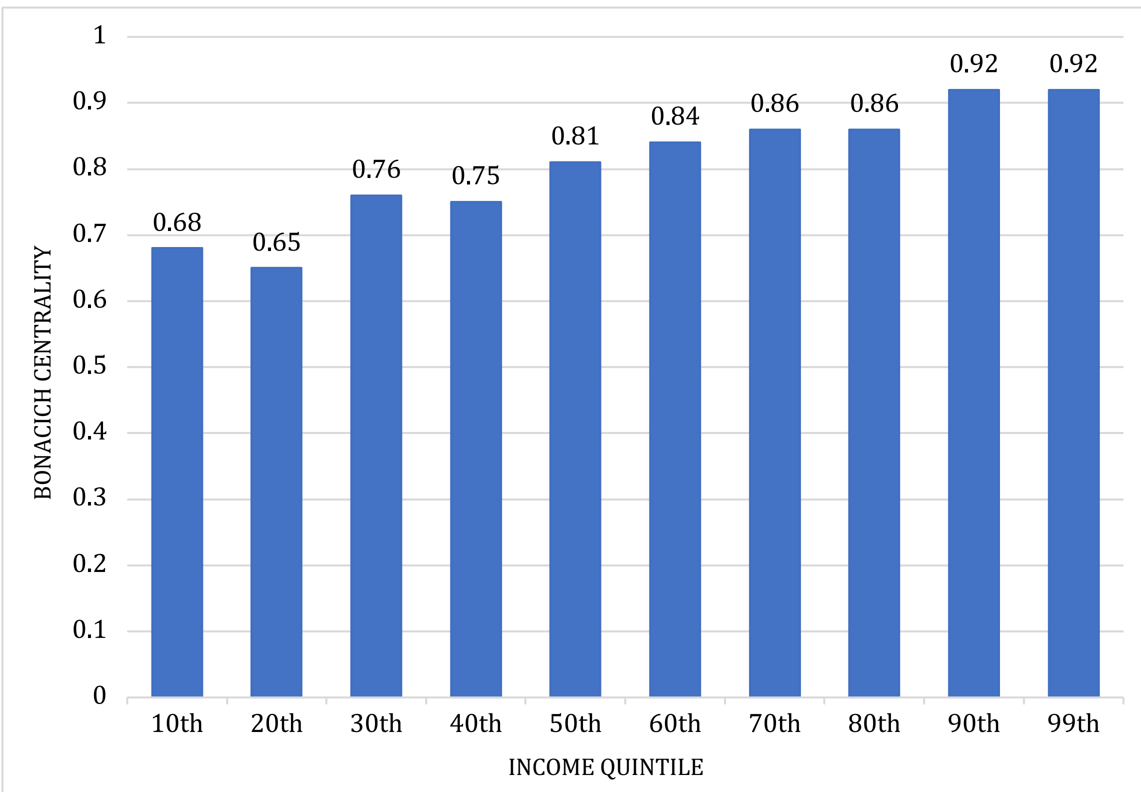


Figure 2.3. Average Bonacich Centrality by Family Income Quintile (N=10,418).

Table 2.4. Intercorrelations between log(Family Income), Bonacich Centrality and Sense of Belonging

	log(Family Income)	Bonacich Centrality	Sense of Belonging
log(Family Income)	1		
Bonacich Centrality	0.12	1	
Sense of Belonging	0.05	0.20	1

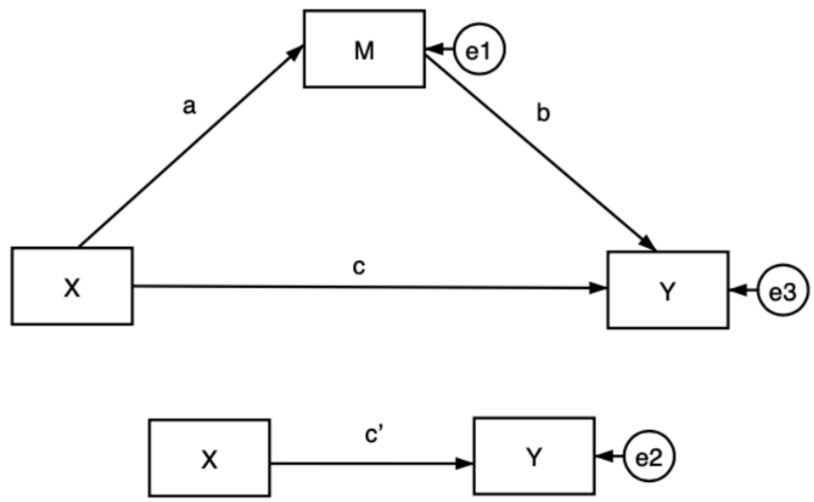


Figure 2.4. Mediation Model with Independent Variable (X), Mediator (M), and Dependent variable (Y).

Table 2.5. Bonacich Centrality, Family Income and Sense of Belonging by Student Participation in Extracurricular Activities

	Participants		Non-participants	
	M	*SD*	*M*	*SD*
Bonacich centrality	0.84	0.65	0.61	0.56
Log(family income)	3.56	0.81	3.38	0.79
I feel close to people at school	3.77	0.97	3.49	1.06
I feel like I am part of this school	3.94	0.98	3.46	1.09
I am happy at this school	3.78	1.07	3.46	1.15
Belongingness factor score	0.09	1.40	-0.51	1.56
N	8,833		1,585	

Note. The three survey questions were measured on a five point-likert scale between 1 (strongly disagree) to 5 (strongly agree).

Table 2.6. Parameter Estimates, Standard Errors and Confidence Intervals for path a, b, Indirect Effect and Total Effect from Single-level and Multilevel Structural Equation Model Mediation Analyses

	a	b	Indirect effect (a x b)	Total effect (a x b + c)
Model 1	0.10***	0.44***	0.04***	0.1***
	(0.0076)	(0.0038)	95% CI [0.03-0.05]	95% CI [0.08-0.11]
Model 2	0.11***	0.43**	0.05***	0.1***
	(0.008)	(0.022)	95% CI [0.038-0.055]	95% CI [0.063-0.137]

Note. * *p< 0.05*, ***p < 0.01*, *** *p< 0.001*. Model 1 reports results from the single-level mediation model and Model 2 reports results from multilevel structural equations model (MSEM). Standard errors and confidence intervals are estimated from bootstrapping method with 200 replications and they are shown in the brackets.

Chapter 3: Ninth Grade Friendship Closure and High School Outcomes

Background

Ninth grade year is a highly transitional time (Weiss, 2001). The shift in expectations and demands as students enter high school makes the ninth grade year susceptible to poor academic outcomes. Research focused on high school transitions highlights that the ninth grade year is characterized by a drop in GPA (Isakson & Jarvis, 1999; Pharris-Ciurej et al., 2012), decline in attendance (Barone et al., 1991) and increased risk of depression (Newman et al., 2007).

While the decline in grades upon entering high school is common and has been recognized by researchers as the "9th grade shock" (Neild & Weiss, 1999; Pharris-Ciurej et al., 2012), evidence suggests that traditionally vulnerable groups of students experience steeper decline (Roderick, 2003; Sutton et al., 2018). The disparity was evident even for the high performing students, suggesting that the ninth grade year can be a crucial juncture (Neild, 2009) where education stratification occurs (Sutton et al., 2018).

Academic success during ninth grade is a strong and consistent correlate of long-term high school success. Research from the Chicago Public Schools (CPS) finds that credit accumulation and course failures during ninth grade are strongly predictive of high school graduation four years later (Allensworth & Easton, 2005; Allensworth & Easton, 2007). Spurred by the initial findings from Chicago, following evidence from other large urban districts finds a similar pattern; students with academic success during the ninth grade year were also more likely to graduate from high school (Iver & Messel, 2013; Kemple et al., 2013). Evidence drawn from research studies suggests focusing on ninth grade success to improve long-term high school outcomes (Roderick et al., 2014).

An important contributing factor that makes the transition to high school even more difficult is the volatility of social relations during the ninth grade year. As students enter high school, social relationships with teachers and friends from middle school become fragile (Gillock & Reyes, 1996; Heck & Mahoe, 2006; Newman et al., 2007) and the pressure to make new connections heightens (Isakson & Jarvis, 1999). Some programs such as the Ninth Grade Academies (NGA) have been designed to address this issue by fostering an inclusive environment for the incoming high school students. The tenets of the NGA model include creating self-contained learning communities specifically for the ninth graders by providing ninth grade only space, faculty, administrators and team of teachers. Evaluation of the NGA program, however, finds mixed results from the program and uncovers difficulties surrounding its full implementation (Somers & Garcia, 2016). The current study is motivated by the need to deepen understanding in friendship networks formed during the ninth grade year and their relations to long-term high school outcomes.

Friendships during Transitional Times

Research has documented the importance of friends in various domains of development. Friends contribute to the development of social and cognitive skills (Rubin, Bukowski & Parker, 1998). Friends also provide information, support, norms and values (Coleman, 1988, 1990) that are necessary to succeed in schools and can help increase motivation, self-regulation and learning (Eisenkopf, 2010; Harris et al., 2006; Kindermann, 2007). Friends' cultural capital also affects college completion (Cherng et al., 2013). Friends also influence individuals' health decisions and behaviors, such as smoking (Schaefer et al., 2012) and alcohol use (Mundt et al., 2012).

Friendships can be particularly important during transitional times. Presence of positive friendships can make a difference in adjusting to a new environment and research evidence span across different grade levels. Research finds that perceived conflict and exclusivity can lead to lower levels of achievement while validation from friends can assist adjustment in grade schools (Ladd et al., 1996).

Reciprocated friendships also seem to matter. In a two-year longitudinal study where Wentzel et al. (2004) examined the peer relations as students transitioned into middle school, reciprocated friendship was shown to be positively associated with prosocial behaviors, better grades and higher well-being. Langenkamp (2010) found that middle school friends served as a protective factor during transition into high school. Although the association was not present among the low-achieving students, the study found that popularity, measured by in-degree friendship nomination, was an important predictor of academic outcomes.

While there is mounting evidence suggestive of importance of friendships during transitional times, the challenge in uniform understanding of friendships lies in how researchers define and measure social capital using various angles (Newman et al., 2007). For instance, some studies examine peer influence by focusing on characteristics of the best friends' resources (Cherng et al., 2013), some focuses on the number of friends (Langenkamp, 2010), reciprocated friends (Wentzel & Caldwell, 1997) or students' perception of peer relations (Hussong, 2000; Ladd et al., 1996). Research also points to distinct types of friendship and different influence process associated with each (Molloy et al., 2011). The variations in how peer relations are conceptualized and measured in the education literature obscures its meaning and obstructs coherent discourse around the topic.

Network closure as social capital

Coleman (1988) propounded network closure as a form of social capital, which he argued operated by creating obligations, norms, and trust. Network closure is critical when trust is an important component to success because having an enclosed network serves as a sanction to impose norms and prevent undesirable behaviors (Coleman,1988, 1990). In his examination of social capital within family and community for high school sophomores, Coleman (1988) introduced the idea of *intergenerational closure*, which he defined as a closed network created by individual student's parents' connection to their children's friends' parents. Coleman (1988) argued that the intergenerational closure served to impose norms and prevent undesirable behaviors of the children. Although Coleman (1988)'s idea of intergenerational closure was introduced in the paper, challenges around measuring intergenerational closure prevented its empirical testing. In fact, in the original paper, Coleman (1988) looked at family compositions and characteristics, rather than measuring intergenerational closure as he had defined.

Using series of survey questionnaires from the National Education Longitudinal Study (NELS), Carbonaro (1998) was one of the first to measure intergenerational closure using Coleman (1988)'s definition. Carbonaro (1998) used the variants of the survey question repeatedly asked to a student's parent, "Do you know the parents of your child's first friend?", with replacement of the word, "first" with "second", "third" and so on till the "fifth", to estimate the intergenerational closure using the parent's response about their acquaintance to five hypothetical parents of their child's friends. Carbonaro

(1998) summed up the parents' response to the questions and used the metric to gauge the level of intergenerational closure present. Using this approach, Carbonaro (1998) found positive association between intergenerational closure and mathematics achievement.

Ego-centric vs. Whole network data

It is important to note that the approach used by Carbonaro (1998) to construct intergenerational closure is an example use of ego-centric network data. The ego-centric network data rely on an individual[4] respondent's response to obtain information about their connections[5]. It is noteworthy that the *alters* may or may not be included in the survey and we use the *ego*'s response to gauge the *alter*'s information. This ego-centric approach to estimate networks was introduced and employed in the development of network modules in large surveys, such as the General Social Surveys (Burt, 1984).

Although the ego-centric network data help us understand social relations when surveying every individual is not feasible, this approach does not yield a complete picture of a network and is limited by its heavy reliance on the surveyed respondents. A whole-network approach differs from the ego-centric approach in that it attempts to collect data from the entire population of nodes in the network, yielding a more accurate picture of the whole network environment. Despite the difficulties involved in collecting network data from every individual in the network, researchers have used a whole-network approach in studying adolescents' friendships (Flashman, 2012; McFarland et al., 2014), parents' social networks (Quinn et al., 2020) and education professionals' networks (Sweet, 2019). The current study is motivated to add to the growing literature in using a whole-network approach in examining social relations.

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[4] The focal nodes in a network is also known as *ego.*

[5] The nodes to whom *ego* are directly connected to are also known as *alters.*

Triadic closure and Network transitivity

Triadic closure is one of the most widely studied features in network research (Bianconi et al., 2014; Lou et al., 2013; Mollenhorst et al., 2011; Opsahl, 2013). The principle of *triadic closure* stipulates that if two people in a social network have a friend in common, then there is an increased chance that they also become friends (Granovetter, 1973). Triadic closure is an important feature of social relations, which generates behaviors not observed in two-way interactions. For example, a third connection in the network can yield mediation between the two individuals when tensions break (Faust, 2007). The existence of triadic closures also implies that the ties are strong because when a node has a strong tie with its two neighbors, then it is more likely the neighbors are connected (Easley & Kleinberg, 2010). A triadic closure is a characteristic of cohesive network and this connection has been invoked by previous researchers (Holland & Leinhardt, 1971; Moody & White, 2003).

Network transitivity is a formulation of triadic closure in a measurement that can describe an individual node in the network. An individual node's network transitivity is measured by the number of transitive triples in a node that has direct ties to divided by the number of potentially possible transitive triples. A triple of nodes that comprise of i, j, and k is said to be *transitive* if i being connected to j and j being connected to k also implies i is connected k. On the other hand, the triple of nodes is *intransitive* if i is connected to j and j is connected to k but i and k are disconnected.

Figures 3.1 and Figure 3.2 compare networks with and without triadic closures. Each circle denotes an individual *node* and each line represents a *tie* between the nodes. In the network depicted in Figure 3.1, there is no triadic closure because no individual node has two adjacent connections that are also connected. It is also important to note that estimation of network transitivity is only possible for nodes that have at least two direct connections (*degrees*) because a triadic closure requires tie formation between three nodes.

Therefore, in Figure 3.1, network transitivity cannot be estimated for nodes A, F, G and H. Network transitivity for nodes B, C, D, E are all zeros because none of their two immediate neighbors are connected. In Figure 3.2, we add three ties; B-H, C-E, and D-F to the original network in Figure 3.1. We observe that this gives arise to four triadic closures; B-E-H, B-C-E, C-D-E and D-E-F. Table 3.1 summarizes network transitivity estimated for the eight nodes from the network in Figure 3.2.

Table 3.1. Network Transitivity estimated for Individual Nodes in Figure 3.2.

Node	Degree	Possible triples	Transitive triples	Network
A	1	0	0	*
B	4	6	2	0.33
C	3	3	2	0.67
D	3	3	2	0.67
E	6	15	4	0.27
F	2	1	1	1
G	1	0	0	*
H	2	1	1	1

Note. * If degree is one, the node's transitivity cannot be estimated.

Figure 3.1. A Network without Triadic Closures.

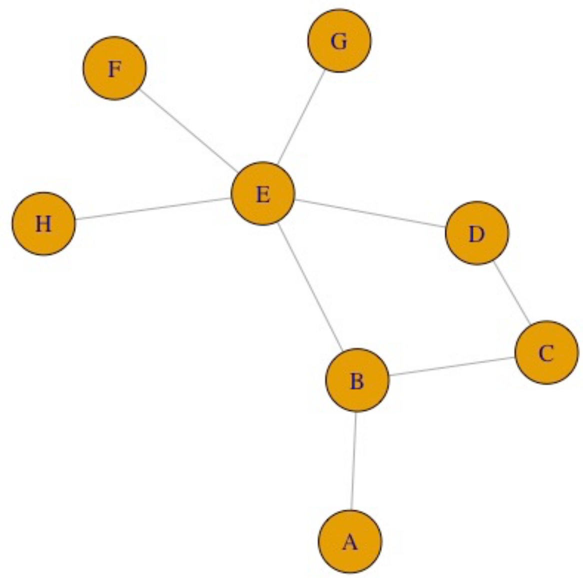
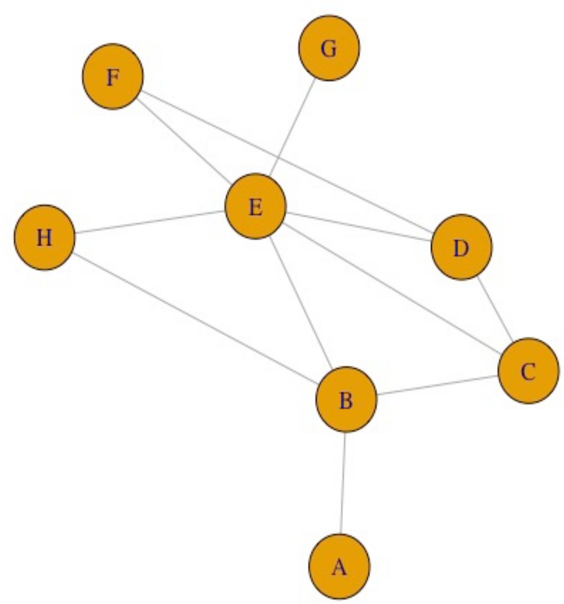


Figure 3.2. A Network with Four Triadic Closures (B-E-H, B-C-E, C-D-E and D-E-F).



The Current Study

Literature on high school transition points to the salience of friendships in successful adjustment. However, lack of clarity in its definition and coherent measure of friendships as a social capital has yielded a wide range of possibilities for measuring friendship using different angles. The current study attempts to address this scientific gap by using a widely studied network measure, *network transitivity*, which aligns with Coleman's theory of social capital as a network closure—and empirically testing its association with long-term high school success.

The current study draws from the theoretical frameworks of social exchange theory (Blau, 1964; Molm & Cook, 1995), which posit that individuals network in such a way that maximizes their self-interests while minimizing potential costs. Given that ninth grade year is an uncertain time, it is plausible that students will choose their friends in ways to best help themselves. We postulate that students who are unable to build enclosed friendship networks during their ninth-grade year will be at a disadvantage compared to students who establish enclosed friendship networks. We assert that the effects of ninth grade friendship networks will be reflected on students' long-term high school academic performance. In this research, we put forward the following hypotheses:

Hypothesis 1. Students with ninth grade friendship network closure are more likely to graduate high school on-time than students without ninth grade network closure.

Hypothesis 2. Students with ninth grade friendship network closure are less likely to fail a course during their high school career than students without ninth grade friendship network closure.

Data and Methods

The National Longitudinal Survey of Adolescent Health

The study uses data from the National Longitudinal Study of Adolescent Health (Add Health), a nationally representative adolescents in grades 7-12 in the United States in 1994-95 who were followed through their adolescence and transition into adulthood (Harris, 2013). General overview of the Add Health has been provided in Chapter 1, so we focus on the details of Wave 1 In-School Survey and the Adolescent Health and Academic Achievement (AHAA) study collected from the Wave III In-Home survey participants, which the current study draws its data from.

The Wave I In-School survey was administered between September 1994 and April 1995, surveying over 90,000 students on a single day during a 45 to 60-minute class period. Questions on the Wave I In-School survey included items on friendship networks, school activities, school context, grades and various health related questions. During the Wave I In-School survey, school administrator from each school was also asked to complete a 30- minute survey covering questions about the school characteristics.

The Wave III In-Home survey was conducted between August 2001 and April 2002 as students were entering their transition into adulthood (aged 18-26). The Wave III data collection included 15,170 respondents[6]. As part of the data collection for the Adolescent Health and Academic Achievement (AHAA) study (Riegle-Crumb et al., 2005), Wave III respondents were also asked to sign a transcript release form authorizing the release of the transcripts from high school. About 91% of the Wave III respondents

[6] It is important to note that not all Wave 1 In-School survey participants were attempted for follow-up during the Wave III In-Home survey. A smaller sample for the longitudinal follow-ups (N= 20,745) was identified in the Wave 1 In-Home survey which took place few months after the Wave 1 In-School survey.

agreed to release their high school transcripts. The AHAA collected detailed information on course takings and grades from the last school attended by the respondent. The transcripts were coded using Classification of Secondary School Curriculum (CSSC), which is the same taxonomy used to code National Educational Longitudinal Study of 1988 (NELS) and National Assessment of Educational Progress (NAEP). Some transcripts were missing due to the following reasons; students did not agree to participate in AHAA, did not attend high school in the U.S., did not provide adequate high school information, the high school was closed, or incomplete or erroneous transcripts were provided (Riegle-Crumb et al., 2005).

Network Data Construction and Network Transitivity

The Wave 1 In-School survey included a network module for all surveyed students. In the network module, each student was asked to name five male best friends and five female best friends. Because the survey was attempted for everyone who were in the school, this yielded an attempt to capture a whole network data. In order to estimate network transitivity from the friendship nomination data, the original survey data set needed to be transformed into a usable network format. We reshaped the survey response from the network module into an *edgelist*, one of commonly used data format to store network data (Kolaczyk & Csárdi, 2014).We estimated network transitivity for each student using igraph package (Csardi, 2013) in R Version 3.5.2 (R Core Team, 2018). Students who did not have any friends were excluded in our analyses and nominations to students outside of their school, or sister school and thus could not be identified were coded as missing. Following previous studies which used Add Health network module

(Haas et al., 2010; McFarland et al., 2014), we further restricted observations to students who attended schools where the response rates for the friendship survey was at least 50%.

Analytic Sample

The analytical sample for the current study is a first-time ninth grade students at the time of Wave I In-School survey (1994-15 school year) who signed transcripts release form at Wave III. Students with missing graduation date or exit status, students whose value on the graduation year variable was not reasonable (preceding 1994-95) were dropped from the analysis. Although about 12,000 students agreed to the release of high school transcript forms during the Wave III data collection, focusing specifically on the ninth grade students at Wave 1 In-School Survey (about 20% of the total Add Health respondents) and further reducing sample to students whose friendship network transitivity could be estimated reduced the final analytic sample to 1,445 students. Most of the loss in analytic sample was due to attrition in Wave III but also by the research design; Wave 1 In-School survey served as a comprehensive census to identify the sample for longitudinal In-Home follow-ups so not all individuals interviewed during the Wave 1 In-School survey were attempted an interview. Because the reduction in analytic sample still yielded a reasonable number of observations, no imputation on the dependent variable was deemed necessary. The final analytic sample of 1,445 students from 68 schools.

Measures

<u>Independent variable</u>

As mentioned previously, *ninth grade friendship network closure* is computed from network transitivity using the igraph package (Csardi, 2013) in R Version 3.5. 2 (R

Core Team). The original network transitivity is a continuous variable that ranges from 0 to 1 and was highly skewed to the right. In our study, we defined ninth grade friendship network closure as students who were at or above the 25th percentile in the distribution of the analytic sample, the cutoff being 0.05, which is equivalent to having 5% of its possible triples being connected. The ninth grade friendship network closure was coded as a binary variable (network closure =1, without network closure= 0) in our study.

<u>Dependent variables</u>

On-time graduation variable is constructed from the transcripts data and information on the exit status collected from the AHAA. I used the high school exit status and timing of the graduation to determine if the student graduated from high school within four years. This variable was coded as a binary variable (graduated on time =1, did not graduate on time =0).

Survival time to course failure is the year to the first time a student fails a course since the beginning of ninth grade year. A student was determined to have failed a course during a given grade in high school if the overall course failure index for a given school year from the AHAA transcripts (Riegle-Crumb et al., 2005) indicated a value greater than zero. The course failure index captures the proportion of failed courses out of the total number of semester-length courses. Failures were determined based on the grades received, not whether or not the transcript indicated the student received a credit for the course. Because the course failure index estimated was for each year, the time to course failure is measured in number of years. The dependent variable is coded as 0 for every person-year event that has not yet occurred and a value of 1 when the event occurred. If a person failed a course, the individual's subsequent observations were removed.

Explanatory Variables

All explanatory variables were measured from the Wave 1 In- School survey. In our models, we adjust for the demographic characteristics of the respondent, such as gender, race, mom's education (1= with college degree, 0=without college degree), living status with parents (1=living with both parents, 0=not living with both parents). We also include students' responses to two questions regarding social relations. We create a binary indicator for students who responded "everyday" or "almost every day" on a five point scale ranging from 0 (never) to 4 (everyday) to the statement that they *have trouble getting along with teacher*. We also created a binary indicator for students who responded "everyday" or "almost every day" on the same scale to the statement that they *have trouble getting along with other students*.

We also include GPA estimated from self-reported grades for each core subject area[7]. Following the method used in previous literature (Flashman, 2012; Sutton et al., 2018), I recoded the letter grade of the core subjects into GPA by assigning A=4, B=3, C=2, and D=1 and averaging them, resulting in a typical continuous scale of GPA. We also include student's participation in extracurricular activities. I coded students' individual responses to activities listed on the survey into three binary variables indicating extracurricular participation in three different categories: academic clubs[8], sports[9], and arts and music[10]. Several network measures were also included. *Bonacich*

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[7] English, Math, Science and Social Studies

[8] French club, German club, Latin club, Spanish club, Book club, Computer club, Debate team, Future Farmers of America, History club, Math club, and Science club

[9] Baseball, Softball, Basketball, Field Hockey, Football, Ice Hockey, Soccer, Swimming, Tennis, Track, Volleyball, Wrestling

[10] Orchestra, Chorus/Choir, Cheerleading, Dance club, Drama club, Yearbook club

centrality (Bonacich, 1987), in-degree and out-degree were included. All three network measures were provided by the Add Health (Bearman et al., 1997). Finally, several school-level characteristics were also included: size of school (> 775), grade span (9-12), urbanicity of the school, and proportion of students reporting feeling safe in school by selecting “strongly agree” or “agree” to a five-point scale ranging from 1 (strongly agree) to 5 (strongly disagree) to the statement, *I feel safe in my school*.

Statistical Methods

Hypothesis 1: Propensity Score Matching

We use propensity score matching (Rosenbaum & Rubin, 1983) to test the first study hypothesis. Propensity score matching is one of the most widely used quasi-experimental methods to approximate a randomized experiment. In propensity score matching, propensity score, which is the conditional probability of receiving a treatment is estimated using a set of covariates. The propensity score matching relies on the assumption of *strong ignorability*, which states that if we observe a set of covariates such that the potential outcomes are independent of treatment given the covariates, and the selection probabilities, given the covariates, are strictly between 0 and 1. By matching the observations on the estimated propensity scores, we can account for the non-selection bias (Becker & Ichino, 2002). Although including a rich set of covariates in the propensity score model ensures that assumption of strong ignorability is met and minimizes bias in estimation of the treatment effect (Rubin, 2001), including variables that are unrelated to the treatment can also introduce bias (Shadish, 2013). Therefore, we only include variables that are theoretically related to the outcome or affect both the treatment and the outcome (Austin et al., 2007).

Missing data on the covariates were not severe but did occur; most of the missing data were regarding mother's college level education (15%), GPA (8.6%), response to the question regarding having trouble getting along with the teacher (< 5%), other students (< 5%), living with both parents (< 5%). Because propensity score matching requires that all the covariates are non-missing, we assumed thst the data were missing at random (MAR) and imputed the missing data. We averaged values from five imputed datasets created by Fully Conditional Specification (FCS) with Classification and Regression Trees method. The imputation was implemented in multivariate imputation by chained equations (MICE) package (Buuren & Groothuis-Oudshoorn, 2010) in R Version 3.5.2 (R Core Team, 2013).

After matching on the propensity scores, the final model was evaluated by its ability to achieve balance in all covariates based on the standardized mean difference and having enough area of common support in the propensity scores. We used MatchchIt (Ho et al., 2018) to implement the propensity score matching and we used Zelig (Imai et al., 2009) to estimate the Average Treatment effect on the Treated (ATT) in R Version 3.5.2 (R Core Team, 2018).

Hypothesis 2: Cox proportional hazard model

In order to test the second hypothesis, we use the Cox proportional hazards model (Cox, 1972), one of widely used methods in event history analyses. Event history analyses deal with the occurrence and timing of events (Allison, 2014) and have been used in education research to study student outcomes where timing of events matters, such as dropout behavior of college students (Ishitani & DesJardins, 2002).

Cox's method is a semiparametric method, which does not require a specified probability distribution to estimate the survival time. The Cox model uses partial likelihood as the estimation method and this allows the baseline hazard function, $\boldsymbol{h_0(t)}$ to take any form. The covariates are entered into the model linearly and the model assumes that the covariates in the model shift the baseline hazards function multiplicatively.

$$h(t|\boldsymbol{x_i}) = h_0(t)\exp(\boldsymbol{x_i\beta_x}) \qquad \textbf{(11)}$$

Equation (11) shows the formula for the hazard function. The baseline hazard function is denoted by $\boldsymbol{h_0(t)}$ and $\boldsymbol{x_i}$ is a vector of covariates for student *i* and the regression coefficients from the model, $\boldsymbol{\beta_x}$ are estimated from the data. The ninth grade network closure is included as the independent variable of interest and student-level explanatory variables measured at Wave 1 In-School survey were included as controls. The proportional hazards assumption of the Cox proportional hazards model stipulates that the hazard ratio is constant over time. That is, if the two groups have different hazards of experiencing an event, the ratio of the difference between the two groups are constant. We evaluated this assumption on the basis of the Schoenfeld residuals, which is the residual of the covariate value for a person who experience the event minus the expected value, for all variables in the Cox regression model (Allison, 2010; Schoenfeld, 1982).

The current study is interested in examining the four years of high school career. Therefore, censoring (Allison, 2010) occurred at the end of 1997-98 school year, which is the fourth year of a student's high school career. Students could leave the risk set for several reasons: drop out of high school, missing course grade from the transcripts, move to a different high school, high school closed, incomplete records, no course taken with a grade or graduate from high school. These reasons could make the censoring highly *informative*, which means that the reasons for being censored is closely associated with the probability of course failure. Given the complexities around the school transcripts collection in a large longitudinal study, we were concerned about the presence of informative censoring, which can introduce bias in our estimates if we treat the censoring as *non-informative* (Allison, 2010). Although there is no standard way of formally testing the assumption of non-informative censoring or handling its violation, we follow Allison (2010) in addressing possible informative censoring in our analyses.

One way to correct for the potential bias is by including covariates that are related to both the event time and the censoring time (Allison, 2010). We adopted this approach by adding relevant covariates in our model; GPA, living status with parents, response to the questions about having trouble getting along with teachers and students were added as relevant explanatory variables. Demographic characteristics and individual network measures were also included. Second, we repeated the analyses under two extreme assumptions about the censored cases (Allison, 2014) and report the two results from both models as our main analyses. The first scenario assumes that the students who were censored experience the event (course failure) immediately after they were censored, which corresponds to the assumption that students who were censored were those at a higher risk of course failure. The second scenario assumes that the students who were censored did not experience the event, which corresponds to the assumption that students who were censored were at a lower risk of course failure. In reality, both assumptions are extremes and neither one is likely to reflect the truth in our case (Allison, 2010). However, by deriving and comparing results obtained from both models, we attempt to address and initiate discussions around an important practical issue that may be prevalent in education research which uses transcripts data collected from multiple schools.

As stated previously, missing data problem was not severe but did occur. Most of the missing data occurred in mother's college level education (15%), GPA (8.6%), response to the question regarding having trouble getting along with the teacher (< 5%), other students (< 5%), living with both parents (<5%). Using listwise deletion would have reduced our sample size. Therefore, we report averaged estimates from fifteen imputations from the Markov Chain Monte Carlo (MCMC) method using *mi impute* procedure available in STATA software, version 14 (StataCorp., 2015). We also accounted for possible clustering of repeatedly observed students by reporting the robust standard errors.

Results

Hypothesis 1: Propensity Score Matching

There were statistically significant differences in fourteen of the seventeen baseline covariates between the two groups (Table 3.2). Students with ninth grade network closure were more likely to be white ($p < 0.01$), were more likely to live with both parents ($p < 0.01$) and less likely to report having trouble getting along with other students ($p < 0.001$) or teachers ($p < 0.001$). Students with ninth grade friendship network closure also had higher GPA ($p < 0.001$), and more likely to participate in sports ($p < 0.01$) and arts and/or music ($p < 0.1$). The two groups also notably differed in the characteristics of the schools attended. Students with high network closure were less likely to attend large ($p < 0.001$) urban high schools ($p < 0.001$) with 9-12 grade spans ($p < 0.01$) where students report feeling unsafe ($p < 0.001$). Students with high friendship transitivity also had higher Bonacich centrality ($p < 0.001$), were more likely to receive friendship nominations ($p < 0.001$) and also more likely to nominate friends ($p < 0.001$). Using the seventeen covariates, logistic regression model was used in the final propensity score model to predict the treatment, ninth grade network closure (Table 3.4). The final logistic regression model had McFadden's R^2 of 0.38.

The nearest neighbor matching was first attempted but this resulted in loss of sample size due to unmatched cases. In order to maximize balance in covariates and sample size, we decided to use sub-classification method where observations were grouped into subclasses that maximize balance between the treatment and control groups (Rosenbaum & Rubin, 1984). Students were matched on the logit of the propensity score estimated from the logistic regression model in Table 3.4. We tried 3, 4, 5 and 6 subclasses to identify the ideal number of subclassifications that reaches the most balance for all the covariates. The final model had five sub-classifications and the sample size for each subclass is provided in Table 3.5.

After the matching, we assessed balance in each covariate using the standardized difference, which is the difference in means between students with ninth grade network closure and matched controls as a proportion of the variable's standard deviation before matching. All covariates showed improvements in balance after the matching and had standardized mean difference between the treated and untreated groups of 0.20 or less, with the exception of in-degree[11], which was 0.45 after matching (Table 3.6).

The average treatment effect on the treated was first estimated for each stratum by taking the difference between the expected value for treatment and the control group in

[11] The correlation between in-degree and network transitivity was 0.01.

that stratum setting the explanatory variables at their means. Table 3.7 shows the estimated effects for each subclass. The expected probability of on-time graduation given the covariates for the treated group was 68.7%, 82.6%, 82.5%, 85.9%, and 90.6% in the first through fifth strata. The expected probability of on-time graduation for students for the control group was 64.5%, 81.3%, 76.4%, 86.7%, and 85.1% in the first through fifth stratum, respectively. As expected, the sign of the difference was positive for all subclasses except for subclass 4. However, none of the difference was statistically significant at the stratum-level.

Finally, we aggregated the average treatment effects on the treated across subclasses to obtain the overall effect (Ho et al., 2018; Tipton, 2013). The overall estimated treatment effect was estimated as the weighted average of the stratum-specific differences and the overall standard errors estimated from the weighted stratum-specific standard errors. The overall average treatment effect on the treated was positive, 0.03, but not statistically significant, 95% CIs [- 0.08, 0.15]. We find that even though the directionality of the relationship between the ninth grade friendship closure and the on-time high school graduation was in the expected direction, the difference was not statistically significant.

Hypothesis 2: Cox proportional hazards model

The survival functions for high school course failure for students with and without the ninth grade network closures were different, as implied by the statistically significant log-rank test ($\boxed{\chi^2}(1) = 31.72$, Pr > $\boxed{\chi^2} = 0.00$). We tested the assumption of the proportional hazards by evaluating if Schonfeld residuals for the covariates in the Cox proportional hazards model were independent of time. Schonfeld residuals of all covariates in the model except GPA and in-degree met the proportionality assumption ($p > 0.05$) (Table 3.8). For GPA and in-degree, I further plotted the log-log plots[12]. The lines in the plots (Figure 3.3–3.4) were slightly moved but were reasonably parallel, indicating that the residuals did not vary too much with time. Therefore, we proceeded with the implementation of the Cox proportional hazards model.

Results from Model 1 are presented in Table 3.9 as the hazard ratio for experiencing course failure during high school assuming that censored cases experienced events right after they were censored. The hazards ratios are the exponentiated individual coefficients from the Cox proportional hazards model and have the same interpretations as the odds ratios. The hazards ratio for the ninth grade friendship network closure was less than 1, indicating reduced risk of experiencing course failure (HR = 0.89, $p > 0.05$), but this finding was *not statistically* significant at 0.05 significance level.

Some explanatory variables were strong and significant predictors of high school course failures. White students were less likely to fail a course than non-white students (HR= 0.83, $p < 0.01$) and having trouble getting along with other students during ninth grade year increased the risk of failing a course by 28% (HR= 1.28, $p < 0.001$). Living with both parents reduced the hazard of course failure by 21% (HR= 0.79, $p < 0.001$) and one-unit increase in GPA was associated with reduction in the hazard of course failure by 48% (HR= 0.52, $p < 0.001$).

Model 2 in Table 3.9 assumes that the censored cases did not experience the event. Contrary to our concern that possible non-informative censoring may affect our coefficients differently under the two extreme assumptions, the hazard ratios obtained

[12] The visualization of -ln{-ln(survival)} curve for each covariate versus ln(analysis time) can be used to test the severity of the violation in the proportional hazards assumption (StataCorp, 2017).

from Model 2 were similar to those obtained from Mode1 for most of the coefficients. Similar to Model 1, we find that the ninth-grade friendship network closure is associated with 10% reduction in the hazard of failing a course (HR = 0.90, $p > 0.05$), a finding that is *not statistically* significant. The hazard ratio for being a White student was slightly lower than the estimate from Model 1 (HR = 0.79, $p < 0.01$). Consistent with the findings from Model 1, having trouble with other students during the ninth-grade year increased the risk course failure by 28% (HR = 1.28, $p < 0.001$). Living with both parents reduced the hazard of course failure by 21 % (HR = 0.79, $p < 0.001$) and one-unit increase GPA was associated with reduction in the hazard of course failure by 48% (HR = 0.52, $p < 0.001$).

Discussions

Although research on high school transition identifies friends as an important resource for successful adjustment, previous literature has been fragmented by multiple ways to measure friendships as a form of social capital. The current study attempted to address this issue by integrating a widely studied network feature into the discourse on adolescents' social capital during a transitional time. The current study investigated the relationship between ninth grade friendship network closure and two high school outcomes: on-time graduation and course failures. We did not find statistically significant association between network closure and the two high school academic outcomes. However, the lack of evidence on the relationship is tempered by several methodological challenges.

One of the most difficult methodological challenges had to do with reaching balance for all identified covariates in the propensity score model. As discussed previously, balance in the propensity score model was not achieved for in-degree. The current study proceeded with the analyses because balance for all other covariates were reached as implied by the standardized mean difference of less than 0.20. However, we acknowledge that the inability to reach satisfactory balance in in-degree could have rendered the two groups not equivalent to proceed with the analyses. In addition, we also note the possibility that the relationship between in-degree and network transitivity may differ by the size of the whole network. Our analytical sample included 1,445 students from 68 schools and the size of the schools varied. Although we did try to account for the school size by including an indicator for large schools as a covariate in the propensity score modeling, we did not fully investigate possible complexities surrounding the size of the school and different whole network characteristics with individual nodes' network characteristics. For instance, it is possible network closure is more important for academic success in large high schools than in small schools. Similarly, it is also possible that the importance of network closure varies by the overall network's transitivity. Future research will explore these possibilities.

Another challenge had to do with missing data. The propensity score matching assumes that all measured covariates are observed. Nonetheless, missing data in propensity score matching does occur and is an important methodological issue for researchers (Cham & West, 2016). In our study, missing data in mother's education (15%) and GPA (8.6%) were most severe. While we tried to address the missing covariates by matching on imputed data, it is possible that our choice of one single imputation strategy could have affected our results. Future work will address the missing data issue in more details and incorporate multiple strategies for dealing with missing data problems in propensity score matching (Cham & West, 2016).

A major limitation of this study has to do with the complexities surrounding the use of propensity score matching to study network transitivity – a continuous variable in its original form. Propensity score matching assumes that treatment is binary and that there is only one form of treatment. Because of this methodological constraint, we decided to artificially dichotomize the continuous network transitivity into two groups by using the 25th percentile of the analytic sample's distribution as the cutoff. We made this decision based on the highly skewed distribution of network transitivity and exploratory analyses of the covariates. There have been relatively little existing studies to guide the cutoff point to categorize students based on network transitivity, and we acknowledge we did not have strong empirical evidence to base our decision from. Future work may consider using novel methods to deal with continuous treatment in propensity score matching (Austin, 2018; Fong et al., 2018). Moreover, we also note that using the 25th percentile as our cutoff, the number of students in the treatment group (n=1,075) was larger than the number of students in the control group (n=370). This is also problematic because it is recommended that a pool of controls should be as large as the number in the treatment group in propensity score matching (Austin 2011).

Several adjustments are also needed to refine the Cox proportional hazards model. Due to the complexities around the collection of high school transcripts data, we attempted to address possible informative censoring by reporting results from two models under extreme assumptions as our main analyses. We found that informative censoring may not have been as severe as we had initially suspected. In future analysis, we will report results from the model under the assumption of non-informative censoring as our main analysis. In our Cox proportional hazards model, students were removed from subsequent analysis if they experienced course failure. Because students can experience failures in multiple courses even after their initial course failure, a deeper understanding in the patterns of course failures can have an important implication for practitioners. Future analyses will consider modeling course failures as repeatable events. Finally, we also note that we did not adjust for the hierarchical nature of the data caused by school-level nesting or the design effect of the Add Health. Future analyses will address these two limitations.

Despite the limitations, the current study's main contribution lies in its attempt to use a widely studied network feature in discussing adolescents' social capital during transition to high school. Moreover, although the methodological challenges limit strong causal statements and warrants cautious interpretations, findings from our results can have a number of important implications. First, we note that the predictors of ninth grade friendship network closure are variables that are already known to be associated with high school success; students who reported having trouble getting along with their teacher and had low GPA were less likely to have ninth friendship network with triadic closures, as suggested by our results from the propensity score model. This is an important observation because it suggests that challenges with a ninth grade student's academic life during a transitional period may be visible on their friendship networks - motivating practitioners and researchers to consider identifying visible signs in the friendship networks of the ninth graders; students with less friendship closures during the ninth grade year may be struggling with other social or academic aspects of high school.

Furthermore, our findings unearthed that some structural characteristics of the high school may be important to friendship formations during the ninth grade year. Specifically, we found that school size, grade span, school-safety, and urbanicity of the school were important predictors of ninth grade network with closures. This observation might imply that large urban high schools experience more challenges creating an inclusive environment for their incoming ninth graders due to their structural characteristics. The current study motivates further investigations on these topics.

Table 3.2. Summary of Sample Characteristics by Ninth Grade Friendship Network Closure

	Control	Treatment	Difference
Student characteristics			
Female	0.53	0.54	-0.01
White	0.58	0.66	-0.08**
Mother has a college degree	0.36	0.39	-0.03
Live with both parents	0.71	0.79	-0.08**
Trouble with other students	0.37	0.27	0.10***
Trouble with teachers	0.18	0.10	0.08***
GPA	2.64	2.86	-0.22***
Participates in academic activities	0.26	0.29	-0.03
Participates in sports	0.54	0.62	-0.08**
Participates in arts and/or music	0.31	0.37	-0.06*
School characteristics			
Enrollment greater than 775 students	0.77	0.56	0.21***
Urban	0.31	0.20	0.11***
Grade span 9-12	0.76	0.69	0.07*
% Students feeling safe in school	0.63	0.66	-0.03***
Student network characteristics			
Bonacich centrality	0.64	1.02	-0.38***
In-degree	3.20	5.59	-2.39***
Out-degree	3.75	5.60	-1.85***
N	370	1,075	1,445

Note. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Statistical significance for the mean difference is reported using two sample t-test. The treatment group includes students whose ninth grade friendship network transitivity was 0.05 or higher. The control group includes students whose ninth grade friendship network transitivity was lower than 0.05.

Table 3.3. Percentage of Students who Graduated On-time and Dropped Out of High School by Ninth Grade Friendship Network Closure

	N	% Graduated on time	% Dropped out
Control	370	0.72	0.14
		[0.02]	[0.02]
Treatment	1075	0.82	0.08
		[0.01]	[0.01]

Note. Standard errors are reported in parentheses. The treatment group includes students whose ninth grade friendship network transitivity was 0.05 or higher. The control group includes students whose ninth grade friendship network transitivity was lower than 0.05.

Table 3.4. Parameter Estimates from Logistic Regression Propensity Model Predicting Ninth Grade Network Closure (N=1,445)

	Odds Ratios
(Intercept)	0.85
Student characteristics	
Female	0.85
White	1.01
Mother has a college degree	1.01
Live with both parents	1.13
Trouble other students	0.90
Trouble with teachers	0.54***
GPA	1.20**
Participates in academic activities	0.85
Participates in sports	0.86
Participates in arts and/or music	1.13
School characteristics	
Enrollment greater than 775 students	0.52***
Urban	0.75*
Grade span 9-12	0.76*
% Students feeling safe in school	1.52
Student network characteristics	
Bonacich centrality	2.05***
In-degree	1.19***
Out-degree	1.01

*Note. *p<.10. **p<.05. ***p<.01* Network closure is defined as having ninth grade friendship network transitivity of 0.05 or higher.

Table 3.5. Sample Size from Propensity Score Matching Subclassification

	Subclass 1	Subclass 2	Subclass 3	Subclass 4	Subclass 5
Treatment	215	215	215	215	215
Control	214	66	48	26	16
Total	429	281	263	241	231

Note. The treated group include students with network closure, defined as having ninth grade friendship network transitivity of 0.05 or higher.

Table 3.6. Covariate Balance before and after Propensity Score Matching across All Subclasses

		Means Treatment	Means Control	Standardized Mean Difference
Distance	Unmatched	0.79	0.62	0.17
	Matched	0.79	0.77	0.01
Student characteristics				
Female	Unmatched	0.54	0.53	0.01
	Matched	0.54	0.56	0.02
White	Unmatched	0.66	0.58	0.08
	Matched	0.66	0.61	0.03
Mother has a college degree	Unmatched	0.38	0.36	0.02
	Matched	0.38	0.37	0.03
Lives with both parents	Unmatched	0.79	0.71	0.08
	Matched	0.79	0.75	0.05
Trouble getting along with other students	Unmatched	0.28	0.38	-0.11
	Matched	0.28	0.31	0.02
Trouble getting along with teachers	Unmatched	0.11	0.19	-0.08
	Matched	0.11	0.11	0.02
GPA	Unmatched	2.86	2.61	0.25
	Matched	2.86	2.80	0.05
Participates in academic activities	Unmatched	0.29	0.26	0.03
	Matched	0.29	0.24	0.06
Participates in sports	Unmatched	0.62	0.54	0.08
	Matched	0.62	0.61	0.03
Participates in arts and/or music	Unmatched	0.37	0.31	0.06
	Matched	0.37	0.36	0.02
School characteristics				
School Size (>775 students)	Unmatched	0.57	0.77	-0.20
	Matched	0.57	0.64	0.06
School Location: Urban	Unmatched	0.20	0.31	-0.11
	Matched	0.20	0.23	0.04
Grade span 9 to 12	Unmatched	0.69	0.76	-0.07
	Matched	0.69	0.74	0.05
% Students feeling safe at school	Unmatched	0.66	0.63	0.03
	Matched	0.66	0.65	0.01
Student network characteristics				
Bonacich Centrality	Unmatched	1.02	0.64	0.38

	Matched	1.02	1.02	0.04
In-degree	Unmatched	5.59	3.20	2.40
	Matched	5.59	5.82	0.45
Out-degree	Unmatched	5.60	3.75	1.84
	Matched	5.60	5.62	0.18

Note. The treatment group include students with network closure, defined as having ninth grade friendship network transitivity of 0.05 or higher.

Table 3.7. Average Treatment Effect on the Treated by Subclass

		Expected %	SD	2.50%	97.50%
Subclass 1	Treatment	68.7%	0.03	62.6%	74.6%
	Control	64.5%	0.03	57.4%	70.7%
	First Difference	4.2%	0.05	-4.3%	13.2%
Subclass 2	Treatment	82.6%	0.03	77.4%	87.2%
	Control	81.3%	0.05	70.8%	89.2%
	First Difference	1.3%	0.05	-8.5%	13.5%
Subclass 3	Treatment	82.5%	0.03	77.1%	87.3%
	Control	76.4%	0.06	62.5%	86.5%
	First Difference	6.0%	0.07	-5.8%	20.7%
Subclass 4	Treatment	85.9%	0.02	80.5%	90.1%
	Control	86.7%	0.07	68.9%	95.9%
	First Difference	-0.8%	0.07	-11.5%	16.6%
Subclass 5	Treatment	90.6%	0.02	86.2%	94.1%
	Control	85.1%	0.09	62.2%	96.7%
	First Difference	5.4%	0.09	-7.1%	28.5%

Note. The treatment group include students with network closure, defined as having ninth grade friendship network transitivity of 0.05 or higher.

Table 3.8. Test of Proportional Hazards Assumption with Shoenfeld Residuals.

	rho	chi2	df	Prob>chi2
Ninth grade network closure	0.04	0.98	1	0.32
Mother has a college degree	-0.02	0.32	1	0.57
Female	0.01	0.07	1	0.79
White	0.00	0.01	1	0.94
Trouble with teachers	-0.04	0.72	1	0.40
Trouble with students	0.02	0.33	1	0.57
Live with both parents	0.04	0.67	1	0.41
GPA	0.10	4.56	1	0.03
Bonacich centrality	-0.03	0.41	1	0.52
In-degree	-0.09	3.78	1	0.05
Out-degree	0.04	0.84	1	0.36
Participates in academic activities	0.06	1.81	1	0.18
Participates in arts and/or music	-0.02	0.23	1	0.63
Participates in sports	-0.02	0.29	1	0.59
Global test		14.18	14	0.44

Note. Network closure is defined as having ninth grade friendship network transitivity of 0.05 or higher.

Table 3.9. Hazard Ratios from Cox Proportional Hazard Model predicting High School Course Failure.

	Model 1	Model 2
Student characteristics		
Ninth grade network closure	0.89	0.90
	(0.07)	(0.08)
Mother has a college degree	0.86	0.89
	(0.08)	(0.08)
Female	0.92	0.89
	(0.07)	(0.07)
White	0.83**	0.79***
	(0.07)	(0.07)
Trouble with teachers	1.09	1.12
	(0.09)	(0.09)
Trouble with students	1.28***	1.28**
	(0.07)	(0.08)
Live with both parents	0.79***	0.79**
	(0.08)	(0.08)
GPA	0.52***	0.52***
	(0.05)	(0.05)
Network measures		
Bonacich centraltiy	0.84	0.81
	(0.12)	(0.13)
In-degree	0.99	1.00
	(0.01)	(0.01)
Out-degree	1.01	1.01
	(0.02)	(0.02)
Academic measures		
Participates in academic activities	0.94	0.96
	(0.08)	(0.08)
Participates in arts and/or music	0.94	0.95
	(0.08)	(0.08)
Participates in sports	0.89	0.90
	(0.07)	(0.07)
N	1,438	1,438

*Note. *p<.05*, ***p<.01***p<.001.* Ninth grade network closure is defined as having ninth grade friendship network transitivity of 0.05 or higher. Model 1 assumes that the person experienced the event right after censoring and model 2 assumes the person did not experience the event after being censored. Estimates are from fifteen imputations from Markov Chain Monte Carlo (MCMC) method. Robust standard errors are reported in the parentheses.

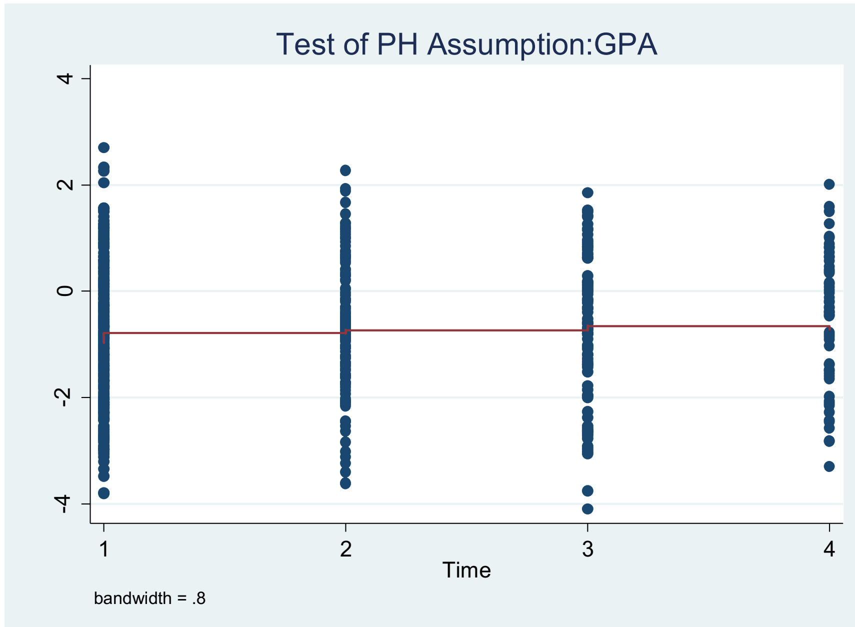


Figure 3.3. Log-log plots to test proportional hazards assumption of GPA.

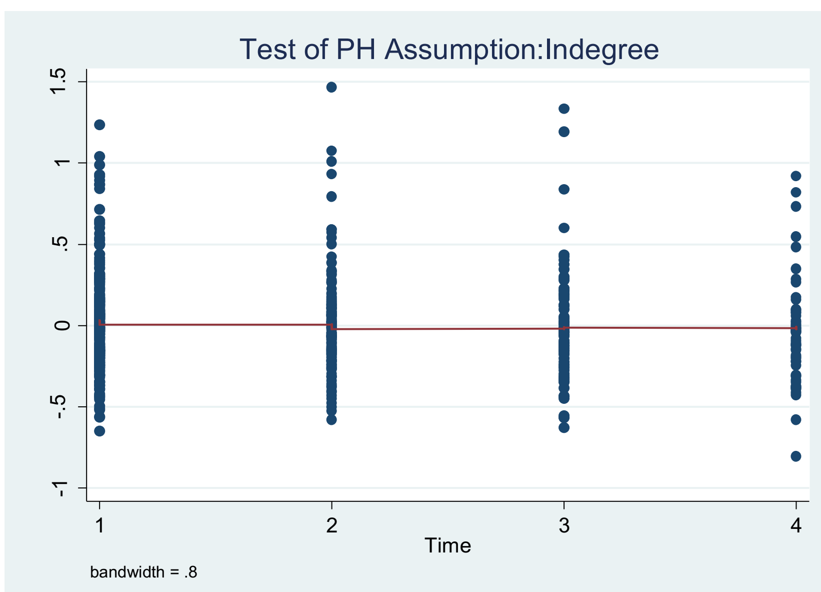
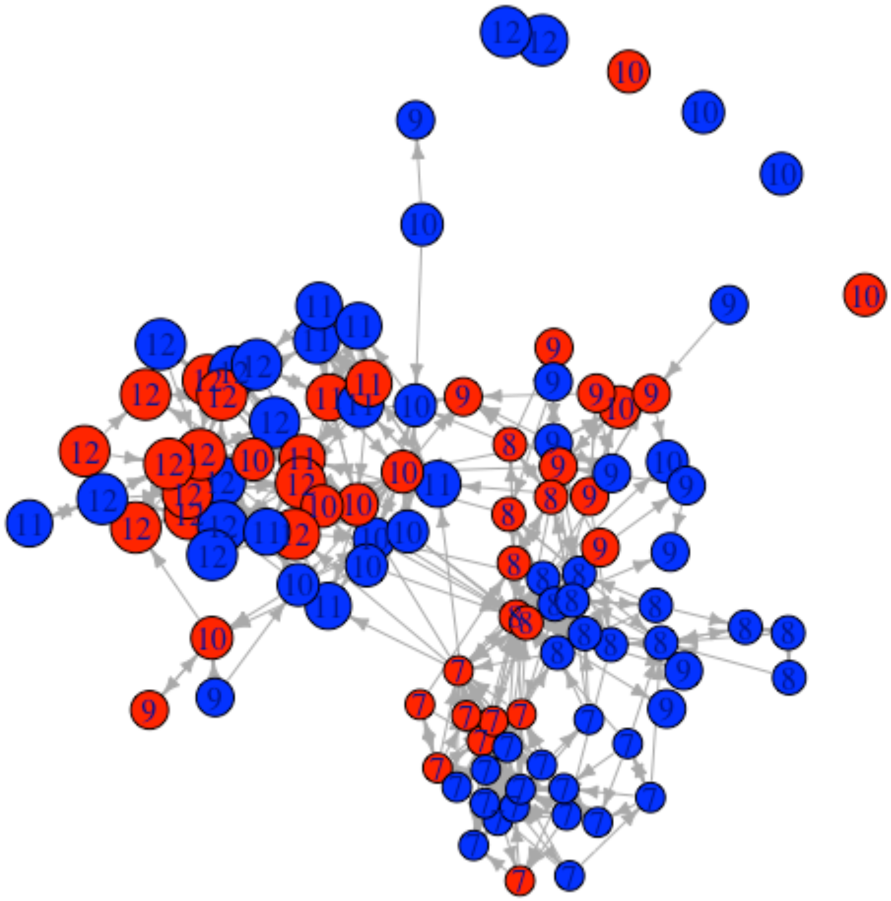


Figure 3.4. Log-log plots to test of proportional hazards assumption for in-degree



Note. Arrows indicate friendship nominations and numbers indicate grade level of the student. Boys are denoted by blue and girls are denoted by red.

Figure 3.5. Friendship Network in a sample Add Health High School.

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