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Social network effects on academic achievement☆

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ABSTRACT

How peer groups contribute to educational outcomes has long interested researchers. However, the possibility that peer groups dominated by either low- or high-achieving youth can have substantively different effects on achievement has been largely ignored. In this paper, we show that while being embedded in a high-achieving network of friends is not associated with increased own achievement, being embedded in a low-achieving network is associated with decreased own achievement. In additional analyses, we present evidence that these associations are at least in part due to influence, as opposed to only selection effects or shared environment. We also examine whether the structure of the network in which a student is embedded might affect their educational achievement. We show that achieving at higher levels positively predicts how centrally located a student is in their network, but being more centrally located does not predict concurrent achievement. This finding suggests that the behavior of individuals is affecting the formation of network structure and not the reverse.

1. Introduction

Peers play a vital role in adolescent development (Petersen, 1993; Ryan, 2000). The socioeconomic status of classmates (Vandenberghe, 2002), how diverse they are (Angrist & Lang, 2004; Hermansen & Birkelund, 2015), and the gender balance of classrooms (Hoxby, 2000; Lavy & Schlosser, 2007) have all been found to influence student achievement. Researchers have increasingly turned to social network analysis to examine peer group formation and peer group influence (Carbonaro & Workman, 2016; Carolan, 2014; Ryabov, 2011). While there is much evidence that friends' achievement can influence own achievement (Altermatt & Pomerantz, 2005; Lefgren, 2004; Ryabov, 2011), either immediate friends or a bigger peer group that is often conceptualized as a classroom or as a school have largely been the focus of researchers' interest. To the best of our knowledge, Carbonaro and Workman (2016) is the only study that directly examines the influence of friends' friends on own educational achievement.

Scholars have not yet examined whether students might be more susceptible to the negative influence of low-achieving friends or to the positive influence of high-achieving friends using social network analysis. Lavy, Silva, and Weinhardt (2012) find that attending a school with a higher number of low-achieving students carries stronger negative consequences compared to the potential benefits of attending a school with a greater number of high-achieving students. The authors, however, conceptualize a student's peer group as their school, which means that they cannot determine with certainty whether the students

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that they examine are connected to each other and belong to the same friendship group. With that said, their finding that being surrounded by high- or low-achieving students can have substantially different effect on own achievement is intriguing and needs to be examined further. Our study design allows us to directly capture the associations that result from students being connected to each other, as opposed to the effects of sharing an environment with low- or high-performing peers.

Since today's adolescents are more connected to each other than ever before in history (Christakis & Fowler, 2009), attempts to better understand the potential effects of friends' achievement on own achievement, as well as the dynamics of friendship formation, are both timely and important. In this paper, we build on work by Carbonaro and Workman (2016) and Lavy et al. (2012) and examine whether the magnitude of the relationship between friends' and own achievement is different in low-achieving social networks and in high-achieving social networks. Our work presents several empirical findings. First, we show that while being embedded in a low-achieving network is associated with own decrease in achievement, being embedded in a high-achieving network is not associated with a change in achievement. Second, we demonstrate that the relationships that we find are driven at least in part by influence. Third, we find that own academic achievement is associated with future network position, indicating that higher achieving students are more likely to be more centrally located in their respective networks. This finding adds to the growing literature on the relationship between network position, network norms, and individual behaviors (Mejs et al., 2010; Ortiz, Hoyos, & López, 2004; Shepherd, 2016).

2. Theory

How the behavior of one individual can influence the behavior of others in the same friendship network has been studied extensively (Christakis & Fowler, 2009; Sacerdote, 2011). The influence that a student's friends and classmates have on their behavior and scholastic outcomes is often referred to as 'peer effects' (Angrist & Lang, 2004; Hoxby, 2000). These peer effects can manifest in several ways. Starting with the development of the Wisconsin model of status attainment (Sewell, Haller, & Portes, 1969), researchers have regularly found that friends' expectations to matriculate into college are positively related to own expectations to matriculate into institutions of higher learning and own eventual educational attainment (Carbonaro & Workman, 2016; Kiuru, Aunola, Vuori, & Nurmi, 2007). Further, one of the most consistent relationships found in the study of peer effects in primary and secondary schools is the positive link between friends' achievement and own achievement (Altermatt & Pomerantz, 2005; Lefgren, 2004; Ryabov, 2011). Research on higher education suggests that a similar relationship might exist in college settings. Some studies have found a significant association between roommate achievement and own achievement (Sacerdote, 2011; Stinebrickner & Stinebrickner, 2006; Zimmerman, 2003).

However, prior work largely ignores the possibility that the effects of low-achieving networks and high-achieving networks can vary. The norms that peer groups induce and reinforce vary extensively. On the one hand, adolescent networks can serve as an important conduit through which students can access resources available to them, thus leading to a more advantaged status and better achievement for those in certain groups (Coleman, 1988). At the same time, the dissemination of negative adolescent culture can adversely affect students, by sabotaging their commitment to education and impairing their academic motivation (Coleman, 1961) as well as by discouraging excellence in low-performing peer groups (Portes, 1998). As such, studies that examine the continuous increase in achievement within networks of friends (Carbonaro & Workman, 2016) might be missing an important conditional relationship, namely that the effect of low-achieving networks might be substantively different from the effect of high achieving networks.

While Lavy et al. (2012) examine this relationship for students and their school peers, our study improves on theirs by examining the students that are linked to each other through their friendship networks. As such, our work offers a more direct test of the relationship. Our sample is also comprised of older students than Lavy et al.'s (2012), which is important since the dynamics of peer groups differ depending on the age and developmental stage of those in the peer group (Gifford-Smith & Brownell, 2003). Building on work by Carbonaro & Workman (2016) and Lavy et al. (2012), we formulate the following hypothesis:

H1. Having a greater number of low-achieving contacts will be associated with decreased own achievement while having a greater number of high-achieving contacts will not be associated with a change in achievement.

Furthermore, many of the findings about own and friends' educational achievement outlined above focus on the potential effects that classmates have on one another. This line of research, while fruitful, has important limitations as outlined by Sacerdote (2011). First, students are not randomly assigned to classrooms, and peers may be selected for them on the basis of achievement. Second, teacher quality may affect all students, causing classmates to appear more similar based on the quality of the instruction they are receiving, which may have nothing to do with peer effects. In order to control for these problems, scholars have used student and teacher fixed effects (Burke & Sass, 2013; Lavy et al., 2012). Other studies, such as Whitmore (2005), use the random assignment of students to classrooms to isolate the causal effect of achievement, finding a clear positive effect. In sum, whether or not the relationship that scholars observe between friends' achievement and own achievement is at least in part causal remains an open empirical question. Given this, our second hypothesis is:

H2. A reliable association between directly tied friends' achievement and own achievement will remain even after controlling for all observed indicators of shared individual characteristics and shared environment.

A student's network context is defined not only by the number of friends that they have but also by how centrally located a student is within the network. While different definitions of centrality exist, the definition that we employ is that an ego is considered more central as the number of their contacts who themselves are more central increases (Faust, 1997). Defined in this way, centrality can be seen as an indicator of an ego's relative importance in the network (Betts & Stiller, 2014; Faust, 1997). It is important to understand what types of students become more centrally located in their networks as these students are in a position to exercise more influence onto others in their network (Borgatti, 2005; Neal, 2010).

Researchers have found that both pro-social and anti-social behaviors are correlated with increased ego network centrality (Gifford-Smith & Brownell, 2003). For example, leadership skills (Farmer & Rodkin, 1996; Gest, Graham-Bermann, & Hartup, 2001) and cooperativeness (Farmer & Rodkin, 1996) are positively associated with students having more central positions in their networks. Many studies have examined the relationship between higher levels of aggression and network centrality (Farmer & Rodkin, 1996; Gest et al., 2001). Some have found that the relationship exists for both genders (Gest et al., 2001), while others found that it only exists for boys, and unlike more aggressive boys, more aggressive girls do not attain higher centrality within their networks (Farmer & Rodkin, 1996).

A number of studies have considered the potential effects of centrality on academic achievement, but they often find differing results. Some studies have found a positive association between centrality and achievement (Ortiz et al., 2004) while others have shown that whether this positive relationship is observed depends on the centrality measure that scholars employ (Hahn, Islam, Patacchini, & Zenou, 2015). Further, Zhang, Rajabzadeh, and Lauterbach (2009) found a reverse U-shape relationship between centrality and academic performance: as centrality increased, student performance increased, but only until relatively high levels of centrality were achieved, after which the relationship reversed. These authors examined very different samples both in terms of age and location, which might explain why they found such different results. To the best of our knowledge, however, no study has yet considered that the reverse relationship is possible as well, that is that higher achieving students might be at a higher likelihood to move to a more central position within their network over time.

A few studies have examined a similar relationship between achievement and popularity though. They showed that achievement positively predicts sociometric popularity, i.e. how much an ego is liked by others in their peer group (Mejs et al., 2010). Mejs et al. (2010), for instance, examined sociometric popularity and found that it predicts higher achievement independently or in its interaction with social intelligence. Perhaps most closely related to our study, Maruyama, Miller, and Holtz (1986) showed that increases in achievement precede increases in popularity, but not vice versa. However, popularity is not the same as centrality. Indeed, both are associated with unique sets of behavioral outcomes (Gest et al., 2001). Centrality should thus be examined as a separate phenomenon. In line with this, we hypothesize the following:

H3. Higher achieving students will over time move more towards the center of their respective social networks as compared to lower achieving students.

3. Materials and methods

3.1. Data

For this study we use data from the National Longitudinal Study of Adolescent Health (Add Health). Add Health is a multiple-wave, nationally representative sample of adolescent students. In Wave I of Add Health, researchers sampled 90,118 students who were in grades 7–12 at 142 schools across the country. Students filled out questionnaires and were given the opportunity to name up to 5 male and 5 female friends. Friend names were later verified using school rosters. These verified social contacts were then used to create social networks for each school. A subsample of those identified at this stage was re-sampled for follow-up questionnaires in Wave I (1994–1995), Wave II (1996), and Wave III (2001–2002). These interviews were conducted at the home of the student. This subsample was interviewed more extensively about the social networks of the students; the students were also asked more in-depth questions about behaviors and attitudes. It is from this subsample that we draw information about the academic achievement of the students. At the beginning of Wave I, the average age of the students was 15.8 years (SD 1.4), and 51% were female. Students were asked what their last grades in four subjects (English, Science, Math and Social Studies) were, on a four-point scale (A = 3, B = 2, C = 1, 0 = D or F). To measure academic achievement, we took the sum of the four self-reported grades. At Wave I, the average score for academic achievement was 7.52; at Wave II, it was 7.46. We only included information from Waves I and II, as by Wave III the respondents were no longer in school.

We also control for variables plausibly related to academic achievement and the dynamics of how friendship networks are formed and developed. More specifically, we control for a number of behaviors, such as smoking, marijuana use, and alcohol use (Christakis & Fowler, 2013; Kobus & Henry, 2010; McLeod, Uemura, & Rohrman, 2012), as well as for whether a student has worked for pay outside the home in the previous four weeks (Mortimer, 2003). We also control for Body Mass Index (BMI) (Ajilore, Amialchuk, Xiong, & Ye, 2014; Crosnoe & Muller, 2004; Christakis & Fowler, 2013), and general health (Ding, Lehrer, Rosenquist, & Audrain-McGovern, 2009; Smith & Christakis, 2008). Further, we control for a number of individual characteristics, such as prior achievement (Casillas et al., 2012; Meijs, Cillessen, Scholte, Segers, & Spijkerman, 2010), age, grade, gender, and race (Aral & Walker, 2012; Currarini, Jackson, & Pin, 2010; Gifford-Smith & Brownell, 2003; Sirin, 2005; Voyer & Voyer, 2014), whether a student speaks English at home (Suarez-Orozco, Suarez-Orozco, & Todorova, 2008), as well as parental income and mother's education (Currarini et al., 2010; Sirin, 2005).

Table 1
Summary statistics. Note that academic achievement is a 4-item scale (0 = D or F; 1 = C; 2 = B; 3 = A) measured in four subject areas (English, Science, Math and Social Science). The resulting academic achievement variable is the sum of these four items. Marijuana use is a dichotomous measure of the use of marijuana in the last 30 days. Smoking is the number of days in which the subject smoked cigarettes in the last 30 days. Alcohol use measures how often a student reports having consumed alcohol over the last 12 months (6 = every day or almost every day; 5 = three to five days a week; 4 = one or two days a week; 3 = two or three days a month; 2 = once a month or less; 1 = one or two days in the past twelve months; 0 = never). General health is a 5-item scale (1 = poor; 2 = fair; 3 = good; 4 = very good; 5 = excellent). Employed captures whether a student has worked for pay (including for things like yard work or babysitting) for anyone outside the home in the previous four weeks. Mother's education is a 10-item scale (0 = never went to school; 1 = eighth grade or less; 2 = more than eighth grade, but did not graduate from high school; 3 = went to a business, trade, or vocational school instead of high school; 4 = high school graduate; 5 = completed a GED; 6 = went to a business, trade or vocational school after high school; 7 = went to college, but did not graduate; 8 = graduated from a college or university; 9 = professional training beyond a 4-year college or university). Age, grade, body mass index, and household income are the actual age of a student, the grade that they attend, their BMI, and the income that their family makes (in 1,000 s of dollars).

Variable	Wave I				Wave II			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Academic achievement, ego	7.52	2.97	0	12	7.46	2.97	0	12
Academic achievement, alter	7.53	2.97	0	12	7.47	2.97	0	12
Academic achievement ≥ 9, ego	0.41	0.49	0	1	0.40	0.49	0	1
Academic achievement ≥ 9, alter	0.41	0.49	0	1	0.40	0.49	0	1
Number of times nominated as a friend	0.71	1.49	0	15	0.72	1.50	0	15
Total number of social contacts	2.19	2.13	1	18	2.19	2.13	1	18
Eigenvector centrality	0.03	0.09	0	1	0.03	0.09	0	1
Marijuana use	0.13	0.34	0	1	0.15	0.36	0	1
Smoking behavior	5.67	10.55	0	30	6.03	10.93	0	30
Body mass index	22.32	4.33	11	63	22.85	4.57	12	61
Alcohol use	1.10	1.42	0	6	1.14	1.51	0	6
Grade	9.45	1.50	7	12	10.29	1.46	7	13
English spoken at home	0.90	0.30	0	1	0.91	0.29	0	1
Employed	0.57	0.50	0	1	0.60	0.49	0	1
General health	2.91	0.90	0	4	2.93	0.89	0	4
No. of social contacts whose academic achievement ≥ 9	0.47	1.01	0	10				
No. of social contacts whose academic achievement < 9	0.72	1.34	0	14				
Age	15.81	1.59	11	21				
Female	0.51	0.50	0	1				
Household income (1000's of dollars)	46.06	52.21	0	999				
Mother's education	5.45	2.40	0	9				
Hispanic	0.17	0.38	0	1				
Black	0.23	0.42	0	1				
Asian	0.07	0.26	0	1				

Table 1 presents descriptive statistics for the variables in our analyses. The details of how each variable is measured are presented in the note to the table.

A key benefit of our research design is that it provides us with the ability to detect directionality in friendship perception. We measure friendships as directed ties in which one participant names another as a friend. This allows us to distinguish between three friendship types: an ego-named friend, an alter-named friend, and mutual friendships in which both the ego and the alter name each other as friends. As is typical in network analysis, we call the individual who we are studying the "ego" and those to whom the ego is connected to "alters." To simplify the interpretation of many of our analyses we dichotomize the academic achievement variable by treating those for whom the academic achievement index is greater than or equal to nine (which would constitute a B average or above) as high academic achievers, and those with averages below nine as low academic achievers. For Wave I, 35.8% of the sample reported an average of 9 or greater and 38.24% in Wave II. By dividing the sample into two parts, we can separately test the relationships inherent in low and high achieving peer networks.

3.2. Statistical analyses

Because we are interested in the association of behaviors among connected people we must be careful to identify the process by which that association takes place. The association of behaviors may be attributable to at least three processes (Christakis & Fowler, 2013): 1) *influence*, in which one person influences another and causes a change in the behavior of the other person; 2) *homophily*, in which individuals base the formation and deletion of social connections (in this case, friendships) on some behavior, and choose preferentially to attach to similar individuals; or 3) *shared environment*, in which connected individuals experience contemporaneous exposures to some aspect of the environment that affects them in the same way (good teachers or tutors). In order to distinguish among these processes, we use longitudinal information about academic achievement and network ties, as well as information about the directionality of the social ties (in this case, who named whom as a friend).

For our primary analyses, we considered the possibilities that the academic achievement of alters may affect the academic achievement of the ego and that higher achieving students might move more towards the center of their networks over time. In supplementary analyses, we conducted regressions of the ego's academic achievement in Wave II as a function of the ego's academic achievement in Wave I and the academic achievement of an alter in both Wave I and Wave II (including control variables). The inclusion of a lag for the ego's academic achievement controls for the ego's latent ability and any intrinsic, sta-

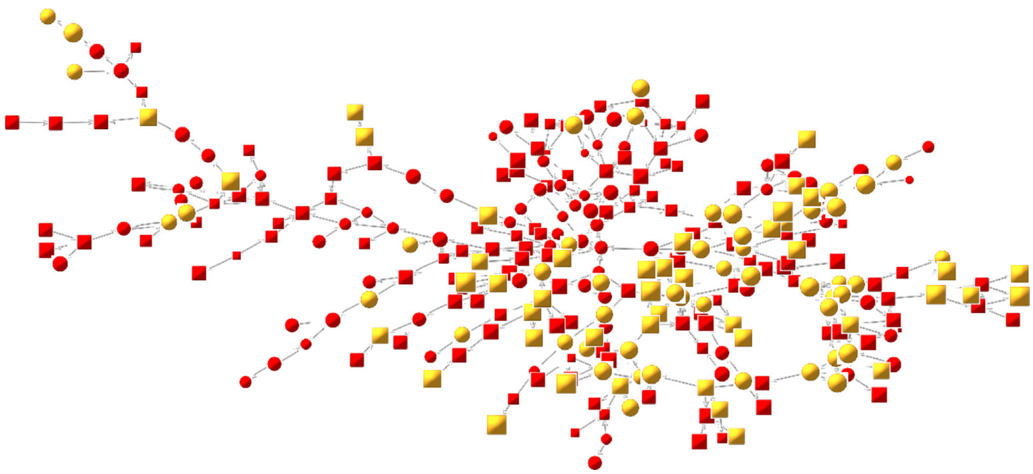

Fig. 1. Network graph. This network graph shows the largest connected component from the largest school during Wave I of the Add Health study. Each point in the graph represents a participant. The shape of the point represents gender (circles are female, squares are male). Arrows between nodes represent named friendships in which the arrow points from the namer to the named friend. Node color represents academic achievement (academic achievement ≥ 9 is yellow, academic achievement < 9 is red). Node size is proportional to academic achievement measured on a 0–12 scale. We place nodes using the Kamada–Kawai algorithm (Kamada & Kawai, 1989). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ble component of academic achievement. Including the alter's behavior in the previous wave helps to control for homophily (Udry, 2003). In these models, the coefficient of interest is that which measures the contemporaneous association between the alter's academic achievement and the ego's academic achievement, which gives our best estimate of the social influence of academic achievement between the pair (Udry, 2003).

We use two dependent variables to capture academic achievement. The first is a dichotomous version of academic achievement that is coded 1 if a student achieved at a level greater than 9 or not. The second is a continuous version of academic achievement. When the dependent variable is dichotomous, we estimate logit models; when the dependent variable is continuous, we estimate ordinary-least squares models. Because we have multiple observations across egos, we used generalized estimating equation (GEE) procedures (Liang & Zeger, 1986). Further, we assume an independent working correlation structure for the clusters (Liang & Zeger, 1986).

In the tables we provide results of the regression analyses in the form of beta coefficients. In the text and figures, however, we report results of the analyses in the form of risk ratios for ease of interpretation. To calculate the risk ratios, we estimated mean effect sizes and 95% confidence intervals through simulation of the first difference in the key coefficient. We estimated the expected difference in the ego's academic achievement as we changed the alter's academic achievement from low (less than nine) to high (greater than or equal to nine). We randomly drew 1,000 sets of estimates from the coefficient covariance matrix and assumed that all other variables in the model took on their mean values (Liang & Zeger, 1986).

While we cannot be certain that omitted variables or other events that affect both egos and alters are not responsible for any associations we observe, we attempt to account for these possibilities by examining how the direction of the social relationship between the ego and alter affects the extent to which we observe an association between ego and alter academic achievement. Were variables we have not accounted for to be responsible for the associations we observe it would be highly unlikely that we would observe particular relationships between the type of social relationship and the extent of social influence. Further, if the academic environment that the pair shares, such as the school, were responsible for increasing associations between individuals we would be unlikely to observe similar relationships within a school. Given that, we also conducted replication analyses using data from a single school.

4. Results

4.1. Academic achievement associations extend up to seven degrees of separation

In Fig. 1 we show visual evidence that there is clustering in the network. The figure shows the largest connected component of the network from the largest school during Wave I. The figure shows clusters of high academic achievers (academic achievement >9), which are significantly larger than we would expect with random re-assignment of scores to students. This suggests that academic achievement does cluster in this network.

As shown in Fig. 2, this clustering of high ego and alter academic achievement is significant for up to seven degrees of separation in Wave II and six degrees of separation in Wave I. In Wave I, a subject is 86% (95% C.I. 80%–92%) more likely to report an average of B or greater if a directly connected alter (distance 1) reports an average of B or greater.

The relationship for a friend of a friend (distance 2, or two degrees of separation) is 43% (39%–47%), for a friend of a friend of a friend (distance 3) is 20% (17%–22%), for distance 4 is 7% (5%–8%), for distance 5 is 2.4% (0.5%–3.7%),

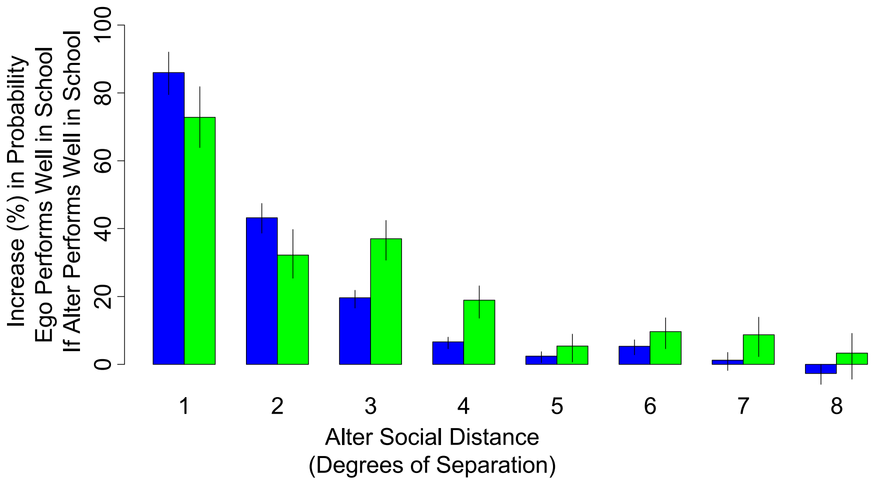

Fig. 2. Spread of academic achievement. Wave I is in blue (left in each pair) and Wave II is in green (right in each pair). The association between ego and alter school performance is significant up to 7 degrees of separation (Wave II) or 6 degrees of separation (Wave I). The figure shows the percentage increase in the likelihood a student is doing well in school academically (school performance index ≥ 9) if a friend at a certain social distance is doing well in school academically. The relationship is strongest between individuals who are directly connected, but remains significantly greater than zero at social distances of other people up to 6 (Wave I) or 7 (Wave II) degrees of separation. Thus, a participant's school performance is significantly associated with others in the same school for up to 7 degrees of separation in the network. Confidence intervals of the estimate are calculated by comparing the observed network relationship to the relationship in a network of identical structure in which the academic achievement variable has been randomly shuffled between individuals (Christakis & Fowler, 2007; Szabo & Barabasi, 2006). Error bars represent 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Academic achievement and social contacts. Table 2 shows the spread of academic achievement. In the first three columns we show the results from an OLS regression of ego academic achievement on alter academic achievement and covariates. In the second three columns we show the results of logistic regression of ego academic achievement on alter academic achievement and covariates.

Dependent variable	Wave II academic achievement (continuous)			Wave II academic achievement (dichotomous)		
	Estimate	SE	Pr (>|t|)	Estimate	SE	Pr (>|t|)
No. of contacts who acad. achieve < 9, Wave I	−0.127	0.030	<0.001	−0.129	0.041	0.002
No. contacts who acad. achieve ≥ 9, Wave I	−0.022	0.037	0.552	−0.025	0.044	0.566
Respondent acad. achievement, Wave I	0.625	0.015	<0.001	2.436	0.098	<0.001
Age	−0.187	0.071	0.008	−0.235	0.091	0.010
Female	0.235	0.078	0.003	0.345	0.096	<0.001
Household income	0.001	0.001	0.105	0.002	0.001	0.011
Mother's education	0.072	0.019	<0.001	0.049	0.023	0.034
Hispanic	−0.080	0.150	0.597	−0.142	0.184	0.440
Black	−0.412	0.106	<0.001	−0.640	0.132	<0.001
Asian	0.129	0.167	0.439	0.183	0.208	0.380
Marijuana use, Wave I	0.033	0.010	0.002	0.020	0.014	0.162
Smoking behavior, Wave I	−0.020	0.005	<0.001	−0.022	0.007	0.002
Body mass index, Wave I	−0.011	0.009	0.260	−0.010	0.012	0.387
Alcohol use, Wave I	−0.068	0.035	0.051	−0.158	0.045	0.001
Grade, Wave I	0.268	0.074	<0.001	0.274	0.094	0.004
English spoken at home, Wave I	0.147	0.198	0.459	−0.012	0.246	0.963
Employed, Wave I	−0.086	0.080	0.283	−0.112	0.100	0.263
General health, Wave I	0.096	0.048	0.048	0.190	0.060	0.002
Constant	2.632	0.680	<0.001	−1.109	0.849	0.191
Null deviance	25414			4015.9		
Deviance	12246			2801		
N	2916			2916		

and for distance 6 is 5.3% (2.8%–7.2%). However, what are these relationships like when we take into account other characteristics that affect both friendship formation and student achievement? Table 2 shows associations between alter academic achievement in Wave I and ego academic achievement in Wave II. These models account for other factors (described in Section 3.1) that may be associated with ego achievement and friendship formation.

These associations are only significant for low-achieving contacts. More specifically, each additional contact whose academic achievement is <9 in Wave I is associated with an increase in the likelihood that the ego's academic achievement is <9 in Wave II by 13% (95% C.I. 5%–21%, $p = 0.002$). In a continuous model of academic achievement, the association is also significant ($p < 0.001$).

Table 3
Academic achievement and centrality. Table 3 shows the association between academic achievement and centrality. In the first three columns we show the results from an OLS regression of ego academic achievement on centrality and covariates. In the second three columns we show the results of OLS regression of ego centrality on academic achievement and covariates. The results show that academic achievement influences network position, but not vice versa.

	Wave II academic achievement			Wave II eigenvector centrality		
	Estimate	SE	Pr (>|t|)	Estimate	SE	Pr (>|t|)
Academic achievement, Wave I	0.625	0.018	<0.001	0.002	0.001	0.021
Eigenvector centrality, Wave I	−0.286	0.556	0.608	−0.010	0.023	0.654
Total degree, Wave I	0.026	0.023	0.254	−0.001	0.001	0.043
Age	−0.135	0.087	0.120	−0.003	0.004	0.397
Female	0.358	0.099	<0.001	−0.004	0.004	0.347
Household income	0.001	0.001	0.068	<0.001	<0.001	0.845
Mother's education	0.075	0.024	0.001	0.001	0.001	0.590
Hispanic	−0.347	0.181	0.055	0.013	0.008	0.105
Black	−0.292	0.127	0.022	−0.009	0.006	0.124
Asian	−0.060	0.219	0.783	−0.004	0.009	0.629
Marijuana use, Wave I	0.022	0.013	0.105	<0.001	0.001	0.710
Smoking behavior, Wave I	−0.015	0.007	0.024	<0.001	<0.001	0.607
Body mass index, Wave I	−0.009	0.012	0.480	<0.001	<0.001	0.638
Alcohol use, Wave I	−0.101	0.044	0.022	−0.003	0.002	0.056
Grade, Wave I	0.259	0.091	0.005	−0.004	0.004	0.296
English spoken at home, Wave I	−0.070	0.259	0.786	0.015	0.010	0.138
Employed, Wave I	−0.079	0.100	0.426	<0.001	0.004	0.939
General health, Wave I	0.090	0.059	0.127	0.001	0.003	0.788
Constant	1.699	0.831	0.041	0.101	0.036	0.005
Null deviance	17193			17.34		
Deviance	8421			16.79		
N	1913			2001		

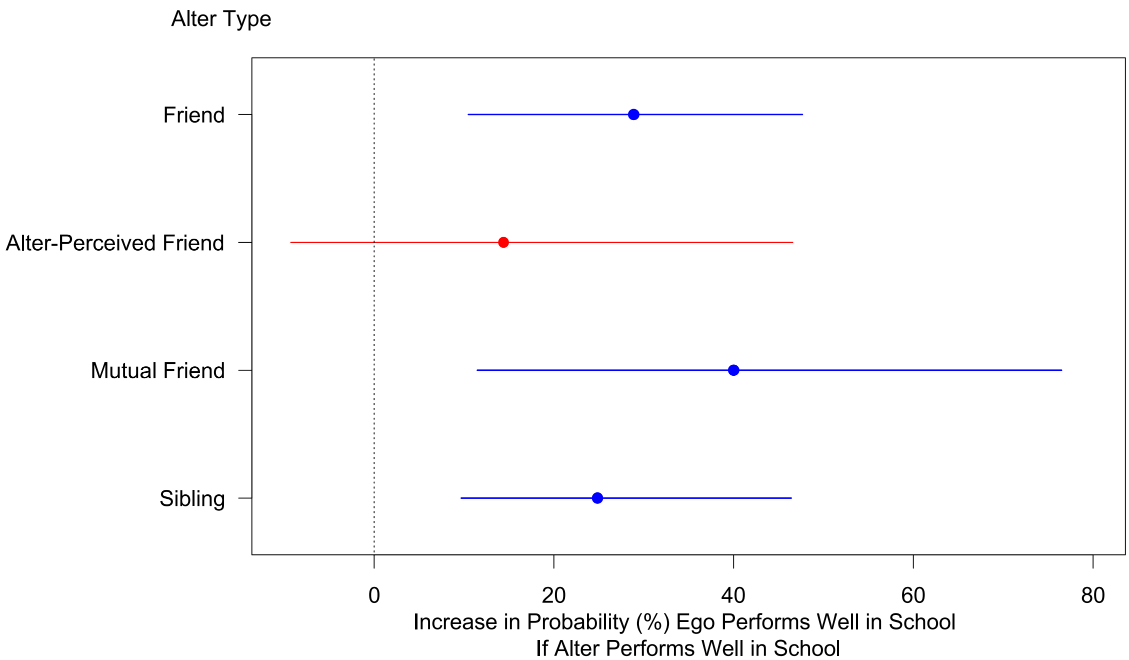

Fig. 3. Spread of school performance. Fig. 3 shows the results of first difference estimates from generalized estimating equation (GEE) logit models of school performance on several different sub-samples of the Add Health social network. See Appendix A for the underlying models.

While we do observe clustering of low academic achievement, the number of contacts whose academic achievement is ≥9 is not associated ($p = 0.566$) with a change in an individual's academic achievement. While having an increased number of low-achieving contacts is negatively associated with ego's achievement, having an increased number of high achieving contacts is not positively associated with ego's achievement.

The models above evaluate the relationship between the overall number of a person's contacts who had high or low academic achievement and ego achievement. This relationship, however, might be different for close friendships ties. Therefore, we examined other models in which we included all ego-alter pairings that met specified criteria. These models also account for the same set of control variables, measured at Wave II, and include the ego's lagged academic achievement. By including the alter's behavior in the previous wave we help to control for social selection processes. Here we are interested in estimating the impact that one person's behavior has on another's, which we estimate using the coefficient on the alter's academic achievement in the present period. Fig. 3 shows the results of these models, for different types of friendship relationship (see Appendix A Tables 4–7 for the underlying models). Each student was asked to name up to 10 friends, but only some of the friendship nominations were reciprocated. Thus, we have three possible types of friendships: friendships in which only the ego named the alter in the friendship ("Friend" in the figure), friendships in which the alter named the ego as a friend, but the ego did not ("alter-perceived friend" in the figure), and friendships in which both the ego and the alter named one another as friends ("mutual friends" in the figure).

When we examine direct ties, if a friend is a high academic achiever, it is associated with an increase in the likelihood that the ego is a high academic achiever by 29% (95% C.I. 11%–48%). In order to ensure that our results are not confounded by some contextual factor, we carried out several additional analyses. First, we conducted the same analysis within a single school and found similar results, which should control for the possibility that school-level factors influenced our results. (See Appendix A Table 8 for the full results of the one-school model.) While the finding that the results are similar within a single school suggest that contextual effects are not confounding our analysis, we rely on the directionality of friendships to further investigate the possibility of confounding variables. Were the source of the relationship between ego and alter academic achievement due to some unobserved variable (such as by teacher- or tutor-effects, for example), our expectation would be that the relationship between ego and alter academic achievement would be equally strong in each of these models. If the associations are, at least in part, attributable to social influence we would expect that the associations would vary based on the type of relationship observed. Specifically, we would expect that mutual friends are the most influential as they would, on average, have the strongest tie. We would also expect that ego-perceived friends would be more influential than alter perceived friends as they are likely to be a stronger connection.

Fig. 3 shows that the association between alter-perceived friends and student academic achievement is not significant ($p = 0.14$). Additionally, mutual friends exhibit the strongest associations. Having a mutual friend who is a high academic achiever is associated with a 40% (12%–77%) increase in the likelihood that the ego is a high academic achiever. These results suggest that at least part of the association between ego and alter academic achievement is due to influence.

Finally, we present results for the association between sibling academic achievement. Having a high-achieving sibling is associated with a 25% (10%–46%) increase in the likelihood that the ego is a high academic achiever. Of course, all sibling relationships are mutual. This makes distinguishing between influence, latent ability, a shared home environment, or other factors impossible. Therefore, while the sibling results are helpful for understanding the friendship results, we remain uncertain as to the extent to which they may or may not measure social influence within a family. This comparison shows that friend associations are larger than sibling associations, which underscores the substantive importance of our empirical findings.

To recap, while an increased number of low-achieving contacts is associated with ego lowered achievement, the number of high achieving contacts is not associated with a change in ego achievement. However, when we narrow the alters and examine the ego's perceived or mutual friends, we find that having a high-achieving ego-perceived or mutual friend is associated with an increase in ego achievement. The observed relationship is at least in part due to influence rather than homophily or shared environment. This means that we have found strong support for H1 and H2.

4.2. *Academic achievement and future network centrality*

In addition to clustering, in Fig. 1 it appears that academic achievement and centrality (literally being more toward the center of the network, in social terms) may be related. That is, participants who are high academic achievers tend to be in the core of the network than in the periphery. We tested this relationship by calculating the centrality of all individuals in the network and found that high academic achievement is indeed associated with future network centrality.

More specifically, those achieving at a higher level at time $t-1$ are more likely to occupy a more central position in the network at time t. The relationship between academic achievement and centrality remains even after accounting for a number of covariates that are related to both achievement and friendship formation. We do not, however, find a significant relationship between centrality and future academic achievement. Thus, we find evidence in support of H3 that higher achieving students are more centrally located in their respective social networks as compared to lower achieving students.

5. Discussion

Our results demonstrate that peer networks may influence one's achievement, and therefore one's life course. We found that having a contact who is a low academic achiever is associated with a decrease in own achievement, but having a contact who is a high academic achiever is not associated with a change in own achievement. This result suggests that while the overall environment created by a friends' network has the potential of dragging a student's achievement down if the network consist of low-achieving students, it may not increase a student's achievement in cases when it consists of high-achieving students. As social networks are likely to form between students who are placed in the same classes (Frank, Muller, & Mueller, 2013), this result then has implications for the debate on whether tracking in schools is beneficial for students (Loveless, 2011). At the very basic level – such as without taking into account potential changes of instructional practices for higher and lower achieving groups – grouping higher performing students together is unlikely to boost student achievement while grouping low-performing students might lead to a decrease in their achievement.

Also, higher achieving students are more likely to occupy more central positions in their respective networks in the future thus increasing their chances of maintaining friendships over time. Being located nearer to the center of the network can be evidence of higher level of social skill—a quality that, if observed in high school, is associated with higher post-graduate earnings (Lleras, 2008). If more centrality is indeed indicative of higher levels of social skills, than higher achieving students might have an additional job market advantage over lower achieving ones. While in school, more centrally located students enjoy an elevated peer standing (Gifford-Smith & Brownell, 2003). Individuals more centrally located in their networks possess a higher potential to establish trends for behavior and collective group opinions, and exert influence over others in the group (Borgatti, 2005; Neal, 2010). As higher achieving students are less likely to engage in drinking, smoking, and illegal drug use (Bryant, Schulenberg, O'Malley, Bachman, & Johnston, 2003), students in their networks might indirectly benefit from the fact that higher achieving students are more likely to be trend-setters in their groups. For this same reason, students in the groups that have high achieving centrally located students might experience a boost in college-going plans, as higher achieving students are more likely to expect to continue their education past K-12 (Jacob & Wilder, 2010). As such, while being a part of a higher achieving network does not necessarily lead to improved academic performance, high-achieving networks might still have a potential of positive, albeit indirect, influence.

Where appropriate, we have emphasized that we are studying associations rather than causal processes because we are not able to fully rule out such processes as selection effects (homophily) or a shared environment (confounding) (Fowler, Heaney, Nickerson, Padgett, & Sinclair, 2011). With observational data it is very difficult, and perhaps impossible (Shalizi & Thomas, 2011), to completely rule out these other processes, but our findings are suggestive that influence plays a role in the associations we found. First, we found that the directionality of the friendship is significant in predicting the clustering of academic achievement. This suggests that interpersonal relationships are important for the clustering of academic achievement and that the covariance in achievement we find is not the result of unobserved contemporaneous exposure to a similar environment. If it were, the associations that we observe would not vary based on the perceived directionality of the relationship. Second, we show that the relationship between friends' academic achievement we study in the overall population is also present in a single school. This suggests that the processes we study are not due to differences in achievement across schools. Third, because our models control for the ego's previous academic achievement, we can account for stable sources of confounding. Finally, controlling for the alter's previous academic achievement accounts for the possibility that students are forming ties based on academic achievement. Our findings that there exists clustering of low academic achievement in student networks, and that friend's achievement is associated with own achievement support the basic idea that education is, at least in part, a social process. Overall, this study provides further evidence that networks phenomena can and should be exploited to better understand scholastic outcomes of students.

Appendix A.

Table 4
Association of academic achievement between ego and ego-perceived friends ("Friends" in Fig. 3). Results for logistic regression of ego academic achievement at Wave II (1 = academic achievement ≥ 9, 0 = academic achievement < 9) are shown. We used GEE procedures to account for multiple observations of the ego across ego-alter pairs.

	Estimate	St. err.	Pr (>|t|)
Alter academic achievement ≥ 9, Wave II	0.412	0.081	<0.001
Ego academic achievement ≥ 9, Wave I	1.919	0.081	<0.001
Alter academic achievement ≥ 9, Wave I	0.163	0.078	0.038
Ego female	0.200	0.081	0.014
Ego age	−0.092	0.076	0.223
Household income	0.004	<0.001	<0.001
Mother's education	0.037	0.018	0.038
Ego hispanic	−0.304	0.146	0.037
Ego black	−0.396	0.115	0.001
Ego Asian	0.167	0.148	0.259
Ego marijuana user, Wave II	−0.319	0.133	0.017
Ego smoking behavior, Wave II	−0.020	0.005	<0.001
Ego body mass index, Wave II	−0.012	0.009	0.188
Ego alcohol use, Wave II	−0.094	0.030	0.002
Ego grade, Wave II	0.139	0.079	0.078
English spoken at home, Wave II	0.017	0.171	0.919
Ego employed, Wave II	0.038	0.082	0.646
Ego general health, Wave II	0.134	0.047	0.005
Constant	−1.987	1.036	0.055
Null deviance	1432		
Deviance	1014		
N	5913		

Drawing network maps

We used the Kamada–Kawai algorithm (Kamada & Kawai, 1989) to create the image in Fig. 1. The algorithm creates a matrix in which the shortest path between each pair of nodes is created and positions the nodes such that the sum of the differences between the distances in the figure and the distances in the network is minimized.

Table 5
Association of academic achievement between ego and alter-perceived friends ("Alter-Perceived Friends" in Fig. 3). Results for logistic regression of ego academic achievement at Wave II (1 = academic achievement ≥ 9, 0 = academic achievement < 9) are shown. We used GEE procedures to account for multiple observations of the ego across ego-alter pairs.

	Estimate	St. err.	Pr (>|t|)
Alter academic achievement ≥ 9, Wave II	0.209	0.141	0.137
Ego academic achievement ≥ 9, Wave I	1.023	0.094	<0.001
Alter academic achievement ≥ 9, Wave I	0.006	0.121	0.961
Ego female	0.233	0.098	0.017
Ego age	−0.359	0.083	<0.001
Household income	0.001	0.001	0.542
Mother's education	0.046	0.021	0.029
Ego hispanic	−0.189	0.128	0.141
Ego black	−0.106	0.128	0.408
Ego Asian	0.025	0.136	0.856
Ego marijuana user, Wave II	−0.206	0.133	0.120
Ego smoking behavior, Wave II	−0.033	0.005	<0.001
Ego body mass index, Wave II	−0.012	0.012	0.305
Ego alcohol use, Wave II	0.071	0.032	0.024
Ego grade, Wave II	0.288	0.078	<0.001
English spoken at home, Wave II	0.087	0.141	0.536
Ego employed, Wave II	−0.092	0.097	0.344
Ego general health, Wave II	0.212	0.063	0.001
Constant	1.249	2.740	0.649
Null deviance	697		
Deviance	594		
N	2909		

Table 6
Association of academic achievement between mutual friends ("Mutual Friends" in Fig. 3). Results for logistic regression of ego academic achievement at Wave II (1 = academic achievement ≥ 9, 0 = academic achievement < 9) are shown. We used GEE procedures to account for multiple observations of the ego across ego-alter pairs.

	Estimate	St. err.	Pr (>|t|)
Alter academic achievement ≥ 9, Wave II	0.524	0.175	0.003
Ego academic achievement ≥ 9, Wave I	1.985	0.169	<0.001
Alter academic achievement ≥ 9, Wave I	0.128	0.191	0.502
Ego female	0.487	0.185	0.008
Ego age	0.118	0.116	0.476
Household income	0.005	0.002	0.024
Mother's education	0.052	0.042	0.218
Ego hispanic	−0.522	0.345	0.130
Ego black	−0.497	0.286	0.083
Ego Asian	−0.206	0.330	0.533
Ego marijuana user, Wave II	−0.319	0.308	0.299
Ego smoking behavior, Wave II	−0.031	0.011	0.004
Ego body mass index, Wave II	0.016	0.019	0.395
Ego alcohol use, Wave II	−0.113	0.072	0.118
Ego grade, Wave II	−0.004	0.178	0.982
English spoken at home, Wave II	−0.353	0.374	0.345
Ego employed, Wave II	−0.222	0.184	0.227
Ego general health, Wave II	0.410	0.107	<0.001
Constant	−5.566	1.988	0.005
Null deviance	308		
Deviance	204		
N	1279		

Table 7
Association of academic achievement between siblings ("Siblings" in Fig. 3). Results for logistic regression of ego academic achievement at Wave II (1 = academic achievement ≥ 9, 0 = academic achievement < 9) are shown. We used GEE procedures to account for multiple observations of the ego across ego-alter pairs.

	Estimate	St. err.	Pr (>|t|)
Alter academic achievement ≥ 9, Wave II	0.337	0.087	<0.001
Ego academic achievement ≥ 9, Wave I	1.758	0.078	<0.001
Alter academic achievement ≥ 9, Wave I	0.296	0.087	0.001
Ego female	0.272	0.075	<0.001
Ego age	−0.139	0.059	0.018
Household income	−0.001	0.001	0.421
Mother's education	0.040	0.017	0.021
Ego hispanic	−0.220	0.129	0.088
Ego black	−0.570	0.098	<0.001
Ego Asian	0.127	0.164	0.439
Ego marijuana user, Wave II	−0.404	0.120	0.001
Ego smoking behavior, Wave II	−0.018	0.004	<0.001
Ego body mass index, Wave II	−0.001	0.008	0.949
Ego alcohol use, Wave II	−0.020	0.030	0.508
Ego grade, Wave Ii	0.181	0.060	0.002
English spoken at home, Wave Ii	−0.023	0.176	0.895
Ego employed, Wave II	−0.011	0.082	0.889
Ego general health, Wave II	0.094	0.044	0.032
Constant	−1.563	0.769	0.042
Null deviance	1142		
Deviance	842		
N	4904		

Table 8
Association of academic achievement between friends in a single school. Results for logistic regression of ego academic achievement at Wave II (1 = academic achievement ≥ 9, 0 = academic achievement < 9) are shown. We used GEE procedures to account for multiple observations of the ego across ego-alter pairs. We replicate our previous models by selecting the largest school in the sample (school 58) and re-running our analyses on just this school. These results suggest that the relationship between ego and alter academic achievement is not driven by between-school variation. There were no black students in this school, so we omit the *ego black* variable.

	Estimate	St. err.	Pr (>|t|)
Alter academic achievement ≥ 9, Wave II	0.0396	0.207	0.056
Ego academic achievement ≥ 9, Wave I	1.790	0.256	<0.001
Alter academic achievement ≥ 9, Wave I	−0.009	0.235	0.969
Ego female	0.391	0.270	0.148
Ego age	0.050	0.255	0.844
Household income	0.021	0.004	<0.001
Mother's education	−0.059	0.064	0.352
Ego hispanic	2.266	1.325	0.087
Ego Asian	2.260	3.688	0.540
Ego marijuana user, Wave II	−0.268	0.400	0.503
Ego smoking behavior, Wave II	−0.024	0.013	0.059
Ego body mass index, Wave II	0.003	0.029	0.916
Ego alcohol use, Wave II	0.019	0.087	0.827
Ego grade, Wave II	0.182	0.275	0.509
Ego employed, Wave II	−0.822	0.316	0.009
Ego general health, Wave II	0.732	0.179	<0.001
Constant	−7.405	7.599	0.330
Null deviance	210		
Deviance	150		
N	974		

Statistical analysis

Table 1 shows summary statistics of the sample. Tables 2 and 3 shows the results of GLM models that use a single observation for each ego and use summary statistics of the alters' behavior. Tables 4–8 in Appendix A show GEE models that analyze ego-alter pairs. We imputed missing data using Amelia, which is a multiple imputation procedure (King, Honaker, Joseph, & Scheve, 2001). All models analyze 10 multiply imputed data sets.

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