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Do More Friends Mean Better Grades?

Student Popularity and Academic Achievement

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Abstract

Peer interactions have been argued to play a major role in student academic achievement. Recent work has focused on measuring the structure of peer interactions with the location of the student in their social network and has found a positive relationship between student popularity and academic achievement. Here we ascertain the robustness of previous findings to controls for endogenous friendship formation. The results indicate that popularity influences academic achievement positively in the baseline model, a finding which is consistent with the literature. However, controlling for endogenous friendship formation results in a large drop in the effect of popularity, with a significantly negative coefficient in all of the specifications. These results point to a negative short term effect of social capital accumulation, lending support to the theory that social interactions crowd out activities that improve academic performance.

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1 Introduction

The relationship between peers and student outcomes has been widely studied in economics.[1] This research has measured peer effects using the unweighted linear mean of behaviors or outcomes from an assigned reference group. Largely due to data limitations, the effects have been aggregated at the school, grade, classroom or dorm level in these studies. Aggregating in this manner, however, ignores significant information both about who students interact with, and the variation in the strength of interactions across different group members.

To account for the structure of interactions, a new line of research has defined peer effects as the centrality of the student within their social networks.[2] These various measures of centrality are generally referred to as popularity. Social networks can capture how information, social norms, obligations and sanctions are conveyed within social groups.[3] If connected individuals are concerned with group perception, as the work on social identity suggests, the relationship between popularity and outcomes will be positive.[4] Evidence of a significant positive relationship between popularity and outcomes can be found in the sociology literature in the context of adolescent criminal behavior and more recently in economic studies examining academic achievement [5].

Maintaining friendships is a time intensive process which can crowd out other activities. For example, there is evidence that adolescents spend a significant amount of time with each other, and that this time spent together is recreational, rather than task oriented.[6] If the crowded out activities impact the outcomes under consideration, then this could lead to popularity and outcomes being negatively related.

While these arguments for the relationship between popularity and outcomes are both com-

[1] Some examples are Evans et al. (1992), Betts & Morrell (1999), Arcidiacono & Nicholson (2001), Gaviria & Raphael (2001), Sacerdote (2001), Hanushek et al. (2003), Zimmerman (2003), and Arcidiacono et al. (2005).

[2] For an introduction to social network analysis, see Wasserman & Faust (1994). The economic theory of networks is reviewed in Jackson (2006).

[3] See Haynie & Payne (2006)

[4] Akerlof & Kranton (2005) examine social identity as a function of individual utility. See Fryer & Jackson (2007) and Antecol & Cobb-Clark (2004) for additional work related to the economics of identity.

[5] See Haynie (2001) results on criminal behavior and Calvo-Armengol et al. (2005) and Fryer & Torelli (2005) for work on academic achievement.

[6] See Montemayor (1982). Summary statistics from the American Time Use Survey indicate that respondents who are under 18 years of age spend less than 3 percent of their time in educational activities when they are with friends.

pelling, they overlook a key concern: individuals choose whom to associate with and these associations may be influenced by characteristics unobserved to the econometrician. For example, a student may have an outgoing personality or be self-confident; these characteristics can lead to more of her classmates choosing her as a friend, and may also lead to stronger academic performance. In this case ignoring the impact of such unobserved characteristics would incorrectly attribute their effect to popularity and lead to biased results.

This paper considers the effect of popularity on academic achievement, and ascertains the robustness of previous results to endogenous friendship formation. Popularity is measured by several indices describing the centrality of the individual in their school network. The impact of these measures is evaluated on academic achievement with and without the inclusion of controls for unobserved characteristics. The effect of endogenous friendship formation is identified from variation in the demographic composition of students within grades by gender in a given school.

The data used in this study is from the National Longitudinal Study of Adolescent Youth (Add Health). This survey contains detailed information on a sample of over 90,000 students. A crucial feature of the data for this analysis is the question asking the respondents to list up to five best male and female friends. These listings can be linked to individual identifiers, allowing for the reconstruction of social networks within the school. A number of popularity indices are calculated on these networks, each measuring a different aspect of peer interaction.

Results from the baseline model without controls for endogenous friendships indicate that popularity has a significant positive effect on academic achievement. Including fixed effects to control for unobserved school/grade quality leads to minor changes in the effect of popularity, with the effects remaining positive and significant.

To control for endogenous friendship formation, an instrumental variables regression is estimated where the interaction of individual demographic characteristics and the grade by gender composition of these characteristics are used as instruments for popularity. These instruments capture the extent to which the individual matches with students in their grade, and are valid if the extent of matching is correlated with friendship formation, but matching does not directly influence academic achievement. This strategy identifies the parameters from variation in composition of demographic variables within schools and grades across genders.

The results from these regressions find strong evidence that friendship selection is endogenous, and diverge significantly from previous findings regarding the impact of popularity on outcomes. The results turn from significantly positive in the baseline model to significantly negative in all of the specifications after instrumenting. For example, considering a person receiving two additional nominations as a friend, the baseline results imply an increase in GPA of .09 points, whereas GPA drops .21 points after controls for selection are included. The results indicate that the negative effect of time constraints outweighs the positive effect of information sharing in the relationship between popularity and academic outcomes.

The paper proceeds in the following manner. Section 2 reviews the relevant literature and explains the major contributions of this paper to this line of research. Section 3 describes the Add Health data and its key feature in making this estimation possible. Section 4 describes the various popularity indices, and Section 5 describes the estimation procedure. Section 6 presents the results, and Section 7 concludes.

2 Related Literature

The impact of social networks on individual outcomes and the process of friendship formation are areas of research that have been studied independently in many social science disciplines. The following section gives a general overview of the literature, and explains how the current study adds to existing work.

2.1 Social Network Effects

The majority of economics studies measure peer effects as a function of student characteristics or student behaviors.[7] These studies assume that associations are within the specified peer group, and

[7]Examples are Arcidiacono & Nicholson (2001), Gaviria & Raphael (2001), Betts & Morrell (1999), and Evans et al. (1992). An exception is Kinsler (2006) which uses peer disruptive behavior as a measure of peer effects.

that these interactions are captured by the unweighted average across the group. Mihaly (2007) shows that using the incorrect peer group can lead to a significant downward bias of the effect of peers on student delinquency. There is also conflicting evidence as to whether using the unweighted linear average is a close approximation of the true nature of interactions.[8] Weinberg (2006) models student association and behavior simultaneously, and uses Add Health data to test implications of a theoretical model. He finds strong evidence that endogenous associations imply nonlinear peer interaction. In addition, Hoxby & Weingarth (2005) find that the linear model is misspecified and leads to biased estimates.

Sociologists have suggested using the peer network structure as a different measure of peer effects. Social network theory holds that individuals in networks are constrained in their behavior to become consistent with norms and behaviors of the network. This implies that the structure of networks has an impact on individual behavior. Haynie (2001) uses Add Health data to examine how the structural properties of social networks influence the association between own and peer delinquency among high school students. The results indicate a negative correlation between network measures and delinquency, where the strongest effects are captured by network density and centrality.

Network effects have recently received more attention in the economics literature.[9] The majority of the studies focus on theoretical models of network formation and interaction.[10] An exception is Calvo-Armengol et al. (2005) which examines social network effects on educational outcomes. They find that a particular measure of network centrality called the Bonacich index emerges as the only Nash Equilibrium to a game where agents embedded in a social network choose actions simultaneously as a function of network member actions. Using Add Health data, they examine the impact of networks on academic achievement and find that increasing centrality in the network implies a significant increase in academic achievement. The key differences between this paper and Calvo-Armengol et al. (2005) is that instead of calculating centrality in a network structure that is

[8]Marmaros & Sacerdote (2003) show there is a positive correlation between friend and average group behavior, where the magnitude depends on the specification of the peer group. See Manski (1993), Moffitt (2001) and Brock & Durlauf (2001) for issues concerning identifying social interactions.

[9]See Jackson (2006) for a review of the literature with an emphasis on theoretical models.

[10]A few examples include Ioannides & Loury (2004) on job search, Calvo-Armengol & Jackson (2004) on labor market inequality, and Bramoullé & Kranton (2007) on public good provision.

assumed to be exogenous, the estimation procedure accounts for the fact that students are sorting into friendships which leads to the network structure.

2.2 Friendship Formation

A number of studies have examined the relationship between race and friendships. There is descriptive evidence that the racial composition of schools influences the extent of interracial friendships.[11] Most studies find that there is significant segregation between students, and the majority of the segregation is along race. In sociology, homophily is the theory that people prefer others who are similar to themselves along multiple dimensions. There is significant evidence of homophily along racial, economic, and cultural lines, which lends support to the use of demographic composition as an instrument for network centrality.[12] This descriptive evidence also indicates that simply redistributing students by race may not imply increased cross-racial interaction if students are choosing to self-segregate.

Echenique & Fryer (2007) examine the extent of within school segregation using a measure similar to the Bonacich centrality index which they show disaggregates to the individual and is a function of the segregation of the individual's network. They emphasize that the level of within school segregation is nonlinear in the percent of the minority in the school.[13]

Marmaros & Sacerdote (2003) measure friendships as the volume of emails exchanged by Dartmouth College students and alumni. They find that race, geographic proximity and same matriculating class are strong predictors of friendships, more important than common interests and similar family background. Mayer & Puller (2008) model the process of friendship network formation using data from Facebook. They find that friendships are significantly influenced by race and similarity in education, and a large percent of friendships can be explained by meeting friends of friends. This last result is suggestive evidence of the importance of social networks effects.

Similar to these last two papers, here we allow network centrality to vary by matching on race

[11] Joyner & Kao (2001) provide correlations of school race and extent of cross-race friendships. Quillian & Campbel (2003) examine the effect of the increase of Hispanics and Asians on black-white cross race friendships.

[12] See Miller McPherson & Cook (2001) for an extensive review of the sociology literature on homophily.

[13] A similar result is found in Moody (2001).

and family background. One difference is that our measures of friendships are directly from students' responses to the survey. While emails exchanged may proxy for true friendships, it is likely that they are noisy measures of the individuals who are influential in a student's life.[14] Another difference is that we take an additional step and examine the effect of friendships on student outcomes. Mayer & Puller (2008) provide some evidence on outcomes, but they do not control for the endogenous nature of the centrality measures.

3 Data

This paper uses data from the National Longitudinal Study of Adolescent Youth (Add Health), a nationally representative longitudinal school-based survey of students in grades 7-12.[15] The survey contains information on 90,118 students in 145 schools, with the first wave of the survey administered in 1994.[16] The research design of the survey focused on capturing the social environment of adolescents. As a result, information was collected from school administrators about school and neighborhood communities, and a random sample of students along with their parents were interviewed in depth about their home environment and individual behaviors.

Along with providing detailed demographic characteristics, all respondents are asked the following question: "List your closest male/female friends. List your best male/female friend first, then your next best friend, and so on." Students were allowed to list up to 5 friends of both gender. Unlike many previous studies on peer influence, the identity of the peers and their characteristics come from the survey responses of the peers themselves rather than the original respondents. The nominated students who attend the survey schools can be linked to student identifiers, which makes it possible to reconstruct social networks within the school.[17]

[14] Similarly, it can be argued that Facebook friendship nominations are noisy measures of who the student interacts with on a daily basis and therefore influences their behavior.

[15] For a description of the data see Chantala (2003) and the Add Health website at http://www.cpc.unc.edu/addhealth.

[16] Subsequent waves of the survey were administered to a sub-sample of the students in 1996 and 2001, with a fourth wave planned to start in 2008. Unfortunately the full friendship nominations were only collected in the first wave, and therefore the longitudinal aspect of the survey is not utilized in this paper.

[17] Approximately 5% of the nominations are dropped because they are students who do not attend the school. An additional 8% are dropped because they are students who are in the school but not on the directory of names used to

Table 1: Same Sex Friendship Nominations

Friends	**Frequency**	**Percent**
0	21,337	29.60%
1	10,613	14.72%
2	11,997	16.64%
3	11,896	16.50%
4	10,232	14.20%
5	6,006	8.33%
Total	72,081	
Mean	1.9605	
Std. Dev.	1.6789	

This paper focuses on same sex friendships within a school and grade.[18] Students are therefore dropped from the sample if they do not have valid information on gender and grade, resulting in a sample of 72,081 students. Table 1 shows the summary statistics for the friendship nominations. It can be seen that the quota restricting the maximum number of friendship listing to 5 only affects up to 8% of the sample. It is interesting to note that approximately 30% of students do not list any same grade, same gender friends.[19]

Summary statistics of the variables used in the estimation of the academic outcome equations are given in Table 2. The sample is equally divided among genders, 59% of the sample is white, and 16% is black. The "Other Race" option was provided in the survey, and it accounts for 12% of the sample. "Mixed Race" students are those respondents who filled in multiple answers to the question of race, and account fo 7% of the sample.[20]

The next few variables describe the family environment the respondents live in. Most students have mothers who work, and 78% live with their biological fathers. Mother's education is included as a proxy for student ability, with approximately 39% having a high school degree or less, and 43%

identify students.

[18] 83% of friendships are within the same grade, therefore this is not a serious restriction. There is reason to believe that opposite sex friendships are not comparable to same sex friendships as they are more likely to be transitory. Similarly, older or younger friends may exert different types of influence than same grade friends.

[19] Some of these zeros result from restricting the sample to same grade, same sex friendships. Section 1 in the Appendix explains the data coding for missing friendships

[20] The answers to this question were non-mutually exclusive.

attending college, regardless of degree completion. Additional variables include 3% of the sample being adopted, 17% living in a family with more than 5 people, and 8% being foreign born.

The outcome variable of interest is summarized in the last line, where academic achievement is measured by *GPA*, the mean of the Math, English, History and Science self-reported grades. These self reported grades refer to the most recent grading period prior to the survey, with a 4 being equivalent to an A and 1 is equivalent to a D or worse.[21] Students score somewhat higher than a C+ on average with a fair amount of variation.

Table 2: Summary Statistics

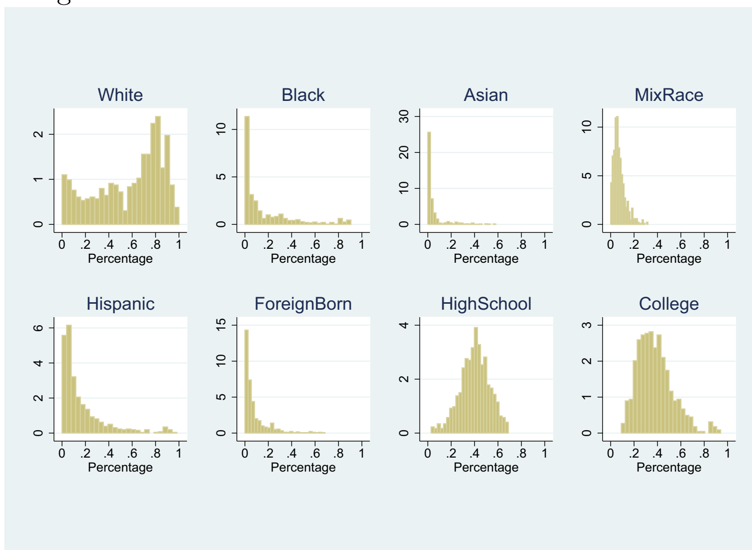
Variable	**Mean**	**Std. Dev.**	**Obs**
Female	0.5026	0.5000	45,611
White	0.5880	0.4922	45,611
Black	0.1618	0.3682	45,611
Asian	0.0505	0.2190	45,611
Native American	0.0127	0.1119	45,611
Other Race	0.1165	0.3209	45,611
Mixed Race	0.0705	0.2560	45,611
Hispanic	0.1658	0.3719	40,451
Mom Not Working	0.1773	0.3819	39,786
Mom HS Grad	0.3908	0.4879	45,611
Mom Some College	0.4261	0.4945	45,611
Adopted	0.0282	0.1655	44,634
Large Family	0.1740	0.3791	44,532
Live with Bio Dad	0.7812	0.4134	44,589
Foreign Born	0.0848	0.2786	44,434
GPA	2.8570	0.7901	45,611

The instruments used in the estimation are the grade by gender composition of race, ethnicity, and mother's education.[22] Because friendships are restricted to be the same gender, the aggregation for the instruments is also within grade by gender. Variation in these characteristics is required to identify the parameters in the instrumenting strategy. Figure 1 shows the distribution of these

[21] Add Health collected transcript data for a small subset of individuals. While these measures are not directly comparable, approximately 12.5% of students report a grade that is more than 1 grade point larger than the grade they received on their transcript, and almost 20% report a grade that is lower than their transcript average. Therefore, there does not seem to be a systematic misrepresentation of grades by the respondents.

[22] See Section 5 for the estimation strategy.

Figure 1: Distribution of Variables used as Instruments



Note: Observations are averages at the school/grade/gender level, with N=634

composition variables. Most of the instruments have considerable variation, and even in the case of percent black and percent mixed race where variation is not as large, there are still a number of gender grades that have high concentrations of these students.

Given that the specification includes school/grade fixed effects, the coefficients will be identified off of within grade variation in the gender level composition of these variables. The composition of demographic characteristics across genders is a plausibly random source of variation. To examine the extent of variation, Table 3 summarizes the difference in Male and Female average composition of demographic characteristics. For example, the first line refers to the difference in the percentage white of boys and girls within a grade by school. As expected, the differences in mean composition are centered around zero. Considering the minimum and maximum values, we can see that there are random composition changes within grade in all of the variables. Returning to the percentage white as an example, a certain grade of a given school has 11.5 percentage points more girls who are white than for boys. This variation is likely random and drives the identification of the parameters in the instrumenting strategy.

Table 3: Difference in Male and Female Composition of Demographic Characteristics

Variable	Mean	Std. Dev.	Min	Max	Obs
% White	-0.0040	0.0367	-0.1167	0.1228	317
% Black	-0.0018	0.0255	-0.1157	0.0949	317
% Asian	0.0023	0.0181	-0.0573	0.1396	317
% Mixed Race	-0.0059	0.0229	-0.0731	0.0685	317
% Hispanic	0.0062	0.0297	-0.1372	0.1215	317
% Foreign Born	0.0021	0.0192	-0.0973	0.0581	317
% Mom HS Grad	-0.0206	0.0386	-0.1585	0.1029	317
% Mom Some College	-0.0082	0.0353	-0.1121	0.1382	317

Note: Percentage variables calculated within grade by gender, differences are percent male minus percent female. Observations are school/grades.

4 Network Measures

Social network theory holds that networks constrain individual behavior to become consistent with norms and behaviors within the network. In order to measure the structural effect of the network on the individual, a number of different tools have been introduced in sociology, mathematics and computer science. To fully understand these measures, some notation is first introduced and the different network measures used are described. The four measures considered can be broken up into two categories: local network measures and global network measures. The local network measure is the in-degree centrality, while the global network measures include network density and two types of eigenvector centrality measures.[23] These four measures each capture different aspects of popularity, and they produce a different ordering when students are ranked based on the indices.

Let $\mathbf{G}$ denote the adjacency matrix of a given network, with $g_{ij} = 1$ indicating a link between node i and j. In the context of this paper the network is the collection of student of the same sex in a given school and grade, the nodes represent the students and the links represent friendships. There is no assumption about g_{ji} if $g_{ij} = 1$, implying that friendships are not restricted to be reciprocal and the adjacency matrix is not symmetric.

A number of different indices have been developed to capture the local centrality of an individual

[23] See Wasserman & Faust (1994) for an introduction to social network analysis, and Borgatti & Everett (2006) for a recent review of centrality measures.

in the network. The simplest of these is the *degree centrality* of the node, which counts the number of connections between the node and others. The *individual in-degree* (IDEG) of a node counts the number of links pointing to that node. This measure captures the influence of the immediate network of the individual - the extent to which friend interaction influences behavior. In graph notation, the individual in-degree is given by the column sum of **G**,

$$C_i^{IDEG} = \sum_{j=1}^{N} g_{ij} = G'1 \tag{1}$$

where 1 is an $N \times 1$ vector of ones, where N is the number of people in network **G**.

A basic measure describing the global network is network *density* (DENS). Density is defined as the number of links in the graph divided by the total possible number of links. The expression for density is given by

$$C_i^{DENS} = \frac{1}{5N} \sum_{j=1}^{N} \sum_{i=1}^{N} g_{ij} \tag{2}$$

This measure differs from the other indices described below because it varies across networks, not individuals.[24] The density captures the cohesiveness of the network, the extent to which information flowing through the network is reinforced.

The next two measures considered are called *eigenvector centrality* indices, which take into account the influence of the entire network in a nonlinear fashion. Individual centrality is a function of friend's centrality, where high individual centrality results for those who are chosen by others who are themselves highly central. First, define G^k with $k = 1, .., K$, the *connected component* of network **G**, as the partitions of the adjacency matrix where each subset containing only those individuals who are directly or indirectly linked to one another. The K subsets are disjoint, requiring that each individual belong to a single connected component. Each element of G^k is given by g_{ij}^k, with $i, j = 1, ..., N_k$.

The first measure of eigenvector centrality considered is the *Spectral Popularity Index* (SPI)

[24]Due to the survey design of Add Health, the denominator is $5N$ instead of $N(N-1)$, since the maximum number of friendship nominations is restricted to 5.

proposed in Bonacich (1972), and developed in the economics context by Echenique & Fryer (2007) as a measure of segregation and Fryer & Torelli (2005) to measure within race popularity. This measure takes centrality to be the weighted average of the individual's friends' centrality. It is defined recursively as

$$C_i^{SPI} = \frac{1}{\bar{C}^{SPI}} \sum_{j=1}^{N_k} g_{ij}^k C_j^{SPI} \tag{3}$$

where $\bar{C}^{SPI}$ is the average of the individual Spectral Popularity Indices within the connected component.

This system of equations can be solved using eigen decomposition. Let λ^k be defined as the largest eigenvalue of connected component G^k, with the corresponding eigenvector denoted by x^k. The solution to Equation 3 is given by

$$C_i^{SPI} = \frac{1}{\bar{x}^k}(\lambda^k x_i^k) \tag{4}$$

Echenique & Fryer (2007) derive three properties of this index: monotonicity (an increase in the number of connections implies an increase in popularity), homogeneity (multiplying the eigenvector by its eigenvalue allows comparability across connected components), and linearity (dividing by the average eigenvector normalizes the effect of popularity within the connected component).

Bonacich (1991) introduced a more flexible formulation of eigenvector centrality. The *Bonacich Eigenvector Centrality* (BONA) allows for discounting the centrality of those further away from the node, and assumes a different normalization. The recursive formulation is

$$C_i^{BONA} = \beta \sum_{j=1}^{N} (g_{ij}^k C_j^{BONA} - \alpha) \tag{5}$$

where α is a normalizing parameter, and β is a measure of the extent to which the centrality of those further in the network is weighted. Solving for the index results in

$$C_i^{BONA} = \alpha(I - \beta G^k)^{-1} G^k 1 \tag{6}$$

Setting $\beta = \frac{1}{\lambda^k}$ and α to the inverse of the mean connected component centrality results in $C_i^{SPI} = C_i^{BONA}$. In this application β is chosen to be $\frac{1}{2\lambda^k}$, implying that the centrality of those further in the network are weighted half as much as in the Spectral Popularity Index.[25]

The popularity indices described above are summarized in Table 4. Standard features of social networks are exhibited in the Add Health friendship networks. The degree distribution is right skewed with a low mean, and a fat tail. There is significant variation in the density and the centrality of individuals as measured by both of the eigenvector centrality indices.

Table 4: Popularity Measures - Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
IDEG	2.1488	1.9960	0.0000	13.0000	45,611
DENS	0.4057	0.1355	0.0359	0.7848	45,611
SPI	0.0458	0.1064	0.0000	0.7676	45,611
BONA	0.7480	0.5927	0.0000	3.8519	45,611

Table 5 shows the correlation matrix of the popularity indices. The Bonacich Centrality measure is more correlated with density than the Spectral Popularity Index because it weighs the popularity of closer friends more heavily. There is a fair amount of correlation between the two eigenvector centrality measures, but it is evident that they are not identical. From the correlation matrix it is clear that each of the popularity indices will result in a different ranking of students within networks and will capture different aspects of popularity therefore measuring different types of information sharing.

[25] The parameter α is chosen such that the norm of the eigenvector equals the number of observations, thereby controlling for network size. This results in an index where a value of 1 corresponds to the median centrality in that network. It is interesting to note that this measure of centrality is similar to PageRank, the algorithm used by Google to rank web pages.

Table 5: Popularity Measures - Correlation

Variable	IDEG	DENS	SPI	BONA
IDEG	1.0000			
DENS	0.3463	1.0000		
SPI	0.1995	-0.0026	1.0000	
BONA	0.7969	0.1969	0.4577	1.0000

5 Estimation

The primary equation of interest is the academic achievement function. It is modeled as a function of demographic, school and peer variables. While previous studies use various measures of peer effects, here the impact of peers on individual achievement is captured by the popularity of the student among her peers. A student's popularity can improve achievement if this sense of security allows for improved concentration, but can also detract from achievement if being popular taxes a student's limited time, and leads to less studying.

The achievement equation of student i is given by:

$$Y_i^a = X_i' \beta^a + \delta C_i + \phi_{sg} + \epsilon_i. \tag{7}$$

The X_i include demographic characteristics, and unobserved differences at the school/grade level are controlled with fixed effects denoted by ϕ_{sg}. To allow for the most flexible formulation of the model, there is a separate fixed effect for each school/grade combination. C_i are the four measures of popularity described in Section 4, and are assumed to be known by the student. The main parameter of interest is δ which captures the effect of student popularity on academic achievement.

If some students are more likeable than others because, for example, they match on observable characteristics with others in their grade, then they will have higher measures of popularity, and the coefficient of interest δ will be biased. To correct for this type bias, an instrumenting strategy is implemented. Equation 7 is estimated, with the first stage being

$$C_i = X_i' \beta^f + Z_i' \gamma + \phi_{sg} + \nu_i \tag{8}$$

where $Z_i = X_i \times \bar{X}_{gg}$. The instruments used are the interactions of individual characteristics X_i with the mean of that characteristic in the grade by gender. The characteristics used include race, ethnicity and mother's education, and are summarized in Table 2. These instruments control for the endogeneity of the popularity measures by capturing the extent of matching on observable characteristics by students with those in their grade and of the same gender.

The identification of the peer effect parameter comes from within school variation across grades in the mean demographic characteristics of students. Figure 1 shows that there is significant variation in these measures. An underlying assumption is that the mean characteristics calculated at the grade/gender level interacted with the individual characteristics do not directly influence the academic achievement of the student.

6 Results

6.1 Baseline Model

Table 6 shows the results from the baseline academic achievement equation, with each column labeled by the respective popularity measure used in the regression. Focusing first on the demographic characteristics, in all of the equations coefficients are of the expected sign and magnitude. The size of the coefficients do not vary across the specifications, so they will be considered in general. Girls report sizeably higher grades than boys. Compared to the white students, who are the excluded category, most races report significantly lower grades, with the exception of asian students who score 1/4 of a grade point average higher. Hispanics report lower grades than non-hispanics, while stay at home mothers do not significantly affect reported grades. Having a mother with some college education has a significant positive impact on achievement, and the effect of living with the biological father is also large and significant.

Turning to the popularity measures, note that they are all positive and statistically significant at the 1% level. Having an additional classmate nominate the student as a friend implies a small increase in GPA. Attending a school that is more dense has a larger positive effect. The two eigenvector centrality measures also imply an increase in GPA, although the magnitude of the effects vary considerably, a concern which is addressed below.

Including school/grade fixed effects in the specification results in minor changes to the demographic coefficients. These fixed effects control for unobserved school and neighborhood quality, as well as differences across grades. The demographic coefficients now being identified off of within school/grade variation in the characteristics. The results are reported in Table 7. The most noticeable change is the improvement in the precision of the regressions, with all of the Adjusted R^2 measures increasing in these specifications. The explanatory variables remain the same, with the exceptions of the coefficient on foreign born becoming statistically significant and more positive, indicating that these students typically attend lower quality schools. The coefficients on popularity do not change, with the exception of Density. The decrease in the coefficient on density can be explained by considering that this is the only centrality measure that is defined at the network, not individual level.

To ease comparability of the popularity measures and standardize the size of the coefficients, Table 8 isolates the effect of popularity on academic achievement from the above regressions. In addition, the effect of a one standard deviation increase in the popularity measure on achievement is considered. The Individual In-degree and Bonacich Eigenvector Centrality measures have the largest effects, with the other two popularity measures having a similar, though smaller effect. The magnitude of these effects are somewhat smaller than the effect of demographic characteristics.

Table 6: Achievement Results - Baseline Model

Variable	IDEG	DENS	SPI	BONA
Popularity	0.0473**	0.4701**	0.3672**	0.1783**
	(0.0018)	(0.0298)	(0.0328)	(0.0060)
Female	0.1435**	0.1202**	0.1653**	0.1514**
	(0.0070)	(0.0076)	(0.0070)	(0.0069)
Black	-0.2741**	-0.2629**	-0.2933**	-0.2732**
	(0.0101)	(0.0104)	(0.0102)	(0.0101)
Asian	0.2589**	0.2803**	0.2494**	0.2511**
	(0.0171)	(0.0172)	(0.0172)	(0.0171)
Native American	-0.1720**	-0.1801**	-0.1872**	-0.1654**
	(0.0314)	(0.0315)	(0.0315)	(0.0313)
Mixed Race	-0.0393**	-0.0417**	-0.0527**	-0.0381**
	(0.0139)	(0.0140)	(0.0140)	(0.0139)
Other Race	-0.0682**	-0.0609**	-0.0810**	-0.0690**
	(0.0142)	(0.0143)	(0.0143)	(0.0142)
Hispanic	-0.1737**	-0.1585**	-0.1863**	-0.1752**
	(0.0129)	(0.0130)	(0.0129)	(0.0128)
Mom Not Working	0.0523**	0.0471**	0.0445**	0.0530**
	(0.0098)	(0.0098)	(0.0099)	(0.0098)
Mom Some College	0.2930**	0.3075**	0.3022**	0.2879**
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Adopted	-0.1060**	-0.1180**	-0.1148**	-0.1018**
	(0.0211)	(0.0202)	(0.0213)	(0.0210)
Large Family	-0.0387**	-0.0446**	-0.0451**	-0.0364**
	(0.0094)	(0.0095)	(0.0095)	(0.0094)
Live with Bio Dad	0.1562**	0.1605**	0.1670**	0.1548**
	(0.0089)	(0.0090)	(0.0090)	(0.0089)
Foreign Born	0.0237	0.0249	0.0058	0.0246
	(0.0140)	(0.0141)	(0.0141)	(0.0140)
Constant	2.5210**	2.4327**	2.5956**	2.4859**
	(0.0114)	(0.0158)	(0.0110)	(0.0117)
Sigma	0.7368**	0.7404**	0.7415**	0.7354**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummies	Y	Y	Y	Y
School/Grade FE	N	N	N	N
N	45,611	45,611	45,611	45,611
Adjusted R^2	0.1304	0.1217	0.1193	0.1338

Note: ** is significant at the 1% level, * is significant at the 5% level.

Table 7: Achievement Results - Baseline Model with Fixed Effects

Variable	**IDEG**	**DENS**	**SPI**	**BONA**
Popularity	0.0430**	0.1970*	0.3926**	0.1718**
	(0.0018)	(0.0972)	(0.0319)	(0.0058)
Female	0.1572**	0.1585**	0.1778**	0.1644**
	(0.0068)	(0.0124)	(0.0068)	(0.0067)
Black	-0.2388**	-0.2518**	-0.2436**	-0.2242**
	(0.0119)	(0.0119)	(0.0119)	(0.0118)
Asian	0.2130**	0.2201**	0.2191**	0.2138**
	(0.0181)	(0.0182)	(0.0182)	(0.0181)
Native American	-0.2033**	-0.2172**	-0.2128**	-0.1927**
	(0.0300)	(0.0301)	(0.0301)	(0.0299)
Mixed Race	-0.0708**	-0.0803**	-0.0771**	-0.0640**
	(0.0137)	(0.0137)	(0.0137)	(0.0137)
Other Race	-0.1046**	-0.1096**	-0.1073**	-0.0999**
	(0.0140)	(0.0141)	(0.0140)	(0.0139)
Hispanic	-0.1421**	-0.1450**	-0.1439**	-0.1373**
	(0.0130)	(0.0131)	(0.0131)	(0.0130)
Mom Not Working	0.0452**	0.0390**	0.0397**	0.0468**
	(0.0094)	(0.0095)	(0.0095)	(0.0094)
Mom Some College	0.2618**	0.2751**	0.2719**	0.2568**
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Adopted	-0.1035**	-0.1132**	-0.1109**	-0.0991**
	(0.0202)	(0.0202)	(0.0203)	(0.0201)
Large Family	-0.0456**	-0.0520**	-0.0515**	-0.0429**
	(0.0090)	(0.0091)	(0.0091)	(0.0090)
Live with Bio Dad	0.1424**	0.1508**	0.1492**	0.1387**
	(0.0085)	(0.0086)	(0.0086)	(0.0085)
Foreign Born	0.1163**	0.1060**	0.1076**	0.1220**
	(0.0141)	(0.0142)	(0.0142)	(0.0141)
Constant	2.5246**	2.5479**	2.5816**	2.4741**
	(0.0814)	(0.0892)	(0.0818)	(0.0812)
Sigma	0.6993**	0.7039**	0.7027**	0.6971**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummy	Y	Y	Y	Y
School/Grade FE	Y	Y	Y	Y
N	45,611	45,611	45,611	45,611
Adjusted R^2	0.2166	0.2064	0.2090	0.2217

Note: ** is significant at the 1% level, * is significant at the 5% level,

Table 8: Achievement Results - Summary

Variable	IDEG	DENS	SPI	BONA
	Excluding School/Grade Fixed Effects			
Coefficient	0.0473**	0.4701**	0.3672**	0.1783**
	(0.0018)	(0.0298)	(0.0328)	(0.0060)
Std. Dev. Increase	0.0944	0.0637	0.0391	0.1057
	Including School/Grade Fixed Effects			
Coefficient	0.0430**	0.1970*	0.3926**	0.1718**
	(0.0018)	(0.0972)	(0.0319)	(0.0058)
Std. Dev. Increase	0.0858	0.0261	0.0418	0.1018

Note: ** is significant at the 1% level, * is significant at the 5% level. Std. Dev. Increase is the effect of a one standard deviation increase of the popularity measure on individual academic achievement.

6.2 Instrumental Variables

To correct for the possible bias due to selection in the popularity indices the instrumenting strategy is implemented. Table 9 shows the results from estimating equations 7 and 8.[26] There are no significant changes in the effect of demographics after instrumenting. However, the coefficient on all of the popularity measures become statistically significantly negative in these equations.[27] In addition, the magnitude of coefficients on popularity is now significantly larger. These results indicate that the baseline coefficients are biased due to endogeneity.

Table 10 isolates the peer effect coefficients from Tables 7 and 9 and displays the effect of a one standard deviation increase in the popularity measures. In considering the magnitude of these effects, it is useful to express the change in GPA relative to its standard deviation. Prior to instrumenting, a one standard deviation increase in the popularity measures lead to a one-eighth standard deviation increase in GPA. After the instrumenting strategy is implemented, the results indicate a drop in GPA of up to two-thirds of a standard deviation. The magnitude of the drop in the GPA in some cases outweighs the effect of many of the demographic characteristics.

[26] The first stage coefficients are jointly significant in all four regressions. Table 2 in the Appendix gives the results of various specification tests for the 2SLS estimation.

[27] The results for the spectral popularity index are not as strong as the other specifications, but the coefficient is still negative. The instruments for spi do not pass the rule of thumb test for weak instruments. See Table 2 in the Appendix for more information.

Table 9: Achievement Results - Instrumental Variable Results Effects

Variable	**IDEG**	**DENS**	**SPI**	**BONA**
Popularity	-0.1027**	-3.6021**	-2.2936**	-0.2424**
	(0.0393)	(1.7912)	(1.0589)	(0.1020)
Female	0.2337**	0.5652**	0.1896**	0.2016**
	(0.0218)	(0.1919)	(0.0090)	(0.0115)
Black	-0.2845**	-0.2505**	-0.3034**	-0.2922**
	(0.0176)	(0.0121)	(0.0263)	(0.0208)
Asian	0.2324**	0.2250**	0.2288**	0.2241**
	(0.0208)	(0.0187)	(0.0205)	(0.0197)
Native American	-0.2478**	-0.2172**	-0.2274**	-0.2498**
	(0.0348)	(0.0307)	(0.0366)	(0.0390)
Mixed Race	-0.1023**	-0.0808**	-0.1134**	-0.1023**
	(0.0173)	(0.0140)	(0.0183)	(0.0175)
Other Race	-0.1226**	-0.1082**	-0.1373**	-0.1241**
	(0.0161)	(0.0143)	(0.0174)	(0.0162)
Hispanic	-0.1546**	-0.1493**	-0.1456**	-0.1584**
	(0.0145)	(0.0135)	(0.0150)	(0.0147)
Mom Not Working	0.0233*	0.0412**	0.0420**	0.0274*
	(0.0118)	(0.0097)	(0.0108)	(0.0111)
Mom Some College	0.3052**	0.2733**	0.2873**	0.3000**
	(0.0144)	(0.0079)	(0.0122)	(0.0134)
Adopted	-0.1402**	-0.1103**	-0.1448**	-0.1373**
	(0.0235)	(0.0207)	(0.0244)	(0.0230)
Large Family	-0.0700**	-0.0561**	-0.0552**	-0.0673**
	(0.0115)	(0.0094)	(0.0105)	(0.0111)
Live with Bio Dad	0.1708**	0.1521**	0.1584**	0.1675**
	(0.0120)	(0.0087)	(0.0106)	(0.0111)
Foreign Born	0.0841**	0.1062**	0.0975**	0.0862**
	(0.0180)	(0.0145)	(0.0163)	(0.0177)
Constant	2.8674**	3.9280**	2.7409**	2.8471**
	(0.1237)	(0.6560)	(0.1869)	(0.1225)
Sigma	0.7497**	0.7156**	0.7534**	0.7354**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummy	Y	Y	Y	Y
School/Grade FE	Y	Y	Y	Y
N	44,434	45,611	40,451	44,434

Note: ** is significant at the 1% level, * is significant at the 5% level.

Table 10: Achievement Results - Summary

Variable	IDEG	DENS	SPI	BONA
Baseline Model with School/Grade Fixed Effects				
Coefficient	0.0430**	0.1970*	0.3926**	0.1718**
	(0.0018)	(0.0972)	(0.0319)	(0.0058)
Std. Dev. Increase	0.0858	0.0261	0.0418	0.1018
Instrumental Variables Model				
Coefficient	-0.1027**	-3.6021**	-4.9897**	-0.2424**
	(0.0393)	(1.7912)	(1.6087)	(0.1020)
Std. Dev. Increase	-0.2050	-0.4881	-0.5309	-0.1437

Note: ** is significant at the 1% level, * is significant at the 5% level. Std. Dev. Increase is the effect of a one standard deviation increase of the popularity measure on individual academic achievement.

7 Conclusions

This paper provides evidence on the robustness of previous findings on the relationship between popularity and academic outcomes. The Add Health dataset is used to reconstruct social networks in schools and calculate various indices of network centrality previously used in works by sociologists. The instrumenting strategy controls for the endogenous nature of friendships, using plausibly exogenous variation in the school/grade/gender group composition of student characteristics.

The results indicate that in the baseline regression popularity has a significant positive effect on academic achievement, similar to the findings in previous work. Adding fixed effects to control for unobserved school/grade quality does not change the estimates but does improve the precision of the model. Controlling for the endogenous nature of friendships with the instruments result in a significant drop in the coefficients on popularity, with all of the specifications now having statistically significantly negative coefficients.

While the exact avenue for this negative effect cannot be explained by this model, it does appear that given the time constraints students face in their daily lives and the types of activities they engage in with friends, more popular students perform worse in school. Further research is required to understand the avenues of these effects and to examine whether restricting student interactions to those where learning activities are encouraged can lead to better performance in school.

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8 Appendix

8.1 Missing Friendships

The Add Health survey asked students to up to list five male and five female friends. The analysis in this study focuses on same sex friendships, resulting in the maximum number of friends being restricted to five. In addition, the friends are restricted to be in the same grade as the respondent. This results in approximately 16 percent of friendships being dropped from the analysis.

In addition to the cases where no friends were listed, there were three types of friendships recorded where there was no survey information available about the friend, and would therefore show up in the data as zero friends. The first case is where the respondent listed a friend who did not attend either the respondent's school or the feeder middle school. The second case is where the friend listed attended the feeder school but did not fill out the survey. Finally, there were students listed as friends who were known to attend the respondent's school but did not themselves fill out a survey. Because the instrumenting strategy relies on the composition of the school, and these friends could not be included in the composition calculation, they were coded as missing friends. Table 1 summarizes the breakdown of missing friendships.

Table 1: Types of Missing Same Grade, Same Sex Friendships

Type	**Percent**
No Friend Listed by Respondent	52.24
Friend Does not Attend Add Health School	17.00
Friend Attends Feeder School, No Survey Data	4.85
Friend Attends Respondent's School, No Survey Data	9.13
Friend Listed is in Higher Grade	9.38
Friend Listed is in Lower Grade	7.40
All Missing Friendships	100.00

8.2 Specification tests

The table below displays the results from various specification tests for the instrumental variable regressions. The first tests for endogeneity with a regression based test described in Wooldridge (2002).

Table 2: IV Specification Tests

	IDEG	**DENS**	**SPI**	**BONA**
Endogeneity				
Hausman Test	0.1671	5.5710	4.3435	0.5039
p-value	0.0000	0.0090	0.0000	0.0000
Instrument Relevance				
F Statistic	20.86	15.57	6.59	27.50
p-value	0.0000	0.0000	0.0000	0.0000
Overidentifying Restrictions				
Hansen J Statistic	26.35	28.94	23.89	28.33
$\chi^2(7)$ p-value	0.0000	0.0000	0.0002	0.0000