Does "Connectedness" Matter? Evidence From a Social Network Analysis Within a Small-School Reform

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***Background/Context**: Though cast in many styles and given different labels, the notion that one can improve schools by improving or changing the social context of learning is a common thread that runs through the arguments of many education reformers and scholars. Indeed, a common assertion in education reform is that one needs to create school environments with stronger community, where people are "better connected." At the heart of such claims—and the topic of investigation for this article—is the notion that the nature of social interactions in schools is a crucial part of schooling.*

***Purpose/Objective**: In this article, we use social network analysis—a powerful yet underused method in educational research—to gain insight into how social relations give rise to relative advantage within a group of students at a large public high school engaged in small-school reform. More specifically, we ask three questions of this sample of students: First, to what extent is academic performance "contagious" among peers? Second, after accounting for individual characteristics, is a student's location in a social network, as indicated by network density, associated with academic performance? If so, is a norm-enforcing or horizon expansion mechanism primarily responsible for this association? Third, is there a joint effect of peer achievement and network density on academic performance?*

***Setting**: A large urban public high school implementing a school-within-a-school reform.*

***Population/Participants/Subjects:** Grade 10 students within one of the schools-within-a-school.*

***Research Design**: We connect variations in network composition and network structure to hypotheses about the interpersonal mechanisms at work between students. We combine detailed network data on the social relations between students with individual-level data from school records and then attempt to exploit variation in network characteristics across*

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students to make inferences about the role of social relations with respect to academic performance.

***Data Collection and Analysis**: The specific data come from two sources: (1) school administrative records that contained information on student grade point averages, absences, standardized test scores, and demographics, and (2) the administration of a Web-based social network survey asking students to cite those with whom they interact in several academic and social contexts.*

***Conclusions**: We find that network composition (as measured by lagged peer achievement) and network structure (as measured the density of ties between a student's peers) have no average association with student performance after accounting for individual-level characteristics. However, when interacting network composition and network structure, we find a significant joint effect. This implies that the advantages and disadvantages arising from a student's social relations are context dependent and, moreover, suggests that in order to diagnose the impact of building stronger community in schools, it is necessary to consider the network structure of students' relationships when examining the influence of peers.*

INTRODUCTION

Though cast in many styles and given different labels, the notion that one can improve schools by improving or changing the social context of learning is a common thread that runs through the arguments of many education reformers and scholars (Baker, Terry, Bridger, & Winsor, 1997; Bryk & Driscoll, 1988; Bryk & Schneider, 2002; Cotton, 1996a; Dorsch, 1998). Indeed, a large number of empirical studies support the idea that relational constructs such as "social capital" and "social support" are associated with positive outcomes for students (Battistich, Solomon, Kim, Watson, & Schaps, 1995; Lee & Smith, 1999; Pittman & Haughwout, 1987; Stiefel, Berne, Iatarola, & Fruchter, 2000). At the heart of this claim is the notion that the nature of social interactions in schools is a crucial part of schooling.

In this article, we use social network analysis—a powerful yet underused method in educational research—to gain insight into how social relations give rise to relative advantage within a group of students at a large public high school that is engaged in small-school reform. Students participating in a small-school reform present an interesting population to study because small-school reform strongly foregrounds organizational design choices intended to increase social capital. A core belief is that smaller schools lead to more "connected" social environments in which children and adults are much more likely to know each other and care about one another's progress (Cotton, 1996a, 1996b; Raywid, 1997). In some cases, like the one investigated in this study, the reform involves

creating a smaller "school-within-a-school" to create a more intimate and personal environment for the students.

The goal of this article is to frame the beliefs of small-school reformers from a social network perspective and look for evidence that the nature and structure of social relations impact student performance. More specifically, we ask three questions of this sample of students: First, to what extent is academic performance "contagious" among peers? Second, after accounting for individual characteristics, is a student's location in a social network, as indicated by network density, associated with academic performance? If so, is a norm-enforcing or horizon expansion mechanism primarily responsible for this association? Third, is there a joint effect of peer achievement and network density on academic performance?

SOCIAL CAPITAL, NETWORKS, AND SCHOOL REFORM

A common assertion in education reform is that one needs to create school environments with stronger community, in which people are "better connected." This connectedness is viewed as an asset that improves performance by facilitating coordination, trust, and the spread of information—a notion often referred to as social capital (Bourdieu & Wacquant, 1992; Coleman, 1990; Putnam, 1993). Unfortunately, the rhetoric and research pertaining to social capital in schools can easily fall near one of two ends of a spectrum. On one hand, education reformers are apt to discuss connectedness or social capital in metaphorical terms that, although rooted in the wisdom of clinical experience, often leave underspecified the mechanisms through which social structure impacts student performance. On the other hand, researchers trying to measure the impact of social capital in schools often reduce social relations to a set of variables that capture the properties emerging from interpersonal interactions within a social structure but do not necessarily capture the features of that social structure itself. Consequently, though such studies are very valuable in revealing the association between properties such as perceptions of trust, collegiality, adherence to norms, availability of information and support, and educational outcomes of interest (e.g., Battistich et al., 1995; Goddard, 2003; Lee & Smith, 1999), they usually stop short of attempting to disentangle the relational mechanisms responsible for the associations.

By providing a way to frame, map, and quantify the relations between people, the ideas and tools of social network analysis can help bridge the gap between the mechanisms implicit in reformers' arguments and the empirical rigor required by researchers to draw valid inference.[1] The

starting point is an image of social structure such as the one depicted in Figure 1, in which the nodes are people and the links are relations defined by a criterion of interest (such as doing schoolwork together, for example). In such an image, one's social relations, or connectedness, can aid performance in one of two general ways. One is that the individuals to whom one is directly tied can provide information, support, positive influence, or other relevant resources. We will refer to this as the role of *network composition.* A second way that connectedness can matter is that the location one occupies in a social structure may provide some kind of advantage, such as increased trust or better access to information. This latter idea we will refer to as the role of *network structure.* We discuss each in turn.

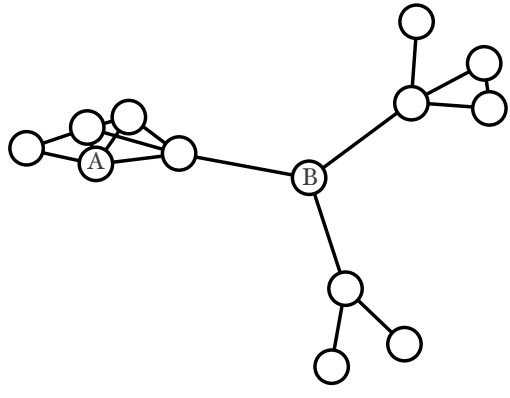


Figure 1. In this hypothetical social network, Person A and Person B occupy different types of local positions, with Person A occupying a network position with much higher "closure" than Person B. The two positions imply different mechanisms for social capital generation. Person A's norm-enforcing social structure may lead to a social context with high trust and support. Person B's horizon-expanding network may lead to access to a greater diversity of information and greater freedom from unwanted social pressure.

THE ROLE OF NETWORK COMPOSITION

The composition of the network refers to the characteristics and resources of the people in the network. Differences in network composition can lead to differences in performance due to direct influence, information, or assistance from others in one's network. For example, a struggling student with knowledgeable friends may gain assistance from those friends in completing a difficult assignment. Alternatively, a student's high-achieving peers might exert pressure on the student to succeed.

This idea has been formalized in network models of social influence,

or *contagion* (Friedkin, 2003; Leenders, 2002; Marsden & Friedkin, 1993), and has been used to estimate the "contagiousness" of preferences and behaviors ranging from teacher adoption of technology (Frank & Zhao, 2004), to the prescription of a new drug (Burt, 1987; Coleman, Katz, & Menzel, 1966), to the convergence of political behavior (Mizruchi, 1989). More specifically, the idea behind social contagion models is that a person's behavior is a function of his or her own individual beliefs and characteristics, the beliefs and characteristics of others in his or her network, and a set of non-network-related attributes specific to the individual.[2]

The most straightforward application to student achievement would be to model a student's performance as a function of the mean prior achievement of his or her friends, as well as individual characteristics of the student, such as his or her previous academic performance and socioeconomic status. Indeed, though not usually discussed in network terms, this is the approach implicit in many standard peer effects models in the sociology and economics of education (e.g., Davies & Kandel, 1981; Summers & Wolfe, 1977; for review, see Wilkinson et al., 2000). Such models can help distinguish between the differences in performance attributable to the relations with peers—a form of social capital—from the differences attributable to other determinates of academic performance, such as family background or teacher quality. They are limited, however, in helping one distinguish between the mechanisms that are potentially responsible for an average peer effect. To draw further inference about mechanism, we must go beyond average peer effects and examine what one might think of as the student's location in a broader social structure—a topic that we discuss in more detail in the following section.

THE ROLE OF NETWORK STRUCTURE

Network structure refers to the location of a student in a network or, stated differently, the pattern of interrelations among the people in the student's network. Two characterizations of network structure are often associated with social capital: closure and structural holes.[3] Networks that exhibit closure are networks in which everyone is connected in a way that their behavior cannot help but be observed by others. The image here is of a very dense network in which the friends of your friends are likely to be friends themselves (see Figure 1). Such a network is hypothesized to increase conformity to norms, resulting in greater trust between the members of the group (Coleman, 1988, 1990)—an idea that closely resembles part of the intuition of small-schools reform. For example, one

might conjecture that a knowledgeable classmate would be more likely to help a struggling student if the two students share at least one friend. In this example, the sharing of mutual friends is a statement about the closure of the student's network.[4]

The "dark side" of network closure, however, is that a dense network structure potentially limits the diversity of information that enters a group, as well as one's freedom to pursue ideas outside the norms of the group. Indeed, an alternative network mechanism associated with social capital is Burt's (1992) notion of structural holes. The proposition is that those who bridge network holes between groups of people who otherwise do not pay particular attention to the activities of one another enjoy informational and control benefits of that network position. In other words, people in networks with less closure are hypothesized to have a greater diversity of information and a greater freedom to act. Though coming from samples of business mangers rather than schools or students, Burt (1992, 2001, 2004) has accumulated substantial evidence for the association between individuals with networks rich in structural holes and individual performance.

Morgan and Sorensen (1999) framed the difference between the two network mechanisms very nicely for a school context in a test of Coleman's closure hypothesis. They characterized as a "norm-enforcing" school one in which the dominant form of social capital came in the form of network closure, and contrasted it with a "horizon-expanding" school in which social capital primarily came from a brokerage mechanism—terminology that we adopt and use throughout this article. They also distinguished between the social closure of student friendship networks and the social closure of parent networks. Using the National Education Longitudinal Study to construct student and parent measures of network closure, they concluded two things. One is that closely tied student networks are positively associated with school performance, as measured by growth in math achievement. The other is that social closure of parental networks is negatively associated with school performance, contradicting Coleman's argument about the benefits of closure in parental networks. They considered the net effects to be "not overwhelming in size, but substantively meaningful," with a one-standard-deviation increase in student closure resulting in a 6.5% increase in mathematics achievement, and a one-standard-deviation increase in parental closure corresponding to a 5.5% decrease (p. 671). Interestingly, when looking across school sectors (Catholic vs. public), they also found evidence that their results are sector dependent and mostly driven by public schools. More specifically, horizon-expanding social relations characterized the most effective public schools, but

norm-enforcing social relations characterized the most effective Catholic schools. Two points must be noted about Morgan and Sorensen's work with respect to the limitation of their data, however. The first is that their measure of student closure is the number of relationships inside a school, not the density of the network. To test the closure hypothesis, we would prefer a measure that captures the extent to which the students included in that number are also friends with each other. Second, and even more troubling, is that the student friendships are based on parent responses. For adolescents, parents may not have the clearest picture of their children's relationships in and out of school.

In addition to the hypothesized independent effects of network composition and network structure on academic achievement, the third-party norm enforcement mechanism hypothesized by network closure also implies a potential interaction effect between network structure and network composition. For instance, one might expect high network density to amplify the influence of one's peers, regardless of whether that influence from network composition is positive or negative. Using data from the National Longitudinal Study of Adolescent Health to examine adolescent delinquency, Haynie (2001) found that several features of network structure, most notably network density, do indeed moderate the association between an adolescent's behavior and the behavior of his or her peers. More specifically, the apparent peer effects are strongest for individuals located in highly dense networks and weakest for those in less dense networks. This finding underscores the importance of investigating the joint effects of network structure and composition. It also illustrates a point easy to overlook in education reforms that emphasize increased social cohesion: Increasing network density has the potential to lead to undesirable outcomes for students.

SUMMARY AND HYPOTHESES

The social capital available to a student can be viewed as arising from mechanisms that can be measured by network composition and network structure. With regard to composition, network data can be used to create measures of peer traits and behaviors to associate with student performance. All else being constant, a significant positive association between lagged peer achievement and student grade point average would constitute evidence of contagion in academic performance.

With respect to network structure, students located in dense, norm-enforcing networks may reap the benefits of increased trust and conformity that come from network closure. Students located in less dense, horizon-expanding networks may reap the benefits of increased diversity

of information and autonomy. If a norm-enforcing mechanism were the primary source of social capital, then we would expect a significant positive association between egocentric network density and student achievement. If a horizon expansion mechanism were primarily responsible, then we would expect a significant negative association between egocentric network density and student achievement.

Moreover, both theory and prior work on adolescent behavior suggest an interaction effect between network composition and network structure. If network density (structure) moderates the association between peer achievement (composition) and student performance, or if peer achievement moderates the association between network density and student performance, we would expect a significant interaction between network density and peer achievement.

DATA AND METHODS

The data in this article were collected as part of an in-depth investigation of a large public high school engaged in a small-school reform effort. As part of the reform, the school expects to divide all its students into several "schools-within-a-school," a plan to be phased in over several years. The idea is that the small size, coupled with additional efforts to personalize the instruction and the social experience of the students, would lead to the creation of strong communities of learning at the school. Within a small school, most of the students take the same core classes (English, math, science, and social studies) from the same core teachers, and every effort is made for these teachers to stay with the same students until they graduate from the school. When the data for analysis were collected, one small school had been in existence for several years, and five new small schools within the school had just been formed. Students within a small school are not tracked by ability.

The specific data come from two sources. First, the high school made available administrative records that contained information on student grade point averages, absences, standardized test scores, and demographics. Second, through the use of a Web-based survey, we collected social network data from the 10th graders in the first and most established small school. Because of preexisting research relationships with the small school, we were able to schedule times when the entire cohort could come on a classroom-by-classroom basis to a computer lab and take the survey. Consequently, we surveyed 88% of the 101 tenth graders in the small school. The survey was administered in the middle of the spring semester and asked four name-generating questions to elicit discussion partners. Each question asked the students to type in the first and last

name of up to seven people (1) with whom they discuss schoolwork the most, (2) with whom they discuss personal and private concerns or worries the most, (3) whom they hang out with the most, and (4) whom they try to avoid. For each contact, students were also asked to indicate the frequency of interaction with that person. As a final question, students were asked about the frequency of communication between the names they cited—that is, their perception of how often the people they listed spoke to each other.

INDIVIDUAL STUDENT ATTRIBUTES

School records contained a number of individual-level attributes for the students. To assess a student's academic performance (our dependent variable), we use a student's grade point average earned in the semester in which the network survey data were collected (GPA2). The mean GPA2 for our sample is 2.39, with a standard deviation of 1.1. Student records also include data on the eighth-grade reading scores from the Iowa Test of Basic Skills (READ). The mean scores for our sample are 257, with a standard deviation 19. The national norm for eighth graders on the test is 250. Other information available from administrative data include data on the cumulative grade point average at the beginning of that same semester (GPA1), total absences from school (AB), gender, and race. When compared with the means of the rest of the 439 tenth graders at the high school, the small school has better grades (2.39 vs. 1.95), has higher incoming reading scores (257 vs. 212), is slightly less African American (9% vs. 18%), and is slightly more Hispanic (78% vs. 87%). Table 1 summarizes the values of the individual student attributes, as well as the peer and network measures described in the following sections.

Table 1. Means and Standard Deviations of Student Survey and Background Variables

Variable	
No. of observations	85
Second semester grade point average (GPA2)	2.39 (1.1)
Cumulative grade point average before second sem. (GPA1)	2.69 (.78)
Network size	5.90 (2.5)
Network density (x 100)	28.2 (21.3)
Lagged peer achievement (PEER)	2.64 (.48)
Total absences (AB)	6.18 (6.0)
Iowa Test of Basic Skills Reading Score (READ)	257 (19)
Percent male	47.1
Percent African American	8.2
Percent Hispanic	87.1

Note: Standard deviations in parentheses

NETWORK DEFINITION AND BOUNDARY

The student network survey data were collapsed and transformed into a symmetric matrix of relations, with each cell in the matrix representing whether a relation between two students exists. The rows and columns of the network matrix include both the network survey respondents, as well as other students in the small school they cited for whom we had data. With the exception of the question about avoidance, discussion partners cited with a frequency of "at least once a month" or more on any of the name-generating questions were included as relations. In cases in which relationship information between students was missing because a student in the matrix was not a respondent of the survey, the answers to the final question about frequency of communication between people cited were used. This matrix was used to identify peers for the calculations of lagged peer achievement and network density, as described in the following sections.

Seventy-one percent of the total number of students cited as relations by the small school respondents were students also enrolled in the small school, verifying that the school-within-a-school is sociometrically distinct from the larger school in which it is embedded.

LAGGED PEER ACHIEVEMENT (PEER)

Lagged peer achievement serves as our measure of network composition. Using the matrix of relations to define a set of peers for each survey respondent, lagged peer achievement was calculated as the weighted average of the grade point averages of a respondent's peers before the start of the semester of interest for this analysis. The weights assigned to each cited student are proportional to the amount of interaction between the students.[5] For the calculation of peer achievement, we focus only on students one step away in the network and do not consider second-order contacts (i.e., friends of friends get a weight of zero unless they are also directly a friend of the respondent).[6] The average weighted peer GPA for students in our sample ranged from 1.37 to 3.72, with a mean of 2.64 and a standard deviation of 0.48.

NETWORK DENSITY (DENSITY)

As a measure of network closure, we use egocentric network density—a respondent-specific density measure that takes into account the actual and possible ties only between direct contacts of a respondent. It was calculated as the total number of ties that exist between the first-order

contacts of a respondent (within the small school) divided by the number of all possible ties that could exist between those contacts, multiplied by 100. The density of the students in this sample ranged from 0 to 100, with a mean of 28.2 and a standard deviation of 21.3.

ANALYSIS

The network data were combined with student-level performance and background data to estimate ordinary least squares regression models of student academic performance, as measured by GPA2. The initial independent variables of interest are network density and lagged peer achievement. Controls include the student's cumulative grade point average as of the end of the first semester of the school year, as well as demographic characteristics of the student.[7]

All else being constant, a significant positive association between lagged peer achievement and student grade point average would constitute evidence of contagion in academic performance among peers. A significant association between network density and student grade point average would also constitute evidence of social capital impacting performance, but the source of that social capital would depend on the direction of the relationship. If a horizon expansion mechanism were primarily responsible, then we would expect a significant negative association between network density and student achievement. If a norm-enforcing mechanism were the primary source of social capital, then we would expect a significant positive association between network density and student achievement.

Additionally, we test for an interaction effect between network density and peer achievement by including a multiplicative interaction term. If network density moderates the association between peer achievement and student performance, or if peer achievement moderates the association between network density and student performance, we would expect a significant association between the density–peer interaction and student performance. It is important to note that although we cannot statistically distinguish the density-moderates-peer-achievement and peer-achievement-moderates-density explanations in our analysis, both interpretations have theoretical and substantive meaning in this particular case.

Finally, acknowledging the limitations of a statistical analysis of a relatively small sample collected from a single school, we used indices developed by Frank and colleagues (Frank, 2000; Frank & Min, 2007; Pan & Frank, 2004) to quantify the robustness of our inferences.

RESULTS

OLS ESTIMATES

Table 2 presents the results from three models used to test the hypotheses about the associations between student achievement, network structure, and peer achievement. All models use versions of PEER and DENSITY that are centered on their respective means. Model I provides estimates of a social contagion model containing both individual-level attributes and lagged peer achievement as covariates. Not surprisingly, measures of prior student achievement (GPA1 and READ) are positively associated with current student achievement, and the number of student absences (AB) is negatively associated with achievement. When holding constant the other factors, males also appear to perform about 0.33 GPA points worse on average in this small school. Of most interest, the association between peer achievement and student performance appears to be rather small and not statistically significant, indicating that on average, there is no aggregate contagion with respect to academic performance.

Model II replaces the lagged peer achievement of a student with the egocentric network density of a student (DENSITY). As we can see in Table 2, the aggregate association between network density and student performance is indistinguishable from zero, providing little evidence of either a norm-enforcing or horizon-expanding mechanism at work in the social structures of the students.

Although the main effects of the network variables in Models I and II are not significant, that does not mean that network features are irrelevant. More specifically, there are two important relationships that may be missed by examining only the main effect—one masking the effect of network composition (PEER), and one the effect of network structure (DENSITY). The first is that the extent to which a student is susceptible to peer influence may depend on his or her location in the social structure. For example, a student located in a network characterized by low density may be less susceptible to peer influence than a student in a very dense network. The second is that the association between network density and student performance may vary as a function of peer achievement. It is quite possible, for example, that network density enforces performance-enhancing norms in some groups and performance-hindering norms in others, resulting in a net effect of zero.

To test for such moderating effects, we include a multiplicative interaction term between peer achievement and network density in Model III. In this model, the coefficient of the interaction term is significant at the 0.05 level. With respect to the interaction term, the significance of the

Table 2. Ordinary Least Squares Estimates of Students' Second-Semester GPA (n = 85)

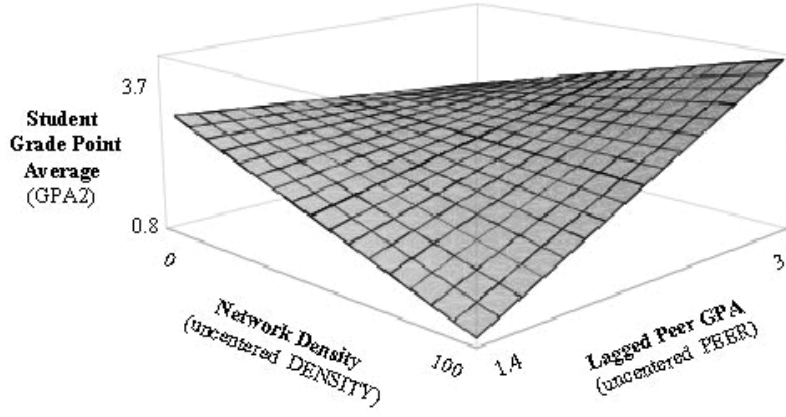
	I	II	III
PEER	.090		.173
(mean centered)	(.136)		(.139)
DENSITY		.000 (.003)	-.001
(mean centered)			(.003)
DENSITY x PEER			.014 **
			(.006)
GPA1	.965 ***	.980 ***	.944 ***
	(.093)	(.090)	(.092)
AB	-.052 ***	-.052 ***	-.049 ***
	(.010)	(.010)	(.010)
READ	.0056 *	.0057 *	.0045
	(.003)	(.003)	(.003)
MALE	-.333 **	-.353 ***	-.259 *
	(.134)	(.131)	(.136)
AA	.261	.262	.386 *
	(.219)	(.222)	(.225)
Intercept	-1.19	-1.26	-.926
Adj-R-sq	.7762	.7750	.7850

Note: Standard errors in parentheses.
*** $p < .01$. ** $p < .05$. * $p < .10$.

coefficient can be meaningfully interpreted (1) as network density moderating the marginal effect of peer achievement on student performance, or (2) as peer achievement moderating the marginal effect of network density on student performance. We examine both interpretations below. With respect to the coefficients of PEER and DENSITY, it is tempting to interpret them as the respective marginal effects on student achievement, but it is incorrect to do so because the relationship is now modeled as nonadditive (Brambor, Clark, & Golder, 2006; Cohen, Cohen, West, & Aiken, 2003). For example, the coefficient of DENSITY reflects the marginal effect of density for only one particular case: where PEER equals zero.[8] Similarly, the standard error reported for the coefficient represents the standard error only for the case where PEER equals zero. It is in fact very difficult to interpret the relationship by only examining the values presented in Table 2. To gain a more complete picture of the estimates, we summarize the findings about the relationship between peer achievement, network density, and student achievement in Figures 2, 3, and 4.

Using the estimates from Model III, Figure 2 summarizes the joint

Figure 2. The joint effect of lagged peer achievement and network display on student grade point average



effect of PEER and DENSITY on student GPA, evaluated at the mean values of the other independent variables. The height of the surface in the Figure 2 represents the predicted GPA2. Note that the highest region of the surface occurs at high levels of both DENSITY and PEER, and the lowest region is at high levels of DENSITY and low levels of PEER. For example, the predicted GPA2 evaluated at one standard deviation above the mean for DENSITY and one standard deviation above the mean for PEER equals 2.61. In contrast, the predicted GPA2 evaluated at one standard deviation above the mean for DENSITY and one standard deviation below the mean for PEER equals 2.15. Note also that the largest marginal effects—that is, the steepest slopes on the surface—occur toward the edges of the surface, primarily along the edges of high DENSITY, and high and low PEER.

Figures 3 and 4 provide a more detailed look at the marginal effects. Figure 3 depicts the density-moderates-peer-achievement interpretation of the interaction. The straight undashed line represents the marginal effect of peer achievement on student performance across the entire range of observed network density, and the curved dashed lines represent the 95% confidence interval around the estimate.[9] Two aspects of this relationship are worth noting. First, peer influence has a statistically significant marginal effect on student performance for the range of (uncentered) density values higher than 39.7—the point at which the lower bound of the 95% confidence interval rises above the zero line. About one quarter of our sample falls into this range. Second, for a large

Figure 3. The marginal effect of lagged peer achievement on student grade point average.

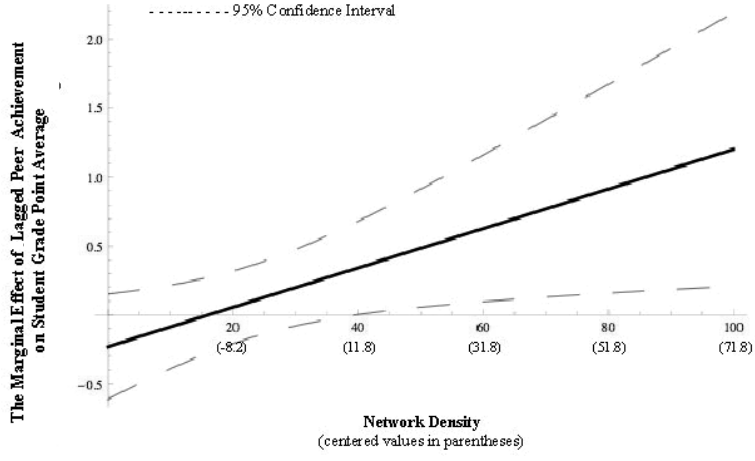
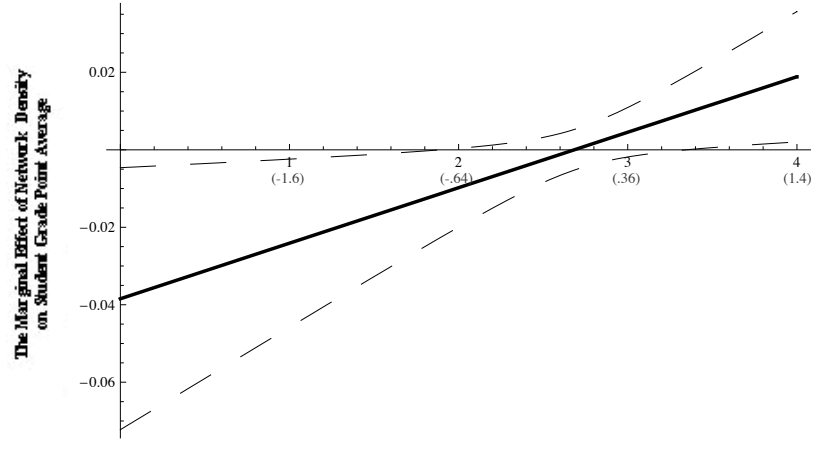


Figure 4. The marginal effect of network density on student grade point average.



portion of the range of network density and for all the network density range that is statistically significant, the association between peer achievement and student performance is positive. At the lower end of the significance range (density = 39.7), the size of the marginal effect is modest,

but not trivial, with a 1-point change in peer achievement predicting a 0.34-point change in student GPA. Moreover, the marginal effect grows stronger as network density increases. For a student with a rather high density of 70, a 1-point change in peer achievement predicts 0.77-point change in student GPA.

Figure 4 illustrates the range of significance for a second interpretation of the interaction—the peer-achievement-moderates-density interpretation. The straight undashed line represents the marginal effect of network density on student performance across the entire range of observed peer achievement, and the curved dashed lines represent the 95% confidence interval around the estimate. The most interesting thing to note about Figure 4 is that the marginal effect of network density on student performance changes signs and has ranges of significance in both the positive and negative areas. On the positive end of the association, the marginal effect of a one-standard-deviation increase in density ranges from a 0.21-point increase in student GPA, where the relationship first becomes significant (peer achievement = 3.36), to a 0.32-point increase in student GPA at the maximum peer achievement that we see in our sample (3.72). On the negative end, the marginal effect of a one-standard-deviation increase in density ranges from a 0.24-point decrease in student GPA at the point where the negative relationship first becomes significant (peer achievement = 1.89), to a 0.40 point decrease in student GPA at the minimum peer achievement that we see in our sample (1.37).[10] We should note, however, that although peer achievement levels of 3.36 and 1.89 are plausible values, they only constitute approximately 10% of our sample.

In summary, we find a significant joint effect of network density and peer achievement on student achievement, with highly dense networks of low-performing peers associated with the largest negative effect on student achievement, and highly dense networks of high-performing peers associated with the largest positive effect on achievement. Examining the marginal effect of peer achievement gives us one indication of how social structure matters for this population of students: Peer effects appear context dependent, with a significant positive association between peer achievement and student performance being observed at high, but not necessarily unrealistic, levels of network density. This is a finding consistent with the idea that norm enforcement arising from network density amplifies the direct effect of peer influence. Additionally, examining the marginal effect of network density on student achievement suggests that network density can both help and hurt students, depending on the achievement level of their peers. The significance of this association,

however, is limited to relatively extreme levels of peer achievement in our sample.

ROBUSTNESS OF THE INFERENCE

Although using observational data from a small sample collected in a single school has the advantage of providing complete network data for a community of students, it also raises questions of internal and external validity. Acknowledging the potential limitations of our sample, in this section, we attempt to quantify our concerns using indices of robustness developed by Frank and colleagues (Frank, 2000; Frank & Min, 2007; Pan & Frank, 2004), as we describe next.

With regard to internal validity, of particular concern for models of social contagion is that individuals with similar levels of the dependent variable might be more likely to create network ties with each other, thereby overstating the role of group influence (Manski, 1993). The implication is that even after controlling for a prior level of the dependent variable, the estimated model is still missing an unobserved, confounding variable. For example, in this analysis, one might hypothesize that students create network ties not only on based on prior achievement but also on an unobserved desire to achieve academically.

Because our analysis implies that peer achievement is associated with student achievement through network structure, we focus our robustness analysis on the density–peer interaction. Here, one might argue that students choosing friends of similar achievement levels makes peer achievement appear as if it moderates the benefits of network density. Framing it as a confounding variable problem, one might more specifically hypothesize that we have not controlled for an unobserved student-level characteristic that also operates through network density.

To quantify the concern of a potential confounding variable, Frank (2000) asked what one would have to believe about (a) the correlation, r_{vx}, between a potential confounding variable, v, and an independent variable of interest, x; and (b) the correlation, r_{vy}, between v and a dependent variable, y, to invalidate an inference of interest. He defined the "impact" of a confounding variable on an estimated regression coefficient as the product of these two correlations, $r_{vx} \times r_{vy}$, and developed an expression for the impact threshold of a confounding variable (ITCV)—the level of impact necessary to invalidate an inference based on some specified criteria (for example, the minimum correlation necessary to observe statistical significance at the 0.05 level).[11] To create a benchmark for comparison for the ITCV, one can then use the data in the sample to

calculate the impact of the other covariates.

Using statistical significance at the 0.05 level as our threshold criterion, the ITCV for the density–peer interaction term equals 0.016.[12] To provide points of comparison, we create a reference distribution of the impacts of other interactions that imply that a student characteristic is associated with student achievement through network density (i.e., other potential multiplicative density-covariate interaction terms). Comparing the ITCV with the impacts ($r_{vy} \times r_{vx}$) of other density–covariate interactions, we see that it would take a confounding variable with an impact larger than any of the other potential interactions to invalidate the inference that the density–peer interaction term is significant at the 0.05 level.[13] Moreover, the 0.0016 estimate of the ITCV is a conservative one because it assumes that the confounding variable is not correlated with any of the existing covariates. To the extent that the confounding variable correlates with covariates other than the interaction term, the ITCV of the interaction term would be higher. In short, although not eliminating all concern, the ITCV comparisons do increase our confidence in the inferences drawn from the density–peer interaction term.

With regard to external validity, if one views this study as a case illustrating how network structure can mask the effect of peer achievement, then part of determining the extent to which this case might generalize to other situations requires understanding the conditions under which the masking may not occur—that is, situations in which the main effect of peer achievement would be statistically different from zero. To quantify the answer to such a question, Frank and Min (2007) proposed considering what proportion of the cases in a sample, π, must be replaced with cases from an unobserved sample—with a different correlation—to invalidate the inference drawn from the observed sample. Drawing on mixture models (McLachlan & Peel, 2000), they stated the combined correlation in the new, hypothetical sample as the weighted average of the observed and unobserved correlations between a variable of interest, x, and a dependent variable, y, as $r_{xy}^{combined} = (1 - \pi)\, r_{xy}^{observed} + \pi r_{xy}^{unobserved}$—a relationship that can equivalently be expressed in terms of regression coefficients, $\beta_{xy}^{combined} = (1 - \pi)\beta_{xy}^{observed} + \pi\beta_{xy}^{unobserved}$. Replacing $\beta_{xy}^{combined}$ with a threshold value of relevance allows one to then explore the combinations of π and $\beta_{xy}^{unobserved}$ that would invalidate the inference.

The primary virtue of this approach is that instead of focusing only on the "surface similarity" (Shadish, Cook, & Campbell, 2002) of the observed and unobserved samples, it places the emphasis on how those differences in surface similarity might manifest themselves in differential associations with the dependent variable. In our masking-the-peer-effect case, the specific concern would be that differences in achievement

levels and ethnicity between our sample and a population of interest manifest themselves in differences in the strength of the marginal effect of peer achievement. Using the described relationship, we quantify how large that difference would have to be in order to draw a new inference from the data: Assuming that we replaced half of our observed sample with cases from an unobserved sample, the average marginal effect of peer achievement in the unobserved sample would have to be at least 0.44 to observe a statistically significant main effect of peer achievement.[14] This implies that observing a main effect in a similarly sized sample would require that for half of the cases in the sample, a 1-point change in peer GPA would result in almost a half-point change in student GPA, even after controlling for all other covariates. The considerable size of this value is due in large part to the small size of the sample. Recalculating with a sample size 5 times larger than ours results in a required marginal effect in the unobserved sample of 0.14—a lower and more plausible value, but one that is still approximately 1.5 times larger than the marginal effect in our sample. For sample sizes between 5 and 6 times larger than ours, the required unobserved marginal effect drops to 0.09, implying that a sample of that size would have been large enough to make our observed average effect of peer achievement significant at the 0.05 level (but would still hide the heterogeneity of the effect across network locations).

DISCUSSION

This article has framed in network terms three interpersonal mechanisms through which a student's "connectedness" can impact academic performance. The first is related to the composition of a student's network, or the *who* of the network, and is similar to standard peer effects models in education research. The idea is that a student's peers can directly influence, inform, or assist a student, and therefore, the composition of the student's peer group matters. The other two mechanisms incorporate the pattern of interrelations among those peers, or the structure of the network. Students located in dense, norm-enforcing networks may reap the benefits of increased trust and conformity that come from network closure. Students located in less dense, horizon-expanding networks may reap the benefits of increased diversity of information and autonomy.

We attempt to exploit variation across students in both network composition and network structure to make inferences about the interpersonal mechanisms at work in a school-within-a-school created at a large urban high school. By collecting detailed network data on the social relations

between students and combining them with individual-level data from school records, we first look for evidence of an aggregate association between network characteristics and academic performance when holding constant the individual-level attributes of the students. We find no evidence of aggregate effects from either network composition or network structure, implying that there is no dominant social capital-generating mechanism at work in this sample. However, examining only the main effects of the network composition and network structure masks the potential moderating impact that they can have on each other. When including an interaction between peer achievement and network density in the analysis, we find a significant joint effect of network density and peer achievement on student achievement, with highly dense networks of low-performing peers yielding the largest negative effect on student achievement, and highly dense networks of high-performing peers yielding the largest positive effect on achievement.

When the interaction is viewed as network density moderating the marginal effect of peer achievement on academic performance, we see that the association between peer achievement and student performance grows stronger as network density increases—a finding consistent with the notion that network closure amplifies the effect of peers. The significance of this association is limited to a range of high, but plausible, levels of density. When the interaction is viewed as peer achievement moderating the marginal effect of the benefits of network density, the association between network density and student performance is positive for levels of relatively high peer achievement, and negative for levels of relatively low peer achievement—a finding consistent with the idea of a norm-enforcing mechanism at work in this community of students. However, the significance of this association is limited to relatively extreme levels of peer achievement, for which we have few data points in our sample.

IMPLICATIONS FOR RESEARCHERS

For researchers, the findings of this study suggest a danger in the use of standard peer effects models that do not take network structure into account. Moreover, the context dependence of peer effects may help explain differences across peer effects studies. In a review of literature about the influence of peer effects on learning outcomes, Wilkinson et al. (2000) made two observations with respect to this point. One is that the average "compositional effects" of learning environments have large variability between studies and are small to moderate in size—a finding that they point out is at odds with descriptive studies that document the

influence of peers on a student. The other is that effect sizes have a predictable pattern across levels of aggregation. Studies that use small groups as the unit of analysis find higher compositional effect sizes than do studies that use classrooms, which in turn find higher effect sizes than studies that use schools. One explanation that Wilkinson et al. put forth for these two findings is that

> data aggregated at the school or class level, or even at the group level, may not capture the relevant processes by which peer effects occur. This could be because they don't have the fidelity to pick up small effects or because there are counterbalancing forces—some "groups" within the class or school are productive groups and some are not, so they cancel or reduce each other's effects. (p. 117)

Although only providing one case as an example, our findings are certainly consistent with this explanation. This study also provides an example of how a social network approach can help bridge the gap between what Wilkinson et al. referred to as "outcome-based research" and descriptive studies that place greater emphasis on understanding the social processes that give rise to those outcomes.

The approach taken here could also be used to study aspects of school reform that go beyond peer effects. For example, one can imagine applying a similar framework to study the hypothesized benefits of social control that comes from closure in a student's adult network (teachers and parents). One might also apply a social network approach at the school level to study horizon expansion efforts of many small schools that create programs and alliances with external partners. For future applications to other student outcomes, however, it is important to keep in mind that the a priori hypotheses put forth here about the relationship between network characteristics and academic achievement may not necessarily be the same for all dependent variables. The particular case we have in mind is a student's likelihood of dropping out of school. In this case, one might still hypothesize that network closure of low-achieving peers hurts students with respect to achievement, but one might also predict that the increased sense of belonging that comes from social closure helps students by increasing the probability of staying in school (assuming that the student's peers do not drop out). Simply put, the prediction of the effect of network closure on students depends on the student outcome of interest.

Finally, we note that future research designs involving a probability sample of students across schools (as opposed to collecting complete

network data inside schools) will benefit greatly from a survey question eliciting the student's perception of the strength of relation between listed contacts. In our case, such a question was used as a small supplement to our data. In cases in which one does not survey a large portion of the network of interest, however, such a question provides the second-order contact information necessary to calculate structural measures of the student's social network such as density.[15]

IMPLICATIONS FOR REFORMERS

For reformers, this article presents a finding consistent with the underlying assumptions of small-schools reform; namely, that social relations play a role in determining student performance, even after accounting for individual-level factors and characteristics. Perhaps less consistent with small-school reformers' beliefs, however, this analysis also suggests that increased "connectedness" does not always result in positive outcomes for students. More specifically, connectedness in the form of high network density appears to hurt the achievement of students with low-achieving peers. To the extent that the student population one is trying to help contains a large population of low achievers, this finding leads to the counterintuitive conclusion that it may not be beneficial to encourage a student social environment in which "everyone knows everyone else."

One way to view this finding is as the network version of a teacher's intuition to split up two students in a class who seem to be bad influences on each other. In that sense, the message here is not necessarily novel. However, it may be easy to overlook applying this idea at the level of a student's broader network in reforms that place a strong emphasis on the positive aspects of network closure. For example, in the high school studied here, students are assigned to homeroom classes for the first 20 minutes of the day. Homeroom periods in this school serve primarily an administrative function (attendance taking, announcements, and the like), leaving plenty of time for socialization and relationship building to take place among the students. Homeroom assignments are random, with one notable exception: Students who were held back a grade for academic reasons are purposely placed in homeroom periods together. It should be clear that our findings suggest that situations like this should be avoided.[16]

LIMITATIONS

Several notes of caution about the analysis and conclusions are

warranted. First, although we present a detailed analysis of the interaction between peer achievement and network density, we should reiterate that this is a relatively small sample. As one can see from the rapid "flaring out" of the confidence intervals in Figures 3 and 4, the size of the sample becomes of particular concern when drawing inferences near the extremes of the peer achievement and network density distributions. Consequently, a conservative interpretation of these data would place greater emphasis on the existence of a significant joint effect of peer achievement and density as compared with the precise location of the significance thresholds, or estimates of the conditional marginal effects.

Second, a valid criticism of social contagion models is that an observed association between network variables and the dependent variable of interest is more a function of individuals with similar levels of the dependent variable choosing to create network ties with each other, as opposed to the network variables causing some change in the dependent variable (Evans, Oates, & Schwab, 1992; Manski, 1993). This criticism points to the importance of collecting longitudinal network data as well as longitudinal performance data for future work (Snijders, 2005). Although we cannot definitively rule out that such a selection process takes place among the students in our sample, several factors mitigate against the possibility that selection bias accounts entirely for the associations that we report here. First, we know that the students in this small school are not tracked by achievement. Any systematic network selection would have to take place largely as a result of student choice in an academically heterogeneous environment. Second, although we do not use longitudinal network data, we do have longitudinal performance data and include two measures of prior achievement as controls. Finally, the possibility of student network selection on the basis of similarity in achievement is most threatening to estimates of *direct* peer influence. The primary finding of this article, however, is about the *joint* effect of peer achievement and network density on student performance. Moreover, framing the network selection issue as a confounding variable problem and quantifying the robustness of the density–peer interaction helps put this concern into perspective: To invalidate the inference that the density–peer interaction is significant at the 0.05 level, we calculate that a hypothetical confounding variable correlated with both student achievement and the density–peer interaction would have to have an impact larger than the impact of any density–covariate interaction for which we have data.

A third major concern with this study is that we cannot be certain that the findings reported here are not just a consequence of a particular peer group dynamic at a single school. Because we do not have data across schools, we do not claim that these results must apply to small schools in

general. Instead, we interpret the substantive results of this study as a case illustrating the joint effect of network structure and composition, and we attempt to quantify situations in which this interaction would *not* mask a main effect often of interest in educational research—the effect of a student's peers. One such case is for a sufficiently large sample, which our robustness calculations indicate is between five and six times the size of our current sample. For a similarly sized sample, we calculate that in order to observe a statistically significant main effect for peer achievement, we would have to replace half of our sample with observations from another sample in which a 1-point change in peer GPA results in a 0.44 change in student GPA—a marginal effect almost 5 times larger than the one observed in our data.

CONCLUSION

In this study, we adopt a social network perspective on the advantages that arise from increasing "connectedness" or "building community" in schools. Drawing on existing work from a network perspective of social capital, we hypothesize that students located in dense, norm-enforcing networks may reap the benefits of increased trust, conformity, and belonging that come from network closure. Students located in less dense, horizon-expanding networks may reap the benefits of increased diversity of information and autonomy. Moreover, both theory and prior work on adolescent behavior suggest an interaction effect between network composition and structure.

Using social network data collected from a large urban high school implementing a school-within-a-school reform, we find that lagged peer achievement and network density have no average association with student performance after accounting for individual-level characteristics. The average associations, however, mask an important interaction between the characteristics of a student's peers and the location of the student in a network structure. When interacting lagged peer achievement and network density, we find a significant joint effect, implying that the benefits arising from a student's social relations are context dependent.

While keeping in mind the limitations of data that come from a single school, these findings imply that to the extent that the student population one is trying to help contains a large population of low achievers, increasing connectedness in the form of network closure can be detrimental to academic performance. More broadly speaking, they suggest that to diagnose the impact of building stronger community in schools,

it is necessary to consider the network structure of students' relationships, particularly when examining the influence of peers.

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Notes

1. For an introduction to the use social network analysis in social science research, see Scott (2000). For a historical account of the development of the field, see Freeman (2004). A more technical treatment of the tools and techniques of social network analysis can be found in Wasserman and Faust (1994).

2. The key to these models is creating the appropriate measure for each individual, *i*, that aggregates the characteristics of each of the other individuals in their network, *j*. This is done by assigning a weight, w_{ij}, to each *j* based on considerations about *j*'s relationship to *i*. We discuss one specification of the weight matrix in the text. See Leenders (2002) for an extended discussion on alternate specifications in models of social contagion.

3. We discuss some of the applications next. Review of this work can be found in Burt (2000).

4. In fact, much of Coleman's evidence for closure comes from an educational setting—an analysis of differences in high school student dropout rates. Coleman emphasized that in a network in which children's parents are more likely to know each other, the closure between parents facilitates trust by providing community norms that reward favored behaviors and sanction unwanted ones for the children.

5. Respondents were asked whether they interacted with the people they cited *at least once a day* (81% of the total responses), *at least once a week* (13% of the total responses), *at least once a month* (5% of the total responses), or *rarely* (1% of the total responses). We used these responses to weigh student ties by frequency of interaction, where the weight was the proportion of total interactions in a semester that could be attributed to a particular contact. Given the large number of responses that fall into the *at least once a day* category, the results presented in the next section are not sensitive to the precise operationalization of the weights. For example, when estimating Model III with ties of equal weight, the coefficients (and standard errors) of PEER, DENSITY, and DENSITY x PEER are .125 (.145), -.001 (.027), and .013 (.0065), respectively.

6. Defining the peer group in this way implies a belief that contagion takes place through close ties. This definition is a strict version of defining peer groups through

cohesion—social proximity in terms of the number, length, and strength of the paths that connect actors. In principle, one can also define peer groups and related weights through *structural equivalence*—social proximity in terms of the extent to which actors have similar relations with other actors. The two definitions reflect differences in the belief about the social processes through which contagion takes place. Defining reference groups through cohesion reflects the belief that contagion takes place through direct influence and communication, whereas defining reference groups through equivalence implies contagion through social comparison (see Burt, 1987; Marsden & Friedkin, 1993). We take a social cohesion approach in this article because it more closely reflects the social capital arguments in the education literature.

7. As a formal model of social contagion, the base model used in this analysis can be expressed as follows: $GPA2_i = \beta_o + \beta_1 DENSITY + \beta_2 PEER + \beta_3 GPA1_{i1} + \beta_4 X_{i2} + \ldots + \beta_{k+3} X_{ik} + \epsilon_{it}$ where *PEER* is $\sum_{j=1, j\neq i}^{n-1} w_{ij} GPA1_j$, w_{ij} is the weight given to each relationship between i and j based on frequency of interaction, X_{i1} to X_{ik} are a set of individual-level attributes gathered from school records, and *GPA2*, *GPA1*, and *DENSITY* are as described in the text.

8. Because PEER is mean centered, the coefficient of DENSITY can be interpreted as the marginal effect of DENSITY for a student with average peer achievement. Similarly, because DENSITY is mean centered, the coefficient of PEER can be interpreted as the marginal effect of PEER for a student with average DENSITY.

9. The marginal effects in Figures 2 and 3 were found by taking the partial derivative with respect to the variable of interest of the regression equation estimated in Model III. The standard errors used to plot the confidence interval were calculated as $\sqrt{\mathrm{var}(b_1) + Z^2\,\mathrm{var}(b_2) + 2Z\,\mathrm{cov}(b_1 b_2)}$, where b_1 is the estimated coefficient of the variable of interest, and b_2 the estimated coefficient of the "moderating" variable *Z*. See Brambor et al. (2006) and Cohen et al. (2003, p. 273).

10. To give a sense of the relevance of the effect size, we note that the value of density is not that difficult to change (at least numerically speaking). For a student with the average network density and average number of peers, adding one peer to her network who is not tied to any of the other peers decreases density by 0.38 standard deviations. Adding two unrelated peers decreases density by 0.61 standard deviations. For example, given a mean network size of 5.9, a mean density or 28.2 implies that 8.15 connections exist among this hypothetical student's peers, that is, 28.2 = 8.15 / (5.9 * (5.9 – 1)). Adding one peer results in a density of 8.15 / (6.9 * (6.9 – 1)) = 20.0. The change expressed as a standard deviation of density is (28.2 – 20.0) / 21.3 = 0.38.

11. The ITCV for the bivariate case presented in Frank (2000) can be expressed as $(r_{xy} - r^{\#})/(1 - |r^{\#}|)$, where $r^{\#}$ is the threshold for making inferences from a correlation. $r^{\#}$ is given by $t_{critical} / \sqrt{(n^{ob} - q) + t^2_{critical}}$, where t_{critical} corresponds to the significance level of interest, n^{ob} is the number of observations, and q is the number of estimated parameters in the model. For the multivariate case with additional covariates, **z**, the ITCV expression is adjusted by the factor $\sqrt{(1 - R^2_{x|z})(1 - R^2_{y|z})}$, where $R^2_{x|z}$ and $R^2_{x|z}$ are the multiple correlation coefficients of **z** with the variable of interest and dependent variable, respectively.

12. For a sample size of 85, and a 0.05 level of significance, $r^{\#}$ equals 0.22. Using the expression for the multivariate case, a $r^{\#}$ of 0.22 translates into the ITCV reported in the text.

13. It would take an impact 1.2 times larger than the density–male interaction (impact = 0.082 x 0.16 = 0.013), 1.6 times the impact of density–reading scores interaction (impact = .086 x 0.11 = 0.010), or 3 times the density–absences interaction (impact = 0.092 x 0.057 = 0.005). We also calculate the impact of the density–race interaction and find a small but

negative impact (- 0.024 x -0.040 == -0.001), implying a suppression effect on the density–peer interaction.

14. Given a sample size of 85, we calculate that the marginal effect of peer achievement needed to observe a statistically significant main effect at the 0.05 level in the hypothetical combined sample is 0.265. Solving $0.265 = 0.091(1 - 0.5) + 0.5\ \beta_{xy}^{unobserved}$ yields a $\beta_{xy}^{unobserved}$ of 0.44. Note that this calculation assumes that the means and variances of the observed and unobserved samples are equal, an assumption that might be incorrect given a mean GPA of 2.37 in the observed sample. As a check, we use the full expression provided in Appendix B of Frank and Min (2007), which allows us to assume that the GPA of the unobserved sample is a much higher value. Using GPA of 3.0, this calculation yields a slightly higher, but similar, $\beta_{xy}^{unobserved}$ of 0.46.

15. For more on network sampling, see Marsden (1990).

16. We note that there were no students in our sample who were placed in such a homeroom.

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