ESSAYS ON PEER EFFECTS

by

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Dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy
in the Department of Economics
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ABSTRACT

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Abstract

This dissertation considers the relationship between peer and individual student interaction. The central finding is that self reported friends play a crucial role in individual behaviors, a role that is more significant than other students in their school. Also, using the network of friendships within a school it is possible to construct new peer effect measures and account for endogenous peer group formation. It is however important to distinguish these peer measures from unobserved individual characteristics that may also influence behavior.

The first chapter examines the effect of potentially misidentifying the reference group on peer effect estimates. The differential impact of school, grade and friend level peer effects on student decisions to smoke and drink are calculated. Friendship nominations come from the Add Health dataset, where students can list up to 10 friends from the school. The bias due to endogenous peer group formation and simulteneity are considered using various instrumenting strategies. Peer effects are found to be large and significant at the friends level for both delinquency variables. It is possible to show that misidentifying the peer group can result in peer effect estimates that are understated by as much as 40%.

The second chapter of the dissertation further examines the role of peer interactions, this time considering the effect of popularity on student academic achievement. Recent work has found a strong positive relationship between these variables. In this chapter I ascertain the robustness of these previous findings to controls for unobserved student heterogeneity using and instrumenting technique and a structural model. The results indicate that popularity influences academic achievement positively in the baseline model. However, instrumenting for popularity or including measures of unobserved student characteristics results in a large drop in the effect of popularity, and leads to a significantly negative coefficient in the majority of cases. Interestingly, popularity influences future earnings and attitudes positively, where this effect is robust to the inclusion of unobserved type. Policy simulations where

students are redistributed based on race or income indicate that the predicted number of friendships and popularity fall but academic achievement increases. Since student popularity increases happiness and earnings, the overall effect of the redistribution policies have to be considered before implementation.

Contents

List of Figures

List of Tables

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Chapter 1

Peer Effects of Actual Peers

1.1 Introduction

There is an increasing body of research in economics focusing on the role of social interactions in individual outcomes. This is especially true in the context of student behavior since adolescents spend a majority of their time in the company of their peers. Given that the existence of peer effects has implications for policy makers designing ability tracking, voucher and school desegregation programs, consistently estimating the magnitude of these effects has been the goal of recent literature. In addition, if peers influence individual outcomes, small initial changes in individual behavior induced by policy reform may imply large changes over time due to social multiplier effects.

While many recent studies have estimated the impact of peers in a variety of contexts, a major shortcoming of the literature is the possible misidentification of the peer group. In his seminal work on the identification of social effects, Manski (1993) states that "...informed specification of reference groups is a necessary prelude to analysis of social effects." Most recent studies use school, grade, classroom or dorm-level peer groups to study the effect of peer behavior or peer characteristics on individual outcomes. However, it is likely that the people the teenager chooses to interact with, namely her friends, comprise the relevant reference group.

This chapter uses the National Longitudinal Study of Adolescent Youth (Add Health) dataset to study the differential effect of school, grade and friend level peer effects on two delinquent behaviors: smoking and drinking. Friends are self-reported responses to the question asking the respondents to list their five best male and five best female friends. This unique dataset allows for the friend listings to be linked to the their student identifiers, making it possible for the full set of behaviors and demographics of the friends to be recovered from their own survey responses.

The estimation strategy first compares the relative sizes of the peer effects using the various peer group specifications. While these baseline estimates are informative, they potentially suffer from a number of biases. These biases are due to omitted variables, endogenous peer group formation and simulteneity. A number of corrections for these biases are considered.

First, school and school/grade fixed effects are used to control for omitted variables such as school and neighborhood quality and unobserved grade effects. Following Gaviria and Raphael (2001) the bias due to endogenous peer group formation is considered by examining the differences in the peer effect of students by residential mobility status. Another methodology considers instrumenting the friendship level peer effect with the grade level peer effect. This strategy illustrates the extent to which using an incorrect peer group such as the grade leads to an understatement of the peer effect. Additionally, the first stage coefficient can be interpreted as the strength of assortative matching among students. Identification for the peer effect comes from variation in the grade level delinquent behavior within schools.

To control for the bias due to simulteneity previous work has used the mean peer characteristics as instruments for mean peer behavior. However, using the rich information about friendship networks available in the Add Health dataset it is possible to consider a new instrumenting methodology. Therefore the original methodology is compared to this new strategy where the mean behavior of friends of friends who are not the individual's friends are used as an instrument for the peer effect.

In the baseline specifications peer effects are found to be large, positive and statistically significant for all of the peer group. Smoking exhibits larger peer effects than drinking in all of the specifications. The results from the instrumenting strategies controlling for endogeneity indicate that friends still have a strong influences on individual behavior. There is evidence of endogenous peer group formation from both the residential mobility estimates and the instrumenting strategy. These effects are not large in magnitude but significant for both smoking and drinking. There is also evidence that simulteneity is a concern, especially with the correlated effect instruments. Using the behavior of friends of friends may control for simulteneity but itself suffers from bias due to endogenous peer group formation, leading to the results being inconclusive.

The remainder of the chapter is organized in the following manner. Section 2 considers the recent literature on peer effects, and Section 3 describes the Add Health dataset in detail. Section 4 details the empirical methodology, Section 5 describes the results, and finally Section 6 concludes.

1.2 Recent Literature

The literature on peer effects is diverse in its application and methodology. Many authors have focused on educational outcomes, such as college student achievement measured with transcript data (Arcidiacono, Foster, Goodpaster, and Kinsler (2005)), grade point average (GPA) (Betts and Morrell (1999) and Zimmerman (2003)), GPA and fraternity membership (Sacerdote (2001)), medical school achievement (Arcidiacono and Nicholson (2001)), and elementary school achievement (Hanushek, Kain, Markman, and Rivkin (2003), Vigdor and Nechyba (2004), and Hoxby (2000)). In the context of teenage delinquent behavior, Evans, Oates, and Schwab (1992) examine peer effects on teenage pregnancy and school dropout, and Gaviria and Raphael (2001) analyze peer effects of drug use, smoking, drinking, church attendance, and school dropout. Many of these studies find significant peer effects.

The difficulties in estimating peer effects were formalized by Manski (1993), who describes three avenues of peer influence on individual behavior: (1) an *endogenous effect*, where the behavior of the individual is causally influenced by the behavior of the group, (2) an *exogenous (contextual) effect*, where the behavior of the individual is influenced by the characteristics of the group, and (3) a *correlated effect*, where the individual and the group behave in the same way due to similar environments. The author shows that identifying (1) and (2) separately in a reduced form linear model is not possible (a result known as the "reflection problem").

Two additional concerns have been raised in estimating peer effects. Peer effects may be biased due to selection, since peer groups are chosen by the individual or their family. For peer variables measured at the school or grade level, selection comes from sorting across neighborhoods due to differences in the parents' preferences for local amenities. In peer variables measured at the friends level, selection is compounded by the fact that students choose their friends. The resulting peer estimates may be biased away from zero due to sorting, with positive peer effects exhibiting a positive bias. The second additional concern is omitted variables bias from having inexact measures of the actual outcomes of interest and/or lack of information on past individual characteristics or measures of school quality.

Previous work has attempted to overcome these issues of estimation using various data selection and econometric techniques. Most studies overcome the reflection problem by assuming that contextual effects are zero (an exception is Evans, Oates, and Schwab (1992) where only contextual effects are measured). These studies argue that the characteristics of the peers only matter in how they influence behavior. Sacerdote (2001) and Zimmerman (2003) use random assignment to peer groups to overcome selection. Since college dorm mates are assigned to rooms randomly, the authors argue that selection is mitigated when using dorm-mates as peers. Hoxby

(2000) uses variation in the gender and race of the classroom to overcome the same issue. Fixed effects are used in Arcidiacono, Foster, Goodpaster, and Kinsler (2005), Hanushek, Kain, Markman, and Rivkin (2003), and Vigdor and Nechyba (2004) to overcome problems of selection into peer groups and imperfect measures of outcomes. By including fixed effects at the school or school-grade level, these papers control for common components of the ability measure, thereby accounting for sorting across peer groups and a majority of the measurement error. Hanushek, Kain, Markman, and Rivkin (2003) overcome the problem of correlated effects by estimating a first difference in outcomes, which allows them to identify the influence of peers on a value added achievement gain measure and reduces the need for historical data. Finally, instrumental variables are used in Evans, Oates, and Schwab (1992) and Gaviria and Raphael (2001) to correct for selection. To identify the parameters of interest, this method requires variables that influence friendship formation but not the outcome measure directly.

An issue that has received far less attention in the literature is the proper selection of the peer group. Most studies consider the peer group as given at the school, classroom or dorm-mate level, and assume that this is the relevant peer group for the outcome variable considered. One exception is Evans, Oates, and Schwab (1992), where the authors model the formation of the peer group at the school level directly based on exogenous characteristics. The concern with both of these methods is that neither may capture the actual reference group the individual is reacting to.

1.3 Data

The dataset for this study is the National Longitudinal Study of Adolescent Youth (Add Health). It is a nationally representative, school-based longitudinal survey of students in grades 7-12. Most importantly, respondents are asked to identify up to

10 friends in the school, which allows for the identification of the friend level peer effect unavailable in previous studies.

While the current release of the survey contains 3 waves, this study will focus on wave 1 information collected in 1994-95. 90,118 students were administered the in-school questionnaire, and a stratified random sample of 20,745 were given the more detailed in-home questionnaire (Chantala (2003)). The parents of students completing the in-home questionnaire were also surveyed. A detailed set of information about the respondent can be obtained by combining these multiple data sources.

The design of the survey insured that the resulting population of students are nationally representative. A set of 80 high schools were chosen from around the country based on size, school type, census region, level of urbanization and percent white. In addition, for each high school a representative middle (feeder) school was selected, where the selection was based on the percent of the students provided by the school. This resulted in 52 middle schools.

All students who were present at school on the day the survey was administered were given the in-school survey. This survey covered topics on social and demographic characteristics, education and occupation of parents, risky behaviors and friendships. A random sample of the students on the school roster were chosen for the in-home survey. This survey was typically completed in the respondent's home, and included audio computer-assisted self-interviews for more sensitive questions. Topics covered included nutrition, employment, romantic and sexual partnerships and criminal activities. The mother of the respondent was also asked to complete a questionnaire covering topics such as marriage, neighborhood characteristics, income, school involvement and expectations about their child's future.

Both samples of analysis have advantages and disadvantages. The in-home survey has the advantage of providing more detailed information about the social environment of the respondent, including information about the residential location of the student. However, a disadvantage of this sample is that the behavioral variables of the peers are only available if they were also selected for the in-home survey. The analysis therefore uses behavioral information from the in-school survey merged with the more detailed demographic information and parental survey responses from the in-home survey.

Most relevant to this study are the questions which appear in the in-school survey asking the respondent to name up to 5 best male and 5 best female friends. These responses can be linked to the unique identifiers used in the survey based on the school roster, which leads to detailed information on friends who attend the school and filled out a questionnaire. The mean behavior of the friends was calculated using their responses to the in-school questionnaire.

This chapter focuses on delinquent behaviors of respondents. The variable *smoke* is a dummy variables for whether the respondent smoked at least once or twice a week in the past year. The variable *drink* refers to drinking at least two or three times a month in the past year. The responses to this question are summarized in Table 1.1.[1] The first column shows the average of the delinquency variable at the individual level. 15% of the respondents report smoking and 18% report drinking based on the definitions above. The second column shows the summary statistics of the school average delinquency rate, and the third column shows the same information for the grade average delinquency rate in each school. The final column shows summary statistics for the average friends level delinquency.

Note that while the means of the peer variables are relatively constant across the various peer specifications, the standard deviations increase as the size of the peer

[1]These responses are from the in-school questionnaire with the sample restricted to those students in the in-home questionnaire with valid demographic information

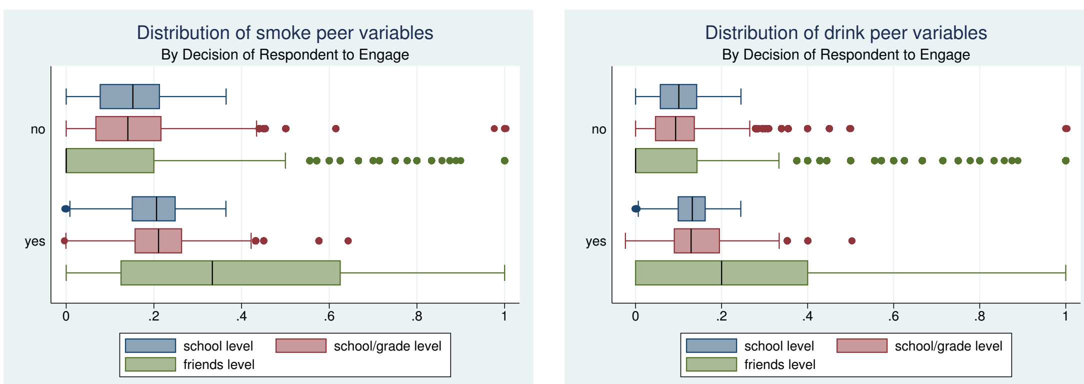
Table 1.1: Behavioral Variables: In-School Sample

behavior	individual	school	grade	friends
smoke	0.1521	0.1561	0.1561	0.1606
	(0.3592)	(0.0801)	(0.0964)	(0.2493)
	12,234	*11,736*	*11,732*	*12,131*
drink	0.1803	0.1876	0.1884	0.2047
	(0.3845)	(0.0817)	(0.1059)	(0.2575)
	12,234	*11,715*	*11,711*	*12,126*

Note: Standard Deviations in parentheses, number of observations in italics.

group falls. The standard deviation for the friends peer group is more than double the standard deviation for the school or grade peer groups. This will have important implications for interpreting the results of the peer effects regressions, since a one standard deviation increase in the peer variable will imply different sized peer effects.

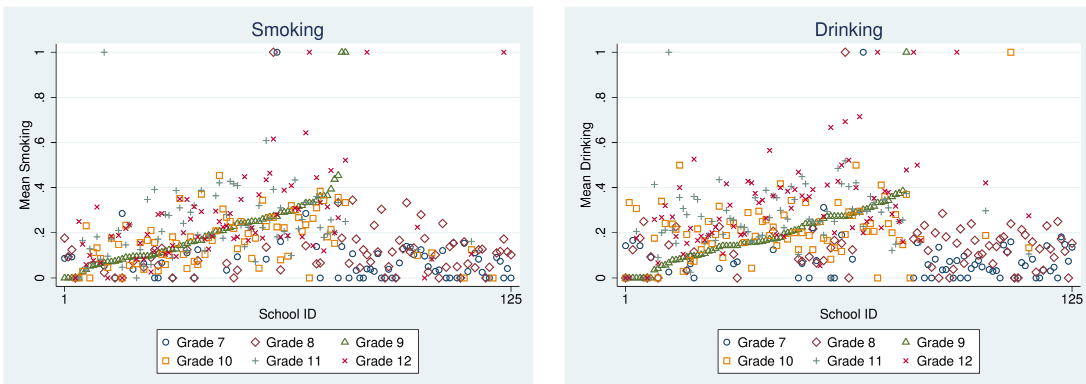
Figure 1.1: In-school sample - Box Plots



Note: The lower edge of the box represents the 25th percentile, while the upper edge represents the 75th percentile. The black line inside the box represents the median, and the markers are values outside 1.5 times the interquartile range.

The trend in the standard deviation for the delinquency variables can be seen in Figure 1.1. The box plots display the distribution of the peer smoking and drinking broken down by whether or not the student participates in the delinquent behavior. In general, as the size of the peer group falls, the distribution of the delinquency variable becomes more spread out. Also, from these plots it can be seen that the median of the peer variable for non-users is smaller than the median for users, indicating that peers of delinquents are more likely to be delinquent than peers of non-delinquents. This preliminary analysis lends support to the argument that individual and peer delinquent behavior are correlated.

Figure 1.2: Within School Variation in Grade Level Delinquency



The variation in the grade level delinquency is further explored in Figure 1.2. This shows the within school variation in the two delinquency variables broken down by grade. The schools have been sorted on ninth grade delinquency, which forms a line in the middle of the graphs, to provide a fixed point for comparison.[2] There are two general takeaway messages from these graphs. First, there is a significant amount of variation in the grade level delinquency within a school for both smoking and drinking. Second, in the case of smoking there is no clear age trend in delinquency, because 12th grade smoking is just as likely to exceed 9th grade smoking as it it to

[2]The last 30 schools do not have a ninth grade because they are either middle schools with grade 7 and 8, or they are senior high schools with grades 10-12. As a result there is no information on 9th grade delinquency.

fall below it. However, in the case of drinking there is evidence of an age trend, since 12th grade drinking rarely falls below 9th grade drinking in any of the schools. This trend will be addresses in the estimation strategy below.

The explanatory variables used in the analysis are summarized in Table 1.2. 54% of the respondents are female, and 22% are black. The respondents are between grades 7 and 12, with more students in high school than middle school, and with dropouts affecting the number of students in 12th grade. The mean of *religious* indicates that 66% of the respondents believe that "the scriptures are the word of God".

The responses to the parent survey are summarized in Panel (b) of Table 1.2. The mean income is $36,000, and 24% of the mothers report being single. 21% of the mothers have a college education, and 48% of them work full time. 54% of parent respondents report fighting with their partners some or a lot. Of the respondents, 38% report having smokers in the household, and 10% report drinking in the household at least 3-5 times a week. The next 2 variables indicate parental involvement in education - 12% chose the neighborhood specifically because of the school, and 40% indicate that they would be very disappointed if their child did not attend college.

Panel (c) summarizes the variables used as instruments in the proceeding sections. Due to the nature of the survey design there is a significant variation in the demographic characteristics within schools, across grades. The last two variables summarize the behavior of the friends of the individual's friends.[3] The trends in these behavioral variables are very similar to the trends in the friend behaviors, and again exhibit a significant amount of variation.

[3]Excluded from this mean are the behaviors of the individual if they are a friend of a friends (a reciprocated friendship) and the behaviors of the friends of friends who are also friends with the individual

Table 1.2: Summary Statistics

Variable	Mean	(Std. Dev.)
Panel (a) - Individual Survey		
Female	0.5444	(0.4980)
Hispanic	0.1474	(0.3545)
Black	0.2179	(0.4129)
American Indian	0.0327	(0.1777)
Asian	0.0811	(0.2730)
Other Race	0.0801	(0.2715)
Grade 7	0.1361	(0.3429)
Grade 8	0.1310	(0.3374)
Grade 9	0.1840	(0.3875)
Grade 10	0.1993	(0.3995)
Grade 11	0.1867	(0.3897)
Grade 12	0.1596	(0.3663)
Religious	0.6580	(0.4744)
Panel (b) - Parental Survey		
1994 Income	35.999	(50.770)
Mom single	0.2391	(0.4266)
Mom college grad	0.2130	(0.4095)
Mom work full time	0.4808	(0.4997)
Parents fight	0.5416	(0.4983)
Smoke in hhld	0.3804	(0.4855)
Parents drinker	0.1049	(0.3064)
Live here school	0.1160	(0.3203)
Want college	0.3987	(0.4896)
Panel (c) - Instruments		
Grade % Hispanic	0.1673	(0.3065)
Grade % Black	0.2050	(0.3683)
Grade % Mom no work	0.1680	(0.2235)
Grade % Dad no work	0.0353	(0.1100)
Frnd of Frnd Smoke	0.1593	(0.1785)
Frnd of Frnd Drink	0.2154	(0.1904)
N	12,234	

Table 1.3: Distribution of the Number of Friends by Sample of Analysis

Number of Friends	In School	In Grade
1	1,092 (8.93)	1,054 (11.54)
2	1,279 (10.45)	1,237 (13.55)
3	1,407 (11.50)	1,380 (15.11)
4	1,598 (13.06)	1,358 (14.87)
5	1,554 (12.70)	1,230 (13.47)
6	1,327 (10.85)	962 (10.54)
7	1,318 (10.77)	817 (8.95)
8	1,212 (9.91)	575 (6.30)
9	954 (7.80)	354 (3.88)
10	493 (4.03)	164 (1.80)
Total	12,234	9,131

Note: Proportions in parentheses

Table 1.3 shows the distribution of the number of friendships listed in the in-school sample. The first column shows the total number of friendships listed. There is a fairly even distribution in the number of friends listed, with the exception that few students list more than 8 friends. The second column restricts the friendship nominations to those students who are in the same grade as the individual. These friendships make up 75% of the total number of friendships, with the distribution similar to all school friends.

1.4 Empirical Methodology

The analysis in this chapter examines the relationship of individual delinquency to individual characteristics and peer delinquency. The baseline specification is the following linear model:

$$P(Y_i = 1 | X_i, \overline{Y}_{-ip}) = c + X_i\beta + \alpha_p \overline{Y}_{-ip} + \epsilon_i \tag{1.1}$$

The the left hand side is the probability of person i engaging in the delinquent behavior Y, X_i are individual and parental characteristics, $\overline{Y}_{-ip}$ is the proportion of individual i's peers p engaging in the delinquent behavior, and ϵ_i is a random disturbance term. This specification assumes that the contextual effect is zero, namely that the characteristics of the peers only influence the individual through the peer behavior variable $\overline{Y}_{-ip}$. The peer groups p that are separately considered include the school, grade and friends, and α_p is the peer effect coefficient of interest. Equation 1.1 is estimated using the linear probability model and probit.

It is likely that the estimates of peer effects from these regressions are biased due to reflection, omitted variables and endogenous peer group selection, as described earlier. To correct for the bias due to omitted school variables, the following equation is estimated:

$$P(Y_i = 1|X_i, \overline{Y}_{-ip}, I_s) = c + X_i\beta + \alpha_p\overline{Y}_{-ip} + \gamma I_s + \epsilon_i \tag{1.2}$$

This equation adds school dummy variables I_s to Equation 1.1, and is estimated for the grade and friend level peer groups. The resulting Fixed Effect model controls for unobserved school variables such as school and neighborhood quality, and identifies the peer effect from within school variation. In the case of the friend level peer effect this model can be extended to include school/grade fixed effects, allowing for identification from within school/grade variation in the peer effect variable. This model controls for unobserved variables at the grade level.

The relative influence of each of the peer groups can be estimated by the following equation:

$$P(Y_i = 1|X_i, \overline{Y}_f, \overline{Y}_{ig}, \overline{Y}_{is}) = c + X_i\beta + \alpha_1\overline{Y}_f + \alpha_2\overline{Y}_{-ig} + \alpha_3\overline{Y}_{-is} + \epsilon_i \tag{1.3}$$

This equation includes all of the peer variables in one equation, where the behavior of the individual is excluded from the grade and school averages and the mean grade behavior is excluded from the school average. After scaling the resulting coefficient by the size of the peer group, it is possible to compare the relative effect of adding an additional person to the friend group, grade or school on the probability of engaging in the delinquent behavior.

The next two sections explore the different sources of bias on the peer effect parameter, taking equation 1.2 as the starting point.

1.4.1 Endogenous Peer Groups

One source of bias in these equations arises from endogenous peer group formation. As mentioned in Gaviria and Raphael (2001) grade level peer effects are biased away from zero if parents choose their residential location based on the peer group composition. This bias is compounded in the case of friend level peer effects as students may assortatively match on the behavioral variable of concern.

One strategy to handle this type of bias is to use changing residential location, as suggested by Glaeser (1996). By comparing the peer effects of those respondents who moved in early childhood (*movers*), those who moved in the past 2 years (*recent movers*), and those who have lived in the same house since early childhood (*stayers*) we can test for endogenous peer group formation. According to this argument, the peer effects of movers would be larger than for stayers if students are sorting into peer groups based on the delinquency variable or unobservables correlated with it, with the peer effect of recent movers being the largest. For example, we would expect recent movers who are risk takers to have chosen friends who are also risk takers, whereas those who have not moved would have friends from early childhood who are likely to be a mix of risk takers and risk averse students. This would imply larger peer effects for recent movers in the risky behavior. To test this strategy, Equation 1.2 will be estimated separately for these three subsamples of students.

There are some concerns with this type of strategy. The information in the dataset about changing residential locations is not an exact measure of whether the students changed schools, which would be required for new friendships to form. Also, the decision for the family to move may be related to the delinquent behavior or may reflect some other unobservable characteristics of the student or parents. Finally friendships can change regardless of changing residential location, so movers may not correspond to students who have changed friendships.

An alternative way to control for bias due to endogenous sorting is the following instrumenting strategy:

$$Y_i = c + X_i\beta_1 + \alpha_f \overline{Y}_{-if} + \gamma_1 I_s + \epsilon_i \tag{1.4}$$

where $\overline{Y}_{-if}$ is the friend level peer effect, and the first stage estimates:

$$\overline{Y}_{-if} = c + X_i\beta_2 + \delta\overline{Y}_{-ig} + \gamma_2 I_s + \nu_{if} \tag{1.5}$$

Identification in this model comes from variation in the grade level delinquency within schools. Note that by plugging Equation 1.5 in to Equation 1.4, this reduced form equation equals Equation 1.2 with the grade level peer group [4] . As a result, the following relationship can be established between the peer effect coefficients:

$$\alpha_s = \alpha_f * \delta \tag{1.6}$$

If the friendships are restricted to same grade friendships then δ is between zero and one. This coefficient captures assortative matching among students as they form friendships within the grade, and also represents the extent to which the grade level peer effect underestimates the true friendship peer effect.

[4] Here the β coefficients are also scaled by δ

1.4.2 Simulteneity

As pointed out by Manski (1993) a source of bias in peer effect equations comes from simulteneity. The peer effect coefficient will be biased away from zero because by the nature of peer effects students influence one another, and these effects are compounded as the behavior appears on both sides of the peer effect equation.

To correct for this source of bias, the peer variable is instrumented with the peer contextual effect similar to Gaviria and Raphael (2001). Those authors argue that the background characteristics of the peers provide a good set of instruments for the peer behavior since the contextual effects do not directly influence the individual. The equations to be estimated are:

$$Y_i = c + X_i\beta_1 + \alpha_f\overline{Y}_{-if} + \gamma_1 I_s + \epsilon_i \tag{1.7}$$

$$\overline{Y}_{-if} = c + X_i\beta_2 + \delta\overline{X}_{-if} + \gamma_2 I_s + \nu_{if} \tag{1.8}$$

The concern with these instruments is that if the assumption about irrelevance of the contextual effects are incorrect then the coefficients from the instrumenting strategy will be inconsistent. The design of the Add Health survey provides for a possible solution to the simulteneity problem. Using the information on friendship nominations it is possible to reconstruct the friendship networks in schools. We can then instrument for the friend level peer effect with the friends of friends mean behavior. By removing the behavior of individual i and the behaviors of i's friends from this friend of friend mean we have an instrument that is likely correlated with the friend mean behavior but not the individual. This instrumenting strategy estimates the following equations:

$$Y_i = c + X_i\beta_1 + \alpha_f\overline{Y}_{-if} + \gamma_1 I_s + \epsilon_i \tag{1.9}$$

$$\overline{Y}_{-if} = c + X_i\beta_2 + \delta\overline{Y}_{-ifof} + \gamma_2 I_s + \nu_{if} \tag{1.10}$$

While this strategy handles the simulteneity concerns, the coefficients in these equations will be biased if endogenous peer group formation is a concern. The friends of friends mean delinquency suffers from the same concern as the friend level peer effect if assortative matching is occurring among students. Therefore these estimates should be interpreted with caution.

1.5 Results

1.5.1 Baseline Estimates

Table 1.4 shows the results of estimating Equation 1.1 using OLS with smoking as the delinquency variable. Focusing first on the explanatory variables, there is no difference in reporting smoking regularly between males and females for any of the peer groups. Blacks are 10% less likely to report smoking based on the school peer variable, and 7% less likely based on the friends sample. This result is consistent with the results in Gaviria and Raphael (2001) and other peer effect studies. Asians are approximately 6% less likely to report smoking. From the grade fixed effects, it is evident that older children are more likely to smoke for all of the peer group specifications, with the largest differences in the later grades (grade 7 is the omitted variable). Parental behaviors also have a significant influence on reporting smoking. Respondents living in single-parent families are around 3-5% more likely to report smoking. The presence of other smokers in the household implies the probability of reporting smoking increases by as much as 12%.

Now turning to the peer group effect coefficients, note that they are all large, positive, and highly significant. The size of the coefficient falls as the peer group size falls. To compare the size of the peer effects across these specifications it is possible to consider a one standard deviation increase in the peer variable. Individual smoking

Table 1.4: Peer Effect Regression Main: Smoking

	School Level		Grade Level		Friends Level	
Variable	**Coef**	**(SE)**	**Coef**	**(SE)**	**Coef**	**(SE)**
School Peers	0.6167***	(0.0514)				
Grade Peers			0.5939***	(0.0432)		
Friend Peers					0.5184***	(0.0125)
Female	-0.0040	(0.0065)	-0.0046	(0.0065)	-0.0088	(0.0059)
Hispanic	-0.0259*	(0.0121)	-0.0246*	(0.0120)	-0.0297***	(0.0106)
Black	-0.1045***	(0.0091)	-0.1042***	(0.0089)	-0.0731***	(0.0079)
American Indian	0.0488***	(0.0183)	0.0483***	(0.0183)	0.0375**	(0.0167)
Asian	-0.0590***	(0.0128)	-0.0567***	(0.0128)	-0.0525***	(0.0113)
Other Race	0.0003	(0.0148)	0.0001	(0.0147)	-0.0072	(0.0134)
Grade 8	0.0476***	(0.0126)	0.0205	(0.015)	0.0203*	(0.0113)
Grade 9	0.0672***	(0.0126)	0.0520***	(0.0127)	0.0613***	(0.0106)
Grade 10	0.0512***	(0.0124)	0.0300***	(0.0127)	0.0489***	(0.0105)
Grade 11	0.0924***	(0.0124)	0.0575***	(0.0132)	0.0771***	(0.0107)
Grade 12	0.0954***	(0.0129)	0.0562***	(0.0138)	0.0762***	(0.0111)
Religious	-0.0255***	(0.0085)	-0.0255***	(0.0085)	-0.0167**	(0.0079)
1994 Income	0.0000	(0.0001)	0.0000	(0.0000)	0.0000	(0.0000)
Mom single	0.0482***	(0.0101)	0.0470***	(0.0101)	0.0271***	(0.0092)
Mom college grad	-0.0016*	(0.0086)	-0.0001	(0.0085)	-0.0064	(0.0078)
Parents fight	0.0078	(0.0093)	0.0076	(0.0092)	0.0004	(0.0084)
Smoke in hhld	0.1139***	(0.0073)	0.1152***	(0.0072)	0.0860***	(0.0066)
Parents drinkers	0.0154	(0.0108)	0.0141	(0.0108)	0.0089	(0.0099)
Live here school	-0.0369***	(0.0104)	-0.0358***	(0.0104)	-0.0303***	(0.0095)
Want college	-0.0207***	(0.0072)	-0.0216***	(0.0072)	-0.0162**	(0.0065)
Mom work full time	0.0185***	(0.0071)	0.0176**	(0.0071)	0.0170***	(0.0065)
Intercept	-0.0223	(0.0178)	0.0048	(0.0169)	-0.0106	(0.0150)
Missing Dummies	YES		YES		YES	
School FE	NO		NO		NO	
N	11,581		11,577		11,970	
R^2	0.3469		0.3462		0.3208	

*Note: Peer effect regressions estimated using OLS. * significant at 10%, ** significant at 5%, *** significant at 1%*

increases 4.94 percentage points when school smoking is increased, 5.13 percentage points when grade smoking is increased, and 12.92 percentage points when friend smoking is increased in this manner. Therefore we can see that the friends peer effect is more than double the size of the school or grade level peer effects and that this effects is large compared to the other explanatory variables in the friend level peer effect equation.

Table 1.5 shows the results for the peer effects from estimating Equations 1.1 and 1.2 using OLS for smoking as the dependant variable. The results for the peer effect coefficients from Table 1.5 have been transferred to the first row of this table. The second row of the table depicts the results of estimating Equation 1.2 with school fixed effects. After controlling for unobserved school and neighborhood quality the grade level coefficient drops in magnitude. Some of the grade level effect can therefore be attributed to unobserved school and neighborhood quality. Note that the fit of the model improves significantly with the inclusion of school fixed effects for both the grade and friend level peer effects. The third row gives estimates of Equation 1.2 with school/grade fixed effects. The friend level peer effect remains unchanged in magnitude, where identification in this equation comes from within school/grade variation in the peer effect variable.

The results displayed in Table 1.6 for drinking show similar patterns as the results from smoking. The baseline coefficients are positive and statistically significant. The magnitude of the coefficients fall more drastically as the peer group size falls, however in considering a one standard deviation increase in peer group delinquency the friend level peer effect dominates. The resulting percentage point increases in individual smoking are 2.54, 2.76 and 6.00 for the school, grade and friend level respectively. The magnitude of these coefficients are generally smaller than the peer effect for smoking, especially when considering the friend level peer effect. The smaller peer effects

Table 1.5: Peer Effect Regression Results with and without Fixed Effects: Smoking

	School Level	Grade Level	Friend Level
Peer Smoking	0.6167**	0.5939**	0.5184**
	(0.0514)	(0.0432)	(0.0125)
Demographic Controls	YES	YES	YES
Missing Dummies	YES	YES	YES
School Fixed Effect	NO	NO	NO
School/Grade Fixed Effect	NO	NO	NO
N	11,581	11,577	11,970
R^2	0.0941	0.0975	0.1992
Peer Smoking		0.2719**	0.5178**
		(0.0803)	(0.0177)
Demographic Controls		YES	YES
Missing Dummies		YES	YES
School Fixed Effect		YES	YES
School/Grade Fixed Effect		NO	NO
N		11,503	11,503
R^2		0.2528	0.3399
Peer Smoking			0.4846**
			(0.0131)
Demographic Controls			YES
Missing Dummies			YES
School Fixed Effect			NO
School/Grade Fixed Effect			YES
N			12,120
R^2			0.3560

*Note: Each cell represents a different specification. Standard Errors in parentheses below peer effect coefficients. ** significant at 1%*

Table 1.6: Peer Effect Regression Results with and without Fixed Effects: Drinking

	School Level	Grade Level	Friend Level
Peer Drinking	0.6082**	0.5770**	0.3853**
	(0.0545)	(0.0487)	(0.0162)
Demographic Controls	YES	YES	YES
Missing Dummies	YES	YES	YES
School Fixed Effect	NO	NO	NO
School/Grade Fixed Effect	NO	NO	NO
N	11,558	11,554	11,968
R^2	0.0741	0.0764	0.1258
Peer Drinking		0.1993**	0.3780**
		(0.0771)	(0.0173)
Demographic Controls		YES	YES
Missing Dummies		YES	YES
School Fixed Effect		YES	YES
School/Grade Fixed Effect		NO	NO
N		11,477	11,477
R^2		0.2610	0.3029
Peer Drinking			0.3438**
			(0.0171)
Demographic Controls			YES
Missing Dummies			YES
School Fixed Effect			NO
School/Grade Fixed Effect			YES
N			12,115
R^2			0.2059

*Note: Each cell represents a different specification. Standard Errors in parentheses below peer effect coefficients. ** significant at 1%*

for drinking persist throughout this study regardless of controls for endogeneity. A possible explanation for this discrepancy is that smoking is more likely to occur is smaller groups, whereas drinking takes place at larger social events such as parties. In considering the size of the school fixed effect coefficients (not reported here), they are more than twice as large for drinking than for smoking, indicating that the school atmosphere contributes more to an individual's decision to drink.

The explanatory variables for drinking have been left out for expositional purposes, but they exhibit expected trends, similar to the results from smoking in Table 1.5. Women are 5% less likely to report drinking and the racial differences for drinking are much less pronounced. Older students are more likely to report drinking, but the age differences are smaller in magnitude than for smoking. Respondents from homes where the parents report drinking regularly are more likely to drink, as are those with smokers in the household.

Gaviria and Raphael (2001) estimate a model similar to Equation 1.1 using the National Education Longitudinal Study (NELS), and find school level peer effects of .158 and .186 for smoking and drinking, respectively. Similar to this study their peer effects are positive and statistically significant. While their peer effect coefficients are smaller in magnitude, the difference can be attributed to the differing definitions for delinquency in the surveys. Since the definitions based on the Add Health survey require more frequent use to qualify for delinquency than the ones in NELS, the difference in magnitude can be explained by stronger peer effects for more serious users.

Appendix A reports the results from estimating equations 1.1 and 1.2 using probit instead of OLS. The results are qualitatively similar when comparing the OLS coefficients to the marginal effects of the probit regressions. The peer coefficients are all large, positive and significant, with the friend level coefficients somewhat smaller in magnitude. Given the small difference in the coefficients the remaining regressions are estimated using a linear specification.

Table 1.7: All Peer Effect Results: Single Sepcification

Sample	**Smoking**	**Drinking**
School Peer Effect	0.1035	0.2098**
	(0.0765)	(0.0755)
Grade Peer Effect	0.1449**	0.1419**
	(0.0679)	(0.0679)
Friends Peer Effect	0.5248**	0.3854**
	(0.0177)	(0.0173)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
N	11,503	11,477
R^2	0.3245	0.3642

Note: Each column represents a different specification.
Standard Errors in parentheses below peer effect coefficients.
*** significant at 1%*

The results from estimating Equation 1.3 are in Table 1.7. The peer effect coefficients are positive and significant in most cases. For smoking, the friend level effect is clearly the largest. It is possible to standardize the coefficients to reflect the mean size of the given peer group. For smoking the standardization results in peer effects of 0.0002, 0.0013, and 0.1078 for the school, grade and friends, respectively. Therefore adding a student who smokes to the school or grade will have a negligible effect on the individual's probability of smoking, but adding a friend who smokes increases the probability of smoking by 11 percentage points. From the results on drinking a similar calculation reveals relative peer effects of 0.0003, 0.0011, and 0.0639. These relative effects are smaller than for smoking, but similarly the friend level effect dominates, and more so than the coefficients reflect.

1.5.2 Endogenous Peer Group Formation

To control for individuals sorting into peer groups based on the delinquency variable or unobservables correlated with it, two strategies are pursued. First, the differences in peer effects are considered by residential mobility status. Equation 1.2 is estimated on three sub-samples of respondents: students who report having moved after the age of 6 (*movers*), those who report having moved in the past 2 years (*recent movers*), and those who have lived in the same house since before they were 6 years old (*stayers*). If endogenous sorting is a concern then individuals will sort into peer groups according to the delinquent behavior, which would bias peer effects away from zero. If the estimates for these sub-samples are similar in magnitude, it can be argued that selection is not an important concern.

The results from these regressions are displayed in Table 1.8. Comparing the results for stayers and movers there is evidence that peer group formation is endogenous based on the results from smoking. The peer effect for those students who changed residences after 6 years of age is larger than for those who have not moved since before this time. The t-statistic for the test of the difference between the coefficients for stayers and movers equalling zero is 2.35. The peer effect remains large for students who recently moved, and persists even once delinquency prior to the move is controlled for in the case of smoking[5] .The coefficients for drinking exhibit less of a difference for the sub-samples. Once delinquency prior to the move is controlled for the difference in the coefficients disappears, indicating that endogenous sorting based on drinking is less of a concern.

The second strategy for testing endogenous peer group formation examines the

[5]The t-statistic for the difference in the coefficients for stayers and recent movers is 2.04 if prior delinquency is not controlled for, and 1.17 if prior delinquency is controlled for

Table 1.8: Testing Endogenous Sorting with Residential Mobility

Sample	Smoking	Drinking
Stayers Peer Effect	0.4118**	0.3203**
	(0.0367)	(0.0389)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School/Grade Fixed Effect	YES	YES
N	1,989	1,988
R^2	0.4372	0.4412
Movers Peer Effect	0.5104**	0.3536**
	(0.0202)	(0.0224)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School/Grade Fixed Effect	YES	YES
N	5,284	5,284
R^2	0.4115	0.3489
Recent Movers Peer Effect	0.5152**	0.3275**
	(0.0350)	(0.0382)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School/Grade Fixed Effect	YES	YES
Delinquent Before Move Control	NO	NO
N	2,101	2,100
R^2	0.5189	0.4487
Recent Movers Peer Effect	0.4712**	0.2628**
	(0.0348)	(0.0366)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School/Grade Fixed Effect	YES	YES
Delinquent Before Move Control	YES	YES
N	2,101	2,100
R^2	0.5384	0.5043

Note: Each cell represents a different specification.
Standard Errors in parentheses below peer effect coefficients.
*** significant at 1%*

Table 1.9: Testing Endogenous Sorting with Instruments

Sample	**Smoking**	**Drinking**
Friend Level Peer Effect (α_f)	0.4841**	0.3169**
	(0.1339)	(0.1415)
First Stage Coefficient (δ)	0.5617**	0.6288**
	(0.0473)	(0.0494)
Product of (α_f) and (δ) (α_g)	0.2719	0.1993
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School Fixed Effect	YES	YES
Grade Fixed Effect	YES	YES
N	11,503	11,477

Note: Each column represents a different specification.
Standard Errors in parentheses below coefficients.
*** significant at 1%*

effect of instrumenting friend level smoking with grade level smoking. The results from estimating Equations 1.4 and 1.5 are displayed in Table 1.9, where the equations were estimated using 2SLS. The peer effect coefficients fall in magnitude for both smoking and drinking, with a larger fall in the coefficient on drinking. This indicates that endogenous sorting is a concern, although not a serious one. Note that the first stage coefficients are 0.56 and 0.63. Therefore, by using the grade level peers the true peer effect is understated by around 40%, assuming that the friend level peer effects are correct. By taking the product of the first and second stage we obtain the grade level peer effects found in row two, column two of Tables 1.5 and 1.6 as expected. The grade level fixed effects included in this specification control for trends in the delinquency variable as the students get older. These trends are most pronounced for drinking, as can be seen in Figure 1.2.

1.5.3 Simulteneity Results

To consider endogeneity bias due to simulteneity, Equations 1.7 and 1.8 are estimated with the results displayed in Table 1.10. The instruments in this case are the average characteristics of the peers such as percent black, percent hispanic, and percent with parents not working. Comparing the results in this table to those in row three in Tables 1.5 and 1.6, the peer effect coefficient falls for smoking and increases for drinking. In the case of smoking this is evidence that the original peer effect coefficients are biased due to simulteneity. It appears that the mean characteristics are not a strong instrument in the case of drinking, resulting in upward biased parameters from 2SLS.

Table 1.10: Simulteneity Controls Using Peer Characteristics

Sample	**Smoking**	**Drinking**
Friend Level Peer Effect	0.3955**	0.7321**
	(0.1164)	(0.1247)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School/Grade Fixed Effect	YES	YES
N	11,321	11,301

Note: Each column represents a different specification.
Standard Errors in parentheses below peer effect coefficients.
*** significant at 1%*

Given the concern that the correlated effects are not exogenous, the second strategy examines the effect of instrumenting with the behavior of the friends of friends. Table 1.11 show the result of this regression where the first stage includes the mean delinquency of the friends of friends who are not the respondent and who are also not friends with the respondent. Comparing these estimates to the third column, second row of Tables 1.5 and 1.6 we can see that the coefficients for both smoking and drinking are increased. While we would expect the OLS estimates to be biased upward due to simulteneity, the 2SLS coefficients are surprisingly higher. This can likely be explained by endogenous friendship formation for all students, implying that the friends of friends mean behavior is also biased upward.

Table 1.11: Simulteneity Controls Using Friends of Friends Peer Effect

Sample	**Smoking**	**Drinking**
Friend Level Peer Effect	0.7973**	0.7872**
	(0.0324)	(0.0519)
Demographic Controls	YES	YES
Missing Dummies	YES	YES
School/Grade Fixed Effect	YES	YES
N	11,358	11,336

Note: Each column represents a different specification.
Standard Errors in parentheses below peer effect coefficients.
*** significant at 1%*

1.6 Conclusion

This chapter estimated the effect of school, grade and friend level peer effects on the probability of engaging in delinquent behaviors such as smoking and drinking. Friends are defined as students nominated by the individual in their school, with information coming from the Add Health dataset. The results indicate that friend behaviors influence individuals to a larger extent than school mates or students in the same grade. These results are robust to the inclusion of fixed effects at the school or grade level, and hold in the case where all of the peer effect measures are estimated simultaneously.

A number of sources of bias are examined. Endogenous peer group formation is found to bias the friend level peer effect coefficient away from zero, where evidence for this is found with both the residential mobility strategy as well as the instrumenting strategy. The second strategy is especially useful in that it allows for the underestimation of the peer effect in the case that an incorrect peer group is used to be quantified. This is found to be a significant 40%, indicating that choosing the correct peer category for analysis is important in obtaining exact measures of peer effects.

The results on the bias due to simulteneity are mixed. While the instrumenting strategy using correlated effects as instruments find simulteneity a concern in the case of smoking, the evidence is less clear for the case of drinking. In addition, using the mean behaviors of friends of friends may not help in correcting for simulteneity if endogenous peer group formation is leading to biased results for all of the peer effect variables.

Chapter 2

Too Popular for School? Friendship Formation and Academic Achievement

2.1 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. However, aggregating 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 student popularity within social networks.[2] Network embeddedness 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 the significant positive relationship between popularity

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[1]Some examples are Evans, Oates, and Schwab (1992), Betts and Morrell (1999), Arcidiacono and Nicholson (2001), Gaviria and Raphael (2001), Sacerdote (2001), Hanushek, Kain, Markman, and Rivkin (2003), Zimmerman (2003), and Arcidiacono, Foster, Goodpaster, and Kinsler (2005).

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

[3]See Haynie and Payne (2006)

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

and outcomes can be found in the sociology literature in the context of adolescent criminal behavior (Haynie (2001)), and more recently in economic studies examining academic achievement (Calvo-Armengol, Patacchini, and Zenou (2005) and Fryer and Torelli (2005)).

However, 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.[5] 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 compelling, they overlook a key concern: individuals choose whom to associate with and these associations may be influenced by unobserved individual characteristics. If these unobservable characteristics influence both the likelihood of being chosen as a friend and success in academics, then ignoring their impact would incorrectly attribute their effect to popularity, leading to biased results.

This chapter considers the effect of popularity on academic achievement, and ascertains the robustness of previous results to the inclusion of unobserved heterogeneity. Popularity is measured by several indices describing the location of the individual in the school network. The impact of these measures is evaluated on academic achievement with and without the inclusion of controls for unobserved characteristics.

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

[5]See Montemayor (1982)

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.

The baseline results indicate that popularity has a significant positive effect on academic achievement. The inclusion of controls for unobserved school quality lead to a small reduction in the effect of popularity, with the effects remaining positive and significant.

Two strategies are used to handle bias due to selection. An instrumental variables regression is estimated where the interaction of individual and school characteristics are used as instruments for popularity. This strategy maintains the assumption that school composition is exogenous, and identifies the parameters off of variation within the school. The results from these regressions find evidence that selection is a concern, with the coefficient on popularity decreasing in all cases and becoming significantly negative in three of the four cases.

The second strategy estimates a joint model of friendship nomination and academic achievement, with unobserved type controlled for using finite mixture distributions. Students are assumed to be a particular unobserved discrete 'type', where these types are inferred using Bayes' Theorem and enter both the friendship nomination and achievement equations.[6] This allows for the decomposition of the unobserved effect into individual likeability as captured by the type parameter and school level unobservables which are absorbed by the school fixed effects. The effect of unobserved heterogeneity is identified from variation in the characteristics of students across schools, which leads to observably similar students getting nominated a differ-

[6]Examples of other work using mixture distributions include Arcidiacono (2005), Keane and Wolpin (1997), Eckstein and Wolpin (1999) and Cameron and Heckman (1998).

ent number of times by others as friends.

The results from the joint specification confirm the instrumental variables results, and diverge significantly from previous findings regarding the impact of peers on outcomes. Including unobserved type results in the effect of network location decreasing in all specifications. The results turn from significantly positive to significantly negative in three of the four specifications. For example, considering a person receiving two additional nominations as a friend, the results imply an increase in GPA of .04 points prior to unobserved characteristic controls, but a drop in GPA of .05 points after these controls 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 type parameter enters positively and significantly in all specifications of popularity.

As a robustness check of the model, outcomes in which unobserved type is not expected to impact the effect of popularity are considered. The results from these models indicate that the effect of popularity remains positive even when controlling for unobserved type. For example, more popular students report feeling closer to the school and also report higher future earnings, where earnings are measured in a later wave of the survey. These effects persist with the inclusion the type parameter. This result points to the tradeoff between acquiring human and social capital, as both can play an important role in determining current and future outcomes.

Finally, using the results from the joint model specification it is possible to test the impact of redistributing students across schools on the distribution of the number of friends and grades attained. The two redistribution policies considered include race-based redistribution where school assignment is based on the racial composition of the school and income-based redistribution, where school assignment is based on the socioeconomic status of students. The effect of these policies are evaluated on the expected number of friendship and grade distributions of the two policy school. The number of friendship nominations fall and the grades improve in both schools following both policies. There is evidence that the grade distributions are equalized and that this effect is present for all sub-samples of the school population.

The chapter proceeds in the following manner. Section 2 reviews the relevant literature and explains the major contributions of this chapter 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 model along with the estimation procedure. Section 6 presents the results, and Section 7 considers the policy simulations. Finally Section 8 concludes.

2.2 Related Literature

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

2.2.1 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.[7] 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

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

racial, economic, and cultural lines.[8] This descriptive evidence indicates that simply redistributing students by race may not imply increased cross-racial interaction if students are choosing to self-segregate.

Echenique and Fryer (2005) examine the extent of within school segregation using a measure which 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.[9] The model of friendship formation presented in this chapter is flexible enough to capture nonlinearities between friend and school minority race.

Marmaros and 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 and Puller (2007) 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 two studies, friendships are allowed to to vary by matching on race and family background. This specification deviate from previous work in two important ways. These measures of friendships are directly from students' responses to the survey. While previous studies have used proxies to measure friendships, it is likely that friend nominations are less error prone measures of the individuals who are

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

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

influential in a student's life. Second, controls for unobserved friend characteristics as measured by student type are allowed to influence the friendship nomination decision. If students choose friends based partially on these characteristics then student type will control for the bias induced by selection.

2.2.2 Social Network Effects

The majority of economics studies measure peer effects as a function of student characteristics or student behaviors.[10] These studies assume that associations are within the specified peer group, and 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 understatement of the effect of peers on student delinquency. There is conflicting evidence as to whether using the unweighted linear average is a close approximation of the true nature of interactions.[11] 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.

Sociologists have suggested using centrality indices on peer networks as alternatives measures 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

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

[11]Marmaros and 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 and Durlauf (2001a) for issues concerning identifying social interactions.

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.[12] The majority of the studies focus on theoretical models of network formation and interaction.[13] An exception is Calvo-Armengol, Patacchini, and Zenou (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 chapter and Calvo-Armengol, Patacchini, and Zenou (2005) is that instead of taking the network structure is given, the process of network formation is modeled as a choice variable where this choice and the academic achievement of the student depends on unobserved student characteristics.

2.3 Data

This chapter 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.[14] The survey contains information on 90,118 students in 145

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

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

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

schools, with the first wave of the survey administered in 1994.[15] 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 peers themselves rather than the original respondents. The nominated students who attend the school can be linked to student identifiers, which makes it possible to reconstruct social networks within the school.[16]

Table 2.1: 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	

[15]Subsequent waves of the survey were administered to a sub-sample of the students in 1996 and 2001, with a fourth wave planned for 2008. The longitudinal aspect of the survey is not utilized in this chapter.

[16]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 identify students.

This chapter focuses on same sex friendships within a school and grade.[17] 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 2.1 shows the summary statistics for the friendship nominations. It can be seen that the quota restricting the maximum number of friendship listing to 5 affects at most 8% of the sample. It is interesting to note that approximately 30% of students do not list any friends[18] .

There is a concern when estimating friendship nominations that school size influences the number and type of friendships. Figure 2.1 shows friendship nominations broken down by school size quartiles. There are no significant differences in the distribution of the number of friends nominated by school size quartile. Most students nominate zero friends in both small and large schools, and the least number of students nominate five friends in schools of all sizes.

An additional concern is that the extent of segregation differs across schools of different size. Figure 2.2 considers the distribution of black-white friendships broken down by school size quartile. There is no strong relationship between school size and the extent of segregation within the schools, as can be seen from the same shape of the distribution of cross-race friendships. The evidence from these two figures indicates that there are no observable differences in friendship nominations by school size. These findings affect the estimation of the friendship nomination equation which will be explained in Section 5.

Summary statistics of the variables used in the friendship nomination and acad-

[17] 81.95% 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.

[18] Some of these zeros result from restricting the sample to same grade, same sex friendships. Table B.1 in the Appendix shows the breakdown of friendships by the type of missing data

Figure 2.1: Number of Friendship Nominations by School Size Quartile

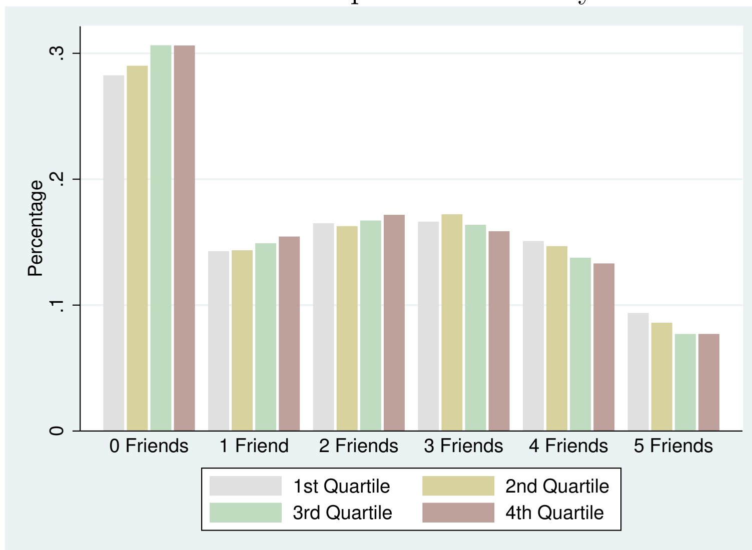
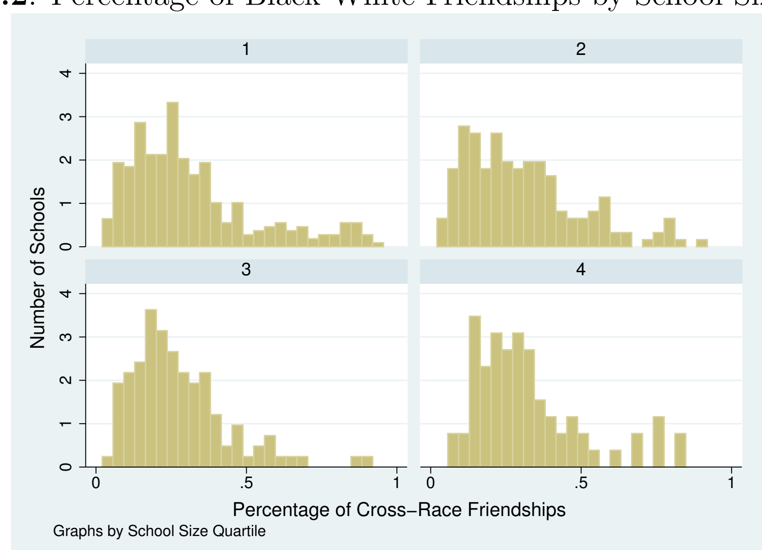


Figure 2.2: Percentage of Black-White Friendships by School Size Quartile



emic outcome equations are given in Table 2.2. The sample is equally divided among genders, 60% of the sample is white, and almost 20% is black, largely due to oversamlping. Most students have mothers who work, and 76% live with their biological fathers. The last four variables summarize school level measures of race and mother's education. These are used in the friendship nomination equation to account for preferences for similarity in characteristics as a function of minority status.

Table 2.2: Independent Variable - Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Obs**
Female	0.4957	0.5000	72,081
White	0.6048	0.4889	72,081
Black	0.1911	0.3932	72,081
Asian	0.0701	0.2554	72,081
Hispanic	0.1981	0.3986	63,543
Mom Not Working	0.1808	0.3848	60,851
Mom Some College	0.4971	0.5000	56,168
Adopted	0.0296	0.1695	69,967
Large Family	0.1851	0.3884	69,729
Live with Bio Dad	0.7590	0.4277	69,683
Foreign Born	0.0983	0.2977	69,902
School % White	0.6048	0.2900	72,081
School % Black	0.1911	0.2356	72,081
School % Asian	0.0701	0.2554	72,081
School % Mom Col	0.3874	0.1479	72,081
School % Mom HS	0.3919	0.1184	72,081

The outcome variables are summarized in Table 2.3. The academic variable considered is *GPA*, which is the mean of the Math, English, History and Science self-reported grades, where 4 is equivalent to an A and 1 is equivalent to a D or worse.[19] The next set of outcome variables are Attitudes, and they are summarized in the

[19] Add Health collected transcript data for a 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 smaller than their transcript average.

second panel of the table. *Close to School* is the response to whether the student feels close to the school environment and *Happy* is whether the respondent felt happy most or all of the time in the last week. Finally, using data from Wave 3 of the survey, the last panel of the table summarizes the earnings of students who were in grades 11 or 12 in the first wave of the survey.[20] While this is a small sample of students, these are respondents who are older than 23, and would likely be in the workforce regardless of college attendance.

Table 2.3: Outcome Variables - Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Academic					
GPA	2.8570	0.7901	1.0000	4.0000	45,611
Attitudes					
Close to School	0.6605	0.4736	0.0000	1.0000	13,268
Happy	0.7742	0.4181	0.0000	1.0000	13,268
Future Earnings					
Income	18.7812	21.1814	0.0000	500.9090	2,774

Note: Income is in thousands of year 2000 dollars.

2.4 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

[20]The questions asked for income received from earnings from wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment.

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.[21] These four measures each capture different aspects of popularity, since 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 chapter 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 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 $\mathbf{G}$,

$$C_i^{IDEG} = \sum_{j=1}^{N} g_{ij} = G'1 \tag{2.1}$$

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

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

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

of links. The expression for density is given by

$$C_i^{DENS} = \frac{1}{5N} \sum_{j=1}^{N} \sum_{i=1}^{N} g_{ij} \tag{2.2}$$

This measure differs from the other indices described because it varies across networks, not individuals.[22] 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 $\mathbf{G}$, 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) proposed in Bonacich (1972), and developed in the economics context by Echenique and Fryer (2005) as a measure of segregation and Fryer and 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

$$C_i^{SPI} = \frac{1}{\bar{C}^{SPI}} \sum_{j=1}^{N_k} g_{ij}^k C_j^{SPI} \tag{2.3}$$

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

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[22]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.

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 2.3 is given by

$$C_i^{SPI} = \frac{1}{\bar{x}^k}(\lambda^k x_i^k) \tag{2.4}$$

Echenique and Fryer (2005) 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

$$C_i^{BONA} = \beta \sum_{j=1}^{N} (g_{ij}^k C_j^{BONA} - \alpha) \tag{2.5}$$

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

$$C_i^{BONA} = \alpha(I - \beta G^k)^{-1} G^k 1 \tag{2.6}$$

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.[23]

[23]The parameter α is chosen such that the norm of the eigenvector equals the number of observa-

The popularity indices described above are summarized in Table 2.4. 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 2.4: Popularity Measures - Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
IDEG	1.9605	1.9262	0.0000	13.0000	72,081
DENS	0.3921	0.1354	0.0359	0.7848	72,081
SPI	0.0426	0.1058	0.0000	0.7676	72,081
BONA	0.6889	0.5879	0.0000	3.8519	72,081

Table 2.5 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.

Table 2.5: Popularity Measures - Correlation

Variable	IDEG	DENS	SPI	BONA
IDEG	1.0000			
DENS	0.3512	1.0000		
SPI	0.1953	-0.0024	1.0000	
BONA	0.7986	0.2088	0.4569	1.0000

tions, 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.

2.5 Model

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:

$$Y_i^a = X_i'\beta^a + \delta^a C_i + \phi_s + \epsilon_i^a. \tag{2.7}$$

The X_i include demographic characteristics, and differences in school quality are controlled with school fixed effects denoted by ϕ_s. C_i are the measures of popularity, and are assumed to be known by the student. The main parameter of interest is δ^a which captures the effect of student popularity on academic achievement. The error term is assumed normal, with mean 0 and variance σ^a. The parameters to be estimated for the achievement equation are:

$$\Theta^a = (\beta^a, \delta^a, \sigma^a). \tag{2.8}$$

The popularity measure may be endogenous if some students are unobservably more likeable than others. This effect can come from matching well with students in the grade and individual level unobserved characteristics. The instrumenting strategy and the joint model of friendship nomination and academic achievement consider these concerns.

2.5.1 Instrumental Variables

If some students are more likeable than others because they match with others in their grade they will have higher measures of popularity, and the coefficient of interest δ^a will be biased as a result of omitted variables. To correct for this bias, an instrumenting strategy is implemented. Equation 2.7 is estimated, with the first stage being

$$C_i = X_i'\beta^f + Z_i'\gamma^f + \phi_s + \nu_i \tag{2.9}$$

where $Z_i = X_i \times \bar{X}_g$. The instruments used are the interactions of individual characteristics with the mean of that characteristic in the grade.[24] These variables control for the endogeneity of the popularity measures by capturing the extent of matching on observable characteristics by students with those in their grade. The coefficient on popularity is identified off of variation in these interaction terms across grades within schools.

2.5.2 Joint Model

To control for bias due to unobserved individual characteristics a more formal model of friendship nomination and academic achievement is estimated. Along with Equation 2.7 the process of nominating friendships is modeled. Students nominate individuals in their grade as friends where friendships in this model are defined as the decision to nominate a person, regardless of whether the nomination is reciprocated. Individuals obtain utility from matching on observable characteristics with their potential friends. The preference for a match on the characteristic is allowed to vary with the extent to which this characteristic is in a minority in the school. In addition, individuals receive an unobserved shock to the match with a known distri-

[24]For example, the percent of college educated mothers in the grade interacted with whether the student has a college educated mother.

bution. The utility for i from forming a friendship with individual j is given by the following equation:

$$u_{ij}^f = X_{ij}'\beta^f + \overline{X}_s X_{ij}'\gamma_1^f + \overline{X}_s^2 X_{ij}'\gamma_2^f + \epsilon_{ij}^f \tag{2.10}$$

where X_{ij} are the interactions of demographic characteristics such as race and mother's education of individual i and friend j, and $\overline{X}_s$ is the average of characteristic X in the school. The school level variables enter both linearly and with a square term to allow for changes in the returns to nominating friends as the school composition changes. The observed utility from not forming the friendship with student j is normalized to zero. The parameters from the friendship formation equation are given by:

$$\Theta^f = (\beta^f, \gamma^f). \tag{2.11}$$

Estimation

Assuming the errors are independent and identically distributed with Type 1 extreme value distribution across friends and individuals, the probability of person i nominating person j is given by:

$$P_{ij}^f = \frac{exp(X_{ij}'\Theta^f)}{1 + exp(X_{ij}'\Theta^f)}. \tag{2.12}$$

This implies that the likelihood of the friendship equation is given by

$$\mathcal{L}^f(d|\Theta^f, X_{ij}, \overline{X}_s) = \prod_{i=1}^{N} \left(\prod_{J_C} P_{ij}^f \prod_{J_N} P_{ij}^f \right) \tag{2.13}$$

where J_C are the nominations that were accepted by the individual, and J_N are the nominations that were considered but not chosen. An interesting feature of this setting is that choices are themselves people. This implies that estimating Equation 2.13 is the same as estimating:

$$\mathcal{L}^f(d|\Theta^f, X_{ij}, \overline{X}_s) = \prod_{j=1}^{N} \left(\prod_{I_C} P_{ij}^f \prod_{I_N} P_{ij}^f \right), \tag{2.14}$$

where the outer product is now over j and I_C refers to the choices where i was chosen as a friend. This change of variables will be significant in identifying the unobserved parameter.[25]

The difficulty in estimating Equation 2.14 is that the set I_N is unobserved - there is no information about people who were considered but not chosen. To overcome this problem, the unobserved choices will be simulated with the assumption that all respondent consider a fixed J number of students as possible friends.[26] A likely violation of this assumption would occur if different sized schools imply different choice sets for students. However, Figures 2.1 and 2.2 show that there is no difference in the number or composition of chosen friends by school size.[27] As there is no observable difference in the nominations of students across different sized schools, the assumption being made is that the unobserved portion of the choice sets are also similar.

The unobserved portion of the choice set is simulated to integrate out over all possible choice sets in the school. The likelihood contribution of friendships is replaced by the following simulated likelihood:

$$\hat{\mathcal{L}}^f(d_j|\Theta^f, X_{ij}, \overline{X}_s) = \sum_{r=1}^{R} \left(\frac{\prod_{I_C} P_{ij}^f \prod_{I_N} P_{ijr}^f}{R} \right) \tag{2.15}$$

where I_C are the observed choices and the likelihood associated with these choices are the same for each simulation, and I_N are the unobserved simulated choices with

[25]See Section 5.4

[26]The literatures in environmental economics and recreational demand have considered the bias resulting from inaccurate choice set designation. See Swait and Ben-Akiva (1987) and Parsons and Hauber (1996) for methods of choice set estimation.

[27]To further investigate the impact of school size on friendship nominations, an ordered probit for the number of friends nominated is estimated. The effect of school size on the number of nominations is close to zero and insignificant. Additionally, a probit for the probability of a cross-race friendship results in no significant effect of school size.

varying likelihoods. Simulated maximum likelihood yields consistent estimates of the parameters, assuming a sufficient number of draws are used.[28]

Assuming the errors are independent across the two parts of the model, the log likelihood function can be divided into two pieces:

$\hat{\mathcal{L}}^f(d_{ij}|\Theta^f, X_{ij}, \overline{X}_s)$ - the simulated likelihood contribution of friendships;

$L^a(Y_j^a|\Theta^a, X_j, C_j, \phi_s)$ - the log likelihood contribution of achievement.

The total likelihood function is given by

$$L(\Theta^f, \Theta^a) = \sum_{j=1}^{N} ln\hat{\mathcal{L}}^f(d_{ij}|\Theta^f, X_{ij}, \overline{X}_s, m) + \sum_{j=1}^{N} L^a(Y_j^a|\Theta^a, X_j, C_j, \phi_s). \qquad (2.16)$$

The two parts of this model can be consistently estimated separately assuming the errors are independent. The friendship nomination equation can be estimated with simulated maximum likelihood, and the outcome equation with OLS.

Unobserved Heterogeneity

The estimated parameters from these equations will be biased if there are unobserved (to the econometrician) characteristics of individuals which influence their attractiveness as friends and their academic achievement. For example, students with a more friendly demeanor may be chosen more often as a friend and may also impress their teachers, leading to better grades. The presence of these unobserved characteristics implies that the independence of the errors across individuals in the friendship formation equation is violated. In addition, excluding this variable from the achievement equation can lead to biased estimates of all parameters.

Unobserved student heterogeneity is allowed to enter the model by the inclusion of

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[28] See Hajivassiliou and Ruud (1994) for the properties of simulated estimators.

an unobserved 'type' parameter through the use of a mixture model.[29] While these types are never observed, it is possible to calculate the probability that a student is type m using Bayes' Theorem. Types are assumed to be known to the student, and enter the model through the use of a type dummy in both the friendship and achievement equations.

The total likelihood function is written as the weighted sum of the likelihoods, with the weights being the unconditional probability of student types:

$$L_j(\Theta^f, \Theta^a) = ln\left[\sum_{m=1}^{M} \pi_m \hat{\mathcal{L}}^f(d_j|\Theta^f, X_{ij}, \overline{X}_s, m)\mathcal{L}^a(Y_j^a|\Theta^a, X_j, C_j, \phi_s, m)\right] \quad (2.17)$$

where π_m is the unconditional probability of the student being type m, and $\mathcal{L}$ refers to the likelihood, not log likelihood.

The total likelihood function is no longer additively separable due to the inclusion of the unobserved type parameter. This significantly complicates the estimation, and implies longer computation time. Arcidiacono and Jones (2003) show that using the Expectation-Maximization (EM) algorithm restores the additive separability in the maximization step and speeds up the computation without a significant loss in efficiency. They show that the first order conditions from maximizing Equation 2.17 are the same as the first order conditions used to maximize:

$$L_j(\Theta^f, \Theta^a) = \sum_{m=1}^{M} \pi_{jm}\left(ln\hat{\mathcal{L}}^f(d_j|\Theta^f, X_{ij}, \overline{X}_s, m) + L^a(Y_j^a|\Theta^a, X_j, C_j, \phi_s, m)\right) \quad (2.18)$$

where π_{jm} is the conditional probability of student j being type m, defined as:

$$\pi_{im} = \frac{\pi_m \hat{\mathcal{L}}_m^f \mathcal{L}_m^a}{\sum_{m'=1}^{M} \pi_{m'} \hat{\mathcal{L}}_{m'}^f \mathcal{L}_{m'}^a}, \quad (2.19)$$

[29]Examples of papers using mixture distributions include Keane and Wolpin (1997). Eckstein and Wolpin (1999) and Cameron and Heckman (1998).

and π_m is calculated as the average of the conditional probability:

$$\pi_m = \frac{1}{N}\sum_{j=1}^{N}\pi_{jm}. \tag{2.20}$$

The estimation iterates two steps: first calculate the expected log likelihood function given the conditional probabilities at the current parameter estimates, and second estimate the parameters by maximizing the expected likelihood function holding the conditional probabilities fixed. The unconditional probabilities of being a particular type are updated using the whole sample in the expectations step. This uses information from both the friendship and achievement equations. The friendship equation is estimated using weighted simulated maximum likelihood, where the weights correspond to the conditional probability of being a particular type. The achievement equation is estimated using weighted OLS with the same weights. In practice, the number of student types are limited to two.[30]

The attractiveness of this setup is that additional equations containing the unobserved parameter can be estimated simultaneously without additional computation time. An example is the estimation of the effect of high school popularity on future earnings. Specifying the equation similar to the academic achievement production, the new conditional probability of being type m can be estimated by multiplying by the likelihood contribution of earnings as follows:

$$\pi_{im} = \frac{\pi_m \hat{\mathcal{L}}_m^f \mathcal{L}_m^a \mathcal{L}_m^p}{\sum_{m'=1}^{M} \pi_{m'} \hat{\mathcal{L}}_{m'}^f \mathcal{L}_{m'}^a \mathcal{L}_{m'}^p}, \tag{2.21}$$

where the earnings likelihood contribution enters the numerator and denominator, and is denoted by superscript p. The new total log likelihood to be maximized is:

[30]Three types did not yield significantly different results because two of the types were very similar.

$$L(\Theta^f, \Theta^a, \Theta^p) = \sum_{m=1}^{M} \pi_{im} \left(ln\hat{\mathcal{L}}^f(d_j|\Theta^f, \cdot, m) + L^a(Y_j^a|\Theta^a, \cdot, m) + L^p(Y_j^p|\Theta^p, \cdot, m) \right) \tag{2.22}$$

where the dots refer to the data. This equation can still be maximized in two steps, where the second step now includes estimating the new equation by weighted OLS.

2.5.3 Identification

For the instrumenting strategy the identification of the peer effect parameter comes from within school variation across grades in the mean demographic characteristics of students. Table 2.2 shows that there is significant variation in these measures. An underlying assumption is that the mean grade characteristics interacted with the individual characteristics do not directly influence the academic achievement of the student.

For the joint model, the identification of the preference parameters in the friendship nomination equation come from variation in the demographic characteristics within and across schools. The significant variation in the popularity measures helps in identifying the effect of the indices on academic and other outcomes.

The probability of the student being a particular type is identified by variation in the number of times observably similar students are nominated by others as friends, and the variation in the academic achievement of observably similar students. Given two students who are observably identical, if one is nominated many times as a friend while the other is nominated a few times and the first student also performs better in school than the second, the methodology assigns a higher probability to the first student being a higher type. In the friendship nomination equation the type parameter is identified off variation in the friendship choices of others in the grade, while in the academic achievement equation it is identified off of individual level variation.

2.6 Results

2.6.1 Baseline Model

Table 2.6 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, coefficients are of the expected sign and magnitude. Girls report higher grades than boys, and hispanics and blacks report lower grades than whites. 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. The popularity measures all enter positively and significantly in these regressions.

Similar results can be seen in Table 2.7, where school fixed effects are also included. These fixed effects control for unobserved school and neighborhood quality, with the demographic coefficients now being identified off of within school variation in the characteristics. There are no significant changes in three of the four popularity measures. The decrease in the coefficient on density is due to the definition of this variable which is specified at the network, not individual level. The race variables change significantly with the inclusion of school quality controls, as does the effect of being foreign born. Specifically, the coefficients on black and foreign born increase with the inclusion of school fixed effect, indicating that these students typically attend lower quality schools.

To ease comparability of the different popularity measures Table 2.8 shows the coefficients from the above regressions with the effect on achievement of a one standard

Table 2.6: Achievement Results - Baseline Model

Variable	IDEG	DENS	SPI	BONA
Constant	2.4602**	2.3795**	2.5234**	2.4240**
	(0.0154)	(0.0183)	(0.0153)	(0.0156)
Popularity	0.0473**	0.4660**	0.3673**	0.1787**
	(0.0018)	(0.0298)	(0.0328)	(0.0060)
Female	0.1443**	0.1213**	0.1661**	0.1522**
	(0.0070)	(0.0076)	(0.0070)	(0.0069)
White	0.0584**	0.0518**	0.0693**	0.0596**
	(0.0118)	(0.0119)	(0.0118)	(0.0117)
Black	-0.2067**	-0.2027**	-0.2154**	-0.2049**
	(0.0133)	(0.0134)	(0.0133)	(0.0132)
Asian	0.2774**	0.2900**	0.2768**	0.2723**
	(0.0162)	(0.0162)	(0.0163)	(0.0161)
Hispanic	-0.1862**	-0.1718**	-0.2003**	-0.1870**
	(0.0121)	(0.0123)	(0.0213)	(0.0121)
Mom Not Working	0.0517**	0.0465**	0.0437**	0.0523**
	(0.0099)	(0.0099)	(0.0099)	(0.0098)
Mom Some College	0.2951**	0.3095**	0.3043**	0.2899**
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Adopted	-0.1092**	-0.1218**	-0.1183**	-0.1047**
	(0.0211)	(0.0212)	(0.0213)	(0.0211)
Large Family	-0.0373**	-0.0433**	-0.0436**	-0.0350**
	(0.0094)	(0.0095)	(0.0095)	(0.0094)
Live with Bio Dad	0.1542**	0.1588**	0.1647**	0.1526**
	(0.0089)	(0.0090)	(0.0090)	(0.0089)
Foreign Born	0.0303**	0.0317**	0.0131	0.0309**
	(0.0139)	(0.0141)	(0.0140)	(0.0139)
Sigma	0.7368**	0.7405**	0.7415**	0.7353**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummy	Y	Y	Y	Y
School FE	N	N	N	N
N	45,611	45,611	45,611	45,611

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

Table 2.7: Achievement Results - Baseline Model with School Fixed Effects

Variable	IDEG	DENS	SPI	BONA
Constant	2.3502**	2.3457**	2.4110**	2.3189**
	(0.0521)	(0.0553)	(0.0523)	(0.0519)
Popularity	0.0436**	0.2342**	0.3901**	0.1745**
	(0.0018)	(0.0448)	(0.0321)	(0.0058)
Female	0.1621**	0.1597**	0.1833**	0.1694**
	(0.0068)	(0.0083)	(0.0068)	(0.0068)
White	0.0841**	0.0886**	0.0863**	0.0799**
	(0.0118)	(0.0118)	(0.0118)	(0.0117)
Black	-0.1461**	-0.1548**	-0.1483**	-0.1365**
	(0.0138)	(0.0139)	(0.0139)	(0.0138)
Asian	0.2571**	0.2663**	0.2629**	0.2552**
	(0.0167)	(0.0168)	(0.0167)	(0.0166)
Hispanic	-0.1552**	-0.1593**	-0.1571**	-0.1490**
	(0.0125)	(0.0126)	(0.0126)	(0.0124)
Mom Not Working	0.0467**	0.0404**	0.0402**	0.0484**
	(0.0096)	(0.0096)	(0.0096)	(0.0095)
Mom Some College	0.2659**	0.2794**	0.2758**	0.2606**
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Adopted	-0.1109**	-0.1213**	-0.1212**	-0.1070**
	(0.0204)	(0.0205)	(0.0205)	(0.0203)
Large Family	-0.0418**	-0.0481**	-0.0466**	-0.0390**
	(0.0091)	(0.0092)	(0.0092)	(0.0091)
Live with Bio Dad	0.1425**	0.1509**	0.1496**	0.1389**
	(0.0086)	(0.0087)	(0.0087)	(0.0086)
Foreign Born	0.1226**	0.1123**	0.1116**	0.1281**
	(0.0143)	(0.0143)	(0.0143)	(0.0142)
Sigma	0.7101**	0.7147**	0.7137**	0.7079**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummy	Y	Y	Y	Y
School FE	Y	Y	Y	Y
N	45,611	45,611	45,611	45,611

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

Table 2.8: Achievement Results - Summary

Variable	IDEG	DENS	SPI	BONA
		Excluding School Fixed Effects		
Coefficient	0.0473**	0.4660**	0.3673**	0.1787**
	(0.0018)	(0.0298)	(0.0329)	(0.0060)
Std. Dev. Increase	0.0911	0.0631	0.0389	0.1051
		Including School Fixed Effects		
Coefficient	0.0436**	0.2342**	0.3901**	0.1745**
	(0.0018)	(0.0448)	(0.0321)	(0.0058)
Std. Dev. Change	0.0840	0.0317	0.0413	0.1026

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.

deviation increase in the popularity measure. The Individual In-degree and Bonacich Eigenvector Centrality measures have the largest effects regardless of school quality controls. The magnitude of these effects on academic achievement are similar to that of being female. The other two popularity measures have a smaller effect, similar to the effect of having a stay at home mom on academic achievement.

One test for the existence of endogeneity due to selection in the popularity indices is to examine the effect of instrumenting for individual popularity. Table 2.9 shows the results from estimating Equations 2.7 and 2.9. These results provide a first look at the possible impact of selection on the estimates of popularity.[31] It is evident that selection is likely a problem, since the popularity drop in magnitude, and become statistically significantly negative in three of the four cases.

Table 2.10 isolates the peer effect coefficients from Tables 2.7 and 2.9 and displays the effect of a one standard deviation increase in the popularity measures. It is clear from these estimates that the baseline coefficients are biased due to endogeneity. The positive effect from a one standard deviation increase of three of the four measures

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

Table 2.9: Achievement Results - Instrumental Variable Results Effects

Variable	IDEG	DENS	SPI	BONA
Constant	2.5970**	2.6264**	2.1937**	2.6100**
	(0.0821)	(0.1112)	(0.0768)	(0.0890)
Popularity	-0.0753**	-0.4580**	3.2457**	-0.2426**
	(0.0296)	(0.2429)	(0.6821)	(0.1007)
Female	0.2248**	0.2347**	0.1705**	0.2070**
	(0.0171)	(0.0271)	(0.0080)	(0.0115)
White	0.0956**	0.0878**	0.0715**	0.1000**
	(0.0127)	(0.0119)	(0.0133)	(0.0133)
Black	-0.1704**	-0.1554**	-0.1071**	-0.1807**
	(0.0157)	(0.0127)	(0.0181)	(0.0180)
Asian	0.2814**	0.2653**	0.2404**	0.2809**
	(0.0185)	(0.0168)	(0.0189)	(0.0186)
Hispanic	-0.1647**	-0.1574**	-0.1454**	-0.1721**
	(0.0133)	(0.0127)	(0.0139)	(0.0143)
Mom Not Working	0.0278**	0.0386**	0.0435**	0.0277**
	(0.0110)	(0.0097)	(0.0104)	(0.0112)
Mom Some College	0.3017**	0.2783**	0.2520**	0.3045**
	(0.0121)	(0.0078)	(0.0102)	(0.0134)
Adopted	-0.1443**	-0.1268**	-0.1068**	-0.1456**
	(0.0230)	(0.0207)	(0.0225)	(0.0234)
Large Family	-0.0570**	-0.0461**	-0.0404**	-0.0591**
	(0.0103)	(0.0092)	(0.0101)	(0.0108)
Live with Bio Dad	0.1662**	0.1519**	0.1380**	0.1684**
	(0.0108)	(0.0087)	(0.0098)	(0.0115)
Foreign Born	0.0894**	0.1068**	0.1197**	0.0860**
	(0.0171)	(0.0145)	(0.0156)	(0.0181)
Sigma	0.7449**	0.7165**	0.7734**	0.7471**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummy	Y	Y	Y	Y
School FE	Y	Y	Y	Y
N	45,611	45,611	45,611	45,611

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

Table 2.10: Achievement Results - Summary

Variable	IDEG	DENS	SPI	BONA
		Baseline Model		
Popularity	0.0436**	0.2342**	0.3901**	0.1745**
	(0.0018)	(0.0448)	(0.0321)	(0.0058)
Std. Dev. Change	0.0840	0.0317	0.0413	0.1026
		Instrumental Variables		
Popularity	-0.0753**	-0.4580*	3.2457**	-0.2426**
	(0.0295)	(0.2420)	(0.6821)	(0.1007)
Std. Dev. Change	-0.1450	-0.0620	0.3434	-0.1426

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.

has turned negative, and in many cases increased in magnitude.

2.6.2 Joint Model

The instrumental variables results are indicative of the impact that omitted variables can have on the effect of popularity on academic achievement. There are two main advantages to using the simultaneous equations model. First, it provides a way to decompose the effect of unobserved heterogeneity into the individual and school level component. The effect of the school level component is included in the school fixed effect, while the effect of individual likeability is given by the parameter on unobserved type. Second using the joint model allows for the identification of the unobserved parameter from both the friendship nomination and academic achievement equations, leading to more precise estimates.

Table 2.11 shows the results from the achievement equation when unobserved heterogeneity is controlled using mixture distributions, and the friendship nomination and academic achievement regressions are estimated jointly. The inclusion of the type parameter turns the effect of the popularity index significantly negative in three of the four cases. Especially for the case of density, which Haynie (2001) indicated as an

Table 2.11: Achievement Results - Unobserved Heterogeneity Effects

Variable	IDEG	DENS	SPI	BONA
Constant	2.1038**	1.9930**	2.3096**	1.9660**
	(0.0154)	(0.0171)	(0.0228)	(0.0147)
Type	1.1834**	1.1954**	0.5454**	1.1929**
	(0.0032)	(0.0029)	(0.0045)	(0.0030)
Popularity	-0.0549**	-0.1429**	0.0655**	-0.0466**
	(0.0008)	(0.0188)	(0.0212)	(0.0025)
Female	0.1674**	0.1521**	0.1600**	0.1402**
	(0.0031)	(0.0035)	(0.0045)	(0.0029)
White	0.1523**	0.1134**	0.1653**	0.1235**
	(0.0053)	(0.0049)	(0.0078)	(0.0050)
Black	-0.0332**	-0.0649**	-0.0518**	-0.0590**
	(0.0062)	(0.0058)	(0.0091)	(0.0059)
Asian	0.2494**	0.2194**	0.2941**	0.2253**
	(0.0074)	(0.0070)	(0.0110)	(0.0071)
Hispanic	-0.1510**	-0.1303**	-0.1583**	-0.1363**
	(0.0056)	(0.0053)	(0.0083)	(0.0053)
Mom Not Working	0.0319**	0.0401**	0.0539**	0.0366**
	(0.0043)	(0.0040)	(0.0063)	(0.0041)
Mom Some College	0.2317**	0.2106**	0.2698**	0.2138**
	(0.0035)	(0.0033)	(0.0051)	(0.0033)
Adopted	-0.1056**	-0.0874**	-0.1001**	-0.0914**
	(0.0091)	(0.0086)	(0.0135)	(0.0087)
Large Family	-0.0317**	-0.0283**	-0.0350**	-0.0306**
	(0.0041)	(0.0038)	(0.0060)	(0.0039)
Live with Bio Dad	0.1180**	0.1089**	0.1301**	0.1101**
	(0.0039)	(0.0036)	(0.0057)	(0.0037)
Foreign Born	0.1144**	0.0744**	0.1448**	0.0876**
	(0.0064)	(0.0060)	(0.0094)	(0.0061)
Sigma	0.3144**	0.2987**	0.4680**	0.3020**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Missing Dummy	Y	Y	Y	Y
School FE	Y	Y	Y	Y
N	45,611	45,611	45,611	45,611

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

important measure of popularity, we see a very large drop in the magnitude, indicating that students in more dense networks have significantly lower academic achievement once we control for type. While the coefficient on the Spectral Popularity Index remains positive, its magnitude has been reduced to $1/6^{th}$ of its original size. The type parameter is positive, indicating that the high types perform better in school. In addition, including the type parameter leads to a significant increase in all of the race coefficients.[32]

Table 2.12: Achievement Results - Summary

Variable	IDEG	DENS	SPI	BONA
Excluding Unobserved Heterogeneity				
Coefficient	0.0436**	0.2342**	0.3901**	0.1745**
	(0.0018)	(0.0448)	(0.0321)	(0.0058)
Std. Dev. Change	0.0840	0.0317	0.0413	0.1026
Including Unobserved Heterogeneity				
Coefficient	-0.0549**	-0.1429**	0.0655**	-0.0466**
	(0.0008)	(0.0188)	(0.0212)	(0.0025)
Std. Dev. Increase	-0.1058	-0.0560	0.0028	-0.0321

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.

Comparing the results on popularity from Tables 2.7 where unobserved type is excluded and 2.11 where unobserved type is included, Table 2.12 shows the impact of a one standard deviation increase in the popularity measures. Not only have the signs switched for three of the four measures, in these measures the change in the magnitudes have also been significant. For example, the Individual In-Degree now has a negative effect on academic achievement, with the magnitude being even larger than prior to controlling for unobserved type.

[32]The standard errors for these results have not been adjusted for the noise from the first stage of the EM Algorithm. Preliminary analysis indicates that the adjusted standard errors are larger, but the coefficients all remain statistically significant at the 1% level.

Table 2.13: Friendship Formation Results - Baseline Models

Variable	**Baseline 1**	**Baseline 2**
Constant	-2.6073**	-2.6271**
	(0.0070)	(0.0069)
*Type*1		
$Female_i * Female_j$	0.2701**	0.2765**
	(0.0060)	(0.0060)
$White_i * White_j$	0.9507**	1.6574**
	(0.0070)	(0.0536)
$Black_i * Black_j$	0.9399**	2.9419**
	(0.0105)	(0.0512)
$Asian_i * Asian_j$	1.3602**	2.0772**
	(0.0198)	(0.0866)
$Col_i * Col_j$	0.4523**	0.9016**
	(0.0079)	(0.0222)
$HS_i * HS_j$	0.1831**	0.3360**
	(0.0085)	(0.0335)
$\%Black * Black_i * Black_j$		-5.4928**
		(0.2012)
$\%White * White_i * White_j$		-1.4837**
		(0.1613)
$\%Asian * Asian_i * Asian_j$		-0.0192
		0.4564
$\%Black^2 * Black_i * Black_j$		3.1321**
		0.1726
$\%White^2 * White_i * White_j$		0.7424**
		0.1174
$\%Asian^2 * Asian_i * Asian_j$		-2.9750**
		0.5093
$\%Col * Col_i * Col_j$		-0.8840**
		(0.0417)
$\%HS * HS_i * HS_j$		-0.3055**
		(0.0703)
N	72,081	72,081

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

The next set of results report the coefficients from the friendship nomination equations. The baseline results are given in Table 2.13.[33] ,[34] Column 1 shows the results from the first baseline regressions where unobserved type and school level variables are excluded. There is strong evidence for the theory of homophily from these results, as all coefficients are positive and highly significant. Preferences for matching on race are larger than those for matching on mother's education, with asians having the largest preference for matching on race. The negative constant term reflects the fixed cost associated with having friends.

Column 2 shows the results of including school characteristics in the baseline specification. For the race parameters this includes a linear term in the percentage of that race in the school, as well as a square term which allows for nonlinear preferences for matching with the friend on the percent minority. The preferences for matching on race changes significantly, with blacks having a much higher base preference for blacks than whites do for whites or asians do for asians. As the percentage of black students in the school increases, the preference of blacks for matching with other blacks falls at a decreasing rate. White students exhibit a similar pattern of preference, but the effects are quantitatively much smaller. Asian students' preference for matching on race falls at the fastest rate overall.

Table 2.14 shows the results of including the unobserved type parameter when the friendship formation and outcome equations are estimated simultaneously. The coefficient for Type 1 students is large, positive, and highly significant in all speci-

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[33]All of the explanatory variables (except for *Type 1*) are indicators for whether the individual matched with the friend on that particular measure: for example $Black_i * Black_j$ is a dummy variable which equals 1 if both the individual and friend are black.

[34]The standard errors in these equations were calculated using a numerical approximation of the Hessian matrix. They are not adjusted for the noise due to the first stage of the EM algorithm. Preliminary analysis indicates that the adjusted standard errors are larger, but the coefficients that were statistically significant remain significant.

Table 2.14: Friendship Formation - Unobserved Heterogeneity

Variable	IDEG	DENS	SPI	BONA
$Constant$	-3.2529**	-3.0646**	-3.7289**	-3.1177**
	(0.0085)	(0.0083)	(0.0093)	(0.0083)
$Type1$	1.0149**	0.6952**	1.7082**	0.7861**
	(0.0066)	(0.0065)	(0.0073)	(0.0065)
$Female_i * Female_j$	0.2574**	0.2639**	0.2373**	0.2619**
	(0.0061)	(0.0061)	(0.0063)	(0.0061)
$White_i * White_j$	1.7645**	1.7010**	1.8931**	1.7121**
	(0.0551)	(0.0541)	(0.0579)	(0.0544)
$Black_i * Black_j$	3.2169**	3.0845**	3.5595**	3.1249**
	(0.0532)	(0.0523)	(0.0560)	(0.0525)
$Asian_i * Asian_j$	2.0496**	2.0393**	2.1288**	2.0459**
	(0.0880)	(0.0871)	(0.0934)	(0.0873)
$Col_i * Col_j$	0.8524**	0.8826**	0.8963**	0.8591**
	(0.0228)	(0.0224)	(0.0237)	(0.0225)
$HS_i * HS_j$	0.3335**	0.3255**	0.3666**	0.3282**
	(0.0342)	(0.0338)	(0.0356)	(0.0339)
$\%Black * Black_i * Black_j$	-5.9903**	-5.7169**	-6.5133**	-5.8167**
	(0.2079)	(0.2045)	(0.2181)	(0.2054)
$\%White * White_i * White_j$	-1.6163**	-1.5242**	-1.5391**	-1.5276**
	(0.1654)	(0.1628)	(0.1732)	(0.1636)
$\%Asian * Asian_i * Asian_j$	0.2737	0.1438	1.0052**	0.1558
	(0.4638)	(0.4591)	(0.4904)	(0.4601)
$\%Black^2 * Black_i * Black_j$	3.3971**	3.2277**	3.5773**	3.2989**
	(0.1778)	(0.1751)	(0.1863)	(0.1758)
$\%White^2 * White_i * White_j$	0.7519**	0.7281**	0.5386**	0.7163**
	(0.1202)	(0.1184)	(0.1255)	(0.1190)
$\%Asian^2 * Asian_i * Asian_j$	-3.3501**	-3.1684**	-4.3819**	-3.1937**
	(0.5179)	(0.5128)	(0.5454)	(0.5139)
$\%Col * Col_i * Col_j$	-0.8410**	-0.8990**	-0.8466**	-0.8518**
	(0.0428)	(0.0421)	(0.0442)	(0.0424)
$\%HS * HS_i * HS_j$	-0.24515**	-0.24563**	-0.34009**	-0.24582**
	(0.0719)	(0.0710)	(0.0747)	(0.0712)
N	72,081	72,081	72,081	72,081

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

fications, implying that unobserved likeability plays a major role in the whether an individual is nominated as a friend. The baseline preference for race rises, and the interaction term on race is more negative in all specifications. The coefficients on the demographic characteristics and unobserved type are similar in magnitude regardless of the popularity index used, indicating that the unobserved effect captured by type does not vary across specifications of popularity.

2.6.3 Additional Outcomes

This section considers the effect of unobserved heterogeneity on other adolescent outcomes, including the attitude of the student as captured by whether they feel close to the school and whether they were mostly happy in the week prior to the survey, and information on earnings from Wave 3 of the survey. Table 2.15 shows the results from excluding unobserved heterogeneity in the first part of each panel, and including it in the second part, isolating the peer effect coefficient in each case. In the first two panels, all indices of popularity influence the *Close to School* and *Happy* outcome measures positively. Additionally, there is no significant change in the size of the parameters once the unobserved type measure is included. Being popular in school has a significant positive effect on whether the student feels close to the school and the student's general mental well-being, regardless of controls for unobserved characteristics. The type parameter is positive and significant in all specifications, indicating that high type students have a more positive attitude.

The third panel of Table 2.15 shows the results of the effect of popularity on future earnings. Academic achievement was included on the right hand side as a regressor in these equations to control for student ability. The results are significant for two of the popularity measures, although none of the coefficients change in magnitude with controls for unobserved characteristics. In the case of earnings, this evidence supports the idea that high school popularity is an indicator for social skills which translate to higher earnings, and these results are not affected by omitted individual unobservables.

Table 2.15: Attitudes and Income Results - Summary

Variable	IDEG	DENS	SPI	BONA
Panel (a) - Close to School				
Excluding Unobserved Heterogeneity				
Coefficient	0.0261**	0.2814**	0.1659**	0.0987**
	(0.0016)	(0.0393)	(0.0267)	(0.0050)
Including Unobserved Heterogeneity				
Coefficient	0.0226**	0.2616**	0.1518**	0.0922**
	(0.0017)	(0.0393)	(0.0267)	(0.0052)
Type 1	0.0331**	0.0518**	0.0511**	0.0277**
	(0.0063)	(0.0059)	(0.0059)	(0.0061)
Panel (b) - Happy				
Excluding Unobserved Heterogeneity				
Coefficient	0.0107**	0.1585**	0.0414*	0.0437**
	(0.0014)	(0.0345)	(0.0234)	(0.0044)
Including Unobserved Heterogeneity				
Coefficient	0.0068**	0.1412**	0.0287	0.0353**
	(0.0015)	(0.0345)	(0.0234)	(0.0046)
Type 1	0.0378**	0.0454**	0.0458**	0.0360**
	(0.0056)	(0.0052)	(0.0052)	(0.0053)
Panel (c) - Earnings				
Excluding Unobserved Heterogeneity				
Coefficient	0.3385*	10.5157	0.9975	1.3739**
	(0.1784)	(6.3450)	(2.1633)	(0.4916)
Including Unobserved Heterogeneity				
Coefficient	0.3458*	10.5685	1.1016	1.4394**
	(0.1952)	(6.3482)	(2.1649)	(0.5068)
Type 1	-0.0070	-0.0021	-0.1747	-0.3915
	(0.0076)	(0.0072)	(0.7162)	(0.7336)

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

2.7 Policy Simulations

Since the passing of *Brown v. Board of Education* by the Supreme Court in 1954, school integration has been contentious policy enacted by state and local governments. The broad goals of these policies have been to improve academic achievement and social mobility of disadvantaged students and to foster interracial interactions and social cohesion. Using the results from the joint model it is possible to test whether a redistribution policy achieves these goals by examining the change in the predicted number of friendship nominations and predicted grade distribution within the school before and after any policy.

On June 28, 2007 the Supreme Court struck down the use of race as a sole factor in reassigning students to schools with its decision on *Parents Involved in Community Schools v. Seattle School District* and *Meredith v. Jefferson County Board of Education*. The Seattle and Jefferson school districts attempted to maintain school-by-school diversity by limiting transfers across schools by race or using race as a "tiebreaker" in admissions. An alternative to these raced-based integration plans has been used in Wake County, North Carolina and San Francisco, California where integration has instead been based on the socioeconomic status of students as measured by participation in free or reduced price lunch programs.

The policy simulations in this section consider the effect of redistributing students in two sample schools based on these two types of policies. The first policy will reassign students to schools such that the mean percent white is equal across the two schools, keeping the number of students within schools constant before and after the policy. This will be referred to as the race-based reassignment plan. The second policy will use the percent of students whose mothers are college educated as a proxy for socioeconomic status and reassign students such that this percentage is equal across the two schools. This is the income-based reassignment policy.

The two schools for the simulation were chosen to fit a number of criteria. First, they were selected because they draw students from the same geographic area and therefore reassignment would be feasible.[35] Another consideration for the choice of the schools was the existence of a difference in the two policy variables. It was necessary to find two schools whose racial and income composition would change after the redistribution plans.

Table 2.16 displays the summary statistics for the two schools used in the policy simulations. School 1 contains fewer students and is predominantly non-white Hispanic with $1/5th$ of students whose mothers are college educated. School 2 is a large high school with mostly white students and a high proportion of mothers who attended college. Both schools teach grades 9-12 which implies that after the policy simulation the friendships can be recalculated within the grade. The correlation between the student being white and having a college educated mother is 0.2236. This indicates that the two redistribution policies can be considered separately because they do not result in the same set of students being moved between the two schools. By calculating the mean of the policy objectives the race-based redistribution plan the policy assigns students such that 62.47% are white in both schools, and for the income-based plan 44.9% students have college educated mothers in both schools.

The policy simulations are conducted based on the following steps. First, students are reassigned to a school based on one of the redistribution policies mentioned above, keeping the number of students who attend both schools the same. Next, the type parameter is drawn based on the conditional probability of the students being a high type. Each students is assigned a random choice set, and the coefficients from

[35]Because school identities and location are restricted for privacy reasons, student addresses were used to choose the two schools. For the sub-sample of students whose address information was available from the in-home survey the schools were chosen such that they both attract students who live in the same neighborhood

Table 2.16: Sample School Characteristics

Variable	School 1	School 2
% Female	0.4660	0.5113
% White	0.2310	0.8577
% Black	0.1644	0.0675
% Asian	0.0462	0.0362
% Hispanic	0.6182	0.0378
% Mom Col	0.2147	0.5876
School Size	736	1,244
Grades Taught	9-12	9-12

the friendship nomination equation are used to predict the friendships that form given the new composition of the schools. Based on the friendships the popularity of each student is calculated, where the Individual In-degree is used as the measure of popularity. Finally, based on the predicted popularity and the coefficients from the academic achievement equation the grade point average of the students is predicted.[36] This procedure is repeated until a sufficient number of simulations have been achieved.

The results from the policy simulations are presented in Tables 2.17 and 2.18. The first table displays the means and standard deviations of the predicted number of friendships in the two schools prior to any policy and after both of the policies are implemented. Focusing first on prior to the policies, we see in the first two columns of the table that students in School 2 list more friends than students in School 1, and this trend continues for most breakdowns of the sample by demographics. Whites in both schools list more friends than non-whites, and students with college educated mothers list more friends than those with no college.

In comparing the predicted number of friendships before and after either of the

[36]The school fixed effects are dropped from the simulations both prior to and after the policies are implemented. The changes in the grade distribution can therefore be interpreted as coming from changes in the popularity measure and not as a result of changing schools.

Table 2.17: Policy Simulation Results - Predicted Number of Friends

	Prior to Policy		Race-Based Policy		Income-Based Policy	
Sample	**School 1**	**School 2**	**School 1**	**School 2**	**School 1**	**School 2**
All Students	**1.4164**	**1.8403**	**0.7134**	**0.7240**	**0.5806**	**0.8818**
	(0.7219)	(0.5988)	(0.9310)	(0.9495)	(0.8606)	(1.0509)
	736	*1,244*	*736*	*1,244*	*736*	*1,244*
Whites	**1.8200**	**1.9117**	**0.9398**	**0.9516**	**0.8520**	**1.0914**
	(0.5834)	(0.5390)	(1.0144)	(1.0350)	(0.9936)	(1.1081)
	170	*1,067*	*462*	*775*	*344*	*893*
No Col	**1.7604**	**1.9946**	**0.7489**	**0.6964**	**0.6527**	**0.8546**
	(0.5443)	(0.5484)	(0.8868)	(0.8715)	(0.8415)	(0.9533)
	134	*441*	*232*	*343*	*141*	*434*
Col	**2.0417**	**1.8534**	**1.1317**	**1.1547**	**0.9899**	**1.3156**
	(0.6729)	(0.5249)	(1.0954)	(1.1074)	(1.0650)	(1.1944)
	36	*626*	*231*	*431*	*203*	*459*
Non-whites	**1.2953**	**1.4096**	**0.3313**	**0.3482**	**0.3427**	**0.3481**
	(0.7159)	(0.7453)	(0.6003)	(0.6279)	(0.6352)	(0.6271)
	566	*177*	*274*	*469*	*392*	*351*
No Col	**1.1761**	**1.3653**	**0.2712**	**0.2601**	**0.2605**	**0.2757**
	(0.6225)	(0.6977)	(0.5319)	(0.5228)	(0.5393)	(0.5350)
	444	*72*	*200*	*316*	*270*	*246*
Col	**1.7287**	**1.4400**	**0.4948**	**0.5295**	**0.5238**	**0.5186**
	(0.8561)	(0.7780)	(0.7314)	(0.7710)	(0.7774)	(0.7774)
	122	*105*	*74*	*153*	*122*	*105*

Note: Table reports mean of distribution and standard deviation in parentheses. Number in italics is actual sample size prior to the policy and mean sample size post policy.

Table 2.18: Policy Simulation Results - Predicted Grade Point Average

Sample	Prior to Policy		Race-Based Policy		Income-Based Policy	
	School 1	School 2	School 1	School 2	School 1	School 2
All Students	**2.6295**	**2.8590**	**2.9475**	**2.9755**	**2.9149**	**2.9856**
	(0.6561)	(0.6061)	(0.6405)	(0.6441)	(0.6380)	(0.6462)
Whites	**2.8583**	**2.8735**	**3.0262**	**3.0555**	**3.0373**	**3.0425**
	(0.6471)	(0.6094)	(0.6373)	(0.6383)	(0.6381)	(0.6391)
No Col	**2.8489**	**2.8551**	**2.8294**	**2.8316**	**2.7991**	**2.8415**
	(0.6467)	(0.6240)	(0.6127)	(0.6134)	(0.6076)	(0.6167)
Col	**2.8932**	**2.8865**	**3.2241**	**3.2335**	**3.2021**	**3.2328**
	(0.6591)	(0.5991)	(0.5992)	(0.6006)	(0.6060)	(0.6007)
Non-whites	**2.5608**	**2.7712**	**2.8146**	**2.8434**	**2.8077**	**2.8408**
	(0.6436)	(0.5797)	(0.6237)	(0.6317)	(0.6184)	(0.6417)
No Col	**2.5111**	**2.7802**	**2.7524**	**2.7586**	**2.7427**	**2.7535**
	(0.6363)	(0.6130)	(0.6110)	(0.6087)	(0.6047)	(0.6162)
Col	**2.7419**	**2.7650**	**2.9841**	**3.0180**	**2.9508**	**3.0461**
	(0.6398)	(0.5587)	(0.6265)	(0.6425)	(0.6242)	(0.6537)

Note: Table reports mean of distribution and standard deviation in parentheses.

policies we see that the number of friendships have declined significantly in both cases for the entire sample. The race-based policy resulted in the predicted friendship distribution equalizing across schools, whereas the income-based policy resulted in students in School 2 still listing more friends, similar to the results from prior to any policy. Whites in both schools after both policies still list more students as friends, and students with college educated mothers are also listing more friends in both schools after both policies.

The drop in the number of friendships listed can be explained by the school composition variables appearing in the friendship nomination equation. As we saw in Table 2.14, while students have a preference for matching with others on both race and education of parents, the size of the coefficient on the interaction of race with the school composition variables is much larger. As a result of the policy not only do the persons in the choice set of the student change but so does the school composition, leading to a drop in the number of friendships.

The predicted grade distributions are summarized in Table 2.18. From the first two columns it is evident that students in School 2 have higher grades on average than students in School 1. This difference is primarily driven by the difference in grades of non-whites in both schools, and specifically by the difference in the grades of non-white students whose mothers did not attend college. After both of the policies we see that the mean grade point average increases for all students. This increase comes from all of the demographic groups, with non-whites having higher GPA's in both education samples for both policies.

2.8 Conclusions

This chapter has provided evidence on the robustness of previous measures of the relationship between popularity and academic outcomes. The Add Health dataset was used to reconstruct social networks in schools and calculate various indices of network centrality used in previous work. Two methodologies control for unobserved characteristics, with the instrumenting strategy capturing school level unobserved characteristics such as matching on demographics with others in the grade, and the joint model controlling for individual level unobservables using mixture distributions. The results indicate that in the baseline regression popularity has a significant positive effect on academic achievement, similar to the results in previous work. Both methods of controlling for unobservables result in a drop in the coefficients on popularity, with three of the four specifications now having significantly negative coefficients.

From the policy simulations it is evident that both race-based and income-based redistribution can achieve the goals of improving the academic performance of students. However, much of this is driven by a fall in the number of friendships students form after a redistribution policy. If improving social cohesion is a secondary goal of redistribution policies, given the preferences that students have for matching with others on observable characteristics these goals may not be reached.

The results from including student attitudes and future earnings further indicate that there are tradeoffs to consider when designing a student redistribution policy. Sending students to schools where they are different from the school population implies an increase in academic scores if these students are not chosen as friends. However, these students may feel less secure in their school environment, and may also fail to acquire social capital which can lead to better jobs and higher earnings in the future. These effects should be considered in their entirety when policy decisions are being made.

Appendix A

Peer Effects of Actual Peers

A.1 Probit Results

Table A.1: Peer Effect Regression Results using probit: Smoking

	School Level	Grade Level	Friend Level
Peer Smoking	0.5407**	0.4866**	0.3320**
	(0.0480)	(0.0401)	(0.0120)
Demographic Controls	YES	YES	YES
Missing Dummies	YES	YES	YES
School Fixed Effect	NO	NO	NO
School/Grade Fixed Effect	NO	NO	NO
N	11,581	11,577	11,971
Peer Smoking		0.2042**	0.3386**
		(0.0671)	(0.0128)
Demographic Controls		YES	YES
Missing Dummies		YES	YES
School Fixed Effect		YES	YES
School/Grade Fixed Effect		NO	NO
N		11,284	11,284
Peer Smoking			0.3340**
			(0.0130)
Demographic Controls			YES
Missing Dummies			YES
School Fixed Effect			NO
School/Grade Fixed Effect			YES
N			10,985

Table A.2: Peer Effect Regression Results using probit: Drinking

	School Level	Grade Level	Friend Level
Peer Drinking	0.5888**	0.5125**	0.3037**
	(0.0547)	(0.0456)	(0.0127)
Demographic Controls	YES	YES	YES
Missing Dummies	YES	YES	YES
School Fixed Effect	NO	NO	NO
School/Grade Fixed Effect	NO	NO	NO
N	11,558	11,554	11,968
Peer Drinking		0.1237	0.2979**
		(0.0753)	(0.0137)
Demographic Controls		YES	YES
Missing Dummies		YES	YES
School Fixed Effect		YES	YES
School/Grade Fixed Effect		NO	NO
N		11,195	11,195
Peer Drinking			0.2881**
			(0.0139)
Demographic Controls			YES
Missing Dummies			YES
School Fixed Effect			NO
School/Grade Fixed Effect			YES
N			10,109

Appendix B

Too Popular for School? Friendship Formation and Academic Achievement

B.1 Missing Friendships

Table B.1: Number of Missing Friendships By Type

Number	1	2	3
0	76.03%	92.86%	88.62%
1	12.54%	4.21%	7.36%
2	5.85%	1.57%	2.10%
3	2.96%	0.79%	0.99%
4	1.42%	0.30%	0.48%
5	1.21%	0.27%	0.47%

Column 1: Friend listed is not in own or feeder school

Column 2: Friend listed is unknown student in feeder school

Column 3: Friend listed is unknown student in own school

B.2 Specification tests

Table B.2: IV Specification Tests

	IDEG	DENS	SPI	BONA
Endogeneity				
Hausman Test (residual)	0.1191	0.7462	-2.9479	0.4385
p-value	0.0000	0.0020	0.0000	0.0000
Instrument Relevance				
F Statistic	23.91	164.18	12.89	20.95
p-value	0.0000	0.0000	0.0000	0.0000
Overidentifying Restrictions				
Hansen J Statistic	56.22	64.76	33.54	56.22
$\chi^2(7)$ p-value	0.0000	0.0000	0.0000	0.0000

Bibliography

Akerlof, G. A., and R. Kranton (2005): "Identity and the Economics of Organizations," *Journal of Economic Perspectives*, 19(1), 9–32.

Antecol, H., and D. A. Cobb-Clark (2004): "Identity and Racial Harassment," IZA Discussion Paper, No. 1149.

Arcidiacono, P. (2005): "Affirmative Action in Higher Education: How Do Admission and Financial Aid Rules Affect Future Earnings?," *Econometrica*, 73(5), 1477–1524.

Arcidiacono, P., G. Foster, N. Goodpaster, and J. Kinsler (2005): "Estimating Spillovers in the Classroom with Panel Data," Working Paper, Duke University.

Arcidiacono, P., and J. B. Jones (2003): "Finite Mixture Distribution, Sequential Likelihood, and the EM Algorithm," *Econometrica*, 71(3), 933–946.

Arcidiacono, P., and S. Nicholson (2001): "Peer Effects in Medical School," *Journal of Public Economics*, 89(2-3), 327–350.

Austen-Smith, D., and R. Fryer (2005): "An Economic Analysis of 'Acting White'," *Quarterly Journal of Economics*, 120(2), 551–583.

Betts, J. R., and D. Morrell (1999): "The Determinants of Undergraduate Grade Point Average: The Relative Importance of Family Background, High School Resources and Peer Group Effects," *Journal of Human Resources*, 34(2), 268–293.

Bonacich, P. (1972): "Factoring and Weighting approaches to status scores and clique identification," *Journal of Mathematical Sociology*, 2, 113–120.

——— (1991): "Simultaneous group and individual centralities," *Social Networks*, 13(2), 155–168.

Borgatti, S., and M. Everett (2006): "A Graph-theoretic Perspective on Centrality," *Social Networks*, 28(4), 466–484.

Bramoullé, Y., and R. Kranton (2007): "Public Goods in Networks," *Journal of Economic Theory*, 135(1), 478–494.

Brock, W., and S. Durlauf (2001a): "Discrete Choice with Social Interactions," *Review of Economic Studies*, 68, 235–260.

——— (2001b): "Interactions-Based Models," in *Handbook of Econometrics*, ed. by J. J. Heckman, and E. E. Leamer, vol. 5, chap. 54, pp. 3297–3380. Elsevier Science.

Cairns, R. B., B. D. Cairns, H. J. Neckerma, S. D. Gest, and J.-L. Gariepy (1988): "Social Networks and Aggressive Behavior: Peer Support or Peer Rejection," *Developmental Psychology*, 24(6), 815–823.

Calvo-Armengol, A., and M. O. Jackson (2004): "The Effect of Social Networks on Employment and Inequality," *American Economic Review*, 94, 426–454.

Calvo-Armengol, A., E. Patacchini, and Y. Zenou (2005): "Peer Effects and Social Networks in Education," Mimeo, Universitat Autonoma de Barcelona.

Cameron, S. V., and J. J. Heckman (1998): "Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males," *Journal of Political Economy*, 106(2), 262–333.

Chantala, K. (2003): *Introduction to Analysing Add Health Data*Carolina Population Center, http://www.cpc.unc.edu/projects/addhealth/files/analyze.pdf.

Echenique, F., and R. Fryer (2005): "On the Measurement of Segregation," NBER Working Paper No. 11258.

Eckstein, Z., and K. Wolpin (1999): "Why Youth Drop Out of High School: The Impact of Preferences, Opportunities and Abilities," *Econometrica*, 67(6), 1295–1339.

Epple, D., and R. Romano (1998): "Competition Between Private and Public Schools, Vouchers and Peer-Group Effects," *American Economic Review*, 88(1), 33–62.

Evans, W. N., W. E. Oates, and R. M. Schwab (1992): "Measuring Peer Group Effects: A Study of Teenage Behavior," *Journal of Political Economy*, 100(5), 966–991.

Foster, G. (2005): "Making Friends: A Non-Experimental Analysis of Social Group Formation," *Human Relations*, 58, 1443–1465.

Fryer, R., and M. O. Jackson (2007): "A Categorical Model of Cognition and Biased Decision Making," forthcoming, Contributions in Theoretical Economics, B.E.Press.

Fryer, R., and P. Torelli (2005): "An Empirical Analysis of Acting White," NBER Working Paper No. 11334.

Gaviria, A., and S. Raphael (2001): "School-Based Peer Effects and Juvenile Behavior," *Review of Economics and Statistics*, 83(2), 257–268.

Glaeser, E. L. (1996): "Discussion to 'Spatial Effects upon Employment Outcomes: The case of New Jersey Teenagers' by O'Reagan, K., and J. Quigley," *New England Economic Review: Federal Reserve Bank of Boston*, pp. 58–64.

Hajivassiliou, V. A., and P. A. Ruud (1994): "Classical Estimation Methods for LDV Models Using Simulation," in *Handbook of Econometrics*, ed. by R. Engle, and D. McFadden, chap. 40, pp. 2384–2441. Elsevier Science, Volume 4.

Hanushek, E. A., J. F. Kain, J. M. Markman, and S. G. Rivkin (2003): "Does Peer Ability Affect Student Achievement," *Journal of Applied Econometrics*, 18, 527–544.

Haynie, D. (2001): "Delinquenct Peers Revisited: Does Network Structure Matter?," *American Journal of Sociology*, 106(4), 1013–1057.

Haynie, D., and D. Payne (2006): "Race, Friendship Networks and Violen Delinquency," *Criminology*, 44(4), 775–805.

Hoxby, C. (2000): "Peer Effects in the Classroom: Learning from Gender and Race Variation," *NBER Working Paper 7867*.

Ioannides, Y., and L. D. Loury (2004): "Job Information Networks, Neighborhood Effects, and Inequality," *Journal of Economic Literature*, 42(4), 1056–1093.

Jackson, M. O. (2006): "The Economics of Social Networks," in *Advances in Economics and Econometrics, Theory and Applications: Ninth World Congress of the Econometric Society*, ed. by R. B. W. Newey, and T. Persson, vol. 1, chap. 1. Cambridge University Press.

Joyner, K., and G. Kao (2001): "School Racial Composition and Adolescent Racial Homophily," *Social Science Quarterly*, 81(3), 810–825.

Keane, M., and K. Wolpin (1997): "The Career Decisions of Young Men," *Journal of Political Economy*, 105(3), 473–522.

Kinsler, J. (2006): "Suspending the Right to an Education or Preserving It: A Dynamic Equilibrium Model of Student Behavior, Achievement and Suspension," *Dissertation*.

Krauth, B. (2006): "Simulation-Based Estimation of Peer Effects," *Journal of Econometrics*, 133, 243–271.

Manski, C. F. (1993): "Identification of Endogeneous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60(3), 531–542.

Marmaros, D., and B. Sacerdote (2003): "How Friendships Form," Working Paper, Dartmouth College.

Mayer, A., and S. Puller (2007): "The Old Boy (and Girl) Network: Social Network Formation on University Campuses," *Journal of Public Economics*, forthcoming.

Mihaly, K. (2007): "Peer Effects of Actual Peers," Duke University.

Miller McPherson, L. S.-L., and J. M. Cook (2001): "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology*, 27, 415–444.

Moffitt, R. (2001): "Policy Interventions, Low-Level Equilibria, and Social Interactions," in *Social Dynamics*, ed. by S. Durlauf, and P. Young. MIT Press.

Montemayor, R. (1982): "The Relationship between Parent-Adolescent Conflict and the Amount of Time Adolescents Spend Alone and with Parents and Peers," *Child Development*, 53(6), 1512–1519.

Moody, J. (2001): "Race, School Integration, and Friendship Segregation in America," *American Journal of Sociology*, 107(3), 679–716.

Parsons, G. R., and B. A. Hauber (1996): "Choice Set Boundaries in a Random Utility Model of Recreation Demand," University of Delaware, Department of Economics, Working Paper 96/3.

Quillian, L., and M. E. Campbel (2003): "Beyond Black and White: The Present and Future of Multiracial Friendship Segregation," *American Sociological Review*, 68(4), 540–566.

Sacerdote, B. (2001): "Peer Effects with Random Assignment: Results for Dartmouth Roommates," *The Quarterly Journal of Economics*, 116(2), 681–704.

Swait, J., and M. Ben-Akiva (1987): "Incorporating Random Constraints in Discrete Choice Models of Choice Set Generation," *Transportation Research*, 2, 91–102.

Vigdor, J., and T. Nechyba (2004): "Peer Effects in North Carolina Public School," Duke University and NBER.

Wasserman, S., and K. Faust (1994): *Social Network Analysis: Methods and Applications*. Cambridge University Press.

Weinberg, B. (2006): "Social Interactions and Endogenous Associations," NBER Working Paper No. 13038.

Zimmerman, D. J. (2003): "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment," *Review of Economics and Statistics*, 85(1), 9–23.

Biography

I was born on June 10, 1979 in Budapest, Hungary. After completing three years of elementary school I moved to the United States with my parents and sister. I graduated from Ward Melville High School in East Setauket, New York in 1997, and went on to college at Cornell University in Ithaca, New York. I obtained my Bachelor of Science degree in Policy Analysis and Management from the College of Human Ecology at Cornell. While there I participated in varsity sports by joining the fencing team, and was recognized for my academic and athletic achievement with a 400 Club award.

Upon completing my degree in 2001, I moved to Washington, DC, and worked at the Federal Trade Commission for two years as a Research Analyst in the Consumer Protection Division of the Bureau of Economics. In 2003 I came to Duke University to complete a Ph.D. in Economics. I received a full scholarship upon entry, and while here I also received the Shauna Saunders Memorial Fellowship and the PARISS Fellowship.